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# Machine Learning-Based Defect Detection for Printed Circuit Board

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**Abstract -** *This work presents a deep learning system that uses the principle of the You Only Look Once (YOLO) methodology to perform PCB (printed circuit board) quality inspections. Deep learning algorithms have been widely used in many different fields because of their remarkable efficiency and accuracy. Comparably, there has been a lot of interest in the accurate detection of PCB flaws using deep learning techniques, such as the You Only Look Once (YOLO) method. The synthetic dataset from Kaggle was used in the suggested strategy. 1386 pictures representing 6 PCB flaws make up the dataset. Defects include missing holes, mouse bites, open circuits, short circuits, spurious copper, and shorts are present in the dataset. A YOLOv8X model is then trained using the data to identify PCB flaws. With a batch size of 16, the suggested model successfully identified defects in PCBs with 97.9% accuracy.*

***Key Words*: YOLO; deep learning; printed circuit board; printed wiring board; missing hole; mouse bite; open circuit; short, spur; spurious copper**

## 1.INTRODUCTION

An essential part of electrical devices is the printed circuit board (PCB), sometimes known as the printed wiring board (PWB). PCBs are used in a vast range of electronic products, such as satellites, communication devices, laptops, computers, cellphones, military weapons, and electronic watches. The size of electronic device components has decreased dramatically due to advances in integrated circuit and semiconductor technologies. As a result, the PCBs that hold these parts together have grown delicate and complex. Therefore, in order to satisfy client requests, it is essential to ensure high-quality production. An illustration of a PCB is provided in Figure 1.

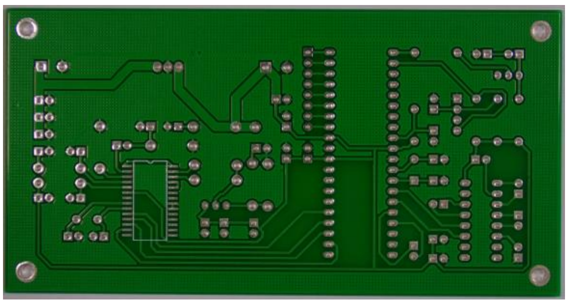

**Fig -1**: Printed Circuit Board

Printing boards, arranging components, and soldering are all included in PCB production. During these phases, there is a possibility of several potential flaws, such as incorrect solder joins, short circuits, empty or open circuits, and excess solder (which appears as overflowing solder on solder points). These flaws could jeopardize the board's stability or perhaps cause the board to break entirely. Thus, it is imperative to implement a highly effective and precise automatic detection module for the purpose of examining various flaws during the PCB manufacturing process. Figure 2 illustrates examples of surface defects in PCBs.

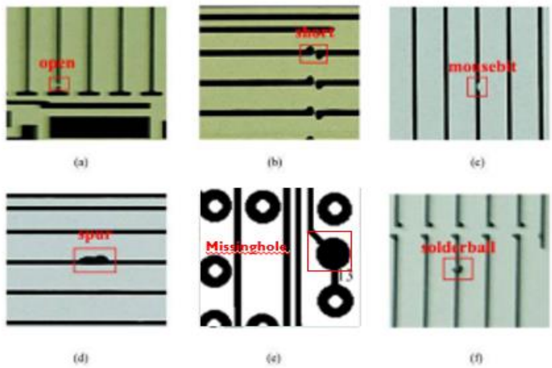


**Fig -2**: Defects in Printed Circuit Board

## 2.Related works

Two datasets were used to train the VGG16 model, which uses both transfer learning and an unsupervised deep learning technique. Four defect categories were identified by this model: abrasion, damaged PCB edge, missing washer/extra hole, and scratches. 60 PCBs chosen at random were tested, and the results showed that the PCB-G dataset had an accuracy of 87.49% while the PCB-1 dataset had an accuracy of 74.12%. The reduced dataset size for PCB-1 is thought to have contributed to the lower accuracy, which highlights the difficulties and costs involved in gathering large numbers of faulty samples [1]. An upgraded convolutional neural network that made use of the MobileNet-v2 model was used. Four types of defects were successfully identified by this model: mouse bite, open, short, and spurs. It accomplished an impressive 92.86% total accuracy. In particular, it achieved 93.33% for spurs, 94.29% for shorts, 98.57% for open, and 88.33% for mouse bites [2].

## 3. Methodology

### 3.1 Dataset overview

The dataset must follow the Pascal VOC format for YOLOv8 to work properly, and each image must have a matching annotation file in the.txt format. Train and Validate subsets should be created from the dataset.

The dataset used in this experiment was obtained from Kaggle. 1386 photos with six different types of defects—missing hole, mouse bite, open circuit, short, spur, and spurious copper—are included in this freely accessible synthetic PCB dataset. The inclusion of these flaws makes detection and classification tasks easier.

### 3.2 proposed YOLOv8

The YOLOv8 real-time object detector is the most advanced model in the YOLO series, offering state-of-the-art performance in terms of accuracy and speed. By introducing novel features and improvements, YOLOv8 builds on the innovations of its predecessors and proves to be a strong option for a variety of object identification tasks in a wide range of applications.

### 3.3 YOLOv8 Architecture

YOLOv8's architecture is an extension of the YOLO algorithm series' earlier models. It makes use of a convolutional neural network, which consists of the head and the backbone. The foundation of YOLOv8 is built using a modified version of the CSPDarknet53 architecture, which has 53 convolutional layers and cross-stage partial connections to improve the information flow between the layers. Multiple convolutional layers at the front of YOLOv8 are followed by fully connected layers, and their job is to predict bounding boxes, objectness scores, and class probabilities for objects that are discovered. The addition of a self-attention mechanism to the network's brain is noteworthy since it enables the model to focus on various areas of the image and modify the weight of variables according to their significance.

Besides these characteristics, YOLOv8 uses a feature pyramid network to achieve superior performance in multi-scaled object detection. The model can detect things in an image, no matter how big or little, because this network has numerous layers that are specifically built to detect objects at different scales.

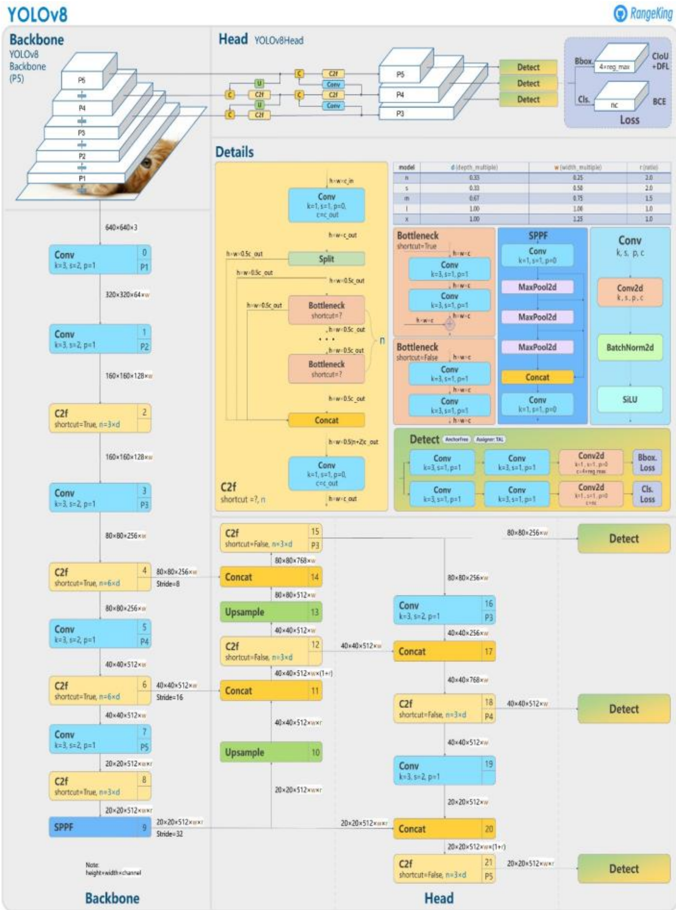


**Fig -3**: YOLOv8 Architecture

## 4. Result

To determine the weights, the PCB-YOLO model was subjected to several training cycles on the training set. The test set's images were used to test the model using the ideal weights that were determined during the training phase. The experimental findings show that the mean average precision (mAP) of 0.995 for the detection of missing holes is quite good. The unique characteristics and fewer diversified shapes associated with missing holes are the reason for this performance. Similar to spurious copper, open circuits, and shorts have high mAP values because of their decreased vulnerability to other flaws and background interference. Due to their physical similarities, spur and mouse bite defects can be difficult to identify from one another, which could result in misidentifications once the regional density reaches a certain point. In spite of this intricacy, the PCB-YOLO-v8 model is able to detect all six flaws with a mean average precision of 0.979.

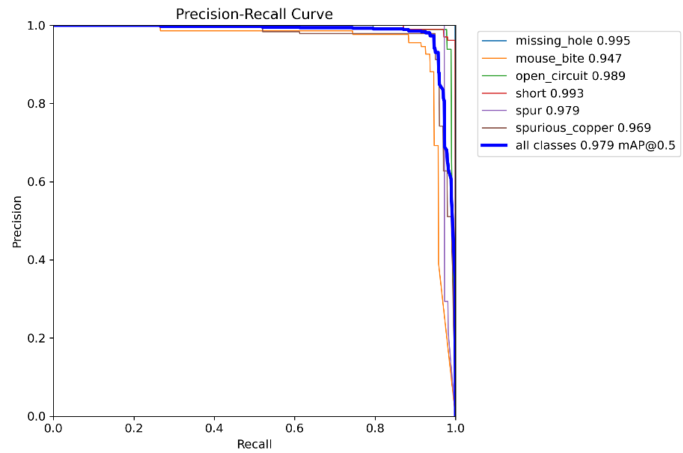


**Chart -1**: Precision Recall Curve

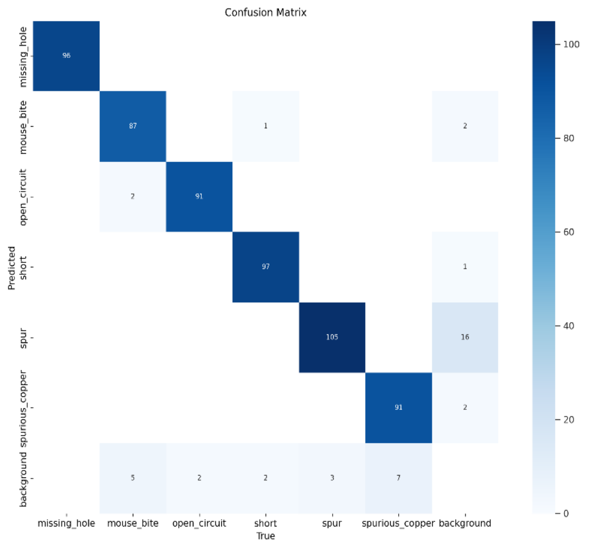


**Chart -2**: Confusion Matrix

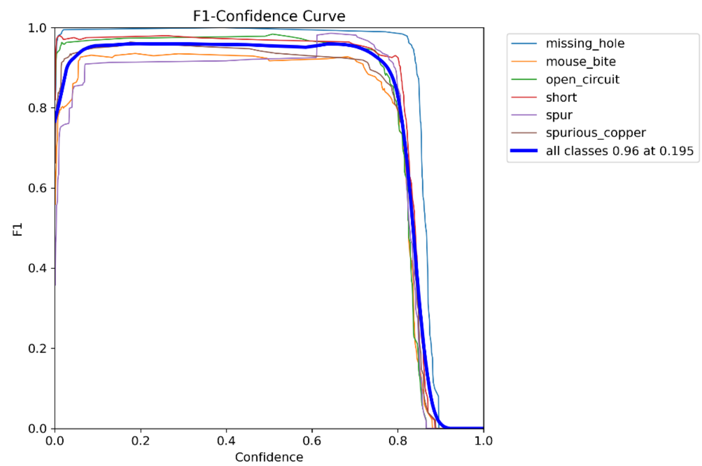


**Chart -3**: F1-Confidence Curve

## 5. CONCLUSIONS

PCB devices, which are essential parts of many different electronic products, have significantly improved human life. Production and sorting processes can be accelerated by effectively classifying and detecting defects in PCB image data. This development addresses the rising need for PCBs while also increasing production and recycling efficiency. Significant efforts have been made by industry and academic organizations to improve PCB defect detection and categorization. In this work, we provide YOLOv8, an inventive single-shot object identification model designed especially for PCB fault classification. With an overall accuracy of 97.9%, our model is very effective when compared to other models that are currently in use.

However, this study acknowledges significant limitations that provide up possibilities for further investigation. Since the dataset used in this study is synthetic, more research is needed to determine how well our method functions on actual PCBs. In-depth research and validation are therefore required to guarantee the model's correctness and suitability for use in practical situations.

## 6. REFERENCES

[1] Detection Defect in Printed Circuit Boards using Unsupervised feature extraction upon transfer learning, Volkau Ihar, Abdul Mujeeb, Dai Wenting, Erdt Marius, Sourin Alexei, 2019 International Conference on Cyberworlds (CW), © IEEE 2019.

[2] Printed Circuit Boards Defect Detection Method Based on Improved fully Convolutional Networks, Jianfeng Zheng, Xiaopeng Sun, Haixiang Zhou, Chenyang Tian, Hao Qiang, 10.1109/ACCESS.2022.3214306 © IEEE 2022.

[3] Detection of PCB surface defects with improved faster-RCNN and feature pyramid network, Bing Hu, Jianhui Wang, 10.1109/ACCESS.2020.3001349 © IEEE 2020.

[4] Yolo v4-MN3 for PCB surface defect detection, Xinting Liao, Shengping Lv, Denghui Li, Yong Luo, Zichun Zhu, Cheng jiang, 10.3390/app112411701 © MDPI 2021.

[5] Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey, Qin Ling, Nor Ashidi Mat, 10.1109/ACCESS.2023.3245093 © IEEE 2023.

[6] PCB Defect Detection Based on Deep Learning Algorithm, Chun Chen, Rey-Chue Hwang, Huang-Chu Huang, 10.3390/pr11030775 © MDPI 2023.

[7] LPViT: A Transformer Based Model for PCB Image Classification and Defect Detection, Kang AN, Yanping Zhang, 10.1109/ACCESS.2022.3168861 © IEEE 2022.

[8] Feature-Learning-Based Printed Circuit Board Inspection via Speeded-Up Robust Features and Random Forest, Eun Hye Yuk, Seung Hwan Park, Cheong-Sool Park, Jun-Geol Baek, 10.3390/app8060932 © MDPI 2018.

[9] Defect Detection in Printed Circuit Boards Using You-Only-Look-Once Convolutional Neural Networks, Venkat Anil Adibhatla, Huan-Chuang Chih, Chi-Chang Hsu, Joseph Cheng, Maysam F. Abbod, Jiann-Shing Shieh, 10.3390/electronics9091547 © MDPI 2020.

[10] Defect Detection in Printed Circuit Boards Using Semi-Supervised Learning, Thi Tram Anh Pham, Do Kieu Trang Thoi, Hyohoon Choi, Suhyun Park, 10.3390/s23063246 © MDPI 2023.