

# A Hybrid GAN–Diffusion Framework for Data Augmentation in brain Tumor and Chest X-Ray Classification: A Review

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## Abstract

Data insufficiency and class imbalance are still significant issues in medical image classification tasks, especially in brain tumor magnetic resonance imaging (MRI) and chest X-ray image analysis. However, generative data augmentation has been identified as an effective technique to increase the diversity of the dataset and improve the performance of deep learning models. This review provides a thorough examination of Generative Adversarial Networks (GANs), particularly DCGAN-based methods, and diffusion models for medical image generation. The latest developments in GAN-based augmentation for brain MRI and chest X-ray image classification tasks and diffusion-based generative models are critically discussed. In addition, the potential of hybrid generative approaches that combine GAN and diffusion models to improve the diversity and realism of generated data is also examined. This paper reveals the research gaps in the current studies and proposes a conceptual framework of a hybrid GAN and diffusion model for medical image classification.

**Keywords:** GAN, Brain MRI, DCGAN, Diffusion Model, Chest X-Ray, Data Augmentation, Medical Image classification

## INTRODUCTION

Medical imaging is a crucial part of disease diagnosis, treatment, and prognosis. In recent years, deep learning-based computer-aided diagnosis (CAD) systems have shown impressive results in brain tumor identification using magnetic resonance imaging (MRI) and pulmonary disease identification using chest X-ray images. However, the performance of such models relies greatly on the availability of large, balanced, and high-quality annotated datasets. In practical clinical settings, medical imaging datasets are typically small, imbalanced, and costly to annotate because of privacy and ethical issues, as well as the need for expert radiological interpretation. Generative Modeling has recently been identified as a promising approach to counter the issue of data unavailability in the medical imaging field. Initial works emphasized the use of Generative Adversarial Networks (GANs) for the synthesis of medical images [1]. Later works showed that the use of GANs for augmentation purposes can lead to a substantial improvement in the accuracy of classification tasks for chest X-ray images [2], [3]. Various reviews also emphasized the effect of GANs on the synthesis of medical images and their increasing importance in the medical field [4], [5]. Recently, systematic reviews have emphasized the need for augmentation tech-

niques based on deep learning for improving diagnostic accuracy [6].

Concurrent with the development of GANs, diffusion probabilistic models emerged as a promising generative approach. Diffusion models learn to reverse a noise corruption process step by step, allowing for stable and high-quality image generation. Various surveys have shown that diffusion models provide better training stability and mode collapse issues than GANs [7]. Systematic reviews on augmentation methods also validated the importance of having stable generative models that can maintain anatomical structures [8].

GAN-based augmentation has been successfully employed for synthesizing brain MRI for tumor classification tasks [9], and conditional diffusion models have shown great potential for medical image synthesis tasks [10]. GAN-based methods have been investigated for brain tumor detection tasks [11] and more advanced architectures like StyleGANv2-ADA have been employed for radiogenomic classification tasks [12]. Diffusion-based models have also shown great potential for medical image reconstruction and enhancement tasks [13].

GAN-based image synthesis for chest X-ray images has been demonstrated to improve the accuracy of pneumonia detection [14]. Nevertheless, GAN-based models tend to have drawbacks such as mode collapse, adversarial training difficulties, and the creation of subtle visual details that could impact the reliability of the results [5]. Diffusion models, on the other hand, have been shown to improve robustness in neuroimaging image synthesis tasks [15]. Diffusion models have been successfully used for conditional brain tumor image synthesis and classification [16]. GAN-based learning models have further enhanced MRI-based tumor classification accuracy [17].

However, recent studies have begun to investigate the use of hybrid generative models, which combine the strengths of two or more generative paradigms. Hybrid models that combine GANs and diffusion models have been suggested to overcome the challenges of data scarcity [18]. Breakthroughs in diffusion-based augmentation methods [19], cycle-conditional models [20], and longitudinal image synthesis [21] indicate the rapid progress being made in the field of generative models. Diffusion-based image-to-image translation models that have been presented at leading conferences like MICCAI [22] and segmentation-enhanced diffusion models [23] illustrate the adaptability of these models. Methods for counterfactual augmentation based on diffusion models have also been explored to enhance robustness [24]. On the adversarial learning front, progressive GAN models [25] and enhanced GAN models [26] have demonstrated excellent classification results in thoracic imaging.

More recently, hybrid generative mixing approaches like GenMix have been proposed to combine the strengths of GAN and diffusion models [27]. Taxonomy-based studies of deep generative models like VAE, GAN, and diffusion models have emphasized the importance of unified frameworks and evaluation protocols [28].

### **Motivation**

Deep learning networks for classifying brain tumor MRI images and chest X-ray images require a substantial number of well-balanced samples, which are not readily available in practical environments. Although GAN-based methods can enhance data diversity, they can also cause instability and artifacts [1]-[6], whereas diffusion models produce realistic images with a higher computational requirement [7], [15]. Recent studies on hybrid models indicate the potential benefits of combining these two paradigms [18], [27], but comprehensive studies are still lacking.

### **Problem statement**

Generative models have been extensively employed for medical image augmentation tasks, but GAN-

based methods are prone to instability and artifact generation, whereas diffusion models are computationally expensive despite their superior quality. Most of the existing works assess these paradigms separately, and there is less comparative study and exploration of hybrid model integration. Moreover, there is a lack of standardized evaluation frameworks. Hence, a hybrid GAN-Diffusion model is required to improve the robustness and reliability of brain tumor and chest X-ray classification tasks.

## RELATED WORK

Generative data augmentation is currently a prominent research topic in the field of medical image analysis, as the problem of limited and imbalanced datasets remains a challenge. Initial research on medical image synthesis was mainly based on Generative Adversarial Networks (GANs). Singh et al. [1] published one of the early comprehensive surveys on the use of GANs for medical image synthesis and data augmentation. Follow-up studies showed that GAN-based data augmentation can effectively improve the classification accuracy on chest X-ray image datasets by increasing the number of samples in the minority class [2], [3]. GAN-based synthesis methods were also reviewed to highlight their use in various types of imaging modalities [4], [5].

More organized surveys have been conducted on deep learning-based strategies for image augmentation. Kebaili et al. [6] conducted a systematic review of GAN, VAE, and hybrid methods for image augmentation, pointing out the challenges of training instability and inconsistency in evaluation. Garcea et al. [8] also reviewed data augmentation techniques, emphasizing the role of structural fidelity in synthetic medical images.

### A. GAN based Augmentation in Chest X-ray and Brain MRI

GAN-based models have been extensively used for the generation of brain MRI images. The use of GAN-based image augmentation was shown to enhance the accuracy of tumor classification by Alrumiah and Al-Zahrani [9]. Mahnoor et al. [11] also utilized GAN-based image augmentation for brain tumor detection and found it to improve the accuracy of classification. Moreover, Yurtsever et al. [12] used sophisticated GAN models like StyleGANv2-ADA for radiogenomic classification of brain tumors, thus establishing the potential of GAN models to learn complex patterns of brain tumors. GAN-based image augmentation has also been used to develop explainable machine learning models for improved diagnostic interpretability [17].

In the context of thoracic imaging, the application of GAN-based image augmentation has achieved promising outcomes. The application of GAN-synthesized chest X-ray images was demonstrated to enhance pneumonia classification performance by Motamed et al. [2]. Sundaram and Hulkund [3] further confirmed the efficacy of GAN-based image augmentation for pulmonary disease detection. Progressive GAN models were used for pneumonia detection by Porkodi et al. [25], and enhanced GAN models for chest X-ray image synthesis were reported in [26]. In addition, Ng et al. [14] investigated the application of GAN-based image synthesis for chest X-ray classification performance enhancement. Although GAN-based methods have achieved success, they often face challenges including mode collapse, adversarial training instability, and artifact generation, which may affect their reliability in clinical applications [1], [5].

### B. Diffusion Model in Medical Imaging

Diffusion probabilistic models have recently been introduced as a promising alternative to GANs. A recent survey by Kazerouni et al. [7] reviewed diffusion models in medical imaging and demonstrated their superior training stability and image quality. Hung [10] studied conditional diffusion models for

medical image synthesis and showed improved structural consistency. In neuroimaging, Mallardi et al. [15] investigated diffusion-based augmentation for brain MRI, observing improved anatomical preservation. Yu et al. [16] presented a conditional diffusion model for synthesizing and classifying brain tumors, which showed high diagnostic accuracy. Diffusion-based reconstruction and enhancement methods have also been investigated for medical imaging tasks [13].

Recent architectural breakthroughs further widened the scope of diffusion applications. Alimisis et al. [19] discussed recent breakthroughs in diffusion-based augmentation techniques. Zhu et al. [20] proposed cycle-conditional diffusion models for noise removal in diffusion-weighted imaging. Dao et al. [21] analyzed conditional diffusion models for longitudinal medical image synthesis. Diffusion-based image-to-image translation techniques were published in the MICCAI proceedings [22], and spatial-attention-aggregated conditional diffusion models were proposed for segmentation [23]. Counterfactual augmentation via diffusion generative models was analyzed to enhance model robustness [24].

### C. Hybrid Generative Approach

To overcome the challenges associated with traditional generative models, there has been a recent interest in the development of hybrid models that combine different paradigms. Belde [18] developed a hybrid model that combines GANs and diffusion models to overcome the problem of limited data in medical imaging. Similarly, Maier et al. [27] developed GenMix, a hybrid generative mixing model that combines the diversity of GANs with the fidelity of diffusion models to improve classification robustness. Taxonomy-based studies on generative models have highlighted the importance of hybrid models in medical image generation [28].

## GAN BASED DATA AUGMENTATION

Generative Adversarial Networks (GANs) have emerged as one of the most popular generative modeling approaches for medical image data augmentation. GANs were proposed as an adversarial learning algorithm, which involves two deep neural networks: a generator and a discriminator that are trained simultaneously in a minimax game. The generator is trained to generate fake images that can fool the discriminator into thinking they are real images, while the discriminator is trained to correctly classify images as real or fake. The minimax game can be formulated as follows:

$$\min_G \max_D V(D, G) = E_{X \sim P_{data}} [\log D(X)] + E_{Z \sim p_z} [\log(1 - D(G(z)))] \quad \text{----- (1)}$$

Where G represents the Generator,

D represents Discriminator

$P_{data}$  denotes the real data distribution

$P_z$  is the latent noise distribution

### A. Overview of GAN Architectures in Medical Imaging

The initial works demonstrated the applicability of GANs in the field of medical image synthesis and augmentation [1]. DCGAN brought convolutional layers, batch normalization, and proper architectural constraints to enhance the quality of image synthesis [4], [5]. Later, various GAN models such as Conditional GAN (cGAN), Progressive GAN, and StyleGAN have been used for medical imaging tasks. The importance of GAN-based augmentation has been emphasized in the literature to improve classification accuracy in low-data settings [6], [8]. The issues of mode collapse and adversarial training instability have been recognized as some of the long-standing problems in GANs [1], [5].

### B. GAN-Based Augmentation in Brain MRI

The MRI datasets of brain tumors are likely to face the problem of class imbalance, especially in the ca-

se of gliomas, meningiomas, and pituitary tumors. GAN-based augmentation has been used to generate more tumor samples to balance the datasets and improve the accuracy of classification. Alrumiah and Al-Zahrani [9] showed that the use of GAN-generated MRI samples can improve the accuracy of tumor classification by increasing the number of samples in the minority class. Mahnoor et al. [11] further extended the use of GAN-based augmentation for brain MRI tumor detection and showed substantial improvement in the accuracy of CNN-based classification. More advanced GAN models like StyleGANv2-ADA have been used by Yurtsever et al. [12] for radiogenomic classification and showed improved feature learning abilities. Moreover, GAN-based augmented explainable machine learning models have been proposed to improve both classification accuracy and interpretability for brain tumor analysis [17].

### C. GAN-Based Augmentation in Chest X-Ray Classification

Classification problems in chest X-ray images, including pneumonia and pulmonary diseases, have also been aided by GAN-based augmentation. Motamed et al. [2] showed the improved accuracy of pneumonia classification from GAN-synthesized chest X-ray images. Sundaram and Hulkund [3] proved the efficacy of GAN-based augmentation in pulmonary disease classification tasks.

Progressive GAN models have been used for pneumonia classification [25], and better variants of GANs for chest X-ray image synthesis were proposed in [26]. Ng et al. [14] investigated the use of GAN-based synthesis for thoracic imaging, showing that adversarially generated samples improve the minority class and prevent overfitting.

The above studies prove that GAN-based augmentation is highly effective in handling the problem of class imbalance in chest X-ray image datasets. However, the artifacts introduced in adversarial training might affect the reliability of the results.

### D. Limitations of GAN-Based Augmentation

However, GAN-based approaches have some drawbacks despite being widely used:

1. Mode Collapse: The generator can generate a few variations of the samples, thereby affecting diversity [1], [5].
2. Training Instability: The adversarial training process can cause convergence problems.
3. Artifact Generation: The generated images can have unrealistic textures or structural inconsistencies, which can be a serious problem in medical imaging.
4. Evaluation Challenges: There is no common evaluation metric to measure the clinical realism of the generated images [6], [8], [28].

The above-mentioned drawbacks make it necessary to investigate other generative paradigms, such as diffusion models, which provide better stability and realism.

## DIFFUSION BASED DATA AUGMENTATION

Diffusion probabilistic models have recently been introduced as a new and competitive approach to Generative Adversarial Networks (GANs) for the generation of medical images. Unlike GANs, diffusion models are based on the step-by-step removal of noise from an image, which is more stable and less prone to problems such as mode collapse and convergence instability [7]. Recent reviews point out diffusion models as a promising approach to generative modeling in medical imaging because of their high accuracy and consistency [7], [19].

### A. Fundamental of Diffusion Models

Diffusion model consists of two processes

1. Forward Diffusion process (Noise addition)
2. Reverse Diffusion process (denoising Process)

### 1. Forward process

In the forward process, Gaussian Noise is gradually added to the real image over multiple time steps

$$q(x_t | x_{t-1}) = N(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I) \text{ -----(2)}$$

Where  $x_0$  = original medical image

$X_t$  = Noisy Image at time  $t$

$B_t$  = Noise Variance schedule

$N$  = Gaussian Distribution

After many steps, the image becomes purely noise.

### 2. Reverse Process

The model learns to reverse this process,

$$P_\theta(x_{t-1} | x_t) \text{ -----(3)}$$

Where  $\theta$  represents learnable parameters of neural network.

The model is trained to predict and remove the noise step by step until realistic Synthetic medical image is generated.

### B. Diffusion Models in Brain MRI Augmentation

Diffusion-based augmentation has been proven to have great potential in neuroimaging challenges. Mallardi et al. [15] showed that diffusion models are capable of maintaining anatomical consistency in brain MRI augmentation. The conditional diffusion model has been used in brain tumor synthesis and classification, and it has been shown to have high diagnostic accuracy [16]. Moreover, diffusion models have been explored in medical image reconstruction challenges [13] and structural correction in diffusion-weighted imaging [20]. The conditional diffusion model for longitudinal medical image generation has also been explored [21], further broadening its scope.

The above-mentioned works indicate that diffusion models are highly effective in maintaining tumor boundary details and structural details, which are of utmost importance in accurate brain tumor classification.

### C. Diffusion Models in Chest X ray Augmentation

For thoracic image applications, diffusion models have shown better realism and detail preservation than adversarial models in image generation. The application of conditional diffusion models for medical image generation was successfully shown by Hung et al. [10]. More advanced diffusion models have been introduced in the MICCAI proceedings [22] and conditional diffusion models for segmentation tasks in [23], which have further improved the quality of synthetic images. The application of diffusion models for counterfactual medical image augmentation has also been investigated for enhancing the robustness of classifiers [24]. It has been confirmed in various surveys that diffusion-based image augmentation has improved the stability of classifiers while preserving plausibility [7], [19].

### D. Advantageous Diffusion Based Augmentation

Diffusion models have the following advantages over GAN-based models:

1. Stable Training: No adversarial optimization is required [7].
2. High Image Fidelity: Better structural and anatomical details are preserved [15], [16].
3. Less Mode Collapse: More diverse synthetic outputs are generated.
4. Better Clinical Reality: Better texture and boundary accuracy.

**E. Limitation of Diffusion Models**

However, diffusion models have some weaknesses despite their advantages:

1. High Computational Complexity: The process of multiple denoising steps is computationally expensive [19].
2. Slow Sampling: The reverse diffusion process for generating samples is iterative.
3. Hardware Requirements: Diffusion models require high memory and GPU requirements.

**COMPARATIVE ANALYSIS OF GAN AND DIFFUSION**

From Table 1 Comparative analysis of GAN and Diffusion Based on the literature trends,

1. The accuracy of the GAN-based augmentation is reported to have an improvement of 2-6%.
2. Improvements in the F1-score and recall have been observed in the minority classes of tumors.
3. Improvements reported in the Diffusion-based image augmentation are:
  - a. Lower FID scores
  - b. Higher SSIM values
  - c. Improvements in the AUC scores
  - d. Diffusion improves structural Consistency, which enhance the generalization.

Ref. No.	Criteria	GAN based Model	Diffusion based Model
[1]	Training Mechanism	Adversarial Training	Likelihood based Denoising.
[5]	Image Fidelity and structural Preservation	Realistic Structure but may subtle artifacts in MRI	Superior Anatomical Preservation and Boundary Consistency
[7]	Diversity and Class imbalance Handling	Significant Minority Class balancing; improves dataset variability.	Boarder Distribution modelling with Lower Repetition Risk
[19]	Computational Complexity	Faster Training Interference; suitable for limited hardware.	Computationally Intensive; slow iterative sampling
[9] [11] [15] [16] [19]	Performance parameter	<b>Accuracy:</b> Increases 2 to 6 %, <b>F1 Score:</b> Increase <b>Recall:</b> increase in imbalance dataset <b>FID and SSIM :</b> limited reported	<b>AUC:</b> Increases <b>Robustness:</b> Increases <b>FID:</b> Lower <b>SSIM:</b> Higher Improved Generalization stability

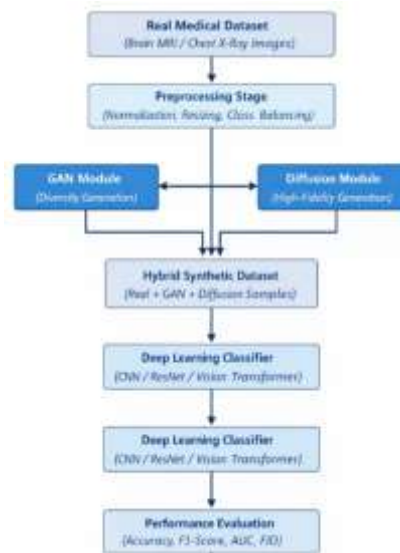
**Table 1 Comparative analysis of GAN and Diffusion**

**PROPOSED HYBRID GAN- DIFFUSION CONCEPTUAL FRAMEWORK**

The proposed hybrid framework integrates GAN-based diversity generation with diffusion-based fidelity enhancement to address data scarcity in brain tumor MRI and chest X-ray classification. The GAN module improves minority class representation, while the diffusion module ensures structural

consistency and anatomical realism. The synthetic images from both models are merged with real data to form a hybrid dataset used to train a deep learning classifier. This integration leverages the complementary strengths of both generative paradigms to improve robustness, generalization, and clinical reliability.

Figure 1 illustrates the conceptual architecture of the proposed hybrid GAN-diffusion model for medical image data augmentation and classification. The proposed model starts with a set of real medical image data, which can include MRI scans and X-ray images of the human brain. The image data are then subjected to a set of pre-processing steps to ensure standardized image representation. The pre-processed image data are then fed into a set of parallel image generators, which include a GAN-based image generator to ensure image diversity and class balance, and a diffusion-based image generator to ensure image realism.



**Fig. 1 Proposed Framework**

The output from these image generators is then combined with the original image dataset to create a hybrid image dataset. The proposed image dataset is then subjected to a set of image classification tasks using a set of deep neural network models, including CNN, ResNet, and Vision Transformer. The proposed image classification model is then subjected to a set of quantitative evaluation metrics to ensure image classification and generator quality.

### RESEARCH GAP IDENTIFIED

Although there have been major breakthroughs in the application of generative data augmentation in medical imaging, there are still some research gaps that have not been addressed. The current literature is mainly centered around either GAN-based [1]–[6], [9], [11], [12], [25], [26] or diffusion-based models [7], [10], [15], [16], [19]–[24] separately, without any structured comparison between the two for the classification of brain tumor MRI and chest X-ray images. Although GAN-based models are beneficial for increasing the diversity of the dataset and the accuracy of the classification results, they are often plagued with the problems of instability in training, mode collapse, and the generation of artifacts [1], [5]. On the other hand, diffusion models provide better image quality and preservation of structure but at the cost of increased computational complexity and slower inference times [7], [19].

One of the major gaps in the current literature is the absence of standardized frameworks for benchmarking the generative augmentation approaches. Most of the literature focuses on improving the accuracy of classification, but validation of the generative quality is less common and is not measured using standardized parameters such as FID, SSIM, and clinical validation criteria [6], [8], [28]. Cross-validation across datasets is also not common. Although hybrid generative approaches that combine GANs and diffusion models have been recently proposed in [18], [27], their use in medical imaging is still in its infancy. There is a lack of experimental comparisons between standalone and hybrid models on clinically relevant classification tasks. Moreover, there is a lack of focus on 3D volumetric MRI diffusion Modeling, multi-modal augmentation, and privacy-preserving generative learning.

Thus, there is a need for,

1. A comparative analysis of GAN and diffusion models.
2. The development of hybrid GAN and diffusion models for augmentation.
3. Evaluation protocols for generative and classification performance.
4. Analysis of computational efficiency and scalability.
5. Clinical validation and privacy-focused generative modeling.

These research gaps must be addressed in order to develop efficient and scalable generative augmentation models for brain tumor and chest X-ray classification.

#### **FUTURE RESEARCH DIRECTION**

Although considerable progress has been made in medical image classification by generative data augmentation, there are a number of potential research directions that are yet to be explored.

1. First, there is a need to build faster and more computationally efficient diffusion models to make data augmentation faster, particularly for clinical settings [7], [19].
2. Secondly, there is a need to concentrate future research in the area of 3D volumetric medical image generation, particularly for MRI brain image datasets. Most image augmentation techniques are 2D slice-based, which does not adequately account for spatial tumor characteristics in images [15], [16]. The extension of hybrid GAN-diffusion models to 3D MRI image datasets can greatly contribute to better anatomical consistency and reliability in image diagnosis.
3. Thirdly, there is a need to develop benchmarking protocols to facilitate a fair comparison of different GAN-based, diffusion-based, and hybrid image generative models. The majority of existing image generative models employ diverse datasets and evaluation criteria, which limits direct comparisons between different image generative models.
4. Fourth, the concept of privacy-preserving generative modeling is an important direction for the future. As medical data is highly sensitive, incorporating differential privacy mechanisms or federated learning mechanisms in the framework of hybrid generative modeling can ensure the security of synthetic data generation.
5. Fifth, the effectiveness of the hybrid approach in the framework of generative modeling needs to be explored in the future. Although initial studies have shown the effectiveness of the hybrid approach in the framework of GANs and diffusion models, the effectiveness of the approach in the framework of medical image domains still needs to be explored, as the initial studies have been conducted in the framework of two medical image domains only, while the effectiveness in the framework of multiple medical image domains is still unknown.

6. Finally, clinician-in-the-loop validation should be included in future augmentation pipelines. Quantitative improvements in classification accuracy must be complemented by radiological evaluation to ensure anatomical plausibility and safety.

## CONCLUSION

In this review paper, a detailed review of the GAN-based data augmentation techniques as well as the diffusion-based data augmentation techniques was presented for brain tumor MRI as well as chest X-ray image classification. Although the use of GAN-based models has improved the diversity of the dataset as well as the computational efficiency, the instability of the model as well as the generation of artifacts has limited their use. On the other hand, the use of diffusion models has improved the image fidelity as well as the structure, but at the cost of increased computational efficiency. A conceptual model for a hybrid model that uses the features of both models was presented, which could improve the robustness as well as the efficiency of the image classification model. It can be noted that more research needs to be conducted to improve the efficiency as well as the efficacy of the image classification model.

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