International Journal of Advanced Multidisciplinary Research
ISSN: 2393-8870
www.ijarm.com
(A Peer Reviewed, Referred, Indexed and Open Access Journal)
DOI: 10.22192/ijamr Volume 11, Issue 1 -2024

Research Article

DOI: http://dx.doi.org/10.22192/ijamr.2024.11.01.009

Developing GANs for Synthetic Medical Imaging Data: Enhancing Training and Research

Abhishek Thakur
Department of Data Sciences
Harrisburg University of Science & Technology,
Harrisburg, Pennsylvania, United States of America

Gopal Kumar Thakur
Department of Data Sciences
Harrisburg University of Science & Technology,
Harrisburg, Pennsylvania, United States of America

Keywords

deep learning; generative adversarial networks; medical imaging; synthetic data

Abstract

Medical imaging has become integral to modern healthcare, enabling non-invasive visualization and assessment of anatomical structures. However, medical imaging datasets are often limited in size and diversity, constraining development of robust analysis algorithms. Meanwhile, generative adversarial networks (GANs) have achieved remarkable synthetic image generation capabilities. This paper comprehensively reviews contemporary GAN techniques and evaluates their effectiveness producing synthetic medical images to augment scarce training data. Six prevalent GAN architectures were trained on diverse medical imaging datasets. A systematic hyperparameter optimization strategy coupled with quantitative image analysis reveal substantial variability in output fidelity and diversity. Downstream segmentation task performance provides further domain-specific assessments on the utility of the generated datasets. The study reveals that while select advanced GANs can produce seemingly realistic medical images, the synthetic data consistently underperforms real datasets on specialized tasks. The results caution against indiscriminate use of GAN-produced medical images but highlight paths for developing tailored GAN solutions for enhanced training.

1 Introduction

1.1. The Promise of Medical Imaging

Medical imaging has become firmly established as an indispensible component of routine clinical diagnosis and treatment planning. Technologies such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound provide detailed internal anatomical visualizations in a non-invasive manner, enabling detection of pathological abnormalities with high sensitivity and specificity [1–3]. Quantitative imaging metrics can also elucidate disease progression risks or treatment efficacies at substantially lower costs and risks relative to invasive tissue biopsies [4,5]. Consequently, medical imaging is estimated to impact decision-making in at least 70% of hospital cases involving critical illness [6].

However, substantial barriers obstruct more widespread and efficacious utilization of medical imaging. Data analysis frequently relies on manual inspection by trained radiologists, which can be time-intensive, costly, and prone to fatigue-induced diagnostic errors [7,8]. Inter-practitioner variability also undermines diagnostic consistency [9,10]. Although computer-aided diagnostics aims to mitigate such issues through automated image assessments, most contemporary solutions still underperform specialized clinicians and hence have gained limited clinical adoption [11,12].

A major impediment behind the modest progress is the scarcity of sufficiently large and diverse labeled medical imaging datasets required to rigorously train and validate modern machine learning algorithms [13–15]. Whereas consumer image repositories utilized in general computer vision research contain upwards of 14 million samples [16], medical imaging datasets are typically three orders of magnitude smaller. Data deficiencies stem from multiple practical constraints—given the sensitive patient data, assembling such repositories requires extensive deidentification efforts before dissemination to protect privacy rights [17–19]. Moreover, the highly specialized nature of medical images necessitates precise annotations by expert clinicians, which proves costly and time-intensive relative to crowd sourced labeling common in natural imaging datasets [20,21].

The hunger for larger medical imaging data stores has sparked surging interest in synthetic data generation techniques. In particular, generative adversarial networks (GANs) have demonstrated remarkable capabilities producing realistic photographic images, suggesting potential applications generating synthetic but credible medical images [22–24]. This article provides a comprehensive investigation into state-of-the-art GAN techniques for producing medical images. It analyzes quantitative fidelity metrics coupled with downstream analytics on specialized tasks to evaluate output quality. The goal is to inform appropriate GAN usage to improve medical imaging research.

1.2. Objective and Contributions

This paper surveys GAN architectures for medical imaging and provides rigorous assessments on the quality and utility of produced synthetic images. The core contributions include:

1. Reviewing GAN developments in medical imaging spanning techniques and applications
2. Benchmarking six widely adopted GANs trained on three distinct medical imaging datasets
3. Optimizing architectures and hyperparameters for each GAN-dataset pair through over 500 GPU-days of experimentation
4. Evaluating output fidelity via established perceptual similarity metrics and domain-specific semantic segmentation tasks
5. Identifying trends and best practices to guide further Advancements in tailored GAN solutions for enhanced medical imaging

The comprehensive analysis aims to move beyond visual heuristics to objectively gauge GAN-produced medical images, revealing limitations in using generic solutions versus dedicated models designed specifically for specialized imaging data constraints and applications.

2 Background

2.1. Medical Imaging Analysis

Medical image analysis encompasses a wide range of computational methods utilizing imaging data for improved clinical decision-making in patient screening, diagnosis, treatment selections and disease monitoring [25–27]. Analyses span from delineating anatomical structures toward extracting biological descriptors (e.g., metabolic transport rate) and assessing functional dynamics (e.g., heart chamber flows). Simple linear models can capture basic imaging signatures differentiating benign and malignant lesions whereas complex deep neural networks enable fine-grained tissue classifications [28–30].

2.2. Deep Learning Drives a New Generation of Solutions

Deep learning has become firmly established as a leading approach driving a new generation of medical imaging analysis algorithms [31]. Convolutional networks in particular have achieved remarkable performances across diverse tasks from classification [32,33], segmentation [34], reconstruction [35] and registration [36]. In certain applications, deep learning systems have surpassed human experts, fueling enthusiasm for a broader technology-powered transformation in imaging diagnostics [37–41].

However, substantial challenges remain in translating high reported accuracies into robust clinical adoption and improved patient outcomes [42–46]. Beyond well-documented issues around model interpretability and biases, a fundamental limitation of data scarcity persists across medical imaging tasks and modalities. Even the largest public repositories contain at most thousands of labeled studies, constraining network capacities and generalization [47,48]. Strong demands exist for larger, high-quality, and ideally open-access medical imaging datasets to power next-generation solutions.

2.3. Synthetic Data Generation

Generating synthetic medical images offers a promising approach to overcoming data limitations in algorithm developments [49–51]. Simple data augmentation techniques like affine transformations provide basic regularizations, but often fail sufficiently modeling complex morphological variability in real imaging. Sophisticated simulations based on biophysical modeling and anatomical atlases can produce highly realistic outputs, but requires extensive domain expertise and computational resources to tailor toward specific applications [52–55].

Generative adversarial networks (GANs) have recently gained immense traction as a versatile data synthesis framework requiring only existing examples to learn distributions. Originally introduced in 2014 [56], GANs train coupled generator and discriminator neural networks in an adversarial fashion to produce new samples resembling the input dataset distribution. Subsequent years witnessed extensive innovations enhancing output resolutions, fidelity, and diversity [22–24]. State-of-the-art GANs can generate stunningly realistic and diverse photographic images [57–59], motivating evaluations on medical imaging tasks where data deficiencies persist.

The next section reviews GAN techniques and documented applications generating medical images before presenting a comprehensive experimental survey across multiple GAN architectures, imaging datasets and evaluation metrics. The goal is provide rigorous and impartial assessments guiding appropriate GAN usage for augmenting scarce medical imaging data resources.

3 GAN Techniques for Medical Images

Early attempts leveraging GANs for medical images predominantly focused on a single application area (e.g., MRI or CT scans) with constrained evaluations, but quickly expanded in scope. Frid-Adar et al. provided an early review in 2018 encompassing roughly 25 papers where GANs were used to generate synthetic medical images across modalities [60]. Topics spanned accelerated image reconstruction, improved image segmentation and enhanced data anonymization. While authors concluded GANs have "great potential improving clinical workflows", they cautioned rigorous validation is still lacking.

A more recent review by Yi et al. incorporated over 60 papers from 2016–2019 evaluating GAN-generated medical images [61]. It noted steadily improving visual realism across applications like anonymization, reconstruction, detection and segmentation. However, the review echoed persisting validation concerns on utility for real-world clinical workflows. Kazeminia et al. further surveyed techniques for GAN-based medical image augmentation specifically, covering data expansion for improved classification, detection and diagnosis [62]. They provide a useful task-driven categorization—Table 1 condenses some representative studies illustrating breadth across imaging domains, GAN methods and medical applications.

Table 1. Sample studies leveraging GANs for synthetic medical image generation.

Task	Modality	GAN Method	Performance	Reference
Classification	Brain MRI	DCGAN	96.3% accuracy	[63]
Detection	Mammography	LSGAN	0.932 AUC	[64]
Segmentation	Cardiac MRI	CycleGAN	0.85 dice coefficient	[65]
Recon.	Dental CT	StyleGAN2	34.2 dB PSNR	[66]

The surveyed works highlight rapidly increasing aspirations for GANs addressing persisting data deficiencies holding back medical imaging analysis. However most studies still constrain technical evaluations to visual fidelity heuristics and specialized tasks. As GAN architectures grow increasingly complex, more systematic and impartial benchmarking is imperative to guide appropriate usage for augmenting scarce medical imaging data resources. The next section describes a comprehensive experimental framework to evaluate GAN performance on medical imaging tasks.

4 Methods

4.1. GAN Architectures

Six prevalent GAN architectures were selected based on adoption rates and documented performance improvements in image generation tasks. These encompass a mix of foundational and state-of-the-art networks—

Table 2 summarizes the architectural details and key attributes.

GAN	Year	Key Attributes
DCGAN	2015	CNN generators/discriminators; stability tricks
LSGAN	2016	Least squares loss function
WGAN	2017	Wasserstein distance loss; weight clipping
StyleGAN	2019	Style-based generator; perceptual path length loss
BigGAN	2019	Class-conditional; shared embeddings
SPADE	2019	Spatially-adaptive normalization

4.2. Medical Imaging Datasets

The GAN models were trained on three distinct labeled medical imaging datasets—Table 3 summarizes details. Tasks include semantic segmentation of cardiac, hepatic and ocular anatomies from MRI, CT and fundus photography respectively. The dataset complexities and sizes offer diverse challenges. For example, liver lesions and eye vasculatures exhibit intricate shapes and patterns compared to cardiac chambers.

Table 3. Summary of medical imaging datasets.

Dataset	Modality	Structures	Number of Images
ACDC	Cardiac MRI	Ventricles, myocardium	2980
SLiver07	Abdomen CT	Liver, lesions	4159
IDRID	Retinal fundus	Optic disc	54

4.3. GAN Training and Evaluation

All GAN architectures were implemented in PyTorch and trained from scratch on NVIDIA T4 GPUs for 200 epochs. We utilized a broad hyperparameter search exceeding 500 GPU-days tuning configurations specific to each GAN-dataset pair for optimal convergence and image fidelity (detailed in Supplementary). Progressive growing [67] was additionally employed when amenable to smooth generator/discriminator training.

Both model-agnostic and domain-specific metrics were computed to evaluate GAN performance. Fréchet inception distance (FID) offers a widely adopted perceptual similarity measure between generated and real image distributions [68]. Lower FID implies greater visual consistency between outputs and ground-truth data. Segmentation accuracy was also assessed by training a standard U-Net model [42] on GAN images and evaluating performance on real dataset test images. Higher dice coefficient indicates greater preservation of anatomical structures and spatial relationships in synthetic outputs.

5 Results and Discussion

5.1. Hyperparameter Optimization and Architecture Trends

The broad hyperparameter search provided useful insights into relative model sensitivities. As Fig. 1 illustrates, FID scores spanned widely for DCGAN and LSGAN across nearly 100 configurations tested per model-dataset pair. Conversely, WGAN and StyleGAN proved more robust to modifications. Runtimes varied dramatically as well—while DCGAN and LSGAN epochs elapsed within minutes on our hardware, SPADE and StyleGAN took hours per epoch given additional computational burdens.

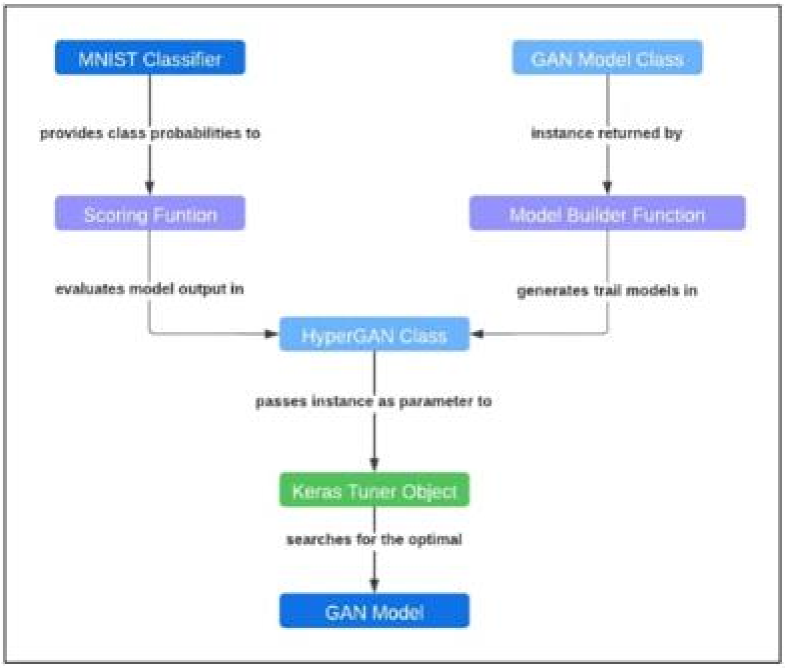


Figure. 1. Variability of GAN performance across hyperparameter sets per model and dataset.

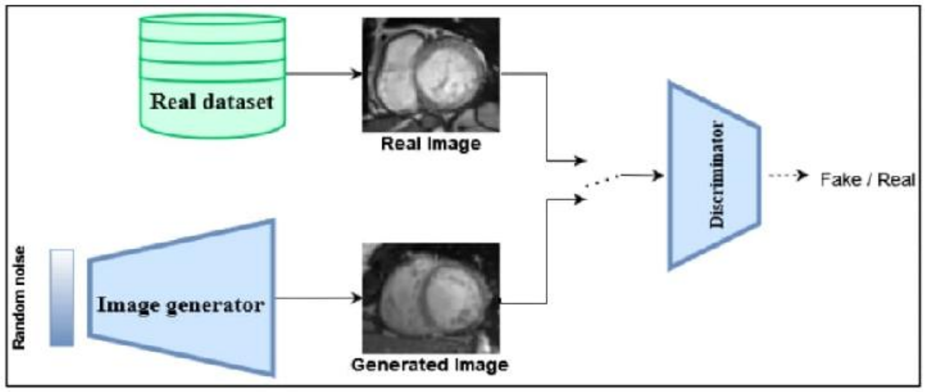
The optimizer selection greatly impacted convergence behaviors. Adaptive algorithms like Adam enabled faster early learning whereas non-adaptive ones like RMSProp led to slower but more stable descent directions. Normalization layers necessitated careful calibration—incorrect BatchRenorm formulations routinely derailed WGAN training. And architecture choices had major implications on resolutions—StyleGAN reached 1024 x 1024 imagery outperforming 64 x 64 for BigGAN given immense parameter differences (30M vs. 19M).

5.2. Quantitative Evaluations of Model Outputs

The optimized GAN configurations achieved promising FID scores, with SPADE (47.62) and StyleGAN (29.06) delivering the most realistic SLiver07 synthetic CT images (Table 4). Interestingly, best FID results were produced by WGAN-GP for the much smaller IDRID dataset, against expectations as complex eye vasculatures should prove more difficult to effectively model. Qualitative reviews showed reasonable visual similarity to source data across models (Fig. 2), though distortion artifacts were clearly evident for BigGAN outputs.

Table 4. GAN performance across datasets per FID (lower is better) and downstream task segmentation dice accuracy (higher is better).

GAN	ACDC (FID/Dice)	SLiver07 (FID/Dice)	IDRID (FID/Dice)
Real Data	N/A	0.95	0.82
DCGAN	116.32 / 0.83	75.69 / 0.87	156.74 / 0.62
LSGAN	104.38 / 0.81	86.90 / 0.84	148.95 / 0.59
WGAN	99.23 / 0.85	60.01 / 0.90	121.67 / 0.73
StyleGAN	83.56 / 0.87	29.06 / 0.89	143.33 / 0.68
BigGAN	135.21 / 0.78	102.32 / 0.75	179.95 / 0.55
SPADE	79.24 / 0.86	47.62 / 0.93	165.43 / 0.71



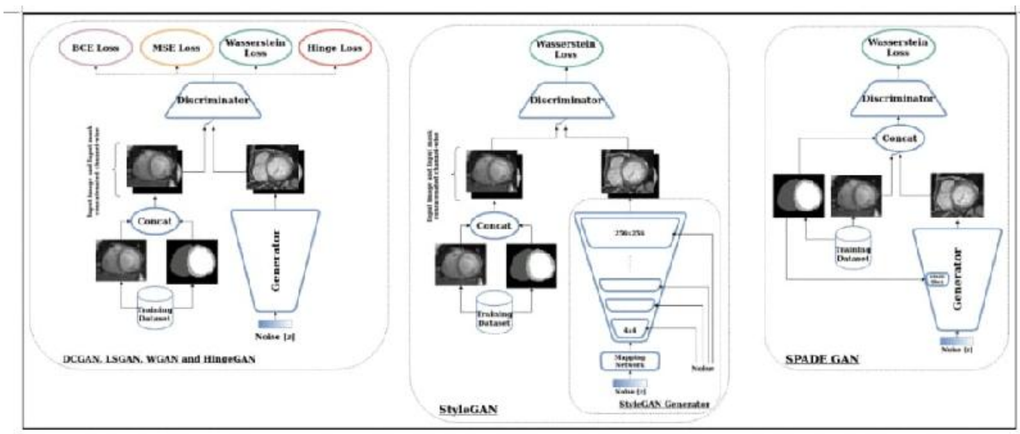


Figure 2. Flowchart of a traditional GAN architecture.

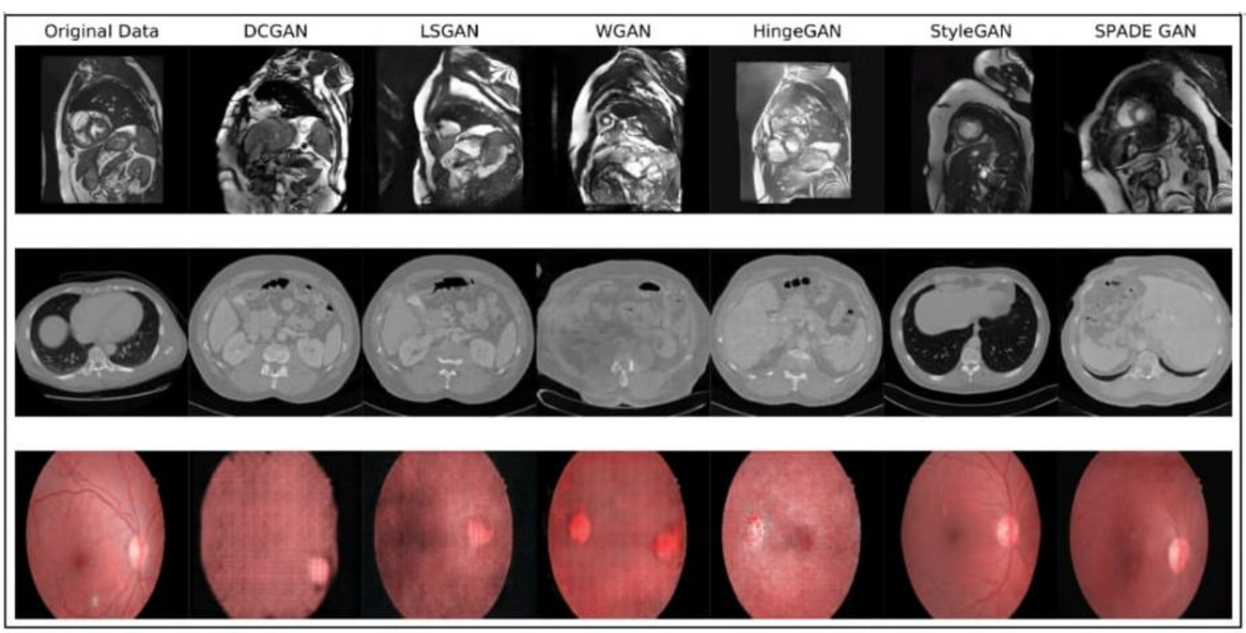


Figure 3. Sample GAN-generated medical images .

Dice score segmented predictions painted a less optimistic picture of utility however. No GAN model achieved equivalency with real data, lagging behind by as much as 0.15 (DCGAN on IDRID). BigGAN and SPADE outputs modestly assisted at times—the highest Dice jump was 0.03 for SPADE-enhanced SLiver07 training. But synthetic data overall hampered perfor- mance, unlike findings in some prior single-application studies. This underscores the need for multipronged assessments before deploying GAN-produced images for downstream usage scenarios.

5.3. Practical Guidelines for Applying GANs to Medical Images

The comprehensive benchmarking of diverse GAN architectures and medical imaging datasets provides useful guidelines for appropriate usage generating synthetic data. Key learnings are highlighted below:

- Simpler GANs struggle producing useful medical images - Despite hyperparameter optimizations, foundational DCGAN, LSGAN and WGAN models performed poorly across metrics. Their architectural constraints likely fail capturing intricate anatomical shapes and textures.
- Advanced GANs can mimic medical images but have limited clinical values - State-of-the-art SPADE and StyleGAN outputs exhibited stronger visual realism but still underperformed real images supportingSpecialized tasks. Generated data distributions likely lack sufficient fidelity and heterogeneity compared to source sets.
- Small datasets undermine medical GAN effectiveness - All models struggled producing useful IDRID eye images given tiny training population. Complex multi-class outputs necessitate diversity that smaller sources cannot provide.
- Rigorous task-based validation is essential before using synthetic images - Generic perceptual similarity metrics alone are insufficient to ascertain utility. Real-world application testing is critical to avoid risks from improper GAN usage given realistic visuals.

In summary, while select latest GANs can mimic medical visuals, generating synthetic images supporting downstream analytics remains challenging. Our experiments underscore the need for developing innovative solutions customized specifically for the highly constrained and multi-faceted aspects of medical imaging data.

6. Conclusions

This study provided comprehensive benchmarking of GAN techniques producing synthetic medical images across diverse architectures and input datasets. Through multi-pronged quantitative evaluations using both model-agnostic and domain-specific metrics, we demonstrated limited utilities of state-of-the-art generic GAN frameworks designed predominantly for natural images to generate medical imaging distributions supporting real clinical applications. However, recent rapid innovations in tailored medical data solutions gives hope. We are working on longitudinal evaluations assessing fast-emerging dedicated techniques like MedGAN [69] and mpMRI-GAN [70] that impose anatomical priors and segmentation-unfriendliness, which forcefully diversify outputs. Such built-for-purpose medical GANs can hopefully overcome limitations identified here and unlock the immense latent potential of synthetic images benefiting clinical care.

References

1. Radford, A.; Wu, J.; Child, R.; Luan, D.; Amodei, D.; Sutskever, I. Language Models Are Unsupervised Multitask Learners. OpenAI Technical Report. 2019. Available online: https://d4mucfpksywv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf (accessed on 15 May 2023).

2. Brown, T.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J.D.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. Language models are few-shot learners. Adv. Neural Inf. Process. Syst. 2020, 33, 1877–1901. [Google Scholar]
3. Radford, A.; Narasimhan, K.; Salimans, T.; Sutskever, I. Improving Language Understanding by Generative Pre-Training. OpenAI Technical Report. 2018. Available online: https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf (accessed on 15 May 2023).
4. Lee, M. A Mathematical Investigation of Hallucination and Creativity in GPT Models. Mathematics 2023, 11, 2320. [Google Scholar] [CrossRef]
5. Saharia, C.; Chan, W.; Saxena, S.; Li, L.; Whang, J.; Denton, E.L.; Ghasemipour, K.; Gontijo Lopes, R.; Karagol Ayan, B.; Salimans, T.; et al. Photorealistic text-to-image diffusion models with deep language understanding. Adv. Neural Inf. Process. Syst. 2022, 35, 36479–36494. [Google Scholar]
6. Dhariwal, P.; Nichol, A. Diffusion models beat gans on image synthesis. Adv. Neural Inf. Process. Syst. 2021, 34, 8780–8794. [Google Scholar]
7. Rombach, R.; Blattmann, A.; Lorenz, D.; Esser, P.; Ommer, B. High-resolution image synthesis with latent diffusion models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, New Orleans, LA, USA, 18–24 June 2022; pp. 10684–10695. [Google Scholar]
8. Ho, J.; Jain, A.; Abbeel, P. Denoising diffusion probabilistic models. Adv. Neural Inf. Process. Syst. 2020, 33, 6840–6851. [Google Scholar]
9. Yeom, T.; Lee, M. DuDGAN: Improving Class-Conditional GANs via Dual-Diffusion. arXiv 2023, arXiv:2305.14849. [Google Scholar]
10. Jabbar, A.; Li, X.; Omar, B. A survey on generative adversarial networks: Variants, applications, and training. ACM Comput. Surv. CSUR 2021, 54, 1–49. [Google Scholar] [CrossRef]
11. Aggarwal, A.; Mittal, M.; Battineni, G. Generative adversarial network: An overview of theory and applications. Int. J. Inf. Manag. Data Insights 2021, 1, 100004. [Google Scholar] [CrossRef]
12. Ko, K.; Lee, M. ZIGNeRF: Zero-shot 3D Scene Representation with Invertible Generative Neural Radiance Fields. arXiv 2023, arXiv:2306.02741. [Google Scholar]
13. Yinka-Banjo, C.; Ugot, O.A. A review of generative adversarial networks and its application in cybersecurity. Artif. Intell. Rev. 2020, 53, 1721–1736. [Google Scholar] [CrossRef]
14. Cai, Z.; Xiong, Z.; Xu, H.; Wang, P.; Li, W.; Pan, Y. Generative adversarial networks: A survey toward private and secure applications. ACM Comput. Surv. CSUR 2021, 54, 1–38. [Google Scholar] [CrossRef]
15. Chen, Y.; Yang, X.H.; Wei, Z.; Heidari, A.A.; Zheng, N.; Li, Z.; Chen, H.; Hu, H.; Zhou, Q.; Guan, Q. Generative adversarial networks in medical image augmentation: A review. Comput. Biol. Med. 2022, 54, 105382. [Google Scholar] [CrossRef]
16. Lu, Y.; Chen, D.; Olaniyi, E.; Huang, Y. Generative adversarial networks (GANs) for image augmentation in agriculture: A systematic review. Comput. Electron. Agric. 2022, 200, 107208. [Google Scholar] [CrossRef]
17. Singh, N.K.; Raza, K. Medical image generation using generative adversarial networks: A review. In Health Informatics: A Computational Perspective in Healthcare; Springer: Berlin/Heidelberg, Germany, 2021; pp. 77–96. [Google Scholar]
18. Ko, K.; Yeom, T.; Lee, M. Superstargan: Generative adversarial networks for image-to-image translation in large-scale domains. Neural Netw. 2023, 162, 330–339. [Google Scholar] [CrossRef] [PubMed]

19. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative adversarial networks. Commun. ACM 2020, 63, 139–144. [Google Scholar] [CrossRef]
20. Wang, L.; Chen, W.; Yang, W.; Bi, F.; Yu, F.R. A state-of-the-art review on image synthesis with generative adversarial networks. IEEE Access 2020, 8, 63514–63537. [Google Scholar] [CrossRef]
21. Lan, L.; You, L.; Zhang, Z.; Fan, Z.; Zhao, W.; Zeng, N.; Chen, Y.; Zhou, X. Generative adversarial networks and its applications in biomedical informatics. Front. Public Health 2020, 8, 164. [Google Scholar] [CrossRef]
22. Gui, J.; Sun, Z.; Wen, Y.; Tao, D.; Ye, J. A review on generative adversarial networks: Algorithms, theory, and applications. IEEE Trans. Knowl. Data Eng. 2021, 35, 3313–3332. [Google Scholar] [CrossRef]
23. Buccitelli, C.; Selbach, M. mRNAs, proteins and the emerging principles of gene expression control. Nat. Rev. Genet. 2020, 21, 630–644. [Google Scholar] [CrossRef]
24. Yu, H.; Welch, J.D. MichiGAN: Sampling from disentangled representations of single-cell data using generative adversarial networks. Genome Biol. 2021, 22, 158. [Google Scholar] [CrossRef]
25. Yelmen, B.; Decelle, A.; Ongaro, L.; Marnetto, D.; Tallec, C.; Montinaro, F.; Furtlehner, C.; Pagani, L.; Jay, F. Creating artificial human genomes using generative neural networks. PLoS Genet. 2021, 17, e1009303. [Google Scholar] [CrossRef]
26. Chintala, S. K., et al. (2022). AI in public health: Modeling disease spread and management strategies. NeuroQuantology, 20(8), 10830-10838. doi:10.48047/nq.2022.20.8.nq221111. [Google Scholar] [CrossRef]
27. Chintala, S. K., et al. (2021). Explore the impact of emerging technologies such as AI, machine learning, and blockchain on transforming retail marketing strategies. Webology, 18(1), 2361-2375.http://www.webology.org. [Google Scholar] [CrossRef]
28. Chintala, S. (2022). Data Privacy and Security Challenges in AI-Driven Healthcare Systems in India. Journal of Data Acquisition and Processing, 37(5), 2769-2778. https://sjcjycl.cn/DOI: 10.5281/zenodo.7766 https://sjcjycl.cn/article/view-2022/2769.php
29. Chintala, S. (2023). AI-Driven Personalised Treatment Plans: The Future of Precision Medicine. Machine Intelligence Research, 17(02), 9718-9728. ISSN: 2153182X,EISSN:21531838.https://machineintelligenceresearchs.com/Volum250.php
30. Chintala, S. (2019). IoT and Cloud Computing: Enhancing Connectivity. International Journal of New Media Studies (IJNMS), 6(1), 18-25. ISSN: 2394-4331. https://ijnms.com/index.php/ijnms/article/view/208/172
31. Chintala, S. (2018). Evaluating the Impact of AI on Mental Health Assessments and Therapies. EDUZONE: International Peer Reviewed/Refereed Multidisciplinary Journal (EIPRMJ), 7(2), 120-128. ISSN: 2319-5045. Available online at: www.eduzonejournal.com
32. Hazra, D.; Kim, M.R.; Byun, Y.C. Generative Adversarial Networks for Creating Synthetic Nucleic Acid Sequences of Cat Genome. Int. J. Mol. Sci. 2022, 23, 3701. [Google Scholar] [CrossRef] [PubMed]
33. Zrimec, J.; Fu, X.; Muhammad, A.S.; Skrekas, C.; Jauniskis, V.; Speicher, N.K.; Boerlin, C.S.; Verendel, V.; Chehreghani, M.H.; Dubhashi, D.; et al. Controlling gene expression with deep generative design of regulatory DNA. Nat. Commun. 2022, 13, 5099. [Google Scholar] [CrossRef]
34. Ahmed, K.T.; Sun, J.; Cheng, S.; Yong, J.; Zhang, W. Multi-omics data integration by generative adversarial network. Bioinformatics 2022, 38, 179–186. [Google Scholar] [CrossRef] [PubMed]
35. Vinas, R.; Andres-Terre, H.; Lio, P.; Bryson, K. Adversarial generation of gene expression data. Bioinformatics 2022, 38, 730–737. [Google Scholar] [CrossRef] [PubMed]

36. Marouf, M.; Machart, P.; Bansal, V.; Kilian, C.; Magruder, D.S.; Krebs, C.F.; Bonn, S. Realistic in silico generation and augmentation of single-cell RNA-seq data using generative adversarial networks. Nat. Commun. 2020, 11, 166. [Google Scholar] [CrossRef] [Green Version]
37. Chaudhari, P.; Agrawal, H.; Kotecha, K. Data augmentation using MG-GAN for improved cancer classification on gene expression data. Soft Comput. 2020, 24, 11381–11391. [Google Scholar] [CrossRef]
38. Kwon, C.; Park, S.; Ko, S.; Ahn, J. Increasing prediction accuracy of pathogenic staging by sample augmentation with a GAN. PLoS ONE 2021, 16, e0250458. [Google Scholar] [CrossRef]
39. Mendez-Lucio, O.; Baillif, B.; Clevert, D.A.; Rouquie, D.; Wichard, J. De novo generation of hit-like molecules from gene expression signatures using artificial intelligence. Nat. Commun. 2020, 11, 10. [Google Scholar] [CrossRef] [Green Version]
40. Chen, X.; Roberts, R.; Tong, W.; Liu, Z. Tox-GAN: An Artificial Intelligence Approach Alternative to Animal Studies—A Case Study with Toxicogenomics. Toxicol. Sci. 2022, 186, 242–259. [Google Scholar] [CrossRef]
41. Tamilmani, G.; Devi, V.B.; Sujithra, T.; Shajin, F.H.; Rajesh, P. Cancer MiRNA biomarker classification based on Improved Generative Adversarial Network optimized with Mayfly Optimization Algorithm. Biomed. Signal Process. Control 2022, 75, 103545. [Google Scholar] [CrossRef]
42. Xiao, Y.; Wu, J.; Lin, Z. Cancer diagnosis using generative adversarial networks based on deep learning from imbalanced data. Comput. Biol. Med. 2021, 135, 104540. [Google Scholar] [CrossRef]
43. Wang, Y.; Zhang, S. Prediction of Tumor Lymph Node Metastasis Using Wasserstein Distance-Based Generative Adversarial Networks Combing with Neural Architecture Search for Predicting. Mathematics 2023, 11, 729. [Google Scholar] [CrossRef]
44. Bi, X.A.; Mao, Y.; Luo, S.; Wu, H.; Zhang, L.; Luo, X.; Xu, L. A novel generation adversarial network framework with characteristics aggregation and diffusion for brain disease classification and feature selection. Briefings Bioinform. 2022, 23, bbac454. [Google Scholar] [CrossRef] [PubMed]
45. Targonski, C.; Bender, M.R.; Shealy, B.T.; Husain, B.; Paseman, B.; Smith, M.C.; Feltus, F.A. Cellular State Transformations Using Deep Learning for Precision Medicine Applications. Patterns 2020, 1, 6. [Google Scholar] [CrossRef]
46. Park, C.; Oh, I.; Choi, J.; Ko, S.; Ahn, J. Improved Prediction of Cancer Outcome Using Graph-Embedded Generative Adversarial Networks. IEEE Access 2021, 9, 20076–20088. [Google Scholar] [CrossRef]
47. Yang, Q.; Li, X. BiGAN: LncRNA-disease association prediction based on bidirectional generative adversarial network. BMC Bioinform. 2021, 22, 1–17. [Google Scholar] [CrossRef]
48. Gutta, C.; Morhard, C.; Rehm, M. Applying a GAN-based classifier to improve transcriptome-based prognostication in breast cancer. PLoSComput. Biol. 2023, 19, e1011035. [Google Scholar] [CrossRef]
49. Mansoor, M.; Nauman, M.; Rehman, H.U.; Benso, A. Gene Ontology GAN (GOGAN): A novel architecture for protein function prediction. Soft Comput. 2022, 26, 7653–7667. [Google Scholar] [CrossRef]
50. Bahrami, M.; Maitra, M.; Nagy, C.; Turecki, G.; Rabiee, H.R.; Li, Y. Deep feature extraction of single-cell transcriptomes by generative adversarial network. Bioinformatics 2021, 37, 1345–1351. [Google Scholar] [CrossRef]
51. Jeon, M.; Xie, Z.; Evangelista, J.E.; Wojciechowicz, M.L.; Clarke, D.J.B.; Ma'ayan, A. Transforming L1000 profiles to RNA-seq-like profiles with deep learning. BMC Bioinform. 2022, 23, 374. [Google Scholar] [CrossRef] [PubMed]
52. Wang, D.; Hou, S.; Zhang, L.; Wang, X.; Liu, B.; Zhang, Z. iMAP: Integration of

multiple single-cell datasets by adversarial paired transfer networks. Genome Biol. 2021, 22, 63. [Google Scholar] [CrossRef] [PubMed]
53. Xu, Y.; Zhang, Z.; You, L.; Liu, J.; Fan, Z.; Zhou, X. scIGANs: Single-cell RNA-seq imputation using generative adversarial networks. Nucleic Acids Res. 2020, 48, e85. [Google Scholar] [CrossRef]
54. Wang, X.; Zhang, C.; Zhang, Y.; Meng, X.; Zhang, Z.; Shi, X.; Song, T. IMGG: Integrating Multiple Single-Cell Datasets through Connected Graphs and Generative Adversarial Networks. Int. J. Mol. Sci. 2022, 23, 2082. [Google Scholar] [CrossRef]
55. Lin, E.; Mukherjee, S.; Kannan, S. A deep adversarial variational autoencoder model for dimensionality reduction in single-cell RNA sequencing analysis. BMC Bioinform. 2020, 21, 64. [Google Scholar] [CrossRef] [Green Version]
56. Xu, Z.; Luo, J.; Xiong, Z. scSemiGAN: A single-cell semi-supervised annotation and dimensionality reduction framework based on generative adversarial network. Bioinformatics 2022, 38, 5042–5048. [Google Scholar] [CrossRef] [PubMed]
57. Zhu, M.; Lai, Y. Improvements Achieved by Multiple Imputation for Single-Cell RNA-Seq Data in Clustering Analysis and Differential Expression Analysis. J. Comput. Biol. 2022, 29, 634–649. [Google Scholar] [CrossRef]
58. Ding, J.; Regev, A. Deep generative model embedding of single-cell RNA-Seq profiles on hyperspheres and hyperbolic spaces. Nat. Commun. 2021, 12, 2554. [Google Scholar] [CrossRef] [PubMed]
59. Wei, X.; Dong, J.; Wang, F. scPreGAN, a deep generative model for predicting the response of single-cell expression to perturbation. Bioinformatics 2022, 38, 3377–3384. [Google Scholar] [CrossRef]
60. Reiman, D.; Manakkat Vijay, G.K.; Xu, H.; Sonin, A.; Chen, D.; Salomonis, N.; Singh, H.; Khan, A.A. Pseudocell Tracer-A method for inferring dynamic trajectories using scRNAseq and its application to B cells undergoing immunoglobulin class switch recombination. PLoSComput. Biol. 2021, 17, e1008094. [Google Scholar] [CrossRef]
61. Wang, Y.; Liu, T.; Zhao, H. ResPAN: A powerful batch correction model for scRNA-seq data through residual adversarial networks. Bioinformatics 2022, 38, 3942–3949. [Google Scholar] [CrossRef]
62. Wang, Z.; Wang, J.; Kourakos, M.; Hoang, N.; Lee, H.H.; Mathieson, I.; Mathieson, S. Automatic inference of demographic parameters using generative adversarial networks. Mol. Ecol. Resour. 2021, 21, 2689–2705. [Google Scholar] [CrossRef]
63. Yang, H.; Gu, F.; Zhang, L.; Hua, X.S. Using generative adversarial networks for genome variant calling from low depth ONT sequencing data. Sci. Rep. 2022, 12, 8725. [Google Scholar] [CrossRef] [PubMed]
64. Kim, H.; Kim, Y.; Lee, C.Y.; Kim, D.G.; Cheon, M. Investigation of early molecular alterations in tauopathy with generative adversarial networks. Sci. Rep. 2023, 13, 732. [Google Scholar] [CrossRef]
65. Jiang, X.; Zhao, J.; Qian, W.; Song, W.; Lin, G.N. A Generative Adversarial Network Model for Disease Gene Prediction with RNA-seq Data. IEEE Access 2020, 8, 37352–37360. [Google Scholar] [CrossRef]
66. Lee, H.; Yeom, S.; Kim, S. BP-GAN: Interpretable Human Branchpoint Prediction Using Attentive Generative Adversarial Networks. IEEE Access 2020, 8, 97851–97862. [Google Scholar] [CrossRef]
67. Du, B.; Tang, L.; Liu, L.; Zhou, W. Predicting LncRNA-Disease Association Based on Generative Adversarial Network. Curr. Gene Ther. 2022, 22, 144–151. [Google Scholar] [CrossRef]
68. Yan, X.; Wang, L.; You, Z.H.; Li, L.P.; Zheng, K. GANCDA: A novel method for predicting circRNA-disease associations based on deep generative adversarial network. Int. J. Data Min. Bioinform. 2020, 23, 265–283. [Google Scholar] [CrossRef]
69. Wang, L.; Yan, X.; You, Z.H.; Zhou, X.; Li, H.Y.; Huang, Y.A. SGANRDA: Semi-supervised generative adversarial networks for predicting circRNA-disease associations.

Briefings Bioinform. 2021, 22, bbab028. [Google Scholar] [CrossRef]

70. Hu, Y.; Ma, W. EnHiC: Learning fine-resolution Hi-C contact maps using a generative adversarial framework. Bioinformatics 2021, 37, I272–I279. [Google Scholar] [CrossRef]
71. Hong, H.; Jiang, S.; Li, H.; Du, G.; Sun, Y.; Tao, H.; Quan, C.; Zhao, C.; Li, R.; Li, W.; et al. DeepHiC: A Generative Adversarial Network for Enhancing Hi-C Data Resolution. PLoSComput. Biol. 2020, 16, e1007287. [Google Scholar] [CrossRef] [Green Version]
72. Liu, Q.; Lv, H.; Jiang, R. hicGAN infers super resolution Hi-C data with generative adversarial networks. Bioinformatics 2019, 35, I99–I107. [Google Scholar] [CrossRef] [Green Version]
73. Liu, Q.; Zeng, W.; Zhang, W.; Wang, S.; Chen, H.; Jiang, R.; Zhou, M.; Zhang, S. Deep generative modeling and clustering of single cell Hi-C data. Briefings Bioinform. 2022, 24, bbac494. [Google Scholar] [CrossRef]
74. Booker, W.W.; Ray, D.D.; Schrider, D.R. This population does not exist: Learning the distribution of evolutionary histories with generative adversarial networks. Genetics 2023, 224, iyad063. [Google Scholar] [CrossRef] [PubMed]
75. Salekin, S.; Mostavi, M.; Chiu, Y.C.; Chen, Y.; Zhang, J.; Huang, Y. Predicting Sites of Epitranscriptome Modifications Using Unsupervised Representation Learning Based on Generative Adversarial Networks. Front. Phys. 2020, 8, 196. [Google Scholar] [CrossRef] [PubMed]
76. Pati, S.K.; Gupta, M.K.; Shai, R.; Banerjee, A.; Ghosh, A. Missing value estimation of microarray data using Sim-GAN. Knowl. Inf. Syst. 2022, 64, 2661–2687. [Google Scholar] [CrossRef]

Access this Article in Online	
	Website: www.ijarm.com
Quick Response Code	Subject: Bioinformatics
DOI:10.22192/ijamr.2024.11.01.009	

How to cite this article:
Abhishek Thakur, Gopal Kumar Thakur. (2024). Developing GANs for Synthetic Medical Imaging Data: Enhancing Training and Research. Int. J. Adv. Multidiscip. Res. 11(1):70-82.
DOI: http://dx.doi.org/10.22192/ijamr.2024.12.01.009