INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD
ISSN(O): 2455-0620 [Impact Factor: 9.47]
Monthly, Peer-Reviewed, Refereed, Indexed Journal with IC Value : 86.87
Volume - 12, Issue - 2, February - 2026

DOIs:10.2015/IJIRMF/202602011 --:-- Research Paper / Article / Review

PCB Solder Defect Detection Using Machine Learning

[1] **Sandhya Shinde,** [2] **Prem Ghodekar,** [3] **Vedant Tekale,** [4] **Sarvesh Kolwadkar**
[1]Asst.Professor, Department of Semiconductor Engineering, [1]D.Y. Patil International University, Akurdi, Pune, India
[2]Student, Electronics and Telecommunication, Dr. D.Y. Patil Institute of Engineering Management and Research, Akurdi, Pune, India
[3]Student, Electronics and Telecommunication, Dr. D.Y. Patil Institute of Engineering Management and Research, Akurdi, Pune, India
[4]Student, Electronics and Telecommunication, Dr. D.Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune, India
Email – [1] sandhya.shinde@dypiu.ac.in, [2]premghodekar.rg@gmail.com, [3]vedanttekale01@gmail.com, [4]sarveshkolwadkar@gmail.com

Abstract: *Printed Circuit Boards (PCBs) serve as the foundation of nearly all modern electronic systems, where minor defects can lead to complete device malfunction. Therefore, ensuring accurate and efficient inspection is essential. Conventional inspection methods, including manual visual checking and Automated Optical Inspection (AOI), often fall short when it comes to precision, especially in detecting minute or concealed flaws. To address these limitations, this project presents an automated PCB defect detection framework powered by deep learning and computer vision techniques. In this study, we utilized the Mixed PCB Defect Dataset from Mendeley, which contains real-world samples with various defect types such as open circuits, short circuits, mouse bites, spurious copper, pinholes, and defect-free boards for reference. The images were preprocessed using OpenCV to enhance visibility and uniformity of key features before training. A YOLOv8 object detection model was then employed to simultaneously identify multiple defects with high accuracy and real-time efficiency. The developed system enables users to simply upload a PCB image, after which the trained model automatically detects and marks defective areas with bounding boxes and confidence scores. Designed for accessibility, the system can be extended to operate with standard mobile or USB cameras, offering a cost-effective and practical solution for industrial quality control. This approach not only accelerates inspection but also improves consistency and reliability, contributing to the advancement of intelligent and automated manufacturing.*

Key Words: *PCB defect detection, YOLOv8, Deep learning, Computer vision, OpenCV, Mixed PCB Defect Dataset, Object detection, Automated inspection, Industrial quality control.*

1. INTRODUCTION:

Printed Circuit Boards (PCBs) form the electrical backbone of nearly all modern electronic devices, from low-power consumer gadgets to complex aerospace and defense systems [1], [2]. Even microscopic defects in solder joints—such as open circuits, shorts, spurious copper, or excess solder-can compromise functionality, leading to catastrophic system failure or significant reliability loss Traditional inspection approaches such as manual visual inspection and Automated Optical Inspection (AOI), though widely adopted, present major limitations. Manual inspection is slow, inconsistent, and highly dependent on operator skill, while AOI systems often fail under varying illumination or irregular board textures [6]. These systems depend on static rule-based algorithms like edge detection and template matching, which lack adaptability to complex, nonuniform PCB structures [7], [8]. As a result, inspection accuracy drops significantly when dealing with fine solder joints or hidden defects. The rapid progress of deep learning (DL) and computer vision has introduced powerful alternatives to conventional inspection. Deep learning models automatically learn visual features—edges, shapes, and spatial patterns—directly from image data without requiring handcrafted rules [9], [10]. Among these, Convolutional Neural Networks (CNNs) and modern You Only Look Once (YOLO) architectures have demonstrated superior performance in object detection, classification, and localization tasks across various domains, including manufacturing and medical imaging [11]– [13]. The latest YOLOv8 framework provides anchor-free detection, improved spatial feature fusion, and real-time processing capabilities, enabling both speed and precision in industrial visual inspection [14].

Existing PCB defect detection studies have explored different architectures such as CNN-based classifiers [15], Faster R-CNN models [16], and earlier YOLO versions [17], [18]. However, most of these systems rely on small or synthetic datasets, limiting their robustness in real manufacturing scenarios. To address these limitations, this research employs the Mixed PCB Defect Dataset from Mendeley, which includes real-world samples containing various defect types—open circuits, short circuits, mouse bites, spurious copper, pin holes, and defect-free boards. This dataset provides the visual diversity required for deep models to learn and generalize effectively in industrial settings.

In this work, an automated PCB defect detection system is proposed using YOLOv8 integrated with OpenCV for preprocessing and visualization. preprocessing pipeline standardizes image dimensions, enhances feature visibility, and improves contrast uniformity. The trained YOLOv8 model then performs simultaneous defect localization and classification, outputting bounding boxes, and confidence scores for each detected defect. The system achieves high mean Average Precision (mAP), precision, and recall, demonstrating strong performance across multiple defect classes. The objective of this research is to develop a cost-effective, scalable, and intelligent inspection system that minimizes human dependency while maintaining industrial-grade reliability. The proposed method accelerates inspection, enhances consistency, and enables straightforward integration into existing production lines.

2. LITERATURE REVIEW:

The identification of solder defects in Printed Circuit Boards (PCBs) has remained a critical challenge in electronics manufacturing, as the reliability of electronic products depends heavily on accurate inspection. Over time, researchers have experimented with numerous approaches—starting from classical image processing methods and progressing to modern deep learning models—to automate the detection and classification of PCB defects. Early research primarily aimed to enhance the effectiveness of traditional machine-vision systems. Fan et al. [1] explored this direction by proposing an improved Faster R-CNN model for identifying solder joint defects and PCB components. Their method achieved higher detection accuracy than earlier feature-engineered approaches, but its heavy computational load reduced practicality for real-time inspection. In a different line of work, Zhang et al. [2] introduced a Cascaded Zoom-In technique to refine the detection of small and intricate solder joints. Although the method improved fine-grained localization, its multi-stage structure increased overall processing complexity, making deployment on large production lines challenging.

Focusing on efficiency, Tham et al. [3] combined deep learning with hardware-level optimizations to accelerate inference on embedded systems. Their results showed that performance bottlenecks in deep neural networks can be significantly reduced when optimized for specialized hardware, supporting the need for real-time PCB inspection solutions. Complementing these studies, Ling and Isa [4] conducted an extensive review of image processing, machine learning, and deep learning techniques for PCB defect detection. Their survey highlighted that deep learning models consistently outperform traditional approaches, offering better adaptability and robustness under varying manufacturing environments.

Gao et al. [5] applied an image segmentation–based deep learning model to identify solder joint defects. Their study demonstrated that combining segmentation with classification significantly improved accuracy for localized defects. However, segmentation models required pixel-level annotations, which are time-consuming to generate. Selvam et al. [6] proposed YOLO-DefXpert, an improved YOLOv11 architecture tailored for PCB surface defects. Their model achieved high precision and recall, demonstrating the potential of YOLO-based architectures for industrial inspection systems.

Zhang et al. [7] explored the use of the Random Forest algorithm for detecting Surface-Mount Device (SMD) defects. Although effective for simple defects, its rule-based learning limited generalization to complex solder anomalies. Subbulakshmi et al. [8] conducted a comparative study on machine learning models for PCB defect detection, highlighting that convolutional neural networks outperform traditional classifiers like SVMs and Random Forests in terms of adaptability and accuracy.

Mankad et al. [9] implemented a Convolutional Neural Network (CNN) model for PCB classification and demonstrated the importance of feature extraction from high-resolution images. However, their system was limited to classification tasks and did not support precise defect localization. Chowdhury et al. [10] introduced a YOLOv5-based model for surface defect inspection, achieving strong detection accuracy and real-time performance. Their study established YOLO as a suitable foundation for industrial inspection systems due to its end-to-end, single-shot detection capability.

Across these studies, several trends emerge. Earlier models such as Faster R-CNN [1]– [2] provided strong accuracy but lacked the speed required for industrial use. Classical algorithms [7], [8] performed well on simple datasets but failed under diverse lighting and texture variations. More recent YOLO-based architectures [6], [10] offer a balanced trade-off between speed, precision, and scalability, making them ideal candidates for real-time PCB inspection systems.

Many earlier studies were developed using small or artificially generated datasets, typically collected in controlled laboratory environments. As a result, these models often struggle when applied to real manufacturing conditions where factors such as noise, glare, irregular lighting, and inconsistent solder patterns frequently occur. To address these limitations, this work employs the Mixed PCB Defect Dataset (Mendeley Data), which contains real production-level PCB images across six categories: open circuit, short circuit, mouse bite, spurious copper, pin hole, and defect-free boards. Using this dataset as a more realistic representation of industrial inspection challenges, the proposed YOLOv8-based system is designed to enhance both detection accuracy and robustness, ensuring reliable performance in practical PCB quality-control settings.

Sr. No.	Author(s) & Year	Method / Model Used	Dataset / Defect Type	Key Findings / Contributions	Limitations
1.	Fan et al., 2021	Improved Faster R-CNN	PCB solder joints and components	Improved detection accuracy compared to traditional image-processing methods	High computational cost; not suitable for real-time inspection
2.	Zhang et al., 2018	Cascaded Zoom-In Deep Learning Model	Small and complex solder joint defects	Enhanced localization of minute solder defects	Multi-stage pipeline increases processing complexity
3.	Tham et al., 2022	Deep learning with hardware optimization	PCB soldering defects	Reduced inference time using embedded system acceleration	Requires specialized hardware
4.	Ling & Isa, 2023	Survey of IP, ML, and DL techniques	Various PCB defects	Concluded deep learning methods outperform classical approaches	No experimental implementation
5.	Gao et al., 2019	Image segmentation with deep learning	Solder joint defects	High accuracy in detecting localized defects	Requires pixel-level annotations
6.	Selvam et al., 2025	YOLO-DefXpert (YOLOv11-based)	PCB surface defects	Achieved high precision and recall in industrial settings	Increased architectural complexity
7.	Zhang et al., 2025	Random Forest algorithm	SMD defects on PCBs	Effective for simple and structured defects	Limited performance on complex solder defects
8.	Subbulakshmi et al., 2023	Comparative ML study (CNN, SVM, RF)	PCB defects	CNN models outperform classical ML methods	Real-time performance not addressed
9.	Mankad et al., 2021	Convolutional Neural Network (CNN)	PCB image classification	Demonstrated effective feature extraction	Does not support defect localization
10.	Chowdhury et al., 2025	YOLOv5 object detection	PCB surface defects	Achieved real-time detection with good accuracy	Older YOLO version compared to recent models

3. RESEARCH METHOD:

The proposed system is designed to automatically identify and classify solder defects on printed circuit boards (PCBs) using a combination of deep learning and computer vision. The workflow involves four key stages: data acquisition, preprocessing, model training, and defect detection and visualization. A. Data Acquisition The system begins with the input of PCB images obtained from the Mixed PCB Defect Dataset. This dataset contains real industrial circuit boards with a variety of solder defect types such as open circuits, short circuits, mouse bites, spurious copper, and pin holes. The images serve as the raw visual data from which the model learns to identify faulty patterns. At this stage, no processing or analysis is performed—the focus is solely on collecting consistent, high-quality inputs that represent all defect categories required for training and evaluation.

B. Image Preprocessing

Before model training, all images undergo an essential preprocessing stage using the OpenCV library.

This phase ensures standardized image quality, reduces noise, and enhances the visibility of fine solder features so that the YOLOv8 model can learn defect patterns effectively.

The preprocessing pipeline includes the following operations:

- Resizing:

All PCB images are resized to 640 × 640 pixels, ensuring that every input matches YOLOv8's required image dimensions.

This uniformity helps maintain consistent feature extraction during training.

- Noise Reduction:

Gaussian and median filtering techniques are applied to suppress random noise and unwanted background artifacts.

These filters smooth the image while preserving important structural edges around solder joints and copper traces.

- Contrast and Brightness Enhancement:

Histogram equalization and adaptive contrast enhancement are used to improve the visibility of fine defect regions.

This step makes subtle irregularities—such as tiny gaps, excess solder, or thin copper traces—more distinguishable to the model.

- Normalization:

Pixel intensities are scaled between 0 and 1, preparing the images for stable gradient updates during training.

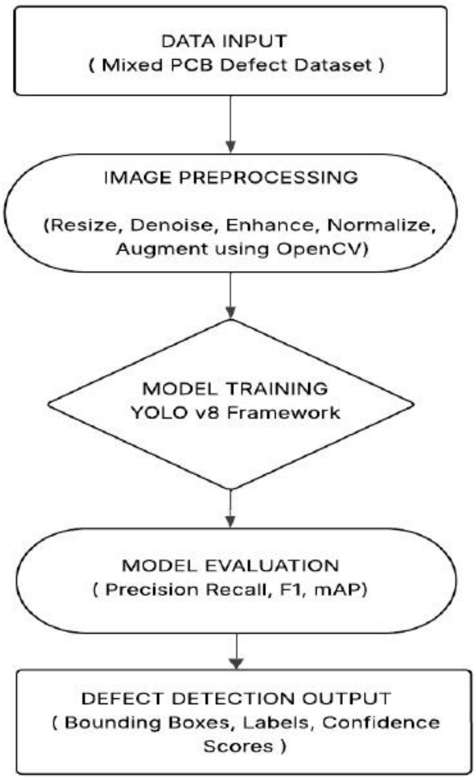
Normalization also prevents large pixel-value variations from slowing down the learning process.

- Data Augmentation:

To increase dataset diversity and reduce overfitting, several augmentation techniques are applied, including horizontal flips, slight rotations, illumination changes, and other minor geometric transformations.

These variations help the model generalize better to real-world PCB images captured under different lighting and viewing angles.

BLOCK DIAGRAM:



C. Model Training

In this stage, the preprocessed images are used to train the YOLOv8 deep learning model. The network learns to recognize different defect types by extracting hierarchical visual features through its convolutional layers. YOLOv8 performs both localization and classification simultaneously, refining its predictions over multiple epochs. During training, loss values, precision, recall, and F1-score are monitored to ensure that the model converges properly and does not overfit. By the end of this stage, the model has learned to differentiate between various solder defects with high accuracy.

D. Defect Detection and Visualization

Once training is complete, the system is ready to detect defects in new PCB images. The trained YOLOv8 model analyzes each input image and produces an output containing bounding boxes around defective regions, class labels indicating the type of fault, and confidence scores representing prediction certainty. These outputs are visualized using OpenCV, providing a clear and interpretable representation of detected defects. This stage transforms raw images into actionable insights, enabling fast, automated, and reliable PCB quality assessment.

4. CONCLUSION:

This work presents an automated PCB solder defect detection system using the YOLOv8 deep learning framework and OpenCV-based preprocessing. The model was trained on the Mixed PCB Defect Dataset and demonstrated high accuracy in identifying multiple defect types, including open circuits, shorts, spurious copper, mouse bites, and pin holes. By combining standardized preprocessing with an efficient object detection architecture, the system provides reliable and consistent defect localization. The results show that the proposed approach can significantly improve inspection speed and reduce manual effort, making it suitable for integration into industrial quality control processes. Overall, the system offers a practical, scalable, and cost-effective solution for modern PCB manufacturing environments.

REFERENCES:

1. F. Fan, B. Wang, G. Zhu, and J. Wu, “Efficient Faster R-CNN: Used in PCB Solder Joint Defects and Components Detection,” IEEE 4th Int. Conf. on Computer and Communication Engineering Technology (CCET), pp. 20–24, 2021
2. Z. Zhang, H. Wang, S. Zhou, R. Zhou, and L. Sun, “A Cascaded Zoom-In Method for Defect Detection of Solder Joints,” Proc. ICSP 2018, pp. 1081–1086, 2018.
3. M.-L. Tham, B. Y. Chong, Y. H. Tan, Y. K. Wong, S. L. Chean, and W. K. Tan, “Optimizing Deep Learning Inference to Detect PCB Soldering Defects,” IEEE Int. Conf. on Artificial Intelligence in Engineering and Technology (IICAIET), 2022.
4. Q. Ling and N. A. M. Isa, “Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey,” IEEE Access, vol. 11, pp. 15921–15950, 2023.
5. S. Gao, H. Zhang, and H. Mi, “Solder Joint Defect Detection Based on Image Segmentation and Deep Learning,” IEEE Conf. on Industrial Informatics, 2019.
6. P. Selvam et al., “YOLO-DefXpert: An Advanced Defect Detection on PCB Surfaces Using Improved YOLOv11 Algorithm,” IEEE Access, vol. 13, pp. 143085–143101, Aug. 2025.
7. W. Zhang, Y. Lu, T. Chen, and J. Li, “A Random Forest Algorithm for PCB SMD Defect Detection,” IEEE Trans. on Components, Packaging and Manufacturing Technology, vol. 15, no. 5, pp. 1135–1143, May 2025.
8. S. T. Subbulakshmi, R. Madhavan, V. Ramachandran, M. Revathi, P. Anand, and G. H. Subramanian, “Machine Learning Models for PCB Defect Detection: A Survey,” 6th Int. Conf. on Recent Trends in Advanced Computing (ICRTAC), pp. 1–6, 2023.
9. V. Mankad, M. I. Patel, N. Bhanvadia, and R. Gajjar, “PCB Classification using Convolutional Neural Network,” 3rd Int. Conf. on Advances in Computing, Communication Control and Networking (ICACCCN), pp. 986–990, 2021.
10. A. K. Chowdhury et al., “Printed Circuit Board Surface Defect Inspection via YOLOv5 Deep Learning Algorithm,” IEEE 6th Int. Conf. in Robotics and Manufacturing Automation (ROMA), pp. 259–264, Aug. 2025.