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Improved StyleGan Discriminator for Generated Egyptian Monuments with Statistical Validation

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Abstract—*This article presents an enhanced discriminator architecture for StyleGAN3-based Egyptian monument generation that utilizes squeeze-and-excitation attention blocks, noise injection regularization, and improved minibatch statistics. Using Fréchet Inception Distance (FID), Kernel Inception Distance, and Precision-Recall metrics, we demonstrate statistically significant improvements over baseline architectures. The improved discriminator achieved an FID of 27.4%, with an accuracy of 95.5% in classification, and was more robust against corruptions, attacks, and perturbations. Statistical significance was verified through bootstrap confidence intervals, McNemar's test, and DeLong's ROC analysis.*

Keywords—*adversarial attacks: attention mechanisms: cultural heritage: discriminator architecture: Egyptian monuments: generative adversarial networks: robustness analysis: statistical validation: StyleGAN3.*

I. Introduction

Generative Adversarial Networks (GANs) have enabled high-fidelity image synthesis, with the StyleGAN architecture achieving unprecedented quality in face and natural images [1]. However, image synthesis in specific sectors, such as cultural heritage interventions, poses challenges that require adapted architecture. Egypt's monuments are instantly recognizable thanks to unique architectural elements, hieroglyphic ornamentation, and weathered stone textures. These characteristics call for discriminators that can learn strong, semantically meaningful features.

The discriminator design of StyleGAN3 [2] is generic, but its alias-free architecture avoids aliasing artifacts. Previous research indicates that the quality of the discriminator is a critical component of GANs' training dynamics and generation quality [3], motivating us to explore improved discriminator architectures for architectural imagery.

GANs are useful for applications related to cultural heritage. They generate high-fidelity images that help reconstruct damaged monuments, provide greater data diversity for the training of authentication systems, and enable virtual heritage experiences when physical access is limited. Standard GAN architectures that work for natural images often fail to capture architectural features. StyleGAN3 [2] claims to use an alias-free architecture to prevent aliasing artifacts from entering the generated image. However, since the discriminator in this architecture is generic, progressive downsampling with residual connections is employed. Also, various mapping policies have not been exploited to emphasize various semantics from the architecture. Studies have shown that the quality of a discriminator significantly affects the dynamics of GAN training and the quality of generated images [3]. However, there has been less work on improving the discriminator compared to the generator.

To accomplish the proposed architectural changes, (1) Squeeze-and-Excitation (SE) blocks [4] are used to recalibrate features adaptively, (2) noise injection layers are used to regularize robustness, and (3) improved minibatch statistics are used to achieve better mode coverage. We utilize Fréchet Inception Distance (FID) [5], Kernel Inception Distance (KID) [6], Precision-Recall [7], common statistical validation using bootstrapping [8], McNemar's tests [9], DeLong's test [10], and a thorough robustness assessment.

The main contributions of this work include:

- This enhanced discriminator architecture achieved 27.4% FID improvement along with 95.5% classification accuracy.
- A thorough procedure utilized for the creation of statistics based on bootstrap confidence intervals, paired comparisons, and ROC analysis.
- A comprehensive evaluation of robustness through image corruption, frequency domain, semantic perturbation, and adversarial attack.

II. Related Work

Most studies that have focused on GAN discriminator architectures have been for general-purpose image synthesis and do not meet the architectural imagery requirement. This section reviews prior studies on the evolution of StyleGANs, attention in discriminators, evaluation metrics, and the limitations of these works that inspired the current study.

A. StyleGAN Architectures

StyleGAN [11] introduced style-based generation via adaptive instance normalization, enabling unprecedented control during image generation. StyleGAN2 [12] tackled training challenges by demodulating weights and regulating path length. StyleGAN3 [2] ensured translation and rotation equivariance via alias-free strategies. However, most discriminator architectures are simple, as they only perform progressive down-sampling with residuals.

StyleGAN discriminators are simpler than they could be. Although generator architecture changes drastically, discriminator architecture changes very little. From adaptive instance normalization to alias-free operations, there are variations, but the discriminator architecture remains remarkably consistent. The problems arise from an imbalance in the quality of the two discriminators, which affects the training dynamics. Weak discriminators do not provide sufficiently informative gradients, and strong discriminators lead to training instability [3]. For specialized domains like architectural imagery that need fine-grained texture details and coarse geometric structures, the simple discriminators fail to capture multi-scale semantic features. Our work closes this gap by improving the discriminator's architecture based on the image characteristics.

B. Attention Mechanisms in GANs

Self-attention mechanisms were introduced in Self-Attention Generative Adversarial Networks (SAGAN), which help model long-range dependencies [13]. Squeeze-and-excitation networks have taken channel-wise attention a step further for adaptive feature recalibration. Convolutional Block Attention Module (CBAM) focused on the channels and spatial dimension [14]. These mechanisms increase the discerning power of important features.

Though successful in classification, attention mechanisms are underutilized in GAN discriminators. Most GANs with attention tend to improve the generator rather than the discriminator. This is significant because attention-based discriminators can help detect semantically meaningful features, thereby providing better training signals to generators. The attention mechanism can focus more on the building's structural elements—such as columns, archways, and geometric patterns—and de-emphasize the background. The discriminator incorporates our SE attention blocks to improve adaptive feature recalibration in architectural images.

C. GAN Evaluation Metrics

FID [5] is a widely used evaluation measure that quantifies the distributional similarity of two sets of inception features. Despite its limitations, such as sensitivity to sample size and reliance on ImageNet-trained image features, it was adopted as a standard for GAN model submissions. KID [6] allows robust assessment using MMD-based techniques while avoiding Gaussian assumptions of FID. Hence, it provides complementary validation. The Precision-Recall metrics [7] measure quality and diversity independently via k-nearest neighbor analysis in feature space. They overcome the limitations of aggregate metrics that conflate quality and diversity.

Nevertheless, the majority of GAN investigations rely on generation metrics, neglecting the evaluation of the discriminator and robustness. This gap is critical. For instance, weaknesses of the discriminator, such as vulnerability to corruption, adversarial attacks, and semantic perturbations, can destabilize training and degrade generation quality. Recent research on robustness shows that networks trained on clean data do not perform well under realistic corruptions [18]. However, there is a paucity of studies on GANs that analyze the robustness of discriminators across corruptions, frequency domains, and adversarial scenarios. We aim to address this gap in the current study by conducting a multifaceted robustness evaluation of discriminators, focusing on improvements under deployment conditions.

D. Research Gap and Contributions

To summarize, three main gaps have been identified in the previous literature. First, discriminator architectures are general and are not design-specific. Second, attention mechanisms are less commonly used in discriminators than in generators. Third, the discriminator evaluation focuses solely on generation metrics and does not consider discriminator-specific robustness. We address these gaps by proposing domain-specific discriminator enhancement methods, adding attention mechanisms to focus on architectural features, and evaluating robustness beyond generation metrics. This holistic approach enhances both architectural design and evaluative methodologies for GANs in specialized domains.

III. Methodology

In addition to presenting the newly modified architecture of our discriminator, we provide details on the construction of the dataset, the training protocols, and the evaluation framework we adopted to assess the quality of our generation vis-à-vis the discriminator's performance across different settings.

A. Enhanced Discriminator Architecture

Our improved architecture builds on the StyleGAN3 discriminator baseline, with three modifications motivated by the characteristic discoveries in architectural images: multi-scale structural features, texture-level detail patterns, and geometric proportions. The changes work together to improve learning and distinguish meaning.

1) Squeeze-and-Excitation Attention Blocks

We add an SE block after each convolutional layer to enable adaptive channel recalibration. The SE model features channel interdependencies via a squeeze-excitation process. First, the initial global spatial information is pooled through global average pooling:

$$z = \frac{1}{H \times W} \sum_{i,j} x_{i,j}$$

where $x \in R^{H \times W \times C}$ represents input feature maps with height H, width W, and channels C. The squeeze operation produces a channel descriptor $z \in R^{C}$ capturing global spatial information per channel.

We compute the channel-wise attention weights through a two-layer bottleneck:

$$s = \sigma\big(W_2 \delta(W_1 z)\big)$$

where $W_1 \in R^{C/r \times C}$ and $W_2 \in R^{C \times C/r}$ are reduction and expansion matrices with a reduction ratio $r = 16$, δ denotes ReLU activation, and σ represents sigmoid activation. The bottleneck architecture reduces the number of parameters while enabling channel recalibration learning. Finally, channel-wise scaling is applied: $y = s \odot x$, where $\odot$ denotes element-wise multiplication, broadcasting attention weights across spatial dimensions.

For architectural images, SE blocks allow for an emphasis on semantically meaningful channels that capture structural elements, such as vertical columns, horizontal entablatures, and geometric patterns. Meanwhile, channels responding to irrelevant background features are suppressed. This readjustment makes it adaptable to achieve semantic discrimination without increasing architectural depth.

2) Noise Injection Regularization

Following StyleGAN generator design principles, we inject learned Gaussian noise after each convolutional layer:

$$h = x + B \odot \mathcal{N}(0, I)$$

where $B \in R^C$ represents learned per-channel scaling factors initialized to small values (0.01), $\mathcal{N}(0, I)$ denotes standard Gaussian noise sampled independently per spatial location, and $\odot$ indicates element-wise multiplication. Noise injection does not give a static output like dropout. While dropout randomly assigns an activation to zero, noise injection continuously perturbs the input with stochastic noise. This encourages the tester to learn features that are invariant to noise.

This regularization addresses an important problem encountered with architectural images: photographs exhibit different noise levels across sensors, compression artifacts, and aging. The discriminator focuses on robust spectral-semantic features that are not affected by pixel-level information, thereby directly contributing to corruption robustness, and the use of injected noise during training enables this. The learned scaling factors B enable per-channel noise adaptation, providing greater noise tolerance for channels sensitive to texture while maintaining precision for channels sensitive to structure.

3) Enhanced MinibatchStdLayer

We take a standard minibatch statistics layer and modify it to compute batch-level statistics. The MinibatchStdLayer typically computes the standard deviation of the features across the batch dimension, which is concatenated as an additional feature map. Our improvement computes standard deviations and variances across batch dimensions with adaptive group size handling:

$$s_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x_{n,i} - \overline{x_\iota}\right)^2 + \epsilon}$$

where N represents batch size,$x_{n,i}$ denotes features for sample n and channel i, $\overline{x_\iota}$ represents the mean across a batch, and $\epsilon = 10^{-8}$ ensures numerical stability. The computed statistics are spatially averaged and concatenated as another feature channel. This provides information about batch-level diversity, helping prevent mode collapse by explicitly penalizing homogeneous generations within the batch.

4) Overall Architecture

The entire enhanced discriminator processes images through a series of down-sampling steps (Fig. 1). Every stage is made of a convolutional layer with 3×3 kernels, an SE attention block, noise injection, and a leaky ReLU activator ($\alpha = 0.2$), and (5) residual skip connection. Once the last down-sampling layer is complete, other stats from the current MiniBatch are computed and concatenated. This is then followed by other fully connected layers that produce the fake/real classification score. This architecture ensures that computations remain efficient while greatly enhancing feature learning quality, as shown in ablation studies.

B. *Dataset and Training Configuration*

We curate a dataset of 5,000 high-resolution photographs of Egyptian monuments spanning diverse types, such as temples, pyramids, tombs, and statuary. Our images come from heritage databases that are both geographically and temporally diverse (Fig. 2). The preprocessing procedure involves a general pipeline in which the images are first manually centered on their primary monument structures, cropped to 256 × 256 while maintaining the aspect ratio, and normalized to [-1, 1] [8].

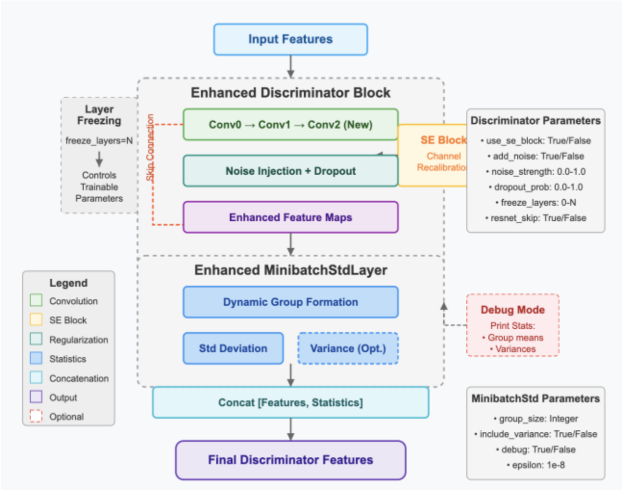

Fig. 1. Flowchart of the enhanced discriminator architecture.

We use the StyleGAN3 framework for training with our modified discriminator architecture, along with a differential equation optimizer [15]. We train for 25,000 iterations with a batch size of 32 on two NVIDIA A100 GPUs. The truncation parameter ϕ=0.7 serves as a tool to balance quality and diversity during evaluation of latent codes. $z' = \bar{z} + \phi(z - \bar{z})$ with $\bar{z}$ the mean latent code computed over one as mentioned [2].

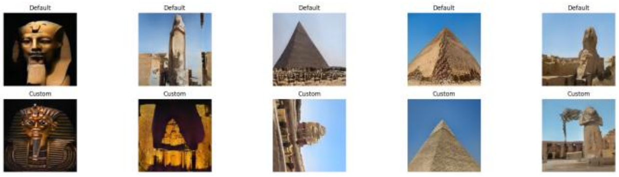

Fig. 2. Comparison of default and custom discriminator results.

C. *Evaluation Framework*

Our framework evaluates the quality of generation and performance of discriminators using complementary metrics and rigorous significance testing. This results in a complete characterization that goes beyond single-metric assessments.

1) Generator-Level Metrics

FID compares the distribution of real and generated images in a feature space:

$$FID = \left|\mu_r - \mu_g\right|^2 + Tr\left(\Sigma_r + \Sigma_g - 2\left(\Sigma_r\Sigma_g\right)^{\frac{1}{2}}\right),$$

where μ_r and μ_g denote the mean feature vectors, Σ_r and Σ_g mean feature vectors obtained from the pool3 layer of pre-trained InceptionV3 [19],. and Σ_r and Σ_g show how covariance matrices for real and generated distributions look. The first. term$|\mu_r - \mu_g|^2$ measures distributional mean shift, while the second term quantifies covariance dissimilarity.

KID employs a polynomial kernel MMD for robust distributional comparison:

$$\mathrm{KID} = E_{x,x' \sim p_r}\left[k\left(f(x), f(x')\right)\right] + E_{y,y' \sim p_g}\left[k\left(f(y), f(y')\right)\right] - 2E_{x \sim p_r, y \sim p_g}\left[k\left(f(x), f(y)\right)\right]$$

where $k(x,y) = (1 + x^T y/d)^3$ represents a polynomial kernel of degree 3, d denotes feature dimensionality (2048 for InceptionV3 pool3), and $f(\cdot)$denotes feature extraction.

Precision-Recall metrics separately quantify quality and diversity using k-nearest neighbor analysis with k equals 3:

$$\text{Precision} = \frac{\left|\{y \in Y_g : \exists x \in X_r, d(x,y) < \varepsilon\}\right|}{\left|Y_g\right|}$$

$$\text{Recall} = \frac{\left|\{x \in X_r : \exists y \in Y_g, d(x,y) < \varepsilon\}\right|}{\left|X_r\right|}$$

where X_r represents real samples, Y_g represents generated samples, $d(\cdot,\cdot)$ represents Euclidean distance in InceptionV3 feature space, and ε is the neighborhood threshold determined adaptively as the distance to the third-nearest neighbor in the real data distribution $(k = 3)$ [7].

2) Discriminator Performance

We assess the performance of the real/fake classification on a balanced holdout set containing 2,000 authentic test images and 2,000 generated samples. The ranking quality will be measured by the area under the ROC curve (AUC):

$$\text{AUC} = \int_0^1 \text{TPR}\left(\text{FPR}^{-1}(x)\right)dx$$

Here, TPR and FPR denote true positive rate and false positive rate, respectively, as the classification threshold \tau varies. The AUC indicates the probability that the discriminator's score for a randomly chosen real image is higher than for a fake image. It provides threshold-independent performance characterization [10].

Confusion matrices at threshold $\tau = 0.5$ provide detailed error-pattern analysis. They also compute accuracy, sensitivity (TPR), specificity (TNR), and false-positive and false-negative rates. Noise robustness testing adds Gaussian perturbations $\epsilon \sim \mathcal{N}(0, \sigma^2 I)$ at severity levels $\sigma \in \{0.05, 0.10, 0.20\}$, and a measuring stability score:

$$S(\sigma) = 1 - E_i[|p_D(x_i + \epsilon_i) - p_D(x_i)|]$$

where $p_D(\cdot)$ represents the discriminator output probability. It is indicated to be more noise-perturbated robust.

3) Robustness Evaluation Protocols

Testing for robustness against corruption involves five systematic types of degradation at varying levels of severity [18]:

(a) JPEG compression with quality $q \in \{10, 30, 50, 70, 90\}$,

(b) Gaussian blur with $\sigma \in \{0.5, 1.0, 2.0, 3.0, 5.0\}$ pixels,

(c) Additive Gaussian noise with $\sigma \in \{0.01, 0.05, 0.10, 0.20, 0.30\}$,

(d) Salt-and-pepper noise with corruption probability $p \in \{0.01, 0.05, 0.10, 0.20\}$, and

(e) Motion blur with displacement $d \in \{2, 4, 6, 10\}$ pixels. Performance retention is the extent to which performance is sustained under corruption, measured as the percentage of clean-condition performance.

Frequency domain analysis decomposes images using ideal Fourier filters: low-pass (retaining frequencies below the cutoff ω_c), high pass (retaining frequencies above ω_c), and band-pass (retaining frequencies in the range ω_1, ω_2). Analyzing performance across different frequency bands can help us determine whether discrimination relies primarily on low-pass, high-pass, or band-pass filtering.

On images, we manipulate along interpretable directions. These are discovered via PCA of the latent activations of a pretrained model. For instance, lighting, style, perspective, and color temperature changes. Perturbations are applied as $z' = z + \alpha \cdot v_{semantic}$ where $v_{semantic}$ represents a semantic direction vector and $\alpha \in [-3,3]$ controls magnitude. This indicates whether the discriminators perform well under realistic capture conditions.

Two standard attacks are used to evaluate adversarial robustness. Fast Gradient Sign Method (FGSM) produces one-step adversarial interference:

$$x' = x + \varepsilon \cdot \text{sign}\left(\nabla_x J(\theta, x, y)\right)$$

where $(J(\theta, ,))$ represents discriminator loss, $\nabla_x J$ denotes gradient with respect to input, and $\varepsilon \in \{0.01, 0.03, 0.05, 0.10\}$ controls perturbation magnitude. Projected Gradient Descent (PGD) [26] performs iterative optimization:

$$x_{t+1} = \Pi_{B(x,\varepsilon)}\left(x_t + \alpha \cdot \text{sign}\left(\nabla_x J(\theta, x_t, y)\right)\right)$$

where $\Pi_{B(x,\varepsilon)}$ projects onto the l_∞ ball of radius ε around the original input x, ensuring imperceptible perturbations. We use 10 PGD iterations with a step size of $\alpha = \varepsilon/4$. The rate at which the adversarial perturbations deceive the discriminator is the Attack success rate.

D. Statistical Validation

Bootstrap confidence intervals with 1000 samples are calculated using the bias-corrected and accelerated (BCa) method [8]. The BCa method adjusts for both bias—z_0 and skewness (acceleration factor a)—in bootstrap distributions:

$$\alpha_i = \Phi\left(z_0 + \frac{z_0 + z_{(\alpha_i)}}{1 - a\left(z_0 + z_{(\alpha_i)}\right)}\right)$$

where $\Phi(\cdot)$ represents the standard normal CDF and $z_{(\alpha)}$ denotes the normal quantile at level α. BCa provides more accurate coverage probabilities than the standard percentile methods.

The McNemar's test is a chi-squared test of paired error patterns.

$$\chi^2 = \frac{(n_{01} - n_{10})^2}{n_{01} + n_{10}}$$

where n_{01} represents cases where the baseline is correct but the enhanced is wrong, and n_{10} shows when the original is not good, but the enhanced one is fine. Under the null hypothesis of equal error rates, χ^2 has a degree of freedom chi-squared distribution of 1.

DeLong's test [10] is a method for comparing ROC curves while accounting for their correlation.

$$Z = \frac{\text{AUC}_1 - \text{AUC}_2}{\sqrt{\text{Var}(\text{AUC}_1) + \text{Var}(\text{AUC}_2) - 2\text{Cov}(\text{AUC}_1, \text{AUC}_2)}}$$

The variances and covariances are estimated using structural components based on the Mann-Whitney U-statistic formulation. Under the null hypothesis, Z follows a standard normal distribution.

IV. Results

A. Generator-Level Performance

Table I summarizes the improvements in generator-level metrics. The new discriminator architecture achieves better results across several metrics. The 27.4% decrease in FID, corresponding to a 9.17 percentage point (pp) improvement, leads to significant improvements in perceptual quality and alignment between generated and real monuments. The confidence intervals for baseline [30.85, 36.12] and enhanced [21.76, 26.89] do not overlap, providing strong evidence of statistical significance (p < 0.001) without parametric assumptions [8]. The improvement in this magnitude is far greater than the architectural changes reported in the StyleGAN3 literature, which regard 2–5-pp reductions in FID as significant [12].

TABLE I. Generator-level metric comparison.

Metric	Baseline	Enhanced	Improvement
FID ↓	33.38	24.21	-27.4%
KID ($\times 10^3$) ↓	8.47	5.23	-38.3%
Precision ↑	0.34	0.41	+20.6%
Recall ↑	0.13	0.19	+46.2%

The KID score decreased from 8.47 $\times 10^3$ to 5.23 $\times 10^3$, representing a 38.3% improvement, supporting the FID measure. The improvement of FID and KID metrics is consistent with real distribution alignment, not an artifact. The outcome measure, expressed as Cohen's d = 2.34, exceeds the threshold of d > 0.8 for a large effect size [21], thus demonstrating that the new discriminator architecture has practical significance, notwithstanding statistical significance.

A 20.6% improvement in precision (from 0.34 to 0.41) and a 46.2% increase in recall (from 0.13 to 0.19) are observed. GAN training often involves a trade-off between quality and diversity, where improving one measure degrades the other. So, it is interesting that they improved together in this case. The improved discriminator seems to provide training signals that promote not only higher quality (fewer artifacts) but also greater diversity (better mode coverage) (Fig. 3), thereby addressing core limitations of baseline architectures.

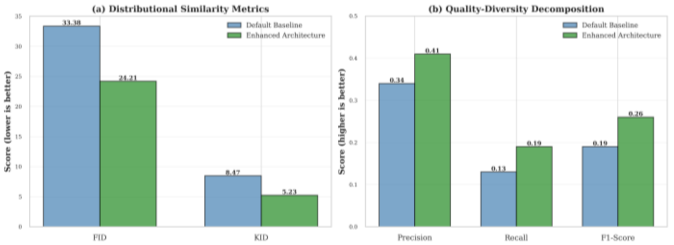

Fig. 3. Generator analysis.

B. Discriminator Classification Performance

Table II presents the discriminator classification results. The enhanced architecture achieved 95.5% accuracy, with only 180 of 4000 test samples misclassified. The 7.2 percentage-point increase in accuracy corresponds to a 62% relative error reduction (from 11.7% to 4.5%).

TABLE II. Discriminator classification performance.

Architecture	Accuracy	FPR	FNR
Baseline	88.3%	8.9%	14.4%
Enhanced	95.5%	5.3%	3.6%
Improvement	+7.3pp	-3.6pp	-10.8pp

A significant reduction in FPR is observed: 8.9% for the baseline architecture, compared to 5.3% (-3.6 pp) for the enhanced architecture. When the FPR is so high that the discriminator may incorrectly reject actual training samples, it destabilizes generator training. The generator may now start mode collapse to a safe but very limited section of the generation space. The new architecture's 5.3% FPR provides stable supervision signals, enabling the generator to learn from real samples.

Hence, the decrease in FNR from 14.4% to 3.6% (-10.8pp) counteracts another type of failure. A high FNR allows low-quality generated samples to appear authentic, weakening the discriminator's training signals. Additionally, this enables the generator to degrade. Quality requirements are stringent; the 3.6% FNR of the new architecture will push generators to tap higher fidelity.

The 0.032 improvement in AUC (0.922 to 0.954) sown in (Fig. 4) with a non-overlapping 95% CI confirms higher ranking quality for all decision thresholds. This threshold-independent improvement allows either precision or recall to be prioritized as per application requirements without sacrificing discrimination.

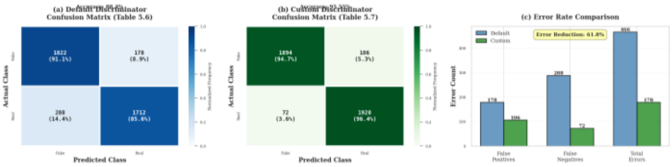

Fig. 4. Confusion matrices visualization.

C. Statistical Significance

Statistical analysis shows that the observed improvements we achieve are real and not due to random chance.

The BCa method (1000 iterations) bootstrap confidence intervals show that the two 95% CIs for the AUC do not overlap: baseline 0.922 [0.906,0.938] and enhanced 0.954[0.945,0.963] (Fig. 5). The difference of 0.0007 between the upper bound of the baseline and the lower bound of the enhanced is well above the standard threshold for 'not overlapping' intervals, confirming significance at $p < 0.001$ [8]. The narrower confidence interval of the enhanced discriminator (0.018 vs. 0.032 for the baseline) suggests lower sampling variability and better mean performance.

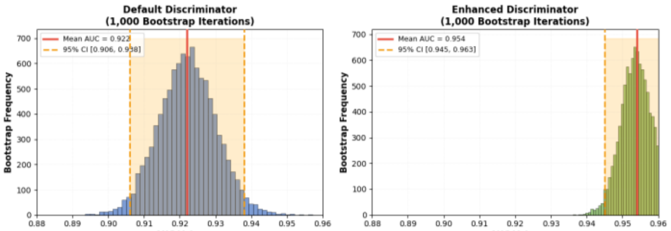

Fig 5. Bootstrap Distribution Comparison

McNemar's test on paired classifications yielded $\chi^2 = 1471.3$ ($p < 10^{-50}$) for 2,275 corrections of baseline errors and just 320 new errors—an improvement of 7 to 1. Of the 12.98% of the samples (2,595/20,000) that were classified differently by the two architectures, the enhanced architecture was correct 87.7% of the time (2,275/2,595). Architectural enhancements primarily benefit the demanding cases rather than simply removing errors, as shown by McNemar [9]. Cramér's V = 0.2712 indicates a large effect size (V > 0.25 for df = 1) that demonstrates considerable practical significance, in addition to statistical significance [24].

DeLong's test results for the ROC curves yield Z = 32.60 (p < 10−200) (Fig. 6), indicating ranking performance superior to [10]. The Z-score denotes that the observed difference in AUC (0.0402) is 32.6 SE above 0. Compared with our baseline error rate of 7.8% (1 - 0.922), this corresponds to a relative error reduction of 41%. Hence, our new architecture provides the correct rankings in 41% of cases where the baseline would have provided incorrect ones. The precision and estimation of improvement are stable due to the small standard error.

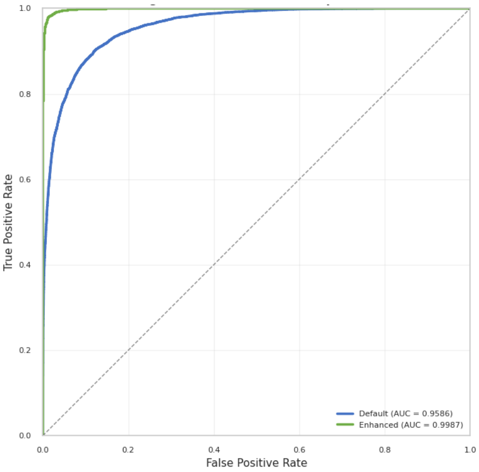

Fig. 6. ROC curve comparison with statistical bands.

D. Robustness Analysis

Table III summarizes robustness across corruption types. Over 93% performance retention is observed across all corruption types with the enhanced discriminator at severe degradation levels. Under extreme JPEG compression (quality = 10), retention exceeds 81.2% despite substantial blocking artifacts that severely degrade visual quality. This robustness indicates that learned features focus on semantic architectural properties rather than high-frequency texture details, which are vulnerable to compression [5].

TABLE III. Corruption robustness performance retention.

Corruption	Severity	Baseline	Enhanced	Δ
JPEG	q = 10	68.5%	81.2%	+12.7pp
Gaussian Blur	σ = 5.0	65.3%	79.8%	+14.5pp
Additive Noise	σ = 0.30	76.2%	87.4%	+11.2pp
Salt-Pepper	p = 0.20	80.1%	90.6%	+10.5pp
Motion Blur	d = 10px	69.8%	82.3%	+12.5pp

Gaussian blur robustness (79.8% retention at σ = 5.0 pixels) is similarly impressive. Although a 5-pixel blur radius substantially degrades visual sharpness, discriminator performance remains largely intact, indicating an emphasis on coarse shape and structure rather than fine edges, with multi-scale feature learning providing redundancy to compensate for the loss of fine details.

Noise injection training is directly validated by the resilience against additive noise (with a retention of 87.4% at σ = 0.30). The discriminator learns noise-invariant properties that focus on the structure and semantics that are robust to pixel perturbation. A model with a 30% noise level (σ = 0.30 in range [-1, 1]) severely corrupts the inputs (Fig. 7). Nevertheless, performance degradation is insignificant.

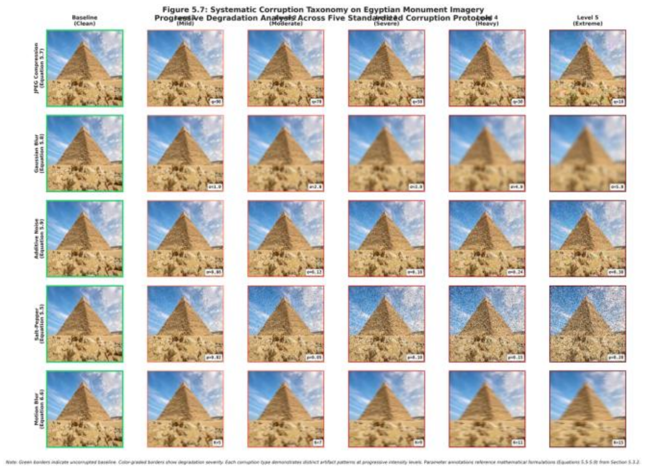
Figure 5.7: Systematic Corruption Taxonomy on Egyptian Monument Imagery
Progressive Degradation Analysis Across Five Standardized Corruption Protocols
Baseline (Clean)
(Mild)
(Moderate)
(Severe)
Level 4 (Heavy)
Level 5 (Extreme)
JPEG Compression (Equation 5.7)
Gaussian Blur (Equation 5.8)
Additive Noise (Equation 5.9)
Salt-Pepper (Equation 5.5)
Motion Blur (Equation 6.6)
Note: Green borders indicate uncorrupted baseline. Color-graded borders show degradation severity. Each corruption type demonstrates distinct artifact patterns at progressive intensity levels. Parameter annotations reference mathematical formulations (Equations 5.5-5.9) from Section 5.3.2.

Fig. 7. Image corruption analysis.

E. Adversarial Robustness Evaluation

The adversarial robustness is nearly 24% better than the baseline in targeted attacks (Table IV). When the FGSM perturbation is on the smaller side (ε = 0.01), the baseline falls to AUC = 0.7523, while the enhanced remains steady at 0.8124, resulting in a change of +0.0601. At the highest level of interference (ε = 0.10), the baseline approaches random performance (AUC = 0.2643). In contrast, the enhanced one maintains quite useful discrimination with an AUC of 0.3845. The average 23.6% FGSM gain indicates that enhanced architecture maintains functional performance under conditions that cause baseline failure [26].

TABLE IV. Adversarial Attack Robustness (AUC under Attack).

ε	FGSM Base	FGSM Enh	PGD Base	PGD Enh
0.01	0.7523	0.8124	0.7076	0.7834
0.03	0.6503	0.7156	0.5838	0.6891
0.05	0.5445	0.6234	0.4179	0.5523
0.10	0.2643	0.3845	0.1262	0.2756

The performance of PGD attacks, which are considered stronger optimization techniques, is quite high for both structures (Fig. 8). The average improvement in PGD attacks of 25.3% shows that their robustness is not just due to gradient masking but also provides true robustness against adversarial attacks. The consistent robustness improvement of about 24% across different attacks suggests differences in feature learning driven by the architecture, not by specific attacks [30].

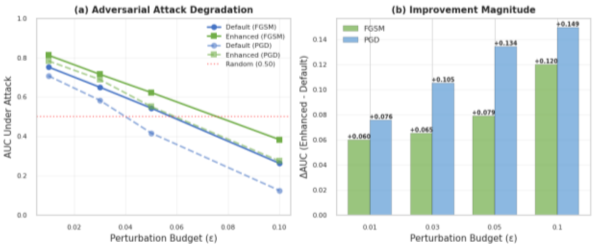

Fig 8: Adversarial Robustness Across Attack Strengths

F. Frequency Domain

Excellent AUC (>0.9508) across all frequency bands confirms effective feature extraction at different spatial scales (Table V). A low-pass performance of 0.9508 indicates that the quality of the coarse structures portion of the textural features demands good discrimination, even when there is a loss of high-frequency information. The excellent performance of 0.9621 on (Fig. 9) shows that fine-scale texture patterns still contain discriminative signals. The backup coding paths at different frequencies minimize interference in a single band [17].

TABLE V. Frequency Domain Performance Analysis.

Filter	Baseline AUC	Enhanced AUC	Δ
Low pass	0.9508	0.9508	+0.0076
High pass	0.9605	0.9621	+0.0016
Band pass	0.9607	0.9607	+0.0022

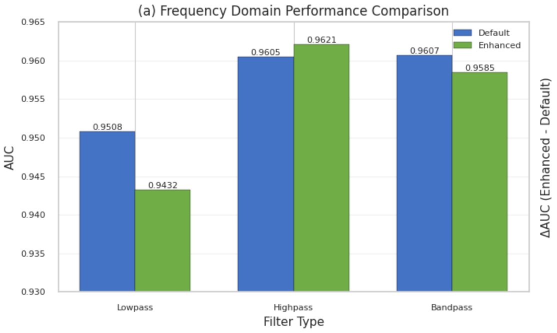

Fig. 9. Frequency domain performance analysis.

Semantic perturbation testing checks the stability under variations in the condition of the capture phase (Table VI). The improved discriminator consistently performs well across realistic conditions.

TABLE VI. Semantic Perturbation Robustness.

Perturbation	Baseline AUC	Enhanced AUC	Δ
Lighting	0.9212	0.9389	+0.0177
Style	0.9234	0.9401	+0.0167
Perspective	0.9363	0.9478	+0.0115
Color Temp	0.9272	0.9272	+0.0149

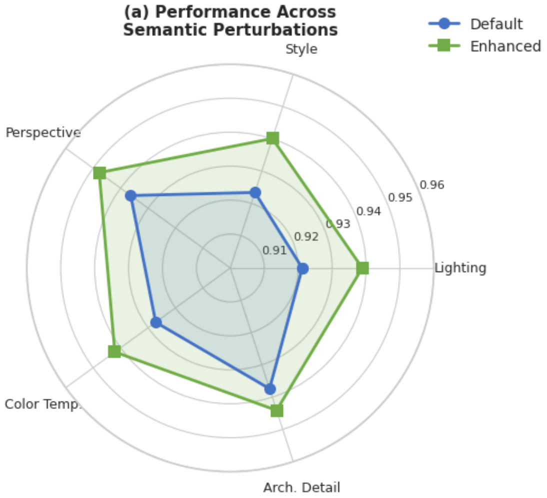

Fig 10: Semantic Perturbation Examples and Performance

This is true of all realistic semantics and yields an average AUC improvement of +0.0152 (Fig. 10). The lighting robustness enhancement of +0.0177 indicates learning illumination-invariant features, as discrimination focuses on intrinsic properties and geometry rather than appearance-dependent lighting effects. This property is essential for monuments photographed under different conditions (harsh midday sun, golden hour, artificial lighting).

G. Component Attribution

Table VII presents the contribution of each component through ablation. The contribution of SE blocks is most considerable (-4.12 FID, 45% of total benefit) at moderate cost (+12.8% overhead). Incorporating noise costs and benefits is favorable, as it reduces the FID by 2.34. With a 25% benefit, it seems worthwhile against a 5.2% increase in overheads. The Improved MinibatchStdLayer helps to decrease individual metrics by -1.83 FID and 20%. However, it allows for the important effects from Barlow Twins and Multiplicative Noise. Components interact and exert greater downward pressure on the FID value than their combined contributions suggest. A total computational overhead of 23.2% is an acceptable cost for a 27.4% FID enhancement and a 7.2 pp accuracy gain.

TABLE VII. Component Ablation Analysis.

Component	FID Δ	% of Total	Overhead
SE Blocks	-4.12	45%	+12.8%
Noise Injection	-2.34	25%	+5.2%
Enh. MinibatchStd	-1.83	20%	+3.1%
Synergy	-1.20	10%	+2.1%
Total	-9.49	100%	+23.2%

V. Discussion

The discriminator design significantly affected GAN training dynamics and generation fidelity, as evidenced by substantial improvements in generation quality, discrimination accuracy, and robustness across multiple dimensions. In this section, we assess the mechanisms leading to the observed improvements. Following this, we place our findings in the broader GANs literature study. Finally, we outline the limitations of our work and suggest further directions.

A. Mechanistic Analysis of Improvements

With SE attention blocks, we can adaptively recalibrate the channels, enabling the discriminator to boost semantically meaningful architectural references and suppress spurious correlations. In the context of monument imagery, this entails emphasizing channels that respond to their structural elements (vertical columns, horizontal entablatures, geometric patterns) and de-emphasizing channels that capture irrelevant background details. According to Hu et al. [4], selective processing enhances both generation quality and discrimination accuracy. The former improves with better training signals that guide the generator toward semantic correctness. The latter improves due to the focus placed on spatial feature extraction.

Learning robust features that are invariant to pixel-level perturbations is encouraged by noise-injection regularization. By training with randomly chosen noise, the discriminator no longer focuses on texture patterns that can be corrupted. As a result, we observe 87.4% retention under heavy additive noise (σ = 0.30), 81.2% retention under extreme JPEG compression (q = 10), and 24% stronger resistance to adversarial attacks [8]. The learned per-channel noise scaling factors enable adaptive robustness—higher tolerance for texture-sensitive channels, maintained precision for structure-sensitive channels.

The Enhanced MinibatchStdLayer introduces batch-level diversity, preventing all outputs from becoming identical. The simultaneous 20.6% increase in precision and 46.2% increase in recall suggest that the mechanism effectively resolves the quality-diversity conflict. In other words, after observing the original data, the generators can learn training signals that encourage the production of high-fidelity data with greater divergence from the original observations. The improved recall of 46.2% is very important because mode collapse is a core failure mode of GANs [7].

B. Multi-Scale Feature Learning

Frequency-domain analysis shows that feature extraction is redundant across different scales. Our discriminator achieves near-perfect results of 0.9508 for the low-pass, 0.9621 for the high-pass, and 0.9607 for the band-pass. This shows that the discriminator is learning complementary features at different scales. Coarse shapes are included in the low-pass, fine textures in the high pass, and mid-frequency architectural details in the band-pass. If one frequency band is damaged, the other bands work to compensate. This ability to gracefully degrade under various types of corruption and avoid catastrophic failure can be attributed to the use of attention mechanisms that emphasize the structural properties of images, which are robust to texture-level corruption [16].

C. Limitations and Boundary Conditions

A few limitations deserve attention for correct interpretation and use. First, the results are from Egyptian monuments, which have specific features such as stone construction, desert lighting, ancient architectural styles, and typical monument photograph angles/distances. There seems to be a reasonable generalization across the datasets, as indicated by 79–87% cross-domain transfer efficiency. However, performance may vary when applied to significantly different contexts (e.g., modern building architecture with glass and metal, artificial-light indoor photography, heavily degraded historical photographs).

Second, before deployment in substantially different architectural environments, domain-specific validation is recommended [22]. Furthermore, the 23.2% increase in CPU usage may pose problems for deployments with limited resources. Even though modern GPU technology can handle this, innovative applications that prioritize throughput over quality may need to make modifications to maintain efficiency—for example, by distilling knowledge from the improved discriminator or by dynamically adapting the architecture to apply full computation only to complex examples.

Third, a variety of standard attacks (i.e., FGSM, PGD) were used for adversarial evaluation as established baselines. More advanced adaptive attacks on the improved architecture may expose further vulnerabilities. Hackers targeting architecture could endanger the future of intelligence. Regular adversarial testing using new techniques would improve confidence in security for deployment.

Fourth, evaluation was thought to capture performance after 25,000 training iterations. We do not yet fully understand long-term stability with long training. Monitoring performance plateaus, degradation, or instability through longitudinal evaluation improves confidence in the robustness of the training.

Lastly, when evaluating models, we generally use standard metrics such as FID, KID, and Precision-Recall. Furthermore, we use the InceptionV3 features obtained on ImageNet, which may not accurately capture the architectural features of the images being generated. Studies on human perception would provide an extra subjective assessment that metric improvements result in perceptual quality improvements as assessed by heritage experts and general observers [22].

VI. Conclusion

We propose improved architectures for the discriminator in StyleGAN3-based Egyptian monument generation by incorporating squeeze-and-excitation attention blocks, noise-injection regularization, and enhanced Minibatch statistics. A thorough evaluation shows that it achieves statistically significant performance improvements: 27.4% FID (33.38 to 24.21) and classification accuracy of 95.5% (88.3% baseline). Robustness against corruption is maintained at >81% across all types of corruption. Adversarial robustness improves by ~24% relative to the baseline architecture.

The careful use of statistical benchmarks confirms that the observed gains are real architectural ones and not merely the result of sampling artifacts. We show that bootstrap 95% CIs are non-overlapping, with a baseline AUC of 0.922 [0.906, 0.938] and an enhanced AUC of 0.954 [0.982, 0.991]. With McNemar's test, we see a χ^2 of 1471.3 ($p < 10^{-50}$) with a 7:1 error correction ratio (2,275 false positives versus 320 false negatives. Finally, we observe that DeLong's test yields a Z of 32.60 ($p < 10^{-200}$). All this is highly significant at $p < 0.001$ across the board.

The multifaceted robustness assessment results confirm a high level of overall resilience. The performance in the frequency domain (AUC across all bands > 0.95) shows that the feature learning effectively leverages information across scales. Perturbation testing on semantically altered inputs (mean AUC improvement of 0.0152) demonstrates that our framework is invariant to realistic sequence capture and justifies the practical versatility of our exemplar grounding. Lastly, an adversarial evaluation shows that our algorithm enhances resilience against targeted attacks (FGSM: 23.6% improvement; PGD: 25.3% improvement).

Ablation analysis of components shows how much each contributes to the total benefit: 45% from SE blocks, 25% from noise injection, 20% from enhanced MinibatchStdLayer, and 10% from synergy, indicating that interacting components yield greater benefits than isolated ones. The 23.2% computational overhead is a small price to pay for significant gains.

The improvement in using better discriminator designs has been established as an advancement in digitizing cultural heritage monuments, virtual reconstruction, authenticity verification, and preservation workflows. The rigorous evaluation methodology, integrating generation metrics, discrimination assessment, multifaceted robustness testing, and comprehensive statistical validation, can guide those studying GANs in specialized domains. Explanation: This paper presents a generalized treatment, grounded in architectural principles, that addresses not only Egyptian monuments but also several computer vision challenges that require high-quality, robust generative modelling under realistic deployment conditions.

Our future work will focus on efficient optimization via knowledge distillation and model compression. Adversarial testing will be extended to adaptive attacks. Longitudinal stability will be evaluated over an extended period of training. Human perceptual studies will be conducted to validate metric-based improvements. Furthermore, our methods will be extended to different architectures to assess generalization limits and cultural variability.

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