Trade-offs in Few-shot Image Generation: Stability, Fidelity, and Adaptability in Data-Efficient GANs

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Abstract. This study presents a comparative analysis of data-efficient GANs, evaluating training stability, output fidelity, and cross-domain adaptability under few-shot conditions. Our findings reveal a distinct trade-off between performance and specialization. StyleGAN2-ADA achieves strong stability and fidelity with small datasets. D3T-GAN performs best when the source and target domains share similar structures. WeditGAN and DEff-GAN improve controllability and diversity, but they need careful parameter tuning. Smoothness Regularization increases consistency, though it may reduce variation. LDM-GAN offers semantic richness and diversity, but it often oversmooths and struggles with very limited data. Model choice depends on the task. StyleGAN2-ADA is best for general small-sample fidelity. D3T-GAN is suited for domain transfer. LDM-GAN works well when diversity is the priority. Future work should prioritize hybrid frameworks, combining augmentation and transfer learning for more robust performance. Progress will also depend on better evaluation metrics and reproducible benchmarks. These steps mark the most promising path for robust and practical few-shot image generation.

1 Introduction

Generative Adversarial Networks (GANs) generate realistic images. They are widely applied in faces, art, medical scans, and synthetic data. Most GANs still rely on large datasets. When data is scarce, such as in art restoration, industrial design, or fine-grained style generation, they often overfit, collapse, or fail to train.

This study compares five methods under few-shot conditions. The evaluation considers training stability, output fidelity, and adaptability. The analysis includes augmentation, latent editing, domain transfer, and smoothness regularization. Each method shows strengths and weaknesses. For example, StyleGAN2-ADA achieves strong fidelity with only 100 samples. D3T-GAN performs well in domain transfer when similarity is high. LDM-GAN increases diversity but requires more data.

These results clarify the trade-offs. Each method has strengths and limitations. The study offers a practical guide for model selection in few-shot scenarios and suggests directions for future research.

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2 An Overview of Models

To understand how GANs perform with limited data, this section introduces several key models and strategies from recent research. All share the same goal of improving GAN training under data constraints, but they differ in complexity, architecture, and use of augmentation.

2.1 StyleGAN2-ADA

StyleGAN2-ADA builds on StyleGAN2 to handle small datasets more effectively. The model introduces adaptive augmentation, which applies random transformations—such as cropping and flipping—to both real and generated images. The probability of applying these transformations changes according to feedback from the discriminator. This change helps reduce overfitting and also improves generalization. Models like ViT-StyleGAN2-ADA use transformer-based discriminators to make feature learning stronger [1]. In practice, StyleGAN2-ADA has shown good performance in tasks such as defect image generation when data is limited [2].

2.2 D3T-GAN (Data-Dependent Domain Transfer GAN)

D3T-GAN improves few-shot generation by transferring knowledge from a large source domain to a smaller target domain. The main module changes the domain distribution. Domain-specific discriminators refine the outputs. Recent studies show that D3T-GAN achieves strong results in artistic style transfer and cross-domain tasks with limited data [3]. The method works best when the source and target domains share strong structural similarity [4].

2.3 WeditGAN

WeditGAN gives another way for few-shot generation. It works in latent space and not in pixel space. It does not change images directly, but it changes the generator's internal codes to fit the target domain. It focuses on representation-level adaptation, and WeditGAN makes images more natural and higher in quality. It has shown strong potential in face generation and few-shot augmentation [5]. This method also allows controlled attribute changes while preserving realism, as demonstrated in earlier work such as L2M-GAN [6].

2.4 Smoothness Similarity Regularization

Smoothness similarity regularization makes gradual transitions in latent and image spaces. This helps the generator make consistent outputs even with very few samples. It also cuts down mutations that show overfitting. By keeping continuity in the data manifold, the method works as a type of semantic enhancement. It improves visual consistency and does not need extra data. Studies show that this method lowers FID scores and improves generalization in few-shot tasks [7]. Other studies show that smoothness constraints reduce mode collapse and keep training stable, making the method a reliable solution [8].

2.5 DEff-GAN (Data-Efficient GAN)

DEff-GAN enhances class-level separability and transfer by using auxiliary classifiers and structural priors. Its goal is to preserve both visual diversity and semantic consistency with only a small number of samples. This strikes a balance between fidelity and variety [9]. When combined with differentiable augmentation, DEff-GAN performs well on datasets such as CIFAR-10 and ImageNet [10]. The framework is more complex and often sensitive to hyperparameter choices.

3 Unified Comparative Framework

3.1 Training Stability Analysis

GAN training is often unstable due to oscillating losses and poor convergence. These issues appeared in FFHQ-140 and MetFaces. Adaptive augmentation reduced instability under variation in identity and lighting, improving convergence and generalization.

3.1.1 Metrics

We measured stability using three indicators: discriminator loss convergence, generator loss smoothness, and Fréchet Inception Distance (FID). These metrics track how reliably each model learns and how consistently image quality improves.

3.1.2 Results

StyleGAN2-ADA achieved the smoothest convergence with low variance and stable FID. D3T-GAN was stable only in similar domains. WeditGAN sometimes collapsed but was steadier than pixel-based methods. Smoothness Regularization reduced oscillations and improved output. DEff-GAN showed moderate stability, balancing transfer and convergence. Overall, ADA and Smoothness Regularization were the most stable, while D3T-GAN and LDM-GAN were sensitive to domain similarity and data scarcity.

3.2 Output Fidelity Benchmark

3.2.1 Quantitative Metrics

We used Fréchet Inception Distance (FID) and Inception Score (IS) to measure image quality. FID compares real and generated distributions. IS evaluates diversity and classification ease. Together, they capture fidelity. StyleGAN2-ADA achieved the best score, with the lowest FID (18.4). D3T-GAN followed with 23.7. LDM-GAN performed worst, with 35.2. For IS, both ADA and D3T-GAN did well, with ADA slightly ahead.

3.2.2 Human Evaluation

We also ran a blind human study. Participants ranked samples by realism and semantic accuracy. The results matched the metrics. ADA ranked first, D3T-GAN second, LDM-GAN last. Participants noted that ADA images looked sharper and better aligned with prompts. LDM-GAN often produced vague or incomplete outputs. These findings support earlier studies that link adaptive augmentation to sharper and more consistent results.

3.2.3 Artifact Analysis

LDM-GAN showed less stability than augmentation-based models. Its loss curves were noisy, and FID dropped more slowly. Two main artifacts appeared. The first was semantic collapse, where outputs converged to similar forms under limited data. Collapse rates reached 32% with fewer than 500 samples, compared to 8% for ADA [10]. The second was oversmoothing, where denoising removed fine details. On LSUN Landscapes-100, 78% of LDM outputs showed blur, compared to only 12% with ADA [11]. These results highlight a trade-off. LDM-GAN produces diverse outputs but is prone to artifacts. In contrast, StyleGAN2-ADA preserves fidelity more reliably in low-data settings.

3.3 Domain Adaptability

3.3.1 Cross-Domain Tests

We tested adaptability on FFHQ, Oxford Flowers102, and LSUN Landscapes, each sampled with few images per class. StyleGAN2-ADA generalized best with minimal overfitting. D3T-GAN worked but needed tuning. Models trained on CIFAR-10 transferred poorly to STL-10, confirming known issues. ADA stayed resilient, while LDM-GAN produced domain-specific artifacts, especially in faces, and lacked stability.

3.3.2 Data Requirements

We also tested the minimum data required for usable training. ADA maintained strong performance with as few as 250 samples. D3T-GAN degraded quickly when training data fell below 500 samples. LDM-GAN was nearly unusable with fewer than 1000 samples. These findings suggest that ADA’s adaptive discriminator augmentation is particularly effective in low-data regimes.

3.4 Method-Wise Summary

3.4.1 StyleGAN2-ADA: Strengths & Limitations

StyleGAN2-ADA extends the StyleGAN2 framework with adaptive augmentation, adjusting transformations based on overfitting signals to stabilize training with limited data. It achieves high fidelity with as few as 100–500 samples, and the feedback loop improves generalization while reducing overfitting. However, it produces less diversity than diffusion models, which makes it weaker in varied domains. Despite this limitation, it has proven reliable in tasks such as defect detection and fine-grained art restoration, where fidelity is more important than diversity.

3.4.2 D3T-GAN: Strengths & Limitations

D3T-GAN improves few-shot generation through domain transfer, aligning a source generator with a structurally similar target domain. It adapts well when the two domains overlap, preserving structure and lowering training costs. Performance declines sharply when domains differ, leading to weaker stability and fidelity. Still, it remains effective in industrial and design tasks where domains share strong similarities, such as ShapeNet variations or synthetic-to-real adaptation.

3.4.3 WeditGAN: Strengths & Limitations

WeditGAN relocates latent codes in the generator's latent space instead of using pixel-level augmentation. This enables representation-level adaptation. It offers fine-grained attribute control and meaningful variation from very few examples. It is sensitive to poor initialization. Under severe data scarcity, mode collapse can occur. Its controllable editing effects make it particularly suitable for creative and design tasks such as style transfer and fashion design.

3.4.4 Smoothness Similarity Regularization: Strengths & Limitations

This method applies explicit smoothness constraints in latent and image space. It reduces training oscillations, limits mode collapse, and improves consistency without requiring extra data. Over-regularization may reduce diversity. Performance depends on careful parameter tuning. Well-suited for tasks needing stable adaptation with very little data, such as medical imaging or other low-resource domains where structural consistency is essential.

3.4.5 DEff-GAN: Strengths & Limitations

DEff-GAN adds auxiliary classifiers and structural priors to expand class-level variation. It balances fidelity and diversity, supports multiple attribute edits, and reduces overfitting through class-level guidance. Training is more complex and sensitive to design choices. With extremely scarce data, diversity gains do not always lead to stable convergence. Useful in attribute-driven tasks such as facial manipulation or product design.

3.5 Integrated Comparison

Table 1 compares five representative models: StyleGAN2-ADA, D3T-GAN, WeditGAN, Smoothness Regularization, and DEff-GAN. It highlights their performance across three key dimensions: stability, fidelity, and adaptability. This condensed view shows the trade-offs more clearly while keeping the focus on core strengths.

Table 1. Formatting sections, subsections and subsubsections.

Model	Stability	Fidelity	Adaptability
StyleGAN2-ADA	High	High	Moderate
D3T-GAN	High	High	High (if domains similar)
Wedit GAN	Moderate	Moderate	Attribute-Level
Smoothness Reg.	High	Moderate	Moderate
Deff-GAN	Moderate	High	High (multi- class)

StyleGAN2-ADA stands out as the most stable and reliable option, even with very few images. D3T-GAN excels in domain transfer tasks when the source and target are closely aligned. WeditGAN is useful for fine-grained attribute control but requires careful initialization. Smoothness Regularization improves stability under scarcity but offers less diversity. DEff-GAN supports multi-class synthesis and broader diversity, though it often needs extra tuning.

In summary, each model brings unique strengths. ADA is best for fidelity in small-sample cases. D3T-GAN is suited for domain transfer. WeditGAN works for controlled editing. Smoothness Regularization stabilizes training under scarcity. DEff-GAN supports broader diversity. No single model dominates. The right choice depends on the priorities of the task.

4 Conclusion

This study systematically compared six leading few-shot GAN methods, establishing a clear taxonomy of performance trade-offs. No single model dominates across all dimensions; instead, each specializes in specific areas such as fidelity (ADA), domain adaptation (D3T-GAN), or diversity (LDM-GAN).

For practitioners, this work provides a decision framework for model selection. For researchers, it highlights that future progress hinges on developing hybrid solutions that combine these specialized strengths.

We identify two critical paths forward: 1) developing hybrid frameworks (e.g., ADA + LDM-GAN) to bypass existing trade-offs, and 2) creating standardized benchmarks for fair and reproducible evaluation.

In the end, progress will not come from one dominant model. It will come from integrated frameworks that combine complementary strengths. Future systems must be flexible, stable, and efficient. Only then can few-shot generation meet the demands of real-world applications.

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