Diffusion-Based Data Augmentation for Industrial Anomaly Detection

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The Cold-Start Problem in Industrial Inspection

“In the relentless pursuit of manufacturing excellence, industrial anomaly detection stands as a cornerstone of quality assurance.”

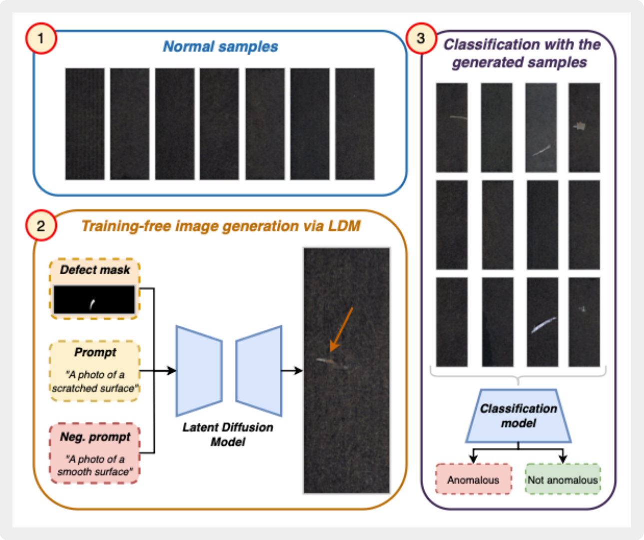
- Industrial datasets are dominated by normal, defect-free samples
- Anomalous examples are scarce, diverse, and unpredictable
- Traditional supervised learning becomes impractical
- Real-world consequence: missed defects, manufacturing waste, safety risks

DIAG: Synthetic Anomaly Generation with Expert Guidance

DIAG uniquely combines:

- Domain expert knowledge, “human-in-the-loop”
- Latent Diffusion Models
- Spatial and textual conditioning
- In-distribution realism

Result: Synthetic defects statistically indistinguishable from real anomalies



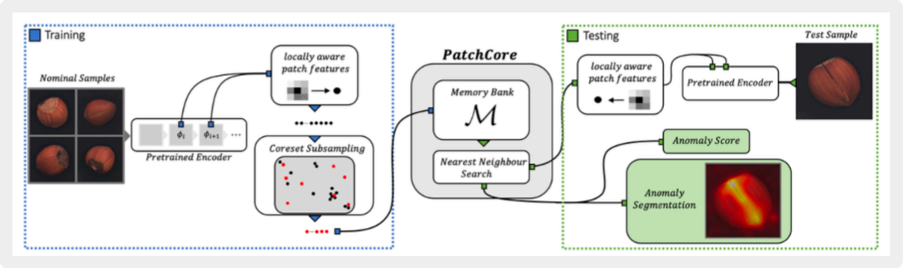
Memory Bank Approach for Anomaly Detection:

Key components:

- Pre-trained feature extraction
- Normal patch memory bank
- Coreset subsampling (efficiency)
  - select a smaller representative subset
- Nearest-neighbor search
- Anomaly score –> distance from normal patterns

Strengths:

- Effective in cold-start scenarios
- Needs only defect-free samples
- Optimal performance



Dual Memory Bank PatchCore

"This thesis explore a dual memory bank approach for PatchCore designed to move beyond modeling only normal data distributions by incorporating real and synthetic anomalies."

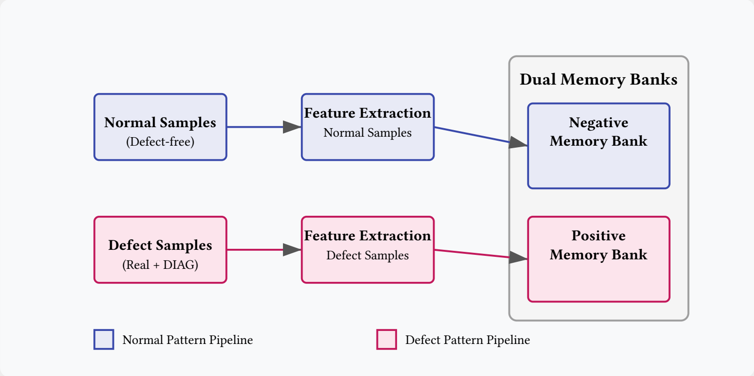
Standard PatchCore:

- Single memory bank (normal)
- Anomaly = distance to normals

Our Dual Bank Extension:

- Negative bank (normal patterns)
- Positive bank (real and synthetic anomalies)
- Aims to:
  - create a more comprehensive decision boundary
  - enhance detection accuracy

Dual Memory Bank Architecture



Negative Memory Bank:

- Normal patch features
- Captures “normality” distribution
- Distance = deviation from normal

Positive Memory Bank:

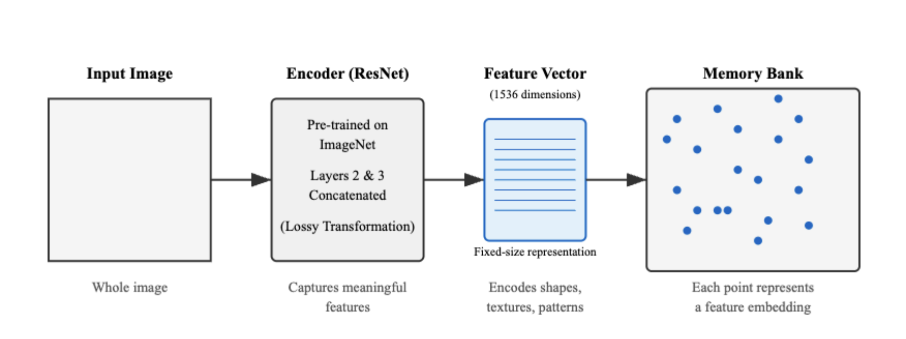
- Defective patch features
- Combines real + synthetic anomalies
- Distance = similarity to defects

Negative Memory Bank Construction Process

Feature Extraction: ResNet50 backbone, layers 2 & 3

Feature Concatenation: 1536-dimensional patch features

Coreset Subsampling: 2% subsampling rate to maintain a representative subset



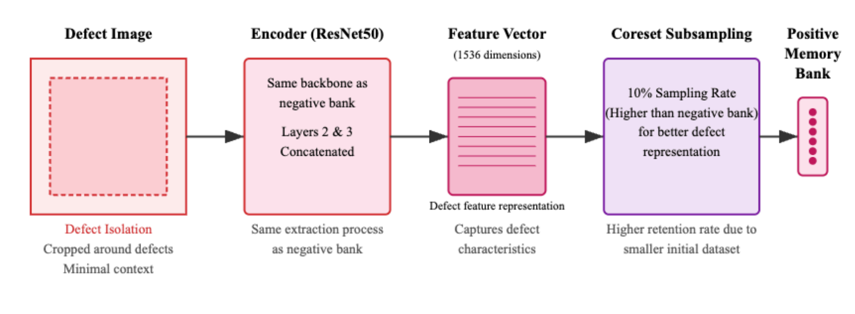
Positive Memory Bank Construction Process

Defect Isolation: Cropped images around defects, minimizing context.

Feature Extraction: ResNet50 backbone, layers 2 & 3

Feature Concatenation: 1536-dimensional patch features

Coreset Subsampling: 10% subsampling rate for better defect representation



(i) Image-Level Anomaly Scoring Approach

1. Negative Distance Calculation:

- Distance to nearest normal patch (s_N^*):

$$s_N^* = \|m^{\text{test},*} - m^*\|$$

where:

$$m^{\text{test},*}, m^* = \text{argmax}_{m^{\text{test}} \in P(x^{\text{test},*})} \text{argmin}_{m \in M_N} \|m^{\text{test}} - m\|_2$$

- Neighborhood-aware weighting:

$$w_N = 1 - \left(\frac{\frac{e^{S_N^*}}{\sqrt{d}}}{\sum_{m \in N_b(m^*)} e^{\frac{||m^{\text{test},*} - m||_2}{\sqrt{d}}}} \right)$$

2. Positive Distance Calculation:

- Distance to nearest anomalous patch (s_P^*):

$$s_P^* = \|m^{\text{test},+} - m^+\|$$

where:

$$m^{\text{test},+}, m^+ = \text{argmax}_{m^{\text{test}} \in P(x^{\text{test},+})} \text{argmin}_{m \in M_P} \|m^{\text{test}} - m\|_2$$

- Neighborhood-aware weighting:

$$w_P = \left(\frac{\frac{e^{S_P^*}}{\sqrt{d}}}{\sum_{m \in N_b(m^+)} e^{\frac{||m^{\text{test},+} - m||_2}{\sqrt{d}}}} \right)$$

(ii) Image-Level Anomaly Scoring Approach

Final Anomaly Score (Ratio Score):

Combines both distances into single score: $s_{\text{ratio}} = \frac{s_N}{s_P + \varepsilon}$

Negative Anomaly Score:

$s_N = w_N \cdot s_N^*$

Positive Anomaly Score:

$s_P = w_P \cdot s_P^*$

Intuition:

- A True defect should be dissimilar from normal patterns and similar to known defects
- Multiplicative interaction amplifies true anomalies

Theoretical Advantages of Dual Memory Bank Approach

Challenge	Standard PatchCore	PatchCoreDual
Cold-start problem	Models only normality	Models both normality + anormality
Anomaly variations	Struggles with diverse defects	Leverages real and synthetic samples
Features robustness	Single perspective	Dual complementary perspectives

Key: Combining distance from normal with similarity to defects for more robust and accurate industrial anomaly detection

Comparative Performance Analysis

Method	Image-level AUROC (%)	Pixel-wise AUROC (%)
PatchCore	91.2	95.8
PatchCoreDual	93.1	96.9
PatchCoreDual + DIAG	94.2	97.7

Key Improvements:

- Image-level detection: +3.28% over baseline
- Pixel-level localization: +1.99% over baseline
- Consistent gains across all evaluation metrics

Impact of Synthetic Data

Synthetic Samples	Image AUROC (%)	Pixel AUROC (%)
0	93.1	96.9
50	93.4	97.1
100	94.2	97.7
150	93.5	97.2

Key Observations:

- Performance increases with synthetic samples up to 100
- Optimal performance at 100 samples (50 per prompt)

Implications for Industrial Quality Control

Key Findings:

- Dual modeling creates more nuanced decision boundaries
- Synthetic samples effectively augment limited real defects
- Memory-based approach maintains efficiency
- Cold-start problem effectively addressed

Real-world Impact:

- Reduced false negatives = fewer defective products shipped
- Particularly valuable where defects are rare but critical

Opportunities for Advancement

“This work sets a preliminary analysis that shows that even limited positive samples, when strategically leveraged, can enhance detection capabilities.”

Current Limitations:

- Resize operations affect feature quality
- Limited dataset diversity

Future Directions:

- Different Scoring Mechanism
- Experiment with different Datasets
- Multi-domain adaptability testing

Looking Ahead

"By combining memory-based techniques with diffusion-based synthetic data augmentation, PatchCoreDual shows how dual modeling approaches can help industrial anomaly detection in the face of limited defect samples."

Future of Industrial Inspection:

- Growing demand for robust, adaptable inspection systems
- Generative AI will continue improving synthetic data quality
- Memory-based approaches offer flexible framework for evolution

Thank You For Your Attention!