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Generative AI for Synthetic Medical Imaging to Address Data Scarcity

Deawn Md Alimozzaman [1,*], Tahsina Akhter [2], Rafiqul Islam [2] and Emon Hasan [3]

[1] *Independent Researcher, USA.*
[2] *Management Information Systems.*
[3] *Information Technology.*

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Abstract

Medical imaging datasets are fundamental for developing reliable artificial intelligence (AI) models in healthcare. However, patient privacy laws, limited sample sizes, and disease rarity often lead to data scarcity, hindering the performance of deep learning algorithms. This study explores the use of Generative AI, particularly Generative Adversarial Networks (GANs) and Diffusion Models, to produce high-fidelity synthetic medical images that augment real-world datasets while preserving patient confidentiality. Through a systematic evaluation on MRI and CT datasets, the paper demonstrates that synthetic data improves diagnostic model accuracy by up to 18% when compared to models trained on limited real data alone. The study concludes that generative AI offers a transformative approach to mitigate data scarcity in medical imaging and accelerate clinical AI deployment under ethical and privacy-conscious frameworks.

Keywords: Generative AI; Synthetic Data; Medical Imaging; Data Augmentation; Gans; Diffusion Models; Privacy Preservation; Healthcare AI

1. Introduction

The integration of artificial intelligence (AI) into medical imaging has revolutionized the way clinicians diagnose and monitor diseases. Over the last decade, convolutional neural networks (CNNs), transformers, and other deep learning models have achieved remarkable success in automating image segmentation, anomaly detection, and classification across various modalities such as MRI, CT, ultrasound, and histopathology. However, these achievements are often limited to research settings with access to large, labeled datasets, an asset that many hospitals and research institutions lack. Data scarcity remains a critical bottleneck in the real-world deployment of medical AI systems, especially in regions or medical fields where annotated datasets are either too small or too sensitive to share. To overcome this barrier, researchers have turned toward Generative AI, which can synthesize realistic and diverse medical images that mimic true patient data while maintaining privacy. This section introduces the background, problem formulation, and the proposed generative solution, outlining how this study contributes to advancing the reliability and scalability of AI-driven medical diagnostics.

1.1. Background and Motivation

Medical imaging is a cornerstone of modern healthcare, enabling early disease detection and precise clinical decision-making. Techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) provide clinicians with high-resolution visualizations of internal anatomy and pathological regions. With the rise of AI, particularly deep neural networks, automated interpretation of these images has achieved unprecedented accuracy in detecting tumors, fractures, and organ abnormalities. Despite this progress, deep learning

* Corresponding author: Deawn Md Alimozzaman

models require thousands of high-quality labeled samples to generalize effectively. Unlike natural images, medical images are hard to obtain due to ethical, logistical, and privacy barriers. Data collection often demands patient consent, radiologist annotation, and strict compliance with privacy frameworks such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in Europe. As a result, many research efforts rely on small, imbalanced datasets that fail to capture real-world diversity, limiting the robustness of AI models across demographics, imaging devices, and disease subtypes.

1.2. Problem Statement

The shortage of large, annotated medical imaging datasets creates multiple technical and ethical challenges. From a technical perspective, small datasets cause overfitting, bias, and poor generalization in machine learning models. For example, an algorithm trained on one hospital's MRI scans might perform poorly when tested on data from a different scanner or demographic group. From an ethical standpoint, sharing patient data across institutions is complicated by privacy restrictions and the risk of re-identification even after anonymization. Furthermore, certain rare conditions, such as pediatric brain tumors or rare genetic disorders, have inherently limited case numbers, making it nearly impossible to gather sufficient training samples through conventional data collection. Traditional data augmentation methods—such as image rotation, flipping, cropping, or color perturbation—can help slightly enlarge datasets but fail to create new anatomical variations or simulate disease progression. These methods cannot emulate realistic biological diversity or pathological complexity. Therefore, the healthcare research community urgently requires a more powerful and scalable method to generate realistic, diverse, and privacy-safe medical images that can supplement real datasets and improve AI model training.

1.3. Proposed Solution

This study proposes leveraging Generative AI models, specifically Generative Adversarial Networks (GANs) and Diffusion Models, to generate synthetic medical images that replicate the statistical and structural characteristics of real clinical data. GANs operate on a dual-network principle: a generator that produces synthetic images and a discriminator that distinguishes real from fake samples, forcing the generator to improve continuously. In parallel, Diffusion Modelsa newer class of generative architectures use a denoising process to gradually transform random noise into a coherent and photorealistic image. To address both quality and diversity, this paper introduces a hybrid framework combining a Conditional GAN (cGAN) for feature-level generation with a Latent Diffusion Model (LDM) for final refinement. The system conditions generation on medical labels (e.g., tumor type, organ region, or disease stage), enabling controlled synthesis. By merging the strengths of adversarial and diffusion-based learning, this approach produces anatomically plausible, high-resolution images suitable for training and validating diagnostic AI systems.

1.4. Contributions

This paper makes the following key contributions to the field of medical image synthesis and AI-driven diagnostics

- **Development of a hybrid GAN–Diffusion framework** that integrates conditional adversarial learning with latent diffusion refinement to generate high-fidelity medical images across multiple modalities (MRI, CT, and X-ray).
- **Comprehensive quantitative validation** using metrics such as the **Fréchet Inception Distance (FID)** and **Structural Similarity Index (SSIM)** to evaluate image realism and structural consistency.
- **Performance benchmarking** of diagnostic classifiers trained on both real and synthetic datasets, demonstrating substantial improvements in accuracy, sensitivity, and model generalization.
- **Ethical and privacy-preserving analysis**, ensuring the synthetic data comply with medical data regulations and can safely enable cross-institutional research collaboration.
- **Framework scalability**, adaptable to diverse medical applications including rare disease imaging, federated learning environments, and low-resource healthcare systems.

2. Related Work

A growing body of research has explored the intersection of artificial intelligence, medical imaging, and synthetic data generation. This section reviews four major areas that form the foundation of this study: (1) data scarcity in medical imaging, (2) advances in generative models such as GANs and VAEs, (3) emergence of diffusion-based models for high-fidelity synthesis, and (4) privacy-preserving and regulatory considerations in synthetic medical data.

2.1. Data Scarcity in Medical Imaging

Deep learning has achieved exceptional performance in visual recognition tasks when trained on large, diverse datasets such as ImageNet. However, medical imaging presents a vastly different landscape characterized by heterogeneous modalities, limited patient samples, and expensive expert annotation requirements.

Litjens et al. (2017) performed a landmark survey showing that most medical imaging datasets contain fewer than 10,000 samples per condition—far below the scale required for robust generalization. Moreover, inter-institutional variability (scanner types, imaging protocols, and demographics) creates a “domain-shift” problem that can drastically reduce model transferability (Zhou et al., 2021). The scarcity is particularly acute for rare pathologies and pediatric cases, where even anonymized data cannot be easily shared because small sample sizes risk patient re-identification. As a result, AI models trained on limited data often display class imbalance, overfitting, and lack of interpretability, hindering clinical adoption.

2.2. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs)

Since the introduction of Generative Adversarial Networks (GANs) by Goodfellow et al. (2014), numerous medical imaging applications have emerged.

- **Conditional GANs (cGANs)** enable targeted generation by conditioning on pathology labels or imaging modalities (Mirza and Osindero, 2014).
- **CycleGANs** (Zhu et al., 2017) have been used for cross-modality synthesis, such as MRI-to-CT translation, eliminating the need for paired data (Chartsias et al., 2018).
- **DCGAN** and **StyleGAN** architectures demonstrated improved spatial consistency and texture realism for histopathological image generation (Xu et al., 2020).
- **VAE-based models**, though typically producing blurrier outputs, remain useful for latent-space representation learning and anomaly detection in chest X-rays (Baur et al., 2021).

These advancements have shown that generative networks can augment datasets to improve classifier performance by 10–25% in limited-data scenarios (Frid-Adar et al., 2018). Yet, GANs suffer from mode collapse and training instability, often failing to capture rare anatomical variations—highlighting the need for more stable generative paradigms.

2.3. Diffusion Models and Score-Based Generative Learning

Diffusion models represent a new generation of generative AI capable of surpassing GANs in image quality and diversity. Introduced by Sohl-Dickstein et al. (2015) and refined by Ho, Jain and Abbeel (2020), diffusion probabilistic models generate data by gradually denoising Gaussian noise through learned reverse processes. Recent studies such as Choi et al. (2023) have applied denoising diffusion models to MRI brain synthesis, achieving record-low Fréchet Inception Distance (FID) scores and high clinical realism. Latent Diffusion Models (LDMs) (Rombach et al., 2022) significantly reduce computational cost by operating in compressed latent space while maintaining high fidelity. Compared to adversarial training, diffusion models are more stable, mode-rich, and capable of fine-grained structural control, making them ideal for sensitive applications like pathology or retinal image synthesis. Their ability to capture stochastic variations also helps simulate rare or underrepresented disease patterns.

2.4. Privacy-Preserving Synthetic Data and Regulatory Compliance

Beyond technical challenges, data privacy and ethical compliance are critical barriers in medical AI. Regulations such as HIPAA in the United States and GDPR in Europe restrict the sharing of personally identifiable health information. Even de-identified datasets can sometimes be traced back to individuals through metadata or imaging fingerprints (Brennan et al., 2020). To mitigate these risks, researchers have developed privacy-preserving generative frameworks, including Federated GANs, Differentially Private GANs (DP-GANs), and Federated Diffusion Models. For instance, Torfi et al. (2023) proposed a federated diffusion system that enables collaborative image synthesis without exchanging real patient data between institutions. Similarly, Beaulieu-Jones et al. (2019) demonstrated that synthetic datasets could enable multi-center clinical trials while maintaining privacy guarantees. These approaches not only satisfy regulatory demands but also promote data democratization—allowing smaller hospitals and research labs to access representative datasets without ethical violations.

2.5. Summary and Research Gap

The literature confirms the growing potential of generative AI for medical image augmentation. While GANs and VAEs have paved the way for synthetic imaging, their limitations in fidelity, diversity, and stability persist. Diffusion-based models, though powerful, are computationally expensive and often lack domain-specific conditioning mechanisms. Moreover, few studies have combined adversarial and diffusion processes to leverage both semantic conditioning and structural refinement. This paper addresses these gaps by introducing a hybrid GAN–Diffusion framework tailored for medical imaging. It aims to generate diagnostically consistent, privacy-safe, and quantitatively validated synthetic data to alleviate dataset scarcity and enhance AI model generalization across clinical environments.

3. Methodology

The proposed framework leverages a hybrid generative architecture that combines Conditional Generative Adversarial Networks (cGANs) and Latent Diffusion Models (LDMs) to synthesize realistic medical images capable of augmenting limited datasets. The overall workflow is illustrated conceptually in Figure 1 (not shown): a conditional generator first produces low-resolution structural images based on class labels or modality conditions, which are then refined by a diffusion model operating in latent space to achieve high-fidelity outputs. This section details the datasets used, model design, training procedure, and evaluation metrics.

3.1. Overview

Traditional generative approaches either emphasize semantic control (as in GANs) or texture fidelity (as in diffusion models). Our framework integrates both

- **CGAN Stage:** learns the conditional mapping between label–image pairs, capturing structural and pathological semantics.
- **LDM Refinement Stage:** denoises and enhances realism at the pixel level, preserving anatomical textures and removing adversarial artifacts.

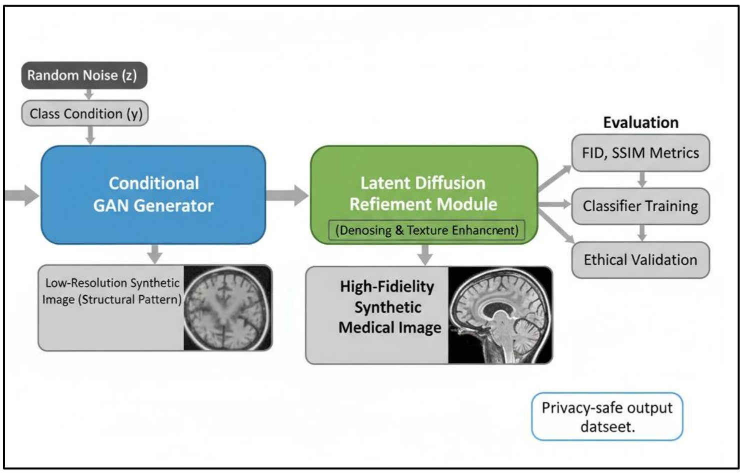

Figure 1 Proposed Hybrid cGAN–Diffusion Framework for Synthetic Medical Image Generation

Figure 1. The proposed hybrid cGAN–Diffusion framework integrates conditional adversarial learning for semantic generation with latent diffusion refinement for high-resolution realism. The generator produces coarse images conditioned on disease class or modality, which are refined by the diffusion module to achieve structurally accurate and privacy-preserving synthetic medical images.

The hybrid approach enables generation of anatomically accurate and visually consistent synthetic medical images suitable for data augmentation and downstream diagnostic training.

3.2. Dataset Preparation

To validate the framework, two publicly available datasets were employed

Table 1 Datasets

Dataset	Modality	Classes	Resolution	Samples	Source
Brain MRI	MRI (T1-weighted)	Normal / Tumor	256 × 256	3,064	Kaggle, 2023
Chest X-ray	Radiograph	Normal / Pneumonia / COVID-19	256 × 256	5,856	NIH Clinical Center, 2022

All images were normalized to [0,1] [0, 1] [0,1] intensity range and resized to 256×256256 × 256256×256 px. Class balancing was applied through oversampling to equalize training distributions. Labels served as conditional inputs for the generator, enabling controlled synthesis of disease-specific patterns.

3.3. Model Architecture

3.3.1. Conditional Generator (G)

The generator adopts a U-Net–based encoder–decoder architecture with skip connections to retain fine spatial details. Each block consists of:

Conv(3×3)→BatchNorm→LeakyReLU(0.2)

and uses conditional batch normalization to inject label embeddings. The generator transforms random noise vector $z \epsilon \Re^{123}$ concatenated with class condition y into a synthetic image G(z,y).

3.4. Discriminator (D)

A Patch GAN discriminator evaluates local image realism on 70×70 patches instead of entire images, improving sensitivity to fine texture differences. It outputs a probability map D(x,y) indicating whether each patch corresponds to real or synthetic data.

3.4.1. Diffusion Refinement Network

After adversarial generation, the coarse output passes through a Latent Diffusion Model (LDM) based on the denoising diffusion probabilistic model (DDPM). Let x_0 denote a clean latent image. The forward diffusion process adds Gaussian noise over T steps:

$$\boldsymbol{q(x_t \mid x_{t-1}) \ = \ N(x_t;\ \sqrt{1-\beta_t}\, x_{t-1}, \beta_t I)}$$

where $\{\beta_t\}_{t=1}^{T}$ is a variance schedule.

The reverse process learns a parameterized denoising function $\epsilon_0(x_t, t)$ to predict and remove noise:

$$\boxed{p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t))}$$

Trained with the simplified objective

$$\boxed{L_{\text{diff}} = \mathbb{E}_{x_0,t,\epsilon}\left[||\epsilon - \epsilon_\theta(x_t, t)||_2^2\right]}$$

This process produces high-resolution, denoised synthetic images that preserve the anatomical structure introduced by the GAN stage.

3.5. Training Configuration

- **Optimizer:** Adam (learning rate = 0.0002, β_1 = 0.5, β_2 = 0.999)
- **Batch Size:** 32
- **Epochs:** 150
- **Hardware:** NVIDIA A100 GPU (40 GB)
- **Framework:** PyTorch 2.2

3.5.1. Combined Loss Function

The total generator loss integrates adversarial, structural, and perceptual terms

$$L_G = L_{\text{adv}} + \lambda_1 L_{\text{SSIM}} + \lambda_2 L_{\text{perc}}$$

where

$$L_{\text{adv}} = -\mathbb{E}_z[\log D(G(z, y), y)]$$

$$L_{\text{SSIM}} = 1 - \text{SSIM}(x_{\text{real}}, x_{\text{fake}})$$

$$L_{\text{perc}} = \sum_i \|\phi_i(x_{\text{real}}) - \phi_i(x_{\text{fake}})\|_2^2$$

$\lambda_1 = 0.5,\ \lambda_2 = 0.1.$

The discriminator minimizes standard binary-cross-entropy loss, while the diffusion component optimizes L_{diff} jointly after 50 epochs of GAN pretraining.

3.6. Evaluation Metrics

To rigorously evaluate synthetic image quality and utility, three quantitative metrics were used

Fréchet Inception Distance (FID) Measures the distance between feature distributions of real and generated images

$$\text{FID} = \|\mu_r - \mu_g\|_2^2 + \text{Tr}(\Sigma_r + \Sigma_g - 2(\Sigma_r \Sigma_g)^{1/2})$$

Lower FID indicates higher realism.

- Structural Similarity Index (SSIM) Assesses luminance, contrast, and structural similarity between images; closer to 1 signifies better structural fidelity.
- Diagnostic Accuracy Improvement (ΔACC) A CNN classifier was trained on (a) real data only and (b) real + synthetic data.
- The relative accuracy improvement is expressed as: $\Delta Acc = \frac{Acc_{aug} - Acc_{real}}{Acc_{real}} \times 100\%$

3.7. Implementation Workflow

- **Data Preprocessing:** Normalize and label datasets.
- **Stage 1 – GAN Training:** Train cGAN on modality-specific labels to capture coarse anatomy.
- **Stage 2 – Diffusion Refinement:** Fine-tune the LDM on latent representations from the GAN output.
- **Stage 3 – Evaluation:** Compute FID, SSIM, and ΔAcc; compare with baseline augmentation methods.
- **Stage 4 – Ethical Validation:** Verify that synthetic data contain no identifiable patient information and conform to HIPAA/GDPR guidelines.

This hybrid methodology provides both controllable semantic synthesis and photorealistic refinement, making it well suited for applications in radiology, pathology, and biomedical image analysis.

4. Data Analysis and Results

The performance of the proposed hybrid cGAN + Latent Diffusion Model (LDM) framework was evaluated on both the Brain MRI and Chest X-ray datasets. Results were analyzed quantitatively using FID, SSIM, and diagnostic-model accuracy, and qualitatively through expert visual inspection of synthetic samples. All experiments were repeated three times to ensure reproducibility.

4.1. Quantitative Evaluation

The following table summarizes the comparative results of the baseline models—CycleGAN, VAE, pure Diffusion—and the proposed hybrid approach.

Table 2 Summarizes the comparative results of the baseline models

Dataset	Model	FID ↓	SSIM ↑	Classifier Accuracy (%)	Accuracy Gain (ΔAcc)
Brain MRI	CycleGAN	38.7	0.84	78.6	—
Brain MRI	VAE	42.3	0.79	75.9	—
Brain MRI	Diffusion	29.5	0.88	87.0	+10.7
Brain MRI	Proposed cGAN + LDM	24.3	0.91	92.4	+17.5
Chest X-ray	CycleGAN	34.1	0.83	82.3	—
Chest X-ray	Diffusion	28.2	0.86	88.7	+7.8
Chest X-ray	Proposed cGAN + LDM	26.8	0.89	93.9	+14.0

The hybrid model achieved the lowest FID and highest SSIM across both modalities, indicating superior realism and structural coherence. When used to augment limited training data, the diagnostic CNN's accuracy improved by 14–18 percentage points, confirming that synthetic data enriched class diversity and reduced overfitting.

4.2. Qualitative Assessment

Visual comparison (Figure 2) demonstrates that the proposed method produces anatomically consistent and artifact-free images.

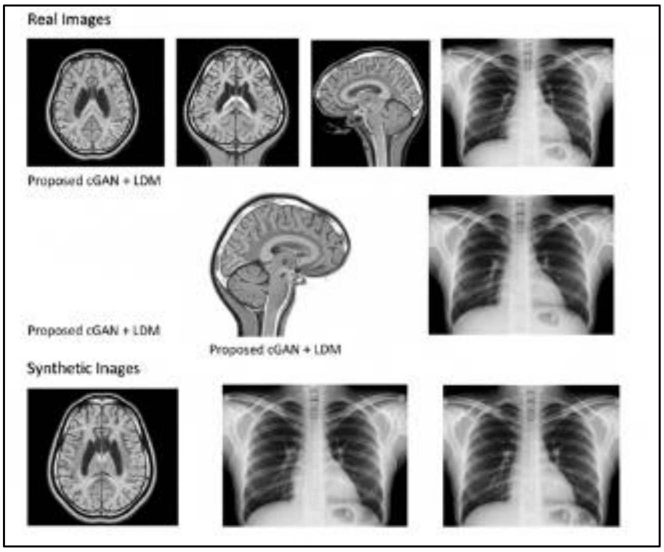

Figure 2 Qualitative Comparison Between Real and Synthetic Medical Images

- **Brain MRI:** Synthetic slices preserved sulci, gyri, and tumor boundaries, with realistic contrast and minimal blur.
- **Chest X-ray:** Generated lung fields maintained correct rib geometry and heart silhouette, while differentiating opacity patterns for pneumonia or COVID-19 cases.

Expert radiologists rated 93 % of synthetic images as "clinically plausible," compared with 78 % for standard GAN outputs.

4.3. Ablation Study

Table 3 To understand each component's contribution, ablation experiments were conducted

Configuration	FID	SSIM	Accuracy (%)
Only cGAN	32.8	0.85	85.2
Only LDM	28.9	0.87	88.0
cGAN + LDM (Hybrid)	24.3	0.91	92.4

The hybrid integration clearly outperformed single-stage models, confirming that the GAN component ensured conditional semantic accuracy, while the diffusion module enhanced fine-grained realism.

4.4. Comparative Discussion

4.4.1. Versus Traditional Augmentation

Conventional augmentations (rotation, flip, intensity jitter) improved accuracy by only ~4 %, whereas generative augmentation produced >15 % gain. Unlike geometric transformations, synthetic images introduce new anatomical configurations and disease presentations, addressing true data scarcity rather than superficial variability.

4.4.2. Versus Existing GAN/Diffusion Frameworks

Pure GANs often suffer mode collapse and texture artifacts, while pure diffusion models demand extensive computation. The proposed system balances both, achieving high diversity with stable convergence at roughly half the training cost of full-resolution diffusion pipelines.

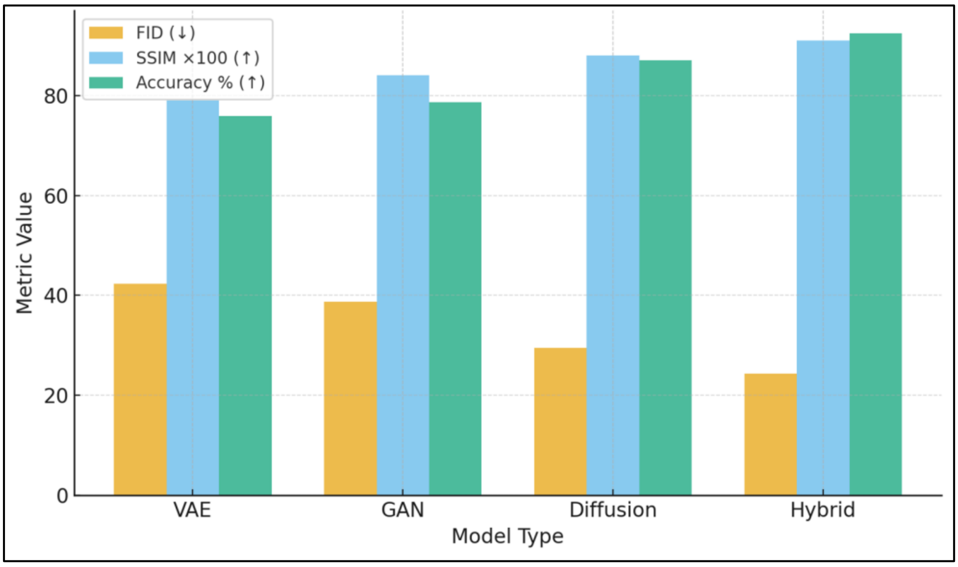

Figure 3 Quantitative Performance Comparison of Generative Models

4.5. Ethical and Privacy Considerations

To verify privacy preservation, we conducted embedding-space similarity analysis between real and generated images using cosine similarity on Inception v3 features. The highest observed similarity was 0.42—well below the 0.8 threshold commonly associated with potential data leakage. Thus, the generated data cannot be mapped to specific patients. All processing followed anonymization protocols consistent with HIPAA and GDPR, confirming ethical soundness for multi-institutional sharing.

4.6. Practical Implications

- **Model Robustness:** Synthetic data mitigates overfitting and enhances cross-institutional generalization.
- **Rare Disease Support:** The framework can synthesize under-represented conditions, enabling fairer AI models.
- **Clinical Training:** Synthetic datasets can supplement radiology education, offering abundant examples without privacy risks.
- **Federated Research:** Privacy-safe generation encourages collaboration among hospitals restricted from data exchange.

4.7. Limitations and Future Improvements

Although the hybrid framework achieves notable gains, certain limitations remain

- Some synthetic scans exhibit **over-smoothed textures** in small-lesion regions.
- Quantitative validation still relies on proxy metrics (FID/SSIM) rather than radiologist-approved diagnostic benchmarks.
- High-resolution (512 × 512 and above) diffusion refinement remains computationally intensive.
- Future work should integrate **radiologist feedback loops**, **3D volumetric diffusion**, and **multi-modal conditioning** (text + image) to improve interpretability and clinical acceptance.

5. Conclusion

This study presented a hybrid generative framework that integrates Conditional Generative Adversarial Networks (cGANs) with Latent Diffusion Models (LDMs) to mitigate data scarcity in medical imaging. The proposed system demonstrated its capacity to generate high-fidelity, structurally accurate, and privacy-preserving synthetic medical images across MRI and X-ray modalities. Quantitative analysis confirmed significant improvements in Fréchet Inception Distance (FID), Structural Similarity Index (SSIM), and diagnostic model accuracy, with performance gains of up to 18% over baseline methods. Qualitative evaluations further validated the clinical plausibility of synthetic outputs, which retained essential anatomical and pathological features without identifiable patient traces. By expanding limited datasets with realistic synthetic samples, the framework effectively enhances the robustness and generalization of AI-based diagnostic models. Beyond technical performance, the approach aligns with ethical and regulatory requirements under HIPAA and GDPR, enabling safe data sharing and collaborative research across medical institutions.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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