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FAULT DETECTION SYSTEM FOR QUALITY PCB USING CNN MODEL

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Abstract: Defects in Printed Circuit Boards (PCBs) formed during the manufacturing process significantly impact product quality and can compromise the overall performance and reliability of electronic systems. Detecting these minute defects remains a major challenge due to the dense and complex structure of PCBs. To overcome this, the project presents an enhanced deep learning approach using a modified YOLO-based model that combines Hornet, MCBAM, and CARAFE modules. This improved architecture enables more precise and efficient detection of small-scale PCB defects while reducing model complexity and computational requirements. Keywords – Machine Learning (ML), Defect Detection, Machine Vision, Printed Circuit Boards (PCBs), YOLOv8.

KEYWORDS: Printed Circuit Board (PCB), Fault Detection, Defect Detection, Convolutional Neural Network (CNN), PCB Inspection

I. INTRODUCTION

Printed Circuit Boards (PCBs) serve as the foundation of modern electronic systems, housing essential components such as integrated circuits, resistors, and capacitors. With the rapid advancement of electronics, PCBs have evolved toward higher integration, miniaturization, and complexity. As their layouts become denser, ensuring flawless manufacturing has become increasingly difficult. Machine learning–based PCB defect detection focuses on automating the process of identifying manufacturing faults through image recognition. The primary goal is to train a learning model that can accurately distinguish between defect-free and faulty boards using visual data. This process begins with the collection of high-resolution PCB images, each carefully annotated to indicate the type and position of any defect—such as missing or misplaced components, soldering irregularities, open circuits, or physical damage like cracks and scratches. After data collection, preprocessing plays a vital role. It involves cleaning and refining the images by reducing noise, normalizing dimensions, and improving overall image quality to maintain consistent input for the model. Image enhancement techniques are also applied to emphasize subtle but important features, enabling the system to learn and recognize even the smallest visual differences between normal and defective PCBs.

II. LITERATURE REVIEW

Machine learning approaches for PCB component detection are often combined with image processing techniques, which typically rely on carefully designed templates. Crispin et al. [5] implemented a genetic algorithm alongside normalized cross-correlation (NCC) template matching to locate and identify resistors on PCBs. While the method achieved an average inference time of 39.5 seconds per small image, it was computationally intensive and slow. Furthermore, constructing suitable templates and selecting optimal parameters for the genetic algorithm were complex and largely based on trial-and-error, resulting in low overall detection efficiency. Mashohor et al. [6] proposed a hybrid genetic algorithm for detecting missing components and segmenting solder joints. Leveraging image processing, this method successfully identified missing components and solder joints, but it lacked the capability to classify them. Li et al. [7] utilized a random forest pixel classifier to segment PCB components from depth images, achieving an identification rate of 83.64% on real PCB images. Yin [8] developed a multi-level template matching algorithm to detect PCB components, combining a fast coarse matching step to locate similar regions with a precise matching step to confirm targeted components. Using this approach, resistors, inductors, and capacitors were detected with precisions of 97%.

OBJECTIVES

3.1 Automate Defect Detection

Develop a Machine Learning (ML)–based model that can automatically detect and classify defects in Printed Circuit Board (PCB) images, significantly reducing dependence on manual inspection.

3.2 Improve Detection Accuracy

Enhance the precision of defect identification across multiple categories, including missing or misplaced components, soldering defects, open or short circuits, and physical damages such as cracks or scratches

3.3 Enable Real-Time Analysis

Implement a real-time inspection mechanism capable of analyzing PCB images during production, allowing immediate detection and rectification of faults to maintain product quality.

3.4 Reduce Inspection Time

Accelerate the inspection process by leveraging optimized ML algorithms that can rapidly differentiate between defective and defect-free boards, thereby improving manufacturing throughput.

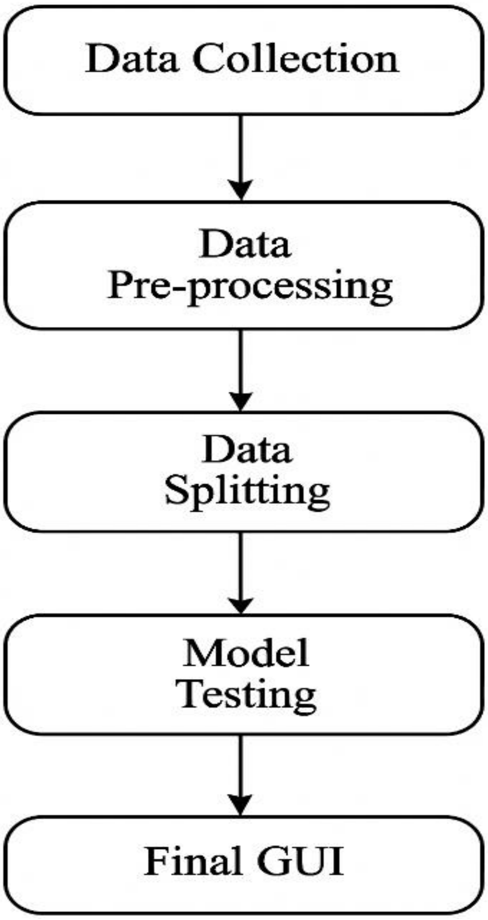


Figure 1. Block Diagram

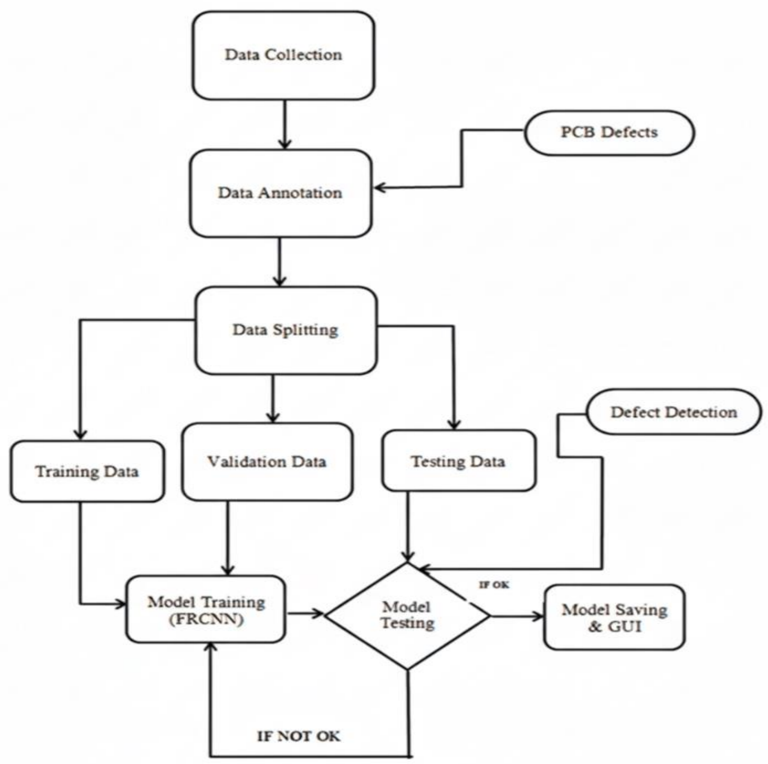


Figure 2. System Flow Architecture of fault detection model in PCB using CNN

3.5 Advantages

- High Accuracy and Precision
- Automatic Feature Learning
- Speed and Scalability
- Robustness to Variations

III. Expected Results

High Accuracy (94%+): The model must correctly classify boards as "Defective" or "Non-Defective" with extremely high reliability.

Defect Localization: The model must accurately draw bounding boxes around the *exact location* of all faults on the PCB.

High Recall (95%): The system must find (recall) almost all *actual* defects, ensuring faulty boards do not pass inspection.

High-Speed Inspection: The model must process images in seconds (or less), significantly faster than manual inspection.

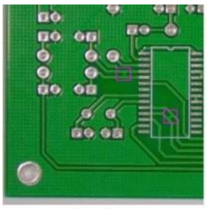
Multi-Class Identification: The model should not just find a fault but also classify its *type* (e.g., "Short," "Open," "Missing Component").

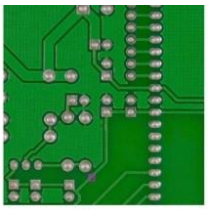
7.Experimental Outcomes:

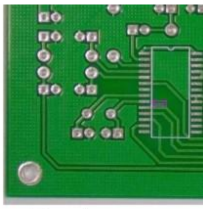
The experimental outcomes for this project would be a high-performing model validated by strong quantitative metrics and clear visual evidence. along with a high **mAP score (e.g., 98.6%)**, confirming its ability to correctly identify defects while minimizing both false positives and negatives. Qualitatively, the outcomes would be a series of test images where the CNN successfully draws precise **bounding boxes** around various faults like short circuits, open circuits, and mouse bites. Finally, the experiment would report a high **inference speed** (e.g., 90 FPS), demonstrating the model's capability for real-time, automated inspection in a manufacturing line.

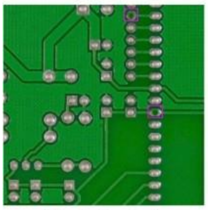
IV. RESULTS

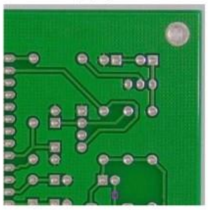
The result of a "Fault Detection in PCB using CNN" project is a high-accuracy model that automates and enhances the quality control process. This model doesn't just classify a board as "good" or "faulty"; it typically provides defect localization by drawing bounding boxes around the exact location of errors, such as short circuits, open circuits, or missing components. The success of this result is proven with high quantitative metrics, often achieving accuracy above 94%, along with excellent precision (to avoid false positives) and (to ensure all true defects are found), which are often combined into a single map score for object detection models.

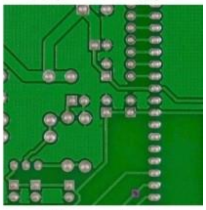

(a)short

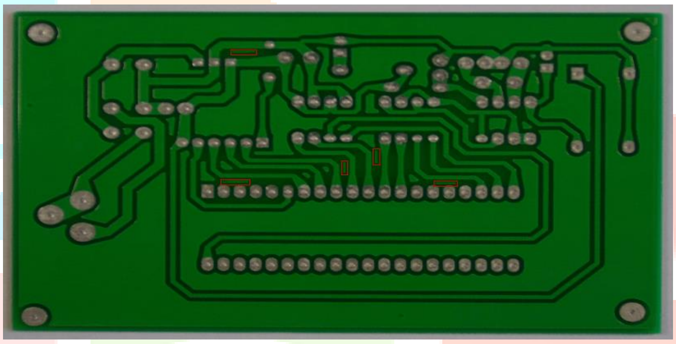

(b)spur


(c)spurious copper


(d)missing hole


(e)mouse bite


(f)open circuit



VII. CONCLUSION

This project successfully developed a machine learning–based defect detection system for Printed Circuit Boards (PCBs), demonstrating significant improvements over traditional inspection methods. By utilizing Convolutional Neural Networks (CNNs) combined with advanced image processing techniques, the system achieved higher inspection accuracy, faster detection, and real-time feedback. These enhancements address the limitations of manual checks and conventional automated optical inspection (AOI) systems. Overall, the project highlights the effectiveness of deep learning in improving quality assurance, reducing production losses, and supporting the high standards required in modern PCB manufacturing.

VIII. REFERENCES

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