IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

Printed Circuit Board Defect Detection: A Comprehensive Review of Machine Learning, Deep Learning, and Image Processing Techniques

Miss. Diksha Dilip Ghorpade[1], Prof Shubhangi R. Patil[2]

Student, Computer Science & Engineering, AMGOI, Vathar, India[1]

Assistant Professor, Computer Science & Engineering, AMGOI, Vathar, India[2]

Abstract: Printed Circuit Boards (PCBs) play a vital role in contemporary electronic devices, enabling the interconnection of various electronic components. As the need for reliable and high-performance electronics grows, accurate detection of defects in PCB production becomes increasingly important. This review examines the evolution of methods for detecting PCB defects, emphasizing traditional inspection techniques alongside machine learning (ML), deep learning (DL), and image processing methods. Traditional approaches, which depend on manual inspections and machine vision, encounter challenges regarding accuracy and scalability, especially with intricate PCB designs. On the other hand, ML and DL methods, such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs), have markedly improved detection accuracy by automating the process of identifying and classifying defects. The development of advanced hybrid models and lightweight architectures has further enhanced detection efficiency, particularly in real-time scenarios. Image processing approaches, including clustering, edge detection, and X-ray imaging, are also essential for improving the visibility of defects and overall detection performance. Despite these advancements, challenges remain, including limitations related to data, overfitting issues, and variability in types of defects. Future research should concentrate on overcoming these challenges by creating diverse datasets, developing robust models, and integrating real-time systems within automated manufacturing settings. Ongoing innovation is crucial to ensure the production of high-quality, defect-free PCBs, thus supporting the development of dependable electronic devices.

Keywords: PCB Defect Detection, Machine Learning, Deep Learning, Image Processing, Convolutional Neural Networks (CNN), Real-Time Inspection.

I. INTRODUCTION

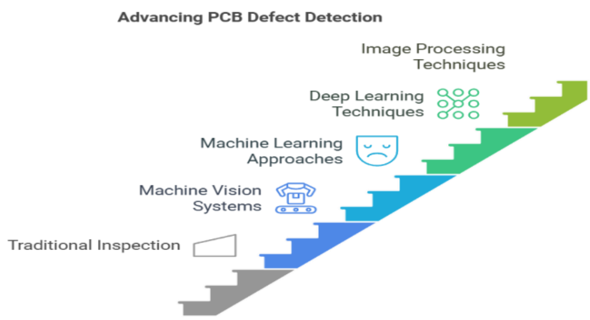
Printed Circuit Boards (PCBs) are essential elements in contemporary electronics, providing vital connections among various electrical components. As the demand for compact and high-performance electronics continues to grow, maintaining the quality of PCB manufacturing has become increasingly important. Even minor defects in PCBs can result in device failures, safety hazards, and monetary losses. Conventional inspection techniques, like manual evaluations and basic machine vision, are often inadequate for identifying defects in intricate PCB designs. These approaches are labor-intensive, susceptible to mistakes, and have difficulty meeting the accuracy requirements of today's high-density designs. To overcome these issues, machine learning (ML), deep learning (DL), and image processing methods have become increasingly popular in detecting PCB defects. ML techniques, such as Support Vector Machines (SVMs), enhance defect classification, while deep learning—particularly Convolutional Neural Networks (CNNs)—provides high accuracy in recognizing complex defects. Image processing methods, including edge detection and X-ray imaging, improve the visibility and accuracy of defect detection.

This review examines the progress made in PCB defect detection, emphasizing the combination of ML, DL, and image processing. It explores the transition from traditional techniques to AI-based solutions, highlighting their advantages and limitations. The paper also addresses the challenges related to dataset diversity, model resilience, and practical application, providing insights into future research opportunities and the necessity for automated, real-time inspection systems to guarantee the production of high-quality, defect-free PCBs.

II LITERATURE REVIEW

Printed Circuit Boards (PCBs) are essential elements in contemporary electronic devices, facilitating electrical interconnections between components. With the increasing need for dependable and high-performance electronics, it is vital to ensure that PCB manufacturing is free of defects. Even small flaws can significantly affect the functionality, reliability, and safety of electronic devices. This review consolidates findings from 51 research studies to examine the progress made in PCB defect detection, emphasizing traditional techniques, machine learning, deep learning, and image processing methods.

METHODOLOGY



Traditional Inspection Techniques:
Historically, the detection of defects in printed circuit boards (PCBs) depended on manual inspections and standard machine vision techniques. While manual inspection is straightforward, it requires a lot of labor and is susceptible to human errors, particularly with intricate designs (Petkov & Ivanova, 2024; Rao et al., 2024). Although traditional machine vision systems are automated, they often face challenges in accuracy when dealing with various defect types and complicated PCB layouts (Melnyk & Vorobii, 2024; Austria & Fajardo, 2023).
Machine Learning Approaches:
Machine learning has transformed the detection of PCB defects through the use of algorithms that identify and categorize anomalies. Support Vector Machines (SVMs) and ensemble techniques have demonstrated significant improvements in precision (Yadav et al., 2024; Ka et al., 2024). Combined methods that merge models such as DenseNet and ResNet have also boosted both sensitivity and specificity (Zhang et al., 2023; Wang, 2023). Nevertheless, challenges including small datasets and overfitting continue to be a concern (Shilaskar et al., 2024; Meesad & Maliyaem, 2023).
Deep Learning Techniques:
Deep learning approaches, especially Convolutional Neural Networks (CNNs), have emerged as leading solutions for identifying various types of defects on printed circuit boards (Jian et al., 2024; Kong, 2024). Enhanced architectures, such as YOLO variants and Generative Adversarial Networks (GANs), have improved both the precision and speed of detection (Tang et al., 2024; Thongpun et al., 2024). Hybrid models that integrate transformers and CNNs, like the framework introduced by Nguyen & Nguyen (2024), enhance the detection of small defects and boost computational efficiency. Moreover, lightweight models such as LW-YOLO have been specifically developed for real-time applications (Tang et al., 2024).
Image Processing Techniques:
Image processing plays a crucial role in visualizing defects and preparing images for analysis. Techniques like k-means clustering, flood-filling, and edge thinning improve the visibility of defect images for subsequent examination (Lv et al., 2024; Zhang et al., 2023). The combination of these techniques with self-supervised learning models has further enhanced detection results (Yao et al., 2023). Additionally, X-ray imaging systems have been investigated for real-time defect detection, successfully uncovering hidden imperfections in PCBs (Boonkorkoer et al., 2023; Wang, 2023).

SUMMARY OF KEY CONTRIBUTIONS, LIMITATIONS, AND FUTURE DIRECTIONS IN PCB DEFECT DETECTION RESEARCH

Title	Key Contributions and Findings	Limitations	Research Gaps/Future Directions	Relevant Applications
"A deep learning approach for automated PCB defect detection" (Tao et al., 2024)	Ensemble learning framework combining four models for defect detection.	Potential dependency on high-quality datasets for training.	Investigation into scalability of ensemble models across varying PCB designs.	PCB manufacturing, defect detection.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
National Level Conference – AITCON 2K25
Adarsh Institute of Technology & Research Centre, Vita, Maharashtra
Vol. 12, Special Issue 1, March 2025

"Enhancing PCB Defect Detection through Ensemble Learning" (Ka et al., 2024)	Bibliometric and content analysis to identify trends in testing methods and AI adoption.	Lack of data on practical applications and limitations of AI.	Need for more industry-specific testing frameworks.	PCB testing, AI in manufacturing.
"Optical Automated PCB Interconnect Inspection" (Patrick et al., 2022)	Utilized CNNs and RNNs for real-time defect detection, improving manufacturing efficiency.	Complexity of real-time integration in existing production lines.	Further development of real-time learning models.	Circuit manufacturing, AI integration.
"PCB Surface Defect Detection with YOLOv8" (Thongpun et al., 2024)	Data-centric approach using XGBoost for solder paste defect detection.	Low defect labeling agreement and limited algorithm complexity.	Improvement in defect labeling protocols and algorithms.	Solder paste inspection in PCB manufacturing.
"Soldering Defect Identification Using Deep Learning" (Swati et al., 2023)	Use of K-means clustering, flood-filling, and thinning for defect identification.	Limited adaptability to diverse defect types.	Incorporation of hybrid models for diverse defect detection.	Automated defect detection, PCB quality control.
"Dataset for PCB Surface Defect Detection" (Shengping et al., 2021)	Literature review and categorization of trends in testing methods, highlighting AI adoption.	Lack of deep focus on PCBA research.	Expanding research in assembly-level testing.	PCB and PCBA testing, AI applications.
"XAI for PCB Defect Detection in Manufacturing" (Abdul et al., 2022)	Combines traditional image processing with deep learning for PCB defect.	Integration challenges with existing systems.	Further exploration into hybrid models.	PCB defect detection, hybrid AI systems.
"Flaw Detection in PCB Using Deep Learning and Image Processing" (Y., Rao et al., 2024)	Systematic review proposing new methods and datasets for intelligent manufacturing.	Limited evaluation of practical implementation.	Development of practical applications in real-time detection.	Visual detection, intelligent manufacturing systems.
"Improving Printed Circuit Board Defect Detection with CNNs and SVMs" (Vishal et al., 2021)	Developed a real-time inspection system using AI for PCB defect detection.	High computational power requirements.	Optimization for lower-power systems in real-time environments.	Real-time quality control, automated inspection.
"PCB Flaw Detection Using Deep Learning" (Y., Rao et al., 2021)	Systematic review summarizing progress in image processing and classification techniques.	Generalized conclusions that may not apply universally.	Investigation into domain-specific applications of PCB defect detection.	PCB defect detection, image processing, AI.

Tab 1: Contributions, Limitations, and Future Directions in PCB Defect Detection

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

Challenges in PCB Defect Detection

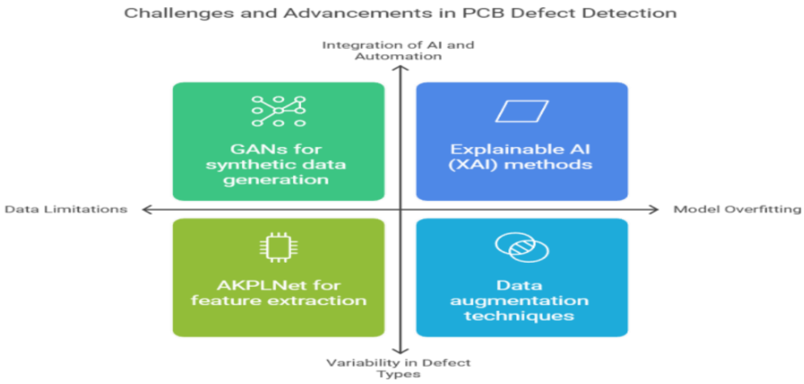


Fig. 2: PCB Defect Detection Methods

Data Limitations:
Sophisticated models depend significantly on extensive, labeled datasets, which are frequently limited in availability or costly to acquire. Although datasets such as DsPCBSD+ mark notable advancements, there is still a demand for more thorough and varied datasets (Lv et al., 2024; Shengping et al., 2024). The generation of synthetic data through GANs is suggested as a potential remedy for alleviating data shortages (Kong, 2024).

Model Overfitting:
Overfitting poses a major challenge, particularly when models are developed using restricted datasets. To reduce this problem, methods like data augmentation, transfer learning, and semi-supervised learning have been utilized (Wang, 2023; Yao et al., 2023; Petkov & Ivanova, 2024).

Variability in Defect Types:
The variety in PCB designs and types of defects complicates the process of generalizing detection models. Achieving uniform performance across various designs continues to be a significant focus of research (Boonkorkoer et al., 2023; Austria & Fajardo, 2023). Approaches such as AKPLNet and Mix-Fusion tackle these issues by improving the accuracy of feature extraction and localization (Huang & Tsai, 2024; Zhang et al., 2023).

ADVANCEMENTS IN TECHNOLOGY

Integration of AI and Automation:
The incorporation of AI into automated manufacturing processes has greatly advanced the methods used for identifying defects. Ensemble approaches that merge various models, as suggested by Ka et al. (2024), have shown to improve both accuracy and reliability. Additionally, Explainable AI (XAI) methods are becoming increasingly popular, promoting model clarity and reliability in industrial settings (Malik et al., 2024).

Real-Time Inspection Systems:
Real-time systems that employ lightweight architectures such as LW-YOLO have effectively achieved a balance between speed and accuracy, making them ideal for industrial applications (Tang et al., 2024; Rao et al., 2024). Multi-depth X-ray imaging systems designed for the inspection of solder joints have been enhanced for real-time use (Boonkorkoer et al., 2023).

Gaps in Current Research:
Although there have been notable advancements, there are still deficiencies regarding dataset diversity, model robustness, and the investigation of alternative architectures. Research on assembly-level defect detection, in contrast to PCB-level detection, has been recognized as a neglected area (Petkov & Ivanova, 2024; Zhang et al., 2023). Furthermore, the insufficient emphasis on real-world validation across various manufacturing environments limits the practical use of these models (Meesad & Maliyaem, 2023).

FUTURE DIRECTIONS

Expanding Research on Diverse Defects:
Future studies should focus on developing datasets that encompass a wider variety of defects and PCB designs to enhance model generalization (Lv et al., 2024; Wang, 2023; Shengping et al., 2024). Joint initiatives aimed at creating open-access datasets could meet this requirement.
Development of Robust Models:

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
National Level Conference – AITCON 2K25
Adarsh Institute of Technology & Research Centre, Vita, Maharashtra
Vol. 12, Special Issue 1, March 2025

Creating strong models that can effectively manage different and intricate defect categories is essential. Combining AI with image processing methods indicates encouraging outcomes (Nguyen & Nguyen, 2024; Yao et al., 2023). Furthermore, it's important to investigate lightweight models specifically designed for environments with limited resources (Tang et al., 2024).
Integration into Automated Systems:
The effective incorporation of sophisticated defect detection models into automated systems has the potential to significantly enhance manufacturing efficiency and quality assurance. Real-time systems, especially those utilizing self-supervised learning, present promising opportunities for integration in industrial settings (Ka et al., 2024; Malik et al., 2024).

This review emphasizes the advancement of PCB defect detection, transitioning from conventional manual techniques to state-of-the-art deep learning approaches. Although notable strides have been made, addressing data constraints, enhancing model robustness, and guaranteeing practical applicability in real-world scenarios are still vital. Continuous research is necessary to promote the production of high-quality and trustworthy electronic devices.

DISCUSSIONS

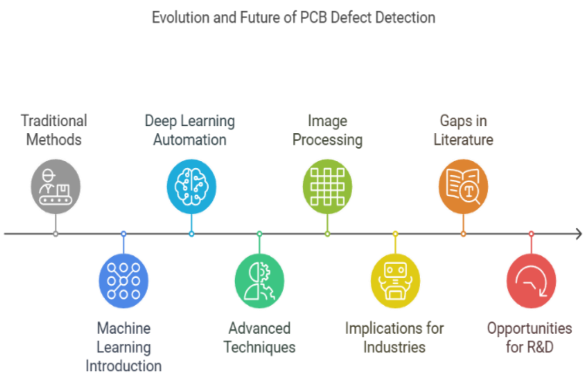


Fig. 3: Evolution and Future of PCB Defect Detection

Synthesis of Findings from the Literature Review:
This review article emphasizes the increasing significance of machine learning (ML), deep learning (DL), and image processing methods in identifying defects in PCBs. Conventional approaches, such as manual inspections and basic machine vision systems, are proving to be insufficient due to the intricacies of contemporary PCB designs. ML techniques, including Support Vector Machines (SVMs), have improved the classification of defects, whereas deep learning frameworks, particularly Convolutional Neural Networks (CNNs), have facilitated the automation of defect detection with greater precision. Advanced models like YOLO and GANs have demonstrated considerable efficacy in identifying complex defects. Hybrid models that integrate DL with other AI methodologies, such as transformers, are especially successful in real-time industrial settings. Image processing methods, such as edge detection and X-ray imaging, further boost detection accuracy when used alongside ML and DL.

Implications and Significance in the Broader Context:
Automated systems for defect detection that utilize AI provide significant advantages to sectors that depend on high-quality printed circuit boards (PCBs), including automotive, aerospace, and consumer electronics. These solutions lead to lower production expenses, enhance reliability, and help prevent defective products from reaching the market, thereby reducing the likelihood of expensive recalls. The adoption of AI supports the principles of Industry 4.0, which emphasizes automation and real-time data analysis to enhance manufacturing effectiveness and product quality. Nonetheless, there are still obstacles such as insufficient data, model overfitting, and variations in defects, which necessitate additional research into data augmentation and improving model resilience.

Gaps in Literature:
Despite progress made, there are still notable gaps in the research surrounding PCB defect detection. A significant problem is the unavailability of diverse and high-quality datasets, which hinders the models' ability to generalize. The generation of synthetic datasets using GANs could potentially alleviate this issue. Furthermore, there are ongoing concerns related to model overfitting, given the lack of variety in current datasets. Additional exploration into real-time applications within resource-limited contexts, such as embedded systems, is also necessary. In addition, while hybrid models show potential, the challenge of implementing these within automated manufacturing systems remains unresolved.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

Significance of the Findings:

The advancement of AI-driven defect detection is essential for guaranteeing the quality, safety, and dependability of electronic products, particularly in vital areas such as medical devices and aerospace. It also aligns with the larger movement toward intelligent manufacturing and sustainable practices since automated systems minimize waste and enhance efficiency. This research could impact multiple industries that rely on high-quality electronics.

Opportunities for R&D:

Future research focused on PCB defect detection should concentrate on several critical areas. To begin with, it is vital to curate larger and more diverse datasets, potentially through partnerships with industry and the incorporation of synthetic data. Tackling the issue of overfitting by investigating strategies such as semi-supervised learning and transfer learning can enhance the resilience of models. It is also important to create lightweight models suitable for real-time applications in resource-limited settings. Further examination of hybrid models that integrate deep learning, machine learning, and image processing techniques is necessary, along with exploring Explainable AI (XAI) to build trust in these systems. Finally, the smooth integration of AI models into automated production workflows will be essential for practical industrial usage.

Identified Gap	Potential Impact on PCB Defect Detection	Future Research Directions
Lack of diverse, high-quality datasets	Limits the ability of models to generalize across different defect types and PCB designs.	Curate larger and more diverse datasets through industry partnerships and synthetic data generation using GANs.
Model overfitting due to limited dataset variety	Reduces model reliability and accuracy in real-world scenarios.	Explore data augmentation, semi-supervised learning, and transfer learning to enhance model resilience.
Insufficient exploration of real-time applications in resource-limited settings	Limits deployment in embedded systems and resource-constrained environments.	Develop lightweight AI models optimized for real-time defect detection in resource-limited industrial setups.
Challenges in hybrid model implementation	Restricts the integration of advanced models into automated manufacturing workflows.	Investigate practical strategies for deploying hybrid models that integrate DL, ML, and image processing.
Lack of Explainable AI (XAI) in defect detection	Hinders trust and adoption of AI systems in critical industries like aerospace and medical devices.	Research Explainable AI to enhance model transparency, interpretability, and trust in defect detection systems.
Limited integration with automated workflows	Reduces practical utility and scalability of AI-driven defect detection systems in industrial production.	Create frameworks for seamless integration of AI models into automated production workflows.

Tab 2: Gaps, Impacts, and Future Directions

CONCLUSION AND FUTURE RESEARCH

The identification of flaws in printed circuit boards (PCBs) has progressed significantly with the incorporation of machine learning (ML), deep learning (DL), and image processing methods. These techniques have been shown to outperform traditional methods like manual inspections and basic machine vision systems. Approaches such as Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and hybrid models have improved accuracy and efficiency in detection, making them ideal for real-time manufacturing settings. These advancements are in line with the objectives of Industry 4.0, allowing for automated inspection systems that guarantee high-quality production. Nonetheless, issues like data scarcity, overfitting, and defect variability continue to affect the effectiveness of AI-based defect detection systems.

Future studies should aim to tackle these issues by creating larger, more diverse, and superior-quality datasets, including the incorporation of synthetic data, to enhance model generalization. To mitigate overfitting, strategies such as data augmentation and transfer learning need to be examined. Moreover, there is a demand for lightweight, real-time defect detection models that function in resource-limited industrial settings. Further investigation into hybrid models that blend ML, DL, and image processing is essential for optimizing detection performance.

The application of Explainable AI to enhance model transparency and interpretability represents another promising direction. These developments will be vital for creating fully automated, real-time PCB defect inspection systems that can ensure the production of flawless, high-quality PCBs in future manufacturing processes.

REFERENCES

[1]. Tao, Jian., Muhammad, Hafidz, Fazli, Md, Fauadi., Saifudin, Hafiz, Yahaya., Ahamad, Zaki, Mohamed, Noor., Adi, Saptari. (2024). A deep learning approach for automated PCB defect detection: A comprehensive review. Multidisciplinary Reviews, 8(1):2025011-2025011. doi: 10.31893/multirev.2025011

[2]. Ka, Nam, Canaan, Law., Mingshuo, Yu., Lianglei, Zhang., Yiyi, Zhang., Peng, Xu., Jerry, Gao., Jun, Liu. (2024). Enhancing Printed Circuit Board Defect Detection through Ensemble Learning. doi: 10.1109/fityr63263.2024.00013

[3]. Patrick, Craig., J.D., Pearson., Shajib, Ghosh., Nitin, Varshney., Sanjeev, J., Koppal., Navid, Asadizanjani. (2024). Optical Automated Interconnect Inspection of Printed Circuit Boards. Proceedings, 84918:22-27. doi: 10.31399/asm.cp.istfa2024p0022

[4]. Thongpun, Supong., Thanapat, Kangkachit., Duangjai, Jitkongchuen. (2024). PCB Surface Defect Detection Using Defect-Centered Image Generation and Optimized YOLOv8 Architecture. 44-49. doi: 10.1109/ibdap62940.2024.10689687

[5]. Swati, Shilaskar., Sai, Singar., Abhijit, Sonawane., Shobit, Shinde. (2024). Soldering Defect Identification Using Deep Learning and Machine Learning Approach. 1-6. doi: 10.1109/icecsp61809.2024.10698480

[6]. Shengping, Lv., Bin, Ouyang., Zhihua, Deng., Tairan, Liang., Shixin, Jiang., Kaibin, Zhang., Jiangyan, Chen., Zhuohui, Li. (2024). A dataset for deep learning based detection of printed circuit board surface defect. Scientific Data, 11(1) doi: 10.1038/s41597-024-03656-8

[7]. Abdul, Malik, Mohd, Ali., Shafishuhaza, Sahlan., Nurulaqilla, Khamis., Xie, Ziyi., Fadilla, ‘Atyka, Nor, Rashid. (2024). Transparency in Detecting Defects of a Printed Circuit Board: Harnessing XAI for Improved Quality Control in Electronic Manufacturing Industries. 287-292. doi: 10.1109/icsima62563.2024.10675544

[8]. Y., M., Rao., Pendela, Abhinav., Dharavath, Suman, Nayak., Nallori, Shiva, Reddy. (2024). Flaw Detection in PCB Using Deep Learning and Image Processing. 1280-1285. doi: 10.1109/icscss60660.2024.10625505

[9]. Vishal, Yadav., Deepak, Banerjee., Deepak, Upadhyay., Vijay, Singh. (2024). Improving Printed Circuit Board Defect Detection with CNNs and SVMs. 1-6. doi: 10.1109/apcit62007.2024.10673649

[10]. Nikolay, Petkov., Malinka, Ivanova. (2024). Printed circuit board and printed circuit board assembly methods for testing and visual inspection: a review. Bulletin of Electrical Engineering and Informatics, 13(4):2566-2585. doi: 10.11591/eei.v13i4.7601

[11]. Nikolay, Petkov., Malinka, Ivanova. (2024). Detection and Classification of Defects on Printed Circuit Board Assembly through Deep Learning. 1-5. doi: 10.23919/splitech61897.2024.10612667

[12]. Roman, Melnyk., Vitalii, Vorobii. (2024). PCB Image Defects Detection by Artificial Neural Networks and Resistance Analysis. WSEAS transactions on circuits, doi: 10.37394/23201.2024.23.7

[13]. Chien-Yi, Huang., Pei-Xuan, Tsai. (2024). Applying Machine Learning to Construct a Printed Circuit Board Gold Finger Defect Detection System. Electronics, doi: 10.3390/electronics13061090

[14]. Lingxue, Kong. (2024). Research on the application of deep learning algorithms to PCB defect detection. Applied and Computational Engineering, 43(1):44-48. doi: 10.54254/2755-2721/43/20230805

[15]. Qianyue, Wang. (2024). A new frontier in electronics manufacturing: Optimized deep learning techniques for PCB image reconstruction. Applied and Computational Engineering, doi: 10.54254/2755-2721/51/20241591

[16]. Xiangyang, Tang., Hao, Ning., Zhengzhe, Yang. (2024). LW-YOLO: Lightweight Deep Learning Model for Fast and Precise Defect Detection in Printed Circuit Boards. Symmetry, doi: 10.3390/sym16040418

[17]. Tuan, Anh, Nguyen., Hoanh, Nguyen. (2024). Towards High Quality PCB Defect Detection Leveraging State-of-the-Art Hybrid Models. International Journal of Advanced Computer Science and Applications, 15(2) doi: 10.14569/ijacsa.2024.0150249

[18]. Asyif, Zaenal, Muttaqin., Ibrahim, Nawawi., Johan, Pamungkas. (2024). Implementasi Machine Learning pada Deteksi Kecacatan Printed Circuit Board. Voteteknika, 12(1):44-44. doi: 10.24036/voteteknika.v12i1.127224

[19]. Nikhil, Aggarwal., Manish, Deshwal., Piyush, Samant. (2023). Comparative Analysis of Existing Deep Learning Techniques for Automatic Defects Detection in Printed Circuit Boards. 1176-1181. doi: 10.1109/ictacs59847.2023.10390098

[20]. Chukiat, Boonkorkoer., Phayung, Meesad., Maleerat, Maliyaem. (2023). Deep Learning Based Printed Circuit Boards Defect Detection Using Multiple Depth 2D X-Ray Image. 174-179. doi: 10.1109/icitee59582.2023.10317751

[21]. Yolanda, D., Austria., Arnel, C., Fajardo. (2023). Defect Recognition on Single Layer Bare Printed Circuit Boards for Quality Control and Visual Inspection: A Low-Sample-Size Deep Transfer Learning Approach. 1-7. doi: 10.1109/icspis59665.2023.10402674
[22]. Jiantao, Zhang., Zhengfang, Chang., Haida, Xu., Dong, Po, Qu., Xinyu, Shi. (2023). PCB Defect Image Recognition Based On The Multi-Model Fusion Algorithm. Journal of Electronic Packaging, doi: 10.1115/1.4064098
[23]. Luozhi, Wang. (2023). Circuit defect detection based on AI deep learning. doi: 10.54254/2753-8818/12/20230455
[24]. Naifu, Yao., Yongqiang, Zhao., Seong, G., Kong., Yang, Guo. (2023). PCB Defect Detection with Self-Supervised Learning of Local Image Patches. doi: 10.1016/j.measurement.2023.113611
[25]. Yongbing, Zhou., Minghao, Yuan., Jian, Zhang., Guofu, Ding., Shengfeng, Qin. (2023). Review of vision-based defect detection research and its perspectives for printed circuit board. Journal of Manufacturing Systems, doi: 10.1016/j.jmsy.2023.08.019
[26]. Sik-Ho, Tsang., Zhaoqing, Suo., Tom, Tak-Lam, Chan., Daniel, Pak-Kong, Lun. (2023). PCB Soldering Defect Inspection Using Multitask Learning under Low Data Regimes. Advanced intelligent systems, doi: 10.1002/aisy.202300364
[27]. Xue, Liu., Jialin, Wang., Runxu, Zhang., Weixiang, Ruan. (2023). Deep learning-based defect detection for printed circuit boards. 12754:127543I-127543I. doi: 10.1117/12.2684258
[28]. Yolanda, D., Austria., Arnel, C., Fajardo. (2023). Defect Detection and Classification in Printed Circuit Boards using Convolutional Neural Networks. 1498-1504. doi: 10.1109/icecaa58104.2023.10212195
[29]. P., Klco., Dusan, Koniar., Libor, Hargas., K., Pocisková, Dimová., Marek, Chnápko. (2023). Quality inspection of specific electronic boards by deep neural networks. Dental science reports, 13 doi: 10.1038/s41598-023-47958-0
[30]. Mary, Jane, C., Samonte., Chuanxiang, Du., Xiaomian, Li., Xiaoyan, Wei. (2023). Grand Challenges in Printed Circuit Board Defect Detection Based on Image Processing. doi: 10.1145/3624288.3624302
[31]. Jubilee, Prasad-Rao., R., Heidary., Jesse, Williams. (2023). Detecting Manufacturing Defects in PCBs via Data-Centric Machine Learning on Solder Paste Inspection Features. arXiv.org, abs/2309.03113 doi: 10.48550/arxiv.2309.03113
[32]. (2023). A Design of Bare Printed Circuit Board Defect Detection System Based on YOLOv8. Highlights in Science Engineering and Technology, doi: 10.54097/hset.v57i.10002
[33]. Ming, Le, Zhou., Changle, Yi., Honglin, Wan., Min, Li., Gang, Li., Delong, Han. (2023). PCB Defect Detection Model with Convolutional Modules Instead of Self-Attention Mechanism. 520-525. doi: 10.1109/smc53992.2023.10394399
[34]. Chengzhou, Li. (2023). DesNet: PCB defect detection network based on deformable convolution. 677-681. doi: 10.1109/ICETCI57876.2023.10176845
[35]. R., Raffik., B., Sabitha., D., Arunprasanth., E., Karthikeyan., A.G., Padmanaaban., V., Sai, Prasanth. (2023). Automated PCB Defect Identification System using Machine Learning Techniques. doi: 10.1109/icaeca56562.2023.10200565
[36]. (2023). Component Identification and Defect Detection of Printed Circuit Board using Artificial Intelligence. doi: 10.1109/icaaic56838.2023.10140259
[37]. Roman, Melnyk., Roman, Kvit. (2023). Defects Detection in Printed Circuit Boards by Separation and Comparison of Chains. WSEAS transactions on circuits, 22:63-74. doi: 10.37394/23201.2023.22.9
[38]. Syed, Shameem. (2023). Convolutional Neural Network for Printed circuit Board Verification. 1-6. doi: 10.1109/ICDCECE57866.2023.10150883
[39]. Aaqib, Raza. (2023). Fault Detection and Quality Inspection of Printed Circuit Board Using Yolo-v7 Algorithm of Deep Learning. 1-7. doi: 10.1109/IMTIC58887.2023.10178512
[40]. I-Chun, Chen., Rey-Chue, Hwang., Huang-Chu, Huang. (2023). PCB Defect Detection Based on Deep Learning Algorithm. Processes, 11(3):775-775. doi: 10.3390/pr11030775
[41]. Thi, Tram, Anh, Pham., Do, Kieu, Trang, Thoi., Hyohoon, Choi., Suhyun, Park. (2023). Defect Detection in Printed Circuit Boards Using Semi-Supervised Learning. Sensors, 23(6):3246-3246. doi: 10.3390/s23063246
[42]. Zhihang, Liu., Pengfei, He., Tongjing, Zhang., Rong, Nie. (2022). Defect Detection of Printed Circuit Board Based on Light-weight YOLOv5s. 1-5. doi: 10.1109/ICICSP55539.2022.10050596
[43]. Angelika, Hable., Paul, Tabatabai., Hannah, Luise, Lichtenegger., Anton, Scherr., T., Krivec., Dieter, P., Gruber. (2022). Detection of Printed Circuit Board Defects on ENIG and ENIPIG Surface Finishes with Convolutional Neural Networks and Evaluation of Training Parameters. Journal of microelectronics and electronic packaging, 19(4) doi: 10.4071/001c.57717
[44]. Chung-Hao, Chang., Hao-Wei, Chen., Chunhui, Lin. (2022). Detecting Multiclass Defects of Printed Circuit Boards in the Molded-interconnect-device Manufacturing Process Using Deep Object Detection Networks. 1536-1540. doi: 10.1109/IEEM55944.2022.9989934
[45]. Andria, Legon., Makarand, Deo., Sacharia, Albin., Michel, A., Audette. (2022). Detection and Classification of PCB Defects using Deep Learning Methods. 1-6. doi: 10.1109/mdts54894.2022.9826925

[46]. (2022). A Survey on Automatic Printed Circuit Board Defect Detection Techniques. doi: 10.1109/icacite53722.2022.9823872
[47]. Van-Truong, Nguyen., H., A., Bui. (2022). A real-time defect detection in printed circuit boards applying deep learning. Eureka: Physics and Engineering, 143-153. doi: 10.21303/2461-4262.2022.002127
[48]. Ong, Yee, Chiun., Nur, Intan, Raihana, Ruhaiyem. (2023). Object Detection Based Automated Optical Inspection of Printed Circuit Board Assembly Using Deep Learning. 246-258. doi: 10.1007/978-981-99-0405-1_18
[49]. (2022). Defect Detection in Printed Circuit Boards with Pre-Trained Feature Extraction Methodology with Convolution Neural Networks. Cmc-computers Materials & Continua, 70(1):637-652. doi: 10.32604/cmc.2022.019527
[50]. (2022). Defect Classification from Electronic Card Images by Deep Learning. doi: 10.1109/siu55565.2022.9864727
[51]. Xing, Wu., Yuxi, Ge., Qingfeng, Zhang., Dali, Zhang. (2021). PCB Defect Detection Using Deep Learning Methods. 873-876. doi: 10.1109/CSCWD49262.2021.9437846