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PCB Defect Detection Using Deep Learning

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ABSTRACT

To cope with the difficulties in the process of inspection and classification of defects in Printed Circuit Board (PCB), other researchers have proposed many methods. In this approach, a PCB dataset containing 693 images with 6 kinds of defects is used for the purpose of detection, classification and registration tasks. Besides, a non-reference based method is proposed to inspect and train an end-to-end convolutional neural network to classify the defects. Unlike conventional approaches that require pixel-by-pixel processing, the proposed method firstly locates the defects and then classifies them by neural networks, which shows superior performance on our dataset.

KEYWORDS: Printed Circuit Board, Automated Optical Inspection, PCB Dataset, Reference Based Method, Convolutional Neural Network.

1. INTRODUCTION

The printed circuit board (PCB) is one of the most vital units in the electronic industry. It plays a key role in electronic devices, mechanically holding up and electrically connecting various electronic parts together. PCBs are used in almost every kind of electronic equipment, from electronic watches, smart phones to computers, communication electronic devices and military weapon systems, as long as integrated circuits and other electronic components are present. Benefitting from the development of integrated circuit and semiconductor technology, the size of electronic device components has shrunk down to a tiny scale. PCBs supporting these components are becoming increasingly complicated, diminutive and delicate. Thus, they must be manufactured at a high quality to meet customer demands.

Quality control in the manufacturing process of PCBs is usually challenging because a variety of defects occur inevitably due to mishandling or technical faults. Figure below shows common defects in bare PCBs, such as open circuit, mouse bite, spur, short, spurious copper and missing hole. All these defects could cause the instability of the board or even damage the entire board. Therefore, an efficient, highly accurate automatic detection module needs to be implemented to inspect diverse defects during the PCB manufacturing process.

2. PROBLEM STATEMENT

It is proposed to work on a PCB related dataset and the aim here is to solve PCB defect detection problem. The task is to detect all the defects in each image taken via dataset with greater accuracy. Manually looking at the sample is a tedious process. And this is where Deep Learning models play such a vital role. They can classify and detect the defects from images with impressive precision.

3. BACKGROUND OF CNN'S

In the last few years of the IT industry, there has been a huge demand for once particular skill set known as Deep Learning. Deep Learning a subset of Machine Learning which consists of algorithms that are inspired by the functioning of the human brain or the neural networks.

These structures are called as Neural Networks. It teaches the computer to do what naturally comes to humans. Deep learning, there are several types of models such as the Artificial Neural Networks (ANN), Autoencoders, Recurrent Neural Networks (RNN) and Reinforcement Learning. But there has been one particular model that has contributed a lot in the field of computer vision and image analysis which is the Convolutional Neural Networks (CNN) or the ConvNets. Around the 1980s, CNNs were developed and deployed for the first time.

When we give an input image into a CNN, each of its inner layers generates various activation maps. Activation maps point out the relevant features of the given input image. Each of the CNN neurons generally takes input in the form of a group/patch of the pixel, multiplies their values (colours) by the value of its weights, adds them up, and input them through the respective activation function.

The first (or maybe the bottom) layer of the CNN usually recognizes the various features of the input image such as edges horizontally, vertically, and diagonally. The output of the first layer is being fed as an input of the next layer, which in turn will extract other complex features of the input image like corners and combinations of edges. The deeper one moves into the convolutional neural network, the more the layers start detecting various higher-level features such as objects, faces and many more.

4. DEEP NETWORKS FOR DEFECT DETECTION

R-CNN extracts a bunch of regions from the given image using selective search, and then checks if any of these boxes contains an object. We first extract these regions, and for each region, CNN is used to extract specific features. Finally, these features are then used to detect objects. Unfortunately, R-CNN becomes rather slow due to these multiple steps involved in the process.

Fast R-CNN, on the other hand, passes the entire image to Conv-Net which generates regions of interest (instead of passing the extracted regions from the image). Also, instead of using three different models (as we saw in R-CNN), it uses a single model which extracts features from the regions, classifies them into different classes, and returns the bounding boxes. All these steps are done simultaneously, thus making it execute faster as compared to R-CNN. Fast R-CNN is, however, not fast enough when applied on a large dataset as it also uses selective search for extracting the regions.

Faster R-CNN fixes the problem of selective search by replacing it with Region Proposal Network (RPN). We first extract feature maps from the input image using Conv-Net and then pass those maps through a RPN which returns object proposals. Finally, these maps are classified and the bounding boxes are predicted.

5. FASTER RCNN

Our object detection system, called Faster R-CNN, is composed of two modules. The first module is a deep fully convolutional network that proposes regions, and the second module is the Fast R-CNN detector that uses the proposed regions. The entire system is a single, unified network for object detection. Using the recently popular terminology of neural networks with 'attention' mechanisms, the RPN module tells the Fast R-CNN module where to look.

A. REGION PROPOSAL NETWORKS

A Region Proposal Network (RPN) takes an image (of any size) as input and outputs a set of rectangular object proposals, each with an objectness score. We model this process with a fully convolutional network for object detection. The RPN works on the output feature map returned from the last convolutional layer shared with the Fast R-CNN. Based on a rectangular window of size nxn, a sliding window passes through the feature map. For each window, several candidate region proposals are generated. These proposals are not the final proposals as they will be filtered based on their "objectness score".

B. ANCHOR

The feature map of the last shared convolution layer is passed through a rectangular sliding window of size nxn, where n=3 for the VGG-16 net. For each window, K region proposals are generated. Each proposal is parametrized according to a reference box which is called an anchor box. The 2 parameters of the anchor boxes are: scale and aspect ratio.

Generally, there are 3 scales and 3 aspect ratios and thus there is a total of K=9 anchor boxes. But K may be different than 9. In other words, K regions are produced from each region proposal, where each of the K regions varies in either the scale or the aspect ratio.

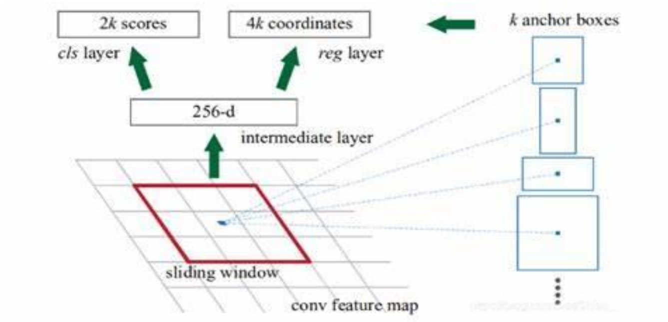

Fig 1: RPN Network

C. OBJECTNESS SCORE

S. No.	Type of Defect	No. of images
1	Missing hole	115
2	Mouse bite	115
3	Open circuit	116
4	Short	116
5	Spur	115
6	Spurious copper	116

The cls layer outputs a vector of 2 elements for each region proposal. If the first element is 1 and the second element is 0, then the region proposal is classified as background. If the second element is 1 and the first element is 0, then the region represents an object.

For training the RPN, each anchor is given a positive or negative objectness score based on the Intersection-over-Union (IoU). The IoU is the ratio between the area of intersection between the anchor box and the ground-truth box to the area of union of the 2 boxes. The IoU ranges from 0.0 to 1.0. When there is no intersection, the IoU is 0.0. As the 2 boxes get closer to each other, the IoU increases until reaching 1.0 (when the 2 boxes are 100% identical).

6. PROPOSED METHOD

D. TRAINING THE MODEL

Training a Faster R-CNN neural network is proposed in the model. Faster R-CNN is a two-stage deep learning object detector: first it identifies regions of interest, and then passes these regions to a convolutional neural network. The outputted features maps are passed to a support vector machine (SVM) for classification. Regression between predicted bounding boxes and ground truth bounding boxes are computed. Faster R-CNN, despite its name, is known as being a slower model than some other choices (like YOLOv4 or MobileNet) for inference but slightly more accurate.

Faster R-CNN is one of the many model architectures that the TensorFlow Object Detection API provides by default, including with pre-trained weights. That means we'll be able to initiate a model trained on COCO (common objects in context) and adapt it to our Case. TensorFlow even provides dozens of pre-trained model architectures on the COCO dataset. Here, we use a PCB defect dataset containing 693 images with 6 defects namely open circuit, mouse bite, spur, short, spurious copper and missing hole.

Table 1: Dataset

E. IMPLEMENTATION

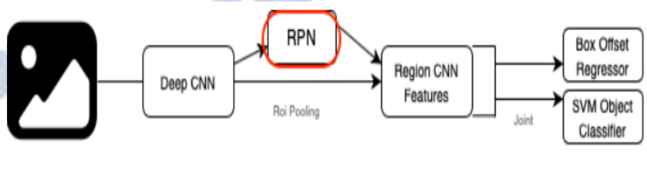

Fig 2: Proposed Method

- Take an input image and pass it to the Conv-Net which returns feature maps for the image.

- Apply Region Proposal Network (RPN) on these feature maps and get object proposals.
- Apply ROI pooling layer to bring down all the proposals to the same size.
- Finally, pass these proposals to a fully connected layer in order to classify and predict the bounding boxes for the image.

7. EXPERIMENTAL RESULTS

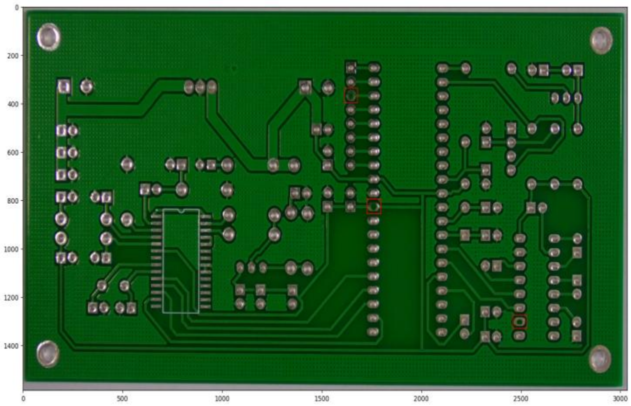

Fig 3: PCB Defect 1

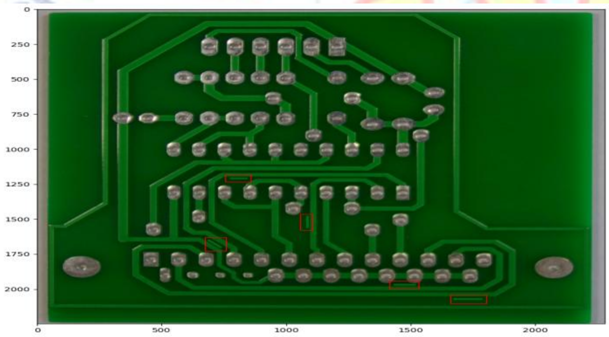

Fig 4: PCB Defect 2

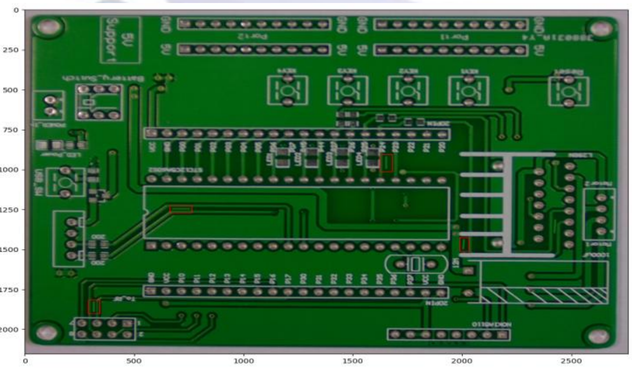

Fig 5: PCB Defect 3

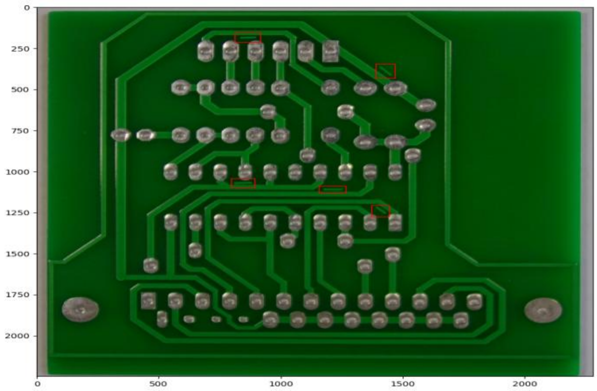

Fig 5: PCB Defect 4

Table 2: Defects

S.No.	Dataset	No. of Id's
1	Total Dataset	3941
2	Trained Dataset	3153
3	Test Dataset	789
4	Valid Dataset	3006

Table 3: Test, Train and Valid Dataset

S. No.	Type of Defect	No. of images	No. of Defects
1	Missing hole	115	994
2	Mouse bite	115	984
3	Open circuit	116	482
4	Short	116	491
5	Spur	115	487
6	Spurious copper	116	503
		693	**3941**

8. APPLICATIONS

The quality of PCBs will have a significant effect on the performance of many electronic products. Bare PCB is a PCB without any placement of electronic component, which is used along with other components to produce electric goods. In order to reduce cost spending in manufacturing caused by the defected bare PCB, the bare PCB must be inspected. The technology of computer vision has been highly developed and used in several industry applications. One of these applications is the automatic visual inspection of PCBs. The automatic visual inspection is important because it removes the subjective aspects and provides fast and quantitative assessments. It is responsible for detecting both cosmetic and functional defects and attempts are often made to ensure 100 percent quality assurance for all finished products.

9. CONCLUSION

With the rapid development of the electronics industry, the demand and production of the PCB are also increasing. The manufacturing process of the PCB is complicated, and defects are easily generated during the production process, so we require defect detection on the PCB. The traditional defect detection methods have low efficiency and high cost, which cannot meet the requirements of large-scale PCB detection at this stage. Machine vision may answer the manufacturing industry's need to improve product quality and increase productivity. The deep convolution neural network model can effectively detect the target category and recognise the characters. The model can use the detection and recognition results to detect defects on the PCB.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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