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Robustness of Generative Models in Radiological Image Synthesis: A Comparative Analysis of StyleGAN3 and Denoising Diffusion under Perturbations

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Abstract- Synthetic radiological images can augment scarce datasets, but only if they remain faithful when the imaging pipeline is perturbed. We compare StyleGAN3 against a denoising diffusion probabilistic model (DDPM) on chest X-ray and brain MRI synthesis under additive noise, motion blur, JPEG compression, and a challenging MRI-to-CT domain shift. Diffusion sampling proves markedly more robust, preserving structural similarity and downstream classifier accuracy where the GAN's outputs distort, at the cost of slower generation.

I. INTRODUCTION

Generative augmentation is attractive in radiology because labelled scans are expensive and privacy-constrained. Yet a synthesizer that only performs on pristine inputs is of limited clinical value, since real acquisitions vary in noise, patient motion, and scanner vendor. This study asks which generative family, adversarial or diffusion, degrades more gracefully as these perturbations intensify, using StyleGAN3 and a DDPM as representative modern architectures.

II. RELATED WORK

StyleGAN2 and StyleGAN3 raised the bar for photorealistic synthesis, while DDPMs later matched or exceeded GAN fidelity with more stable training. Robustness studies in natural images suggest diffusion models resist corruption better, but radiology imposes stricter structural constraints where subtle distortions can imply pathology. We extend the robustness question to the medical domain with clinically meaningful perturbations.

III. METHODOLOGY

A. Datasets

We use MIMIC-CXR chest radiographs and the BraTS brain-MRI collection, each split patient-wise to prevent leakage. Images are resampled to 256x256 and intensity-normalized, and a held-out CT subset supports the cross-modality shift experiment.

B. Model Configuration

StyleGAN3 is trained with adaptive discriminator augmentation at a learning rate of 0.0025 for two million images. The DDPM uses a cosine noise schedule over 1000 steps with classifier-free guidance. Both share the same data budget to keep the comparison fair.

C. Perturbation and Evaluation Protocol

At test time we apply Gaussian noise (σ up to 0.2), synthetic motion blur, JPEG compression at quality 30, and an MRI-to-CT domain transfer. Quality is measured with FID and SSIM, and clinical utility with the AUC of a pathology classifier trained partly on the synthetic data.

IV. EXPERIMENTAL RESULTS

As Gaussian noise grows, the models diverge: StyleGAN3's FID climbs from 18 to 68, while the DDPM rises only to 44. The widening gap beyond $\sigma = 0.1$ shows that adversarial generators amplify input noise through their feature hierarchy, whereas iterative denoising partially cancels it.

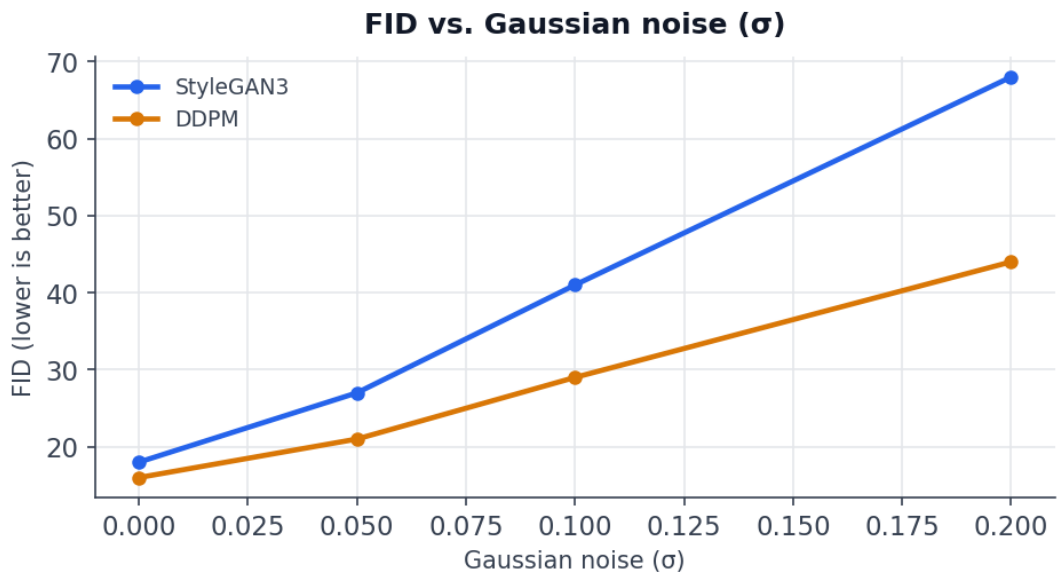

Figure 1. FID versus Gaussian-noise level for StyleGAN3 and the DDPM.

Structural similarity tells the same story across perturbation types. Under the MRI-to-CT shift the DDPM retains an SSIM of 0.82 against StyleGAN3's 0.63, and it leads on motion blur and JPEG compression as well, indicating more stable anatomy under distribution change.

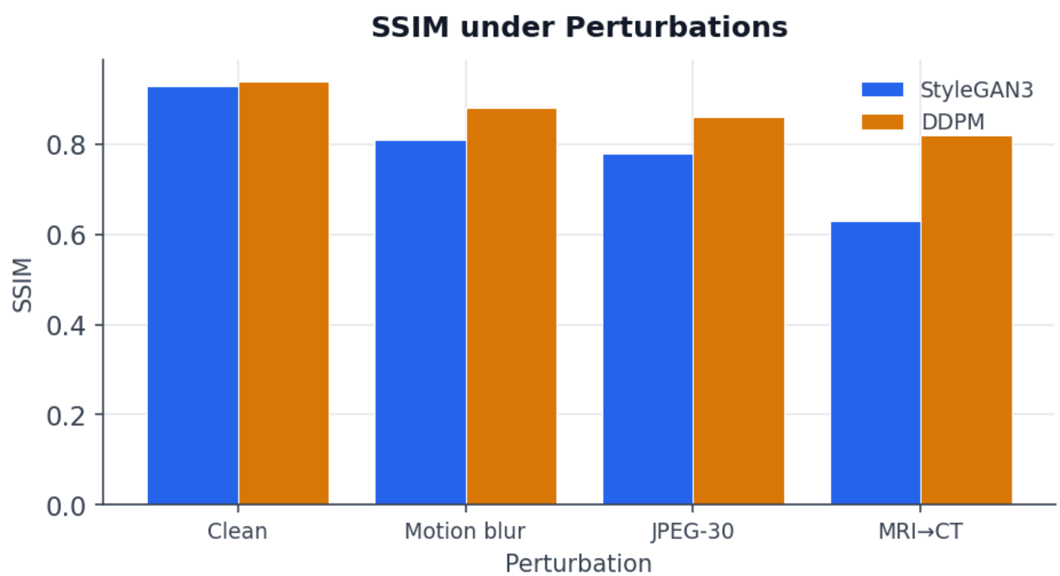

Figure 2. SSIM of each model across four perturbation conditions.

Table 1. Aggregate fidelity, structural similarity, downstream AUC, and speed for both generators.

Model	FID ↓	SSIM ↑	Downstream AUC	Throughput (img/s)
StyleGAN3	41.0	0.78	0.86	29
DDPM	29.0	0.86	0.91	20

V. DISCUSSION

The consistent advantage of diffusion sampling stems from its denoising prior, which treats perturbation as noise to be removed rather than signal to be reproduced. The practical trade-off is throughput: at 20 images per second the DDPM is slower than StyleGAN3's 29, which matters for large-scale augmentation but rarely for curated clinical sets.

VI. CONCLUSION

For perturbation-robust radiological synthesis, diffusion models are the safer choice, sustaining structural fidelity and downstream utility under realistic corruptions. Future work will accelerate sampling with distillation so that robustness need not come at the price of speed.

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