CycleGAN Variants for Industrial Defect Data Augmentation

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Abstract. Industrial visual inspection is constrained by scarce labeled defect samples and complex surface patterns in bearings, steel, and ICs, significantly hindering deep learning detection models. This review conducts a systematic comparative analysis of CycleGAN variants tailored for industrial defect data augmentation, focusing on how they address generic CycleGAN limitations (insufficient detail preservation, training instability, poor environmental adaptability). By synthesizing recent relevant studies, it evaluates four representative models: 1D Cycle-GAN and SN_1D CycleGAN for bearing fault diagnosis (1D vibration signals), and AG-CycleGAN and Enhanced-CycleGAN for steel/IC surface defect detection (e.g., scratch, crack, and pit defects). Analysis shows scenario-specific designs drive efficacy: simulation-driven transfer learning (1D Cycle-GAN) mitigates bearing data scarcity, spectral normalization (SN_1D CycleGAN) stabilizes training dynamics, attention mechanisms (AG-CycleGAN) improve defect contrast, and multi-scale mechanisms (Enhanced-CycleGAN) address scale variability problems. The review concludes industrial CycleGAN success depends on aligning innovations with scenario pain points, establishing a practical framework to guide industrial-oriented model design.

1 Introduction

1.1 Research Background

Industrial visual inspection serves as the core part in product quality control. However, its application faces two key challenges: scarce defect samples and complex defect pattern. These issues are common in components like bearings and steel/IC components, which are hard to solve.

Defect data for these components is either hard to collect or easily distorted. The low-quality datasets will impact deep learning model training. Traditional detection methods also struggle with new defects type, as they rely on defined defect patterns and cannot adapt to new characteristics.

There are some ways to deal with the problem by improving YOLO network. Improved YOLOv5 [1], YOLOv8-LMG [2] are used in bearing defect detection, while improved

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YOLOv7 [3], WSS-YOLO [4] focus on steel defect detection. In this paper, we are reviewing the solving methods from a different perspective -- CycleGAN.

CycleGAN addresses these issues via unpaired image-to-image translation: its cycle-consistent constraints enable converting normal samples to defect samples without paired training data, alleviating sample scarcity. Yet original CycleGANs fail to meet industrial demands—they generate blurred defect details, suffer from training instability, and cannot adapt to complex backgrounds. This paper focuses on CycleGAN variants for defect data augmentation in the components, reviewing model improvements, evaluating performance, and clarifying applicable scenarios for different variants.

1.2 Key Issues and Main Methods

1.2.1 Key Issues

This study focuses on three core pain points in industrial visual inspection:

First, the scarcity of defect samples results in low recognition accuracy and poor generalization of detection models.

Second, existing CycleGAN variants generate samples with insufficient authenticity because they fail to fully consider environmental influences. It means that if a different situation occurs, the model may show poor consistency with real scene.

Third, the lack of effective fusion strategies between generated and real samples makes it difficult to optimize detection model performance through data augmentation.

1.2.2 Research Methods

The analysis mainly explores some strategies to analyze the accuracy and robustness improvement of different models on style transformation in industrial environment. To address specific issues, shape loss and perceptual loss to optimize the structural features of samples is a good point. Another possible approach is to integrate multi-modal data, such as vibration signals and visible light. Some improved models also involve components such as Channel Attention Modules and Spatial Attention Modules. Collectively, these improved CycleGAN models can solve various problems in industrial visual inspection.

1.3 Review Scope and Organization

1.3.1 Review Scope

This review focuses on CycleGAN variants tailored for industrial defect data augmentation, especially three application scenarios: bearing fault diagnosis, steel surface defect detection, and IC surface defect detection. The scope of analysis includes: (1) the architectural innovations of each variant (e.g., 1D convolution adaptation, attention mechanism integration, spectral normalization); (2) performance evaluation based on benchmark datasets (e.g., classification accuracy for bearings, PSNR/SSIM for steel defects, precision/recall for IC defects); (3) limitations of each model in practical industrial applications; and (4) the matching relationship between model designs and scenario-specific pain points (e.g., data scarcity, background interference, multi-scale defects). Non-industrial applications of CycleGAN (e.g., medical image enhancement, agricultural disease detection) and generic GAN models (non-CycleGAN variants) are excluded from the review scope.

1.3.2 Paper Organization

The remainder of this paper is structured as follows: Chapter 2 provides an overview of industrial CycleGAN variants, categorizing models by application scenario (bearings, steel, ICs) and introducing their core architectural innovations and targeted application scenarios. Chapter 3 conducts systematic comparative analysis: Section 3.1 compares two CycleGAN variants for bearing fault diagnosis (1D Cycle-GAN [5] and SN_1D CycleGAN [6]) from the perspectives of core design, performance metrics, and limitations; Section 3.2 contrasts two variants for surface defect detection (AG-CycleGAN [7] and Enhanced-CycleGAN [8]); Section 3.3 summarizes the core challenges of industrial CycleGAN applications, inductively analyzes model-specific solution paths, and constructs a knowledge framework for scenario-model matching. Section 3.4 puts forward cross-domain applicability guidelines, clarifying the applicable scenarios of each model to provide direct reference for industrial practice. Chapter 4 concludes the review by summarizing key findings, emphasizing the practical value of scenario-driven model selection, and outlining directions for future research in this field.

2 An Overview of Models about CycleGAN Improvements in Industry Field

To address the limitations of standard CycleGAN in industrial defect data augmentation (e.g., blurred details, training instability), four representative variants have been proposed for targeted scenarios (bearing fault diagnosis, steel/IC surface defect detection). This section serves as a concise “model index,” briefly introducing each variant’s core purpose and innovation. Detailed comparative analysis, performance evaluation, and limitation discussion are reserved for Chapter 3. Their key attributes are summarized in Table 1.

Table 1. Overview of Reviewed CycleGAN Variants

Model Name	Target Application	Core Innovation	Corresponding Section
1D-CycleGAN	Bearing fault diagnosis	1D convolution adaptation + simulation-driven transfer learning	3.1
SN_1D CycleGAN	Bearing fault diagnosis	1D CycleGAN + discriminator Spectral Normalization	3.1
AG-CycleGAN	Steel surface defect generation	Dual attention modules (CAM+SAM)	3.2
Enhanced-CycleGAN	IC surface defect generation	Multi-scale mechanism	3.2

2.1 1D Cycle-GAN (Numerical Simulation-Driven)

This model adapts CycleGAN to 1D vibration signals (replacing 2D convolutions) and uses numerical simulation-driven transfer learning to alleviate bearing fault data scarcity. Detailed analysis of its design logic, performance, and limitations see Section 3.1.

2.2 SN_1D CycleGAN

This variant optimizes 1D CycleGAN by adding Spectral Normalization to the discriminator, aiming to stabilize training and prevent mode collapse in bearing vibration signal generation. Detailed analysis see Section 3.1.

2.3 AG-CycleGAN

AG-CycleGAN integrates Channel Attention Modules (CAM) and Spatial Attention Modules (SAM) to enhance defect-background contrast, tailored for steel surface defect image generation. Detailed analysis see Section 3.2.

2.4 Enhanced-CycleGAN

This model adopts a hierarchical convolutional multi-scale generator with multi-loss fusion optimizer, designed to capture multi-size defects on IC surfaces. Detailed analysis see Section 3.2.

3 Systematic Analysis of Industrial CycleGAN Variants

3.1 Comparative Analysis of Bearing Fault Diagnosis Models

Bearing fault diagnosis in industrial scenarios often faces challenges like scarce fault data and unstable model training. The following comparison focuses on two representative models on these problems. Table 2 depicts two models' core designs, performance metrics and limitations.

Table 2. Comparative Analysis of Bearing Fault Diagnosis CycleGAN Variants

Dimension	1D Cycle-GAN (Numerical Simulation-Driven)	SN_1D CycleGAN
Model Name	1D Cycle-GAN (Numerical Simulation-Driven)	SN_1D CycleGAN
Core Design	1) 1D CNN Architecture 2) Simulation-driven transfer 3) Class Loss Constraint	1) 1D CNN Architecture 2) Spectral Normalization 3) Residual Block Refinement
Performance Metrics	1) Generated sample: matches real signal fault frequencies 2) Detect Performance: Classifiers (SVM/ELM/CNN) trained on translated signals reach accuracy 89.2%/ 87.0%), higher than DANN (36.0%)/WATN (45.2%)	1) Generated sample: FID ×9, MMD/FOV ×1; 2) Detection: Classification accuracy ↑ 40% for OR_test1
Limitations	1) Simulation-reality gap 2) Poor fine-classification for micro faults	1) High computational complexity 2) Low SNR in generated data

Both models use 1D convolutions to fit vibration signals' time-series nature, preserving fault impulses. 1D Cycle-GAN targets data scarcity via simulation transfer learning, excelling in small-sample accuracy gains; SN_1D CycleGAN focuses on training stability with Spectral Normalization, suitable for standardized inspection. For Performance, 1D Cycle-GAN outperforms baselines, while SN_1D CycleGAN excels in multi-metric consistency. 1D Cycle-GAN has limitations on simulation reliance, which means it suffers from simulation-reality gap and poor fine-classification mechanism. On the other hand, SN_1D CycleGAN requires high computational complexity, and it also results in low SNR in generated data.

3.1.1 The Choice of Cycle-GAN or SN_1D CycleGAN

The 1D Cycle-GAN is particularly recommended when data scarcity and composite fault diagnosis are the key problems. Its numerical simulation-driven transfer learning strategy excels in scenarios where real fault samples are extremely limited. By leveraging physics-based simulated data for pre-training, it reduces reliance on scarce real data, making it ideal for low-resource industrial environments where collecting fault signals is costly or dangerous.

The SN_1D CycleGAN is particularly recommended when training stability and single fault standardization is required. Its Spectral Normalization design addresses the common GAN issue of mode collapse, ensuring stable generation of vibration signals across different fault types. This makes it preferable for scenarios where consistent performance across metrics like FID and MMD is prioritized over data scarcity mitigation.

3.1.2 Scenario-Model Matching for Bearing Fault Diagnosis

Bearing fault diagnosis faces three core pain points: temporal signal sensitivity, data scarcity, and training instability. The models' designs directly target these:

1) 1D convolutions (both models): Vibration signals are inherently 1D time-series, where transient impulses (e.g., periodic impacts from cracks) carry critical fault information. Replacing 2D convolutions with 1D convolutions preserves temporal dependencies, ensuring generated signals retain fault characteristic frequencies and impulse intervals—without this, synthetic data would distort the very features diagnostic models rely on.

2) Transfer learning (1D Cycle-GAN): Real bearing fault data is scarce because faults are transient and unpredictable. By pre-training on simulated data and adding classifiers and cross-entropy loss to ensure translated signals retain original fault categories, the model builds a foundational understanding of fault physics, then fine-tunes on real data to bridge the "simulation-reality gap." This design directly solves the "small sample" problem in industrial settings.

3) Spectral Normalization (SN_1D CycleGAN): CycleGANs, especially GANs often suffer from training instability, leading to generated signals that either lack diversity or fail to match real data distributions. Spectral Normalization constrains the discriminator's Lipschitz constant, stabilizing training and ensuring consistent generation of high-fidelity fault signals. Also, 9 ResNet blocks in the generator enhance feature extraction, partially mitigating low SNR in generated signals.

3.2 Comparative Analysis of Defect Detection Models

Defect detection in industrial components (e.g., steel, ICs) benefits from specialized CycleGAN variants optimized for visual defect generation and enhancement. The following comparison focuses on two representative models. Table 3 depicts two models' core designs, performance metrics and limitations.

Table 3. Comparative Analysis of Surface Defect Detection CycleGAN Variants

Dimension	**AG-CycleGAN (Steel Surface Defect Generation)**	**Enhanced-CycleGAN (IC Surface Defect Detection)**
Model Name	AG-CycleGAN	Enhanced-CycleGAN
Core Design	1) CAM + SAM 2) Weight Demodulation Mechanism 3) Shape Consistency Loss	1) Hierarchical convolutional multi-scale generator 2) multi-loss fusion optimization
Performance Metrics	Generated Sample Quality: PSNR ↑ 13.0%, SSIM ↑ 7.8%, FID ↓ 33.1%.	1) Generated Sample Quality (vs. GAN/VAE/CycleGAN): Broken Die: SSIM=0.91, FID=135.55 No or Missing Die: PSNR=26.39 (Both close to real data) 2) Detection Performance： VGG16: accuracy 91%→99% YOLO11: accuracy 97%→100%
Limitations	Insufficient defect diversity	Require updates with new data

Both models tackle the key challenge of extracting clear defects from complex backgrounds but use scenario-tailored strategies. AG-CycleGAN combines CAM, SAM and weight demodulation mechanism which reduce background interference by 30% and boost PSNR/SSIM. Enhanced-CycleGAN enables close to real data index and improveds detection performance through hierarchical convolutional multi-scale architecture with multi-loss fusion optimization. However, their limitations align with scenario optimizations: AG-CycleGAN lacks defect diversity; Enhanced-CycleGAN still requires updates and adjustments based on specific dataset characteristics.

3.2.1 The Choice of AG-CycleGAN or Enhanced-CycleGAN

In industrial visual inspection scenarios where background texture interference is the key challenge, the AG-CycleGAN is particularly recommended. Specifically, its dual attention mechanisms (CAM + SAM) directly help suppress irrelevant background features, while weight demodulation mechanism can help remove artifacts and white patches efficiently.

In contrast, the Enhanced-CycleGAN is particularly recommended when multi-scale defect generation is most important. IC surfaces feature defects ranging from sub-micron defects to larger-scale defects. Its generator structure with hierarchical 7×7 (for macro defects) and 3×3 (for micro defects) convolution kernels, plus 6 residual blocks and transposed convolution—captures features across resolutions, ensuring no defect size is overlooked.

3.2.2 Scenario-Model Matching: Underlying Logic for Defect Detection

Defect detection in industrial visual inspection faces two key pain points: background-foreground ambiguity and defect scale diversity. The models' designs are tailored to these:

Attention mechanisms (AG-CycleGAN): Industrial surfaces often have defects that are visually similar to background noise. CAM and SAM in AG-CycleGAN prioritize defect-related features by reweighting channels or spatial regions, solving the "defects drowned in background" problem.

Morphology stability via shape constraint (AG-CycleGAN): Steel surface defect detection requires stable texture preservation to avoid some critical defect details. AG-CycleGAN's focus on PSNR/SSIM optimization and shape consistency loss ensures structural consistency between generated and real defects, making it robust for scenarios where defect morphology is key to classification.

Multi-scale feature capture (Enhanced-CycleGAN): IC manufacturing involves micro-scale processes, leading to defects of vastly different sizes. A fixed receptive field would miss either small or large defects. Enhanced-CycleGAN's structure addresses this via hierarchical convolution kernels, 6 residual blocks for feature refinement, and transposed convolution to restore resolution. This expands the receptive field incrementally, ensuring the model captures both sub-micron and macro-scale defects—directly addressing the "scale variability" pain point in IC inspection.

3.3 Industrial CycleGAN: Core Challenges, Solution Paths, and Research Contributions

3.3.1 Core Challenges in Industrial CycleGAN Applications

Across bearing fault diagnosis and defect detection scenarios, all models face three main challenges that define the bottlenecks of industrial CycleGAN deployment, which requires extra effort for model improving.

1) Data Distribution Mismatch: Simulation vs. Reality & Scarcity vs. Diversity: Industrial data is inherently constrained by reality: bearing fault signals are scarce and transient, while steel/IC surface defects exhibit high variability. Simulated data (used in 1D Cycle-GAN) fails to fully replicate real-world complexities (e.g., uneven wear, unmodeled noise), creating a "simulation-reality gap." Meanwhile, generated data often lacks diversity (AG-CycleGAN's insufficient defect types) or fine-grained details (1D Cycle-GAN's poor fine-classification translation in micro faults), limiting its utility for training robust detection models.

2) Performance-Stability-Resource Trade-off: Industrial environments demand models that are accurate, stable, and efficient, but these goals often conflict. SN_1D CycleGAN's optimization improves signal quality but increases computational complexity, requiring more GPU resources and longer training times. AG-CycleGAN's insufficient defect diversity means stable performance relies on specific spots, sacrificing the generality, while Enhanced-CycleGAN's improvement requires updates according to the data, making it difficult to be a stable model.

3) Scenario-Specific Feature Capture Under Complexity: In industrial scenarios, industrial defects are embedded in noisy, variable backgrounds. For instance, bearing vibration signals are masked by environmental noise, steel surfaces have cluttered textures, and IC defects span multi-scale sizes. To address this, models must effectively separate critical features like fault impulses from interference. However, original CycleGAN's architecture fails to prioritize domain-specific features, leading to blurred details or wrong backgrounds.

3.3.2 Model-Specific Solution Paths

To address these challenges, each model has its own strategies based on their scenario characteristics, forming a diversified solution framework. Different solving methods for different challenges are provided in Table 4.

Table 4. Model-Specific Solutions to Core Industrial Challenges

Challenge	**1D-CycleGAN**	**SN_1D CycleGAN**	**AG-CycleGAN**	**Enhanced-CycleGAN**
Data Distribution Mismatch	Simulation-driven transfer learning and add class loss	Multi-metric optimization (align FID/MMD with real data)	Attention-guided enhancement and weight demodulation	Multi-scale structure and multi-loss function
Performance-Stability-Resource Trade-off	1D convolutions (↓computation vs. 2D)	Spectral Normalization (stabilize training)	Hyperparameter tuning and weight demodulation	Batch optimization and learning rate scheduling
Scenario-Specific Feature Capture	1D convolutions and 3 residual blocks	Normalized discriminators and 9 residual blocks	Dual attention	Hierarchical convolutional multi-scale generator

3.3.3 Research Contributions and Knowledge Framework

This analysis of industrial CycleGAN variants yields a good knowledge framework for future research:

1) Scenario-Driven Architecture Design: A core takeaway from the reviewed models is that effective industrial CycleGANs must be tailored to address the unique, scenario-specific challenges of industrial settings. For example, 1D structures are specifically designed for temporal signals. Similarly, attention mechanisms are integrated to handle visual defects. Meanwhile, the transfer learning provides help in scarce data scenarios. This design shows how CycleGAN is improved for industrial challenges where architecture is aligned with scenario pain points.

2) Multi-Objective Optimization with Prioritization: Another key insight is that optimizing CycleGANs for industrial use does not mean balancing all metrics equally. Instead, improvements should be prioritized based on scenario necessities. For instance, bearing diagnosis requires temporal fidelity, and steel defect generation emphasizes background suppression, and IC detection catches sight on multi-scale feature capture. This scenario-aware prioritization not only ensures the model addresses the most critical challenges but also balances overall performance and computational efficiency.

3) The Combination of Simulation and Reality with Hybrid Learning: The third insight centers on using hybrid learning to fuse simulated and real data—a strategy that addresses industrial data scarcity at its source. For example, 1D Cycle-GAN's simulation-driven transfer learning and Enhanced-CycleGAN's updating thoughts give scholars a blueprint for fusing synthetic and real data. In essence, physics-based simulation refined with real samples is a good way to preserve authenticity. This hybrid approach can help address the problem of data scarcity in the industrial field, which can ease the pressure of lacking data.

3.4 Cross-Domain Applicability Guidelines

In summary, this study offers clear model-selection guidance for industrial scenarios. Specifically, 1D Cycle-GAN is designed to address the scarcity of bearing data; SN_1D CycleGAN focuses on enhancing the stability of bearing model training; AG-CycleGAN is dedicated to tackling background clutter in steel-related data processing; and Enhanced-CycleGAN is tailored to handle multi-scale defects in integrated circuits (ICs). Each model targets the pain points of specific scenarios to achieve customized data augmentation, thereby providing a practical reference for selecting the appropriate model in industrial work.

4 Conclusion

This review systematically analyzes CycleGAN variants for industrial defect data augmentation, focusing on their use in bearing fault diagnosis and steel/IC surface defect detection. By comparing the designs, performance, and limitations of four representative models (1D Cycle-GAN, SN_1D CycleGAN, AG-CycleGAN, Enhanced-CycleGAN), it summarizes domain-specific optimization strategies for industrial data challenges (scarcity, background complexity, multi-scale defects).

The core contribution is a structured knowledge framework: first, emphasizing scenario-driven architectures (1D for bearings, attention for steel, multi-scale for ICs); second, proposing priority-based optimization (e.g., transfer learning for bearing data scarcity); third, advocating hybrid learning (via 1D Cycle-GAN's simulation-real fusion) to bridge simulation-reality gaps.

Practically, the review clarifies model applicability: 1D Cycle-GAN for data-scarce bearing diagnosis, SN_1D CycleGAN for stable bearing inspection, AG-CycleGAN for steel background suppression, and Enhanced-CycleGAN for high-precision IC defect capture—providing actionable guidance for practitioners.

Future research should: narrow simulation-reality gaps with physics-informed loss functions; develop hyperparameter auto-tuning to reduce optimization labor; design adaptive architectures for cross-scenario generalization, expanding CycleGAN's industrial utility.

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