

Unsupervised Learning-Based Defect Detection in PCB Circuit Images for Automated Quality Inspection

HyeokSoo Lee*, Youngki Jo**, Minsu Kim**, Jongpil Jeong*

* Department of Smart Factory Convergence, Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon, 16419, Korea

** Research & Development Center, LS-THIRAUTECH Co., Ltd, CK Bldg 7, Hakdong-ro 5-gil Gangnam-gu, Seoul, 06044, Korea

huxlee@g.skku.edu, youngki.jo@ls-thirautech.com, minsul.kim@ls-thirautech.com, jpjeong@skku.edu

Abstract— Printed Circuit Boards (PCBs) are fundamental components in modern electronic devices, and their quality directly affects product reliability. Conventional inspection processes often rely on supervised learning models that require a large amount of annotated defect data. However, collecting and labeling defect samples is costly and impractical due to the diverse and unpredictable nature of PCB defects. In this study, we propose an unsupervised learning-based defect detection framework that leverages PCB circuit images for automated quality inspection. The approach employs convolutional autoencoders to learn standard pattern representations without requiring labeled defect data. Anomalous regions are detected by reconstruction error analysis, and statistical thresholds are applied to classify pass/fail conditions. To evaluate the effectiveness, experiments were conducted on a dataset of PCB circuit images, including both standard and defective samples. The proposed method demonstrated high detection accuracy with minimal false positives, outperforming baseline thresholding and clustering-based approaches. Moreover, the framework showed robustness to varying defect types such as missing tracks, misalignments, and surface contamination. These results suggest that unsupervised learning can serve as a practical alternative to traditional supervised inspection methods in PCB manufacturing. The proposed method reduces dependency on labeled datasets, enhances adaptability to new defect patterns, and contributes to the realization of intelligent and automated quality inspection systems in smart manufacturing environments.

Keywords— Anomaly Detection, Unsupervised Learning, PCB Circuit Images, Smart Manufacturing, Quality Inspection

I. INTRODUCTION

Printed Circuit Boards (PCBs) play a pivotal role in electronic manufacturing as the fundamental platform for electrical connectivity and signal transmission. The rapid growth of telecommunications, automotive electronics, and consumer devices has led to increasingly complex PCB designs with higher component density and miniaturization. Ensuring defect-free PCBs is therefore critical, since even minor defects such as missing tracks, short circuits, or surface contamination can significantly compromise product reliability, safety, and cost efficiency. As industries pursue higher quality standards,

automated and accurate inspection methods have become an essential part of smart manufacturing.

Conventional PCB inspection techniques primarily rely on manual visual inspection or rule-based machine vision systems. Although these methods are widely adopted, they often suffer from limited scalability, subjectivity, and low adaptability to complex defect patterns. With the advancement of computer vision and artificial intelligence, supervised learning approaches have been introduced to improve defect detection accuracy. However, supervised models require extensive labeled datasets that include a wide range of defect types. Collecting such data is both costly and time-consuming, and in practice, it is nearly impossible to capture every possible defect variation that may occur in real manufacturing lines [1,2].

Given the limitations of supervised learning, unsupervised approaches have attracted growing attention as they enable defect detection without relying on labeled defect samples. By learning the intrinsic patterns of defect-free PCB images, unsupervised models can identify anomalies as deviations from standard patterns [2]. This paradigm is particularly advantageous in industrial settings, where defective samples are rare, diverse, and challenging to label comprehensively. Moreover, unsupervised learning provides better adaptability to new or unseen defect types, making it suitable for dynamic manufacturing environments. Despite its potential, research on applying unsupervised learning to PCB inspection remains relatively limited, warranting further investigation [3].

In this paper, we propose an unsupervised learning-based defect detection framework for PCB circuit images to support automated quality inspection. The method employs convolutional autoencoders to learn robust representations of typical PCB structures, and pass/fail judgment is achieved by analyzing reconstruction errors. Through experimental evaluation on PCB datasets, the framework demonstrated strong detection capability across various defect types and showed robustness against false positives compared with baseline methods. The main contributions of this study are threefold: (1) introducing a practical unsupervised defect detection framework for PCB inspection, (2) demonstrating its

effectiveness through experiments with real-world circuit image data.

The paper is organized as follows: Section 2 reviewed the techniques of rule-based traditional machine vision, supervised learning and unsupervised anomaly approaches for defect detection, and applications of AI technology in quality control. Section 3 describes the multi agent based vision solution. In Section 4, we conducted four experiments and explained the experimental results. The conclusions and future research directions are included in Section 5.

II. RELATED WORK

A. Rule-Based and Traditional Machine Vision for PCB Inspection

Early PCB inspection systems were predominantly based on rule-based image processing and classical machine vision techniques. Methods such as template matching, edge detection, and morphological filtering provided straightforward implementations and were suitable for detecting relatively simple defects in low-density boards [1]. These approaches offered advantages in terms of computational efficiency and interpretability, which made them appealing in early industrial inspection settings.

However, rule-based techniques are inherently sensitive to noise, illumination variation, and the growing complexity of PCB designs. As circuit density and miniaturization increased, the handcrafted features used in traditional methods often failed to capture subtle and irregular defects. These limitations resulted in frequent false positives and reduced robustness, highlighting the need for more adaptive and data-driven approaches [2].

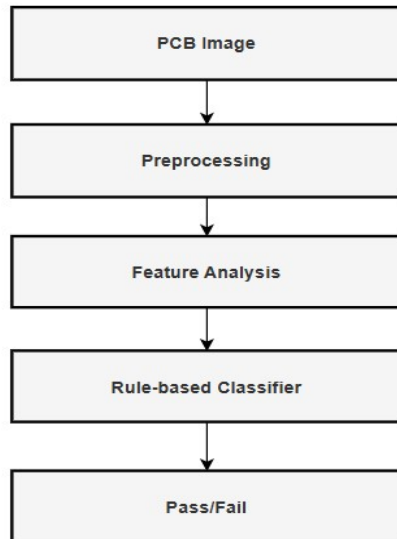


Figure 1. Rule-Based PCB Inspection

B. Supervised Learning Approaches for Defect Detection

The advancement of machine learning, particularly deep learning, has introduced supervised approaches to PCB defect detection. Convolutional Neural Networks (CNNs) and object detection frameworks such as Faster R-CNN and YOLO have

been successfully applied to identify and localize defects in PCB images. With sufficient annotated datasets, these methods achieve high accuracy and demonstrate the ability to generalize across common defect categories, thereby outperforming rule-based methods in practical applications [4].

Despite these improvements, supervised learning approaches face significant challenges in industrial adoption. They rely on large-scale, well-labeled datasets, which are expensive and time-consuming to acquire. Moreover, supervised models often fail to recognize unseen or rare defect types, reducing their robustness in dynamic production environments. This limitation emphasizes the necessity of approaches that reduce dependency on labeled defect data.

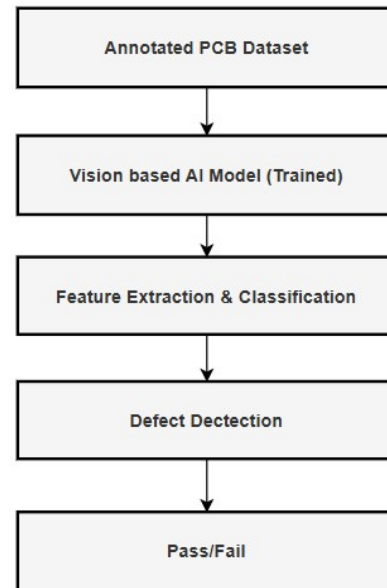


Figure 2. Supervised PCB Defect Detection

C. Unsupervised Anomaly Detection in Manufacturing Inspection

Unsupervised learning methods have been increasingly explored for defect detection in manufacturing contexts. Techniques such as autoencoders, variational autoencoders (VAE), and generative adversarial networks (GAN) learn the underlying distribution of normal, defect-free samples. Anomalies are identified as deviations from these learned patterns, typically using reconstruction error or probabilistic metrics. This approach eliminates the need for explicitly labeled defect data, making it attractive for industrial inspection tasks where defective samples are rare [3, 5].

In the case of PCB inspection, unsupervised methods provide clear advantages. They can adapt to new defect types without retraining on labeled data, enabling greater flexibility in rapidly changing production lines. Recent studies have demonstrated that unsupervised anomaly detection can achieve competitive performance with supervised methods, while offering improved scalability and practicality in real-world applications.

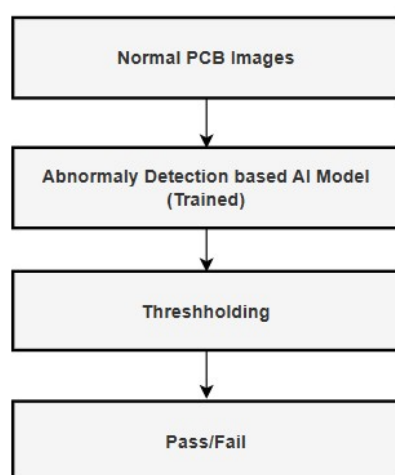


Figure 3. Unsupervised PCB Defect Detection

1) PaDiM: It is an unsupervised visual anomaly detection algorithm that extracts intermediate feature maps from a pre-trained CNN using only normal images during training, modeling the distribution of patches at spatial locations as a multivariate normal distribution. Specifically, it estimates the mean vector and covariance matrix for the normal state at each spatial coordinate. During inference, it calculates an anomaly map based on how much the patch features of the incoming sample deviate from this distribution [6]. It can be trained solely on normal data in manufacturing environments with scarce labels and preserves statistics per spatial location, making it sensitive to subtle local defects (scratches, fine contamination, pattern breaks, etc.). Furthermore, it is simple and stable without complex training, and its computational load during inference is predictable, enabling easy integration into real-time inspection pipelines [6].

2) Dinomaly: It is a Transformer-based unsupervised anomaly detection algorithm that aims for high performance in multi-class environments using Attention and MLP. Its key components are the Foundation Transformer providing universal representations, Noisy Bottleneck utilizing dropout, Linear Attention, and Loose Reconstruction. Input images extract multi-layer features using a ViT-based architecture like DINO/DINOv2, pass through an MLP bottleneck, and are then reconstructed via a Transformer decoder [7]. The anomaly score is calculated by comparing the encoder features with the decoder features. It mitigates the identity mapping issue of traditional reconstruction-based methods, reduces memory and computational costs through Linear Attention, and enhances generalization capabilities [7].

D. Applications of Smart Manufacturing and AI in Quality Control

The broader integration of AI technologies into smart manufacturing has transformed quality control systems across industries. Examples include automated defect detection in semiconductors, surface inspection in automotive parts, and pattern analysis in textiles. These AI-enabled solutions enhance inspection speed, reduce human error, and improve

overall reliability, demonstrating the potential of intelligent inspection systems to support Industry 4.0 initiatives.

Within this context, PCB inspection represents a critical application area due to the essential role of PCBs in electronic products. Incorporating unsupervised learning-based methods into quality inspection processes not only improves detection accuracy but also enables adaptive quality assurance. Such integration contributes to the realization of smart factories, where AI-driven inspection systems continuously optimize manufacturing processes through real-time feedback and data-driven decision-making [3, 4].

III. PROPOSED METHOD

We propose a multi-agent based vision solution that enables real-time quality inspection under high-throughput image streams from multiple cameras and line scanners [8]. The system targets production environments with tight bandwidth and latency budgets, ensuring that frames are ingested, processed, and judged without bottlenecks as sources scale. By decoupling ingestion, inference, and decision stages, the pipeline maintains deterministic latency.

The solution is modular and comprises: (i) an orchestration Agent for high-speed frame acquisition and buffering, (ii) lightweight preprocessing (ROI selection, resizing, denoising, illumination normalization), (iii) delivery to a model-based inference engine, (iv) pass/fail determination using adaptive thresholds and hysteresis, (v) persistent storage of inspection results and metadata, and (vi) operator-facing verification via a user interface. Each stage is encapsulated as a dedicated agent, enabling load balancing, backpressure control, and automatic CPU/GPU pool scaling to minimize end-to-end latency and to isolate faults for easier maintenance.

For scenarios with scarce and diverse defect samples, the inference stage adopts unsupervised learning. We consider two options and select one model per deployment (no ensembling): PaDiM (Patch Distribution Modeling) and Dinomaly. PaDiM uses a frozen, pretrained CNN to extract feature maps and models the multivariate normal (MVN) distribution per spatial location from normal data only. At inference, it computes Mahalanobis distance maps to produce pixel/patch-level anomaly scores. PaDiM is computation-light, interpretable, and well-suited to strict real-time constraints or edge deployments where throughput and explainability are paramount [6].

Dinomaly, in contrast, is a Transformer-based unsupervised anomaly detection approach that leverages ViT features and a loosely enforced reconstruction/similarity objective to learn common “normality” across classes. It yields robust anomaly maps under varying textures and illumination and scales favorably for multi-class or frequently changing SKUs, reducing the need to maintain many per-SKU statistical profiles [7]. While Dinomaly typically demands more compute than PaDiM, it offers stronger generalization to emergent defect modes. Overall, the proposed architecture minimizes dependence on labeled defects while preserving adaptability to new faults, achieving high-throughput, low-

latency inspection suitable for intelligent, closed-loop smart-manufacturing environments.

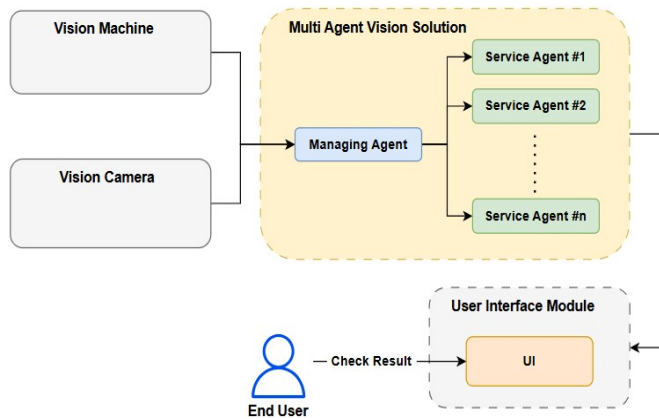


Figure 4. Multi-Agent based Vision Solution Architecture

IV. EXPERIMENT AND RESULTS

A. Experimental Environment and Methods

For this experiment, the SW configuration is minimized to the essential elements of the architecture proposed in section 3. The HW environment is configured as a server-based environment, and the server's specifications are in Table 1.

TABLE 1. HARDWARE SPECIFICATION

Item	Specification
CPU	Intel Core i7-9700(8core)
RAM Size	64GB
Graphic Card	Nvidia Geforce RTX 5090
vRAM	32GB

The dataset used in the experiment is the VisA dataset, which is licensed for use and contains 12 subsets corresponding to 12 different objects. It comprises a total of 10,821 images, of which 9,621 are normal samples and 1,200 are abnormal samples. Among these, four sets are of the PCB data type [9].

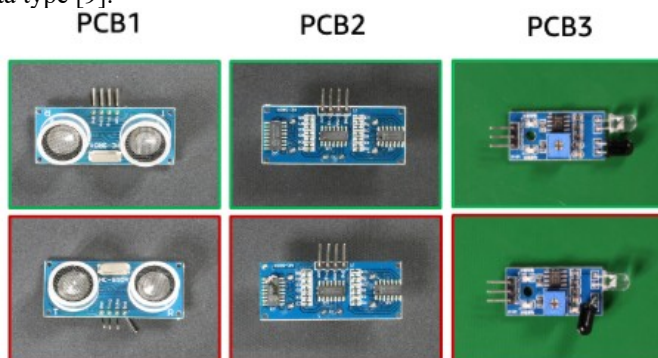


Figure 5. PCB Dataset Sample

This experiment was conducted to analyze images and determine whether they pass or fail. The following steps were taken for the experiment:

- For PCB type #1, training was performed only Dinomally model using 1,004 normal images.
- For PCB type #2, training was performed on the PaDim and Dinomally model using 1,001 normal images. For PCB type #3, training was performed on the Dinomally model only using 1,006 normal images. The Dinomally model was trained on all PCB types: #1, #2, and #3.
- The first experiment compared the performance of the PaDIM model with PCB type #2 and it can be compared with the Dinomally model.
- The second experiment compared the performance of the trained Dinomally model on PCB types #1, #2, and #3.
- Each experiment used 100 normal images and 100 defective images.

B. Metrics for Experiments

In an inspection, predictions and ground truth form a confusion matrix with TP (true positives), FP (false positives), FN (false negatives), and TN (true negatives). In defect detection, TP means correctly detecting a defective sample, FN corresponds to a missed defect, and FP is a false alarm on a good part. Because missed defects directly translate to quality risk, reducing FN is a key operational goal [10].

Recall measures “how many actual defects were successfully detected,” while precision measures “how many predicted defects are truly defective.” Increasing recall aggressively may raise FP, whereas pushing precision too high can increase FN; thus, the two are typically in trade-off. In practice, we adjust the decision threshold to balance the two according to line-specific costs [10].

We used the F1 score, the harmonic mean of precision and recall as metrics in this paper. (1), (2), and (3) show the equations of Recall, Precision and F1-Score [10].

$$\text{Recall} = \frac{TP}{TP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

C. Experimental Results

For each experiment, 13 trials were conducted, and the average F1-score was calculated.

TABLE 2. SUMMARY OF EXPERIMENTAL RESULTS

Data Set #	PaDIM	Dinomally
PCB Type #1	NA	99.5%
PCB Type #2	81%	98.5%
PCB Type #3	NA	98.5%
Mean		98.8%

The first experiment on PCB Type#2 confirmed that the Dinomally model outperformed the PaDIM model by over 17.5%, achieving an F1-Score of 98.5% compared to the PaDIM model's 81%. Furthermore, in the second experiment involving PCB Type #1 and PCB Type #3, the Dinomally model achieved F1-Scores 99.5% and 98.5%. Consequently, the average performance across the three PCB model experiments was approximately 98.8%.

D. Experimental Results Analysis

To validate the proposed method, experiments were conducted. The results confirmed that the Dinomally model outperformed the PaDIM model in this experiment, while also providing deeper insights into the characteristics of each algorithm. The following presents experimental results comparing the characteristics of the Dinomally model against the PaDIM model [6, 7].

TABLE 3. SUMMARY COMPARISON OF MODELS

Aspect	PaDIM	Dinomally
Paradigm	Pretrained CNN features, Mahalanobis anomaly map	ViT/Transformer features, loosely enforced reconstruction/similarity
Inference Speed	Fast	Slow
Memory / Hardware	Low	Higher
Accuracy	Medium	High
Multi Class	Not Support	Support

V. CONCLUSIONS

The main topic of this paper is to propose an unlabeled learning-based pass/fail determination model for PCB image data.

To achieve this, we constructed a vision inspection solution architecture that accepts image data as input, analyzes it using an artificial intelligence model, allows users to view results on a screen, and incorporates a distributed processing environment to accommodate increasing data volumes. Furthermore, two models for pass/fail determination via unsupervised learning on PCB image data were selected and experimentally validated for quality inspection applicability.

In actual manufacturing environments, beyond pass/fail determination, there are numerous limitations to relying solely on unsupervised learning for tasks like defect type analysis and handling new defects. Therefore, even if unsupervised learning-based pass/fail determination is initially introduced, it is judged that precise quality management will only be possible through advanced, supervised learning-based analysis using detailed data. Consequently, future research will focus on technologies for autonomous application, including studies related to defect data augmentation and automated labeling

REFERENCES

- [1] M. Moganti, and F. Erçal, "Segmentation of Printed Circuit Board Images into Basic Patterns", *Computer Vision and Image Understanding*, vol. 70, April, 1998
- [2] H. Rau and C.-H. Wu, "Automatic optical inspection for detecting defects on printed circuit board inner layers", *International Journal of Advanced Manufacturing Technology*, vol. 25, Jan, 2005
- [3] Venkat Anil Adibhatla, Yu-Chieh Huang, Ming-Chung Chang, Hsu-Chi Kuo, Abhijeet Utekar, Huan-Chuang Chih, Maysam F. Abbod, and Jiann-Shing Shieh, "Unsupervised Anomaly Detection in Printed Circuit Boards through Student-Teacher Feature Pyramid Matching", *Electronics*, vol. 10, Dec, 2021
- [4] Abhiroop Bhattacharya and Sylvain G. Cloutier, "End-to-end deep learning framework for printed circuit board manufacturing defect classification", *Scientific Reports*, vol. 12, Jul, 2022
- [5] Jungsuk Kim, Jungbeom Ko, Hojong Choi, and Hyunchul Kim, "Printed Circuit Board Defect Detection Using Deep Learning via A Skip-Connected Convolutional Autoencoder", *Sensors*, vol. 21, Jul, 2021
- [6] Justus Zipfel, Felix Verworner, Marco Fischer, Uwe Wieland, Mathias Kraus, and Patrick Zschech, "Anomaly detection for industrial quality assurance: A comparative evaluation of unsupervised deep learning models", *Computers & Industrial Engineering*, vol. 177, March, 2023
- [7] Willy Fitra Hendria, Hanbi Kim and Daeho Seo, "Multi-model anomaly detection for industrial inspection with dynamic loss weighting and soft-hard features loss", *Neural Computing and Applications*, vol. 37, June, 2025
- [8] Piotr Góral, Paweł Pawłowski, Karol Piniarski and Adam Dąbrowski, "Multi-Agent Vision System for Supporting Autonomous Orchard Spraying", *Electronics*, vol. 13, Jan, 2024
- [9] Github SPot-the-Difference Self-Supervised Pre-training for Anomaly Detection and Segmentation [Online]. Available: <https://github.com/amazon-science/spot-diff?tab=readme-ov-file#data-download>
- [10] Confusion Matrix, Accuracy, Precision, Recall, F1 Score [Online]. Available: <https://medium.com/analytics-vidhya/confusion-matrix-accuracy-precision-recall-f1-score-ade299cf63cd>

HyeokSoo Lee received a M.S. in Computer Science from Fairleigh Dickinson University, New Jersey, US in 1995. He is working toward a Ph.D. in smart factory convergence at Sungkyunkwan University, Suwon, Korea. He was recently an employee as a head of the Research & Development Center of LS-THIRAUTECH Co, Ltd. His research interests are in Smart Factory, Reinforcement Learning, Deep Learning, Robotics, and Data Analysis.

Youngki Jo received the B.S. and M.S. degree in Industrial Engineering from Kumoh National Institute of Technology, Korea in 2018, and 2020. He is currently an employee as a research engineer of the Research & Development Center of LS-THIRAUTECH Co, Ltd. His research interests include generative adversarial networks, deep learning, and time-series modeling and forecasting.

MinSu Kim received the B.S. degree in Psychology from Kyungnam University, Korea, in February 2019. He is currently employed as a research engineer in the Research & Development team of LS-THIRAUTECH Co., Ltd. His research interests include computer vision, especially anomaly detection, segmentation, and Self-supervised Learning.

Jongpil Jeong received a bachelor's degree in engineering from Sungkyunkwan University, Suwon, South Korea, and a master's and Ph.D. degree in computer engineering from Sungkyunkwan University in 2003 and 2008, respectively. He has been with Sungkyunkwan University since 2008 and has been an Associate Professor with the Department of Smart Factory Convergence at Sungkyunkwan University since 2016. He is the principal investigator of MAKE UNIC, a key support area for smart manufacturing at Sungkyunkwan University. His research interests include smart factory, industrial AI, anomaly detection, manufacturing data analysis, AI-based fault diagnosis and prediction, 5G-based smart manufacturing, industrial IoT applications, AI platforms, cloud platforms, and industrial security.