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EXPOSURE OF DEFECTED PCB USINGPYTHON

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Abstract : The importance of having a defect-free Printed Circuit Board (PCB) has increased in today's modern era due to the high demand for low-cost electronic items. Such systems require PCBs with no errors, making it crucial to detect defects and imperfections to create high-quality, error-free PCBs. To accomplish this, a defect detection system that uses images of the PCBs has been developed. The YOLO-v5 model is a new model that has been implemented to detect defects in PCBs. Many models and different approaches have been implemented in the past for the quality inspection of PCBs to detect defects. The YOLO models, including YOLO, YOLO-v2, YOLO-v3, YOLO-v4, and Tiny-YOLO-v2, are the state-of-the-art in the artificial intelligence industry. YOLO-v5 is a game changer for many industries such as the electronic industry as it provides excellent efficiency, precision, and speed. In this project, 1386 images with 6 different types of defects were used, and the YOLO-v5 algorithm was trained with a batch size of 16 and a trained epoch of 500. As a result, this model achieved a defect detection accuracy of over 90% mAP in PCBs.

Index Terms - Convolution Neural Network, YOLO-v5, Deep Learning, Printed Circuit Board (PCB)

1. INTRODUCTION

Printed Circuit Board (PCB) is a term used to describe a board that provides mechanical support and electrical connections for electronic components. These connections are made using conductive tracks, pads, and other features etched from one or more layers of copper that are laminated onto a non-conductive substrate. Electronic components are soldered onto the PCB to connect and fasten them mechanically. PCBs are used in almost all electronic products, including passive switch boxes. Bare PCBs are PCBs without electronic components and are used with other components to produce electronic goods. They support electronic components such as integrated circuits, resistors, and transistors, which are tied in with copper tracks. During the process of mounting these components, the PCB can be damaged, and it must be inspected before it is released to the market. The inspection process has become increasingly important in the modern manufacturing environment. In electronics mass production manufacturing facilities, there is an attempt to achieve 100% quality assurance of all parts, subassemblies, and finished goods.

Detecting defects in PCBs during quality inspection is crucial. In the traditional method, an automatic inspection (AOI) machine initially detects defects, and a skilled quality inspection engineer verifies each PCB. However, some boards classified as defective by the AOI machine may not be defective, as the machine can erroneously classify a PCB as defective due to factors such as scratches, small holes, or the presence of nano particles like dust, paper fragments, or small air bubbles. Slight variations from the reference sample may also result in the AOI machine classifying PCBs as defective. While skilled operators are relied upon to verify defects, this requires considerable human resources and training, and even skilled operators can make errors during inspection. Thus, deep learning systems can replace skilled operators to some extent, as machines programmed with deep learning algorithms can verify defects faster and more accurately. Therefore, the goal of this study was to develop a deep learning-based PCB recognition system that reduces the false detection rate and increases the production rate

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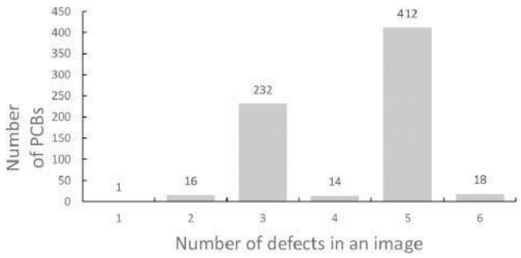


Automatic Visual Inspection is the combination of Machine Vision technology with Computer Vision science applied to the industrial sector. s. Automated visual PCB inspection can provide fast and quantitative information of defects and therefore can prove to be an asset in manufacturing processes. A few examples of PCB defect detection methods can be found in the literature [1–3]. Typically, the template-matching method [4] is used to detect defects in PCBs. Another method for PCB defect detection is OPENCV followed by image subtraction [5]. However, these detection algorithms are limited to a specific type of defect in PCBs. Remarkable progress has been made in the use of convolutional neural networks (CNNs) in several applications, such as image recognition [6,7] and object detection. In particular, object detection is achieved by implementing object recognition methods [8] and region-based CNNs [9]. CNN classifier was trained to recognize various electrical components on a PCB and then detect and localise defects on the PCB components by using Tiny-YOLO-v2, an effective and accurate object detector in [10]

YOLO (you-only-look-once) is an object detection algorithm that uses a single neural network for an image divided into different regions. It predicts the probability of each region and determines the location of bounding boxes based on these probabilities. YOLO is different from other classification methods as it can classify multiple objects in a single image. The algorithm uses full images for training and optimizes its detection performance. It is fast and efficient as it considers the whole image during processing. YOLO learns general representations of objects during training, making it faster than other object detection algorithms [11, 12]. In this paper, we introduce a new approach to detect defects in PCBs using a small size model of YOLOv5 [13]..

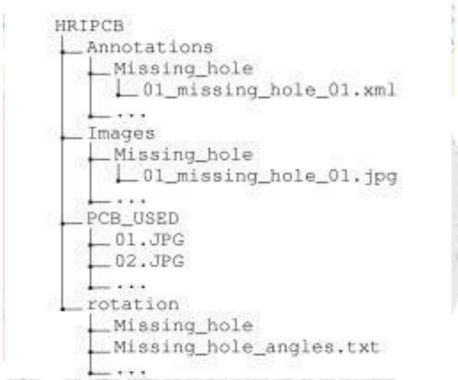
2. NEED OF STUDY

1) This model is Fast and easy to use
2) Higher accuracy in detection
3) Model requires no original PCB to compare
4) No requirement of high resolution pictures of defected PCB

3. RESEARCH METHODOLOGY

3.1 PCB dataset

Usually PCBs consist of complex circuit on a single board which consists on minute structures of copper connections. To train the model for higher accuracy ,This requires a highly resolved camera as shown in fig 3.1. How ever we extracted our required dataset from kaggle website[14].



```
HRIPCB
└─Annotations
  ├─Missing_hole
  │ └─01_missing_hole_01.xml
  └─...
└─Images
  ├─Missing_hole
  │ └─01_missing_hole_01.jpg
  └─...
└─PCB_USED
  ├─01.JPG
  ├─02.JPG
  └─...
└─rotation
  ├─Missing_hole
  ├─Missing_hole_angles.txt
  └─...
```

Fig 3.1 PCB image acquisition system consists of light source, workbench support, camera and image process unit

Fig 3.2 four different folders of dataset

The dataset used in this study was obtained from Kaggle website and is based on a challenging dataset for PCB defect detection [15]. The dataset is divided into four main parts stored in different folders, as shown in Figure 3.2. The images folder contains PCB photos that correspond to the templates, with each defect type having its own folder. The Annotations folder stores the information of the bounding boxes for each image in an XML file. The PCB_USED folder contains the 10 template images used in the dataset. Additionally, the rotation folder includes PCB images with different orientations, with the rotation angles saved in TXT files with the corresponding image names. Table 1 lists the details of the figures for the PCB images and defect samples, where only half of the dataset is presented since the number of PCBs with and without rotation are identical. Figure 3 shows the distribution of defects per PCB, indicating that the majority of PCBs have three or five defects. The largest PCB size in the dataset is 120mm × 120mm, while the smallest is 53mm × 48mm. An API for easy access in Python is provided to facilitate the use of the dataset. The .py file included in the dataset displays the bounding box of each defect in an intuitive manner.

Table 1 Figures for PCB and detect samples (listed in the brackets)

Category	Number(defects)
missing hole	115(497)
mouse bit	115(492)
open circuit	116(482)
short	116(491)
spur	115(488)
spurious copper	116(503)

3.2 YOLOV5

It is very crucial to understand what CNN is. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data [16].A simple understanding of the work done by CNN in order to predict the picture is of zebra or not is shown in fig 3.3.

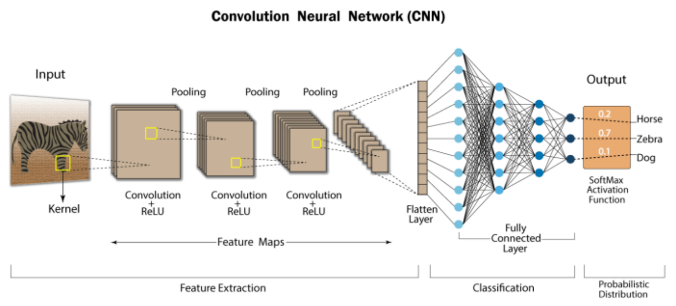


Fig 3.3. A simple understanding of CNN[17]

3.2.1 YOLOv5 Architecture

There is an article around 2021 which has a detailed explanation of yolov5 structure [18].It is also good to mention that YOLOv5 was released with five different sizes namely (n,s,m,l,x) models. All the YOLOv5 models are composed of the same 4 components: Input, **CSP-Darknet53** as a backbone, **SPP** and **PANet** in the model neck and the **head** used in YOLOv4as in [19].

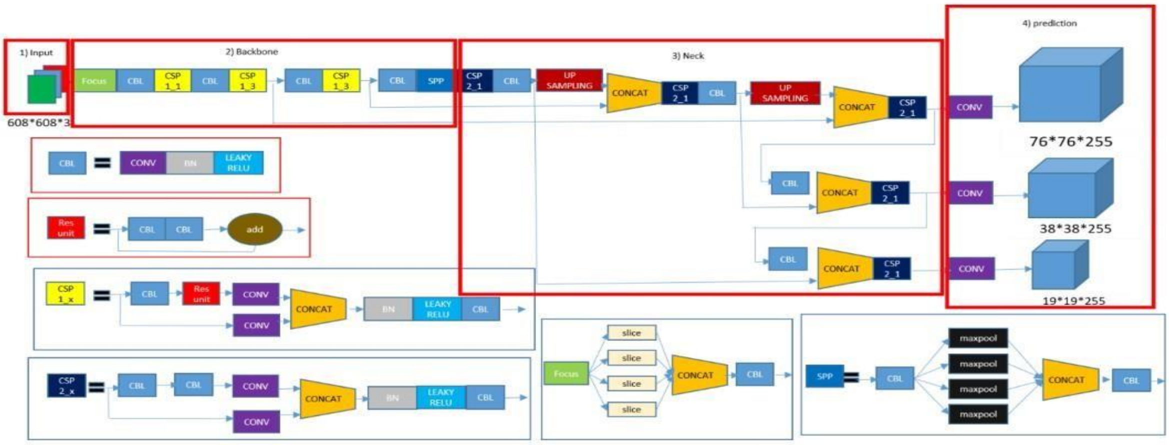


Fig 3.4 Yolo complete structure

A) Input exhibits
1) Mosaic data enhancement [20].
2)Adaptive anchor frame calculation
3) Adaptive image scaling

B) BACKBONE consists of
1) Focus structure

The focus layer was created to reduce layers, parameters, FLOPS, and CUDA memory and improve forward and backward speed while minimizing the impact of mAP.

2) CSP structure

The full name of CSP Net is Cross Stage Partial Network, which mainly solves the problem of a large amount of calculation in reasoning from the perspective of network structure design. The CSP module is used to first divide the feature map of the base layer into two parts, and then merge them through a cross-stage hierarchy, which can reduce the amount of calculation and ensure accuracy[21]. Where BN for batch normalization, and ReLU for rectified linear unit.[22]

3)NECK

YOLOv5 brought two major changes to the model neck. First a variant of Spatial Pyramid Pooling (SPP) has been used, and the Path Aggregation Network (PANet) has been modified by incorporating the Bottle Neck CSP in its architecture.

PREDICTION (head)

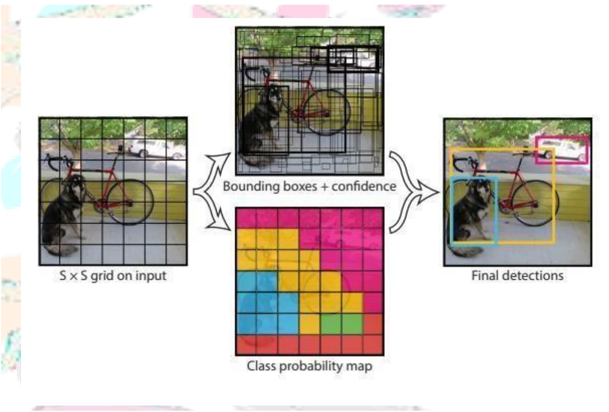
YOLOv5 uses the same head as YOLOv3 and YOLOv4. It is composed from three convolution layers that predicts the location of the bounding boxes (x, y, height, width), the scores and the objects classes.

OUTPUT

It consists of classes, bounding box loss function and non max suppression.

3.2.2 Yolo algorithm:

The algorithm works based on the following four approaches: Residual blocks, Bounding box regression, Intersection Over Unions or IOU for short, Non-Maximum Suppression. This first step starts by dividing the original image (A) into NxN grid cells of equal shape, where N in our case is 4 shown on the image on the right. Each cell in the grid is responsible for localizing and predicting the class of the object that it covers, along with the probability/confidence value. The next step is to determine the bounding boxes which correspond to rectangles highlighting all the objects in the image. We can have as many bounding boxes as there are objects within a given image. YOLO determines the attributes of these bounding boxes using a single regression module in the following format, where Y is the final vector representation for each bounding box. Y = [pc, bx, by, bh, bw, c1, c2].Thirdly Most of the time, a single object in an image can have multiple grid box candidates for prediction, even though not all of them are relevant. The goal of the IOU (a value between 0 and 1) is to discard such grid boxes to only keep those that are relevant. Here is the logic behind it: The user defines its IOU selection threshold, which can be, for instance, 0.5. Then YOLO computes the IOU of each grid cell which is the Intersection area divided by the Union Area. Finally, it ignores the prediction of the grid cells having an IOU ≤ threshold and considers those with an IOU > threshold. fourthly Setting a threshold for the IOU is not always enough because an object can have multiple boxes with IOU beyond the threshold, and leaving all those boxes might include noise. Here is where we can use NMS to keep only the boxes with the highest probability score of detection. [23] . The below expression represents Confidence score.



$$C = P_r(\text{object}) \times \text{IOU}_{\text{pred}}^{\text{truth}}$$

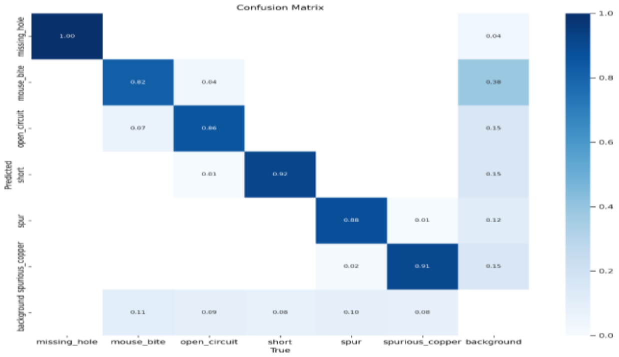
Fig 3.5 yolo algorithm

4. Training on custom data:

In this project ROBOFLOW [24] is considered to train our PCB dataset taken from kaggle. The advantage in this website isit don't need external code to change our xml files to text files as in [25].

Results:

4.1 Weights After training:



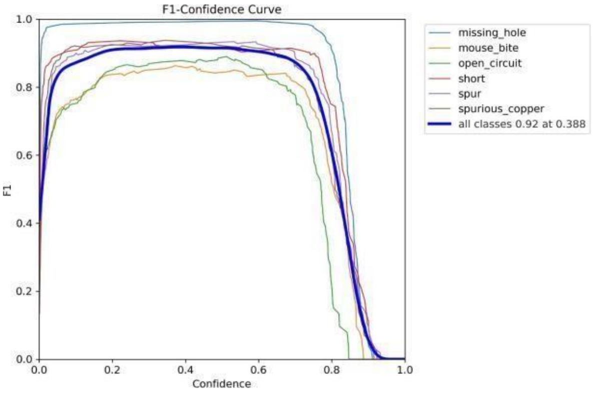
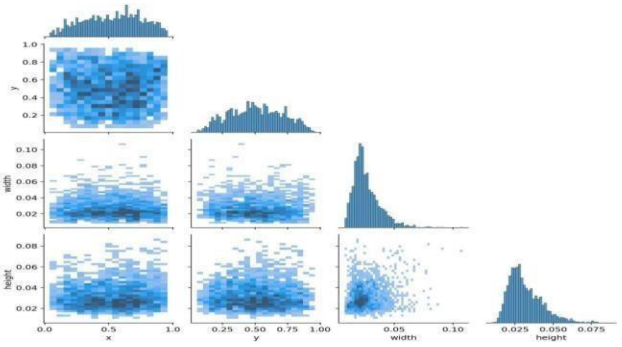


Fig 4.1 Confusion matrix

Fig 4.2 F1-confidence curve



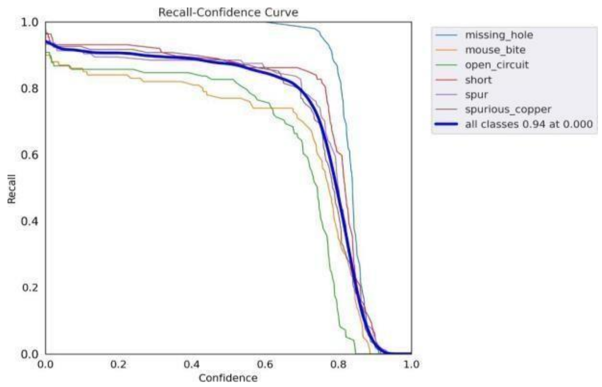


Fig 4.3 Labels Correlogram

Fig 4.4 Precision confidence curve

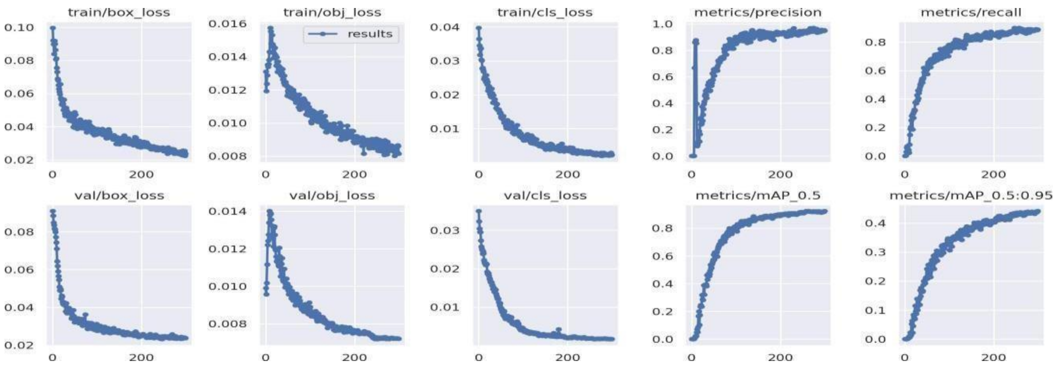
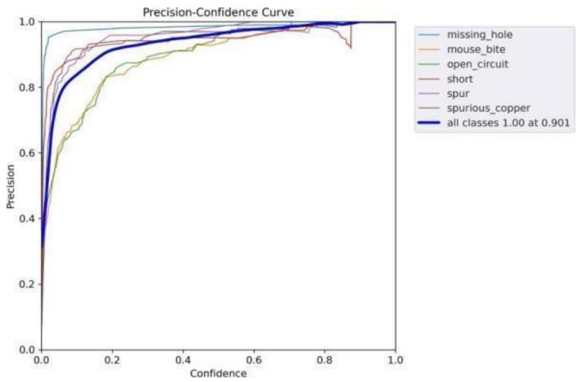


Fig 4.5 All loses



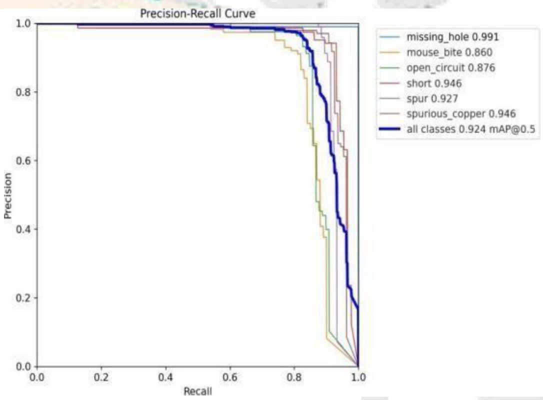


Fig 4.6 Precision-confidence curve

Fig 4.7 Precision-recall curve

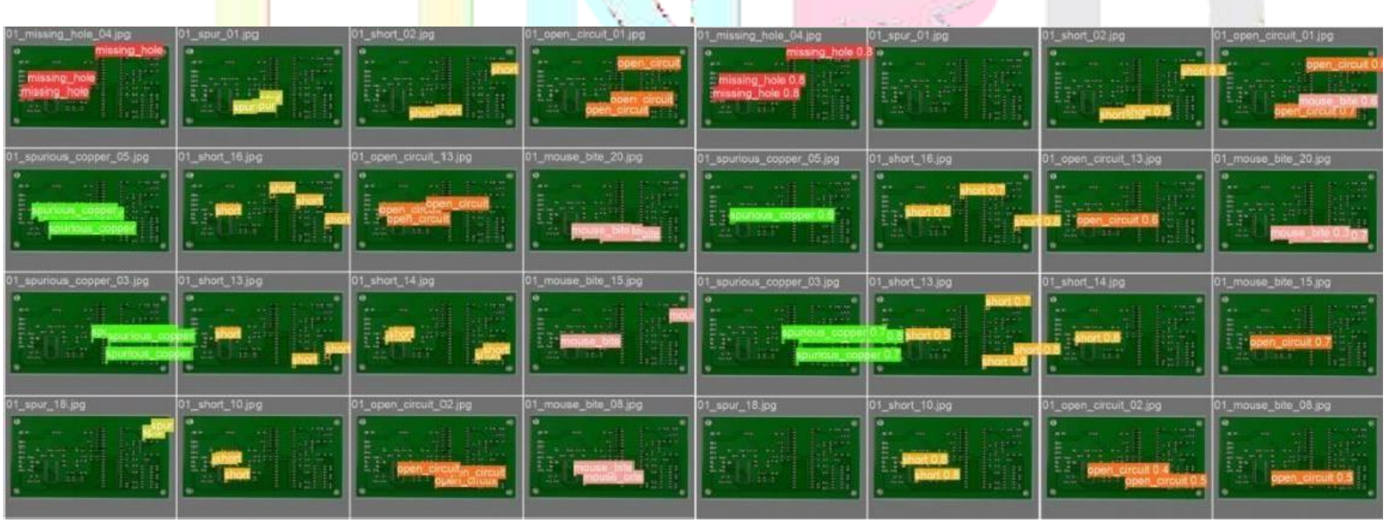


Fig 4.8 a) val_batch0_labels b) val_batch0_pred

4.2 Result of testing images :

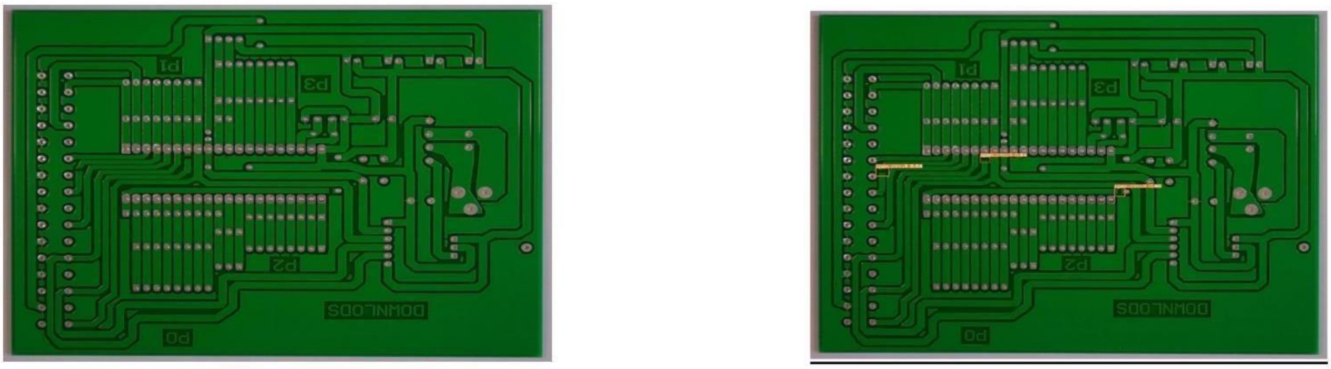


Fig 4.9 a) Defected PCB b) Error Detected PCB

5. Conclusion

The world runs automatically with technology of electronic gadgets where PCBs demand becomes infinite. This approach of detecting defects gives us the more accurate results of defects in PCB irrespective of the information of their original layout. This project mainly focused on recent algorithm called YOLO to detect the minute defects from the picture which also helps in no necessity of high resolution pictures for processing .

In this project python environment is created to detect defective PCB and distinguish the over etched and under etched PCBs. We also used convolution neural networks to further identify the PCBs with 6 types of defects namely Spurious Copper, Spur, Mouse-Bite, Missing Hole, Open Circuit, Short Circuit.

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