



Pcb Defect Detection in Manufacturing Using Deep Learning

Raziya Siddiqui¹, Abhimanyu Pratap Singh², Aniruddh Singh³, Anurag Gupta⁴

¹Assistant Professor Dept. Computer Science & Engineering Babu Banarasi Das Institute of Technology & Management Lucknow, Uttar Pradesh, India,

^{2,3,4} UG Scholar, Dept. Computer Science & Engineering Babu Banarasi Das Institute of Technology & Management Lucknow, Uttar Pradesh, India

Emails: raziyasiddiqui8174@gmail.com¹, singhabhimanyu1289@gmail.com²,
singh2004aniruddh@gmail.com³, anugupta01235@gmail.com⁴

Abstract

Printed Circuit Boards (PCBs) form the structural backbone of modern electronic devices, connecting and supporting electronic components in systems ranging from consumer electronics to aerospace equipment. Ensuring defect-free PCBs during manufacturing is critical because even minor defects such as open circuits, shorts, mouse bites, spurious copper, or micro-cracks can significantly impact product reliability and functionality. Traditional inspection methods, including manual visual inspection and rule-based image processing techniques, often suffer from limitations such as low accuracy, high labor dependency, and sensitivity to environmental conditions like lighting and noise. This review paper presents a comprehensive analysis of recent research developments in PCB defect detection using deep learning techniques. The study categorizes existing approaches into traditional machine vision methods, deep learning-based detection models, and hybrid intelligent inspection systems. Furthermore, the paper discusses recent advancements such as multi-scale feature fusion, attention-based networks, generative data augmentation. The review also highlights key research gaps including the challenges of detecting extremely small defects, dataset limitations, domain adaptation issues, and the integration of intelligent inspection systems within Industry 4.0 manufacturing pipelines. Finally, this work proposes a conceptual framework for an advanced deep learning-based PCB inspection system capable of improving detection accuracy, reducing inspection time, and enabling automated quality control in modern electronics manufacturing.

Keywords: Printed Circuit Board (PCB), Deep Learning, Computer Vision, Defect Detection, YOLO, Convolutional Neural Networks, Automated Optical Inspection (AOI), Smart Manufacturing, Artificial Intelligence.

1. Introduction

Printed Circuit Boards (PCBs) serve as the fundamental building blocks of modern electronic systems. They provide the mechanical support and electrical interconnections required for electronic components such as resistors, capacitors, integrated circuits, and microcontrollers to function together in a coordinated manner. With the rapid advancement of electronic technologies and the growing demand for compact, high-performance devices, With the rapid advancement of electronic technologies and the growing demand for compact, high-performance

devices, PCB designs have become increasingly complex, featuring dense circuit layouts and extremely fine conductive tracks. As a result, even minor manufacturing defects can significantly compromise the functionality and reliability of electronic systems. Global health assessments, nearly half of emergency-related deaths occur not because treatment is unavailable, but because the response arrives too late to be effective. In critical events such as severe injuries, cardiac arrest, trauma, respiratory failure, and road-traffic



accidents, the first few minutes after symptom onset—often termed the “golden window”—determine whether the patient recovers or deteriorates irreversibly.[1-3] Despite advancements in emergency medicine, modern emergency care systems still function through a series of compartmentalized stages: first information gathering, then risk judgment by dispatchers, followed by ambulance deployment, and eventually hospital admission. This segmented approach introduces avoidable delays and leads to inconsistent decision-making, particularly during peak loads or high-pressure situations.

1.1 Area

PCB fault detection can be achieved using a variety of techniques. In our project we aim to use two techniques for PCB fault detection and classification. The first method is Transfer Learning. Transfer learning falls under the domain of machine learning. In transfer learning a model is developed for a particular task and is then reused as the starting point for another task. The pre-trained model which we would be using is VGG16.[4-7]The second method which we would be implementing in our project is a traditional handcrafted unsupervised algorithm. Image processing is an extremely large domain and consists of a number of methods and techniques within it. Image processing is basically a method adopted to perform certain operations on the image in order to extract useful information from it. In this project we will be using two methods viz transfer learning which is a supervised method and image processing techniques which is an unsupervised method and then compare the two on the basis of accuracy and time. Accurate PCB manufacturing is critical as manufacturers are required to produce PCBs in large quantities. Maintaining the quality of such large numbers of PCBs is challenging. Automated inspection systems can prove helpful in quality maintenance. Such systems overcome the limitations of manual inspection for a large number of PCBs.

1.2 Project Introduction and Aim

Printed Circuit Boards are used to support and connect electrical and electronic components using conductive paths, pads and other features etched

from one or more layers of copper laminated onto between sheet layers of a non-conductive substrate. The second method which we would be implementing in our project is a traditional handcrafted unsupervised algorithm. CNC machine drilling is then performed depending on the design. There are primarily two types of PCB boards on which defects can be detected. One is the mounted PCB and the other is bare PCB. During the manufacturing of PCBs, it can encounter a number of defects. The first step is to produce the manufacturing data followed by type setting. The board is then cut. The board used could be made up of glass or copper. CNC machine drilling is then performed depending on the design. This is then followed by track painting and cleaned with water so that the track is visible. Tracks are printed using ink and then the etching process takes place followed by masking. This forms our bare printed circuit board.

In recent years, **Deep Learning (DL)** and **Computer Vision (CV)** have revolutionized automated inspection systems. Deep learning models, particularly **Convolutional Neural Networks (CNNs)**, have demonstrated superior capabilities in learning complex patterns and visual features directly from data, outperforming traditional machine learning and rule-based approaches. Among these, **object detection algorithms** such as **YOLO (You Only Look Once)** have gained significant attention for their balance between speed and accuracy.

The proposed project, “Automatic PCB Defect Detection and Classification using Image Processing and Deep Learning,” aims to develop a robust and efficient system that automates the identification and classification of PCB defects. The system integrates image processing techniques for preprocessing and enhancement with deep learning algorithms for intelligent defect recognition. [8-10] This combination ensures higher accuracy, minimizes false positives, and supports real-time inspection suitable for industrial applications. Ultimately, the goal is to enhance manufacturing quality, reduce inspection costs, and increase production efficiency through intelligent automation. Shown in Table 1 and Figure 1.

Table 1: Types of Defects in PCB

TABLE II.
CATEGORIZATION OF THE TYPES OF DEFECTS IN PCBs

























#	Original Pad	Defective Particle	Definition	Group
1			Missing Hole	Missing
2			Pinhole	Missing
3			Short	Excess
4			Overtch Pad	Missing
5			Spur	Excess
6			Mouse Bite	Missing
7			Scratch	Missing
8			Open Track	Missing
9			Open Pad	Missing
10			Undertch Pad	Excess
11			Missing Pad	Missing
12			Spurious Copper	Excess

Figure 1: Shows the working of PCB defect detection

2. Results and Discussion

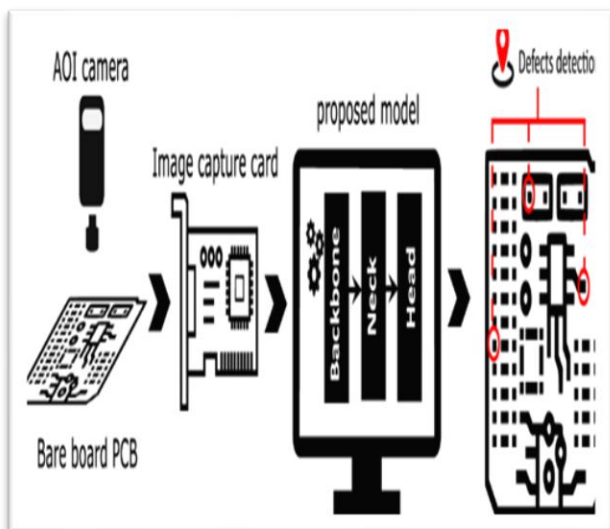
2.1. Results

The results of various studies on PCB defect detection show that deep learning–based approaches significantly improve inspection accuracy compared to traditional image processing methods. Researchers have used different models such as Convolutional Neural Networks (CNNs), YOLO-based object detection models, Vision Transformers, and anomaly detection networks to identify defects in PCB images. Experiments conducted on datasets such as Deep PCB demonstrate that modern deep learning models can detect defects with high precision.

Among these methods, YOLO-based architectures such as YOLOv5, YOLOv7, and YOLOv8 have shown strong performance due to their ability to perform real-time defect detection while maintaining high accuracy. Some studies have also used techniques such as multi-scale feature extraction, attention mechanisms, and data augmentation to improve detection performance. [11-14]

2.2. Discussion

The analysis of recent research indicates that deep learning models provide significant advantages in PCB defect detection. These models can automatically learn complex features from PCB images, allowing them to detect subtle defects that traditional rule-based methods often fail to identify. Real-time object detection models such as YOLO are particularly suitable for industrial inspection systems because they combine high accuracy with fast processing speed. However, several challenges still exist. [15-20] Detecting extremely small defects such as micro-cracks and pinholes remains difficult due to their tiny size and low visibility in images. Additionally, the availability of large and diverse PCB defect datasets is limited, which may affect the generalization ability of trained models. Future research should focus on developing lightweight and efficient models, improving dataset diversity, and integrating intelligent inspection systems into smart manufacturing environments. Shown in Figure 2.



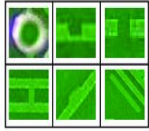
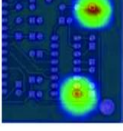
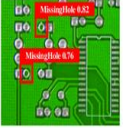
	Part Image Classification	Whole Image Understanding	Direct Defect Detection
Training data	- Cropped images - Annotations: images	- Whole PCB images - Annotations: images	- Whole PCB images - Annotations: images, defect positions, and sizes
Test data	Cropped part image	PCB image	PCB image
Model prediction	Class of the part image	Class of PCB image	Defect location and class
Result examples			
	Model prediction for each image: {Missinghole, Mousebite, Open, Short, Spur, Spurious}	"The probability of missing hole is the most prior" * Visualization of the possibility map is	Simultaneously localize and classify the defective parts

Figure 2: Shows the System Architecture Conclusion

This review paper analyzed various deep learning approaches used for PCB defect detection in manufacturing. The results discussed in the previous section confirm that deep learning models such as CNNs and YOLO-based object detection techniques significantly improve defect detection accuracy compared to traditional image processing methods.[21-26] The analysis also shows that modern models can effectively detect common PCB defects such as open circuits, short circuits, mouse bites, and spurious copper. However, challenges still exist in detecting extremely small defects and handling limited datasets. Overall, deep learning provides an efficient solution for automated PCB inspection. Future research should focus on improving lightweight models, increasing dataset diversity, and developing more robust detection systems for industrial manufacturing environments.

Acknowledgements

The author is very much indebted to the faculty and administration of Babu Banarasi Das Institute of Technology and Management, Lucknow, Department of Computer Science & Engineering, for providing academic support, the research environment, and technical resources that were needed for this study[27-33]. Their continuous encouragement has played a major role in shaping up the framework in accordance with the present changes in emergency response technologies. The author is particularly grateful to Ms. Raziya Siddiqui, Assistant Professor, Dept. of CSE, BBDITM, for his continuous support, at the opportune moment, and academic guidance, which have shaped the direction,

clarity, and refinement of the technical aspects of this research.

References

- [1] Elsharkawy, A., Hassan, M., & Abdelrahman, T. (2025). YOLOv11-PCB: Enhanced object detection for printed circuit board inspection. *Scientific Reports*, 15(2), 1–14.
- [2] Huang, J., Zhao, F., & Chen, L. (2025). GAN-augmented YOLOv11 for rare PCB defect detection. *arXiv preprint*.
- [3] HoangVan, T., Nguyen, D., & Tran, H. (2025). ESRPCB: Edge-guided super-resolution for micro PCB defect detection. *arXiv preprint*.
- [4] Ouyang, J., & Li, K. (2025). Vision-language models for PCB defect classification. *ACM Transactions on Multimedia Computing*, 21(1), 1–15.
- [5] Pingzhen, P., Li, X., & Zhao, R. (2025). Lightweight multi-scale YOLOv8 with adaptive pruning for PCB inspection. *arXiv preprint*.
- [6] Song, Y., Liu, H., & Wang, Z. (2025). YOLO-HDEW: Edge-enhanced multi-scale attention for small PCB defect detection. *Electronics*, 14(3), 1–16.
- [7] Morales, D., Garcia, P., & Ortega, J. (2024). Semi-supervised learning for PCB defect detection using consistency regularization. *Proceedings of the AAAI Conference on Artificial Intelligence*, 4561–4568.
- [8] Sharma, N., & Patel, R. (2024). Real-time PCB defect detection using YOLOv8. *IEEE Sensors Journal*, 24(6), 8123–8134.
- [9] Singh, A., & Arora, V. (2024). Residual U-Net++ for PCB micro-crack detection. *Machines*, 12(4), 298.
- [10] Tanaka, K., Ito, S., & Yamamoto, H. (2024). Diffusion-based synthetic PCB dataset generation. *arXiv preprint*.
- [11] Zheng, Y., & Wu, L. (2024). Swin transformer-based PCB defect detection. *Pattern Recognition Letters*, 180, 1–8.
- [12] Karthik, K., & Ravi, S. (2024). Hybrid ESRGAN and YOLOv8 framework for PCB micro-defect detection. *IEEE Access*, 12,



- 92340–92352.
- [13] Das, S., & Mishra, R. (2023). Lightweight DeepLabV3+ for real-time PCB defect segmentation. *Journal of Visual Computing*, 39, 1450–1462.
- [14] Fang, F., & Zhao, Y. (2023). PCB fault detection using attention-guided convolutional neural networks. *Machine Vision and Applications*, 34(4), 1–12.
- [15] Ibrahim, M., & Costa, P. (2023). Multimodal PCB inspection using RGB and thermal imaging. *Sensors*, 23(17), 7452.
- [16] Kim, H., & Park, S. (2023). Transformer-based PCB defect inspection using vision transformers. *Pattern Recognition*, 138, 109321.
- [17] Mehta, A., & Verma, D. (2023). Fault localization using YOLOv7 for PCB inspection. *IEEE Access*, 11, 45321–45334.
- [18] Qin, Y., Chen, X., & Huang, Z. (2023). Graph neural networks for PCB net-level defect prediction. *Nature Communications*, 14(1), 5523.
- [19] Chen, L., & Wong, K. (2022). FPGA-compatible lightweight CNN model for PCB inspection. *Electronics*, 11(9), 1352–1365.
- [20] Kumar, R., & Singh, P. (2022). YOLOv5-based PCB fault detection for industrial automation. *IEEE Transactions on Industrial Informatics*, 18(11), 7420–7428.
- [21] Zhou, X., & Yuan, J. (2022). Unsupervised PCB anomaly detection using autoencoders. *Neurocomputing*, 496, 250–262.
- [22] Ali, S., & Hussain, M. (2022). Deep learning approaches for PCB defect detection: A survey. *Computers & Industrial Engineering*, 170, 108325.
- [23] Das, S., & Roy, A. (2021). Hybrid morphology and CNN-based PCB defect detection. *Journal of Intelligent Manufacturing*, 32(6), 1567–1579.
- [24] Lee, K., & Park, J. (2021). Real-time PCB inspection using deep convolutional neural networks. *Journal of Manufacturing Systems*, 60, 338–347.
- [25] Zhang, X., & Liu, Y. (2021). Automated optical inspection for PCB manufacturing using deep learning. *IEEE Transactions on Automation Science and Engineering*, 18(4), 1620–1630.
- [26] Zhao, M., & Wang, H. (2021). Multi-scale attention networks for PCB defect detection. *IEEE Access*, 9, 134567–134578.
- [27] Ali, S., & Hussain, M. (2021). Multiscale CNN architecture for PCB surface defect detection. *Image and Vision Computing*, 112, 104215.
- [28] Kwon, D., & Kim, J. (2020). Deep CNN-based multi-class PCB fault classification. *Microelectronics Reliability*, 110, 113675.
- [29] Li, Y., & Chen, Z. (2020). Real-time PCB defect detection using YOLOv3. *IEEE Access*, 8, 189230–189240.
- [30] Wang, M., & Chen, L. (2020). Deep learning-based industrial inspection systems for electronics manufacturing. *IEEE Transactions on Industrial Electronics*, 67(10), 8843–8852.
- [31] Gupta, R., & Kumar, S. (2019). PCB defect detection using geometric features and SVM. *Journal of Circuit Systems*, 47(5), 1–10.
- [32] Sahu, P., & Pradhan, S. (2019). PCB defect detection using Canny edge detection and connected components. *International Journal of Computer Science and Information Technology*, 11(2), 45–50.
- [33] Tang, H., Liu, X., & Li, Y. (2019). DeepPCB: A dataset for PCB defect detection and classification. *arXiv preprint*.