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# Detection of Wrong Components in Patch Component based on Transfer Learning

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Abstract. *Aiming at the shortcomings of image processing steps and low accuracy of on-chip automatic detection system for patch components on PCB, this paper proposes a method based on transfer learning to automatically detect whether there are faulty components in the patch components. This approach incorporates transfer learning techniques and convolutional neural networks. The convolutional neural network has acquired rich image feature extraction capabilities through the training of a large number of images before. Only a small amount of data is needed to train the network to fine-tune the weights, and the network can identify and classify the patch components, which greatly saves the time required to train the network. This paper uses the improved three convolutional neural networks of AlexNet, ResNet-50, and GoogleNet to conduct experiments. The experimental results show that the improved AlexNet network has the best recognition effect on patch components and the shortest training time, which proves that the proposed method is effective and feasible.*
**Keywords:** Transfer learning; CNN; PCB; Wrong components

1. **Introduction.** Many of the electronic products we use today in our daily lives rely on printed circuit boards (PCBs) for their functions. The quality of the PCB largely affects the performance of the electronic product. Once the electronic components on the printed circuit board have problems such as missing components, wrong parts, and solder joints, the PCB needs to be reworked. This not only reduces the product qualification rate, but also increases the cost of the manufacturer. With the rapid development of electronic technology and micro-drilling technology, the performance of printed circuit boards is also constantly improving. At the same time, there are still some other problems. With the development of the process, the component integration density on the PCB is getting larger and larger, and the size of the component is also getting smaller, which will bring great challenges to the online detection of the PCB. In the past, the factory mainly detected the quality of the PCB manually. The long-term work will lead to the decrease of people's energy and the lack of concentration. This will not only lead to slow detection, but also may miss circuit board defects. Moreover, it is more difficult to fulfill the manual detection task nowadays as the devices on the circuit board with smaller size and larger number.

In recent years, some automatic detection PCB devices based on machine vision technology have been developed with fast detection speed. These devices, which are completely run by the computer, can continuously detect the PCB without the problems of missed detection caused by manual detection. However, the key to this technology is image processing. If the acquired image is incomplete or the applied program algorithm is inaccurate, the component will be missed. Therefore, the reliability of the technology needs to be improved. At present, the application of machine vision technology to PCB defect detection is mainly to study effective image processing algorithms and combine it with pattern recognition to improve the recognition efficiency of defects.

A neural network method for solder joint detection[1] was proposed, which did not require any special illumination system. The classification performance of MLP classifier and LVQ classifier was compared in this paper, and the accuracy rate was up to 98.8%. However, this method needed to extract the region of interest (ROI) and extract wavelet features and geometric features in the region of interest before classifying the solder joint defects. The steps were cumbersome. A method for detecting printed circuit boards based on eddy current testing (ECT) technology [2] was developed. The system uses a variety of magnetic sensors. Although it has good detection performance, the scanning speed is limited. A method for detecting defects in PCB and classifying them into all possible 14 categories[3] was proposed. The method is mainly divided into five steps: image registration, image preprocessing, image segmentation, defect detection, defect classification. The defects of solder joints was examined by obtaining the information of the solder joints using a hemispherical illumination system[4]. Convolutional neural networks[5] was used to classify defective or good printed circuit boards, but the recognition accuracy can only reach about 85%. A three-dimensional automatic optical detection method based on the combination of phase method and stereo vision was proposed[6]. This method not only maintains the high-resolution characteristics based on the phase method, but also eliminates the limitation of the measurement range through stereo vision. A genetic algorithm based printed circuit board automatic defect detection system[7] was developed, which does not need to understand the layout design of the circuit board, and does not require relevant domain knowledge, but the recognition accuracy is relatively low.

At present, most methods for automatically detecting PCB defects require very complicated processing of images, and the defect recognition accuracy is low. Therefore, it is urgent to develop a PCB fault detection method with simple operation and high recognition accuracy. Aiming at this problem, this paper proposes a fault detection method for patch components based on transfer learning. The proposed method adopts a convolutional neural network[8] to detect if there is a wrong piece of PCB. Convolutional neural networks, which have been well trained by a large number of pictures, already have a wealth of feature extraction capabilities. As a result, we only need to train the model with a small number of images to fine-tune the parameters, then we can migrate the ability to recognize the original image to identify the patch components. This approach does not require learning from scratch like most networks, saving a lot of time. The experimental results show that the accuracy of identifying patch components can reach up to 99.35%

## 2. Convolutional neural network and transfer learning.

**2.1. Convolutional neural network.** Inspired by cat electrocortical electrophysiological studies, Hubel and Wiesel proposed a convolutional neural network (CNN), a feed forward neural network that performs well for a large number of image processing. Yann Lecun firstly used CNN for handwritten digit recognition. In recent years, convolutional neural networks have made great breakthroughs in speech recognition, face recognition, general object recognition, motion analysis, natural language processing, and even brain wave analysis. Convolutional neural networks differ from ordinary neural networks in that the convolutional neural network consists of a feature extractor consisting of a convolutional layer and a sub-sampling layer. In the convolutional layer of a convolutional neural network, one neuron is only connected to a portion of the adjacent layer neurons. A convolutional layer usually consists of several neurons arranged by a number of rectangles, and the neurons of the same feature plane share weights. Sharing weights not only reduces the connections between layers of the network, but also reduces the risk of over fitting.

2.2. **AlexNet.** AlexNet is a deep convolutional neural network designed by Alex Krizhevsky and Ilya Sutskever of the University of Toronto's Geoff Hinton laboratory in 2012. It won the 2012 ImageNet LSVRC championship and the accuracy rate far exceeds the second place. AlexNet has five layers of convolutional layers and three layers of fully connected layers. Although AlexNet has very few weighted layers, it has 60,000,000 parameters and 650,000 neurons. It has been trained by more than one million images and can classify 1000 objects. The new technologies used by AlexNet are as follows:

(1) Use the ReLU function as the activation function. The convergence speed is very fast, and only one threshold is needed to obtain the activation value, which solves the gradient dispersion problem of the Sigmoid function when the network is deep.

(2) Using the Dropout function to randomly ignore a part of the neurons during training to ensure that the hidden nodes appear randomly with a certain probability, which can effectively prevent the over-fitting of the neural network.

(3) The use of the largest pooling layer in the network avoids the blurring effect brought by the average pooling layer and improves the richness of the extracted features.

2.3. **GoogleNet.** GoogleNet first appeared in the 2014 ILSVRC competition and won the first place with a big advantage. Its biggest feature is that it has achieved very good classification performance while controlling the amount of calculation and parameter, and reduced the error rate of Top5 to 6.67%. Although the model has 22 layers, the parameter quantity is only 1/12 of AlexNet. In order to maintain the sparseness of the neural network structure and make full use of the high computational performance of the dense matrix, GoogleNet proposed a modular structure called Inception. Inception is a network-in-network structure, that is, the original node is also a network. After using Inception, the width and depth of the entire network structure can be expanded, and the performance can be improved by 2 to 3 times.

2.4. **ResNet-50.** ResNet was proposed by He et.al in 2015 and won the first place in the ImageNet competition. It differs from the traditional sequential network architecture in that it incorporates an identity mapping layer, and the network does not degrade in the case of increased depth. ResNet contains a lot of building blocks. The input of one building block goes through two weight layers, and finally adds up with the input to form a micro-architecture module. These microarchitecture modules ultimately form ResNet, which can train very deep networks by using residual modules and regular SGD. Because it is simple and practical, many methods are proposed based on the ResNet-50 or ResNet-101 model.

2.5. **Transfer learning.** Traditional machine learning requires that the source data and the target data obey the same data distribution. However, in actual problems, many situations do not satisfy this condition, which leads us to spend a lot of manpower and time to re-mark large amounts of data. The emergence of transfer learning makes up for this shortcoming. The so-called transfer learning is to use the knowledge and skills

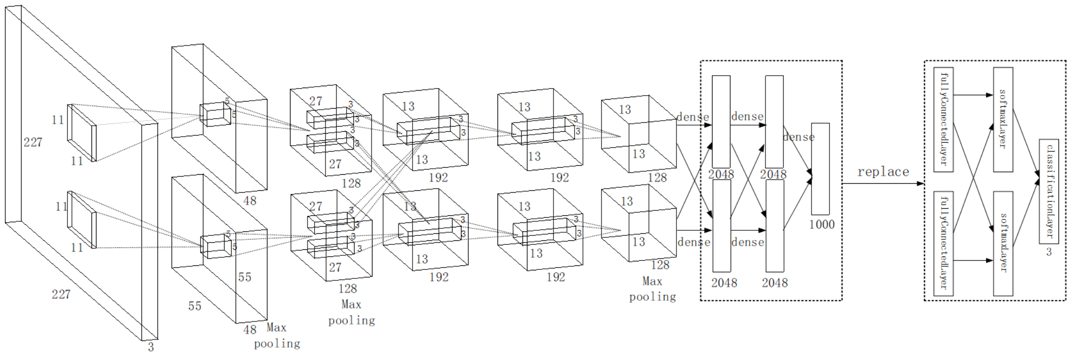


Figure 1. Structure of the S-AlexNet model

of prior learning to identify the learning ability of new tasks. There are four types of transfer learning: instance transfer learning method, feature transfer learning method, parameter transfer learning method and relationship transfer learning method. The parameter transfer learning method is selected in this paper. Most data or tasks are related. The parameter transfer method is to find the parameter information that can be shared between the source data and the target data, and share the parameters that can be utilized in the learned model to the new model in some way. This method can improve the learning efficiency of the new model. It does not need to learn from scratch like most convolutional neural networks, and saves a lot of time.

2.6. **Improved AlexNet.** In this paper, the recognition effects of the three models of AlexNet, ResNet-50 and GoogleNet on the patch components are compared. These three models have been trained with a large amount of data and learned how to extract various image features. Thus we only need to train them with a small number of patch component images to fine-tune the parameters, so that these three models can identify and classify the patch components. Convolutional neural networks need to be improved to adapt to new classification tasks before transfer learning. Here we take AlexNet model as an example to illustrate. Firstly the first five layers of the AlexNet model was extracted and kept unchanged, then the last three layers were replaced with the fully connected layer, the SOFTMAX layer, and the classification output layer. Finally, we set the output of the fully connected layer and the number of categories in the new data. To be consistent, a new convolutional neural network was constructed and called S-AlexNet, as shown in Figure 1. Similarly, the improved ResNet-50 and GoogleNet models are called S-ResNet-50 and S-GoogleNet respectively.

3. **The system hardware structure.** In this paper, the self-built hardware system is used to collect the images of the patch component. The structure is shown in Figure 2. The detection system is mainly composed of two-axis motion control platform, fill light system and image acquisition system. When collecting images, first place the tested component on the workbench, then the computer directly outputs the command to the two-axis motion control system, and the servo motors drive the workbench to send the patch component to be tested directly under the camera. The fill light system adjusts the light intensity and angle, and the control system triggers the camera to take an image and send it to the computer.

3.1. **Two-axis motion control system.** The main function of the two-axis motion control system is the motion control of the workbench. The control system drives the X-axis and Y-axis screw motion by controlling the servo motors, and sends the patch

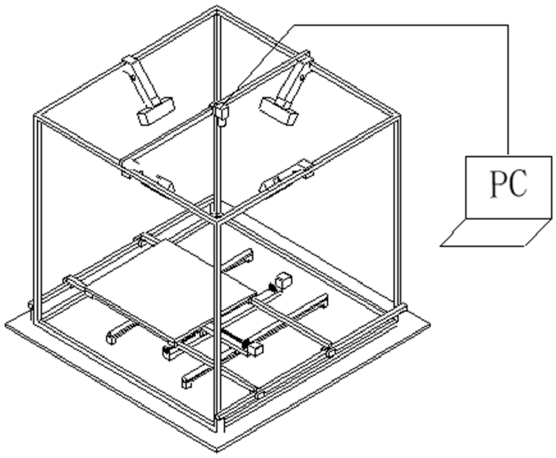



FIGURE 2. Hardware structure of the system

components to the designated position accurately. In order to improve the smoothness and accuracy of the transmission, high-precision AC servo drive motors, motion controllers and guide rails are selected.

3.2. **Filling system.** The fill light system has a great influence on the image quality of the captured image and the recognition effect of the convolutional neural network. This system uses a self-built fill light system. The fill light system consists of a microcontroller and four RGB color LED arrays, each of which can be adjusted in angle and brightness. By adjusting the angle and brightness of each LED array, the optimal exposure of the patch component to be captured can be obtained to capture a clear image.

3.3. **Image acquisition system.** The image acquisition system consists of a computer, an image capture card, an area array camera, and an optical lens. In order to capture clear images, Hikvision's MV-CA-050-20GC digital camera was used with an image resolution of 2592×2048. In order to reduce the chromatic aberration and make the image distortion as small as possible, Huagu Power's 10 megapixel optical lens is selected.

## 4. Experiment.

4.1. **Experimental setup.** The experimental environment adopted in this paper is Windows 10 Professional Edition, and a GTX 1070 graphics card is used to complete the experiment under the framework of MATLAB 2018a. The Loss curve and accuracy curve in the experimental results of this paper are all drawn from the data visualized by MATLAB 2018a, which is used to analyze the performance of convolutional neural networks. The experimental process is shown in Figure 3.

4.2. **Image Preprocessing.** The data set required for the experiment is collected by the self-built shooting platform, which is mainly divided into three types: patch resistors, capacitors and chips, with a total of 2061 images. In the process of selecting training samples, some pictures containing non-target objects (such as watermarks such as text) are used to simulate random noise to improve the generalization ability of the model. Since the picture pixels used in the convolutional neural network are fixed in size, the original picture needs to be pre-processed and scaled to 224×224×3 and 227×227×3 pixels according to the requirements of different models. Figure 4 shows some of the samples with noise and the scaled results.

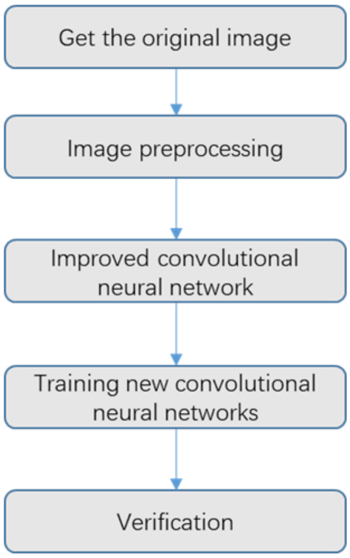
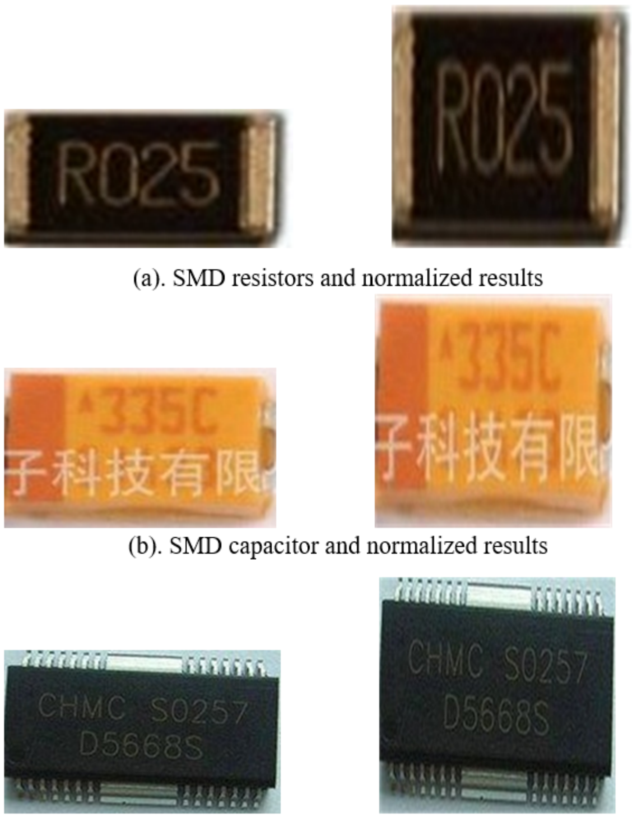



Figure 3. Experimental flow chat




(a). SMD resistors and normalized results

(b). SMD capacitor and normalized results

(c). SMD chip and scaling results

Figure 4. Experimental flow chat

4.3. **Discussions.** This paper compares the S-AlexNet, S-GoogleNet, and S-ResNet-50 models for the classification and recognition of SMD resistors, capacitors, and chips. The evaluation indicators of the experimental results are mainly divided into two parts: one

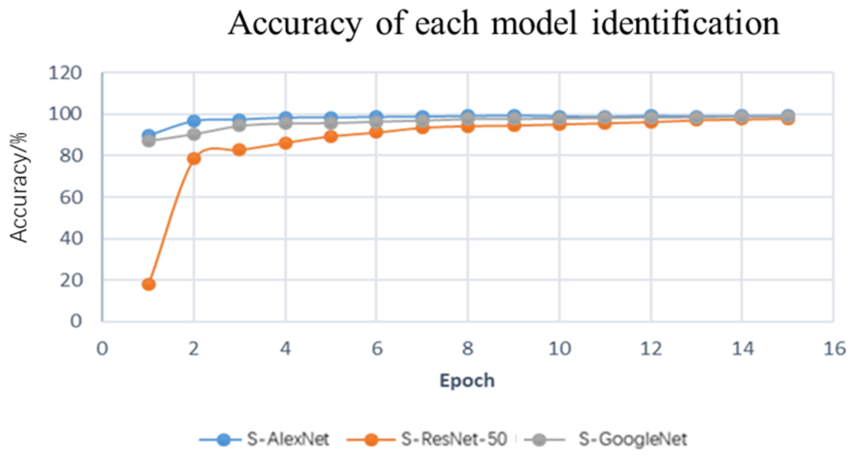



FIGURE 5. Curves showing the accuracy of each model

is the classification recognition accuracy obtained under the same operating environment, and the other is the time spent by different models.

After acquiring the experimental image and pre-processing, the image is placed in the improved model for training and verification. In this paper, all the images are divided into training set and verification set according to a certain proportion by random grouping method. The common parameter setting iteration number of each model is 15, and other main parameters of each model are adjusted through multiple experiments. The main parameters when obtaining the highest accuracy are as follows:

For the S-AlexNet model, the training data accounted for 85%, the verification data accounted for 15%, and the batch number was 25. The recognition accuracy rate is 99.35%. For the S-ResNet-50 model, the training data accounted for 75%, the verification data accounted for 25%, and the batch number was 28. The recognition accuracy rate is 94.56%.

For the S-GoogleNet model, the training data is 75%, the verification data is 25%, and the batch number is 20. The recognition accuracy rate was 97.09%.

Figure 5 shows the variation of the recognition accuracy of the patch elements for each model. It can be seen from the figure that the S-AlexNet model has the highest recognition accuracy and fast convergence; although the S-GoogleNet model converges quickly, the accuracy is slightly lower than the S-AlexNet model; the S-ResNet-50 model has the lowest accuracy, and the convergence is the slowest.

Figure 6 shows the loss function value of each model. The S-AlexNet model showed good generalization ability from the beginning, the loss function value was the smallest, and the convergence was the fastest; the loss function values of the S-GoogleNet model and the S-ResNet-50 model were relatively large, and the convergence was very slow.

In conclusion, the S-AlexNet model takes the shortest training time, and has the highest recognition accuracy and the fastest convergence. Therefore, the S-AlexNet model is most suitable for the identification and classification of patch elements.

## 5. **Summary and Outlook.**

Aiming at the drawbacks of traditional detection of PCB mislabeled components, such as cumbersome steps, poor generalization and low accuracy, this paper proposes a detection method based on transfer learning. The training time of this method is short, the number of samples needed is small, and the recognition accuracy is high. This paper has improved and experimented with three excellent image recognition

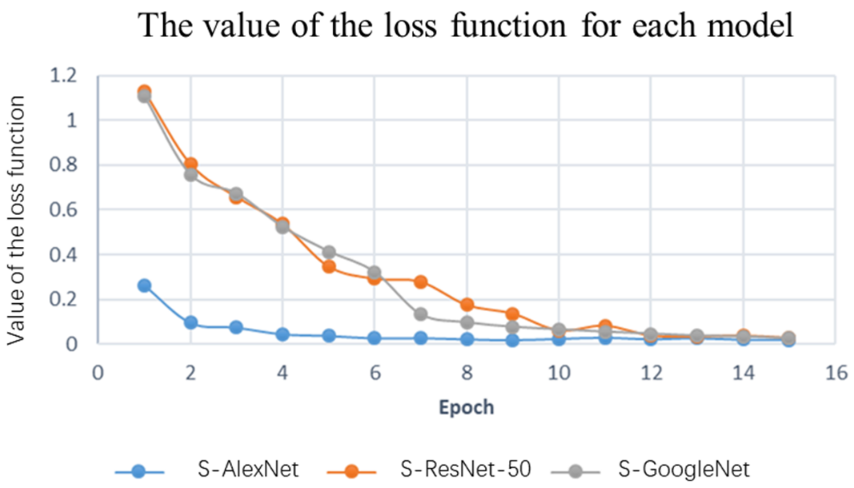



FIGURE 6. The value of the loss function for each model

models: AlexNet, ResNet-50 and GoogleNet. The experimental results show that the S-AlexNet model has the best recognition effect on the patch components, and its recognition accuracy is up to 99.35%. The model convergence speed is the fastest and the training time is the shortest. Compared with the S-ResNet-50 model, the S-GoogleNet model is slightly better in terms of recognition accuracy and convergence speed. The S-ResNet-50 model has 50 layers, more than twice the S-GoogleNet model, but its convergence is slightly different from that of S-ResNet-50 model, which shows its strong advantage in training speed. And the S-ResNet-50 model used in this paper is a model with fewer layers in ResNet series model. The ResNet model which participated in the ISLVR competition in 2015 has reached 152 layers. If we can use this deeper model, we believe it will further improve the recognition accuracy.

At the same time, there are some areas that need to be improved in this paper. For example, we can try to use the ten-fold cross-validation method to conduct experiments. In addition, we can try to extract the components that are misidentified by the convolutional neural network and analyze the causes of the errors so as to make corresponding improvements to the convolutional neural network.

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## REFERENCES

[1] G. Acciani, G. Brunetti and G. Fornarelli, Application of Neural Networks in Optical Inspection and Classification of Solder Joints in Surface Mount Technology, *IEEE Transactions on Industrial Informatics*, 2006. vol. 2, no.3, p. 200-209.

[2] K. Chomsuwan, S. Yamada and M. Iwahara, Improvement on Defect Detection Performance of PCB Inspection Based on ECT Technique With Multi-SV-GMR Sensor. *IEEE Transactions on Magnetics*, 2007. vol. 43, no.6, p. 2394-2396.

[3] V. Chaudhary, I.R. Dave and K.P. Upla, Automatic visual inspection of printed circuit board for defect detection and classification. 2017, *IEEE*. p. 732 - 737.

[4] A. Anu, M. Anouncia and L. Rajaji, Automatic visual inspection of PCB using CAD information. 2012, IEEE. p. 217 - 220.

[5] V. A. Adibhatla ; J. S. Shieh ; Maysam F. Abbod ; H.-C. Chih; C.-C. Hsu ; Joseph Cheng. Detecting Defects in PCB using Deep Learning via Convolution Neural Networks. 2018, *IEEE* , p. 202 - 205.

[6] D. Hong, et al., A 3D inspection system for PCB board by fusing moiré technique and stereo vision algorithm. 2007, *IEEE.* p. 2473 - 2479.

[7] F. A. Xie, Uitdenbogerd and A. Song. Detecting PCB component placement defects by genetic programming. *In 2013 IEEE Congress on Evolutionary Computation*, pp. 1138-1145

[8] A. Krizhevsky, I.Sutskever and G.E.Hinton, ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 2012, vol. 2, p.1097-1105.