

When Textures Deceive: Weakly Supervised Industrial Anomaly Detection with Adapted-Loss CycleGAN

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Abstract

Complex background textures challenge industrial anomaly detection (IAD) due to their intricate spatial variations, yet they are underrepresented in datasets like MVTecAD. Pixel-wise labeling is impractical, while existing weakly supervised and unsupervised methods largely overlook such textures due to the lack of suitable benchmarks. Moreover, subtle domain discrepancies in textures and occluded anomalies can degrade the performance of unsupervised approaches. GAN-based approaches, though widely used, have inherent loss function flaws reducing the effectiveness of IAD in complex environments. We introduce the Manufacturing Complex Background Texture (MCBT) dataset with 1,027 real-world images of diverse machining-induced textures, and propose Adapted-Loss Cycle-Consistent GAN (AL-CycleGAN) that leverages domain transfer while mitigating GAN limitations via a power-switch algorithm. Our analysis demonstrates that (1) MCBT introduces greater texture complexity while complementing standard datasets, (2) AL-CycleGAN achieves state-of-the-art performance on both MCBT and existing benchmarks, and (3) the proposed approach significantly improves GAN-based IAD by addressing critical loss function limitations.

1. Introduction

The industrial anomaly detection (IAD) market is projected to reach \$14.59 billion by 2030, growing at 16.5% annually [1]. This expansion is driven by increased image data availability across automotive, aerospace, and manufacturing sectors, enabling automated surface defect inspection and reducing reliance on manual evaluations [2]. Current state-of-the-art (SOTA) IAD methods employ machine learning to detect pixel intensity and texture variations between normal and anomalous surfaces [3, 4].

However, real-world industrial settings present unique challenges for IAD. Complex background textures—characterized by diverse contrast levels, brightness variations, multi-scale entropy, Gabor filter responses,

and local binary patterns (LBP)—can obscure anomalies, making precise segmentation difficult. Furthermore, the lack of large-scale, precisely labeled datasets limits the effectiveness of supervised learning approaches, as annotating anomalies at the pixel level remains costly and labor-intensive [5]. Unsupervised and weakly supervised learning methods are gaining widespread adoption due to their efficacy in leveraging large-scale datasets with zero or minimal annotation, reducing costs while achieving performance comparable to fully supervised methods [6].

The vast diversity and complexity of industrial surface textures and anomaly morphologies pose another challenge, as they significantly blur the boundary between anomaly-free and anomalous domains. This limits the performance of unsupervised models, which are trained exclusively on anomaly-free data and may fail when anomaly patterns are not distinct from the background texture or when there is high variability within the anomaly-free domain.

In contrast, weakly supervised IAD methods utilize anomaly-free data along with indirect, noisy, or partially labeled anomalous data (e.g., image-level rather than pixel-level labels) to train models. Consequently, they can better capture the complexity of the data than unsupervised methods while reducing the extensive labeling effort required by supervised approaches [6]. A major class of weakly supervised methods relies on GANs. However, GAN-based IAD methods may require extensive post-processing or suffer from errors induced by their flawed loss function (elaborated in Section 4.3).

Moreover, most SOTA weakly supervised IAD methods train on mainstream benchmark datasets such as MVTecAD [7]. However, these datasets predominantly feature simpler and more uniform textures, whereas real-world industrial images exhibit far greater variability. As a result, models trained on these datasets often fail when deployed in industrial scenarios [8][9].

To address these challenges, this paper presents two primary contributions:

1. We introduce the Manufacturing Complex Background Texture (MCBT) dataset, a new IAD benchmark that

captures diverse and intricate manufacturing surface textures. Comprising 1,027 images—800 anomaly-free and 227 defective—MCBT extends beyond existing datasets by incorporating a wider range of machining-induced patterns and complex directional structures. Quantitative texture analysis shows that MCBT exhibits higher mean entropy and Gabor standard deviation than benchmarks like MVTecAD and BTAD, creating a more challenging textural space where defects blend into variable backgrounds. As a result, state-of-the-art IAD models such as SimpleNet [10] and Mixed Supervision [11] struggle in MCBT, highlighting the need for more robust anomaly detection methods.

2. We propose the Adapted-Loss Cycle-Consistent GAN (AL-CycleGAN), which leverages CycleGAN’s domain transfer capabilities [12] and modifies its training loss function to enhance IAD. AL-CycleGAN effectively captures and differentiates complex surface textures and defect patterns through weakly supervised adversarial learning, using generator and discriminator networks trained on anomaly-free and anomalous images with image-level annotations. Defects are detected and localized based on patch-wise discriminator outputs. Notably, AL-CycleGAN effectively addresses the inherent mislabeling error in CycleGAN by refining the loss function and incorporating a power-switch algorithm during model training (elaborated in Section 4). Compared to existing methods, AL-CycleGAN achieves competitive and often superior performance in detecting and localizing anomalies across various benchmark datasets, including the MCBT dataset.

The remainder of the paper is organized as follows. Section 2 provides an overview of related work. Section 3 introduces the MCBT dataset. The details of our loss function modifications and training strategy are discussed in Section 4. Section 5 presents the anomaly detection results, along with comparison and ablation studies. Conclusions are given in Section 6. Code and dataset are publicly available at: <https://github.com/ganatma/AL-CycleGAN>

2. Related work

Weakly supervised IAD methods have gained prominence for capturing subtle differences between non-defective and defective samples without pixel-wise annotations, using indirect or partial supervision signals that make them more practical for real-world industrial applications where fully labeled datasets are scarce.

Feature-based methods leverage pre-trained models, or Class Activation Maps (CAMs) to highlight discriminative regions within an image. Lin et al. [13] proposed LED-Net, integrating CAMs with deep convolutional networks to localize defects using image-wise labels. Although effective, CAM-based methods suffer from sensitivity to net-

work architecture, class imbalance, and computational inefficiencies, limiting their adaptability to diverse industrial textures.

Reconstruction-based methods like AutoEncoders [14] identify anomalies through reconstruction errors but often overgeneralize by restoring defective regions as normal. GAN-based approaches use generators to enhance reconstruction with adversarial learning for better anomaly localization. Models including f-AnoGAN [15], GANomaly [16], and Efficient GAN [17] detect defects by training on normal images and identifying reconstruction deviations, while DefectGAN [18] uses CycleGAN to translate between defective and non-defective domains, generating synthetic defects as weak supervision signals.

Despite their advantages, GAN-based IAD methods face fundamental challenges. Many rely on image comparison metrics such as the Structural Similarity Index Metric (SSIM) [19] to quantify reconstruction differences, making them highly sensitive to artifacts rather than actual defect patterns. Additionally, CycleGAN-based methods often struggle with over-reconstructing defective regions, leading to a reduced defect contrast and limiting their applicability to complex industrial textures (elaborated in Section 4).

These limitations motivate our proposed AL-CycleGAN, which modifies the loss function of CycleGAN to mitigate mislabeling errors and improve weakly supervised IAD in complex background textures. AL-CycleGAN introduces a dual-purpose framework: (i) an efficient anomaly localization method utilizing the discriminator, and (ii) a data augmentation strategy leveraging the generator to synthesize realistic defect patterns.

3. MCBT dataset

High-quality datasets are essential for advancing IAD, particularly for deep learning-based methods that rely on diverse and representative training samples. However, acquiring large-scale, well-annotated industrial datasets presents inherent challenges due to proprietary restrictions, the rarity of defect occurrences, and the high cost of manual labeling. While synthetic data generation provides an alternative, such methods often fail to replicate the intricate, machining-induced textures present in real-world manufacturing. Consequently, standardized benchmark datasets are crucial to ensuring that IAD models generalize effectively across complex industrial surfaces.

While benchmark datasets such as MVTecAD [7], BTAD [20], KSDD [21], and KSDD2 [11] have driven progress in IAD, they predominantly feature structured or uniform textures, making anomalies relatively easier to distinguish. However, real-world industrial surfaces exhibit significantly higher textural complexity, where machining processes introduce directional patterns, varying contrast, and stochastic microstructures that can obscure defects.

This leads to a fundamental challenge: state-of-the-art IAD models, trained on existing benchmarks, often fail to generalize when applied to surfaces where defects blend into highly variable backgrounds.

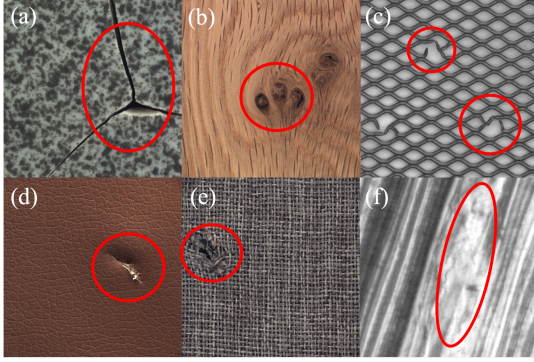


Figure 1. Comparison of textures from MVTecAD (a-e) and MCBT (f). MCBT exhibits higher spatial frequency, directional patterns, and greater complexity.

To address this gap, we introduce the Manufacturing Complex Background Texture (MCBT) dataset, designed to provide a more diverse and challenging benchmark for IAD models. Figure 1 visually compares textures from MVTecAD and MCBT, highlighting how industrial machining results in greater surface irregularity, higher spatial frequency content, and directional variations in MCBT (Figure 1f). Unlike MVTecAD textures (Figures 1a-e), which exhibit structured grain patterns or low-frequency variations, MCBT surfaces contain finer microstructures with overlapping defect-background characteristics, making anomaly localization significantly more challenging. The variability in MCBT reflects real-world manufacturing conditions, where complex surface patterns can introduce false positives (misclassified background textures) and false negatives (defects concealed within machining patterns).

To quantitatively validate these observations, we extracted mean entropy and Gabor standard deviation features across multiple datasets, as shown in Figure 2. Mean entropy, which measures randomness in pixel intensity, is significantly higher for MCBT, indicating a greater presence of stochastic microstructures and varying contrast levels that obscure anomaly boundaries. Likewise, MCBT exhibits a wider spread in Gabor standard deviation, highlighting greater variability in spatial frequency and directional structure, which translates to textures with a mix of high-contrast and low-contrast regions. This confirms that MCBT images feature a broader spectrum of industrial surface patterns, where defects blend more naturally into background textures, unlike other datasets that predominantly consist of regular, lower-entropy textures with distinct defect regions.

MCBT complements existing datasets by introducing a

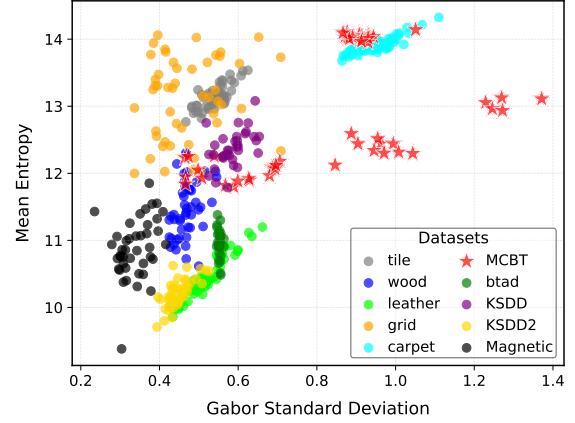


Figure 2. Scatter plot of entropy vs. Gabor standard deviation across datasets. MCBT (red stars) spans a broader, more complex textural space.

broader spectrum of industrial textures, making it a valuable addition to the landscape of IAD benchmarks. Unlike datasets with more uniform backgrounds, MCBT includes higher entropy and diverse directional patterns, forcing models to handle greater texture complexity and defect ambiguity. In Section 5.2.2, we further examine how these textural differences affect model performance, demonstrating that MCBT highlights the limitations of existing SOTA approaches, particularly in weakly supervised settings. By expanding the available textural diversity for benchmarking, MCBT serves as an essential step toward bridging the gap between controlled laboratory datasets and the more intricate surfaces encountered in real-world manufacturing.

4. AL-CycleGAN for IAD

4.1. CycleGAN

CycleGAN [12], an unpaired domain transfer technique, serves as the backbone of our proposed methodology. It enables the translation of images from one domain to another without training on paired images (e.g., with the same background texture) in both domains.

To formalize in the context of anomaly detection, CycleGAN aims to learn bidirectional mapping functions between two domains, denoted as A (anomaly) and B (anomaly-free). This is achieved using N anomalous training images $\{x_i\}_{i=1}^N$ where $x_i \in A$, and M anomaly-free training images $\{y_j\}_{j=1}^M$ where $y_j \in B$.

Figure 3 illustrates the CycleGAN architecture consisting of two generators, $G_{AB} : A \rightarrow B$ and $G_{BA} : B \rightarrow A$, which perform image translation between the domains. Specifically, G_{AB} takes a real anomaly image $x \in A$ as input and attempts to generate an anomaly-free image $G_{AB}(x)$, by removing defect regions while preserving the textu-

ral background. Conversely, G_{BA} transforms anomaly-free images to the anomalous domain.

Additionally, CycleGAN incorporates two adversarial discriminators, D_{AB} and D_{BA} . Discriminator D_{AB} differentiates between real anomaly-free images $y \in B$ and generated anomaly-free images $G_{AB}(x)$, whereas D_{BA} distinguishes between real anomalous images $x \in A$ and generated anomalous images $G_{BA}(y)$.

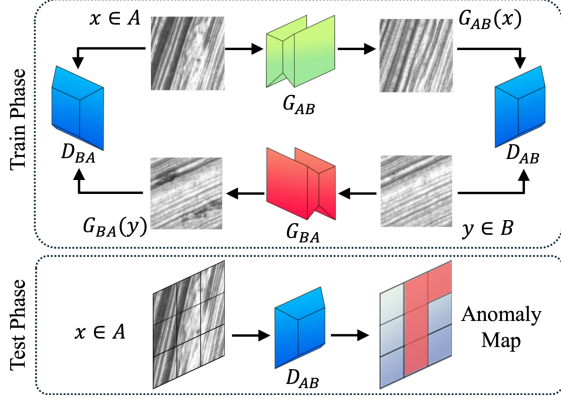


Figure 3. Overview of AL-CycleGAN architecture showing the training and testing phases for IAD.

4.2. CycleGAN patch-wise IAD

To utilize the domain knowledge encoded in CycleGAN for anomaly detection, we modify the discriminator architecture based on PatchGAN [22]. However, instead of employing generators for IAD as in PatchGAN, we utilize the discriminator D_{AB} , which eliminates the need for extensive post-processing. Each modified discriminator consists of a series of convolutional layers, followed by an output layer that provides patch-wise outputs for an input image divided into k patches (see Figure 3). For illustration, we define the following outputs of the two discriminators given different inputs during training:

$$D_{AB}(y) := \{\beta_i\}_{i=1}^k \quad (1a)$$

$$D_{AB}(G_{AB}(x)) := \{\gamma_{B,i}\}_{i=1}^k \quad (1b)$$

$$D_{BA}(G_{BA}(y)) := \{\gamma_{A,i}\}_{i=1}^k \quad (1c)$$

where β_i and $\gamma_{B,i} \in [0, 1]$ represent the probabilities that the i -th real and generated (by G_{AB}) image patch, respectively, belongs to the anomaly-free domain B . $\gamma_{A,i} \in [0, 1]$ represents the probability that the i -th patch, generated by G_{BA} , belongs to the anomalous domain A .

Intuitively, for D_{AB} , an output close to 0 indicates that the corresponding patch is unlikely to be anomaly-free. Based on this, a well-trained D_{AB} produces outputs close to 0 for anomaly patches in a real anomaly image x , while anomaly-free patches in x get values close to 1. This contrast enables CycleGAN-based anomaly localization.

During training, the two generators in a CycleGAN are updated using a shared loss function $\mathcal{L}(G_{AB}, G_{BA})$, which is the sum of three components: *Cycle consistency loss* to ensure that translating an image to the target domain and back to the original domain yields the original image; *Generator adversarial loss* to align the distribution of generated images with real images; *Identity loss* to regularize the generator to preserve the input image when it already belongs to the target domain. On the other hand, each discriminator employs its respective *discriminator adversarial loss*, focusing on distinguishing real images from those generated by the corresponding generator.

4.2.1. Cycle consistency loss

Cycle consistency loss enforces that an image translated from one domain to another and back remains similar to the original. As illustrated in Figure 4 (a), for an image $x \in A$, translating it to domain B using $G_{AB}(x)$ and then back to A via $G_{BA}(G_{AB}(x))$ should reconstruct x . The same principle applies to an image $y \in B$. The cycle consistency loss is formulated as

$$\mathcal{L}_{cyc} = \mathbb{E}_{x \sim P_A} [\|G_{BA}(G_{AB}(x)) - x\|_1] + \mathbb{E}_{y \sim P_B} [\|G_{AB}(G_{BA}(y)) - y\|_1] \quad (2)$$

where $\|\cdot\|_1$ denotes the $L1$ norm, P_A and P_B represent the probabilistic sample distributions of domains A and B , respectively, and $\mathbb{E}$ denotes expectation. Minimizing $\mathcal{L}_{cyc}$ ensures that the generators G_{AB} and G_{BA} accurately learn bidirectional domain mappings while preserving key image characteristics. This constraint prevents arbitrary modifications to input images and reinforces structural consistency during translation.

4.2.2. Generator adversarial loss

The generator adversarial loss compels each generator to produce images that closely resemble those of the target domain, challenging the ability of the associated discriminator to differentiate between real and generated images (see Figure 4 (b)). The adversarial loss is defined as

$$\mathcal{L}_{adv} = \mathbb{E}_{x \sim P_A} [\sum_i^k (\gamma_{B,i} - 1)^2] + \mathbb{E}_{y \sim P_B} [\sum_i^k (\gamma_{A,i} - 1)^2] \quad (3)$$

4.2.3. Identity loss

The identity loss ensures that when an image from a target domain is input to the corresponding generator, the output remains unchanged. As depicted in Figure 4 (c), for an image $y \in B$, passing it through G_{AB} should yield the same image y . Similarly, for an image $x \in A$, $G_{BA}(x)$ should reproduce x . This is formulated as:

$$\mathcal{L}_{idt} = \mathbb{E}_{y \sim P_B} [\|G_{AB}(y) - y\|_1] + \mathbb{E}_{x \sim P_A} [\|G_{BA}(x) - x\|_1] \quad (4)$$

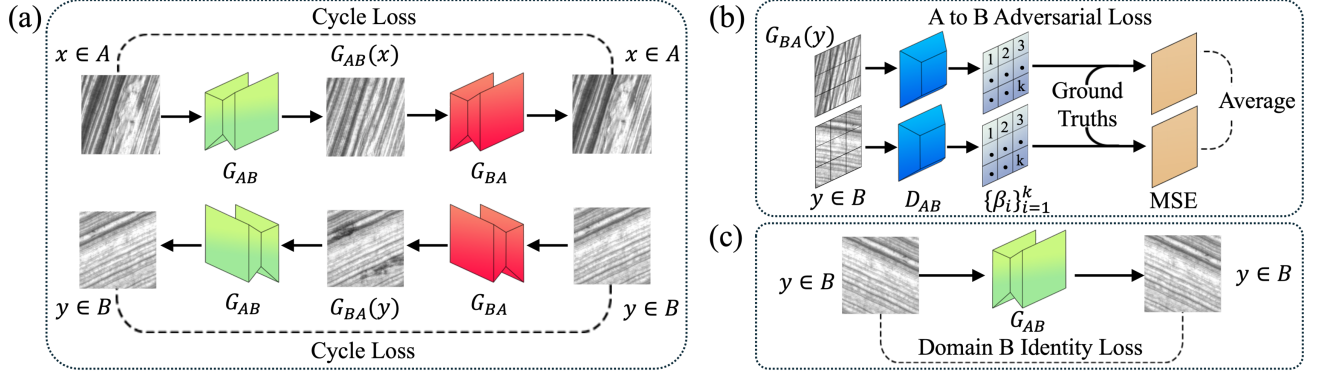


Figure 4. Overview of CycleGAN architecture depicting the loss formulations (a) Cyclic loss, (b) Adversarial loss, (c) Identity loss.

Minimizing $\mathcal{L}_{idt}$ encourages the generators to preserve input image features, stabilizing training and improving the quality of generated images [12].

4.2.4. Discriminator adversarial loss

In CycleGAN, each discriminator network is updated using a loss function that includes only the adversarial term. Here, we focus on the discriminator employed for anomaly detection, D_{AB} . The adversarial loss encourages D_{AB} to effectively distinguish between real anomaly-free images from the domain B and those generated by G_{AB} . Based on Equations 1a and 1b, the loss function of D_{AB} is defined as

$$\mathcal{L}_{D_{AB}} = \mathbb{E}_{x \sim P_A} [\sum_i^k (\gamma_{B,i})^2] + \mathbb{E}_{y \sim P_B} [\sum_i^k (\beta_i - 1)^2] \quad (5)$$

After training, D_{AB} can produce outputs close to 1 for anomaly-free patches in a given anomalous image x , while anomaly patches in x yield values close to 0. This contrast enables CycleGAN-based anomaly detection.

4.3. AL-CycleGAN

However, Equation 5 results in a mislabeling error which significantly limits CycleGAN’s IAD performance.

Definition 1 (Mislabeling error) During training, let m denote the number of correctly generated anomaly-free patches (out of k total patches) in a generated anomaly-free image, $G_{AB}(x)$. As the generator G_{AB} improves, m varies from 0 to k . For D_{AB} -based IAD, the true label of these m patches should be 1 (anomaly-free). However, Equation 5 incorrectly regularizes the discriminator outputs for these m patches, $\gamma_{B,i}$, towards 0. This leads to a mislabeling error quantified as

$$e = \sum_{i=1}^m |(\gamma_{B,i} - 1)^2 - (\gamma_{B,i})^2| = \sum_i^m |-2\gamma_{B,i} + 1| \quad (6)$$

This mislabeling error e exists in weakly supervised settings where only image-level, rather than pixel-level, labels are available and discriminator-based models are used for IAD. It can substantially increase the false positive rate. The following result establishes the condition for which the proposed modifications to $\mathcal{L}_{D_{AB}}$ mitigate e .

Proposition 2 (p -th power loss) The mislabeling error e can be reduced by increasing the exponent in $\mathcal{L}_{D_{AB}}$ from 2 to an even number $p \geq 2$. The updated $\mathcal{L}_{D_{AB}}$ is

$$\mathcal{L}_{D_{AB}} = \mathbb{E}_{x \sim P_A} [\sum_i^k (\gamma_{B,i})^p] + \mathbb{E}_{y \sim P_B} [\sum_i^k (\beta_i - 1)^p] \quad (7)$$

The mislabeling error based on the updated loss is $e_{new} = \sum_i^m |(\gamma_{B,i} - 1)^p - \gamma_{B,i}^p|$. Using the symmetry and convex properties of e_{new} , it can be easily derived that $e_{new} \leq e$ for $\gamma_{B,i} \in [0, 1]$.

Algorithm 1 Adapted-Loss CycleGAN Training

- 1: **Input:** Total epochs T , switching epoch t^* , initial power p_0 , switching power p
- 2: Random initialize G_{AB} , G_{BA} , D_{AB} , D_{BA}
- 3: **for** epoch $t = 1$ to T **do**
- 4: Compute model outputs: $G_{AB}(x)$, $D_{AB}(y)$, etc.
- 5: Update both generators using $\mathcal{L}(G_{AB}, G_{BA})$
- 6: Update D_{BA} using $\mathcal{L}_{D_{BA}}$
- 7: Set power $p_t = p_0$ if $t < t^*$ else $p_t = p$
- 8: Update D_{AB} using $\mathcal{L}_{D_{AB}} = \mathbb{E}_{x \sim P_A} [\sum_i^k (\gamma_{B,i})^{p_t}] + \mathbb{E}_{y \sim P_B} [\sum_i^k (\beta_i - 1)^{p_t}]$
- 9: **end for**
- 10: **Return** G_{AB} , G_{BA} , D_{AB} , D_{BA}

It is noteworthy that e decreases as p increases. However, using an infinitely large p is impractical for two reasons. First, to maintain balanced regularization, p is also applied

to β_i , which, while not inducing mislabeling errors, influences D_{AB} 's ability to identify real anomaly-free patches. Therefore, a large p may hinder D_{AB} and its corresponding generator G_{AB} from effectively capturing image patterns in both domains. Second, higher p values can increase the training time required for the loss to reach a local minimum.

To address this issue while mitigating the mislabeling error during CycleGAN training, we introduce Algorithm 1, which results in the proposed AL-CycleGAN. Algorithm 1 incorporates two key hyperparameters: switching epoch t^* and switching power p . Their impact on model performance is further analyzed in Section 5.

The rationale behind Algorithm 1 is that, during early training, generated images $G_{AB}(x)$ differ significantly from real anomaly-free images y due to random initialization. This leads to a smaller m and a relatively low mislabeling error e . In this phase, setting $p = 2$ allows generators and discriminators to learn image patterns more efficiently before increasing p as training progresses.

5. Experiments

5.1. Experimental details

We conducted comparative experiments evaluating AL-CycleGAN against state-of-the-art IAD methods, including both unsupervised (e.g., SimpleNet [10], DRAEM [23], EfficientAD [24], and CAVGA-Ru [25]) and weakly supervised ones (e.g., Mixed Supervision [11], CAVGA-Rw [25], and GFT [26]). While existing methods were tested using their default configurations, AL-CycleGAN was trained on 256×256 pre-cropped images with a U-Net 256 generator architecture [27]. The discriminator utilized a 30×30 PatchGAN [22], producing patch-wise outputs for $k = 900$ overlapping patches per image. k was carefully chosen to ensure each patch contains minimal overlap between defect and non-defect regions. To address the min-max optimization challenge [12], AL-CycleGAN training followed a two-step procedure, first updating the generator with frozen discriminator weights, followed by updating the discriminator while keeping generator weights fixed.

Experiments were conducted on two datasets covering diverse texture characteristics: the MVTecAD dataset [7] and our MCBT dataset. To ensure a consistent training setup across datasets, anomalous images with image-level labels were incorporated into the training set, with a subset reserved for testing. Specifically, 182 anomalous images from MCBT were used for training, and the remaining 45 images were retained for testing, ensuring a balanced representation across defect types. Models were trained on all defect types within each dataset category to prevent bias towards any particular defect type. All experiments were conducted on an NVIDIA GeForce RTX 4090 GPU and an AMD Ryzen Threadripper Pro 5955WX CPU.

To comprehensively assess model performance, we employed multiple evaluation metrics, including image-level and pixel-level Area Under the ROC Curve, denoted as I-AUROC and P-AUROC, respectively. To provide an aggregated view of the model efficacy, the mean and standard deviation of P-AUROC were calculated across all texture categories. Unless otherwise stated, all references to model performance refer to mean P-AUROC.

5.2. Anomaly localization performance

This section presents a detailed experimental evaluation of AL-CycleGAN on all five texture categories of MVTecAD and the MCBT dataset, focusing exclusively on texture-based IAD. Unlike prior works that include object categories, our study specifically targets highly textured surfaces that pose unique challenges in IAD. The results demonstrate that AL-CycleGAN achieves comparable or superior performance over both unsupervised and weakly supervised methods across multiple texture categories, especially in complex, high-frequency background textures.

5.2.1. Performance on MVTecAD and MCBT

Table 1 reports the I-AUROC and P-AUROC scores across the five texture categories of MVTecAD. AL-CycleGAN achieves the best or second-best performance in three out of five texture classes (tile, wood, leather), while remaining competitive in the other two (grid, carpet). Notably, in the leather category, AL-CycleGAN achieves the highest I-AUROC and P-AUROC (1.0/0.995), highlighting its strong capability in handling irregular, high-contrast textures.

For tile and wood, AL-CycleGAN ties for the highest I-AUROC (1.0) while achieving the best P-AUROC (0.952 and 0.929, respectively), outperforming both SimpleNet and DRAEM. This suggests that adversarial learning can help capture fine-grained textural variations more effectively than feature- and reconstruction-based methods.

On grid and carpet datasets, SimpleNet achieves the highest I-AUROC and P-AUROC, surpassing AL-CycleGAN and all other methods. The structured and repetitive nature of these textures likely favors discriminative approaches such as SimpleNet, which explicitly learn decision boundaries based on regular features. However, AL-CycleGAN still achieves competitive performance in the carpet category, with I-AUROC and P-AUROC scores of 0.957 and 0.973, respectively, ranking among the top methods. These results suggest that while highly structured textures (e.g., grid, carpet) may be better suited to feature-matching-based methods like SimpleNet, adversarial learning techniques like AL-CycleGAN are beneficial for detecting anomalies in complex and irregular textures.

As discussed in Section 3, the MCBT dataset presents unique challenges compared to MVTecAD due to its higher textural complexity and diverse defect morphologies. While MVTecAD comprises relatively structured defect patterns,

Table 1. Image-level AUROC (I-AUROC) / Pixel-level AUROC (P-AUROC) results for MVTecAD texture categories and MCBT dataset. The best performance in each metric is highlighted in **bold red**, while the second-best is in **bold**. Standard deviations for AL-CycleGAN are indicated as subscripts.

Datasets	Methods	Unsupervised Methods				Weakly Supervised Methods			Ours
		EfficientAD [24]	DRAEM [23]	SimpleNet [10]	CAVGA-Ru [25]	CAVGA-Rw [25]	Mixed Supervision [11]	GFT [26]	AL-CycleGAN
MVTecAD	Tile	0.999 /0.915	0.996/ 0.992	0.998/ 0.970	0.72/-	0.86/-	0.995/0.469 _{0.036}	-/0.935	1.0 /0.952 _{0.64}
	Wood	0.994 /0.908	0.991/ 0.964	1.0 /0.945	0.88/-	0.89/-	0.993/0.580 _{0.072}	-/0.908	1.0 / 0.949 _{0.088}
	Grid	0.988/0.939	0.999 / 0.997	0.997 / 0.988	0.78/-	0.81/-	0.934/0.534 _{0.044}	-/0.9318	0.966/0.788 _{0.196}
	Leather	1.0 /0.977	1.0 /0.986	1.0 / 0.992	0.75/-	0.84/-	0.949/0.711 _{0.135}	-/0.984	1.0 / 0.995 _{0.005}
	Carpet	0.993 /0.956	0.970/0.955	0.997 / 0.982	0.78/-	0.82/-	0.918/0.497 _{0.032}	-/0.932	0.957/ 0.973 _{0.063}
MCBT (Ours)		0.9782 /0.892	0.5/0.5	0.848/ 0.896	-	-	0.997/0.488 _{0.047}	-/0.781	1.0 / 0.929 _{0.071}

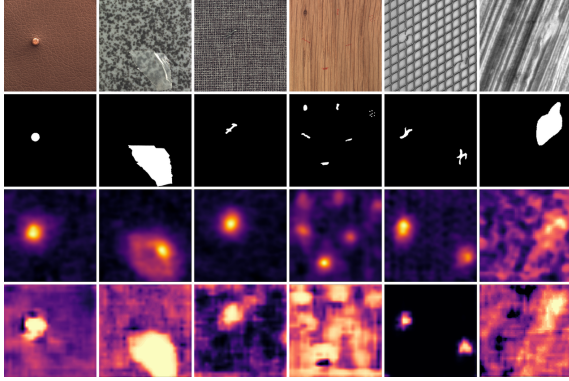


Figure 5. Qualitative results for anomaly localization on MVTecAD [7], and MCBT. From top to bottom: normal sample as the reference, ground-truth, SimpleNet anomaly map, and AL-CycleGAN anomaly map.

MCBT features high entropy and elevated Gabor standard deviation, reflecting intricate and varied industrial surface textures. This requires models to effectively distinguish between anomalies and highly variable background patterns.

AL-CycleGAN achieves the highest I-AUROC and P-AUROC (1.0/0.929) on MCBT, outperforming both unsupervised and weakly supervised baselines. This demonstrates AL-CycleGAN’s robustness in handling complex industrial background textures.

In contrast, DRAEM, which performed well on MVTecAD, suffers a severe performance drop on MCBT (0.5/0.5), indicating its poor generalization to highly textured surfaces. Similarly, SimpleNet, which excelled on grid and carpet categories in MVTecAD, struggles on MCBT (0.848/0.89). This highlights the limitations of feature- and reconstruction-based methods for industrial textures with high local contrast variations. Moreover, MCBT offers valuable insights for evaluating models in complex texture industrial scenarios beyond mainstream benchmark datasets.

5.2.2. Impact of textures on model performance

We conducted an in-depth analysis of textural characteristics across multiple datasets, including MCBT, BTAD, and

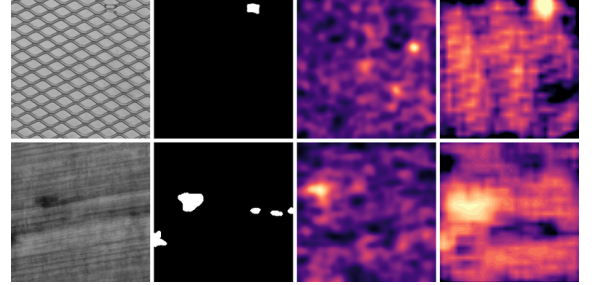


Figure 6. Images Demonstrating Textural Feature Characteristics. Top row: Grid class in MVTecAD dataset and Bottom row: MCBT dataset. Left to right: Sample image; ground truth; anomaly map - SimpleNet; anomaly map - AL-CycleGAN.

MVTecAD, to systematically evaluate texture complexity. Extracted features included global contrast, multi-scale entropy, Local Binary Pattern (LBP) descriptors, and directional Gabor features, providing a comprehensive representation of textural variations.

To examine the influence of texture complexity on model performance, we trained a C5.0 decision tree model [28] to classify whether AL-CycleGAN (the top performer on MCBT) or SimpleNet (the second-best) would yield superior performance based on extracted features. The analysis produced a classification accuracy of 83.9%, revealing that:

- Low mean entropy (≤ 13.014) and high Gabor standard deviation (≥ 0.432) strongly favor AL-CycleGAN for anomaly detection. As shown in Figure 2, this feature space extends beyond the coverage of existing benchmark datasets.
- SimpleNet performs better on structured textures with lower variance, aligning with its feature-based anomaly detection strategy.

This finding highlights AL-CycleGAN’s suitability for highly complex industrial textures, such as those in MCBT, which exhibit significantly greater entropy and Gabor variance than MVTecAD. Figure 6 visually illustrates this contrast, comparing a structured grid texture from MVTecAD (top row) with an irregular industrial texture from MCBT (bottom row). While SimpleNet excels on structured pat-

terns, AL-CycleGAN’s adversarial learning approach better captures anomalies in high-entropy, irregular textures.

5.2.3. Efficiency evaluation

Beyond accuracy, efficiency is crucial for real-world IAD. AL-CycleGAN achieves state-of-the-art performance while maintaining fast training and inference speeds, making it well-suited for real-time applications. On MVTecAD textures, AL-CycleGAN trains in an average of 40.5 minutes per model and achieves an inference speed of 496 frames per second (FPS). On the more challenging MCBT dataset, training for 200 epochs takes approximately 2 hours and 4 minutes, with inference at 180 FPS, significantly outperforming SimpleNet’s 77 FPS [10]. Additionally, AL-CycleGAN’s lightweight architecture (≈ 10 MB) enhances its deployment potential, allowing for fast iterative training and adaptation to local industrial settings without requiring extensive computational resources. These results establish AL-CycleGAN as a highly scalable, efficient, and accurate weakly supervised IAD model, capable of handling both structured and complex textures while maintaining real-time inference speeds.

5.3. Ablation study

To assess the impact of varying loss power p , we trained and evaluated five models with different p values (2, 4, 6, 8, 10) while keeping all other hyperparameters fixed. Due to space constraints, we present results on the MVTecAD wood dataset (Table 2).

The results indicate a clear improvement in AUROC scores with increasing p , confirming that higher power values enhance anomaly localization. However, beyond $p = 8$, the gains diminished, with $p = 10$ failing to surpass the performance of $p = 8$. A plausible explanation is that at very high p , the gradient magnitudes become extremely small, slowing down optimization and leading to diminished model updates. This suggests an optimal p balancing performance and stability, with $p = 8$ achieving the highest P-AUROC (0.9281).

Table 2. Mean Pixel-AUROC model performance under different p on MVTecAD Wood

p	$T = 100$	$T = 200$	$T = 300$
2	0.6068	0.6749	0.7454
4	0.7459	0.7821	0.8034
6	0.826	0.8181	0.8806
8	0.9281	0.7846	0.8371
10	0.8485	0.8639	0.8574

We further evaluated the impact of the power-switch mechanism, which transitions p from 2 to 8 at a specific training epoch t^* , to analyze its role in balancing early train-

ing stability and later-stage optimization efficiency. Four models were trained for 200 epochs ($T = 200$), with t^* increasing from 25 to 175 epochs in steps of 50. Table 3 shows that delaying the switch significantly boosts performance, with the highest AUROC of 0.929 achieved when $t^* = 175$. This suggests that allowing the model to first converge under lower loss power ($p = 2$) before transitioning to higher loss power ($p = 8$) maximizes learning efficiency.

Table 3. Mean Pixel-AUROC under different power-switch epochs t^* for the MCBT dataset.

Power Switch Epoch (t^*)	25	75	125	175
AUROC	0.793 _{0.156}	0.812 _{0.14}	0.833 _{0.16}	0.929 _{0.07}

6. Conclusion and Future Work

IAD remains challenging due to complex textures and diverse defect types in real-world manufacturing, where existing datasets fail to capture intricate background variations that significantly impact model performance. To address this, we introduced the MCBT dataset, a more comprehensive benchmark that better represents real-world industrial complexities. Our analysis demonstrated that SOTA methods, including SimpleNet, struggle on MCBT, reinforcing the need for datasets that encompass higher textural variability. To improve anomaly detection in these scenarios, we proposed AL-CycleGAN, an adaptation of CycleGAN that integrates a p^{th} power loss function and a power-switch strategy. These modifications enhance anomaly localization by improving the discriminator’s ability to distinguish subtle defects while dynamically optimizing the training process. AL-CycleGAN consistently outperforms SOTA methods, achieving a performance boost from 89.0% to 92.9% in anomaly localization on MCBT while maintaining computational efficiency. Additionally, its generator can synthesize realistic defect patterns, opening pathways for improving IAD models through self-supervised learning and synthetic data augmentation.

Future work will focus on refining the power-switch strategy by studying training dynamics to develop an adaptive mechanism for adjusting the power in the loss function. This would ensure that the transition occurs at an optimal stage in training, maximizing stability and localization accuracy. Additionally, optimizing the PatchGAN discriminator to better capture fine-grained anomalies and exploring how AL-CycleGAN’s generator can be leveraged for augmenting defect data could further enhance weakly supervised IAD performance across diverse manufacturing processes.

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