RESEARCH ARTICLE

Vision Based PCB Fault Analyzer with Adaptive Feedback Alignment

K. P. N. K. Arachchi[1], R. A. D. Ravihara[1], S. M. M. L. Karunarathne[1*], S. C. Chandrarathna[1]

[1]*Faculty of Engineering, Sri Lanka Technology Campus, Padukka, Sri Lanka.*

Submitted on: 2025.09.18 Revised on: 2025.10.13 Accepted on: 2026.05.28

Abstract: This paper presents the development of a Vision Based PCB Fault Analyzer designed primarily for electronics repair centers such as computer and mobile phone service shops, as well as for PCB manufacturing and testing laboratories. The system automates the fault-detection process of Printed Circuit Boards (PCBs) and Printed Circuit Assemblies (PCBAs), reducing manual errors and preventing accidental short circuits common in manual troubleshooting. The proposed system integrates vision-based inspection and electrical testing using a flying-probe mechanism controlled by STM32 and PIC microcontrollers. A YOLOv5 deep learning model is employed to detect visual defects such as missing components, misalignments, and soldering faults, while the probe system verifies parameters like voltage, continuity, and resistor or capacitor conditions. To minimize hardware complexity and cost, an adaptive vision-based feedback mechanism replaces traditional servo feedback, dynamically adjusting camera positioning based on prediction confidence scores to ensure accurate alignment. Experimental results demonstrate that the proposed system provides a reliable, low-cost, and adaptive solution for both repair centers and production-line PCB testing environments.

Keywords: PCB Testing, PCBA, Flying Probe Test, Visual Inspection, Yolov5, Template Matching, Opencv, Pyqt5, STM32, PIC Microcontroller

INTRODUCTION

Printed Circuit Boards (PCBs) form the structural and electrical backbone of nearly all modern electronic devices from mobile phones and computers to automotive controllers and industrial systems. As component density increases, the demand for efficient PCB testing methods has become more critical. Traditional inspection techniques are generally divided into Automated Optical Inspection (AOI) and in Circuit or Flying Probe Testing (FPT), each addressing distinct fault types. However, these systems face challenges when implemented in small-scale production or repair environments.

A. Limitations of Conventional Inspection Systems

Conventional AOI systems employ high-resolution cameras and rule-based algorithms to detect surface defects such as spurs, spurious copper, missing holes, and solder bridges [1]. Although accurate, these systems are highly sensitive to lighting conditions and camera alignment. Moreover, advanced AOI equipment is costly and typically confined to large-scale manufacturing facilities. Flying probe testers and bed-of-nails systems perform electrical validation by measuring parameters such as resistance, continuity, and voltage at test points [2], [3].

These devices rely on servo-driven positioning mechanisms and precision alignment systems, making them expensive and difficult to maintain. As a result, such equipment is not viable for computer and mobile phone repair centers or small-batch PCB producers, where affordability, flexibility, and compactness are vital.

B. Advances in Vision-Based and AI-Assisted PCB Testing

Recent studies have shown that deep learning–based vision systems can overcome many of the limitations of traditional AOI [1]. Convolutional Neural Networks

**Corresponding author. E-mail address: migarak@sltc.ac.lk (Migara Karunarathne)*

(CNNs) and object detection models, such as YOLOv5 and Mask R-CNN, have demonstrated superior accuracy

in identifying missing components, misalignments, and soldering faults under varying illumination and orientation conditions, as shown in Table 1. Some hybrid systems have combined deep learning–based optical inspection with probe-based testing. However, these implementations typically rely on servo motors or laser sensors for feedback and calibration, which increases hardware cost and reduces accessibility for smaller enterprises.

C. Adaptive Vision-Based Feedback and Cost Optimization

Unlike existing systems, the proposed Vision-Based PCB Fault Analyzer with Adaptive Feedback Alignment introduces a camera-driven feedback mechanism that eliminates the need for servo feedback or external sensors. The same inspection camera used for defect detection provides feedback signals by analyzing YOLOv5 confidence scores. During movement, the system continuously adjusts its camera position, advancing, reversing, or stabilizing based on the score variation to achieve optimal focus and alignment. This technique significantly reduces mechanical complexity and cost, making it ideal for small repair shops and testing labs.

D. Hybrid Inspection for Broader Application

Beyond visual fault detection, the system integrates a compact flying probe tester controlled by STM32 and PIC microcontrollers to measure voltage, resistance, and continuity across test points [4]. This allows the system to be applied not only in PCB production but also in component testing, such as verifying resistor or capacitor values during repair. The entire testing process is managed through a PyQt5 graphical interface, enabling real-time video visualization, user interaction, and automatic reporting without the need for expert technical knowledge. The system thus bridges the gap between low-cost manual inspection and high-end industrial platforms. While prior studies have improved PCB defect detection using deep learning and automation, most solutions remain cost-intensive and hardware-dependent. The proposed system provides a low-cost, camera-guided, and adaptive alternative that combines computer vision, deep learning, and intelligent feedback for both visual and electrical inspection. This makes it a scalable, accessible, and reliable testing platform for small-scale repair centers and manufacturing laboratories alike.

Table 1: Comparison of Existing Systems and the Proposed System

Methodology	Technique Used	Key Limitation	Improvement in Proposed System
Automated Optical Inspection (AOI)	Rule-based feature extraction	High cost, poor adaptability to lighting	Deep learning–based real-time detection using YOLOv5
Traditional Flying Probe Tester	Servo-controlled mechanical probes	Requires precise calibration costly hardware	STM32/PIC-controlled Probe system with simpler design
Vision-based Deep Learning	CNN and Mask RCNN	Limited to visual inspection only	Combines visual + electrical testing
Hybrid Vision + Servo Feedback	CNN + mechanical servo	Expensive feedback sensors, complex setup	Vision-based adaptive feedback using detection confidence
Industrial AOI and ICT	Fixed test fixtures	Inflexible for small scale repair tasks	Portable, modular, and GUI-controlled PCB/PCBA analyzer

METHODOLOGY

A. General Overview

The PCB Fault Analyzer Figure 1 system follows a structured and modular testing workflow, beginning with system initialization and image capture. The process starts by acquiring real time images of the PCB or PCBA using a mounted camera. In the subsequent PCB Test stage, computer vision techniques are employed to detect visual anomalies such as spurs, spurious copper, mouse bites, missing holes, and short circuits.

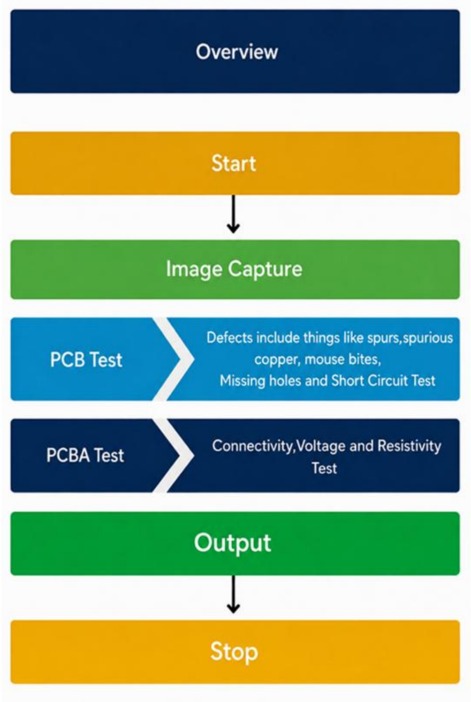

Figure 1: System overview of PCB and PCBA testing workflow

The PCB Fault Analyzer Figure 1 system follows a structured and modular testing workflow, beginning with system initialization and image capture. The process starts by acquiring real time images of the PCB or PCBA using a mounted camera. In the subsequent PCB Test stage, computer vision techniques are employed to detect visual anomalies such as spurs, spurious copper, mouse bites, missing holes, and short circuits.

The PCBA Test then performs physical verification using a flying probe system to measure voltage, connectivity, and resistivity at designated points. Although circuit level testing and thermal camera analysis are planned extensions, they are not yet implemented in the current version. After all, completed tests, results are processed and presented through an output interface.

The system concludes its operation in a controlled stop phase, ensuring the integrity of data and test reports. This streamlined flow allows for flexible integration of future test modules while maintaining an efficient and user-friendly inspection process.

B. Machine Interface

The machine interface Figure 2 consists of various mechanical and electronic components including a camera system, probe drivers, limit switches, and user controls. This subsystem is responsible for executing precise probe movements and capturing visual and electrical test data from the PCB or PCBA under inspection. The following figure illustrates the actual hardware setup and interface layout used in the system.

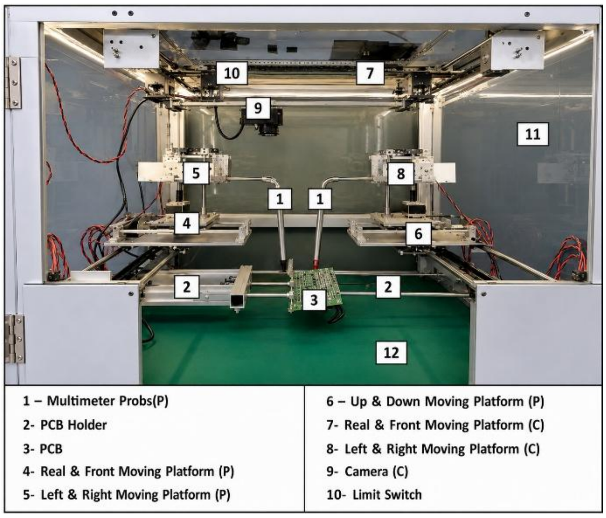

Figure 2: Machine Interface

The machine interface Figure 2 consists of various mechanical and electronic components including a camera system, probe drivers, limit switches, and user controls. This subsystem is responsible for executing precise probe movements and capturing visual and electrical test data from the PCB or PCBA under inspection. The following figure illustrates the actual hardware setup and interface layout used in the system.

The camera platform enables precise two axis movement left – right and front – rear for detailed inspection of PCBs. The left – right motion is driven by a T8 lead screw with an 8 mm pitch, while the front – rear motion is actuated using a GT2 6 mm timing belt and pulley system. Both axes are powered by NEMA 17 stepper motors, which offer reliable torque and fine control for smooth and accurate positioning. The complete platform, including the camera mount, weighs approximately 1 kg and is structurally optimized to minimize vibration and mechanical drift during testing operations.

A standard USB webcam is mounted on the platform to provide real time image capture, with the video feed directly streamed to a host laptop via a USB interface. While a webcam is sufficient for basic testing and prototyping, it is recommended to use a DSLR camera for improved image quality, resolution, and optical performance, especially for applications requiring fine detail analysis or high precision template matching.

C. Machine Structure

The machine Figure 3 has a compact design with dimensions of 72 cm in width, 77 cm in height, and 77 cm in length, making it well suited for users with limited workspace. An aluminum frame is used for the structure to provide both durability and aesthetic appeal, as it supports the attachment of glass panels and enhances the overall professional appearance. The green screen area is constructed using hardboard, while dark tinted glass is used to enclose the system. This not only helps block ambient light from surrounding equipment but also contributes to a cleaner, more refined look. A yellow LED light strip is installed around the system to provide consistent and uniform illumination during testing. Yellow light was specifically chosen because it enhances the camera’s ability to detect fine details and small features on the PCB, improving the accuracy of visual inspections. The probe system “Figure 3” is built within a frame measuring 250 cm in length, 160 cm in width, and 200 cm in height. It is capable of multi axis movement to reach designated test points on the PCB. Rear and front movements are driven by a GT2 timing belt mechanism, providing smooth and fast motion over extended distances. Other movements such as vertical (up/down) and lateral (left/right) positioning are actuated using T8 lead screw bars powered by NEMA 17 stepper motors for precise control.

The system currently achieves an approximate positional accuracy of 60 % relative to the intended target, which is sufficient for basic probing tasks but leaves room for further optimization in high precision applications.

D. PCB Design

The system “Appendix 1” utilizes eight DRV8825 stepper motor drivers, corresponding to eight NEMA 17 motors. Each DRV8825 driver supports up to 1/32 micro stepping, enabling high precision movement by dividing a full step into 32 micro steps. For example, with a typical 1.8° stepper motor (200 steps per revolution) 1/32 micro stepping results in 6400.

Micro steps per revolution, significantly enhancing positioning accuracy and smoothness. A PIC16F877A microcontroller is responsible for generating pulse signals to the STEP pins of each driver, with each pulse having an ON duration of approximately 0.2ms. Meanwhile, an STM32 “Blue Pill” microcontroller is used for communication with the host laptop via serial to UART interface. The STM32 receives commands from the laptop and controls the ENABLE and DIR (direction) pins of the DRV8825 drivers, determining motor activation and rotation direction. In terms of protection, the DRV8825 drivers include built in overvoltage and overcurrent protection. The STM32 microcontroller is safeguarded using Zener diodes for voltage clamping. The entire control system is powered by a 24V DC power supply. A 7805-voltage regulator is used to step down the voltage to 5V for logic level components, and capacitors are included for power line filtering and signal smoothing.

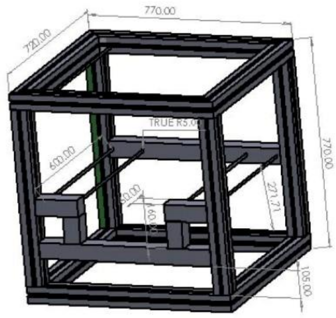

Figure 3: Structure of the machine: Designed using SolidWorks

E. Software Interface

The software for the system is developed using Python with the PyQt5 framework and is currently at version 1.0.0. PyQt5 provides a robust and flexible interface for designing modern graphical user interfaces (GUIs). When the “New” button is pressed within the application “Figure 4”, it dynamically loads the menu bar, allowing the user to access various functions such as test configurations, data logging, and hardware controls. This interface is designed to be user friendly, ensuring that even users with limited technical experience can operate the system efficiently.

1. PCB Test: During the testing phase, the system provides real-time camera feedback while enabling the configuration of visual inspection parameters

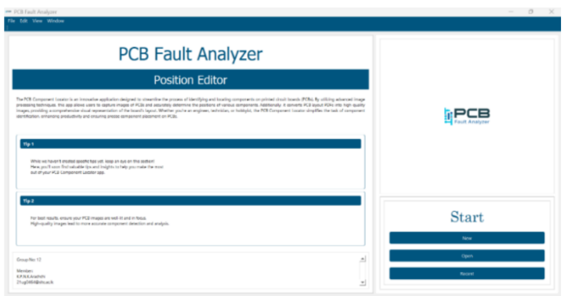

Figure 4: Loading Screen, the internal Interface of the software and the Menu Bar

through the user interface. The inspection process is performed using a YOLOv5-based deep learning model which precisely identifies various PCB defects such as spurs, spurious copper, mouse bites, missing holes, and short circuits. Upon completion of the inspection, the annotated output image is automatically saved to a predefined directory for further analysis, reporting, and documentation.

2. PCBA Test: In this testing phase, users can also upload a PCB image and manually mark specific test points where voltage, current, and continuity measurements are required. For each marked location, the system captures a 400 × 400-pixel image, which is utilized for template matching during the alignment process.

   Once the inspection sequence is initiated, the automated probe system precisely navigates to each designated test point and performs the required physical measurements with high positional accuracy.

F. Yolo Model

Unlike traditional models such as Faster R-CNN or SSD, YOLOv5 provides Figure 5 real-time object detection with high precision, making it ideal for industrial applications like PCB defect inspection where quick and reliable results are critical. Its lightweight architecture allows efficient deployment even on mid-range GPUs or embedded systems and balances detection speed, accuracy, and computational efficiency.

The YOLOv5 model used in this work was trained in a Jupyter Notebook environment using a 1.7 GB custom dataset obtained from Kaggle.com. The dataset was split into 80 % training and 20 % validation to ensure generalization, as indicated in references [5], [6]. Training was performed over 20 epochs with a batch size of 16, optimizing for both accuracy and efficiency. The model learned to detect surface-level PCB defects such as spurious copper, missing drill holes, mouse bites, short circuits, and irregular edges.

G. Algorithm Description

The algorithm powering the PCB Fault Analyzer "Figure 9" is structured to handle multiple inspection modes including PCB testing, PCBA testing, and assembly validation. The workflow begins when PCB enters the system. If PCB testing is selected, the system captures an image and processes it through a YOLOv5 model, which detects potential faults in a single Figure 5. Comparison of frames processed per second (FPS) implementing the Faster R-CNN, R-FCN, SSD and YOLO models. which detects potential faults in a single.

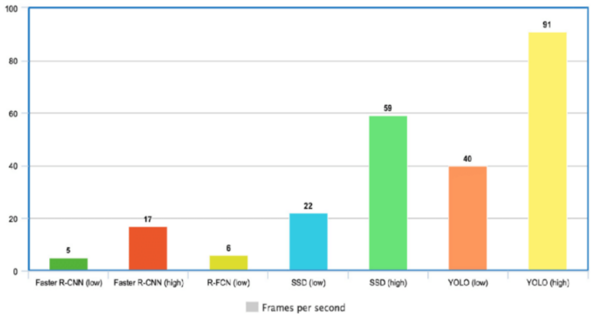

Figure 5: Comparison of frames processed per second (FPS) implementing the Faster R-CNN, R-FCN, SSD and YOLO models. Adapted from [7]

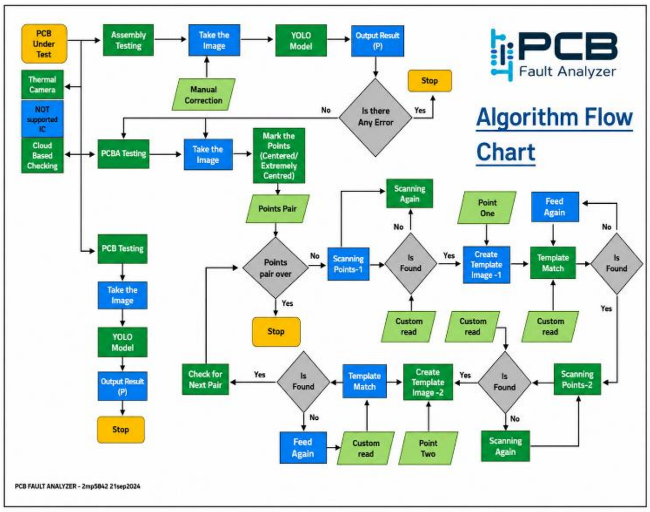

Figure 6: Algorithm Flow Chart

The result is output as a .jpg image, and any errors are flagged for review. For PCBA testing, the user marks inspection points for voltage, resistance, and continuity. The system then pairs the marked points and captures two template images (Point One and Point Two) using the camera feed. These templates are used for matching templates, ensuring accurate positioning of the probes. If the template match fails, the camera repositions and scans again. Once the points are verified, the probes move to the corresponding locations for electrical testing. All data from inspection is stored and compared, and the system checks for the next available PCB. This entire process is managed by a combination of manual control and automated image-based feedback, enabling high accuracy and efficiency in fault detection and analysis.

H. Template Matching Model

The template matching algorithm implemented in this project enables precise and dynamic alignment of the camera view with predefined features on a PCB, facilitating accurate probe positioning. This system operates in real time and is developed using OpenCV for image processing and PyQt5 for GUI integration, with motion commands transmitted via serial communication to a microcontroller. The process begins by capturing a continuous video stream from a high-definition camera (1920×1080).

A vertical strip centered on the frame is extracted to focus alignment along the horizontal axis. Both the live image and the reference template are converted to grayscale, and 1D intensity profiles are generated by averaging pixel intensities column-wise using OpenCV's cv2.reduce() function. These profiles are then compared using OpenCV's cv2.matchTemplate() function with the TM CCOEFF NORMED method, producing a similarity score between 0 and 1. If the score falls below a defined threshold (typically 0.90), movement commands are sent to reposition the camera.

The algorithm monitors these scores, detects peak and decay patterns, and finalizes alignment once the score stabilizes at its optimal value. Throughout the process, the GUI provides visual feedback with a red cross marker for intuitive monitoring. This adaptive, score-based approach ensures robust and accurate alignment without relying on hardcoded parameters, making it highly effective for dynamic PCB inspection scenarios.

RESULTS AND DISCUSSION

A. Performance of the YOLO V5 model

The performance evaluation of the YOLOv5 model is illustrated through the Precision Confidence and Recall Confidence curves Figure 10, which provides a detailed assessment of the model's classification effectiveness across various confidence thresholds. Each curve represents the model's behavior in detecting different types of PCB faults, including missing hole, mouse bite, open circuit, short, spur, and spurious copper. The Precision Confidence curve demonstrates how reliably the model predicts true positives as confidence increases.

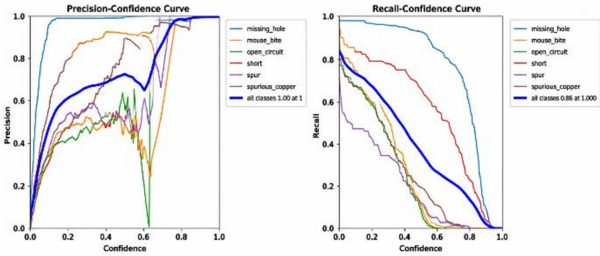

Figure 7: Precision–Confidence and Recall–Confidence Curves 1

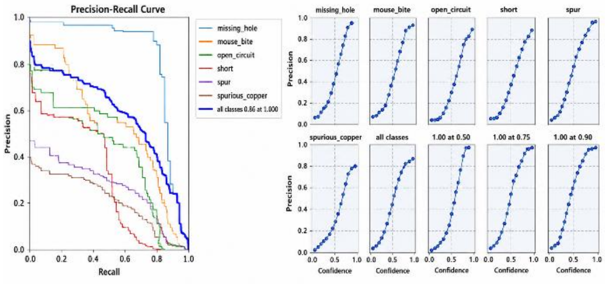

Figure 8: Precision–Recall Curve 1

Confusion Matrix

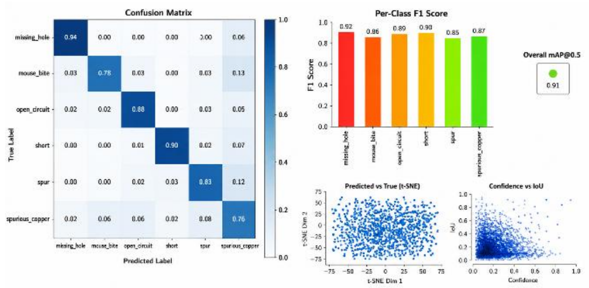

Figure 9: Performance Metrics of the YOLOv5 Model for PCB Fault Detection.

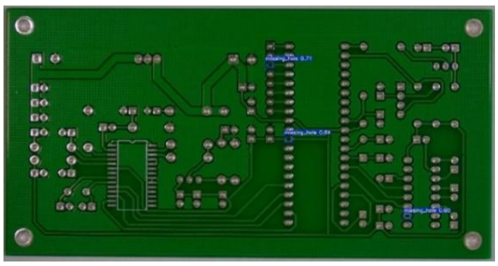

Figure 10: Detected Defects in PCB Using YOLOv5

Notably, the missing hole class achieves consistently high precision across all thresholds, nearing a value of 1.0, indicating excellent defect detection capability with minimal false positives. While other classes like spur and mouse bite show some variability in mid-confidence ranges (0.4 – 0.6), the overall average precision reaches 1.0 at higher thresholds, underscoring the model's robustness when confident.

On the other hand, the Recall Confidence curve reflects the model's sensitivity in identifying all relevant fault instances. As expected, recall is high at low confidence thresholds, capturing most defects but with a potential trade-off in precision. As the threshold tightens, recall gradually decreases, with classes like open circuit and spurious copper experiencing steeper drops. Nevertheless, the missing hole class again stands out with strong recall across all levels, affirming its consistent detectability.

The average recall across all classes begins around 0.84 at the lowest threshold, showcasing balanced performance. Collectively, these results affirm that YOLOv5 provides reliable and efficient defect detection, especially when tuned to higher confidence levels for precision-critical applications in PCB inspection.

B. PCBA Test Result

The output of the defect detection model is illustrated in Figure 11, where the YOLOv5 algorithm successfully identifies multiple instances of the missing hole fault on the PCB. The detected defects are highlighted with bounding boxes and confidence scores. For instance, defects with confidence levels of 0.71, 0.64, and 0.60 are labeled accordingly. Although the model demonstrates the ability to localize and classify missing holes effectively, the relatively moderate confidence scores in some detections suggest that the system's precision could benefit from further refinement.

These results indicate that while the trained model is functional, additional improvements such as increasing dataset diversity, tuning hyperparameters, or incorporating data augmentation may enhance its overall detection accuracy and robustness across different PCB layouts.

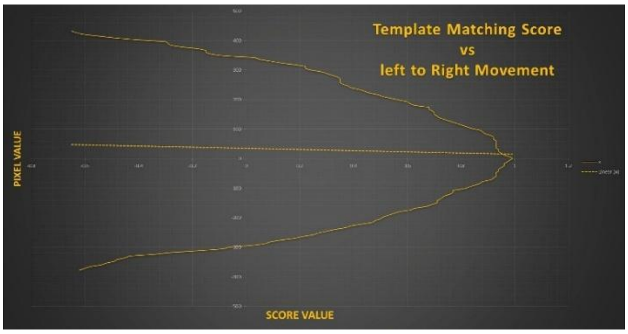

Figure 11: Template Matching Score vs variations in template width

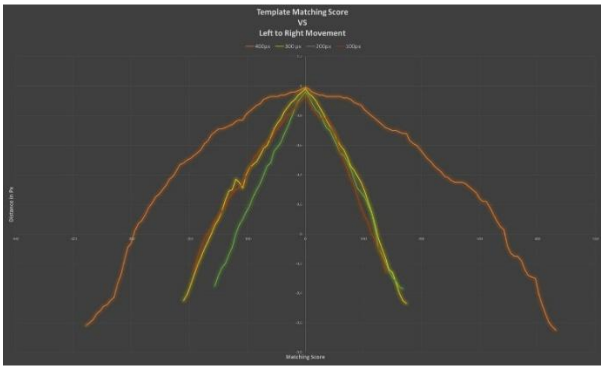

Figure 12: Template Matching Score vs variations in template width

C. PCBA Test Results

In the PCBA testing phase, the template matching algorithm's effectiveness was evaluated by analyzing how the matching score behaves as the camera moves across the target position.

As shown in Figure 12, the template matching score increases progressively as the camera approaches the correct alignment point. Once the camera passes the target, the score begins to decline, albeit slightly indicating a peak score at optimal alignment. This behavior confirms the algorithm's ability to detect alignment through score trends rather than fixed positions. Additionally, a secondary experiment was conducted to assess the algorithm's robustness against variations in template width as indicated in Figure 13.

Starting with a 400-pixel wide template, the width was reduced incrementally by 50 pixels on each side. The results demonstrated that while minor changes in template width slightly influenced the matching score, the overall prediction accuracy remained stable, reinforcing the algorithm's tolerance to template size variation.

This analysis validates the dynamic responsiveness of the system, showing that both motion-based score tracking and adaptive template sizing contribute to reliable visual alignment in real-time PCB testing.

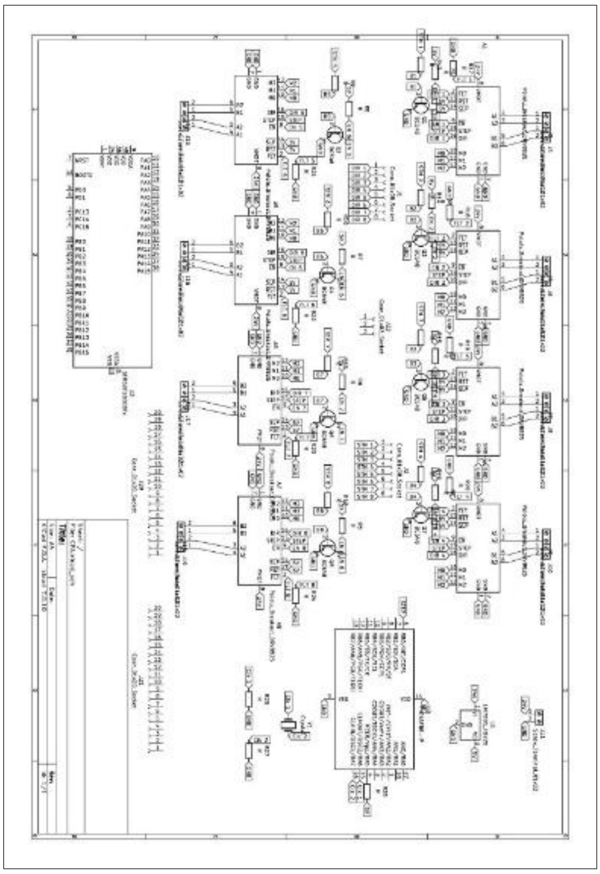

Figure 13: Detailed Schematic of the PCB Fault Analyzer Control Circuit (27 cm × 13 cm)

LIMITATIONS AND FUTURE WORK

While the proposed PCB and PCBA defect detection system show promising results, there are several limitations that need to be addressed in future iterations. One key limitation is the quality and consistency of image data. The current implementation uses a webcam for image capture, which restricts resolution and frame rate, potentially missing fine-grained defects. Upgrading to a high-speed industrial camera or a DSLR would significantly enhance detection accuracy.

Another limitation is the physical construction of the machine, which was manually built. This limits both the precision of movement and long-term durability. A laser-cut chassis with more accurate mechanical alignment could improve the reliability and speed of inspection. The dataset size is also a constraint.

The current training set is approximately 1.7 GB, which restricts the model's ability to generalize to more complex or varied PCBs. Increasing the dataset size to at least 10 GB with diverse defect examples will improve the deep learning model's accuracy and robustness.

Moreover, the current system supports PCB sizes ranging from a minimum of 12 cm to a maximum of 25 cm in length, and from 7 cm to 12 cm in width. This size limitation restricts the machine from inspecting smaller or larger boards used in certain commercial or industrial applications. Extending the mechanical platform and adjusting the vision system accordingly will be essential for handling a broader range of PCB sizes.

In terms of software, while template matching with OpenCV is cost-effective and simple, it has limitations when dealing with rotated or non-uniform PCBs. Future work may integrate feature-based matching or transformer-based object detection models for better flexibility. Additionally, the system currently focuses on visual and structural defects.

Future versions will incorporate thermal imaging to identify overheating components and perform circuit-level analysis to detect electrical failures. Expanding the system's capabilities to test smartphone PCBs, power supply boards, and multi-layered PCBs is also planned.
Overall, while the prototype effectively detects common PCB defects using affordable tools, significant improvements in hardware, dataset size, and algorithmic sophistication will be necessary to meet industrial standards.

CONCLUSION

In conclusion, the developed machine demonstrates promising results in identifying both PCB and PCBA defects, including issues such as spurs, spurious copper, mouse bites, short circuits, and open circuits, as well as performing basic component-level testing. The system effectively leverages template matching techniques using OpenCV in place of more expensive solutions like G-code-controlled systems, significantly reducing cost and simplifying the design.

Although a standard webcam was used for imaging, the overall performance is acceptable; however, integrating a high-frame-rate industrial camera or a DSLR would likely enhance detection precision. Similarly, while the machine was manually constructed, future iterations using laser-cut components could greatly improve speed, stability, and overall performance.

The YOLOv5 model trained on a 1.7 GB dataset performed reasonably well, but expanding the dataset to at least 10 GB would further improve detection accuracy and robustness. Looking ahead, the system could be extended to support more advanced tests, such as thermal imaging and circuit-level diagnostics. Additionally, upgrading the mechanical platform and incorporating highspeed vision systems would make the machine suitable for testing more complex devices like smartphone PCBs and power supply boards.

REFERENCES

[1] S. Zhang et al. Yolo-pdd: A novel multi-scale pcb defect detection method using deep representations with sequential images. arXiv preprint, 2024. [Online]. Available: https://arxiv.org/abs/2407.15427

[2] PCBWay. applications. Pcb flying probe test: Principles, advantages, and PCBWay Blog, 2023. [Online]. Available: https://www.pcbway.com/blog/PCBManufacturingInformation/PCBFlyingProbeTestPrinciplesAdvantagesandApplicationsbc222b0f.html.

[3] ProtoExpress. How flying probe testing works for pcb assembly. ProtoExpress Blog, 2023. [Online]. Available: https://www.protoexpress.com/blog/how-flying-probe-testing-works for-pcb-assembly/.

[4] Automated pcb tester with stm32 and *python GitHub repository*, 2022. [Online]. Available: https://github.com/ryanq04/automatedpcbtester.

[5] JiaLim98. Yolo-pcb defect dataset & detection. *GitHub repository*, 2023. [Online]. Available: https://github.com/JiaLim98/YOLO-PCB.

[6] badboysm890. Pcb defect detection using yolov5. *GitHub repository,* 2023. [Online]. Available: https://github.com/badboysm890/PCB-Defect Detection.

[7] ResearchGate. A review: Comparison of performance metrics of pretrained models for object detection using the tensorflow framework- scientific figure. ResearchGate, 2025. Available: [Online]. *processed-per-second FPS-implementing-the-Faster*-R-CNN-R-FCN SSDfig6342570032[Accessed 4Nov2025]. https://www.researchgate.net/figure/Comparison-of-frames