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Comparative Study of Image Processing and Transfer Learning Techniques for an Automated PCB Fault Detection System

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Abstract: Printed circuit board (PCB) is one of the most crucial components in most electronic devices. PCBs are manufactured in large quantities, and therefore, maintaining the quality of such large numbers of PCBs is important. An automated inspection system can help in the aspect of quality maintenance. Such a system is able to overcome the limitations of manual inspection for a large number of PCBs. It provides fast detection of defects and hence can prove to be an asset in the manufacturing process. This project aims to achieve fault detection of bare PCBs through two different methods; the traditional algorithmic approach using image processing, which makes use of image subtraction method, and a transfer learning approach, which involves the pre-trained CNN VGG16 model. A comparative study of both the methods is done.

I. INTRODUCTION

The objective of this project is to develop an image based fault detection system to identify various defects on bare Printed Circuit Boards (PCBs) [a comparative study of algorithmic computations of image processing and transfer learning approaches]. There are primarily two types of PCB boards on which defects can be detected. One is the mounted PCB and the bare PCB. In this project we will be using two methods viz transfer learning which is a supervised method and image processing techniques which is an unsupervised method and then compare the two on the basis of accuracy and time. PCB manufacturers are usually required to produce PCBs in large quantities. PCB fault detection can be achieved using a variety of techniques. In our project we aim to use two techniques for pcb fault detection and classification. The first method is Transfer Learning, which falls under the domain of machine learning. In transfer learning a model is developed for a particular task and is then reused as the starting point for another task. The pre-trained model which we would be using is VGG16. The second method which we would be implementing in our project is a traditional handcrafted supervised algorithm. Image processing is an extremely large domain and consists of a number of methods and techniques within it. The main focus is to develop a bare PCB inspection technique through an image subtraction algorithm.

II. BACKGROUND

The manufacturing of a printed circuit board is long known to the industry. But one is bound to encounter a number of defects during this process. Printed Circuit Boards are used to support and connect electrical and electronic components using conductive paths, pads and other features etched from one or more layers of copper laminated onto between sheet layers of a non conductive substrate. The first step is to produce the manufacturing data followed by type setting.

The board is then cut. The board used could be made up of glass or copper. CNC machine drilling is then performed depending on the design. This is then followed by track painting and cleaned with water so that the track is visible. Tracks are printed using ink and then the etching process takes place followed by masking. This forms our bare printed circuit board. The errors that can occur during this stage are mouse bite, open circuit, missing hole etc. Detecting these defects at this stage is very essential. It can save a lot of money, time and effort in the long run. Further, the electronic components are mounted on the bare PCB. Depending on the manufacturing process, the PCB defects can be divided into two main parts, fatal and potential defects. Open-circuit defect is a fatal defect, in which the PCB does not meet the objective for which it is designed. Whereas, missing hole and mouse bite defects fall in the potential defects category, in which the defects may compromise the performance of the PCB during utilization.

We will be working with a single layer bare PCB. A single layer bare PCB is subjected to a number of faults such as break out, pin hole, open circuit, underetch, mouse bite, missing conductor, spur, short, wrong size hole, missing hole, spurious copper, excessive short. In this paper we will be focusing on three defects, missing hole, mouse bite and open circuit.

III. LITERATURE SURVEY

In the fields of image processing as well as transfer learning, many researchers have done a lot of work regarding PCB fault inspection. Numerous methods are suggested by the researchers on PCB defect detection and classification. In this section, brief evaluations of a few essential contributions to the existing works of literature are presented as shown in Table 1.

Sr. No.	Paper Title	Publication Journal & Year	Summary	Research gap/Future scope	Author
1.	Study of the Image Processing algorithms for defect detection of PCBs	International Journal of Engineering Technology Science and Research (IJETSR), 2017	<ul style="list-style-type: none"> ● 3 approaches: Template matching, Image subtraction, Image morphology to detect defects and classify them into groups. ● Dataset was created using a Pi camera for capturing images. 	<ul style="list-style-type: none"> ● Some of the defects cannot be addressed individually. ● Future scope includes inspection and analysis of a PCB with Surface Mounted Devices. 	Pratiksha R. Masalkar, Prabha S. Kasliwal
2	Components Free Electronic Board Defect Detection and Classification Using Image Processing Technique	International Journal of Engineering Research and Technology (IJERT), 2018	<ul style="list-style-type: none"> ● Using the subtraction method the defects are identified ● A different algorithm is introduced to classify the 7 defects. 	-	Harshitha R, Apoorva G C, Ashwini M C, Kusuma T S
3	PCB Defect Detection Using OpenCV with Image Subtraction Method	Institute of Electrical and Electronics Engineers (IEEE), 2017	<ul style="list-style-type: none"> ● Enables the system to capture, recognize, and analyze images ● To detect the defects from bare PCBs, the image subtraction method in OpenCV is used. 	<ul style="list-style-type: none"> ● Improve the algorithm of Blob Detection and Morphology to raise the accuracy. ● Apply Hough Transform and Image Segmentation, to increase accuracy and reduce the necessity of having both reference and test images to be of the same size and alignment. 	Fa'iq Raihan, Win Ce
4	Very deep convolutional networks for large-scale image recognition	Published as a conference paper at ICLR 2015	<ul style="list-style-type: none"> ● Input:224*224*3. ● Pre-processing: Subtracting the mean RGB value, computed on the training set from each pixel. ● Filter: 3x3,Stride: fixed to 1 pixel, Spatial pooling: 5 max pooling layers, Fully connected layers: 3 FC, Final layer: softmax layer, All hidden layers are equipped with ReLu. 	-	Karen Simonyan and Andrew Zisserman
5	Detection Defect in Printed Circuit Boards using Unsupervised Feature Extraction Upon Transfer Learning	Institute of Electrical and Electronics Engineers (IEEE), 2019	<ul style="list-style-type: none"> ● Combination of unsupervised deep learning used upon VGG-16 with pre-trained on ImageNet weight coefficients, code in tensorflow and keras frameworks. ● Defects detected are scratch, missing washer/extra hole, abrasion, broken PCB edge. ● More than 90% defects detected. 	<ul style="list-style-type: none"> ● Conduct more experiments with other pre-trained networks, more extensively analyze ResNet50, and compare the results with VGG-16. ● Also, use adaptive threshold for defect detection and calculate it in an automatic way based on distribution of the scores for normal patches. 	Ihar Volkau, Abdul Mujeeb, Dai Wenting, Erdt Marius, Sourin Alexei

6	Automatic Optical Inspection for Defective PCB Detection Using Transfer Learning	Institute of Electrical and Electronics Engineers (IEEE), 2019	<ul style="list-style-type: none"> ● The following paper compares two pre-trained models, VGG-16 and ResNet50. Studies show that VGG-16 delivers more promising results. ● Deep PCB dataset is used. 	<ul style="list-style-type: none"> ● Conduct comparative studies using more pre-trained models. ● Use a large dataset in order to achieve better results. 	Leandro H. de S. Silva, George O. de A. Azevedo, Bruno J. T. Fernandes, Byron L D Benzerra
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Table1. Literature Survey

IV. COMPARISON OF HANDCRAFTED AND TRANSFER LEARNING TECHNIQUES

A. Image Subtraction

Image processing is a method to perform certain operations on an image, which will result in an enhanced image, or extracting some useful information from it. In this type of processing, the input is an image and the output may be an image or characteristics/features associated with that image. Image processing basically includes the following three steps:

- 1) Importing the image via image acquisition tools
- 2) Analysing and manipulating the image
- 3) Output to show the results

The approach used in this system is based on the Image Subtraction technique, in order to detect the PCB defects from the images of bare PCBs. Image subtraction is one of the image processing techniques, also known as pixel subtraction. In this technique, the digital numeric values of pixels from an image are subtracted from the values of pixels of another image. This is done for the purpose of detecting the changes between the two images. The functions used within the system are taken from the OpenCV library of Python. Initially, pre-processing is done on the template and test images, to resize them, so that both are of the same size. This is necessary, since pixel-to-pixel mapping is done during image subtraction. Both the images should also be of the same orientation. Then, they are converted to grayscale images. After that, both images are blurred using a blurring method, and adaptive thresholding is performed on them. Finally, an image subtraction function is applied, which subtracts the test image from the template image, to get the result as the difference image. This image contains the defective part, which is shown as bright(white) pixels on a dark(black) background. We can thus observe the defective part, and easily see where the defects are located. Contour detection is also applied to count the number of defects detected in the test image. This can further be used while calculating accuracy of the system.

B. Transfer Learning

Transfer learning allows solutions to multiple problems and applications. It is primarily a technique in which any neural network model is initially trained on a similar dataset to that of the actual problem. On completion of stage one, certain layers from the then trained model are retrained to generate a new model addressing the required problem statement. A model is initially trained using a larger dataset. The trained layers are frozen and used as it is while addressing a problem statement with a comparatively smaller dataset. In such cases only certain layers, usually the fully connected and output layers are modified as per the problem statement. Hence using this technique models can be trained using smaller datasets as well without compromising the accuracy. Some popular models include ResNet-50, VGG-16, VGG-19, Inception V3, Xception. Various word embedding models include Word2Vec, GloVe, FastText. The pre-trained model which we have used for pcb fault detection is VGG-16.

Using pre-trained models is recommended when one has a large dataset in hand. VGG-16 is a convolutional neural network architecture which was used to win ILSVR (ImageNet) competition in 2014. The original VGG-16 architecture has 2 fully connected layers followed by a softmax for output. The 16 in VGG-16 refers to it having 16 layers that have weights. The network is a pretty large network and it has about 138 million parameters.

All the hidden layers use ReLU as its activation function. ReLU is more computationally efficient because it results in faster learning and it also decreases the likelihood of vanishing gradient problem. When using VGG-16 there is no requirement of a reference image.

C. Points of Comparison

- 1) *Dataset*: A handcrafted Image Subtraction algorithm can be made, tailored to a small dataset, as long as we have a non-defective template image to compare the input to. Any defective/non-defective image can be compared to the template image as long as the image taken is in the exact same format and alignment as the template image. A pre-trained CNN model requires a larger database to fine-tune the model for our exact purpose. Thousands of images are required to obtain a sufficient accuracy but the application of the model is far more versatile than the image subtraction algorithm
- 2) *Degree of Automation*: Once fine-tuned, the pre-trained CNN model simply requires an input to detect the faults in any bare-board PCB irrespective of the angle of camera, the layout of the PCB or the fault to be detected. In the case of handcrafted algorithms the system has to be designed for specific layouts of PCB and the image properties have to be regularized. A generic one-fits-all algorithm cannot be implemented. But once written the algorithm can be used for all cases of the same PCB.
- 3) *Scalability*: In CNN Transfer learning more classes of defects can be added as long as there is a dataset of PCB images with that defect available. The model can further be trained on these defects and different layouts of PCBs to make the system more generic. In Image Processing algorithms, we require the template image of a non defective PCB to perform image subtraction.
- 4) *Point of Application*: Image Subtraction algorithm is a better fit in a regulated environment, such as PCB manufacturing plants, where we already possess information about the PCB, such as its layout and a non defective template image, and can take images in the same angle and quality as the template beforehand, so we can compare the new input to the template to maintain a high accuracy in defect detection. The transfer learning model is a better fit in an unregulated environment where we don't possess enough prior information about the PCB and hence need a more generic system to detect any defect provided through the input.

V. SYSTEM ARCHITECTURE

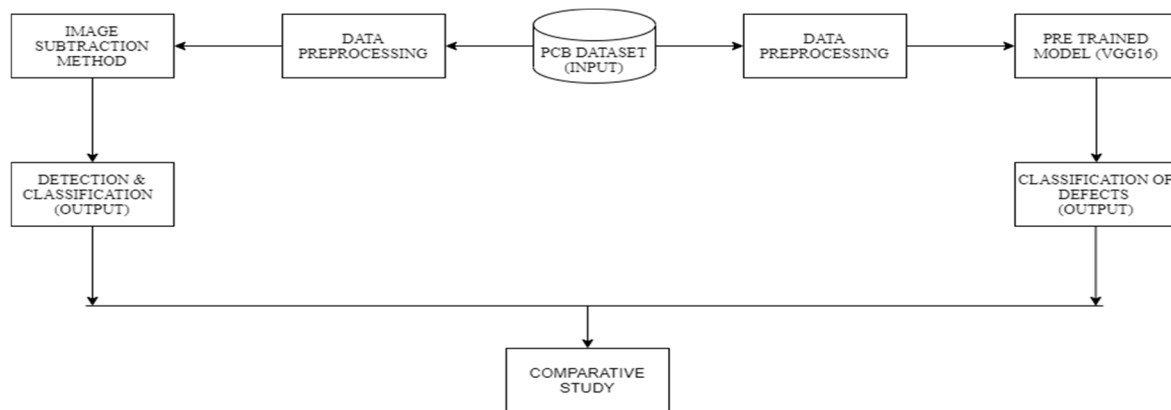


Fig1. Block Diagram (System overview)

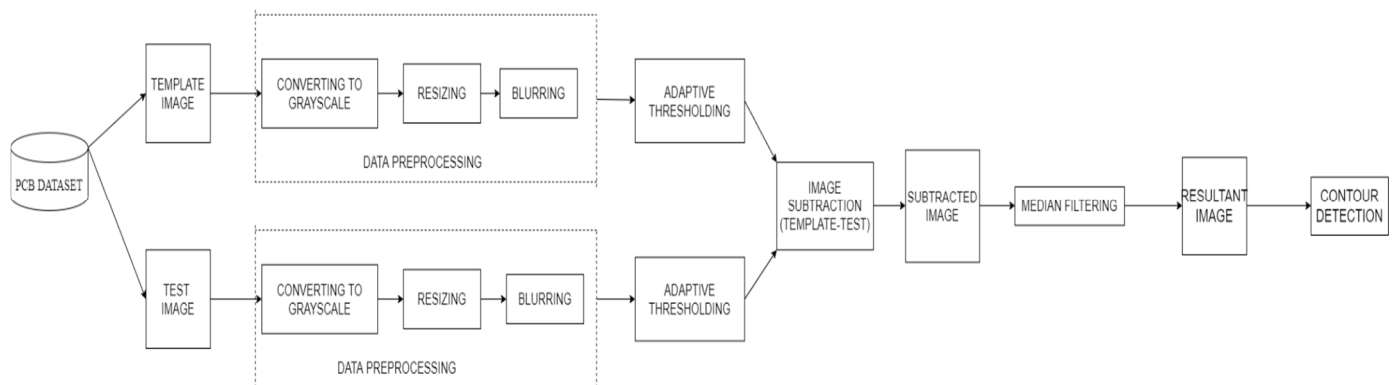


Fig2. Image Processing Module

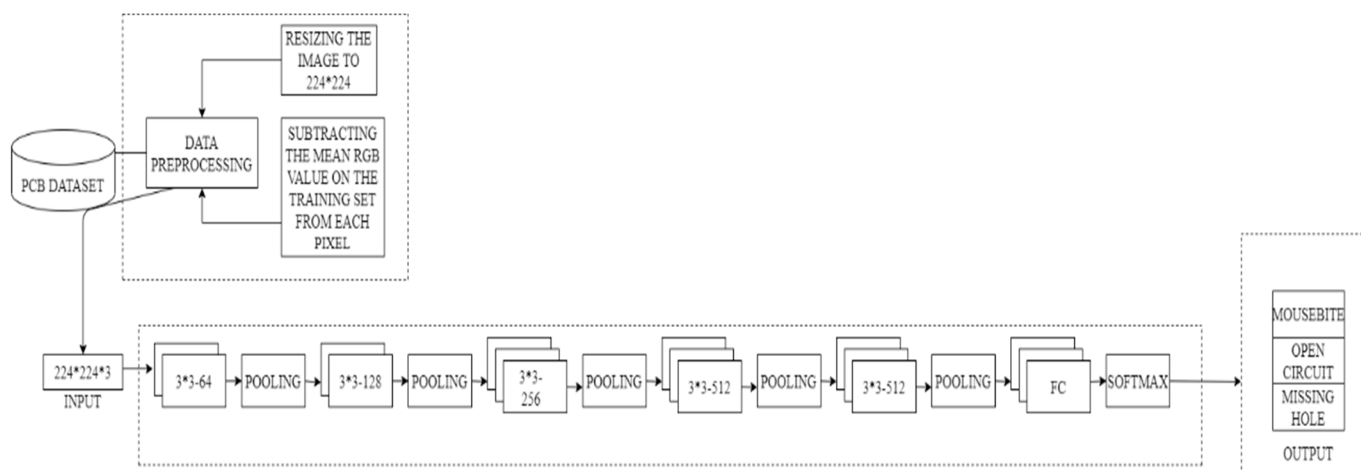


Fig3. Transfer Learning Module Working

A. Image Subtraction: Hand Crafted Method

The Image subtraction strategy differentiates between the test image and template image by using a pixel-by-pixel approach. The output of the subtraction operation will give either a negative or a positive image ("1" can be used to represent a white pixel and "0" is used to represent a black pixel in a binary image).

Since the number of output classes are specified, the dataset is segregated into different folders depending on the type of defect and the algorithm used is defined by us, our technique follows a supervised approach.

Defect /PCB Types	CB 01	CB 05	CB 07	CB 10	CB 11
Missing Hole	20	0	0	5	0
Mouse Bite	20	0	0	5	0
Open Circuit	20	0	0	6	0

Table2. Original dataset of bare PCB images

We also performed rotations of all images at 90, 180 and 270 degrees. As a result, we had 4 times the total number of original images, ie, 166 * 4 = 664.

As Shown in Fig 2 the steps followed in image subtraction process are:

- 1) *Grayscale* - Grayscale is the process of converting an image from other color spaces to shades of gray. By finding the average of the R, G and B values a gray scale image is obtained.

$$\text{Gray scale Value} = (R + G + B)/3$$
 In a grayscale image a single byte for each pixel stores a value from 0 to 255, and thus covers all possible shades of gray.
- 2) *Thresholding* - It is used to turn a grayscale image into a binary image based on a specific threshold value. Pixels below that value are converted to black, and pixels above that value are converted to white. There are two main categories of thresholding: Simple thresholding and Adaptive thresholding. Various types of simple thresholding are binary thresholding, binary thresholding inverted, truncated thresholding, etc.
- 3) *Adaptive thresholding* - It is an advanced type of thresholding. The basic difference in simple and adaptive thresholding is that in simple thresholding - the threshold value is global, i.e., same for all the pixels in the image while in adaptive thresholding - the threshold value is calculated for smaller regions, i.e., different threshold values for different regions. The function used is: `cv2.adaptiveThreshold()`

- 4) *Image subtraction* - The pixel values in two images are subtracted with the help of cv2.subtract()
- 5) Both the images should be of equal size, depth and orientation. The difference between two images img1 and img2 can be expressed as : ResultantImg = cv2.subtract(img1,img2)
- 6) *Detection* - The three types of defects detected are: MissingHole, MouseBite and OpenCircuit. The subtracted image is passed through a median filter to remove the noise. Following is the syntax of this method: medianBlur(src, dst, ksize)
The image thus obtained can detect the different defects.
- 7) *Contour Detection* - In OpenCV, finding contours is like finding white object from black background. The contours are a useful tool for shape analysis and object detection and recognition
The method used for this purpose is: cv2.findContours()
We used a simple percentage calculation method to find the accuracy of detection of the defects.
The formula used is as follows:
 $acc_percent = (total_detected/total_defects)*100$

B. VGG-16: Transfer Learning Method

- 1) *Dataset*: The dataset used for this project is a combination of two open source datasets obtained from github. The dataset has 115 images each of missing hole, mouse bite, open circuit, short, spur and spurious copper. Out of these set of images, we will be working with two defects; missing hole and mouse bite. Further we divided these images into training and validation sets. For mouse bite the training set consists of 84 images and the testing set consists of 31 images. Similarly for missing holes and open circuit the training and testing sets consist of 82 and 33 images respectively. The images in the dataset are synthetic pcb images. From the second dataset we obtained 1570, 1538, 1454 training images for mouse bite, missing hole and open circuit respectively. Also, 282, 294, 299 testing images for mouse bite, missing hole and open circuit respectively. The dimensions of each image are 3034,1586,3. 3 because they are RGB images. Evidently the number of images present in the dataset is very miniscule. In order to increase the number of images in the data set we performed image augmentation which helped us achieve a total of 1680 training and 620 testing images for mouse bite along with 1640 training and 660 testing images for missing holes.
- 2) *Image Augmentation*: Image Augmentation is used to artificially expand the existing dataset by developing a variety of versions of each image present. Image augmentation is performed to increase the number of images which inturn helps train the model more efficiently. Image can be processed in a number of ways such as, horizontal flip, vertical flip, zoom in, zoom out, contrast, rotation at specific or random angles etc. This is achieved using Image Data Generator API from Keras. Hence using this technique we created 20 random augmented images for each of the images present in the original dataset.

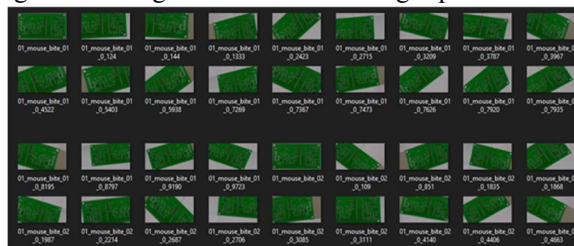


Fig4. Augmented Images

- 3) *Training*: For training we used Transfer Learning in Keras on VGG-16. First and foremost we imported keras and all the methods and functions required to build and train the model. Inorder to import all the images we used ImageDataGenerator from keras. We had to resize the images to 224,224,3 as the model was originally trained using this size. We then import VGG-16 from keras with pre-trained weights which were originally trained on imagenet. Once we have downloaded the model, the model now needs to be modified as per our problem statement. This needs to be done because pcb detection does belong to any of the 1000 classes which was used originally. Next, there were in all 1000 classes, as per our problem statement we have only 3 classes which are missing holes, open circuit and mouse bite. The activation function used was ReLu in the original model. In case of more classes we can also use the softmax activation function. The output layer consists of 1000 neurons, we will have to modify it to 3 output neurons. Along with this we add a flatten layer as well. Whatever output we receive we condense that into one dimension using the flatten layer. The model was trained twice. Once using the original dataset and then using the dataset consisting of the augmented images. Different combinations of epochs were experimented with to attain maximum accuracy.

VI. RESULTS

A. Image Subtraction

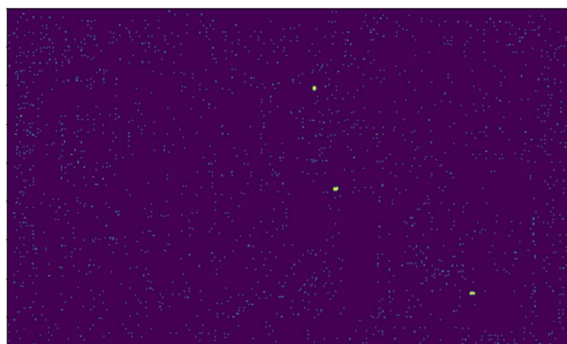


Fig5. After Image Subtraction (Missing hole)

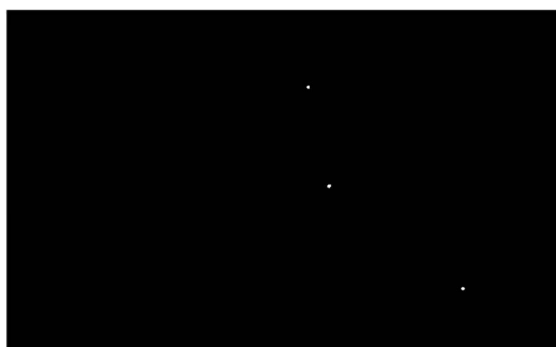


Fig6. After Median Filtering (Missing hole)

Defect	PCB 01	PCB 05	PCB 07	PCB 10	PCB 11	Average accuracy
Missing Hole	93.3	41.3	100	100	95.6	86.05
Mouse Bite	70.8	60.4	72	84	76	72.64
Open Circuit	71.7	84.4	70	93.33	82.7	80.43

Table3. Result table for defect detection(image subtraction)

B. Transfer Learning- VGG-16

DATASET USED	STEPS_PER_EPOCH	EPOCH	LOSS	ACCURACY (ACCURACY METRICS)
ORIGINAL	5	10	4.4146	0.5003
AUGMENTED	5	10	4.3124	0.6072

Table4. Result table for defect detection(VGG-16)

VII. FUTURE SCOPE

In the future work, such a dataset can be used which includes different types (designs) of PCBs, i.e. a variety of PCB images. Also, a dataset with a large number of images can be used.

For an unbiased result a more balanced dataset can be used which contains equal amounts of defected and non-defected images. The system can be modified to incorporate detection of more PCB defects. The system can also be improvised in such a way that real-time defect detection is possible.

An integrated system can be developed in which the defects present on the bare PCB can be detected and localized using image subtraction and the defects can further be classified using a pre-trained model. One can experiment using different pre-trained models, and other handcrafted algorithms.

VIII. CONCLUSION

In this project, we have tried to develop a system that would be helpful in the field of PCB manufacturing. Our prototype models will detect and classify bare PCB defects, which will help in minimizing the waste of defective PCBs which are otherwise discarded altogether. The comparative study will help in identifying the better and more accurate approach among the two implemented, according to the circumstances and available resources. The dataset used is an open-source dataset, which can later be benchmarked and people can use this prototype along with the dataset, for further research and development.

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