Adversarially Robust Image Generation for Medical Imaging: Evaluating StyleGAN2 vs Diffusion Models under Noise and Domain Shift

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Abstract- Medical image generation using deep generative models has emerged as a promising tool for augmenting limited clinical datasets, enabling synthetic data generation for training and improving model generalization. However, adversarial robustness remains a major challenge, especially under noisy or domain-shifted conditions where models may produce artifacts that compromise diagnostic reliability. This study conducts a comprehensive comparison between two state-of-the-art frameworks—StyleGAN2 and Denoising Diffusion Probabilistic Models (DDPMs)—across noise, adversarial attacks, and modality shifts. Our experiments span over 120,000 medical images across chest X-rays and MRI scans. We observe that diffusion models exhibit a 22% higher structural fidelity and a 19% lower Fréchet Inception Distance (FID) under Gaussian and adversarial perturbations. Additional robustness metrics show diffusion models outperform StyleGAN2 in both clean and noisy conditions, making them preferable for safety-critical applications.

I. INTRODUCTION

Deep generative models have transformed medical imaging through realistic data synthesis, enabling advancements in diagnostic augmentation, anonymization, and training of AI-based diagnostic systems. Despite these benefits, robustness under adversarial attacks and environmental noise remains underexplored, which is critical for safe deployment in healthcare. For instance, medical scanners introduce inherent noise variations, and inter-institutional data discrepancies (domain shifts) can cause models to hallucinate unrealistic structures. Therefore, this study aims to quantify the adversarial and environmental robustness of StyleGAN2 and diffusion-based models across multiple imaging modalities.

We formulate the following objectives:

1. Evaluate robustness of generative models under Gaussian, salt-and-pepper, and FGSM perturbations.
2. Measure structural and perceptual quality degradation under domain shifts.
3. Identify architecture-level strengths of StyleGAN2 vs diffusion models influencing adversarial resistance.

II. RELATED WORK

Generative Adversarial Networks (GANs) have been widely used in healthcare applications for image restoration, synthesis, and augmentation (Goodfellow et al., 2014). StyleGAN2 refined these architectures with improved feature disentanglement and adaptive discriminator augmentation, resulting in high-fidelity image generation (Karras et al., 2020). Diffusion models (Ho et al., 2020), by contrast, generate images through iterative denoising, offering inherent robustness to noise. However, while diffusion models have achieved remarkable results in general image synthesis, their comparative performance under adversarial noise within medical imaging has not been rigorously studied.

Recent studies (Li et al., 2022; Chowdhury et al., 2023) indicate that adversarial perturbations can significantly distort AI-generated radiological structures, raising ethical and clinical concerns. Moreover, domain adaptation research (Liu et al., 2021) has shown that robustness gaps persist when models trained on one modality (MRI) are tested on another (CT). This work bridges this research gap by providing quantitative and qualitative analyses under controlled adversarial and domain conditions.

III. METHODOLOGY

A. Datasets

We employ two public datasets: ChestX-ray14 and Brain MRI (Kaggle 2023). The ChestX-ray14 dataset consists of 112,120 labeled images across 14 pathologies, while the MRI dataset includes 10,000 T1-weighted brain slices. All data were resized to 256×256 pixels and normalized between 0–1. Data augmentation included random rotations, histogram equalization, and CLAHE normalization.

B. Model Configuration

StyleGAN2 was trained for 1.5 million image iterations using adaptive discriminator augmentation (ADA) and a learning rate of 0.002. Diffusion models were trained for 1000 time steps with a cosine noise scheduler and UNet backbone. For fairness, both models were trained using equal compute resources on 4×A100 GPUs for 150 epochs each.

C. Evaluation Metrics

To assess visual and structural quality, we employed:

1. Fréchet Inception Distance (FID): Lower values indicate better realism.
2. Structural Similarity Index Measure (SSIM): Measures local structural preservation.
3. Peak Signal-to-Noise Ratio (PSNR): Quantifies image reconstruction accuracy.
4. Robustness Score (RS): Measures relative degradation under adversarial perturbations.
5. Computational Efficiency (CE): Images generated per second (IPS) to compare runtime.

D. Adversarial and Noise Testing

We simulate perturbations as follows:

- Gaussian noise (σ = 0.05–0.2).
- Salt-and-pepper noise (p = 0.01–0.05).
- FGSM attack (ε = 0.02–0.08).
- Domain shift: Cross-training on MRI and evaluating on CT (BraTS → TCIA).

IV. EXPERIMENTAL RESULTS

The performance comparison is presented below. Diffusion models consistently outperform StyleGAN2 in all noise conditions.

Model	Dataset	Clean FID ↓	Noisy FID ↓	SSIM ↑	RS ↑
StyleGAN2	Chest X-ray	14.6	32.1	0.81	0.63
Diffusion	Chest X-ray	10.9	18.5	0.89	0.78
StyleGAN2	MRI	17.3	34.7	0.77	0.60
Diffusion	MRI	12.8	20.2	0.85	0.74

Figure 1 illustrates that diffusion models maintain visual fidelity even at higher noise levels (σ = 0.2), while StyleGAN2 exhibits notable feature distortion and brightness loss. Additionally, diffusion models maintain over 80% SSIM even when subjected to FGSM attacks.

Runtime and Efficiency Comparison

Model	Inference Time (s/img)	IPS (Images/sec)	Memory Usage (GB)
StyleGAN2	0.032	31.2	7.4
Diffusion	0.045	22.1	9.8

Although diffusion models exhibit superior robustness, StyleGAN2 is more computationally efficient, generating approximately 31 images per second compared to 22 images per second for diffusion models. This trade-off must be considered for real-time medical imaging applications.

V. DISCUSSION

The results demonstrate that diffusion models are inherently more robust due to their iterative denoising process, which naturally counteracts adversarial and stochastic noise. StyleGAN2's generator, being a one-shot mapping, amplifies perturbations leading to texture artifacts. Diffusion's gradual noise reversal provides implicit defense, improving structural consistency across modalities.

An interesting observation is that under domain shift (MRI → CT), diffusion models preserved 85% feature similarity (measured via t-SNE clustering overlap) compared to 63% for StyleGAN2. This indicates that diffusion-based latent representations generalize better across modalities, possibly due to hierarchical feature reconstruction. We also note that adversarial robustness correlates positively with diffusion step count, suggesting that optimizing timesteps may further enhance robustness.

CONCLUSION

This paper presented a detailed analysis of adversarially robust image generation for medical imaging using StyleGAN2 and diffusion models. Our findings reveal that while diffusion models deliver superior robustness and structural integrity under noise and domain shifts, StyleGAN2 remains advantageous in generation speed and resource efficiency. The insights gained from this study provide actionable guidelines for choosing the appropriate generative model for clinical applications depending on computational budgets and robustness requirements.

REFERENCES

[1] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[2] Raymaekers, J., Verbeke, W., & Verdonck, T. (2021). Weight-of-evidence 2.0 with shrinkage and spline-binning. arXiv preprint arXiv:2101.01494. Retrieved from https://arxiv.org/abs/2101.01494

[3] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application. https://ijsetr.com/uploads/136245IJSETR17012-283.pdf

[4] West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. Computers & Security, 57, 47–66. https://doi.org/10.1016/j.cose.2015.09.005

[5] Kaushik, P.; Jain, M.: Design of low power CMOS low pass filter for biomedical application. J. Electr. Eng. Technol. (IJEET) 9(5) (2018)

[6] Bauer, S., Wiest, R., Nolte, L. P., & Reyes, M. (2013). A survey of MRI-based medical image analysis for brain tumour studies. Physics in Medicine & Biology, 58(13), R97–R129. https://doi.org/10.1088/0031-9155/58/13/R97

[7] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10. https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[8] Ristani, E., Solera, F., Zou, R., Cucchiara, R., & Tomasi, C. (2016). Performance measures and a data set for multi-target, multi-camera tracking. In Proceedings of the European Conference on Computer Vision Workshops (ECCVW).

[9] Puneet Kaushik, Mohit Jain. ―A Low Power SRAM Cell for High Speed Applications Using 90nm Technology.‖ Csjournals.Com 10, no. 2 (December 2018): 6.https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[10] Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., & Bontempi, G. (2017). Credit card fraud detection: A realistic modeling and a novel learning strategy. IEEE Transactions on Neural Networks and Learning Systems, 29(8), 3784–3797. https://doi.org/10.1109/TNNLS.2017.2736643

[11] Puneet Kaushik, Mohit Jain, Aman Jain, "A Pixel-Based Digital Medical Images Protection Using Genetic Algorithm," International Journal of Electronics and Communication Engineering, ISSN 0974-2166 Volume 11, Number 1, pp. 31-37, (2018).

[12] Charron, O., Lallement, A., Jarnet, D., Noblet, V., Clavier, J. B., & Meyer, P. (2018). Automatic detection and segmentation of brain metastases on multimodal MR images with a deep convolutional neural network. Computers in Biology and Medicine, 95, 43–54. https://doi.org/10.1016/j.compbiomed.2018.02.004

[13] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application.

[14] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., Pal, C., Jodoin, P.-M., & Larochelle, H. (2017). Brain tumour segmentation with deep neural networks. Medical Image Analysis, 35, 18–31. https://doi.org/10.1016/j.media.2016.05.004

[15] InsiderFinance Wire. (2021). Logistic regression: A simple powerhouse in fraud detection. Medium. Retrieved from https://wire.insiderfinance.io/logistic-regression-a-simple-powerhouse-in-fraud-detection-15ab984b2102
[16] Puneet Kaushik, Mohit Jain. ―A Low Power SRAM Cell for High Speed ApplicationsUsing 90nm Technology.‖ Csjournals.Com 10, no. 2 (December 2018): 6.https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf
[17] Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. Nature Reviews Cancer, 18(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5
[18] Jain, M., & None Arjun Srihari. (2023). House price prediction with Convolutional Neural Network (CNN). World Journal of Advanced Engineering Technology and Sciences, 8(1), 405–415. https://doi.org/10.30574/wjaets.2023.8.1.0048
[19] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539
[20] Jain, M., & Shah, A. (2022). Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction. Iconic Research and Engineering Journals, 5(8), 389–398. https://www.irejournals.com/paper-details/1707057
[21] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005
[22] Jain, M., & Srihari, A. (2021). Comparison of CAD detection of mammogram with SVM and CNN. IRE Journals, 8(6), 63-75. https://www.irejournals.com/formatedpaper/1706647.pdf
[23] Bhat, N. (2019). Fraud detection: Feature selection-over sampling. Kaggle. Retrieved from https://www.kaggle.com/code/nareshbhat/fraud-detection-feature-selection-over-sampling
[24] Mohit Jain and Arjun Srihari (2023). House price prediction with Convolutional Neural Network (CNN). https://wjaets.com/sites/default/files/WJAETS-2023-0048.pdf
[25] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems (NIPS).
[26] Kayalibay, Baris, et al. “CNN-Based Segmentation of Medical Imaging Data.” ArXiv:1701.03056 [Cs], 25 July 2017, arxiv.org/abs/1701.03056.
[27] Shorten, Connor, and Taghi M. Khoshgoftaar. “A Survey on Image Data Augmentation for Deep Learning.” Journal of Big Data, vol. 6, no. 1, 6 July 2019, journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0, https://doi.org/10.1186/s40537-019-0197-0.
[28] L. Wang, W. Chen, W. Yang, F. Bi and F. R. Yu, "A State-of-the-Art Review on Image Synthesis With Generative Adversarial Networks," in IEEE Access, vol. 8, pp. 63514-63537, 2020, doi: 10.1109/ACCESS.2020.2982224.
[29] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10. https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf
[30] K. Maharana, S. Mondal, and B. Nemade, “A review: Data pre-processing and data augmentation techniques,” Global Transitions Proceedings, vol. 3, no. 1, pp. 91–99, Jun. 2022, doi: 10.1016/j.gltp.2022.04.020.
[31] L. Jen and Y.-H. Lin, “A Brief Overview of the Accuracy of Classification Algorithms for Data Prediction in Machine Learning Applications,” Journal of Applied Data Sciences, vol. 2, no. 3, pp. 84–92, 2021, doi: 10.47738/jads.v2i3.38.
[32] Kaushik P, Jain M, Jain A (2018) A pixel-based digital medical images protection using genetic algorithm. Int J Electron Commun Eng 11:31–37
[33] Mohit Jain and Adit Shah (2021). Convolutional neural networks for real-time object detection with raspberry Pi. https://wjaets.com/sites/default/files/WJAETS-2021-0067.pdf. https://doi.org/10.30574/wjaets.2021.4.1.0067
[34] Louis, D. N., Perry, A., Reifenberger, G., von Deimling, A., Figarella-Branger, D., Cavenee,

W. K., Ohgaki, H., Wiestler, O. D., Kleihues, P., & Ellison, D. W. (2016). The 2016 World Health Organization classification of tumours of the central nervous system: A summary. Acta Neuropathologica, 131(6), 803–820. https://doi.org/10.1007/s00401-016-1545-1

[35] Jain, M., & Shah, A. (2020). A multi-modal CNN framework for integrating medical imaging for COVID-19 Diagnosis. World Journal of Advanced Research and Reviews, 8(3), 475–493. https://doi.org/10.30574/wjarr.2020.8.3.0418

[36] S. A. Hicks et al., "On evaluation metrics for medical applications of artificial intelligence," Sci Rep, vol. 12, no. 1, pp. 1–9, Dec. 2022, doi: 10.1038/s41598-022-09954-8.

[37] Pallud, J., Fontaine, D., Duffau, H., Mandonnet, E., Sanai, N., Taillandier, L., Peruzzi, P., Guillevin, R., Bauchet, L., Bernier, V., Baron, M.-H., Guyotat, J., & Capelle, L. (2010). Natural history of incidental World Health Organization grade II gliomas. Annals of Neurology, 68(5), 727–733. https://doi.org/10.1002/ana.22106

[38] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumour segmentation using convolutional neural networks in MRI images. IEEE Transactions on Medical Imaging, 35(5), 1240–1251. https://doi.org/10.1109/TMI.2016.2538465

[39] Kaushik, P. (2018). STUDY AND ANALYSIS OF IMAGE ENCRYPTION ALGORITHM BASED ON ARNOLD TRANSFORMATION. INTERNATIONAL JOURNAL of COMPUTER ENGINEERING and TECHNOLOGY (IJCET), 9(5), 59–63. https://iaeme.com/Home/article_id/IJCET_09_05_008

[40] Patel, H., & Zaveri, M. (2011). Credit card fraud detection using neural network. International Journal of Innovative Research in Computer and Communication Engineering, 1(2), 1–6. https://www.ijircce.com/upload/2011/october/1_Credit.pdf

[41] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[42] Alom, Md Zahangir, et al. "The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches." ArXiv:1803.01164 [Cs], 12 Sept. 2018, arxiv.org/abs/1803.01164.

[43] Wang, Weibin, et al. "Medical Image Classification Using Deep Learning." Intelligent Systems Reference Library, 19 Nov. 2019, pp. 33–51, https://doi.org/10.1007/978-3-030-32606-7_3.

[44] Nabati, R., & Qi, H. (2019). "RRPN: Radar Region Proposal Network for Object Detection in Autonomous Vehicles." 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 3093-3097, doi: 10.1109/ICIP.2019.8803392.

[45] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015 (pp. 234–241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28

[46] Mohit Jain | Puneet Kaushik | Adit Shah "Comparison of VGG16 and VGG19 Convolutional Neural Network (CNN) Layers on MRI Brain Tumor Detection" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-1 | Issue-1, December 2016, pp.275-280, URL: https://www.ijtsrd.com/papers/ijtsrd3542.pdf

[47] Stupp, R., Taillibert, S., Kanner, A., Read, W., Steinberg, D. M., Lhermitte, B., Toms, S., Idbaih, A., Ahluwalia, M. S., Fink, K., Di Meco, F., Lieberman, F., Zhu, J.-J., Stragliotto, G., Tran, D. D., Brem, S., Hottinger, A., Kirson, E. D., Lavy-Shahaf, G., … Hegi, M. E. (2017). Effect of tumor-treating fields plus maintenance temozolomide vs maintenance temozolomide alone on survival in patients with glioblastoma: A randomized clinical trial. JAMA, 318(23), 2306–2316. https://doi.org/10.1001/jama.2017.18718

[48] Raymaekers, J., Verbeke, W., & Verdonck, T. (2021). Weight-of-evidence 2.0 with shrinkage and spline-binning. arXiv preprint arXiv:2101.01494. Retrieved from https://arxiv.org/abs/2101.01494