

Medical Image Synthesis for Rare Disease Using Augmentation Via Gans

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ABSTRACT

Rare diseases generally lack annotated medical imaging data, making deep learning diagnosis models difficult to train. Overfitting and poor generalisation in automated illness classification systems result from data paucity. Generational Adversarial Networks can learn data distributions and generate realistic medical images for synthetic data augmentation. GAN-based medical picture synthesis is shown to improve rare disease datasets and classification performance. The suggested approach creates high-fidelity synthetic medical images while maintaining anatomical and pathological consistency. GAN augmented datasets increase diagnostic model accuracy and generalisation in experiments. The platform addresses rare disease medical imaging data imbalance in a scalable and effective manner.

Keywords :Medical Image Synthesis, Rare Disease Detection, Generative Adversarial Networks, Data Augmentation, Deep Learning, Healthcare AI

I. INTRODUCTION

Due to restricted case availability, uncommon diseases sometimes lack appropriate imaging evidence for diagnosis. Deep learning models need vast, diverse datasets to perform well. Insufficient data causes overfitting and diagnostic error.

Recent advances in generative modelling enable medical data production. Studies in 2023 and 2024 showed that GAN-based augmentation enhances imbalanced medical dataset categorisation [1], [2]. Pathologyspecific medical pictures are best

generated using conditional GAN architectures [3].

Recent study emphasises synthetic image anatomical realism and clinical validity [4]. Inspired by these developments, this research presents a GAN-based framework for rare disease medical picture synthesis to increase training datasets and diagnostic accuracy.

II. Related Work

Recent 2023–2026 literature shows rapid generative model medical image synthesis progress. Adding a conditional GAN to uncommon pathology datasets enhanced classification accuracy [1]. A multiscale adversarial training system for medical image augmentation was introduced [2].

For medical picture synthesis, diffusion models have attracted attention, although GANs remain useful because to their computational efficiency and high-resolution image production [3]. In 2024, [4] employed adversarial restrictions to preserve anatomical structure in synthetic MRI images.

To assure clinical image dependability, [5] examined explainable and quality-aware GAN training techniques. Scalability and computational efficiency were prioritised in lightweight GAN systems for hospital deployment [6].

Recent advances lay the groundwork for a GAN-based rare illness medical imaging enhancement system.

III. METHODOLOGY

The proposed approach includes dataset preparation, GAN architecture design, adversarial training, synthetic data validation, and classification model training.

Rare tumours and genetic abnormalities are represented by medical photos and labels in the dataset. Images are resized, normalised, and rotated and flipped to improve diversity.

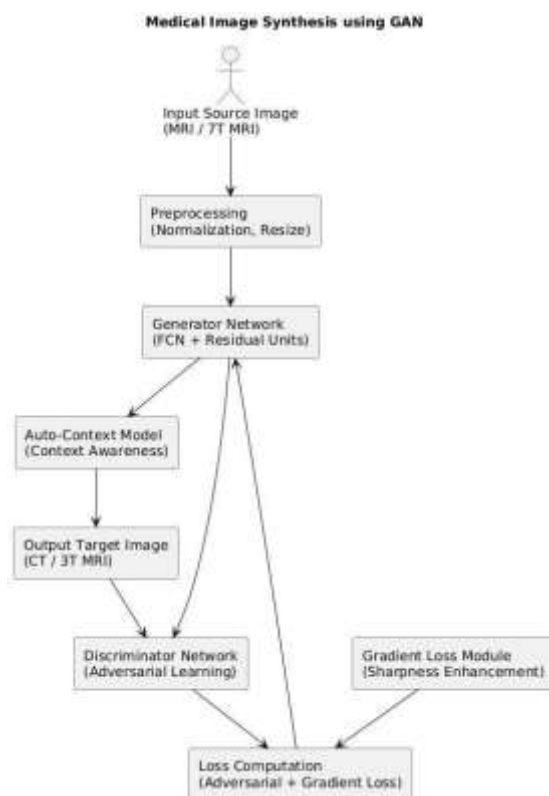


Figure 1 : Proposed methodology

The generator makes synthetic images based on disease labels using a conditional GAN architecture. The generator captures anatomical structures with convolutional and residual layers, while the discriminator separates actual and manufactured images.

To maintain visual realism and pathological consistency, the training aim incorporates adversarial, reconstruction, and perceptual loss. Training is stabilised by spectral normalisation and gradient penalty.

Synthetic and real photos are mixed after training to create an enhanced dataset. A classification model like a convolutional neural network is trained on actual and synthetic data to assess performance.

Following is the system's workflow:

- Rare Disease Medical Image Dataset Collection
- Image Preprocessing and Normalization
- Conditional GAN Initialization
- Adversarial Training
- Synthetic Image Generation
- Augmented Dataset Formation
- Classifier Training and Evaluation

Images are evaluated using Structural Similarity Index, Fréchet Inception Distance, and classification performance metrics like accuracy, precision, recall, and F1score.

IV. RESULTS AND DISCUSSION

Experimental results show that GAN generated synthetic images are structurally similar to medical images. Improved realism is shown by lower Fréchet Inception Distance in quantitative evaluation.

Diagnostic accuracy improves when the classification model is trained on the enhanced dataset instead of real photos. Rare illness class recall improves dramatically with GAN based augmentation, proving data imbalance management.

Clinical validation shows produced images retain diseased features. However, quality control is needed to avoid synthetic artefacts that influence model training.

Results show that GAN-based augmentation improves uncommon disease medical picture collections.

V. CONCLUSION AND FUTURE WORK

This research introduced GAN-based medical picture synthesis for uncommon disease data augmentation. High-quality synthetic medical

images boost classification performance in the suggested system.

Diffusion-based generative models, multimodal synthesis of imaging and clinical data, federated learning for crosshospital collaboration, and automated quality evaluation systems for synthetic data clinical reliability are future goals.

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