International Journal on Engineering Technology (InJET)

*www.kec.edu.np/journal*
*Volume 1, issue no. 1, Nov 2023, Page 62-71*
*Received Date: June 30, 2023*
*Accepted Date: Oct 8, 2023*
*ISSN: 3021-940X (print)*

# Detection of Missing Component in PCB Using YOLO

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**Abstract**

The detection of missing components in printed circuit boards (PCBs) is a critical task in the electronics manufacturing industry. The current practice of manual inspection is time-consuming and prone to human error, which can result in faulty products and increased costs. In this paper, we propose a solution that uses the YOLO (You Only Look Once) object detection algorithm to automatically detect missing electronic components in PCBs. Electronic components detection model is trained using YOLOv3 architecture. Dataset is prepared using high quality printed circuit board images and manual labeling in Label Studio. The model is trained on a dataset of 16 different electronic components commonly found in PCBs including Electrolytic Capacitor, QFP, Toroidal core Inductor, Crystal Oscillator etc. Prepared model recognizes these electronic components with an average map score of 65.8%with IoU 50% and 42.6% with IoU 95%. The results show that the proposed solution can detect the missing components.

*Keywords*: Printed circuit board, Inductor, Capacitors, Resistors, Data labeling, YOLO, Machine learning, Label Studio, Push Button, Automated optical inspection, Mean Average Precision

## 1. Introduction

Detection of electronic components on printed circuit boards (PCB) is very important for manufacturing companies specialized in the 3C (Computer, Communication and Consumer Electronics) which helps them achieve their required quality in products.However, there is large variation in the size, shape and types of the PCB required (ing Li, 2019) If we consider even the simplest PCB there are at least 5 or more than 5 different types of components and those components may have further subtypes Due to the expense of manual data labeling and a highly unbalanced distribution of component types a significant domain shift across boards can be seen. A machine learning method can help in extraction of information across the structure of the board accurately and detect and identify various types of electronic components on a PCB. Different techniques of machine learning and computer vision have been implemented for the detection of the missing components but they are limited to detection of one or two components only and can be used for one type of the PCB. Working manually on such will not be the good option as.most of the people working in the inspection phase don't have complete knowledge of the circuit but only about the places where the components need to be present in the PCB. It becomes very tedious, time consuming and error prone to even fix simple problem when wrong component is set in circuit board. Automated Optical Inspection (AOI) method is used to find defect in different layers of PCB and miss placement and missing of electronic components on the PCB but it is expensive, complex and board specific. So, with the aim of developing the system which will be able to detect the missing components from wide variety of PCB's, this paper focuses on a system which analyzes any preset circuit board that is to be mass produced and find the missing components in rest of the copies through visual processing of the circuit board and provide information about all the missing components.

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## 2. Literature Review

A paper by Lin, Yih-Lon and Chiang, Yu-Min and Hsu, Hsiang-Chen have proposed a capacitor detection method based on YOLO algorithm for printed circuit board (PCB) assembly. To verify the effectiveness of their approach, they took samples of PCB images with nine kinds of capacitors and trained it using YOLO. Experimental results showed all the types of capacitors in PCB could be detected and the average detection time was less than 0.3 second with accuracy of 93.75%. The paper focuses on detection on different types of capacitors only but other components are not included in their research. (Lin, 2018)

Li, Jing and Li, Weiye and Chen, Yingqian and Gu, Jinan (2021) conducted a study about a real-time electronic component detection network which uses effective receptive field (ERF) size and anchor size matching in YOLOv3. According to the authors, the proposed PCB electronic components' detection network was implemented on the YOLOv3, which involved the accurate quantification of the ERF size, compared with the Faster-RCNN (saha, 2018) (regions with convolutional neural network) features, SSD (single-shot multibox detectors) (Wei Liu, 2016), and YOLOv3 (Joseph Redmon, 2018). The paper achieved a very high mAP of 95.03% on the PCB dataset. It also has a very small parameter size which is nearly one third of the original YOLOv3 but they were unable to find the optimal threshold for ERF, for it to be useful for component of every shape. (Li, 2021)

Research done by the Department of Electrical and Electronics Engineering Campus, University Sains Malaysia has da Component recognition system by localization. In the first stage, a simple convolution neural network-based component recognition classifier was developed. For the component recognition, the paper has used various pretrained models including VGG16, DenseNet169 and InceptionV3. The paper displayed 99% accuracy with VGG16 and could recognize up to 25 different components. Following that, object localization was performed using faster region-based convolutional neural network (R-CNN) (Ren, 2017). The localization object detection network achieved 96.54% mean average precision (mAP). For the future works, they proposed that more data could be added so that the even more components can be recognized, and more defects can be localized. (Cheong, 2019)

A research article about the recognition of missing PCB components in which a group of Student of Center for Artificial Intelligence Technology, Faculty of Information Science and Technology of Universiti Kebangsaan Malaysia had proposed the method which includes an acquiring system and Laptop system. A web camera was used in the acquiring system that captures the image of the PCB. It was then processed and post processed using a laptop system. About 147 images were trained for neural network with 104 images for training dataset and 43 for testing dataset. The experimental results have presented the back propagation neural network classifier using three features and 1000 iteration achieves the high recognition rate consists of 97.26 % for training and 97.23 % for testing. They conclude that five missing footprints consist of the Capacitor, Resistor, Transistor, IC and LED have been classified. For the detection, the features used consists of Area, Perimeter, and Compactness, which is extracted and characterized for each type of component. The dataset of the extracted features has been trained by neural network system. However, their research has covered limited components of the bare PCB. (Mogharrebi, 2011)

## 3. Methodologies

### *3.1 System Block Diagram*

The proposed system is shown in Figure 1. It consists of a Pi camera, Raspberry pi, push buttons and a display where each hardware component has their specific purpose in the system. A standard PCB is first input to the system followed by the test PCB. Camera is used to capture images of the PCBs. Raspberry Pi has been used as the processor of the system, which performs the various tasks including image processing, object detection, controlling camera, push button and display. The object detection model is uploaded to the Raspberry Pi and it is responsible for the detection of components in the image of PCB provided through Pi camera. Push buttons are used to control the various operations and modes of the system i.e., capturing images, comparing and stop signals. Display is used for interaction of the user with the system through the designed user interface which includes various states of the system as well as the output. The operation of the system is initiated after the standard PCB is kept on the panel and a push button is used to capture its image. Afterwards, the test PCB is taken and its image is captured. After each image capture i.e., standard and test, the image is passed through the model to get the class and location of each of the components of the PCB. Compare signal is again generated through the push button which compares the components which were detected by the model. Raspberry simultaneously shows the operation in the display. Finally, after the process is completed, we can end the program using the end signal generated by the push button.

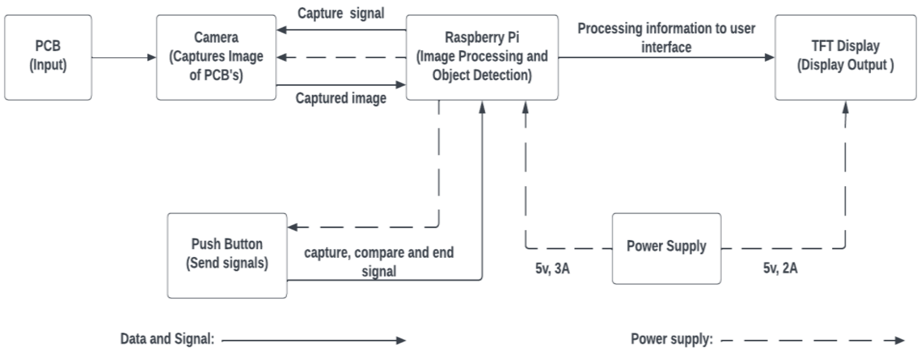



Figure 1 System Block Diagram

### *3.2 System Flowchart*

This flowchart in Figure 2 shows how the system completes its process of detecting the missing components. First of all, the system starts, and checks the state of the push buttons. If the green button is pressed then it takes the picture of the standard PCB and detects its electronic components using the YOLO algorithm (Joseph Redmon, 2018) shown in Figure 4, which is based on Darknet (Redmon, 2013).The choice of YOLO algorithm was done for object detection as it has the fast inference due to which the images can be processed in real time faster.The object are detected in single pass through the neural network. If the Yellow button is pressed it takes the picture of the test PCB and detects electronic components present in it too. The result of detection in both cases is saved and is used for comparison later. So, if the blue button is pressed, the system calculates the IOU of each component between standard and test PCB. IOU is the value ranging in-between 0 to 1. If IOU > 0.5 then the system specifies the component as present, otherwise the system specifies the component as missing and finally shows the information on the display. If we want to test again then we can just capture another image of the test PCB by pressing the yellow button else we can end the program by pressing the red button. And if we want to standardize the PCB again, we can use the green button.

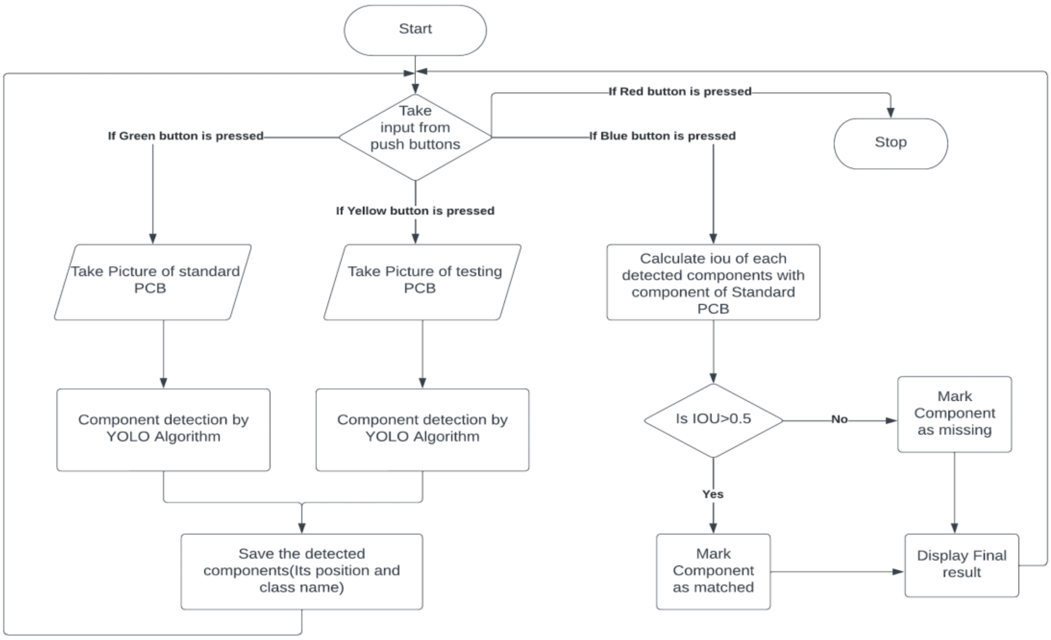



Figure 2 System Flowchart

### *3.3 Model Training and Object detection*

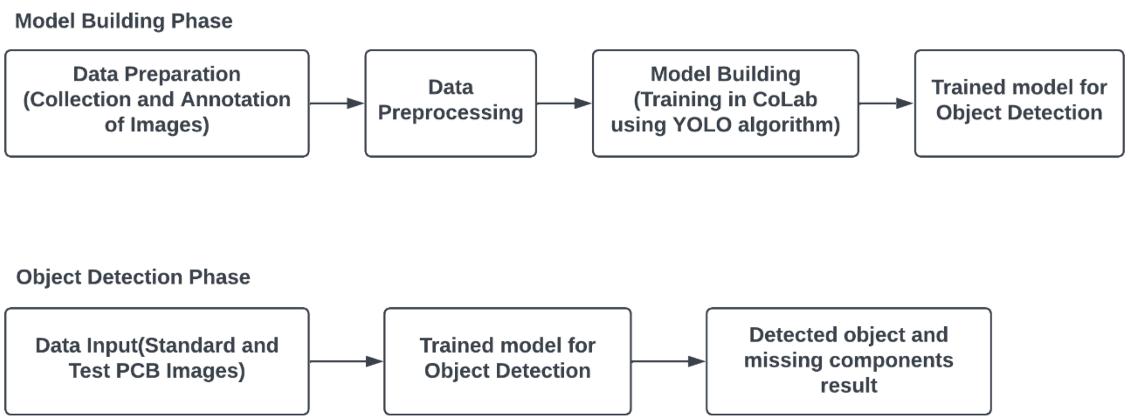



Figure 3 Model Building and Object Detection Phases

Initially, data is prepared by collecting the images of PCB online. For this, high-quality PCB is searched and collected with 16 different electronics components. Each image is resized to be 640x640 pixels. The images are then labelled using Label Studio (Studio, n.d.). For this, the dataset is split into parts and labelled. It is then verified initially by each of the labeler and then cross verified by the other labelers too. This ensures that the dataset has no errors. The labels are then stored in the YOLO format with location, midpoint, width and height. A total of 3048 dataset is prepared. The dataset is then split into test and train set in the ratio 65:35 as shown in Table 1.

Table 1. Number of images in Dataset

| SN | Categories | No of images |
|---|---|---|
| 1 | Train | 1982 |

| | | |
|---|---|---|
| 2 | Test | 1066 |
| | Total | 3048 |

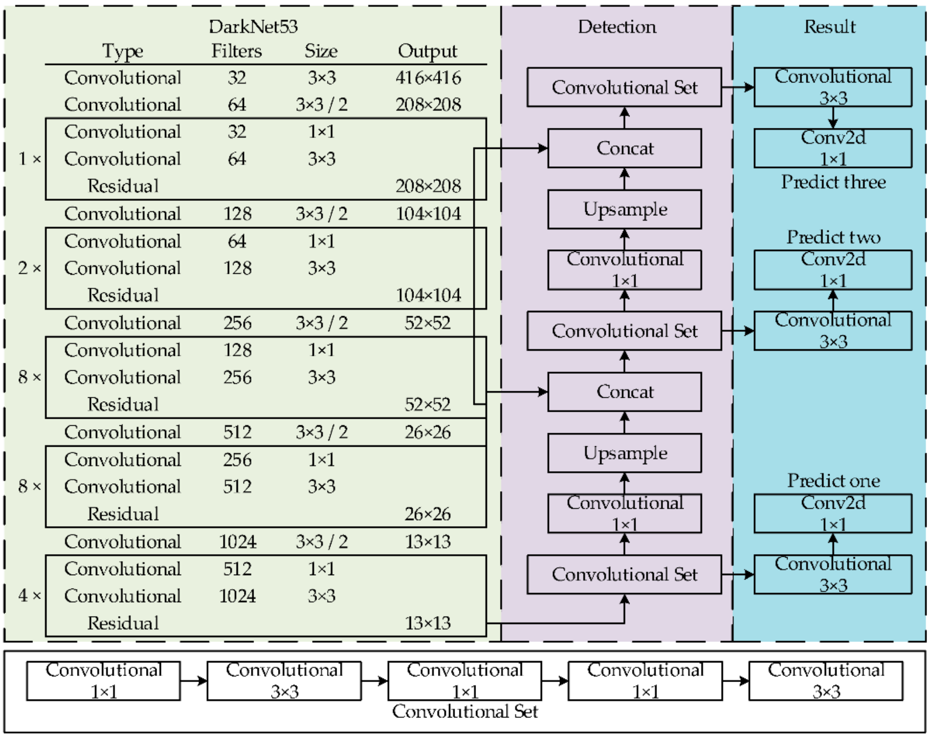
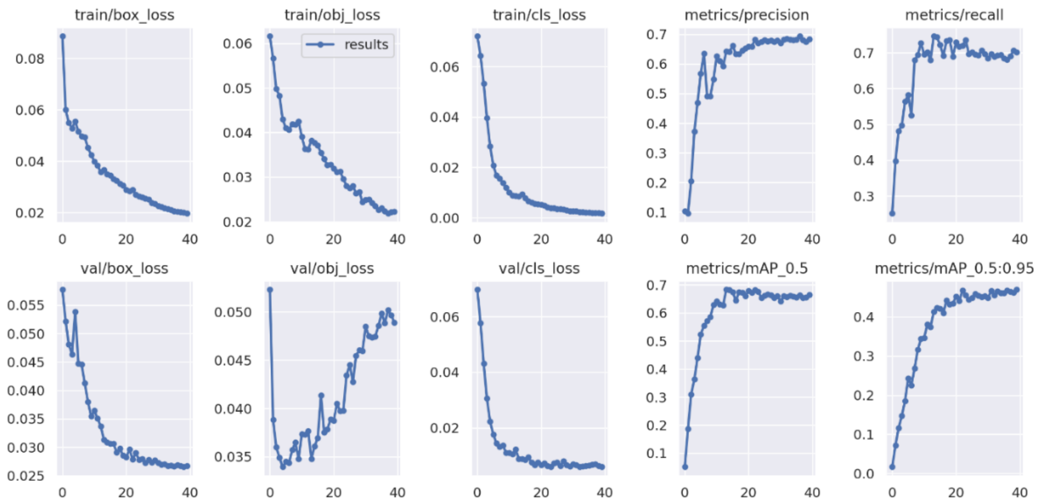



Figure 4 Yolov3 Architecture (Joseph Redmon, 2018)

For the model training, Google Colab is used. YOLOv3 (Joseph Redmon, 2018) is used as the object detection algorithm as shown in Figure 4. The pretrained YOLOv3 is taken and is then fine-tuned using the custom dataset. For this, a total of 200 epochs is run for the dataset whose results are shown in Figure 5. Since Google Colab has limited resources, training was done in 40 epochs at a time. Before training the resized images are grouped into




batch of 16 for improving the efficiency of the inference.

Figure 5 Accuracy curves

After training and evaluation of the model, the model is then converted to TFLite. It is done so because Raspberry Pi has limited processing capacity and memory so that the full model is not efficient on it. The model is then implemented on hardware using a Raspberry Pi 4. The necessary hardware components are interfaced with the Raspberry Pi, and the program uses libraries such as OpenCV (Bradski, 2000), NumPy (Oliphant, 2006) and Torch (Paszke, 2019).

Finally, the integrated system is tested by capturing images of standard and test PCBs. For this, first the standard image is captured. It is sent through the trained model and the components along with their class and location is stored. Afterwards the test images are captured. The test image is then sent through the model and the components and their location is recorded. Now, we follow the following algorithm to compare if any component is missing.

Algorithm 1 Comparison of the standard and test PCB

Step 1: Store all the components and their location of the standard image to standardArray
Step 2: Store all the components and their location of the test image to testArray
Step 3: Initialize an empty array missingComponent
Step 4: Start i=0 and Loop through standardArray
Step 5: Set found=0
Step 6: Start j=0 and Loop through testArray
Step 7: Check IoU for standardArray[i] and testArray[j]. If IoU>0.5, set found=1 and Goto 9
Step 8: Goto Step 7 for next j until end of the array
Step 9: If found=0, add standardArray[i] to missingComponent
Step 10: Goto Step5 with next i until end of the array
Step 11: All the missing components are stored in missingComponent array

Finally, the missing components are marked and drawn on the image using OpenCV. For this, red color rectangles are drawn on the image to mark as missing PCB.

**4. Result**

The mean average precision (mAP) scores obtained for each of the classes is shown in Table 2 below.

Table 2.mAP Scores

| Classes | Precision | Recall | MAP@.5 | MAP@.95 |
|---|---|---|---|---|
| All | 0.693 | 0.692 | 0.658 | 0.462 |
| Aluminum Capacitor | 0.672 | 0.629 | 0.622 | 0.407 |
| Ceramic Capacitor | 0.57 | 0.361 | 0.431 | 0.284 |
| Crystal Oscillator | 0.923 | 0.966 | 0.948 | 0.683 |
| DIP | 0.585 | 0.434 | 0.454 | 0.345 |
| Electrolytic Capacitor | 0.508 | 0.362 | 0.282 | 0.198 |
| Fixed Resistor | 0.231 | 0.423 | 0.176 | 0.118 |
| LED | 0.79 | 0.896 | 0.804 | 0.488 |
| PN Diode | 0.743 | 0.857 | 0.852 | 0.631 |
| QFP | 0.824 | 0.927 | 0.887 | 0.744 |
| SM Inductor | 0.39 | 0.429 | 0.297 | 0.189 |
| Surface Mount Resistor | 0.675 | 0.606 | 0.659 | 0.444 |
| TO252 | 0.676 | 0.834 | 0.778 | 0.593 |
| TO92 | 0.92 | 0.678 | 0.732 | 0.448 |
| Tactile Switch | 0.894 | 0.926 | 0.933 | 0.709 |
| Tantalum Capacitor | 0.773 | 0.82 | 0.767 | 0.491 |
| Toroidal Core Inductor | 0.906 | 0.939 | 0.914 | 0.625 |

During the training, an overall precision of 69.3%, recall of 69.2%, mAP of 65.8% at IoU threshold 0.5 and mAP of 46.2% across different IoU thresholds from 0.5 to 0.95 for PCBs components is obtained.

Figure 6 shows the F1 vs confidence curve of the model for all classes combined. The overall F1 score is 0.69. As evident from the curve, it is seen that various components have different scores. From the mAP score as well as the curve, it can be seen that Toroidal core inductor is detected with high score whereas fixed resistor has the least score. The confusion matrix is shown in Figure 7. Analyzing the result, it can be interpreted that the model is performing well in class separation. However, it is found that there are some false positives between Aluminum Capacitor & Electrolytic Capacitor, Toroidal inductor & Fixed Resistor, DIP & QFT, SM Inductor & Surface Mount Resistor, SM Inductor, TO252 and SM Inductor & Ceramic Capacitor. These errors in classification in relatively low and thus the model can separate the classes well.

Figure 8 shows the GUI with reference standard PCB image that is captured after the program starts. The image is sent through the model which returns the components' class and location. The detected components are marked by a green bounding box with the component's name as shown in Figure 8. Figure 9 shows the test image where the missing components from tested PCB are marked. For this, the image is taken and following Algorithm 1, positions of missing components are shown by drawing red bounding boxes. The green boxes represent the components which are present in the test PCB and the standard PCB. Figure 10 shows the snippet of the GUI displaying the name of missing components in the tested PCB in the message box.

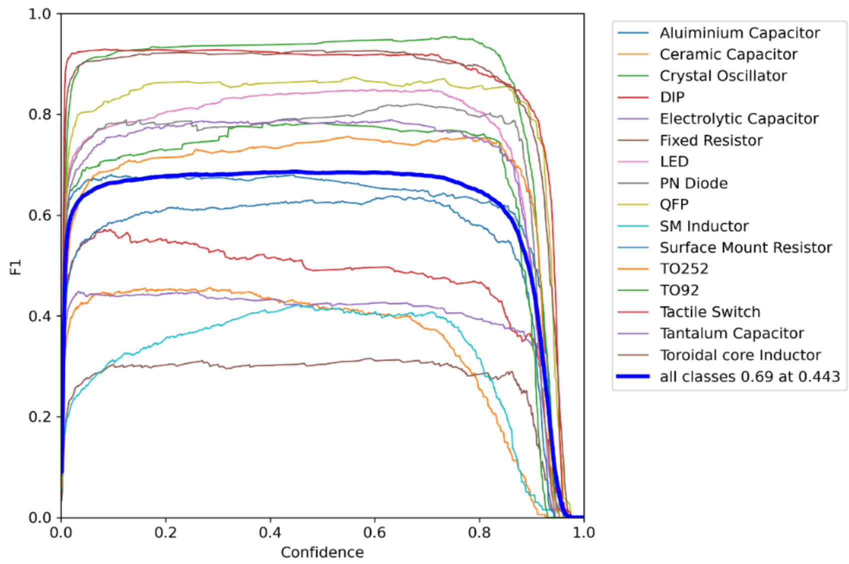



Figure 6 F1 vs confidence curve

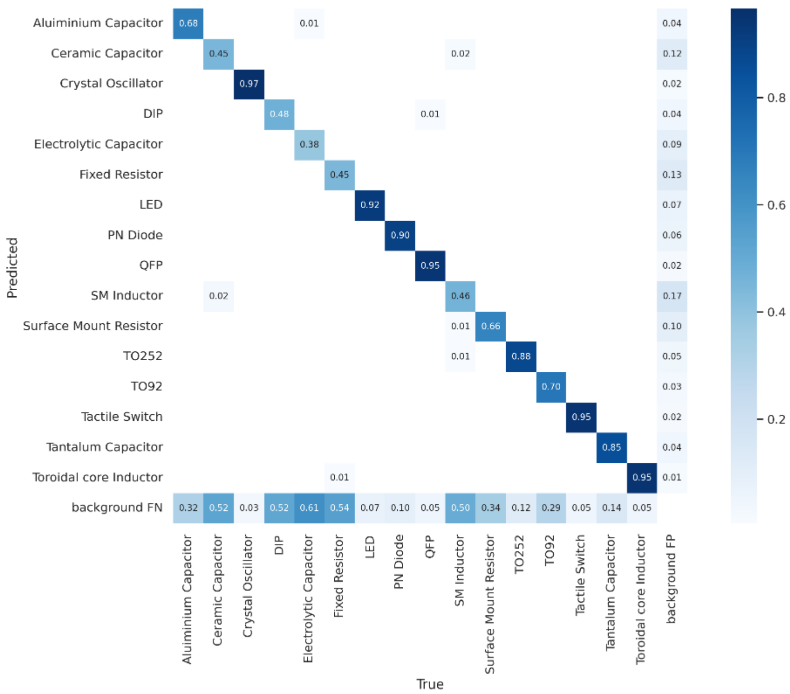



Figure 7 Confusion Matrix


Figure 8 Detection of Components in Standard PCB

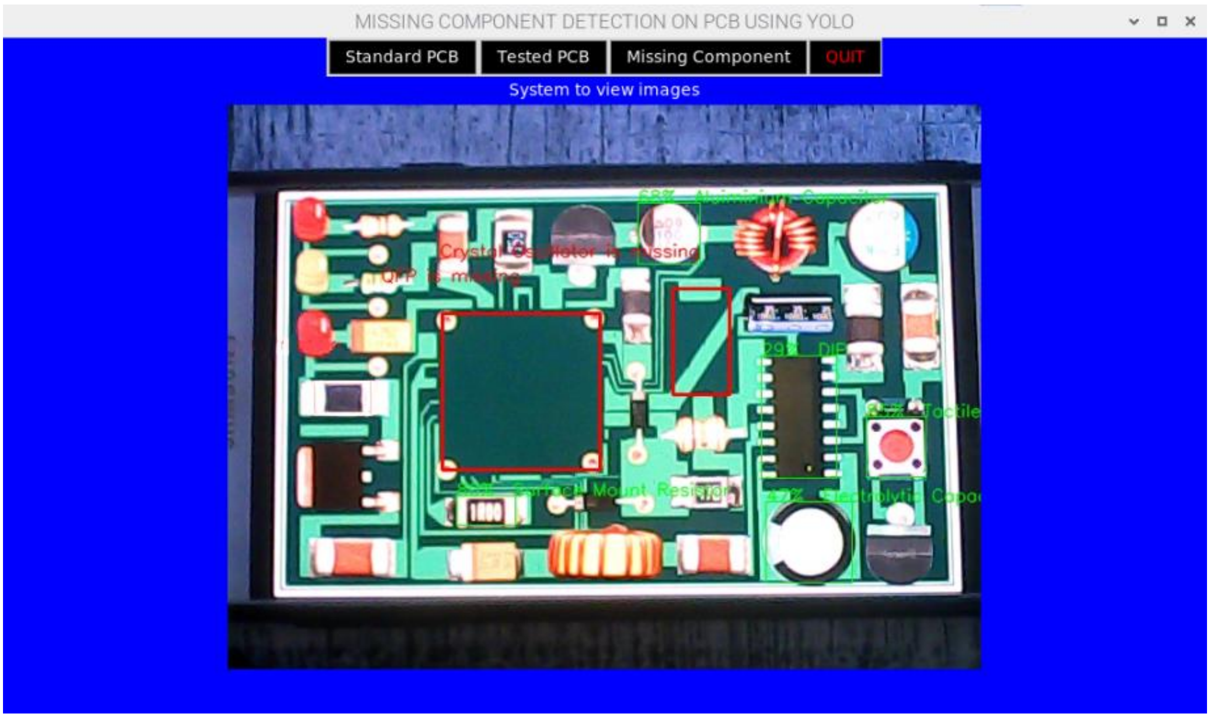



Figure 9 Detection of Missing Components


Figure 10 Missing Components

## 5. Conclusion

This paper aimed to develop a reliable and efficient method for detecting missing components in PCBs. After extensive research and experimentation, a system that uses the YOLOv3 algorithm to analyze images of PCBs and detect any missing components is successfully developed. Testing the system on various PCB designs, an average mAP of 69.3% was achieved in detecting 16 different missing components. However, for Fixed Resistor, SM Inductor, and Electrolytic Capacitor, the accuracy was significantly lower at 23.1%, 39%, and 50.8% respectively. Despite this variance, the system remains quite accurate in detection of the other 13 components. So, we believe this system has edge on other work done till now (which only includes detection of some few components and that also on specific type of PCB's). The comparative result analysis is shown in Table 3. The system can be enhanced to upgrade the quality control processes in PCB manufacturing, minimizing the chances of faulty electronic devices reaching consumers. Additionally, it reduces the time and cost associated with manual inspection, resulting in more efficient production processes. Overall, this research further develops the PCB manufacturing and quality control.

Table 3. Comparative results

| Paper | Accuracy or mAP | No of Components | Locate the exact Position of missing Component |
|---|---|---|---|
| (Lin, 2018) | 93.75% | 9 Different Capacitor | No |
| (Li, 2021) | 95.03% | Not Specified | No |
| S | 96.54% | 25 | Only missing resistors are identified but not exact position. |
| (Mogharrebi, 2011) | 97.23% | 5 | No |
| **Proposed Paper** | **69.3%** | **16** | **Yes** |

## 6. Data Availability

Images used for this study has been prepared form both primary and secondary sources and are available from corresponding authors upon the request.

**Acknowledgements**

This research was supported by Department of Electronics and Computer Engineering, Sagarmatha Engineering College. A sincere gratitude to Er. Bharat Bhatta and Er. Baikuntha Kumar Acharya for their encouragement, suggestions and continuous guidance throughout the course of this research.

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