Defects and Components Recognition in Printed Circuit Boards Using Convolutional Neural Network

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Abstract. This paper introduces an automated components recognition system for printed circuit boards using Convolutional Neural Network (CNN). In addition to that, localization on the defects of the PCB components is also presented. In the first stage, a simple convolutional neural network-based component recognition classifier is developed. Since training a convolutional neural network from scratch is expensive, transfer learning with pre-trained models is performed instead. Pre-trained models such as VGG16, DenseNet169 and InceptionV3 are used to investigate which model suits the best for components recognition. Using transfer learning with VGG-16, the best result achieved is 99% accuracy with the capability of recognizing up to 25 different components. Following that, object localization is performed using faster region-based convolutional neural network (R-CNN). The best mean average precision (mAP) achieved for the defects localization system is 96.54%.

Keywords: Printed Circuit Boards, Convolutional Neural Network, Automated Vision Inspection System, Transfer Learning, Mean Average Precision

1 Introduction

The printed circuit board (PCB) manufacturing is getting more and more important because nowadays, a lot of consumer electronics products, such as laptops, mobile phones, tablets, PCs and so on are the essential in our daily life [1]. With the huge demands of PCBs, manufacturers need to cope with the demands and produce large quantity of PCBs. This situation arises a question, which is how these manufacturers ensure the quality of their PCBs, but still produce large quantities of them. The solution to that is through an automated inspection system. It is an approach to counter difficulties occurred in human's manual inspection which will have a lot of error when the quantity of PCB to be inspected increases in bulk. Automated visual PCB inspection can provide fast and quantitative information of defects which makes it very popular and important in the manufacturing process. A few examples of defect detection methods on PCB can be seen in [1] and [2].

According to [3] there are a lot of different techniques and algorithms developed and published in literature. In [4] template-matching approach is used to detect the PCB components. Another PCB defect detection using OPENCV with image subtraction method is done by [5]. From these existing detection frameworks, it can be inferred that each algorithm is limited to detect only a specific type of defects. With that being said, recently convolutional neural network (CNN) has achieved excellent performance on machine vision tasks, particularly image recognition problems [6][7]. Hence, convolutional neural network is shown to be feasible as the solution

Besides image classification, there are some researchers who use CNN for image localization. For example, recent advances in object detection are driven by the success of region proposal methods [8] and region-based convolution neural networks [9]. Although region-based convolutional neural networks (R-CNN) were computationally expensive as originally developed in [9] their cost has been drastically reduced [10]. In ImageNet Large Scale Visual Recognition Competition (ILSVRC) and Common Objects in Context (COCO) 2015 competitions, Faster R-CNN and region proposal network (RPN) were the core of several 1st place entries [11] in the tracks of ImageNet detection, ImageNet Localization, COCO detection, and COCO segmentation. RPNs can learn to propose regions from data, and therefore easily benefit from deeper and more expressive features (for example, the 101-layer residual nets adopted in [11].) These results suggest that faster R-CNN is an effective and accurate object detector.

The main goal of this research is to develop a deep learning-based recognition system for PCB. We first develop a CNN classifier to recognize different types of electrical components on the PCB. This is to compare and identify the best CNN models among well-known CNN models; Inception V3, VGG-16 and Densenet-169 in classifying the electrical components on the PCB board using transfer learning. Finally, we performed localization and detection of the defects on the PCB components using faster R-CNN.

The remaining of the paper is organized where section 2 explains the method used for training of the CNN in details. Section 3 is the results and discussions where the performance of the model is evaluated and tabulated as results. The last section which is the conclusion summarizes the whole paper and states potential future work.

2 Methodology

PCB Component Classifier (PCB-CC) is the first part of the project which is to develop a system that can classify different components on the PCB. Since there are no publicly available datasets for PCB board, the dataset is built by requesting dummy PCB boards images from Vitrox[1]. Dummy boards are used for tuning newly developed PCB inspection machines at Vitrox[1] and they cover most of the defects that could arise in real would. The images of the PCB board are taken using Vitrox[1] V510XXL AOI machine camera where they are under the same lighting condition, same scale and same angle. 25 different types of components are selected and cropped from the PCB images where each of type of components consists of 15 images as shown in Fig. 1.

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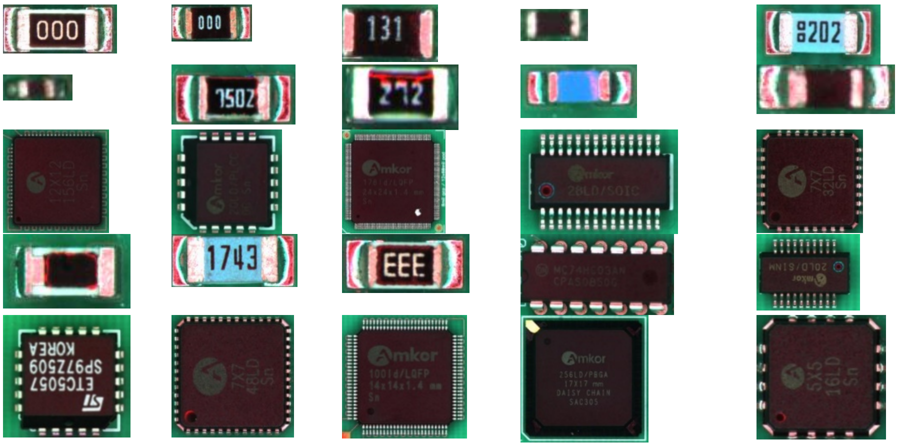

Fig. 1. The 25 different components to be recognized

Data augmentation is used to increase the variety of data in order to avoid overfitting issue. Each component is rotated to four angles, 90, 180, 270 and 360 degrees. In our work, each class uses 10 data samples for training. Data augmentation is then performed to increase the datasize to 40.

Transfer learning is used to train the prepared dataset. Pre-trained model such as VGG-16, Inception V3 and DenseNet-169 is loaded. The final layer of the pre-trained model will be removed and replaced with the new custom layer consisting of the desired components that are to be recognized. Using the testing images, the accuracy of the model is evaluated. Several parameters are configured prior to the training and it affects the performance of the output model. For this project, both the training batch size and validation batch size are set to 32. The percentage of training images is 53.33%, percentage of validation images is 13.33% and the percentage of testing images is 33.33%. Number of epochs are set to 20.

The second part of this work aims to detect the defects on the PCB board like an object, and then localize and classify them at the same time. The data used for PCB defect localization is the same as the data used in component classification part, which is the PCB images provided by Vitrox[1]. Only the missing resistor defect is focused. To prepare the dataset, the full PCB images are cropped into a few parts so that it is has the suitable size. This is because the full PCB images is 7440 x 10596 pixels, making it impossible for a normal computer to perform training because of insufficient CPU and GPU memory. After cropping the images, 50 training images and 10 testing images are formed. Data augmentation method such as cropping, rotation and padding are performed to improve the localization and classification performance of the model.

Using transfer learning on the pre-trained model faster R-CNN inception V2, the training is performed. After training is performed, final testing is done using the testing datasets while the mean average precision (mAP) [12] is used to evaluate the performance of the system. Several parameters need to be configured correctly to achieve an effective training. The first parameter which is the number of class determines how many types of object that is needed to recognize. For this project, only one object or class is focused, which is missing resistor. The number of training images used is 50 and the testing images used is 10. The Image resizer is set to resize images to 750x1050 pixels so that it matches the input image size. The Anchor scales is the size of the anchor. Since the smallest missing resistor defect size is 35 x 10 pixels, the anchor size is set to multiple scales which are 8 x 8, 16 x 16, 32 x 32, 64 x 64, 128 x 128, 256 x 256, 512 x 512 so that even small defects can be detected. The aspect ratio of the anchor is set to 0.5, 1.0 and 2.0, meaning that there are two rectangles and one square anchors.

3 Results and Discussions

In Table 1, the accuracies of using different pre-trained model during training can be observed. For each pre-trained model, 3 K-folds are used to evaluate the model and then the average of the K-folds are then calculated and recorded. Based on Table 1, the average accuracy for 3 K-folds is 99% for VGG-16. Table 1 also shows that the average accuracy of Inception V3 are 95% which is slightly lower than the accuracy of VGG-16 pre-trained model. DenseNet-169 has the lowest average accuracy 88%. CNN models need a large amount of data to achieve good performance in classification. However, VGG-16 performs well even when datasets are very little and limited achieving an accuracy of 99%. VGG-16 shows the best performance followed by Inception V3 and finally DenseNet-169.

Table 1. Number labelling corresponding to each health informatics

Types of Components		Pre-trained model	Number of K-Fold	Results (accuracy)	Average accuracy
25 different components	Data Augmentation (Rotation)	VGG-16	K-fold 1	98%	99%
			K-fold 2	99%	
			K-fold 3	99%	
		Inception V3	K-fold 1	90%	95%
			K-fold 2	96%	
			K-fold 3	98%	
		Densenet-169	K-fold 1	97%	88%
			K-fold 2	74%	
			K-fold 3	94%	

As for the detect localization and recognition task, Table 2 shows the different kinds of experiment perform to get the best object detector model in terms on mean average precision (mAP). These experiments are divided into two major phase which are the experimentation phase and optimization phase. In the first experiment, it was a failure with a mAP of 0% while training with original images. After analysis, it is known that the anchor scale that are set did not match with the defect size in the image. Proceeding to experiment 2, we decided to enlarge the defects in the image by cropping the missing resistor defects out of the image and then resizing it to 750 x 1050 pixels. However, obtained mAP after testing is only 5%. Though the mAP is improved, it is found out that the model does not account for multi scale detections because the model is still able to detect the missing resistors when it has a large ratio of defect to whole image with high accuracy but not when the defects are small in the image. Experiment 3 accounts for the ratio of defect to whole image by padding. Since the ratio is maintained, the mAP shows significant increase to 73.62%. In experiment 4, the background of the defects is taken into considerations. Testing images are cropped randomly from the PCB with a fixed size. As expected, the mAP shows a very high percentage which is at 94.85%. This shows that the training dataset used in experiment 4 is the most suitable among the previous experiments. Experiments 5 and 6 would be the optimization phase where training data are augmented to achieve better mAP. The highest mAP achieved is in experiment 6 which is 96.54%.

Table 2. Project breakdown of PCB defect localization and experiments performed

Exp	Phase	Types of defects	Pre-trained model	Changes from previous phase	Results (mAP)
1	Experimentation phase	Missing resistor	Faster R-CNN Inception V2	Original image	0%
2				Cropped missing resistor defect from original image	5%
3				Padded cropped missing resistor to size of 750 x 1050	73.62%
4				Random Crops from original image to size 750 x1050	94.85%
5	Optimization phase			Add augmentation data (rotation) to data used in experiment 4	95.64%
6				Add padded cropped missing resistor data from experiment 3 to data in experiment 5	96.54%

The output images from the defect localizer system is as shown in Fig. 2. The missing resistor defects are localized by drawing a bounding box around it.

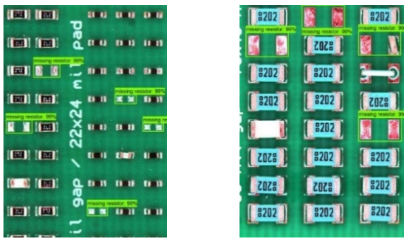

Fig. 2. Localized missing resistor defects produced in proposed method

4 Conclusion

For the first section, a PCB component classification system is built. After experimenting with different pre-trained models, it is found out that VGG-16 works best with the small dataset provided for this experiment where can classify up to 25 different components with 99% accuracy. For the second section, a PCB defect localization system is built using faster-RCNN Inception V2, a CNN based object detection model. A huge improvement in mAP has been observed starting from experiment 4. Through augmentation the highest mAP achieved is 96.54%. For the future works, more data can be added so that the even more components can be recognized, and more defects can be localized.

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