A CNN Based Reference Comparison Method for Classifying Bare PCB Defects

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Abstract

Printed Circuit Board (PCB) inspection is an essential part of PCB production process. Traditional PCB bare board defect detection methods have their own defects. However, the PCB bare board defect detection method based on Automatic Optic Inspection (AOI) is a feasible and effective method, and it is having more and more application in industry. Based on the idea of the reference comparison method, this paper aims at studying the classification of defects. First of all, the method of extracting defect areas using morphology is studied, meanwhile, a data set containing 1818 images with 6 different detailed defect area image parts are produced. Then, in order to classify defects accurately, a traditional classification algorithm based on digital image processing was attempted, and a defect classification algorithm based on convolutional neural network (CNN) was proposed. After experimental demonstration, in the actual results, the defect classification algorithm based on convolutional neural network can achieve a fairly high classification accuracy (95.7%), which is much higher than the traditional method, and the new method has stronger stability than the traditional one.

Keywords: PCB Inspection, Image Processing, Morphological Processing, Convolutional Neural Network

1 Introduction

The Printed Circuit Board (PCB) is the basic structural unit of various contemporary electronic products. The advantage of using a printed circuit board is that it can greatly reduce the likelihood of errors in the wiring and assembly process. Meanwhile, saving considerable space and increasing industrial automation productivity. With the improvement of production processes and the emergence of more and more new technologies in recent years, printed circuit board is also moving into the direction of more complex and more accurate. In the real PCB production process, the inspection of bare printed circuit board is an important task. The purpose is to find and classify defective circuit boards as soon as possible during the inspection process and remove them for processing. It will not only prevent them from entering the subsequent process and generate greater losses, but also save costs. However, traditional detection methods, including manual visual inspection, electrical testing, and X-ray methods all have their own shortcomings.

Automatic Optical Inspection (AOI) is a modern automated inspection technology based on machine vision [1]. Because of its advantages of non-contact and high-tech, it is widely used in PCB inspection industry [2]. The detection system is mainly composed of a camera, an image acquisition device, an image processing device and a motion control device. Automatic optical inspection technology can significantly improve detection efficiency and can also avoid the shortcoming of fatigue in artificial check. The flow chart of PCB inspection using AOI technology is shown in Figure 1.

Vision-based detection methods can be divided into three categories [3]: reference comparison, non-reference comparison, and hybrid comparison. The reference comparison method is to compare the image to be detected with the template image to obtain a defect area. The advantage is that it is intuitive and easy to understand. The disadvantage is that it requires high alignment accuracy and is sensitive to the light environment of the photographing process. The non-reference comparison method is to check whether the traces and layout of the circuit board to be tested are reasonable according to the design rules, but this method is easy to lose large defects and distortion characteristics. The hybrid comparison method takes into account both advantages, but it is difficult to implement and has a large amount of computational complexity.

Figure 1.The flow chart of PCB inspection using AOI

If the detected defect cannot be clearly identified and classified, there is no way to give more accurate information for the next step such as repair. Therefore, the study of defect classification is an important task in the defect detection process.

In this paper, based on the traditional reference comparison method, we propose a method based on the data set we created. This method uses a convolutional neural network for classification, and also proposes a method based on mathematical morphology to eliminate noise and artifacts.

In the second part, an overview of PCB inspection and classification work performed by others is shown. The third part describes the overall framework and methods we used, including the background introduction of convolutional neural networks. The experimental process is given in the fourth part, and in the fourth part, the results of the adopted method are compared and analyzed with the traditional methods. The conclusions and the prospects for the future work are shown in the last part five.

2 Related works

Wu WY [4] proposed a method of PCB template matching by subtracting the image to be detected from the template image, and then positioning and eliminating PCB defects on the residual image. Many people later proposed improved approaches for the algorithm. Ibrahim Z [5] proposed an efficient algorithm for automated visual inspection of PCB inspection systems that can automatically detect and locate any defects on the PCB. Using wavelet-based image difference algorithms to detect defects, excellent time performance demonstrates that second-order Haar wavelet transforms is suitable for the application of automated vision in PCB inspection. Rau H [6] used the defect outer boundary tracking method to separate each defect area and proposed a boundary state transfer method to classify defect types, finally achieved good results. Wang WC [7] has developed a machine vision based inspection system for PCBs. This system can evaluate multiple features of PCB openings and displays the results as bar and target maps. In addition, high-resolution photographs are used and the operation time is also excellently controlled. PC Chang [8] developed a case-based evolutionary identification model for PCB defect classification and proposed a two-phase method for splitting printed circuit board images. In Phase 1, PCB images with defects are retrieved and segmented into basic patterns for comparison with the conceptual space stored in the case library. Phase 2 is learning to capture new patterns in the concept space. The experimental results show that it is expected to identify four kinds of defects. As well as save time, the use of case library can also constantly be updated to meet actual demand. SHI Putera [9] combined the research done in [10] and [11] and introduced a hybrid algorithm to detect and classify defects on exposed single-layer PCBs. The project proposes a PCB defect detection and classification system that uses morphological image segmentation algorithms and simple image processing theory. Zhang Bo [12] pointed out that the existing defect visual inspection system has poor real-time performance and it is difficult to detect problems such as too narrow line width. Firstly, the defect image of PCB is compressed by wavelet transform to improve the real-time performance of the system. Then the wavelet edge detection algorithm is applied to the precise positioning of the defect edge. Finally extracting and identifying specific defects based on specific rules. Zhu Zhen-min [13] proposed a PCB solder joint quality detection method based on feature extraction and support vector machine (SVM) classification. Li Zheng-ming [14] solved the high cost and low efficiency of traditional PCB inspection methods by proposing an automatic optical inspection algorithm based on digital image processing, the number of connected areas, the calculation of Euler numbers and the area of defective areas were used to detect. The results prove that the accuracy is high and real-time requirements are achieved.

3 Methodology

3.1 Image processing

In the actual production conditions, shooting a printed circuit board image requires setting up a special light source and using a CCD camera. Due to the influence of the environment and the light source, the obtained photograph will almost always have problems such as insufficient contrast, many interference factors and uneven picture lighting. Therefore, the image processing method is first used to obtain the desired ideal PCB image to be detected.

- Image filtering

Median filtering is an effective and commonly used filtering algorithm for processing noise signals in a picture. It defines the gray value of each pixel as the median value of all other pixel points within a custom range of the point. The formula is defined as:

$$g(x,y)=med\{f(x-k,y-l),(k,l\in W)\} \quad (1)$$

$f(x,y)$ and $g(x,y)$ are the original image and the processed image, respectively. W is a 2D template, usually 3×3 or 5×5.

- Grayscale enhancement

In order to highlight the contrast between the region of interest and the background region in the displayed image, a grayscale transformation method is used to increase the grayscale dynamic range of the image. Grayscale conversion is also called image point calculation because the transform object is a certain point of the image. The transformation is as following:

$$s=T(r) \quad (2)$$

In this paper, a linear transformation is used. Let r be the gray level before the transformation and s be the gray level after the transformation. The function is defined as:

$$s=a\times r+b \quad (3)$$

Where a is the slope of the line and b is the intercept. Setting different a , b values will have different effects.

- Image threshold segmentation

According to the grayscale feature of the image, the image is divided into two parts, the background and the target, using the Otsu [15] method. Finding a threshold that maximizes the variance between the background and the target. If the image grayscale changes complexly and the detection area is within two ranges of light and dark, then a local adaptive threshold segmentation algorithm [16] is needed to divide the image to obtain multiple different thresholds for binary segmentation.

- Image matching

The purpose of image registration is to ensure the coincidence of the position of the standard image and the image to be detected. At the same time, it is a key step to determine the target defective regions. A matching algorithm based on the SURF feature [17] was used in this paper.

3.2 Defect detection

After getting matched standard images and images to be detected, execute the XOR operation:

$$Z=x\oplus y \quad (4)$$

The result of the operation may contain a lot of noise and other disturbances, as is shown in Figure2(a), which will cause a large number of statistical errors and false regions in Figure2(c). At this point, the morphological operation is used to process the XOR result image so that we can obtain the final defect image. The result is shown in Figure2(b) and Figure2(d).

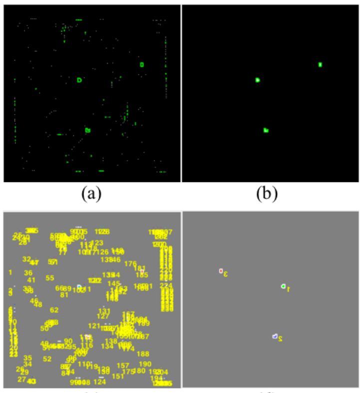


Figure 2. The effect of processing XOR images not using morphological and using morphological methods

3.3 Defect classification

3.3.1 Digital image processing method: In this paper, a total of seven common bare printed circuit board defects are summarized: short circuit, open circuit, burr, cavity, defect, missing hole, and pinhole. The schematic diagram of these seven types of defects is shown in Figure 3. The seven types of defects are classified according to the variations of the area of the binary image, the number of connected regions and the Euler number in the image to be detected and the standard image. The area of binary image, as the name suggests, refers to the area of the colored portion after binarization of the defect area. For example, when the short-circuit condition is compared with the normal condition, the area of the binary image will increase. However, in the case of an open circuit, the area of binary image will decrease. The number of connected fields refers to the number of colored connected components of the binary image of the defective region (the 4 connected regions are considered here in this work). In the case of a short circuit, the number of connected domains decreases, while in the case of open circuits, the number of connected domains increases. The Euler number refers to the usual spatial integrity measure, which is the measure of the number of voids in a hollow area. The Euler number formula for an image region is defined as:

$$E = C - H \tag{5}$$

C indicates the number of individually connected parts in the area, H indicates the number of holes in the area. It should be noted that Euler number may sometimes be unstable.

After theoretical derivation and experimental verification, each defect type and corresponding feature change rules are summarized in the following Table 1.

3.3.2 Convolutional neural network based method: Traditional machine learning methods extract the features in the data set and send them to the classifier for training. However, in some image engineering, it is difficult to obtain the ideal feature vector. Therefore, the deep learning method is needed. This

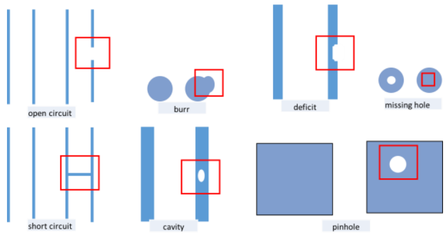


Figure 3. The schematic diagram of these seven types of defects

Table 1. Corresponding rules for defect classification ("+" for increase, "-" for decrease and "=" for constant)

Category	The area of the binary image	The number of connected areas	Euler number
Open Circuit	-	+	+
Short Circuit	+	-	-
Missing Hole	+	=	+
Pin Hole	-	=	-
Burr	+	=	=
Cavity	-	=	-
Deficit	-	=	=

paper uses a convolutional neural network to achieve High-precision classification.

The birth of CNN can be traced back to the 1960s. Hubel and Wiesel [18] discovered the unique network structure in the cat's brain and proposed a convolutional neural network. Today, excellent models such as AlexNet [19], VGGNet [20], Google Inception Net [21] and ResNet [22] have been developed. As shown in Figure 4, a basic CNN structure mainly consists of an input layer, a convolutional layer, a pooling layer (sampling layer) and a fully connected layer. There will also be corresponding functions between the layers to modify and organize the data.

- The input layer. the input image to be classified and identified is our input layer, which is read by the computer as a matrix.
- Convolutional layer. In the convolutional layer, one neuron only connects neurons of some adjacent layers and usually contains multiple feature maps. Typically, a convolutional layer contains multiple feature planes. Each feature plane is composed of several rectangular arranged shared weights. These shared weights are convolution kernels, which will be continuously updated during the training process.

An n*n convolution kernel performs a convolution operation on the input image in accordance with formula 2.20 which is defined as:

$$x_j^l = f\left(\sum_{i \in M_j} x_j^{l-1} * k_{ij}^l + b_j^l\right) \tag{6}$$

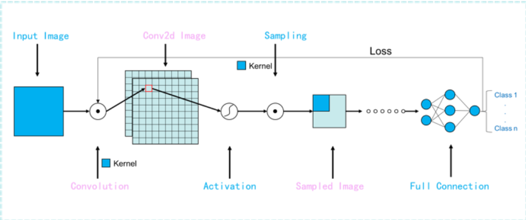


Figure 4. Basic CNN structure

The resulting convolution results will be the input of next layer.

- The activation layer. The activation function is used to improve the nonlinear characteristics of the model, making up for the shortcomings of the lack of linear computing expression. The network used in this article uses the *Relu* activation function. *Relu* is defined as:

$$Relu(x) = max(0, x) \tag{7}$$

- The pooling layer (sampling layer). Pooling layer usually has two pooling methods: maximum pooling and average pooling. It can be said that pooling is a simplified convolution.

If there is an n * n convolution kernel that convolves the input of the pooling layer, the formula is defined as follows:

$$x_j^l = f(W_{x+1} down(x_j^{l-1}) + b_{x+1}) \tag{8}$$

then the output image size will be 1 / n of the input image.

- The fully connected layer consists of a fully connected multi-layer perceptron classifier. After the forward propagation process reaches the full-connected layer, back-propagation will begin to update the weights and biases to reduce losses and improve the classification accuracy. The output layer will also have a softmax function (Equation defined as 9) to calculate the classification probability to determine the classification and cross-entropy loss function (Equation defined as 10) to calculate the Loss value:

$$y(x_i) = \frac{exp(x_i)}{\sum_{i=1}^{M}(exp(x_i))} \tag{9}$$

$$L = -\sum_{j=1}^{T} y_j \log S_j \tag{10}$$

4 Experimental setup and Analyses

This section describes the production of data sets used in experiments and related experimental parameters.

4.1 Datasets

The coordinate information of the suspected defect area located in the image is extracted, and the image in a certain area outside the corresponding coordinates in the grayscale image of the PCB to be detected is taken as new data. A total of 1,818 defects images were produced in 6 types of general bare printed circuit board defects (short circuit, open circuit, defects, burrs, pinholes, and missing holes). Then these six types of defects are divided into three parts: training set, verification set and test set, which are trained and used by the CNN model. The specific sizes and examples of the extracted data sets are shown in Table 2 and Figure 5.

Table 2. The specific sizes of the data set

Category	Open Circuit	Short Circuit	Deficit	Burr	Pin Hole	Missing Hole	Total
Train	168	189	221	130	180	181	1069
Val	35	39	74	63	59	53	323
Test	69	73	75	75	67	67	426

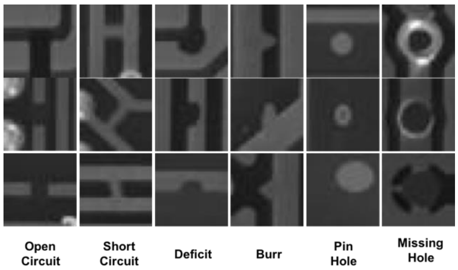


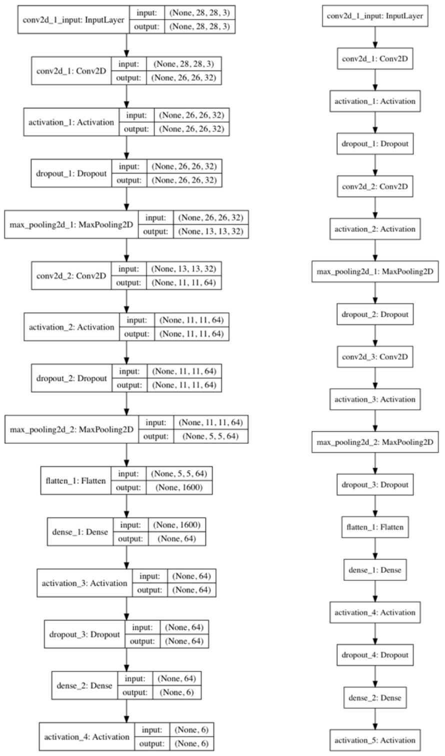
Figure 5. The examples of the extracted data sets

4.2 Training and testing process

The method based on the CNN deep learning model uses the uniformly resized image (with a resolution of 28*28) as the input of the classifier, builds different network structures, and sets different learning parameters to observe the training effect. First, Figure 6(a) shows a model consisting of 2 convolution layers, 2 pooling layers and 3 full connected layers model. 3 dropout functions have also been added, which can largely prevent training overfitting and improve training effects. The specific operation is to temporarily discard the neurons in the network with a certain probability during the training process. Then, a network model consists of 3 convolutional layers, 2 pooled layers and 3 fully connected layers is established, as shown in Figure 6(b). The convolution kernel in the first convolution layer is set to a size of 5*5, the number of convolution kernels is 16, and the convolution kernel size of the latter two layers is set to 3*3. The activation function selects ReLU, besides, the convolution kernel and step size of the pooling layer are both 2, and finally the softmax function is used to set 6 full-connection layer outputs. Then, the two network structures were iteratively trained 100 times, 300 times and 500 times to record the loss and accuracy values in the process. In addition to establishing our own network structure, this paper also uses the VGG16 and ResNet50 network model with pre-training weights as feature extractors. At this point, the size of the input photo needs to be converted to a resolution of 224 * 224. The weight of the network is trained from ImageNet, which is the largest database for image recognition. The full-connection layer of the VGG16 network and the ResNet50 network was changed to be suitable for the number of classifications in this paper, here we set as 6, and iterate 100 times for training. The training process uses the data of the training set and verification set, and the test process uses the data of the test set. The final model effect is based on the accuracy of the test set.

The network of our method is trained on a GTX 1080Ti GPU, and tested on Xeon E5-2600v4 3.4GHz CPU with 64G RAM.

And the deep learning framework we use is Keras.



(a) (b)

Figure 6. Two network structures we set up

4.3 Experimental results and analyses

After adopting two different defect classification algorithms, this part compares the experimental classification results, proves the superiority of our method and also carries out the evaluation of the experiment.

As shown in Figure 7, in the simple PCB to be inspected, the defective part can be identified and marked accurately so that the inspection personnel can find continue to the next step. However, in the case of non-uniform illumination and complicated circuit traces and color information, it is difficult for the traditional rule-based method to identify defects in the circuit board to be inspected and classify them correctly. As shown in Figure 8, 7/11 results are wrong, which is not ideal.

Table 3 illustrates the accuracy of the method based on CNN model with different structures and iterations in the test set. We can see that the best result on the test set reached 95.7%, which is a very satisfactory result. Figure 9 shows the loss and accuracy curves for the network in Figure 6(b) that produced the best result.

By observing the experimental results, we can find that the traditional detection method can have good detection results on simple data sets. However, in the much more complex new PCB image sets, despite the morphological and filtering processing methods used to treat the noise and errors in the XOR results, false positives are still prone to occur. The reason is that the conventional method operates with fewer pixels and requires high position accuracy to calculate the variation of the defect area corresponding index in the standard PCB and the

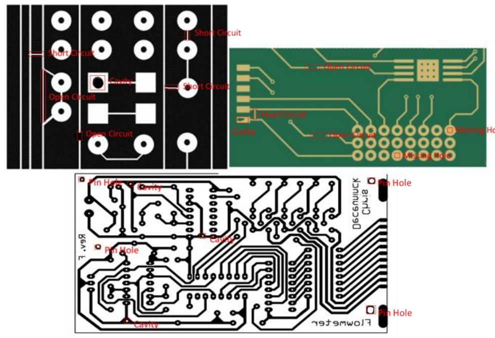


Figure 7. Classification results on simple PCBs using traditional method

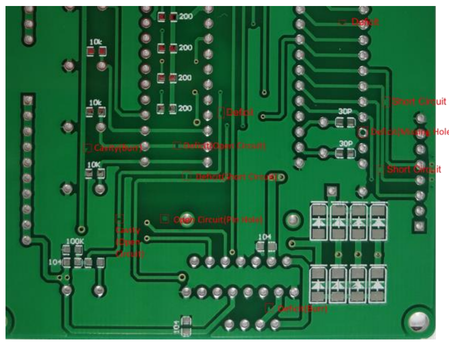


Figure 8. Classification results on complex PCBs using traditional method. Brackets indicate that the result in parentheses is true

PCB graph to be tested. Once the XOR result graph is processed improperly or the threshold segmentation is inaccurate, it is easy to have erroneous results.

We get the best result using our CNN based model. The network that we build by ourselves not only has high classification accuracy, but also needs not much time. Compared with the complex VGG16 and ResNet network architecture, the accuracy of our model is higher and the training time is shortened by several dozen. Because of the image scaling, the image is blurred and it is difficult to extract features for deep convolution network. Therefore, it can be proved that CNN-based defect classification method can effectively classify PCB defects. Compared with the traditional method, the stability of the algorithm has been greatly improved.

Table 3. The accuracy of different models

Method	Description	Epoch	Accuracy(%)
1	7 layers	300	93.1
2	7 layers	500	93.6
3	8 layers	300	95.7
4	VGG16	100	81.2
5	ResNet50	100	94.8

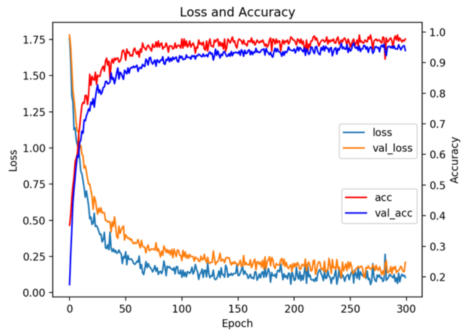


Figure 9. The loss and accuracy curves for the network in Figure 6(b) that produced the best result.

5 Conclusion and Future Work

In modern electronic devices, the PCB acts as a skeleton-like role, carrying circuit components and wire layouts. It can be said that the quality of the PCB determines the quality of electronic equipment. The improved PCB defect classification method based on defect data set proposed in this paper uses convolutional neural networks to train an effective model. Pre-steps include image pre-processing, image registration and positioning and extraction of defect areas. Traditional methods for classifying defects using precise pixel-level operations rely on human's experience to extract features from regions and classify using features they get. These methods have complex operations and limited classification accuracy. On the contrary, there is no such weakness in the classification method based on the convolutional neural network, and the experimental results also prove the effectiveness and reliability of the method in defect classification. Admittedly, our model is limited by the size and characteristics of the dataset and there are many deficiencies. In order to adapt to industrial production, it is necessary to train the model in advance which is a time-consuming task.

The AOI technology for PCB inspection is a complex technology that integrates computer, optoelectronic, machine vision and pattern recognition. It has a very wide industrial application value. This paper has done some research on PCB inspection technology and made some progress. However, the actual AOI detection system is complex in design, requires high design precision and a strong stability of the algorithm. Therefore, there is still much room for improvement, I think. In the future, we can further study the work in the following sections, improving the real-time performance of the algorithm, the accuracy of the preprocessing section, the types and accuracy of defect classification, and extending the method to other industries.

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References

[1] Tae-Hyoung Park and Hwa-Jung Kim, "Path planning of automatic optical inspection machines for PCB assembly systems," *2005 International Symposium on Computational Intelligence in Robotics and Automation*, 2005, pp. 249-254.

[2] Elias N. Malamas, Euripides G.M. Petrakis, Michalis. Zervakis, et al, "A survey on industrial vision systems, applications and tools," *Image and vision computing*, vol. 21, no. 2, pp. 171–188, 2003.

[3] Madhav Moganti, Fikret Ercal, Cihan H. Dagli, et al, "Automatic PCB inspection algorithms: a survey," *Computer vision and image understanding*, vol. 63, no. 2, pp. 287-313, 1996.

[4] Wen-Yen Wu, Mao-Jiun J. Wang, and Chih-Ming Liu, "Automated inspection of printed circuit boards through machine vision," *Computers in Industry*, vol. 28, no. 2, pp. 103–111, 1996.

[5] Z. Ibrahim, S. A. R. Al-Attas, Z. Aspar, et al, "Performance evaluation of wavelet-based PCB defect detection and localization algorithm," *Industrial Technology, 2002. IEEE ICIT '02. 2002 IEEE International Conference on*, 2002, pp. 226-231 vol.1.

[6] H. Rau and C. H. Wu, "Automatic optical inspection for detecting defects on printed circuit board inner layers," *International Journal of Advanced Manufacturing Technology*, vol. 25, no. 9–10, pp. 940–946, 2005.

[7] Wei-Chien Wang, Shang-Liang Chen, Liang-Bi Chen, et al, "A Machine Vision Based Automatic Optical Inspection System for Measuring Drilling Quality of Printed Circuit Boards," in IEEE *Access*, vol. 5, pp. 10817-10833, 2017.

[8] Pei-Chann Chang, Li-Yuan Chen, and Chin-Yuan Fan, "A case-based evolutionary model for defect classification of printed circuit board images," *Journal of Intelligent Manufacturing*, vol. 19, no. 2, pp. 203–214, 2008.

[9] S.H Indera Putera and Z. Ibrahim, "Printed circuit board defect detection using mathematical morphology and MATLAB image processing tools," *2010 2nd International Conference on Education Technology and Computer, Shanghai*, 2010, pp. V5-359-V5-363.

[10] R Heriansyah, SARSA Bakar, and M. Mun'im Ahmad Zabidi, "Segmentation of PCB Images into Simple Generic Patterns using Mathematical Morphology and Windowing Technique," *Universiti Teknologi, Malaysia*, 2002.

[11] Zuwairie Ibrahim and Noor Khafifah Khalid, "An image processing approach towards classification of defects on printed circuit board," *Journal of Neurochemistry*, vol. 60, no. 2, p. 768–771, 2007.

[12] Bo Zhang, Ruihua Li, Nian-Cai Peng, "The research of visual PCB defect inspection based of wavelet," *Journal of system simulation*, vol. 16, no. 8, pp. 1864-1866, 2004.

[13] Zhen-Min Zhu, Zhao-Kang Lv, Rui-Chao Song, et al, "PCB Solder Joint Quality Inspection Based on Machine Vision." *Control Engineering of China*, 2017.

[14] Zheng-Ming Li, Hong Li, Jun Sun, "Detection of PCB Based on Digital Image Processing," *Instrument Technique & Sensor*, vol. 61, no. 8, pp. 87-89, 2012.

[15] Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histograms," in *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66, Jan. 1979.

[16] Ety Navon, Ofer Miller, Amir Averbuch, "Color image segmentation based on adaptive local thresholds," *Image and vision computing*, vol. 23, no. 1, pp. 69-85, 2005.

[17] Herbert Bay, Tinne Tuytelaars, and Luc Van Gool, "Surf: Speeded up robust features," *European conference on computer vision. Springer*, Berlin, Heidelberg, 2006, pp. 404-417.

[18] D. H. Hubel, T. N. Wiesel, "Receptive fields, binocular interaction and functional architecture in the cat's visual cortex," *Journal of Physiology*, vol. 160, no. 1, pp. 106-154, 1962.

[19] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, 2012, pp. 1097-1105.

[20] Karen Simonyan, Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv*:1409.1556, 2014.

[21] Christian Szegedy, Wei Liu, Yang-Qing Jia, et al, "Going deeper with convolutions," *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, 2015, pp. 1-9.

[22] Kai-Ming He, Xiang-Yu Zhang, Shao-Qing Ren, et al, "Deep Residual Learning for Image Recognition," *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.