

Master's Thesis Presentation for the 148th Dissertation Evaluation

A Study on Unsupervised Anomaly Detection in Printed Circuit Boards using Relative Defect Score for Acceptable Local Variation

지역별 정상 편차를 위한 상대적 결함 점수 기반
인쇄회로기판의 비지도 이상 탐지에 관한 연구

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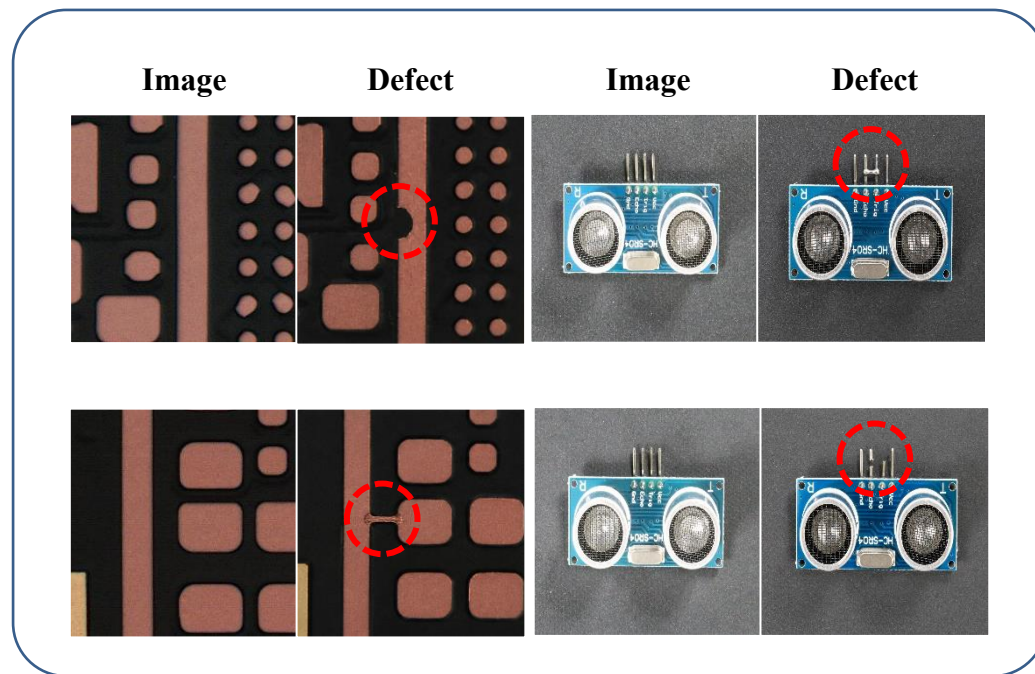
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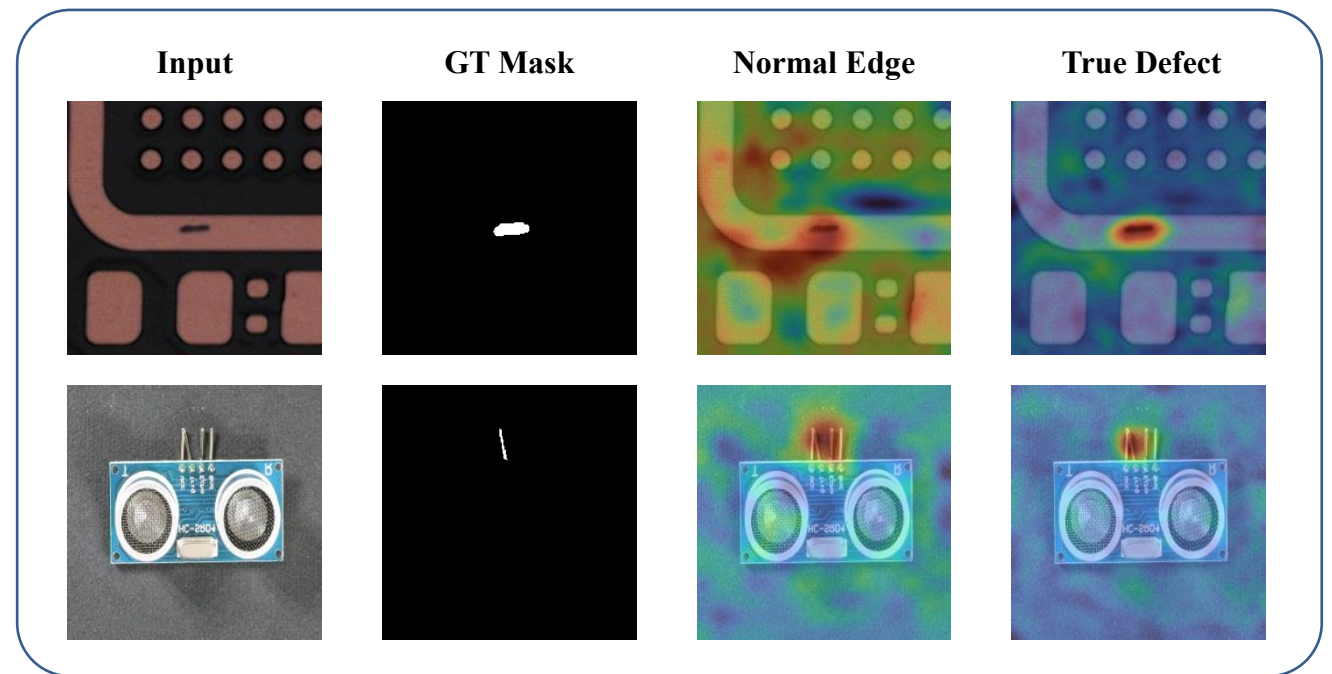
Introduction

What is Unsupervised Anomaly Detection?

- In PCB manufacturing environments, unsupervised anomaly detection aims to identify defect-related abnormal patterns using only normal training samples, enabling reliable industrial automated visual inspection across diverse PCB structures and conditions [1].
- Unlike supervised PCB defect detection methods requiring defect samples that are difficult to obtain in practice, unsupervised anomaly detection learns only normal PCB patterns and identifies defects based on deviations from the learned distribution [2].



[Figure 1] Examples of PCB Defects for Anomaly Detection



[Figure 2] Comparison of Anomaly Responses on Normal Edges and True Defects

[1] Guo, Feng, et al. "Multi-Granularity Relation Enhancement Network for Tiny Defect Detection on Printed Circuit Board." IEEE Transactions on Instrumentation and Measurement, 2025.

[2] Chen, Wei, et al. "Defect Detection Model of Printed Circuit Board Components Based on the Fusion of Multi-Scale Features and Efficient Channel Attention Mechanism." IEEE Access, 2024.

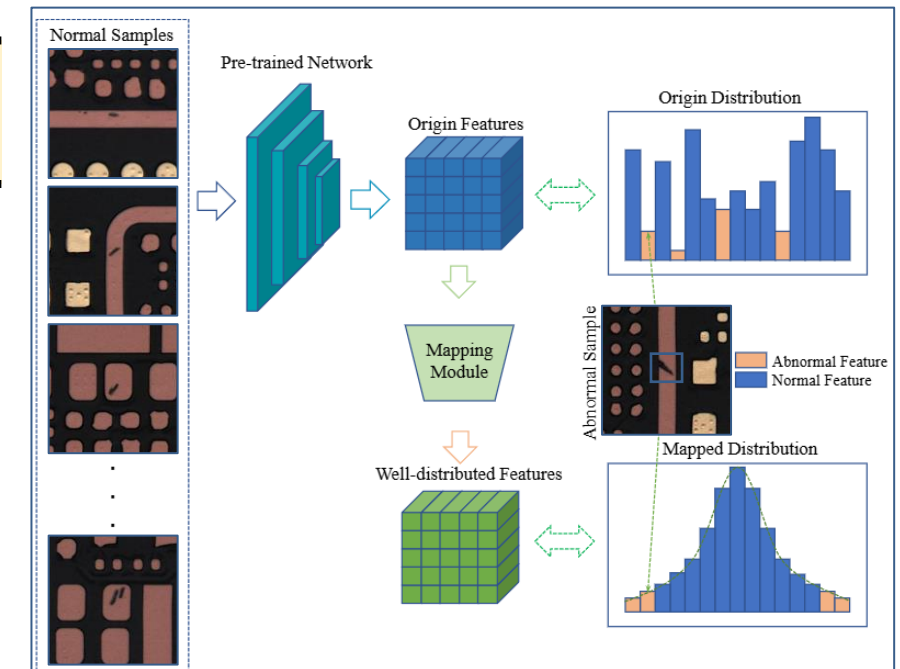
Introduction

Patch-based Anomaly Detection

- Patch-based Anomaly Detection (PAD) models local feature representations by dividing feature maps into patch-level units and identifying anomalous patterns through comparisons with normal reference patches extracted from defect-free training samples [3].
- Considering its suitability for PCB inspection environments, this presentation adopts PAD because it effectively captures subtle local defect characteristics through patch-level feature modeling and enables anomaly detection using only normal training samples.

Table 1. Comparison of Representative PAD Strategies

Strategy	Core Mechanism / Principle
Feature Retrieval-based	Compare patch-level embeddings with normal reference patches to identify subtle local anomalies, making it suitable for distinguishing defect related anomalies from repetitive PCB structures without requiring abnormal images.
Pixel Reconstruction-based	Reconstruct latent feature representations and detect anomalies using feature reconstruction errors, while modeling normal PCB patterns in the feature space.
Feature Reconstruction-based	Reconstruct latent feature representations and detect anomalies using feature reconstruction errors, while modeling normal PCB patterns in the feature space.



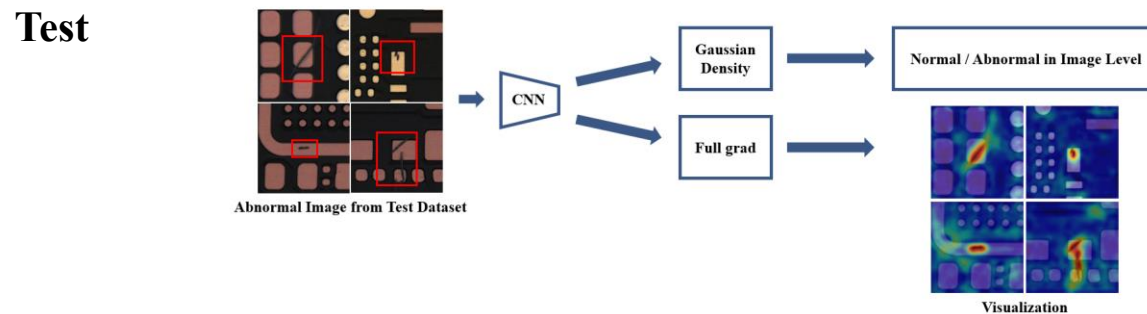
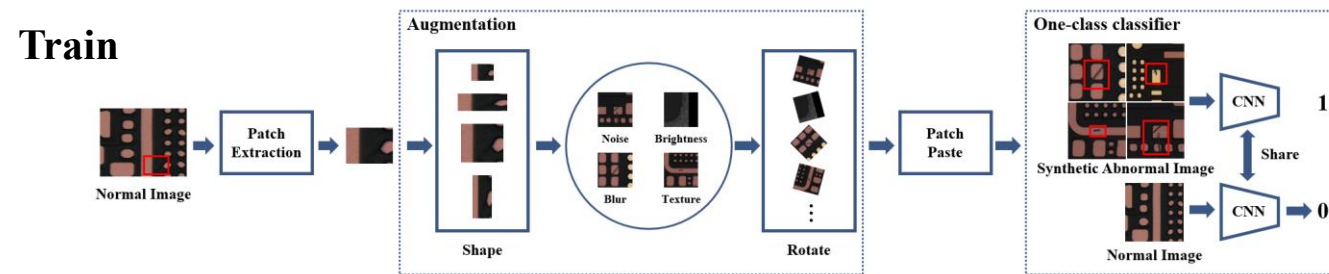
[Figure 3] Defect-free training using only normal samples.

[3] Simões, Francisco, et al. "Attention modules improve image-level anomaly detection for industrial inspection: A diffnet case study." .
Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (CVPR), 2024.

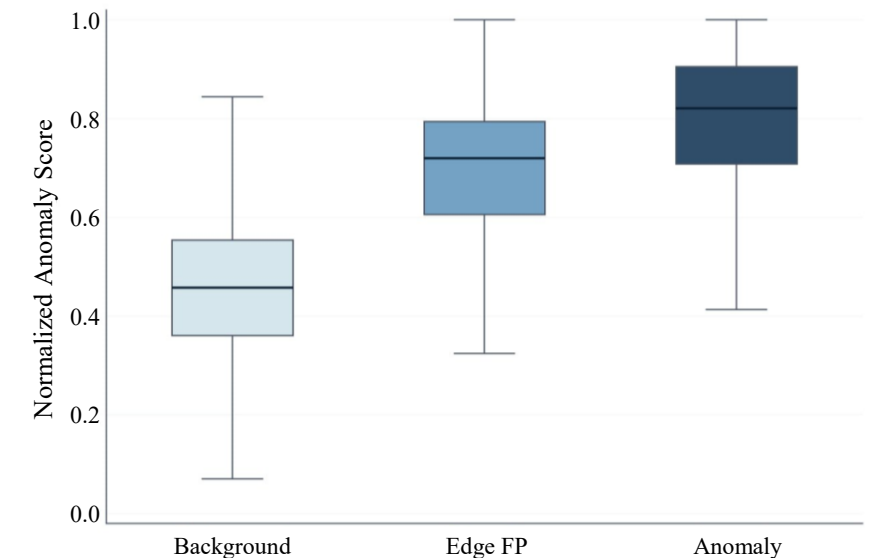
Introduction

Standard Procedure and Ideal Goal

- The standard procedure extracts patch features from PCB images, selects non-redundant representatives to build a memory bank and performs nearest-neighbor retrieval using feature distances to generate initial anomaly scores for accurate defect detection.
- The ideal goal is to compute anomaly scores by considering both the patch anomaly score and neighboring score relationships suppressing repetitive edges and ambiguous normal structures while preserving defect-related anomaly scores across PCB structures.



[Figure 4] Training and Inference Pipeline of Patch-Based Anomaly Detection



[Figure 5] Comparison of Anomaly Score Distributions

[4] A.-T. Ardelean et al., "Blind localization and clustering of anomalies in textures," in Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition (CVPR), 2024.

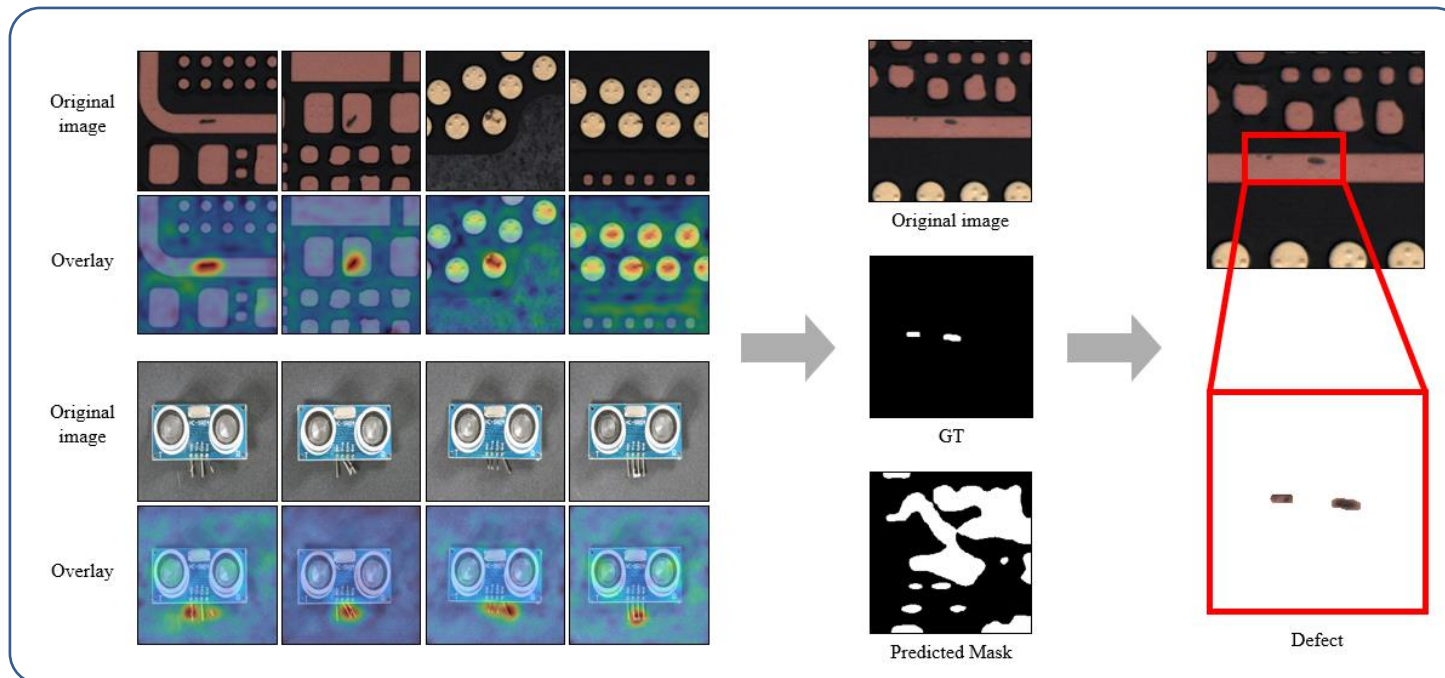
[5] Pei, M., et al. "Self-Supervised Learning for Industrial Image Anomaly Detection by Simulating Anomalous Samples." International Journal of Computational Intelligence Systems, 2023.

[6] T. Bao et al., "MIAD: A maintenance inspection dataset for unsupervised anomaly detection," in Proc. of the IEEE/CVF Int. Conf. on Computer Vision (ICCV), 2023.

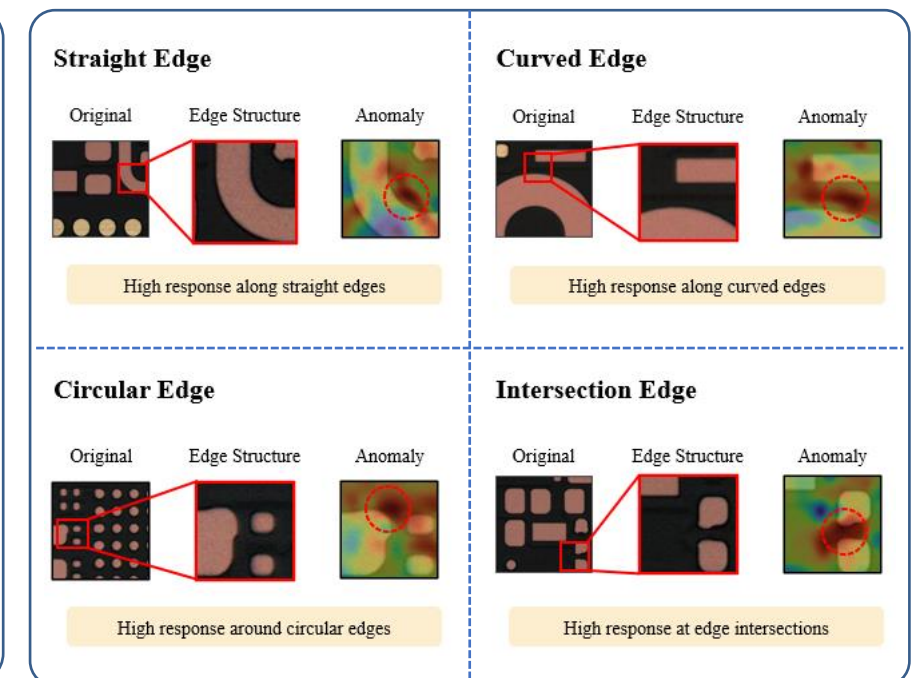
Introduction

Challenge

- In PCB inspection environments, repetitive circuit patterns and similar normal textures frequently appear across different PCB structures and layouts, making it difficult to distinguish subtle defects from normal structures under complex background variations.
- Even when abnormal regions produce high anomaly scores, repetitive edge structures in normal regions can exhibit highly similar score distributions and anomaly score patterns to actual defect regions, limiting ranking separation and increasing false positives.



[Figure 6] Examples of False Positive Responses in PCB Images

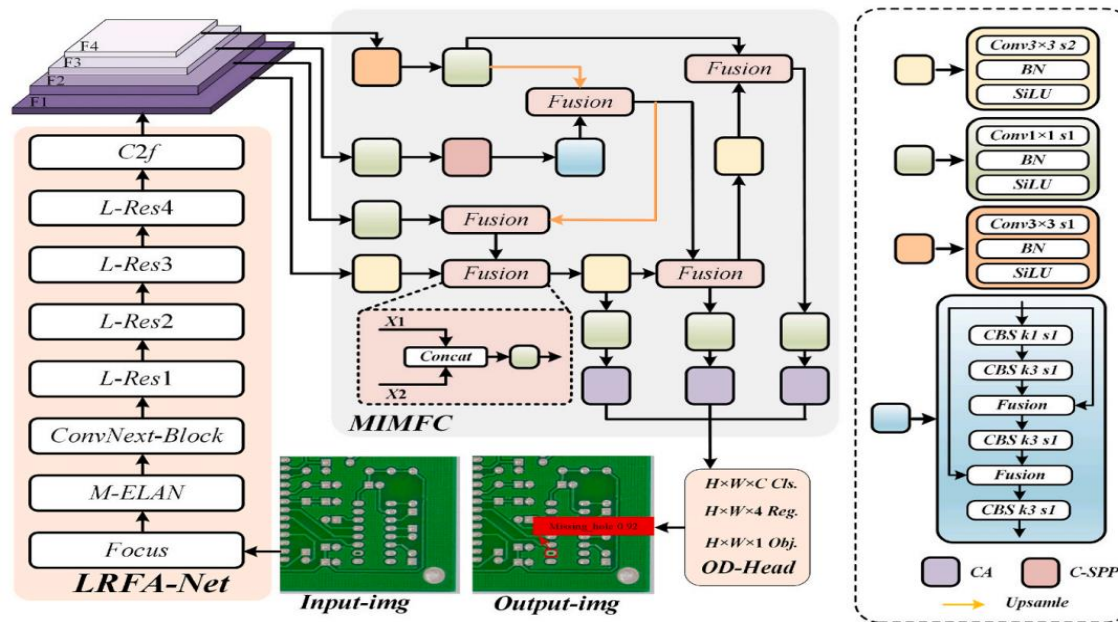


[Figure 7] Examples of Repetitive Edge Structures in PCB Images

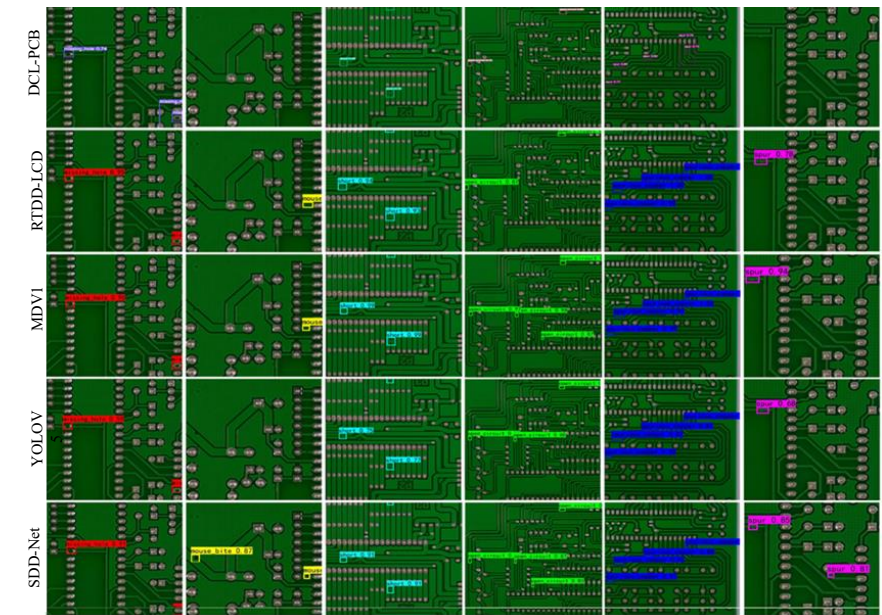
Related Work

Subtle Defect Detection Network: More accurately detect subtle defects on the Printed Circuit Board surface [7]

- SDD-Net enhances PCB defect detection through receptive field augmentation (LRFA-Net), multi-scale feature interaction (MIMFC), Varifocal-CIoU losses, and OD-Head attention to improve subtle defect recognition under complex PCB backgrounds.
- Defect-specific feature optimization relies on annotated defect categories and manually labeled defect samples during training, limiting generalization to unseen and diverse defect patterns and reducing applicability in practical PCB inspection environments.



[Figure 8] Overall framework of EffNet-PCB

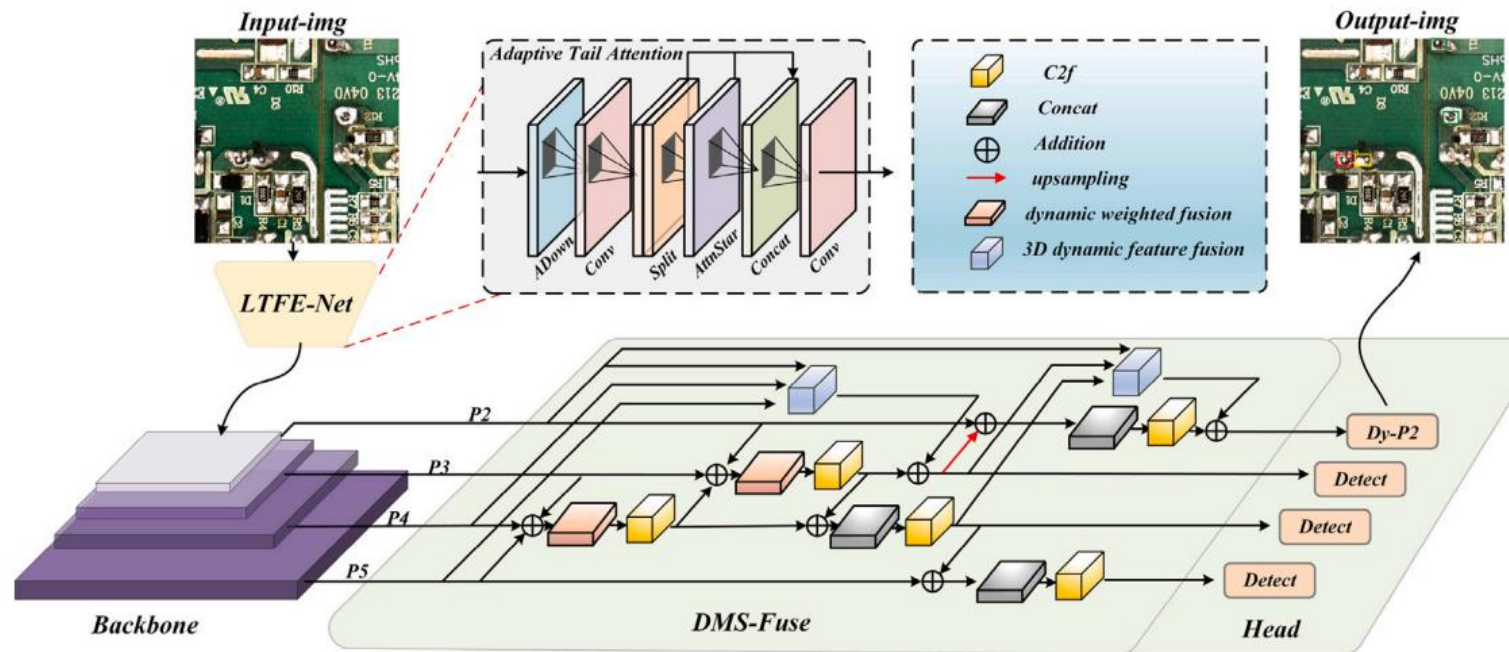


[Figure 9] Qualitative results of PCB anomaly detection

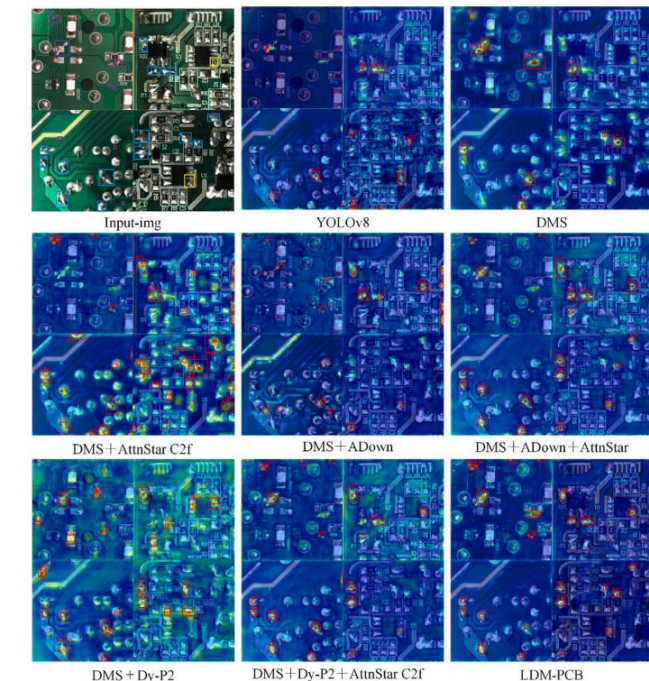
Related Work

A printed circuit board surface defect detection method for long-tail and multi-scale scenarios [8]

- LDM-PCB combines ATA-driven tail feature enhancement, 3D convolution-based DMS-Fuse for dynamic scale integration, and the Dy-P2 layer, thereby addressing long-tail and tiny PCB defect detection by preserving high-resolution semantic details.
- Defect categories with thin structures and low visual contrast remain difficult to recognize, resulting in reduced recall and increased false negative detections, while learning such defect-specific characteristics requires annotated defect samples.



[Figure 10] Overall framework of LDM-PCB

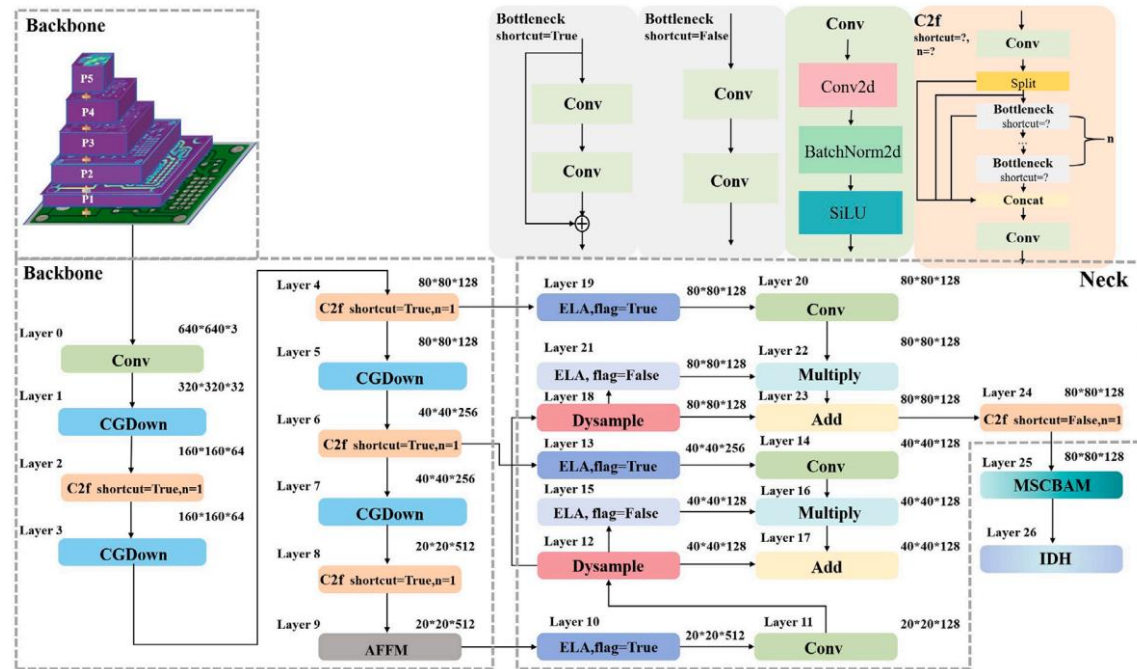


[Figure 11] Qualitative results of PCB anomaly detection

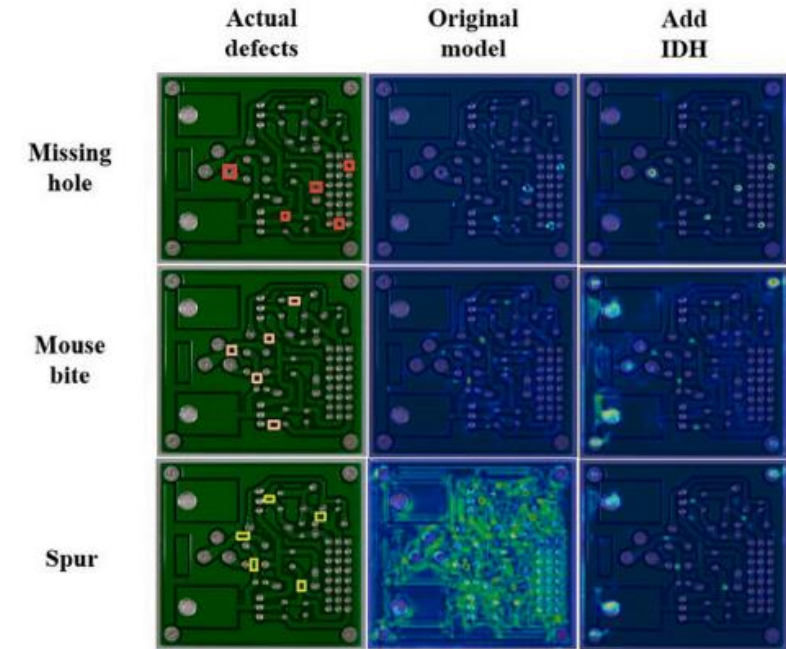
Related Work

A lightweight and high-accuracy framework for Printed Circuit Board defect detection [9]

- EffNet-PCB enhances PCB defect detection through AFFM-based multi-scale feature fusion, HSFPN-E for feature selection, MSCBAM for multi-scale attention, and IDH for localization, improving detection accuracy under complex PCB backgrounds.
- Complex PCB backgrounds and visually similar circuit patterns can still interfere with defect recognition, causing confusion between defect and non-defect regions, while the model relies on learned representations from annotated defect examples.



[Figure 12] Overall framework of EffNet-PCB

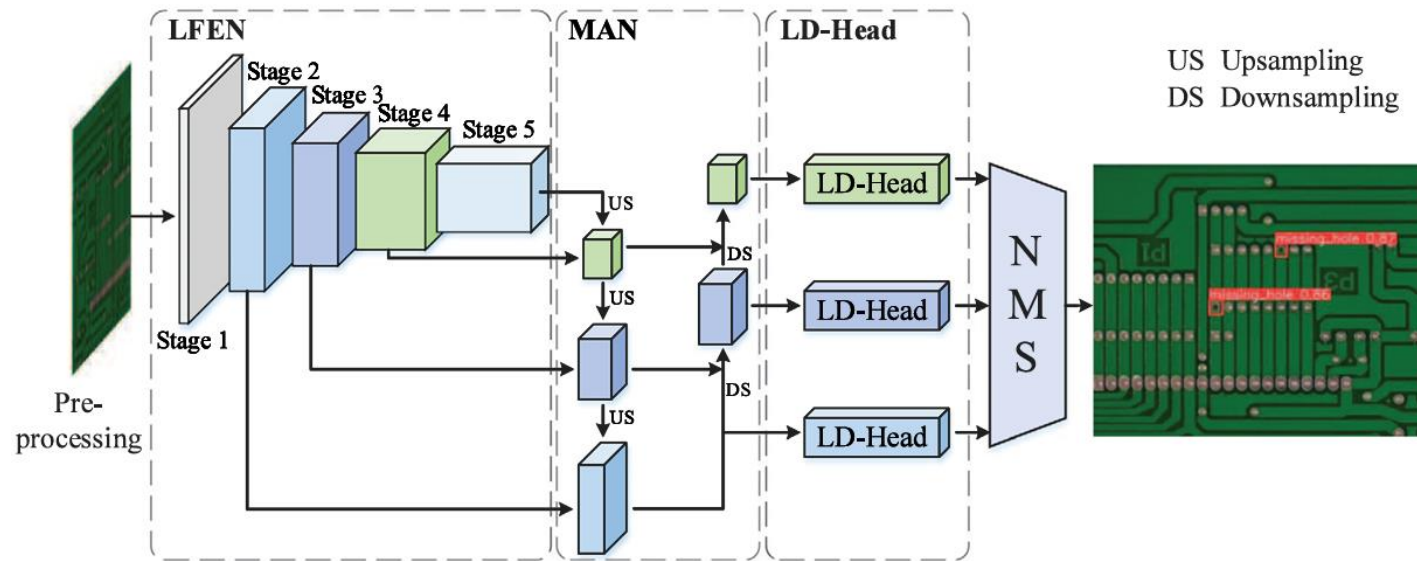


[Figure 13] Qualitative results of PCB anomaly detection

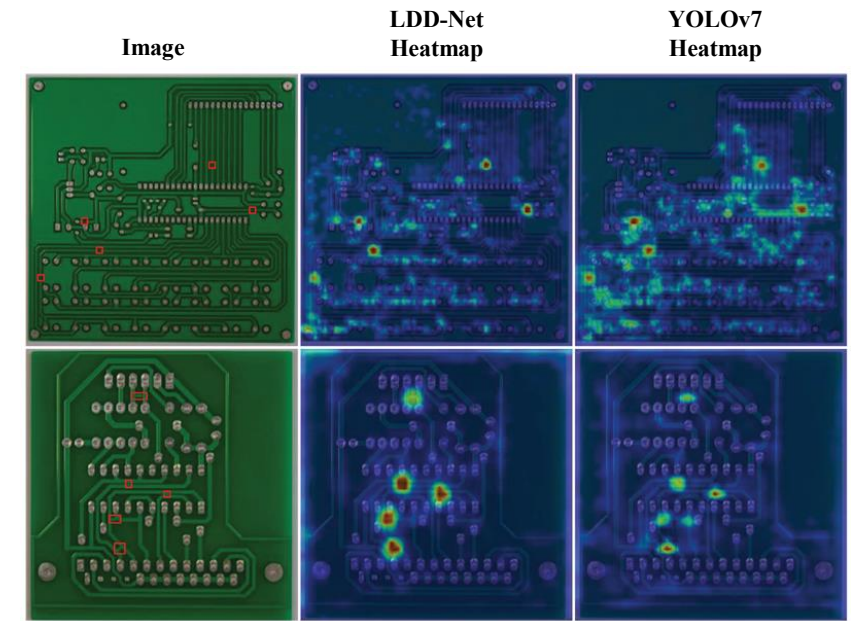
Related Work

LDD-Net: Lightweight printed circuit board defect detection network fusing multi-scale features [10]

- LDD-Net extracts multi scale features through the Lightweight Feature Extraction Network (LFEN), fuses hierarchical information using the Multi Scale Aggregation Network (MAN), and performs PCB defect detection through the lightweight LD Head.
- Supervised defect detection requires predefined defect categories and annotated defect samples, limiting applicability in real manufacturing environments where diverse defect patterns continuously emerge and large scale defect annotation is difficult.



[Figure 14] Overall framework of LDD-Net

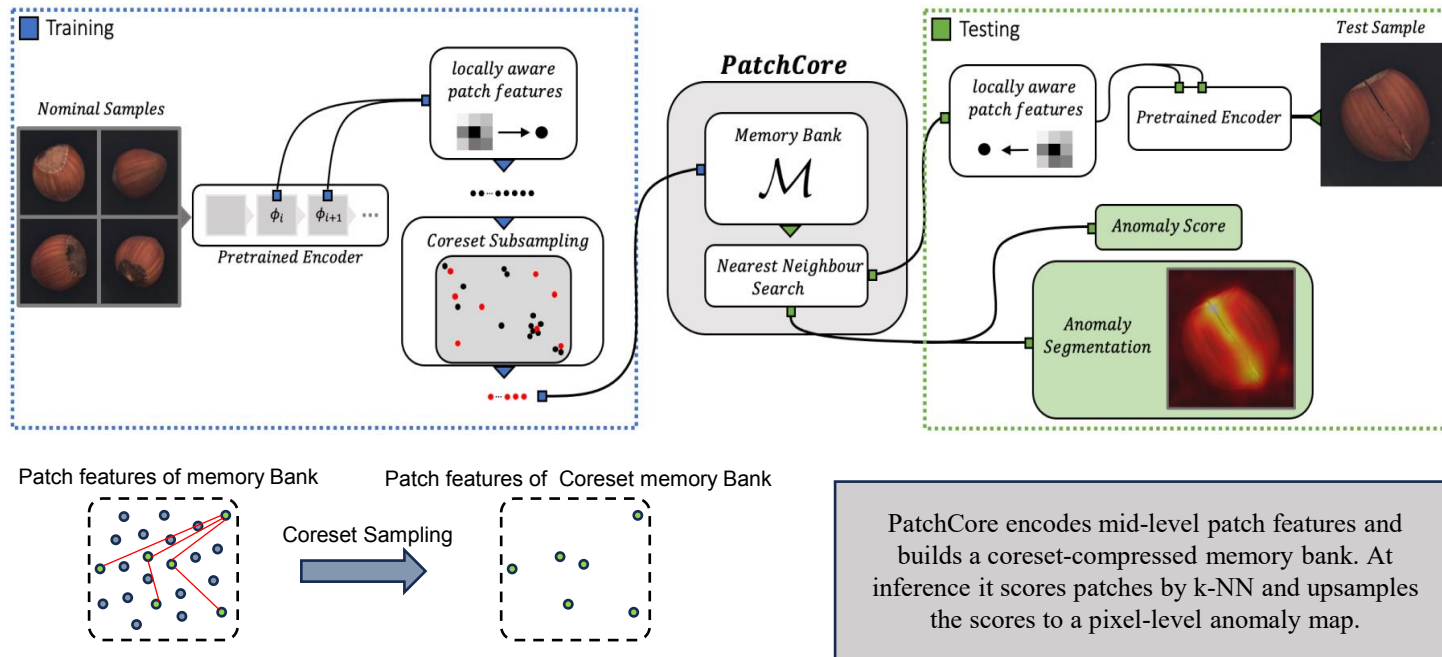


[Figure 15] Qualitative results of PCB anomaly detection

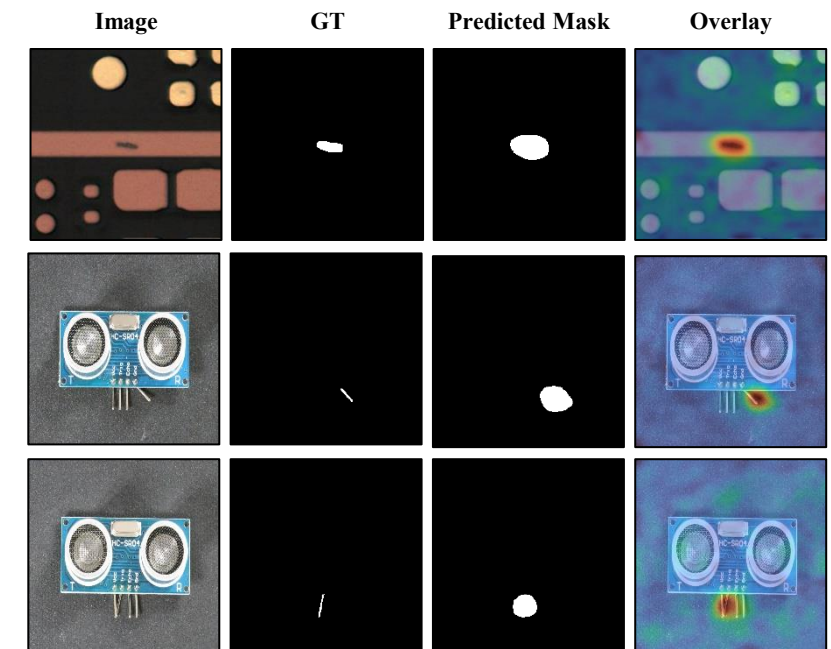
Related Work

Towards Total Recall in Industrial Anomaly Detection [11]

- PatchCore constructs a memory bank by subsampling normal PCB patch features to retain coverage while reducing redundancy, and computes discriminative anomaly scores by comparing each query patch with nearest neighbors in the embedding feature space.
- Similar feature distributions between defect boundaries and normal PCB structures cause anomaly scores to spread into neighboring normal regions, resulting in spatially consistent false positive responses around true defect boundaries and surrounding structures.



[Figure 16] Overall framework of PatchCore

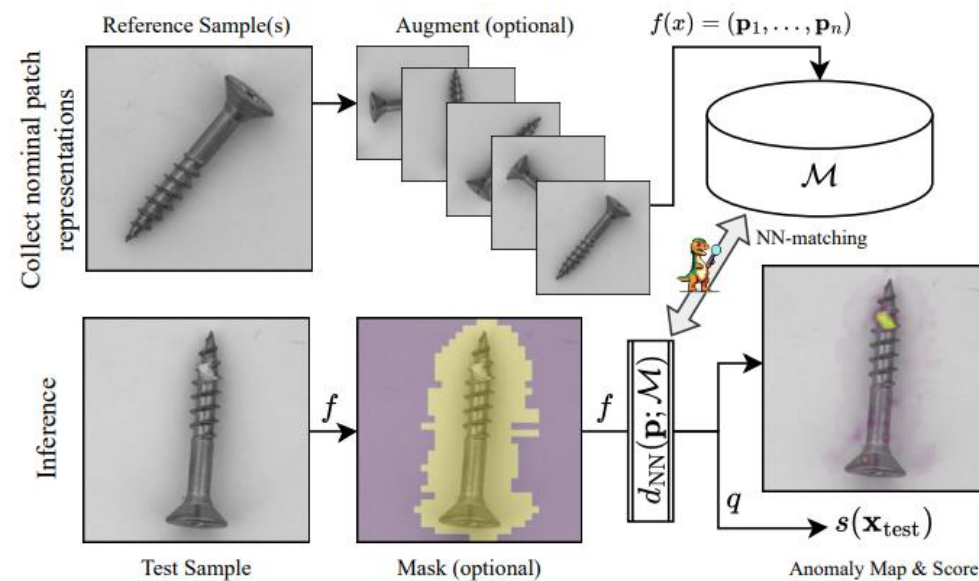


[Figure 17] Qualitative anomaly detection on PCB datasets

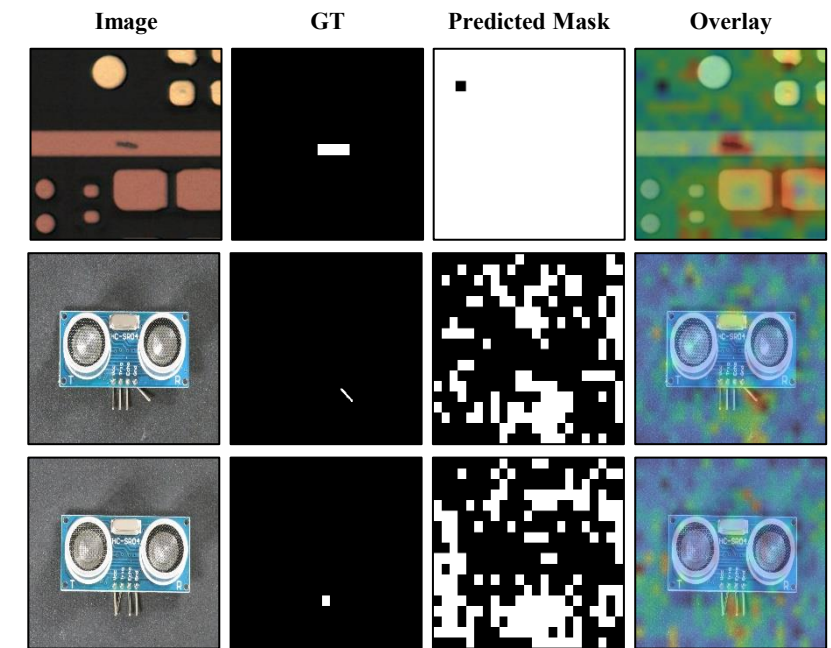
Related Work

AnomalyDINO: Boosting Patch-based Few-shot Anomaly Detection with DINOv2 [12]

- Representative feature patch selection extracts normal patches from DINOv2 ViT using spatial masking and rotation augmentation, builds a representative memory bank, measures patch similarity using cosine distance, and generates discriminative anomaly scores.
- High-level feature representations frequently assign elevated anomaly responses to complex PCB background structures, causing anomaly scores to spread across broad normal regions and producing widespread and spatially diffuse false positive activations.



[Figure 18] Overall framework of Anomaly DINO

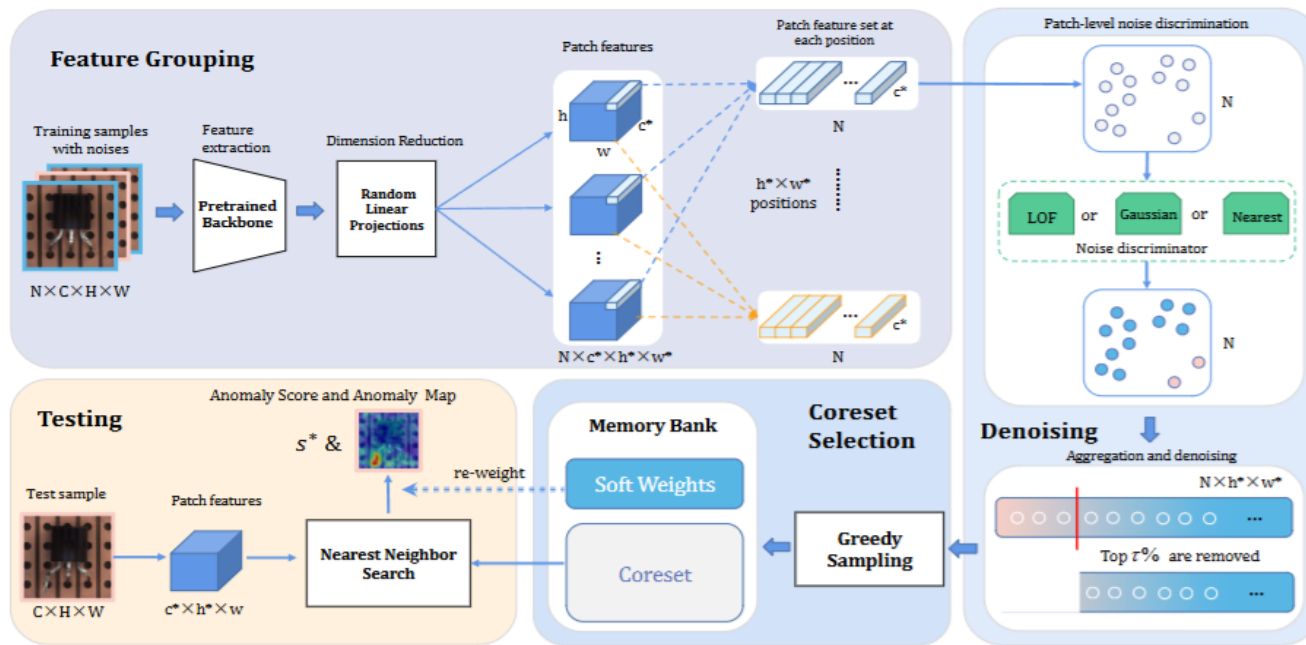


[Figure 19] Qualitative anomaly detection on PCB datasets

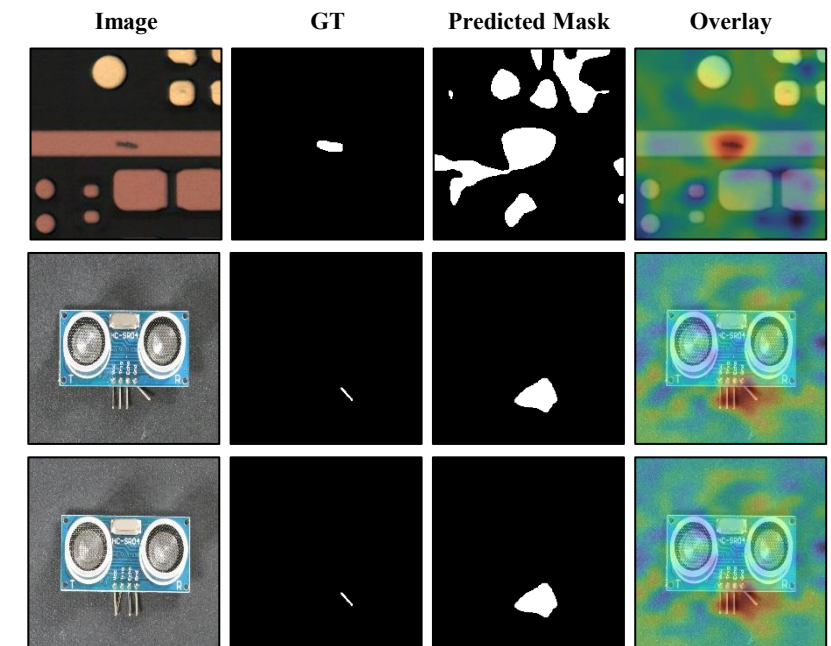
Related Work

SoftPatch: Unsupervised Anomaly Detection with Noisy Data [13]

- SoftPatch utilizes a noise discriminator to assign outlier scores and remove noisy patches, stores the refined patch features in the memory bank to soften the decision boundary, and performs weighted patch k-nearest neighbor retrieval for anomaly scoring.
- Similar anomaly responses between defect regions and surrounding normal backgrounds may remain even after noise suppression, causing anomaly scores to spread across neighboring normal regions and generating spatially consistent false positive responses.



[Figure 20] Overall framework of SoftPatch

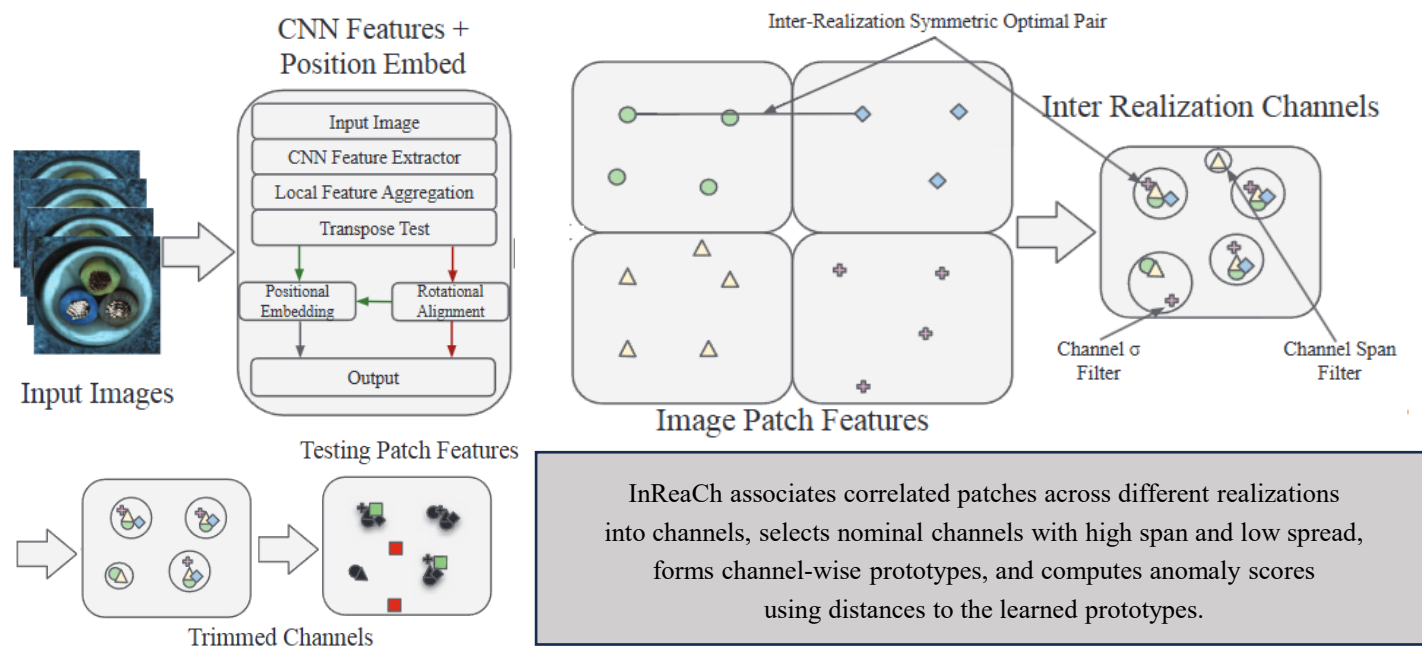


[Figure 21] Qualitative anomaly detection on PCB datasets

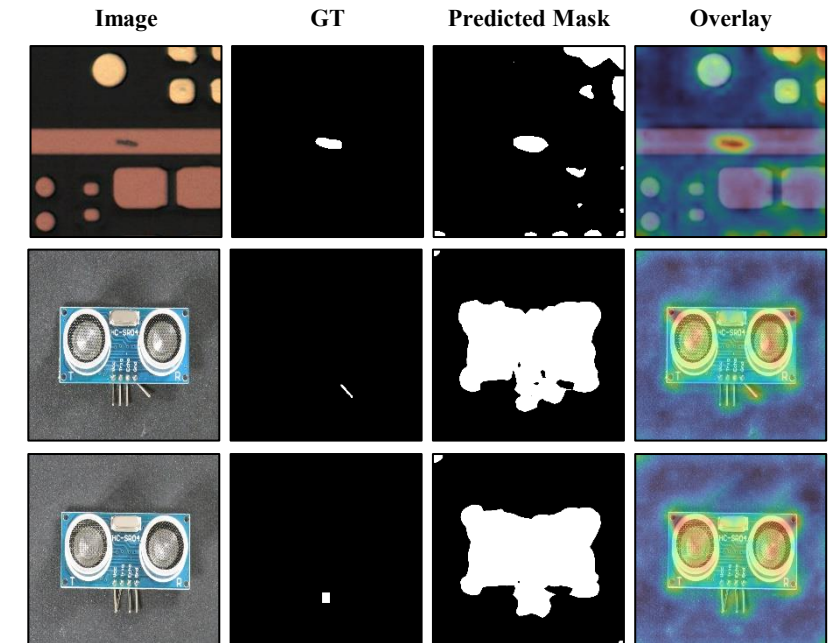
Related Work

Inter-Realization Channels: Unsupervised Anomaly Detection Beyond One-Class Classification [14]

- InReaCh selects channel-wise nominal prototypes by enforcing cross-image consistency between realizations, filters patch features through inter-realization channels, and computes distances to the prototypes for anomaly scoring in feature space representations.
- Dominant circuit structures may be strongly reflected in the learned representations, causing normal circuit regions to receive elevated anomaly responses and generating spatially consistent false positive activations around true defect regions and surrounding boundaries.



[Figure 22] Overall framework of Inter-Realization Channels



[Figure 23] Qualitative anomaly detection on PCB datasets

Related Work

Common Drawback and Solution

- Top anomaly score regions in PCB images can contain repetitive edges and structures, making abnormal regions and normal PCB regions exhibit similar score distributions and causing unstable anomaly score patterns and false positives in normal PCB regions.
- One direct solution for this issue is to compute anomaly scores using neighborhood consistency and structural differences, suppressing repetitive normal patterns and ambiguous edge structures while preserving defect-related anomaly scores across PCB structures.

[7] Zhu, L., et al. "Subtle Defect Detection Network: More Accurately Detect Subtle Defects on the Printed Circuit Board Surface." Engineering Applications of Artificial Intelligence, 2025.
[8] Li, X, et al. "A Printed Circuit Board Surface Defect Detection Method for Long-Tail and Multi-Scale Scenarios." Engineering Applications of Artificial Intelligence, 2026.
[9] Hou, Y., et al. "A Lightweight and High-Accuracy Framework for Printed Circuit Board Defect Detection." Engineering Applications of Artificial Intelligence, 2025.
[10] Zhang, Lei, et al. "LDD-Net: Lightweight Printed Circuit Board Defect Detection Network Fusing Multi-Scale Features." Engineering Applications of Artificial Intelligence, 2024.
[11] Roth, Karsten, et al. "Towards Total Recall in Industrial Anomaly Detection." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022.
[12] Damm, Simon, et al. "AnomalyDINO: Boosting Patch-Based Few-Shot Anomaly Detection with DINOv2." Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 2025.
[13] Jiang, Xi, et al. "SoftPatch: Unsupervised Anomaly Detection with Noisy Data." Advances in Neural Information Processing Systems (NeurIPS), 2022.
[14] McIntosh, Declan, et al. "Inter-Realization Channels: Unsupervised Anomaly Detection Beyond One-Class Classification." Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2023.

Method	Setting	Summary	Common Drawback
Zhu, L, et al. [7] (EAAI, 2025)	Supervised	Detects predefined PCB defect categories using annotated defect samples and multi-scale feature learning.	Although top anomaly score regions in PCB images can contain repetitive edges and structures, abnormal and normal PCB regions often exhibit similar score distributions, causing unstable anomaly responses and false positives , whereas PCB-specific defect detection methods typically rely on supervised learning with manually annotated defect samples .
Li, X, et al. [8] (EAAI, 2026)	Supervised	Detects annotated PCB defect categories through supervised learning with dynamic multi-scale feature fusion.	
Hou, Y, et al. [9] (EAAI, 2025)	Supervised	Learns defect-specific representations from labeled PCB defect samples for supervised defect detection.	
Zhang, Lei, et al. [10] (EAAI, 2024)	Supervised	Detects predefined PCB defect categories using annotated defect samples and attention-guided feature aggregation.	
Roth, Karsten, et al. [11] (CVPR, 2022)	Unsupervised	Computes anomaly scores using nearest-neighbor distances between test patches and memory bank features.	
Damm, Simon, et al. [12] (WACV, 2025)	Unsupervised	Generates anomaly scores from k-NN distances between test patch embeddings and stored normal patch features.	
Jiang, Xi, et al. [13] (NeurIPS, 2022)	Unsupervised	Refines anomaly scores through patch-level denoising and weighted k-NN anomaly scoring.	
McIntosh, Declan, et al. [14] (ICCV, 2023)	Unsupervised	Computes anomaly scores using distances between test features and channel-level nominal prototypes.	

Proposed Method

Notation and Definition

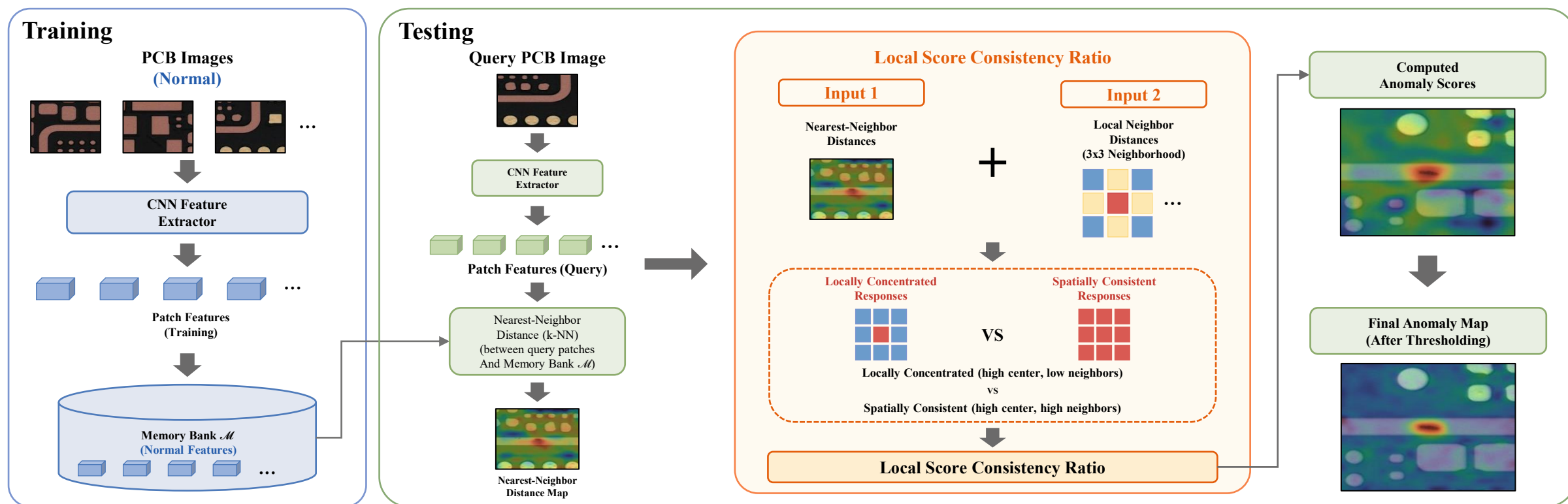
- The PCB dataset is defined as $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, where x_i denotes an input PCB image, y_i represents the corresponding pixel-wise ground truth mask indicating anomalous regions, and N represents the total number of samples in the entire dataset collection.
- A memory bank $\mathcal{M}$ is constructed from non-defective training features, and initial anomaly score map S is generated by computing nearest-neighbor distances d_i between feature patches f_i and their nearest references in $\mathcal{M}$, where larger distances indicate anomalies.

Notation	Name	Definition
$\mathcal{D}$	Dataset	Entire PCB dataset consisting of $\{(x_i, y_i)\}$ pairs
x_i	Input Image	Input PCB image that may contain normal or anomalous regions
y_i	Ground Truth Mask	Pixel-wise binary mask indicating anomalous regions
f_i	Feature Patch	Local feature embedding extracted from encoder backbone
N	Dataset Size	Total number of samples in the dataset
S	Predicted Anomaly Map	Pixel-wise anomaly map generated from nearest-neighbor distances
$\mathcal{M}$	Memory Bank	Set of normal feature embeddings collected from non-defective training images
d_i	Nearest-Neighbor Distance	Distance between f_i and its nearest reference in $\mathcal{M}$
AP	Average Precision	Metric measuring precision-recall area for pixel-wise anomaly detection
F_1	F1 Score	Harmonic mean of precision and recall used as auxiliary evaluation

Proposed Method

Graphical abstract

- In this study, a local consistency based anomaly score computation method is introduced to improve anomaly score separation between defect and normal regions by incorporating neighboring score relationships, enabling anomaly detection across PCB structures.
- Based on patch anomaly scores and local score consistency ratios, the proposed method computes refined anomaly scores to enhance anomaly score separation between defect regions and neighboring normal structures, generating the final anomaly score map S .



[Figure 24] Overview structure of proposed model framework

Proposed Method

Local Consistency-based Anomaly Score

- Starting from patch anomaly scores generated by nearest-neighbor distances, the proposed method computes refined anomaly scores using neighboring score relationships, enhancing anomaly score separation between defect regions and neighboring normal structures.
- The proposed method computes a local score consistency ratio $E(p)$, derives a suppression coefficient $\gamma(p)$, and generates the final anomaly score $S_{final}(p)$, suppressing consistent normal score patterns while preserving meaningful defect related anomaly scores.

Algorithm 1 Local Consistency-based Anomaly Score Computation

Require: Baseline anomaly score map S_{base} , neighborhood size k , suppression factor α , constant ϵ

Ensure: Final anomaly score map S_{final}

```
1:  $S_{final} \leftarrow \emptyset$ 
2: for each patch  $p$  in  $S_{base}$  do
3:    $W(p) \leftarrow$  patches within the  $k \times k$  neighborhood centered at  $p$ 
4:    $L_{sum} \leftarrow 0$ 
5:    $L_{count} \leftarrow 0$ 
6:   for each patch  $q \in W(p)$  do
7:      $L_{sum} \leftarrow L_{sum} + S_{base}(q)$ 
8:      $L_{count} \leftarrow L_{count} + 1$ 
9:   end for
10:   $\mu_{W(p)} \leftarrow L_{sum} / L_{count}$ 
11:   $E(p) \leftarrow \mu_{W(p)} / (S_{base}(p) + \epsilon)$ 
12:   $\gamma(p) \leftarrow \max(0, 1 - \alpha E(p))$ 
13:   $S_{final}(p) \leftarrow S_{base}(p) \times \gamma(p)$ 
14: end for
15: return  $S_{final}$ 
```

Line 1 $\rightarrow$ Initialize the final anomaly score map S_{final} .
Line 2 $\rightarrow$ Iterate over each patch p in S_{base} .
Line 3 $\rightarrow$ Define the local neighborhood window $W(p)$.
Line 4 $\rightarrow$ Initialize the local score accumulator L_{sum} .
Line 5 $\rightarrow$ Initialize the local patch counter L_{count} .
Line 6 $\rightarrow$ Iterate over neighboring patches $q \in W(p)$.
Line 7 $\rightarrow$ Accumulate neighboring anomaly scores.
Line 8 $\rightarrow$ Count neighboring patches.
Line 9 $\rightarrow$ Finish collecting neighboring scores.
Line 10 $\rightarrow$ Compute the local mean anomaly score $\mu_{W(p)}$.
Line 11 $\rightarrow$ Compute the local score consistency ratio $E(p)$.
Line 12 $\rightarrow$ Compute the suppression coefficient $\gamma(p)$.
Line 13 $\rightarrow$ Generate the final anomaly score $S_{final}(p)$.
Line 14 $\rightarrow$ Finish processing patch p .
Line 15 $\rightarrow$ Return the final anomaly score map S_{final} .

Experimental Settings

Dataset

Dataset	Train Image	Test Image	Annotation	Input Size
MeiweiPCB	775	366	Pixel-level mask	Various
PCBBank	3,923	1,400	Pixel-level mask	Various
VisAPCB	3,211	805	Pixel-level mask	Various

Cross Validation

- Method: Per-dataset K-Fold on full PCB dataset (image-level split)
- Folds $\times$ Repeats : 5×3
- Data Split Ratio: Train : Validation : Test = 80% : 10% : 10%
- In the unsupervised setting, only normal PCB images were used for training while both normal and defective PCB images were used for testing.

Experimental Settings

Hyperparameter Settings

NN = Nearest Neighbor

Method	Batch Size	Epochs	Loss Function	Optimizer	Learning Rate
PatchCore [11] (CVPR, 2022)	8 (feature extraction)	0 (index build only)	k-NN (L2) distance; coreset + FAISS	None	(not used)
AnomalyDINO [12] (WACV, 2025)	8 (feature extraction)	0 (index/memory build only)	k-NN distance (L2 or 1-cosine); image score = mean top-1% patch distances	None	(not used)
SoftPatch [13] (NeurIPS, 2022)	8 (feature extraction)	0 (scoring only)	Distance-based scoring	None	(not used)
InReaCh [14] (ICCV, 2023)	8 (feature extraction)	0 (aggregation only)	k-NN (L2) distance (inter-realization aggregation)	None	(not used)

Evaluation Measures

- Pixel-level F1 Score: $F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ Represents the harmonic mean of precision and recall, serving as a complementary quantitative metric that balances the trade-off between false positives and false negatives for pixel-wise anomaly detection in PCB inspection tasks.
- Pixel-level Average Precision (AP): $AP = \int_0^1 \text{Precision}(\text{Recall}) d\text{Recall}$ Represents the area under the precision-recall curve, evaluating the trade-off between precision and recall for pixel-wise anomaly scores in PCB images across all possible threshold settings and score distributions.

Experimental Results

Performance Comparison

- We conducted a controlled comparative study on PCB datasets by unifying feature extraction, retrieval settings, and memory budget across all methods to ensure fair comparisons and evaluate the contribution of the proposed anomaly score computation strategy.
- In this setting, our method (0.4319) outperformed AnomalyDINO (0.3711) and SoftPatch (0.2739), suggesting that improved anomaly score separation between defect and normal regions enhances anomaly detection performance across complex PCB structures.

[Table 2] Comparison of detection performance (F1-score) on PCB datasets

	F1-Score		
	MeiweiPCB	PCBBank	VisAPCB
Proposed	0.3547 ± 0.0467	0.4319 ± 0.0071	0.2476 ± 0.0001
PatchCore	0.2979 ± 0.0076▼	0.2499 ± 0.0008▼	0.1498 ± 0.0007▼
AnomalyDINO	0.0894 ± 0.0111▼	0.3711 ± 0.0032▼	0.2151 ± 0.0093▼
SoftPatch	0.0552 ± 0.0511▼	0.2739 ± 0.0091▼	0.1387 ± 0.0025▼
InReach	0.1756 ± 0.0046▼	0.0270 ± 0.0024▼	0.0300 ± 0.0019▼

[Table 3] Comparison of detection performance (Pixel AP) on PCB datasets

	Pixel AP		
	MeiweiPCB	PCBBank	VisAPCB
Proposed	0.3719 ± 0.0026	0.3503 ± 0.0011	0.2704 ± 0.0001
PatchCore	0.3575 ± 0.0048▼	0.3344 ± 0.0022▼	0.2675 ± 0.0017▼
AnomalyDINO	0.1754 ± 0.0039▼	0.3464 ± 0.0032▼	0.2197 ± 0.0024▼
SoftPatch	0.0843 ± 0.0070▼	0.1951 ± 0.0078▼	0.2124 ± 0.0014▼
InReach	0.0906 ± 0.0035▼	0.0129 ± 0.0012▼	0.0139 ± 0.0008▼

*Best results are marked in bold. A triangle (▼) indicates statistical significance at the 0.05 level based on paired t-tests against the proposed model.

Experimental Results

Qualitative Analysis

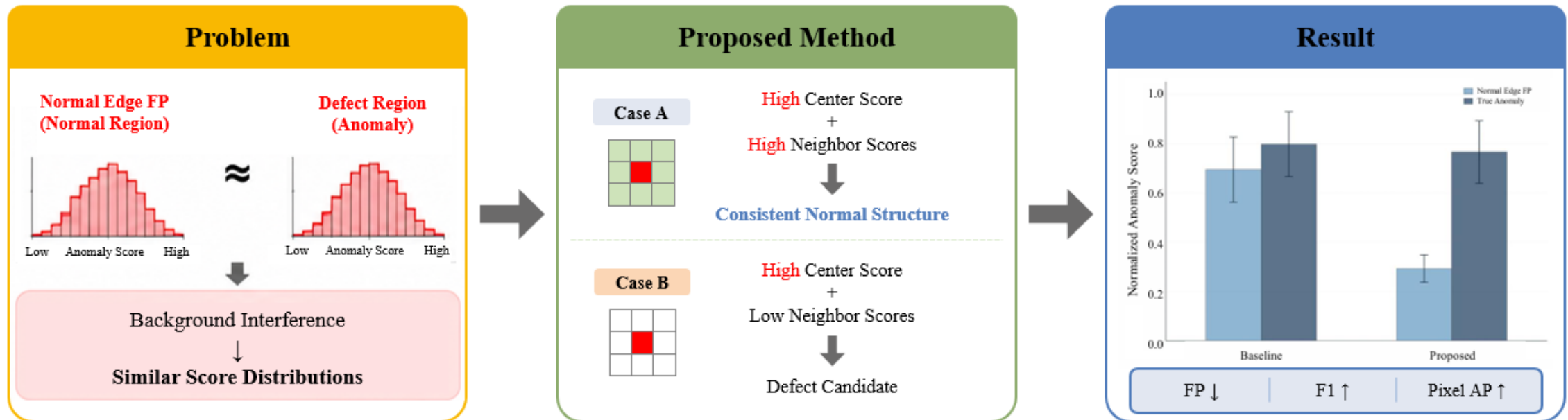
- We conducted an in-depth qualitative analysis on PCB images with repetitive circuit patterns to examine whether our anomaly score computation strategy suppresses repetitive normal structures while preserving anomaly scores on defect regions and edge structures.
- The qualitative comparisons show that while baseline methods often over-activate on repetitive PCB patterns and edge structures, our method focuses on true defects by reducing unstable anomaly score patterns and suppressing false positives across normal structures.

Method / Images	Image01	Image02	Image03	Image04	Image05	Image06	Image07	Image08
Input Images								
Ground Truth								
Mask Overlay (magenta)								
Proposed								
AnomalyDINO (Second best)								
SoftPatch (Third best)								

[Figure 25] Qualitative comparison on images with highly regular patterns, showing anomaly maps from methods ranked by pixel AP, including the proposed approach.

Conclusion

- This study presents a local score consistency-based anomaly score computation method for patch-based anomaly detection, which suppresses background-induced false positives while preserving defect-related anomaly scores in PCB inspection environments with repetitive structures.
- The proposed approach improves pixel-level unsupervised anomaly detection performance under complex and repetitive PCB structures by suppressing repetitive background interference and reducing false positives through local score consistency based anomaly score computation.
- Experimental results confirm that the proposed anomaly score computation strategy reduces unstable anomaly score patterns and background-induced false positives under complex PCB structures, demonstrating its potential for practical industrial PCB inspection applications.



[Figure 26] Summary of the Proposed Approach and Results.

Thank you

Reference

- [1] Guo, Feng, et al. “Multi-Granularity Relation Enhancement Network for Tiny Defect Detection on Printed Circuit Board.” IEEE Transactions on Instrumentation and Measurement, 2025.
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