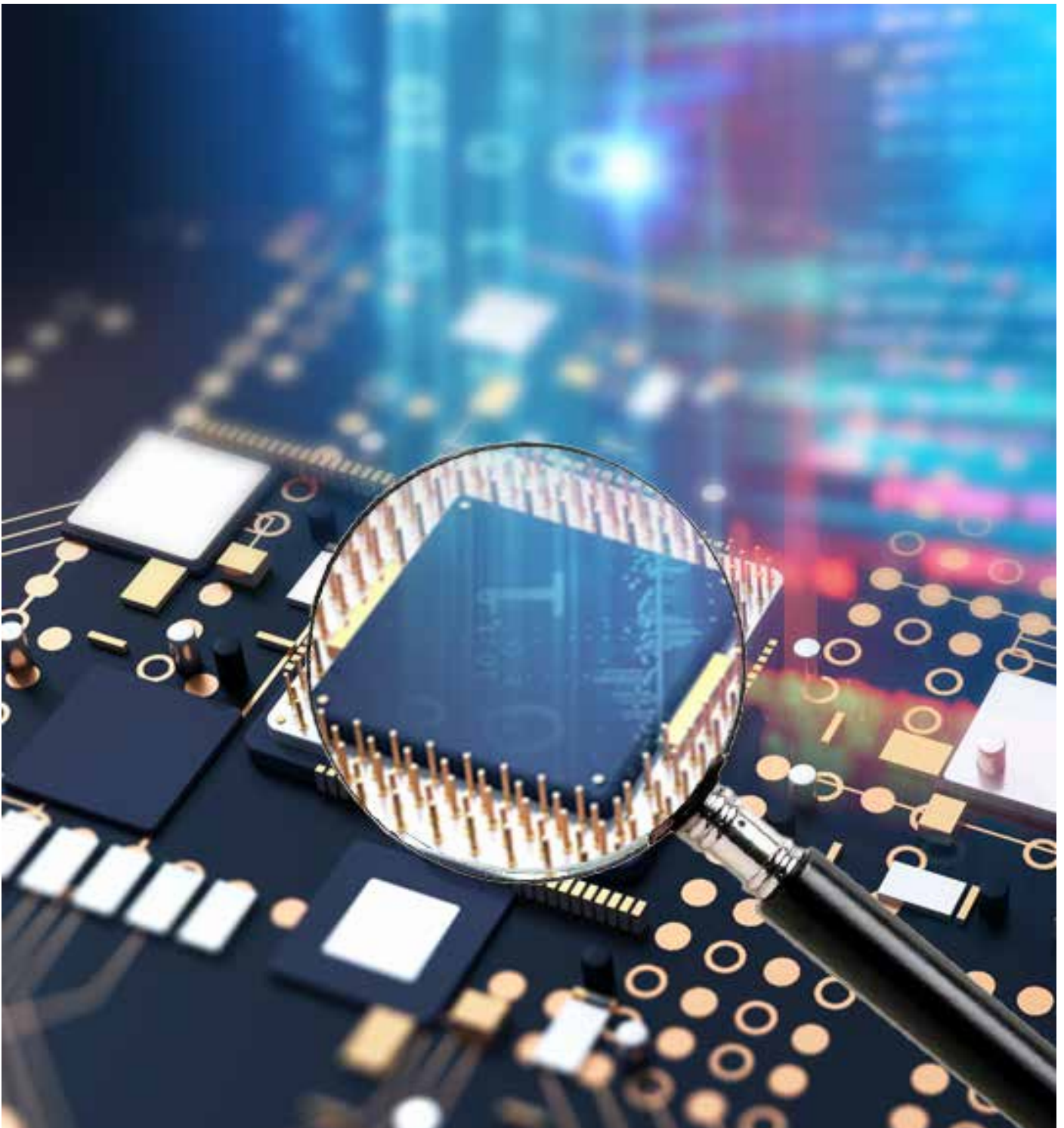


# Image Analysis-based Quality Control in Semiconductor Production

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# 1.

## Introduction

### 1.1 Semiconductor Manufacturing

Semiconductor manufacturing comprises producing Integrated Circuits (ICs) or chips consisting of transistors and wiring on a semiconductor wafer, and then integrating them on a Printed Circuit Board (PCB). These interconnected chips are the building blocks of electronic circuits. They are utilized in all types of electronic devices and have applications in electronics, automotive, telecommunication and numerous other industries. One of the crucial expectations from semiconductor manufacturing is reliability. The chips have to function properly for a long period of time in conditions with high degree of fluctuations in temperature and humidity and withstand stresses and shocks. For instance, semiconductors utilized in industrial settings may have to function properly in the temperature range of -65 to +125 degree Celsius. Their reliability can be affected by various factors such as construction materials, chip design, chip assembly and packaging, etc. Since electronic component functioning depends upon the reliability of semiconductors, ascertaining the quality of semiconductor manufacturing becomes paramount.

### 1.2 What is Semiconductor Quality Control?

Semiconductor manufacturing is a costly and time-consuming affair. Moreover, since effort is constantly being made to increase chip performance by fitting a higher number of transistors and fitting smaller wires on the chip, small random manufacturing anomalies such as a dust particle landing on a wafer can have magnified effects on performance. Apart from this, there could also be systematic or pattern defects due to faults in the manufacturing process. Manufacturing Quality Control (QC) which ensures that the manufactured product quality is maintained to a certain standard becomes critically important in avoiding component malfunction. QC uses human perceptions, industry standards, processes and rules of quality characteristics to ensure the quality of a product. A vital component of semiconductor manufacturing quality control is the ability to detect defects due to systematic and chance events. Defect inspection systems that identify physical defects and pattern defects are thus essential in ensuring quality control in semiconductor manufacturing.

### 1.3 Traditional and Modern Quality Control

Traditional QC is mostly post-production and is limited in reducing loss due to product rejection or rework to assure quality. Modern QC methods on the other hand use sensors and various IoT platforms to collect manufacturing information during the production process. It detects an abnormality in quality at the early stages of production thus avoiding loss of time and money (Schmitt et 2020). However, modern QC has its own challenges and is limited by human perception-based manual inspection. Moreover, the manual process of defect detection in semiconductor components requires intensive training of failure analysts. Training the analysts consumes a significant amount of time and still yields questionable results in the efficiency of defect detection because of the following reasons:

- **Multiple defects in a component:** A single component may have multiple defects and there is a high degree of possibility that some of these are passed on undetected by the analyst while manually inspecting the component.
- **Low error tolerance:** The defects have a very low error tolerance, i.e., the slightest error could result in component malfunctioning. The manual inspection process may fail to detect all of these tolerance errors.
- **Speed of defect detection:** Manual inspection requires high expertise for defect detection and a significant time to analyze the component. It slows down the defect detection process.

## 2.

# Machine Learning for Quality Control

## 2.1 Introduction to ML in QC

Modern QC challenges raise the need for a method that can learn the quality rules, variety of defects, anomalies and adapt this knowledge to various changes in products, while overcoming the limitations of human analysts. Hence, a recent trend in the semiconductor manufacturing process is a gradual move towards a fully automated QC setup. Making this possible are sophisticated Machine Learning (ML) methods developed over the past few years, particularly the maturity of Deep Learning-based image analytics that have ushered in the era of AI-powered visual inspection and anomaly detection for semiconductor manufacturing.

## 2.2 ML Approaches and Applications

Modern QC methods use AI-based visual inspection systems that utilize high-quality images and other meta data of a product to gather rich information related to its quality. These visual inspection systems are powered by image processing tools like OpenCV, PyTorch, Tensorflow, Kornia, Caffe and readymade solutions such as Reasoning-RCNN, Mesh RCNN to support the ML methods in detecting the anomalies from enriched product (image) data. A detailed account of the image processing methods can be found in (Lyalin 2021). AI-based systems use a large corpus of product images in conjunction with Deep Learning methods to train on various features of products. Once trained, the systems provide high-quality inference of a product's defects and anomalies. ML methods with data and image processing tools automate the QC process delivering optimal performance with respect to quality, cost and time.

# 3.

## PCB Anomaly Detection

### 3.1 Introduction

PCB is a complex circuit containing interconnected electronic components and is meant to perform a specific task with high reliability and efficiency.

PCBs are prone to defects caused due to systematic flaws in the production line or unnoticed random manufacturing anomalies. There are different defects such as shorts, spurs, mouse bites and pinholes that cause current leakage or open circuits. Avoiding such defects become important since they degrade the performance of the PCB and result in poor reliability and inefficiency.

This can further cause financial losses and customer dissatisfaction due to product failures.

PCB visual inspection is an important QC exercise to ensure defect-free products and prevent unnecessary damage to its components.

### 3.2 Types of PCB Visual Inspections

**Different types of visual inspections are as follows:**

- **Component classification:** : Component classification is crucial to validate the quality of the PCB under observation. Certain semiconductor's parts look alike and hence require a component classification module to check the correct component placement on the PCB.
- **Component defect detection:** In the PCB development process, semiconductor parts are integrated into the mother chip. As a result, it is possible that defective parts were used in development. Thus, this requires a component defect detection module to check the quality of PCB sub-components.
- **Trace detection:** In the PCB development process, it is possible that a defect may be introduced while fabricating the IC. One such kind of defect which causes hindrance in signal transmission between components is trace defect. Due to trace defects, PCBs can malfunction and may impact different components in the circuit. Thus, a quality control check is required to identify trace defects in the PCB.
- **Via defect detection:** Multi-layer PCB construction uses pads in the corresponding position in different layers which are electrically connected by a hole through the board known as a Via Hole, which is made conductive by electroplating. Defects in Vias can cause PCB malfunction and even damage the components. Thus, this requires a quality control check during PCB development to ensure correct design and conductivity.

### 3.3 Generating Images for Visual Inspection

Different types of camera settings and techniques are used to perform a visual inspection of PCBs. These methods impact the quality of the image and determine the level of pre-processing required before applying any analytics for inspection. The different types of cameras used to capture the PCB board images are:



- **CCD video camera:** Charge-coupled Device (CCD) is a transistorized light sensor on an integrated circuit. CCD devices convert or manipulate an electrical signal into output, including digital values. They are, in other words, digital cameras.
- **Digital microscope:** A digital microscope is a variation of a traditional optical microscope that uses optics and a digital camera to output an image to a monitor.
- **DSLR:** A Digital Single-lens Reflex camera (digital SLR or DSLR) is a digital camera that combines the optics and the mechanisms of a single-lens reflex camera with a digital imaging sensor. The viewfinder of a DSLR presents an image that will not differ substantially from what is captured by the camera's sensor.

### 3.4 Major Challenges in PCB Image Analysis and Solutions

S. No.	Challenge	Description	General Solution
1	Camera parameter setting	Correct calibration of the camera setting and dynamic changes in the setting is required to perform good quality image inspection.	As per the type of inspection, calibration methods and values are preset and followed to capture good quality images.
2	Ambiance light	Ambiance light is an important aspect to capture good quality images of the PCB for high accuracy inspection. Some cameras have in-built self-light, but others require an appropriate ambiance light adjustment.	Different analytical techniques are used to increase the contrast of the image under observation, as well as a proper setup can be used for image snapping.
3	Rotations	PCB images under inspection may have rotation in them, due to which image comparison or component identification becomes a difficult task.	Different techniques like SIFT (Scale Invariant Feature Transform) and SURF (Speeded Up Robust Features) are used to compare the PCB image under observation with a reference template to correct the rotational error.
4	Shadow	While the image is snapped, due to shifts in ambiance light, the shadow of the PCB may be captured in the image. This introduces an additional dark zone in the image and causes difficulty in image comparison and analysis.	HSV (Hue Saturation Value) color space representation of an image for shadow detection and subtraction methods can be used to remove the shadow.
5	Camera resolution	Since capacitors and resistors have the same shape and size, thus higher camera resolution is required to capture the serial number to identify the component on a PCB.	Contrast stretching, slicing and histogram equalization can be used to enhance the resolution of a camera.

## 3.5 Different ML Approaches for PCB Defect Detection

- **Image matching:** This analytical approach relies on template comparison and subtraction. A reference template is used as a base to analyze any type of defect in the PCB under inspection. There are multiple strategies that are adopted to perform the comparison, such as:
  - **Direct subtraction:** The RGB image of the PCB under inspection is directly subtracted from the reference template PCB image. This subtraction process is performed once the pre-processing of the PCB image under inspection is completed. It leads to a generation of dark areas where an exact match is found and light spots where the pixel values are different. These light spots reflect the errors or anomalies in the PCB under inspection.
  - **Binarization and subtraction:** : In this method, first, the image under inspection and the reference image are converted into a binary array of pixels using a threshold value. Then subtraction is performed to generate dark and light areas, where light spots reflect the corresponding anomalies.
- **Feature extraction and analysis:** In this method, multiple mathematical transformations are performed on the reference and image under inspection. These transformations are treated as different features represented by the PCB image. These features are analyzed to understand the variation between the reference image and the image under inspection. A few mathematical transformations include Fourier transformation, Hilbert curves, etc.
- **Deep learning:** A deep neural network-based supervised learning algorithm can be developed to detect anomalies in the PCB image under inspection. In this approach, a training dataset is prepared by tagging different defects in the image to develop a shape and object detection algorithm that can spot specific anomalies.

# 4.

## Mphasis Solution for PCB Defects Detection

### 4.1 Introduction to Problem

The problem involves multiple defects in PCBs, and we aim to identify, classify and register these defects to improve the analysis and repair of the PCBs. We also aim to develop an end-to-end process for defect detection and classification that includes pre-processing of images to handle rotation, shadows and contrast before further analysis for anomaly detection.

In our problem statement, we are looking at the following six types of defects in PCBs:

- **Missing Hole**
- **Mouse Bite**
- **Open Circuit**
- **Short Circuit**
- **Spur**
- **Spurious Copper**

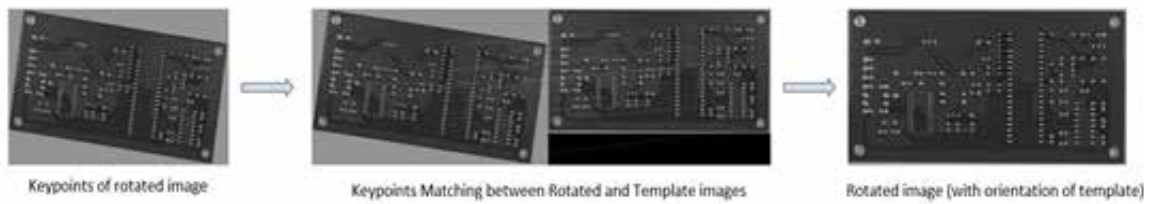
### 4.2 Dataset Description

The dataset consists of multiple PCB templates designed for different business purposes and their reference templates. We also have sample datasets consisting of images of the different defects to train our ML model for the identification and classification of the defects. In total, we have:

- **10 PCB templates**
- **693 images representing 3200 defects**

### 4.3 Challenges and Respective Approaches

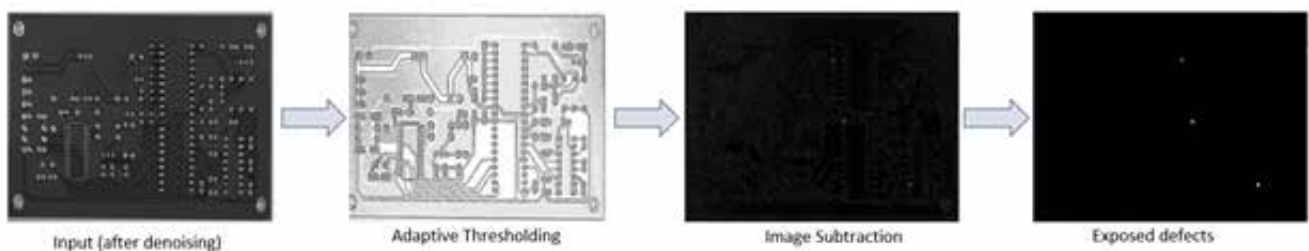
- **Rotated images:** The PCB images under inspection are often rotated, making it difficult to detect and map them to the respective reference templates that hinders defect identification..
  - SIFT and SURF algorithms rotate and map the PCB images to their corresponding templates.
 An illustrative example is as follows:



- **Multiple defects in the same PCB:** Each PCB may contain multiple types of defects and we leverage different strategies to detect them. Different subtraction methods are used for different types of defects.

Algorithm	Tools	Steps	Defects Identified
1	<ul style="list-style-type: none"> <li>▪ Adaptive thresholding</li> <li>▪ Template subtraction</li> </ul>	<ul style="list-style-type: none"> <li>• Apply adaptive thresholding to PCB under inspection and reference template</li> <li>• Subtractions of the two images to expose the defects</li> <li>• Repeat steps 1 and 2 to get good quality defects presentation</li> </ul>	<ul style="list-style-type: none"> <li>• Missing Hole</li> <li>• Mouse Bite</li> <li>• Open Circuit</li> <li>• Short Circuit</li> </ul>
2	<ul style="list-style-type: none"> <li>▪ Image subtraction</li> <li>▪ Binary thresholding</li> </ul>	<ul style="list-style-type: none"> <li>• Apply image subtraction between template and PCB under inspection</li> <li>• Apply binary thresholding to expose the defects</li> </ul>	<ul style="list-style-type: none"> <li>• Spur</li> <li>• Spurious Copper</li> </ul>

Algorithm 1 illustrative example:



Algorithm 2 illustrative example:





- **Identifying clusters of defects:** Once the defects are exposed in the PCB image, we need the boundary coordinates of the defect images so that they can be snipped and further analyzed to be classified into their respective defect type. Contours, which are curves joining all the continuous points (along the boundary) having the same color or intensity are used for this purpose. Contour clustering is applied to detect the boundary coordinates of each defect in the PCB.

#### 4.4 Deep Learning Classifier

Once the pre-processing and defect identification process is complete, the next step is to classify the identified defects into their respective classes. For this, we opt for a convolutional neural network to develop a supervised classifier for all six classes. The dataset provides training data for each class of defects that can be used to train the CNN model. However, it has to be pre-processed before feeding it into a CNN model, and this includes:

- Data Resizing (64x64)
- Class Label Encoding
- Data Standardization
- 80% Training and 20% Testing

Multiple experiments are also performed by changing the number of filters and hidden layers in the architecture to improve the test accuracy and keep overfitting under control to develop the final classification model.

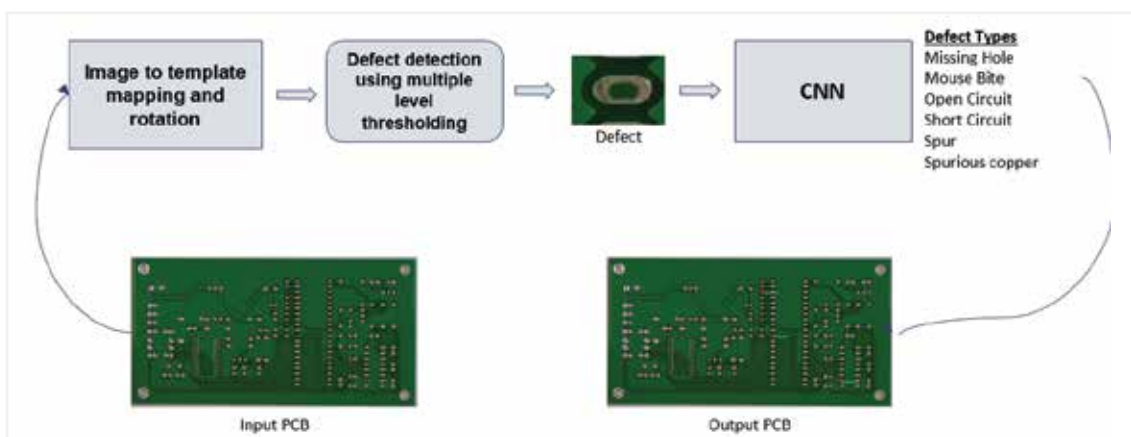
#### 4.5 Overall Workflow

The workflow comprises the following steps:

- Input image is analyzed for possible rotations and is mapped to its reference template
- Then, the registered PCB image is subtracted from the reference template using two different approaches applied sequentially to expose all the possible defects in the image
- Once the defects are exposed, a contour clustering is applied to develop a boundary around the defects
- Using the above-identified boundaries, the defect portion in the PCB image is snipped out
- The snipped-out images are then pre-processed to prepare for classification by normalizing and standardizing the images
- Then, the pre-processed snipped images are passed through a CNN classification model to detect defects in the PCB image

Multiple defects in a PCB are detected and classified using the approach.

The following figure illustrates the complete flow in an inference pipeline.



## 4.6 Results

**Experiment 1** - ((2+ 1FC) Layered network with L2 regularizaton ( $10^{-5}$ )) (best tuned values)

- Training Accuracy - 92%
- Test Accuracy - 89.7%

**Experiment 2** - ((2+ 1FC) Layered network with L2 regularizaton ( $10^{-5}$ ) and Dropouts (0.3)) (best tuned values)

- Training Accuracy - 91%
- Test Accuracy - 91.8%

**Experiment 3** - ((4+ 2FC) Layered network with L2 regularizaton ( $10^{-5}$ )) (best tuned values)

- Training Accuracy - 93.8%
- Test Accuracy - 93.2%

**Good Fit !!!**

**Experiment 4** - ((4+ 2FC) Layered network with L2 regularizaton ( $10^{-5}$ ) and Dropouts (0.3)) (best tuned values)

- Training Accuracy - 92%
- Test Accuracy - 94%

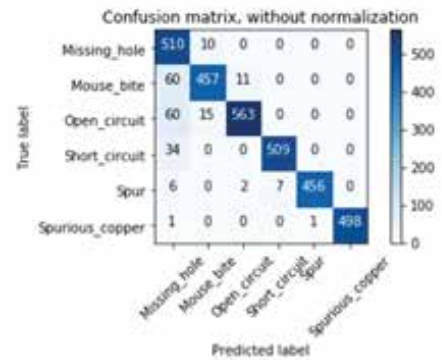
### CNN Architecture :

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 64, 3)	0
conv1 (Conv2D)	(None, 64, 64, 8)	8112
bn1 (BatchNormalization)	(None, 64, 64, 8)	32
activation_1 (Activation)	(None, 64, 64, 8)	0
max_pool_1 (MaxPooling2D)	(None, 32, 32, 8)	0
conv2 (Conv2D)	(None, 32, 32, 16)	4480
bn2 (BatchNormalization)	(None, 32, 32, 16)	64
activation_2 (Activation)	(None, 32, 32, 16)	0
max_pool_2 (MaxPooling2D)	(None, 16, 16, 16)	0
conv3 (Conv2D)	(None, 16, 16, 32)	8128
bn3 (BatchNormalization)	(None, 16, 16, 32)	128
activation_3 (Activation)	(None, 16, 16, 32)	0
max_pool_3 (MaxPooling2D)	(None, 8, 8, 32)	0
conv4 (Conv2D)	(None, 8, 8, 64)	9272
bn4 (BatchNormalization)	(None, 8, 8, 64)	256
activation_4 (Activation)	(None, 8, 8, 64)	0
max_pool_4 (MaxPooling2D)	(None, 4, 4, 64)	0
Flatten_1 (Flatten)	(None, 256)	0
fc_1 (Dense)	(None, 64)	16448
fc_2 (Dense)	(None, 6)	396
Total params: 82,156		
Trainable params: 82,038		
Non-trainable params: 118		

### Inference:

Training Accuracy - 93.8 %

Test Accuracy - 93.2 %



## 5.

## Conclusion and Future Extensions

AI-based PCB visual inspection approaches to detect PCB defects have matured in recent years and can now even exceed the boundaries of human limitations to perform better anomaly detection. AI-based systems represent the future of automated manufacturing quality control. The Mphasis PCB anomaly detection solution provides multiple benefits to handle challenges in automated visual inspection. The solution handles shadow, etc., during pre-processing and can take care of data imbalance issues. Moreover, it can detect multiple minute errors in a single PCB. At a general level, the solution provides a way of tackling some of the most vexing issues in image inspection. Future-planned developments involve more complex algorithms utilizing transfer learning, thus obviating the need for intermediate statistical steps and the utilization of more advanced Deep Learning approaches.

# 6

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Aravindhan holds expertise in logic and algorithms within Next Labs, Mphasis. He collaborates in the active development of various solutions, which include technologies like Big Data, Artificial Intelligence and Cognitive Computing. He has over ten years of research experience and a brief stint in teaching faculty. He holds a PhD from the Department of Management Studies, Indian Institute of Science, Bangalore.



## Ashutosh Vyas

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Ashutosh has 6+ years of experience in the data science domain. He has worked on multiple projects of pattern recognition, time series forecasting, regression modeling, NLP, classification and optimization in Life Science, Finance, FMCG and Media domain. He completed his MTech in 2015 from IIIT-B.

He has expertise in Bayesian methods of Machine Learning and had been working in quantum ML and quantum optimization for the past 2 years and has developed multiple algorithms in image classification, anomaly detection domain using quantum systems that leverage quantum gates and quantum annealer to process information and learn the patterns. At Mphasis, he works as a senior data science manager with an ethos of developing customer-centric and robust solutions.



## Ashwani Singh

Senior Manager - Data Science, NEXT Labs, Mphasis

Ashwani has expertise in emerging technologies and has been a part of several award-winning projects in this space. Having previously worked in analytics and academics, he is currently a part of the leadership team at Mphasis NEXT Labs, where he helps solve business problems by leveraging AI/ML. He has led the development of multiple consumer-centric IP at the lab. He is also a thought leader in behavioral applications of AI and responsible AI. He completed his doctoral studies at IIM Bangalore where his research was focused on Consumer Cognition and Decision Making.

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