Development of Fault Detection system for quality control in PCB fabrication Using CNN Model.

Prof.D.N.Chaudhari[1],Sanket Suresh Dabhade[2] ,Shubham Santosh Vaidya[3], Gokul Nachan[4].
[1234]ZEAL COLLEGE OF ENGINEERING & RESEARCH, PUNE – 41
Department of Robotics & Automation Engineering

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Abstract - The defects of printed circuit boards (PCBs) generated during the manufacturing process have an adverse effect on product quality, which further directly affects the stability and reliability of equipment performance. However, there are still great challenges in accurately recognizing tiny defects on the surface of PCB under the complex background due to its compact layout. To address the problem, a novel YOLO Hornet-MCBAM-CARAFE (YOLO-HMC) network based on improved YOLOv5 framework is proposed in this article to identify the tiny-size PCB defect more accurately and efficiently with fewer model parameters.

Keywords:-Machine learning (ML), Defect defection, Machine vision, Printed circuit boards (PCBs),YOLOv8.

1. INTRODUCTION

Printed circuit boards (PCBs) are the backbone in modern electronic information industry, carrying integrated circuits, resistors, capacitors, and other electronic components. The rapid development of electronic techniques has led to the miniaturization, integration, and diversification of PCBs. PCB defect detection using machine learning revolves around automating the process of identifying defects in printed circuit boards using image recognition techniques. The core idea is to train a machine learning model to differentiate between a defective and a defect-free PCB based on visual input. This typically begins with the collection of high-quality images of PCBs, where each image is meticulously labeled to indicate the presence and type of any defects. These defects might include missing components, misplaced parts, soldering issues, or physical damage like cracks and scratches.

Once the data is collected, preprocessing becomes essential. This involves cleaning the images by removing noise and standardizing their size and quality to ensure that the model receives consistent input. Techniques like image enhancement can be used to highlight critical features that will help the model in learning the difference between a normal PCB and one with defects.

2. PROBLEM STATEMENT

The problem in PCB (Printed Circuit Board) defect detection lies in the complexity and high precision required to identify manufacturing defects in modern PCBs. Traditional methods of manual inspection are time-consuming, prone to human error, and increasingly inadequate as the complexity of PCBs grows. As PCBs become more intricate, with smaller components and denser layouts, ensuring high-quality production and defect-free boards becomes more challenging.

The primary issue is the need for an automated, reliable, and scalable solution to detect defects such as missing components, open circuits, soldering issues, or physical damages like scratches and cracks. These defects can compromise the functionality of the entire electronic system, leading to product failures, increased costs, and delays in manufacturing. An intelligent, machine learning-based solution is required to automatically and accurately inspect PCBs, identify defects in real-time, and reduce dependency on manual labor while improving the efficiency and precision of the quality control process.

At the first occurrence of an acronym, spell it out followed by the acronym in parentheses, e.g., charge-coupled diode (CCD).

3. OBJECTIVES

1. **Automate Defect Detection:** Develop a machine learning model capable of automatically identifying defects in PCB images, reducing the need for manual

inspection.

2. **Improve Detection Accuracy:** Achieve high accuracy in detecting various types of defects, including missing components, soldering issues, open circuits, and physical damages.
3. **Real-Time Analysis:** Implement a system that can analyze PCBs in real-time, enabling immediate identification and correction of defects during the production process.
4. **Reduce Inspection Time:** Minimize the time taken for PCB inspection by leveraging machine learning models to quickly analyze and classify defect-free and defective boards.
5. **Enhance Scalability:** Design the system to be scalable, allowing it to handle increasing production volumes and complexities of PCBs without sacrificing performance.

4. SIGNIFICANCE OF THE PROJECT

The significance of the PCB defect detection project using machine learning extends to the realm of interdisciplinary collaboration, which is essential for the success of the project. It brings together experts from various fields, each contributing unique knowledge and skills to ensure that the system is both technically robust and practically viable. Machine learning and artificial intelligence experts play a pivotal role in developing and fine-tuning the models that will be used for defect detection. They focus on selecting the most suitable algorithms and optimizing the system to accurately detect and classify defects in PCB images. This work requires collaboration with computer vision specialists, who ensure that the model is capable of interpreting complex image data, extracting relevant features, and recognizing patterns that indicate defects.

At the same time, professionals with expertise in PCB design and manufacturing bring invaluable domain knowledge to the project. Their understanding of the specific defects that can occur in PCBs—such as missing components, soldering issues, or open circuits—ensures that the machine learning model is designed to focus on the most critical problems. Electronics engineers, with their deep knowledge of circuit functionality and system reliability, guide the prioritization of defects that can affect the overall performance of the PCB. Their input is crucial in aligning the system's objectives with the practical needs of the industry, ensuring that the detection of defects directly enhances product quality and functionality.

5. PROBLEM SOLVING

The significance of the PCB defect detection project lies in its potential to address key problems faced by the electronics manufacturing industry, particularly in terms of quality control and operational efficiency. Traditional methods of manual inspection are not only time-consuming but also prone to human error, especially as the complexity of printed circuit boards continues to increase. These defects can result in malfunctioning products, leading to high costs from rework, recalls, or warranty claims. This project directly tackles these issues by leveraging machine learning to automate and improve the accuracy of defect detection.

By implementing machine learning, the system offers a scalable and reliable solution to identify defects such as missing components, incorrect soldering, and physical damage. Unlike manual inspection, which is subject to variability due to inspector fatigue or subjective judgment, machine learning models provide consistent and repeatable results. The ability of these models to learn from large datasets and improve over time ensures that the system becomes more efficient at identifying defects, reducing both false positives and false negatives.

6. FEASIBILITY STUDY

- **Technical Feasibility:** The technical feasibility of the project examines whether the necessary technology and resources are available to develop and implement the PCB defect detection system. This includes evaluating the machine learning algorithms, image processing techniques, and hardware requirements. Given the advancements in machine learning frameworks such as TensorFlow and PyTorch, along with the availability of powerful GPUs for training complex models, the project is technically feasible. Additionally, existing datasets of PCB images can be utilized to train the machine learning models, ensuring that the system is built on a solid foundation of data.

- **Operational Feasibility:** Operational feasibility evaluates how the proposed system will fit into the existing manufacturing processes and workflows. Implementing a PCB defect detection system using machine learning would require training existing personnel on the new system and integrating it with current quality control processes. The learning curve for employees is a critical factor to consider, as it can impact the timeline for full implementation. However, the operational benefits of real-time defect detection, such as faster feedback loops and improved production quality, are substantial. Manufacturers will need to ensure that they have the necessary infrastructure to support the system, including robust data management and integration capabilities.
- **Economic Feasibility:** Economic feasibility involves assessing the financial implications of the project, including initial costs, ongoing operational costs, and potential return on investment (ROI). The initial investment would cover software development, hardware procurement, and training of personnel. However, the long-term savings generated by reduced labor costs, improved production efficiency, and lower defect rates can offset these initial costs.

7. SCOPE & LIMITATIONS

- **Scope**

i. Defect Types: The project will focus on identifying a range of common defects in PCBs, such as missing components, soldering issues, open circuits, short circuits, and physical damage.

ii. Machine Learning Techniques: The project will employ advanced machine learning algorithms, particularly Convolutional Neural Networks (CNNs), which are well-suited for image recognition tasks.

iii. Integration into Manufacturing: The project will explore the integration of the defect detection system into existing manufacturing workflows.

iv. Performance Evaluation: The system's performance will be assessed based on metrics such as accuracy, precision, recall, and processing speed.

- **Limitations**

i. Data Quality and Availability: The success of machine learning models heavily relies on the quality and quantity of training data. Limited access to high-quality labeled datasets can hinder the model's ability to generalize and accurately detect defects.

ii. Complex Defect Detection: Some defects may be challenging to detect due to their subtle nature or similarity to normal variations in PCB features.

iii. Training Time and Resources: Training machine learning models, especially deep learning architectures like CNNs, can be resource-intensive and time-consuming.

iv. Integration Challenges: Integrating the machine learning model into existing manufacturing systems may present technical challenges.

8. LITERATURE REVIEW

Machine learning algorithms for PCB component detection are closely integrated with image processing, which usually requires qualified templates. Crispin et al. [5] applied genetic algorithm combined with normalized cross correlation (NCC) template matching to locate and identify resistors in PCBs. The mean inference time reached 39.5s per one small size image. However, this method had large computation cost, leading to a slow running. Moreover, both building the qualified template and optimal parameter choice for genetic algorithm are intricate and experiential, contributing to a low detection efficiency. Mashohor et al. [6] proposed a hybrid genetic algorithm to detect missing components and segment solder joints. With the help of image processing techniques, this method identified missing components or solder joints, but failed to classify them. Li et al. [7] used random forest pixel classifier to segment components based on depth images of PCBs. The component identification rate of 83.64% was performed for real PCB images. Yin [8] designed a multi-level template matching algorithm to detect PCB components. A fast coarse matching was implemented to locate the similar region, then a precise matching was carried out to estimate whether the similar regions were targeted components. This method detected resistors, inductors and capacitors at the precisions of 95.3%, 94.1% and 96.5% respectively.

9. SYSTEM DESIGN & DEVELOPMENT

- **Block diagram**

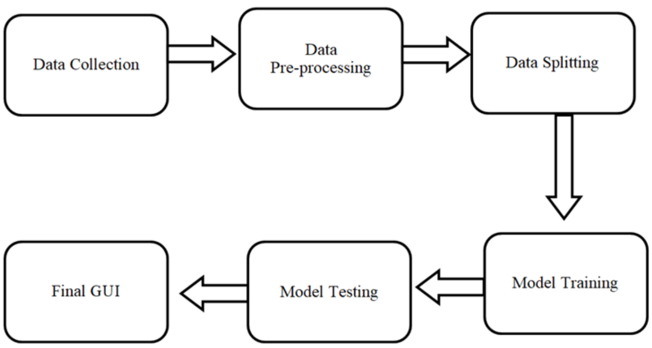

Fig.1 Block diagram

- **Flowchart**

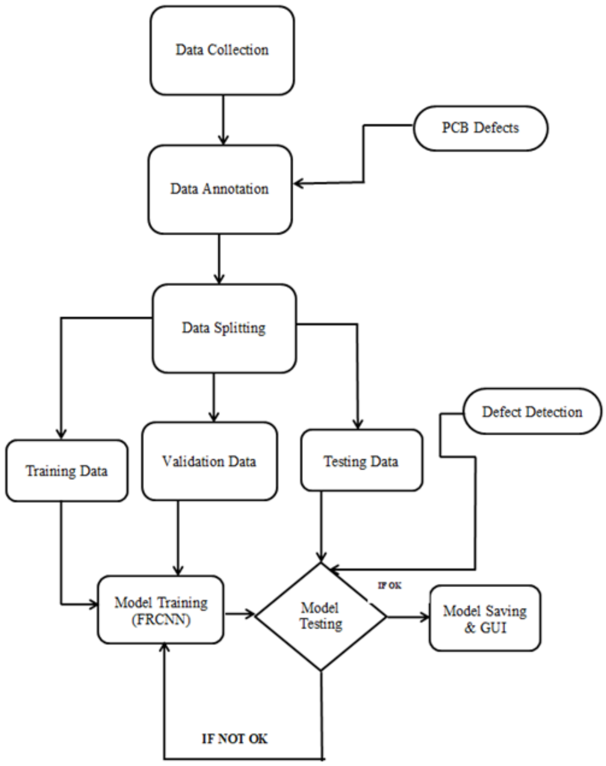

Fig.2 Flowchart

10. HARDWARE

1. Processor: I3T
2. SSD: 250GB
3. RAM: 8GB
4. OS: Window101

11. SOFTWARE

1. Python IDE
2. OpenCV cube
3. Tkinter Programming
4. Tkinter Widgets
5. YOLOv8:Architecture,Training,and Applications

12. EXPERIMENTS AND RESULT

- **Results**

Ablation experiments for the improvements of Ghost con volution module, C2Focal module and Sig-IoU loss are executed to validate their benefits. We set YOLOv8-nano as the baseline to make the ablation. To test the performances of our proposed modifications, 1122 PCB component images are detected. We present the ablation results in Table 7. It indicates that our proposed model is much superior to original YOLOv8-nano on the task of diverse PCB component detection. The introduction of C2Focalmodules to replace the original C2fmodules contribute estoapparent boost to the detection metrics. As shown in Table 7, the recall metric markedly increases by 3.7% compared with the baseline, although the precision value has no evident enhancement yet. The metrics of mAP@0.5 and mAP@0.5:0.95 have significant increases of 1.4% and 0.6% respectively. The improvements in detection performances profit from the perception that FocalNeXt block can enlarge the receptive field of neurons and integrate fine-grained local and coarse-grained global features. Thus, the C2Focal module integrating FocalNeXt block mitigates the adverse impact from the scale variance to achieve preferable results. Moreover, only introducing little additional computation cost, the model with C2Focal modules still reaches the detection speed of 104 frames per second (FPS), which meets the requirement of industrial application. Then, we use the Sig-IoU loss function for bounding box regression. As shown in Table 7, the introduction of Sig-IoU loss shows a little decrease in the precision. However, the recall is observably increased to 85.3% with an increment of 1.5%.

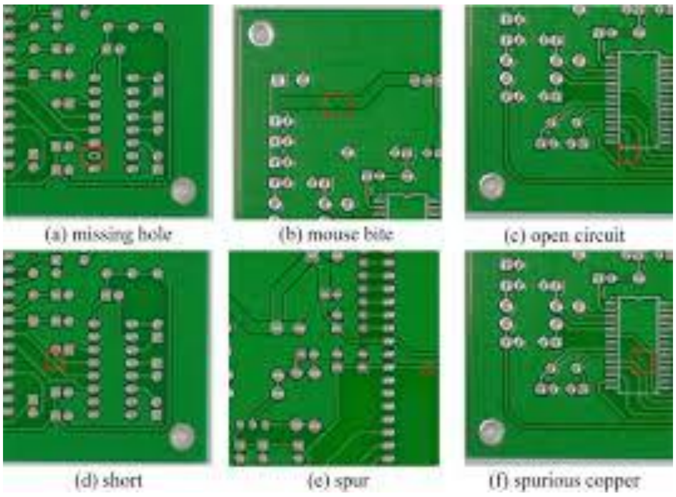

Fig.3 HRIPCB

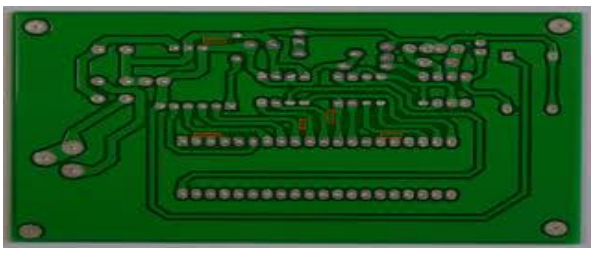

Fig.4 Track Missing

13. CONCLUSIONS

This project explored the development and application of a machine learning-based defect detection system to improve the quality assurance process for printed circuit boards (PCBs). By leveraging convolutional neural networks (CNNs) and advanced image processing techniques, the system aimed to overcome the limitations of traditional inspection methods, such as manual checks and basic automated optical inspection (AOI) systems. The machine learning model enhanced inspection accuracy, sped up the detection process, and provided real-time feedback, which are crucial for the high standards demanded in PCB manufacturing.

14. FUTURE WORK

While this project successfully implemented a machine learning-based defect detection system for PCBs, several opportunities exist for further research and development to enhance its effectiveness and adaptability. Future work can focus on refining the system's capabilities, expanding its applicability, and ensuring that it remains at the forefront of technological advancements in quality control for PCB manufacturing.

Integration of Advanced Deep Learning Models Future work can explore the use of more advanced deep learning architectures, such as transformer-based models or advanced convolutional neural networks (CNNs) that incorporate attention mechanisms.

Real-time Feedback and Active Learning implementing a real-time feedback loop that updates the machine learning model continuously with new data from production can enhance the model's adaptability to evolving manufacturing processes.

REFERENCES

[1] Y. Shi, Z. Xin, P. C. Loh, and F. Blaabjerg, ‘‘A review of traditional helical to recent miniaturized printed circuit board Rogowski coils for power electronic applications,’’ IEEE Trans. Power Electron., vol. 35, no. 11, pp. 12207–12222, Nov. 2020.

[2] M. Yin, ‘‘A template-matching-based fast algorithm for PCB com ponents detection,’’ Adv. Mater. Res., vols. 690–693, pp. 3205–3208, May 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID: 60677124.

[3] Liu, J. Hu, H. Wang, Z. Zhang, X. Lu, C. Sheng, S. Song, and J. Nie, ''Gaussian-IoU loss: Better learning for bounding box regression on PCB component detection,'' Expert Syst. Appl., vol. 190, Mar. 2022, Art. no. 116178. [Online]. Available: https://api.semanticscholar.org/CorpusID:244096237.

[4] Y. Wang, H.-Y. M. Liao, Y.-H. Wu, P.-Y. Chen, J.-W. Hsieh, and I.-H. Yeh, ''CSPNet: A new backbone that can enhance learning capability of CNN,'' in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), Jun. 2020, pp. 1571–1580.