Computer Vision Based Research on PCB Recognition Using SSD Neural Network

Dashuang Li, Lei Xu*, Guangzai Ran and Zhanling Guo
School of Mechanical Engineering, Sichuan University, Chengdu, China

*Corresponding author email: xulei@scu.edu.cn

Abstract. Printed circuit board (PCB) is an important component in the information technology industry, during PCB board assembly process, jack localization and recognition is particularly important. In view of the problem that the accuracy of target detection is not ideal, this paper applies deep learning convolutional neural network framework SSD (single shot multibox detection) to PCB element detection. By obtaining a large number of original PCB images, creating semantic label image dataset, feeding them into neural networks, and adjusting the hyperparameters, the best classification accuracy and localization accuracy are achieved. At the same time, the advantages of different algorithms are analysed after tests with other deep learning network methods. Experiments show that the SSD deep learning algorithm can realize accurate detection process of jack localization and classification, which is better than other algorithms.

Keywords: Machine vision; PCB detection; SSD neural network.

1. Introduction
Printed circuit board (PCB) is an important component in modern industrial production. In order to achieve accurate matching and assembly of connectors, traditional production line companies introduce corresponding matching strategies to complete the matching and assembly process of jacks and pins. However, traditional matching detection algorithms are often with low matching accuracy and high errors, so it is urgent to introduce efficient methods to solve the above problems. Nowadays, deep learning network is now changing the way we work and think. On the one hand, the original algorithm framework is continuously improved on network performance; on the other hand, it is applied to face recognition, clinical medicine, defect detection, playing an irreplaceable role in technological advancement.

Among them, Y. Chen et al [10] introduces a tight convolutional network, which connects each layer with all other layers in the feedforward network. It is tested on 4 recognition platforms, feature enhancement and feature reuse are achieved. Olivier Janssens et al [1] guarantees the arbitrariness of the input size by adding SPP net. Experiments show that this can achieve much better accuracy. Through adjustment of the neural network structure, the network structure most suitable for the corresponding application scenario is continuously obtained. André Teixeira Lopes et al [2] describes a robust facial expression recognition method, emphasizing facial expression on individual independency, rotation, and translation. The experimental results achieved 97.6% accuracy for smile detection. H. R. Roth et al [8] applies two deep learning algorithms to handwritten font recognition. The classification accuracy of CNN and DBN in the MNIST dataset is 99.28% and 98.12% while the actual handwritten fonts are 92.91% and 91.66%. Jixiu Wu et al [5] proposes a deep learning-based convolutional neural network structure to detect wall cracks, and an accuracy of 98% is obtained. K. He et al [6] proposes a bearing condition monitoring model based on feature learning, it shows absolute advantage and accuracy.
improvement (93.61%). At the same time, further processing is performed on the results after recognition and detection, in which denoising and extraction of hidden information can be realized. W. Qiu et al [11] proposes a speckle image convolutional neural network to automatically remove speckles in noisy images. A large number of experiments have confirmed that the proposed algorithm significantly improves the existing algorithms’ performance. G. Xu et al [9] proposes a CNN model based on residual learning for image steganalysis to distinguish innocent images from images with hidden information. Experiments have proved that the DRN model can detect the steganographic information with high accuracy, exceeding most of the newly proposed algorithms. Traditional methods have been taken to realize the detection. Wenbin Zhu et al [4] use an adaptive edge detector to obtain the edge image of PCB and a rapid circle center search algorithm to locate the center of each circle, which turns out a competitive precision. Wei Shi et al [3] propose a novel single shot object detector for tiny defect detection in PCBs, achieves 81.3% mAP. Weibo Huang et al [7] propose a synthesised PCB dataset that contains 1386 images with 6 kinds of defects for the use of detection, classification and registration tasks, and experiment results indicate an outstanding performance. While Deep learning algorithms in image detection and recognition of the mechanical field has also been studied. Can Zhang et al[12] apply an improved bare PCB defect detection approach by learning deep discriminative features, which reduced the high requirement of a large dataset for the deep learning method. The research object of this paper is PCB, and the research mainly focuses on how to use the corresponding algorithm to accurately classify and locate the jack area of the PCB. However, the research objects for PCB and the matching process are almost at a relatively primary stage. Therefore, deep learning algorithm is the best method and related research on deep learning and PCB recognition and detection is carried out.

This paper first elaborates on the structure and feature description of the relevant convolutional neural network used in this article, then defines the elements of the PCB detection. By obtaining a large number of original PCB images, creating a semantic annotated image dataset, feeding it to the neural network and adjusting the hyperparameters, the best classification accuracy and localization accuracy can be realized. Meanwhile, comparison among other deep learning network methods is carried out to analyze the advantages of different algorithms in the PCB image inspection process.

2. Introduction to Deep Learning Network Structure

2.1. Structure of Traditional Algorithms

Traditional deep learning convolutional neural networks include convolutional layers, pooling layers, activation layers, decision-making layers and other network layers as shown in Figure 1.

2.2. Structure of SSD

SSD (Single Shot MultiBox Detector) is a forward-propagation CNN network that generates a series of fixed-size Bounding Boxes, and contains the possibility of object instances in each box, namely Score. The SSD network structure can be divided into two parts: basic network + pyramid network. The basic network is the first 4 layers of VGG-16. The pyramid network is a simple convolutional network that gradually becomes smaller in the feature map. It consists of 5 parts, and its specific structure is shown in Figure 2.

![Figure 1. Structure of Traditional algorithms.](image-url)
2.2.1. SSD network training. The Ground Truth in the SSD training image needs to be assigned to boxes with a fixed output. The SSD output is a number of fixed-size Bounding Boxes defined in advance.

(1) Matching Strategy: It mainly introduces how to form a label from GT and default box. This paper will match Default Box with any Ground Truth Box, as long as the Jaccard Overlap between the two is greater than a threshold, here the threshold is 0.3.

(2) Training Objective:
The total Objective Loss Function is the weighted sum of Localization Loss(loc) and Confidence Loss(conf) shown in Eq.1:

\[ L(x, c, l, g) = \frac{1}{N} L_{\text{conf}}(x, c) + \alpha L_{\text{loc}}(x, l, g) \]  

\( N \) is the number of Default Boxes that match the Ground Truth Box; Localization Loss (loc) is the Smooth L1 Loss in Fast R-CNN; Confidence Loss(conf) is Softmax Loss, and the input is the confidence \( c \) of each category. The weight term \( \alpha \), set to 1, balances the proportion of loc and conf. While \( l \) is Predict Box and \( g \) is Ground Truth Box.

3. Detection and Recognition of Elements on PCB
The experimental operating system in this paper is Windows 10, and the compiling and debugging environment is Pycharm + Python3.7 + Anaconda 3.0 + Tensorflow + Opencv.

3.1. Flowchart of the PCB Detection Test
The flowchart of PCB component detection based on SSD neural network algorithm is shown in Figure 3, which includes the following 4 parts: (a). Dataset production (b). Deep learning training (c). Verification and testing (d). Parameter optimization.

(1) Dataset production, and image accuracy definition

①. The original image
First, a Basler industrial camera is used to collect 500 original images of the PCB with a size of 2592×1944, of which 420 are used for image training and 80 are used for verification and testing. Since the use of small-size images in the deep learning process can facilitate the detection of larger-size images, each original image is divided into 288×324 images, so the total number of images used for training is 22680. And there are 4320 images used for testing and verification, and the rest of the divided images are for training.

②. Image annotation
The 22680 images that need to be trained are labeled by the image labeling software LabellImg. There
are five categories in the image labelling process: (0) background, (1) board hole, (2) welding hole, (3)
number, (4) metal connection.

Definition of accuracy
In this paper, there are two accuracy considerations: one is the ability to accurately classify; the other is
the confidence of localization. And indicators P(precision) and R (recall)are used to judge: Precision:
\[ \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}; \]
Recall: \[ \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \]
TP (true positive): The probability that the judgment result is
correct; FP (false positive): The probability of error in the judgment result; FN (false negative): the
probability of failing to detect the target;

Hyperparameter adjustment
Hyperparameters include learning rate, learning decay rate, batch size and etc. Based on previous
knowledge, the batch size=4, gpu_memory_fraction=0.8, Adam is selected as optimizer, learning
rate=0.0001, weight decay=0.001, and learning rate decay factor = 0.94.

3.2. Test Results

3.2.1. Preliminary Experiment. Among them, different training steps are tested under the same
hyperparameters. The results of training steps of 20,000 and 200,000 times are as follows: In the process
of testing images, due to the large image dataset, some of the selected images are shown in Figure 4.
(No. 1 of raw 1 are welding hole, No. 6 of raw 2 is metal connection, No. 4 of raw 1 is board hole).

Analysis of the experimental results: The classifier has a good effect and can accurately classify. To
judge the category, results of 200,000 times training are taken as an example. The specific results are
shown in Table 1 and 2 and only part of the results are shown.

Based on Table 1 and 2, the result has been significantly improved, and the accuracy of the classifier
maintains at a high level. The data in Bold means classification deviation, which concentrates in the
fourth category. However, it can be seen that the confidence rate has remained at a low level, in order to
improve the confidence rate, the following improvement measures will be made. First, expansion on
the image training dataset; Second, the images of the dataset with poor results are eliminated; Third, the
number of trainings is increased to achieve better training effect.(DP means Detection Precision).

| DP  | 0.571 | 0.327 | 0.494 | 0.437 | 0.802 | 0.388 |
|-----|-------|-------|-------|-------|-------|-------|

Table 1. Detection precision and classification deviation of training 20000 times.

| DP  | 0.576 | 0.547 | 0.533 | 0.542 | 0.445 | 0.389 | 0.477 | 0.499 | 0.738 | 0.307 | **0.332** | 0.323 |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

Table 2. Detection precision and classification deviation of training 200000 times.
3.2.2. Augmentation of the Experimental Dataset. To improve the accuracy of the experiment, data augmentation methods such as rotation and translation are used to expand the training images by 2 times to the number of 37991, among which images of poor quality are eliminated and the number of elements in the PCB training and test image datasets are shown in Tables 3 and 4.

**Table 3. Number of elements in training images.**

| Number of train images | PCBJack | Welding point | Metal connection | number | Supporting hole |
|------------------------|---------|---------------|------------------|--------|-----------------|
| 37991                  | 26383   | 18996         | 4220             | 31659  | 2110            |

**Table 4. Number of elements in test images.**

| Number of test images | PCBJack | Welding point | Metal connection | number | Supporting hole |
|-----------------------|---------|---------------|------------------|--------|-----------------|
| 4320                  | 3001    | 2161          | 480              | 3601   | 240             |

a. Training test

The expanded image dataset is sent into the SSD neural network for training. 200,000/600,000/1,000,000 times’ training on the expanded image dataset are performed, some of the results are shown in Tables 5, 6, and 7.

**Table 5. Results of training 200000 times.**

| DP       | 1     | 0.536 | 0.453 | 0.798 | 0.879 | 0.815 | 0.622 | 0.943 | 0.327 | 0.632 | 0.755 | 0.469 | 0.777 | 0.347 | 0.411 | 0.530 | 2     | 0.395 | 0.569 | 0.374 | 0.355 | 0.326 | 0.358 | 3     | 0.323 | 4     | 0.474 | 0.399 | 0.523 | 0.314 | 0.370 | 0.358 | 0.396 | 0.483 | 0.491 |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

**Table 6. Results of training 600000 times.**

| DP       | 1     | 0.499 | 0.449 | 0.838 | 0.900 | 0.354 | 0.907 | 0.656 | 0.740 | 0.741 | 0.970 | 0.694 | 0.507 | 0.577 | 0.344 | 0.817 | 0.832 | 0.727 | 2     | 0.351 | 0.384 | 0.326 | 0.453 | 0.487 | 0.347 | 3     | 0.305 | 4     | 0.531 | 0.340 | 0.482 | 0.353 | 0.470 | 0.321 | 0.379 | 0.509 | 0.302 | 0.309 |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

**Table 7. Results of training 1000000 times.**

| DP       | 1     | 0.489 | 0.444 | 0.848 | 0.899 | 0.832 | 0.852 | 0.738 | 0.745 | 0.971 | 0.632 | 0.535 | 0.574 | 0.355 | 0.816 | 0.343 | 0.567 | 0.691 | 2     | 0.357 | 0.526 | 0.334 | 0.458 | 0.499 | 0.350 | 3     | 0.304 | 4     | 0.547 | 0.350 | 0.489 | 0.479 | 0.352 | 0.323 | 0.390 | 0.518 | 0.373 | 0.309 |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

Due to the small amount of data for category 3(number), only results of category 1(board hole), category 2(welding hole), and category 4(metal connection) are selected for further processing. And the data results of TP, FP and FN are obtained. Some of the results are shown in Table 8 based on Table 1,2,5,6,7. And the corresponding Precision and Recall values are shown in Table 9 and Table 10.

The PR chart is obtained from the data of all the verification dataset shown in Figure 5, where the abscissa is the Recall value and the ordinate is the Precision value and size of the corresponding area is the detection accuracy as shown in the following table 11.

As can be seen from the above results, classification accuracy has reached a relatively high level, but localization rate does not reach the ideal state.

It can be predicted from the results that with the expansion of the dataset and the increase in the number of trainings, although the localization rate fluctuates slightly, the overall accuracy is improving. At the same time, although the result of training 1,000,000 times is better than that of 600,000 times, it is not significant. Therefore, the result of training may fall into an overfitting state, so further adjustment are required to obtain better results. (line in red refers to welding point, line in yellow refers to number and...
line in blue refers to pcbjack

### Table 9. Part Results of Precision.

| P  | 1     | 2     | 3     | 4     | 5     |
|----|-------|-------|-------|-------|-------|
| 1  | 0.9091| 0.8961| 0.9615| 0.96  | 0.96  |
| 2  | 0.667 | 0.9412| 0.9167| 0.8889| 0.8889|
| 4  | 0.9000| 0.833 | 0.933 | 0.9286| 0.9375|

### Table 10. Part Results of Recall.

| R  | 1     | 2     | 3     | 4     | 5     |
|----|-------|-------|-------|-------|-------|
| 1  | 0.6187| 0.8961| 0.9629| 0.92  | 0.92  |
| 2  | 0.4287| 0.7176| 0.6227| 0.5714| 0.5714|
| 4  | 0.7059| 0.9302| 0.9372| 0.9369| 0.8823|

### Table 11. Precision of three categories

| Pcbjack | Welding point | Number |
|---------|---------------|--------|
| Precision | 0.9495 | 0.7829 | 0.9456 |

### Figure 5. PR of three categories.

### Table 12. Statistic results of TP.

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| normal     | 1    | 0.96 | 0.95 | 0.96 | 0.94 | 0.92 |
|            | 2    | 0.92 | 0.94 | 0.94 | 0.95 | 0.94 |
|            | 4    | 0.88 | 0.87 | 0.90 | 0.87 | 0.85 |

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| enhanced   | 1    | 0.95 | 0.96 | 0.97 | 0.97 | 0.95 |
|            | 2    | 0.93 | 0.93 | 0.95 | 0.96 | 0.94 |
|            | 4    | 0.80 | 0.95 | 0.94 | 0.88 | 0.75 |

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| ideal      | 1    | 0.98 | 0.99 | 0.99 | 0.98 | 0.96 |
|            | 2    | 0.95 | 0.96 | 0.96 | 0.95 | 0.95 |
|            | 4    | 0.90 | 0.91 | 0.93 | 0.95 | 0.91 |

### Table 13. Statistic results of FP

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| normal     | 1    | 0.04 | 0.05 | 0.04 | 0.06 | 0.08 |
|            | 2    | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
|            | 4    | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| enhanced   | 1    | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
|            | 2    | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
|            | 4    | 0.2  | 0.06 | 0.12 | 0.25 |      |

|            | 15w  | 30w  | 45w  | 60w  | 75w  |
|------------|------|------|------|------|------|
| ideal      | 1    | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
|            | 2    | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
|            | 4    | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |

### 4. Results of Tests of Different Conditions and Comparative Tests

From the experiment results in Chapter 3, we can see that the precision relatively high, but the localization rate is indeed not good enough. In order to improve the confidence rate, test images are carefully chosen and pre-processed, and comparative experiments are carried out in combination with other algorithms.

#### 4.1. Testing among Normal, Enhanced and Ideal Images

The original image is selected during the experiment, and the enhanced image and the ideal image are trained for 150,000/300,000/450,000/600,000/750,000 times. To calculate the accuracy, the test data results are counted for TP, FP and FN results as shown in Tables 12, 13, 14. (Normal means original test images, Enhanced means pre-processed images, and Ideal means carefully chosen images, W means 10,000 times).

After processing the data results of TP, FP and FN, Precision and Recall can be obtained according to the corresponding formulas. Some of the results are shown in Tables 15, 16 and a PR map is drawn as shown in Figures 6, 7, 8, where the area of the map represents the final accuracy. The image area or accuracy is 0.9792/0.8459/0.9375 in Figure 6; the accuracy in Figure 7 is 0.9804/0.8613/0.9399; and the accuracy in Figure 8 is 0.9879/0.9439/0.9213.

It can be concluded that the accuracy of detection in category 1 is the highest, higher than the other two groups. And the overall image detection effect under ideal conditions is the best, which can verify our conjecture. And internal factors affecting the test performance of the test image can be drawn, including the following points: clarity of the images; the proportion of target to be tested in the image and complexity of image elements.
4.2. Comparison of Tests among Various Algorithms

It can be predicted that when the test image is under a more ideal state, a better localization rate and classification effect can be achieved. Therefore, the existing datasets are trained to complete the comparison of related algorithms, and the selected algorithms include HOG, SVM, LBP, AlexNet, etc.

4.2.1. Introduction to Experimental Program. The overall plan is to use the above-mentioned image detection algorithm to process the target image separately and the algorithms are combined to a certain extent[12], including HOG+SVM, LBP+SVM, SIFT+BoW+SVM and AlexNet+SVM.

4.2.2. Experimental Results. As shown in Table 18, the accuracy and mAP size obtained by HOG+SVM, LBP+SVM, SIFT+BoW+SVM and AlexNet+SVM are compared with the results obtained by using SSD algorithm for image detection. It can be seen the mAP value of the result obtained under normal image, enhanced image and ideal image are better than the above algorithm results, especially the data obtained under ideal image conditions. In summary, it can be concluded that the SSD algorithm has certain advantages in the PCB hole detection and classification process.

Table 14. Statistic results of TN.

| Precision | 15w  | 30w  | 45w  | 60w  | 75w  |
|-----------|------|------|------|------|------|
| normal    | 1    | 0.96 | 0.95 | 0.96 | 0.94 | 0.92 |
|           | 2    | 0.92 | 0.94 | 0.94 | 0.95 | 0.94 |
|           | 4    | 0.88 | 0.87 | 0.90 | 0.87 | 0.85 |
| enhanced  | 1    | 0.95 | 0.96 | 0.97 | 0.97 | 0.94 |
|           | 2    | 0.93 | 0.93 | 0.95 | 0.96 | 0.94 |
|           | 4    | 0.80 | 0.95 | 0.94 | 0.88 | 0.75 |
| ideal     | 1    | 0.98 | 0.99 | 0.99 | 0.98 | 0.96 |
|           | 2    | 0.95 | 0.96 | 0.96 | 0.95 | 0.95 |
|           | 4    | 0.90 | 0.91 | 0.93 | 0.95 | 0.91 |

Table 15. Test result of Precision.

|     | 15w  | 30w  | 45w  | 60w  | 75w  |
|-----|------|------|------|------|------|
| normal | 1    | 0.07 | 0.03 | 0.03 | 0.07 | 0.07 |
|       | 2    | 0.37 | 0.41 | 0.37 | 0.48 | 0.44 |
|       | 4    | 0.06 | 0.19 | 0.06 | 0.25 | 0.13 |
| enhanced | 1   | 0.07 | 0.03 | 0.03 | 0.07 | 0.07 |
|        | 2   | 0.30 | 0.55 | 0.33 | 0.41 | 0.44 |
|        | 4   | 0.25 | 0.13 | 0.06 | 0.06 | 0.25 |
| ideal  | 1   | 0.04 | 0.02 | 0.02 | 0.04 | 0.06 |
|       | 2   | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
|       | 4   | 0.23 | 0.15 | 0.23 | 0.15 | 0.23 |

Table 16. Test result of Recall.

| Recall | 15w  | 30w  | 45w  | 60w  | 75w  |
|--------|------|------|------|------|------|
| normal | 1    | 0.93 | 0.97 | 0.97 | 0.93 | 0.93 |
|        | 2    | 0.71 | 0.70 | 0.72 | 0.66 | 0.68 |
|        | 4    | 0.93 | 0.82 | 0.93 | 0.78 | 0.87 |
| enhanced | 1  | 0.93 | 0.97 | 0.97 | 0.93 | 0.93 |
|         | 2   | 0.76 | 0.63 | 0.74 | 0.70 | 0.68 |
|         | 4   | 0.762| 0.83 | 0.94 | 0.93 | 0.75 |
| ideal  | 1   | 0.96 | 0.98 | 0.98 | 0.96 | 0.94 |
|        | 2   | 0.89 | 0.90 | 0.90 | 0.90 | 0.90 |
|        | 4   | 0.80 | 0.87 | 0.80 | 0.86 | 0.80 |

Table 17. Precision and Map.

|          | Normal | Enhanced | Ideal |
|----------|--------|----------|-------|
| Recall   |        |          |       |
| 1        | 0.9792 | 0.9804   | 0.9879|
| 2        | 0.8459 | 0.8613   | 0.9439|
| 4        | 0.9375 | 0.9399   | 0.9213|
| Map      | 0.9209 | 0.9272   | 0.9510|

Table 18. Precision of multiple methods.

| Methods      | HOG+SVM | LBP+SVM | SIFT+BoW+SVM | AlexNet+SVM | Normal | Enhanced | Ideal|
|--------------|---------|---------|--------------|-------------|--------|----------|------|
| Map          | 0.4040  | 0.5622  | 0.7506       | 0.9172      | 0.9209 | 0.9272   | 0.9510|

Figure 6. PR of three categories (normal).
Figure 7. PR of three categories (enhanced).
Figure 8. PR of three categories (ideal).
5. Conclusion
This paper first elaborates on the structure of the SSD convolutional neural network used in this article, then defines the elements of the PCB detection. By obtaining a large number of original PCB images, creating a semantically labeled image dataset, feeding it to the neural network and adjusting the hyperparameters, the best classification accuracy and localization accuracy is achieved. Meanwhile, comparison among other deep learning network methods is carried out to analyze the advantages of different algorithms in the PCB image inspection process. The experiment results show that the SSD algorithm performs better than other algorithms in the process of PCB detection.

Acknowledgments
This research was financially supported by Sichuan Provincial Financial Project of Intelligent Manufacturing (2017ZB073), and Made in China 2025 Sichuan Action Fund Project "Construction of Digital Workshop for Intelligent Manufacturing of Electronic Components”.

References
[1] Olivier Janssens, Viktor Slavkovikj, Bram Vervisch, Kurt Stockman, Mia Loocufier, Steven Verstockt, Rik Van de Walle, Sofie Van Hoecke, Convolutional Neural Network Based Fault Detection for Rotating Machinery, Journal of Sound and Vibration, Volume 377, 2016, Pages 331-345
[2] André Teixeira Lopes, Edilson de Aguiar, Alberto F. De Souza, Thiago Oliveira-Santos, Facial expression recognition with Convolutional Neural Networks: Coping with few data and the training sample order, Pattern Recognition, Volume 61, 2017, Pages 610-628,
[3] Shi,Wei et al. Single-shot detector with enriched semantics for PCB tiny defect detection. The Journal of Engineering(2020), 2020 (13):366
[4] Wenbin Zhu, Hong Gu, Weimin Su, A fast PCB hole detection method based on geometric features, Measurement science & technology, Volume 31, Number 9, 2020,
[5] Jixiu Wu, Nian Cai, Feiyang Li, Huiwen Jiang, Han Wang, Automatic detonator code recognition via deep neural network, Expert Systems with Applications, Volume 145, 2020, 113121, ISSN 0957-4174,
[6] K. He, X. Zhang, S. Ren and J. Sun, "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 9, pp. 1904-1916, 1 Sept. 2015, doi: 10.1109/TPAMI.2015.2389824.
[7] Huang,Weibo et al. HRIPCB: a challenging dataset for PCB defects detection and classification. The Journal of Engineering(2020), 2020 (13):303
[8] H. R. Roth et al., "Improving Computer-Aided Detection Using Convolutional Neural Networks and Random View Aggregation," in IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1170-1181, May 2016, doi: 10.1109/TMI.2015.2482920.
[9] G. Xu, H. Wu and Y. Shi, "Structural Design of Convolutional Neural Networks for Steganalysis," in IEEE Signal Processing Letters, vol. 23, no. 5, pp. 708-712, May 2016, doi: 10.1109/LSP.2016.2548421.
[10] Y. Chen, H. Jiang, C. Li, X. Jia and P. Ghamisi, "Deep Feature Extraction and Classification of Hyperspectral Images Based on Convolutional Neural Networks," in IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 10, pp. 6232-6251, Oct. 2016, doi: 10.1109/TGRS.2016.2584107.
[11] W. Qiu, Q. Tang, J. Liu and W. Yao, "An Automatic Identification Framework for Complex Power Quality Disturbances Based on Multifusion Convolutional Neural Network," in IEEE Transactions on Industrial Informatics, vol. 16, no. 5, pp. 3233-3241, May 2020, doi: 10.1109/TII.2019.2920689.
[12] C. Zhang, W. Shi, X. Li, H. Zhang and H. Liu, "Improved bare PCB defect detection approach based on deep feature learning," in The Journal of Engineering, vol. 2018, no. 16, pp. 1415-1420, 11 2018, doi: 10.1049/joe.2018.8275.