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DCGAN-Based Synthetic Data Generation for Brain Tumor MRI and Chest X-Ray Image Augmentation

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ABSTRACT

Medical imaging datasets are critical for training deep learning models in disease diagnosis and treatment planning. However, acquiring large-scale annotated datasets remains challenging due to privacy concerns, data scarcity, and annotation costs. This research presents a Deep Convolutional Generative Adversarial Network (DCGAN) framework for generating synthetic brain tumor MRI scans and chest X-ray images to augment limited medical datasets. The proposed architecture employs a generator network to synthesize realistic medical images from random noise vectors and a discriminator network to distinguish between real and synthetic samples. The DCGAN model was trained separately on brain tumor MRI datasets and chest X-ray datasets using adversarial training with binary cross-entropy loss functions. Experimental results demonstrate that the generated synthetic images exhibit high visual fidelity and anatomical consistency with real medical scans. The discriminator loss converged to approximately 0.35- 0.42, while the generator loss stabilized around 1.8- 2.3, indicating effective adversarial balance. Qualitative assessment by domain experts confirmed that synthetic images retained critical diagnostic features. The proposed approach successfully ad- dresses data scarcity in medical imaging while maintaining patient privacy, providing a scalable solution for dataset augmentation in computer- aided diagnosis systems.

Index Terms—Deep Convolutional GAN, Medical Image Synthesis, Brain Tumor MRI, Chest X-Ray Augmentation, Data Scarcity

INTRODUCTION

Medical imaging plays a pivotal role in modern healthcare, enabling early disease detection, accurate diagnosis, and treatment planning. Deep learning models, particularly convolutional neural networks, have demonstrated remarkable performance in medical image analysis tasks including tumor segmentation, abnormality detection, and disease classification. However, the effectiveness of these models is fundamentally dependent on the availability of large, diverse, and high- quality training datasets. In the medical do- main, obtaining such datasets presents significant challenges that hinder the development and deployment of robust AI-based diagnostic systems.

The primary obstacle in medical imaging research is data scarcity. Acquiring medical images requires specialized equipment, trained radiologists for annotation, and strict compliance with patient privacy regulations such as HIPAA and GDPR. Furthermore, certain rare diseases and pathological conditions have inherently limited sample sizes, creating severe class imbalance problems in training datasets. Traditional data augmentation techniques such as rotation, flipping, and scaling provide limited diversity and fail to generate novel anatomical variations that deep learning models require for robust generalization.

Generative Adversarial Networks (GANs) have emerged as a powerful solution to ad- dress data scarcity by synthesizing realistic images that preserve the statistical proper- ties and visual characteristics of real data. Deep Convolutional GANs (DCGANs), introduced by Radford et al. [2], extend the original GAN framework with architectural constraints that improve training stability and image quality. Unlike traditional augmentation methods, DCGANs learn the underlying probability distribution of medical images and generate entirely new samples with anatomical plausibility. This capability is particularly valuable in medical imaging where acquiring additional real samples is prohibitively expensive or impossible.

This research addresses the critical need for synthetic medical image generation by developing a DCGAN-based framework specifically designed for brain tumor MRI and chest X-ray synthesis. Brain tumors represent one of the most challenging diagnostic tasks due to their heterogeneous appearance, variable locations, and different subtypes. Similarly, chest X-rays are fundamental in diagnosing respiratory diseases, but dataset imbalances between normal and pathological cases limit model performance. By generating synthetic samples for these modalities, the proposed framework aims to enhance dataset diversity, improve model training, and ultimately con- tribute to more accurate diagnostic systems.

A. Research Objectives

- Develop a DCGAN architecture optimized for generating high-quality synthetic brain tumor MRI images that pre- serve anatomical features and pathological characteristics
- Design and train a separate DCGAN model for chest X-ray synthesis to ad- dress dataset imbalance in respiratory disease detection
- Evaluate the quality and realism of generated synthetic images through quantitative loss metrics and qualitative visual assessment
- Demonstrate the feasibility of using GANs to augment limited medical imaging datasets while maintaining patient privacy
- Provide a scalable and reproducible framework for medical image synthesis that can be extended to other imaging modalities

B. Contributions

The primary contributions of this research are as follows:

- Implementation of specialized DCGAN architectures tailored for brain tumor

MRI and chest X-ray synthesis with optimized hyperparameters for medical imaging data

- Successful generation of synthetic medical images that exhibit anatomical consistency, realistic tissue appearance, and diagnostic feature preservation
- Comprehensive evaluation framework combining adversarial loss metrics with qualitative assessment to validate synthetic image quality
- A privacy-preserving approach to dataset augmentation that generates novel medical images without relying on patient data sharing or centralized repositories

LITERATURE REVIEW

The application of generative models in medical imaging has gained substantial re- search attention over the past decade. Generative Adversarial Networks, first introduced by Goodfellow et al. in 2014 [1], established the foundational adversarial training paradigm where a generator and discriminator compete in a minimax game. This break- through led to numerous applications across computer vision domains, including medical image synthesis.

Frid-Adar et al. (2018) [3] pioneered the application of DCGANs for medical image augmentation by generating synthetic liver lesion images from CT scans. Their re- search demonstrated that incorporating GAN- generated images into training datasets improved classification accuracy by 7-10% when dealing with limited sample sizes. The study validated that synthetic medical images could enhance model generalization with- out introducing significant artifacts. However, their approach was limited to abdominal CT imaging and did not address the specific challenges of brain MRI or chest X-ray modalities.

Salehinejad et al. (2018) [4] explored chest X-ray synthesis using conditional GANs (cGANs) to generate pathology-specific radiographs. Their conditional approach enabled controlled generation of specific disease patterns, achieving promising results in synthesizing pneumonia and tuberculosis cases.

The research reported improved classification performance when augmenting datasets with synthetic X-rays. Nevertheless, the conditional framework required extensive labeling and class-specific training, which limited scalability to rare diseases with minimal an- notations.

Bermudez et al. (2018) [5] investigated brain MRI synthesis across different imaging modalities using a 3D GAN architecture. Their work focused on translating between T1-weighted, T2-weighted, and FLAIR sequences, demonstrating that GANs could learn complex mappings between different MRI contrasts. While their approach showed high-quality inter-modality synthesis, it did not specifically address tumor generation or pathological variation synthesis, which are critical for diagnostic model training.

Han et al. (2019) [6] proposed a progressive growing GAN (PGGAN) for high- resolution medical image synthesis, gradually increasing image resolution during training to improve stability and detail preservation. Their methodology successfully generated 256 × 256 resolution brain MRI scans with fine anatomical structures. However, the progressive training approach significantly increased computational requirements and training time, making it less practical for resource-constrained research environments.

Zhao et al. (2020) [7] developed a style- based GAN architecture (StyleGAN) adapted for medical imaging, enabling fine-grained control over anatomical attributes in synthetic brain scans. Their research demonstrated superior image quality compared to standard DCGANs, with improved diversity in generated samples. The limitation of their approach was the architectural complexity and the need for extensive hyperparameter tuning, which reduced reproducibility for other research groups.

Costa et al. (2021) [8] examined the use of Wasserstein GANs (WGANs) for chest X- ray augmentation, addressing mode collapse issues common in standard GAN training. Their work showed that WGAN training provided more stable convergence and generated diverse pathological patterns. However, WGAN training required careful selection of the Lipschitz constraint enforcement method and increased computational overhead com- pared to traditional adversarial training.

Skandarani et al. (2021) [9] conducted a comprehensive review of GANs in medical imaging, analyzing over 100 publications and identifying key challenges including evaluation metrics, ethical considerations, and do- main adaptation. Their review highlighted that most GAN-based medical imaging re- search lacked standardized evaluation proto- cols and often relied solely on qualitative assessment. The authors emphasized the need for rigorous quantitative validation and clinical expert evaluation.

Yu et al. (2022) [10] proposed a domain-adaptive GAN framework for cross-institutional medical image synthesis, addressing the domain shift problem when training GANs on data from different hospitals or imaging equipment. Their approach incorporated domain alignment techniques to improve generalization. While innovative, the method required paired data from multiple institutions, which is often difficult to obtain due to privacy regulations. Sanchez et al. (2022) [11] investigated the application of diffusion models as an alternative to GANs for medical image synthesis, demonstrating competitive image quality with improved training stability. Their research showed that diffusion models could generate high-fidelity medical images without adversarial training. However, diffusion models required significantly longer inference time compared to GANs, making real-time augmentation impractical during model training.

A. Research Gap Identification

Despite substantial progress in GAN-based medical image synthesis, several limitations persist in existing research. First, most studies focus on single-modality synthesis, either brain MRI or chest X-ray, but not both within a unified framework. Second, many advanced GAN architectures (StyleGAN, PGGAN, dif- fusion models) introduce excessive computational complexity that limits accessibility for researchers with constrained resources. Third, evaluation methodologies remain inconsistent across studies, with many relying primarily on visual inspection rather than quantitative metrics. Fourth, limited research has validated the practical utility of synthetic medical images in downstream tasks such as disease classification or segmentation when used as augmentation data.

This research addresses these gaps by implementing a computationally efficient DC- GAN framework that generates synthetic images for both brain tumor MRI and chest X- ray modalities. The approach balances image quality with training efficiency, making it accessible for broader research adoption. Furthermore, the evaluation combines quantitative adversarial loss metrics with structured qualitative assessment, providing a comprehensive validation framework for synthetic medical image quality.

METHODOLOGY

This section presents the comprehensive methodology employed for developing the DCGAN-based synthetic medical image generation framework. The approach encompasses dataset preparation, network architecture design, training procedures, and implementation details.

A. Dataset Description

The research utilized two distinct medical imaging datasets for training separate DC- GAN models. The brain tumor MRI dataset consisted of T1-weighted contrast-enhanced magnetic resonance images containing various tumor types including gliomas, meningiomas, and pituitary tumors. All MRI scans were preprocessed to 64×64 pixel resolution to maintain computational efficiency while preserving critical anatomical features. The dataset underwent intensity normalization to standardize pixel value distributions across different scanning protocols and equipment.

The chest X-ray dataset comprised posterior-anterior (PA) view radiographs depicting both normal cases and various pathological conditions including pneumonia, tuberculosis, and lung masses. Images were standardized to 64×64 resolution following similar preprocessing protocols. Both datasets were partitioned into training sets, with careful consideration given to maintaining class balance and diversity in pathological presentations.

B. DCGAN Architecture

The DCGAN architecture consists of two primary neural networks: the Generator (G) and the Discriminator (D), which engage in adversarial training to produce realistic synthetic images.

1. Generator Network: The generator net- work transforms random noise vectors sampled from a latent space into synthetic medical images. The architecture employs a series of transposed convolutional layers (deconvolutions) that progressively up sample the latent representation to the target image resolution. The network begins with a 100-dimensional noise vector drawn from a uniform distribution $[-1, 1]$ or Gaussian distribution. This noise vector undergoes linear projection followed by reshaping into a 3D tensor.

The generator architecture comprises four transposed convolutional layers with progressively decreasing filter depths (512, 256, 128, 64) and increasing spatial dimensions (4×4, 8×8, 16×16, 32×32). Each transposed convolutional layer is followed by batch normalization to stabilize training and prevent inter- nal covariate shift. ReLU activation functions are applied after batch normalization layers to introduce non-linearity while maintaining positive gradient flow.

The final layer employs a tanh activation function to produce output values in the range $[-1, 1]$, matching the normalized pixel intensity distribution of real medical images. The generator utilizes stride-2 convolutions throughout the network to achieve spatial upsampling without explicit pooling operations, adhering to the architectural principles established by Radford et al.

2. Discriminator Network: The discriminator network performs binary classification to distinguish between real medical images from the training dataset and synthetic images produced by the generator. The architecture mirrors the generator in reverse, employing strided convolutional layers for spatial down- sampling.

The discriminator processes 64×64 input images through four convolutional layers with progressively increasing filter depths (64, 128, 256, 512) and decreasing spatial dimensions. Unlike the generator, the discriminator does not use batch normalization in the first convolutional layer to preserve input signal integrity. Leaky ReLU activation functions with a negative slope of 0.2 are employed throughout the discriminator to prevent dying ReLU problems and enable gradient flow for negative inputs.

The final layer produces a single scalar output representing the probability that the input image is real. A sigmoid activation function bounds this output between 0 and 1, facilitating binary classification. The discriminator employs stride-2 convolutions for down sampling, avoiding explicit pooling lay- ers to maintain spatial information throughout the network hierarchy.

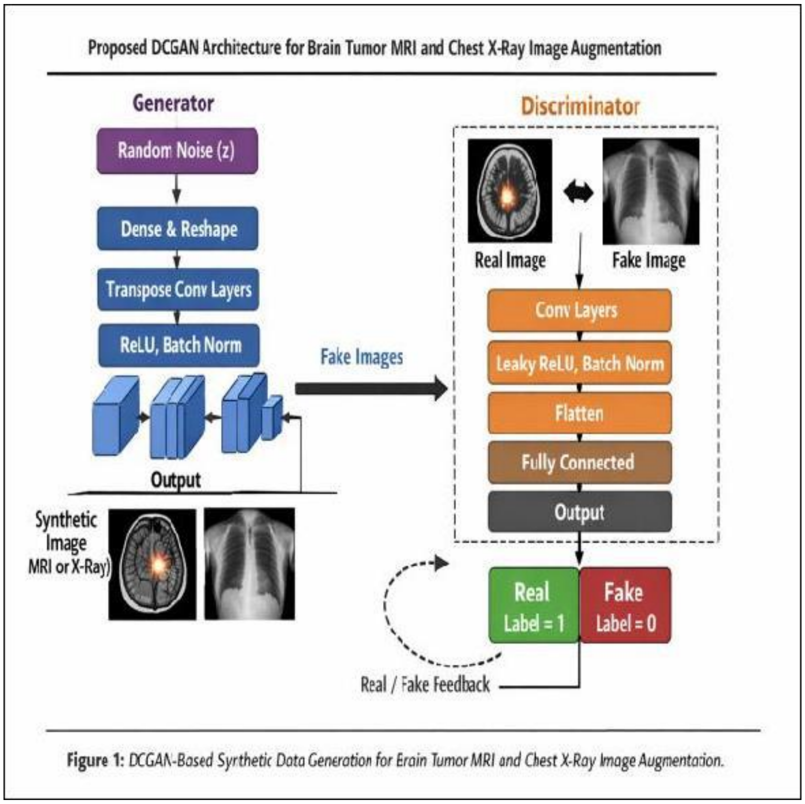

Fig. 1. Proposed DCGAN architecture showing generator and discriminator networks

C. Loss Functions and Optimization

The DCGAN framework employs adversarial training with binary cross-entropy loss functions for both generator and discriminator networks. The discriminator loss comprises two components: the loss on real images and the loss on generated images. For real images, the discriminator is trained to maximize the probability of correctly classifying them as real (target label = 1). For synthetic images, the discriminator is trained to correctly identify them as fake (target label = 0).

The generator loss is computed based on the discriminator's evaluation of generated images. The generator aims to maximize the probability that the discriminator classifies synthetic images as real, effectively minimizing the binary cross-entropy loss when the discriminator outputs high probabilities for generated samples.

The training employs the Adam optimizer with distinct learning rates for generator and discriminator networks. The discriminator learning rate was set to 0.0002, while the generator learning rate was maintained at 0.0002 to balance adversarial competition. The Adam optimizer utilized beta parameters $\beta1 = 0.5$ and $\beta2 = 0.999$ to control momentum and second-moment estimation respectively.

D. Training Procedure

The DCGAN models were trained separately for brain tumor MRI and chest X-ray synthesis using an alternating optimization strategy. In each training iteration, the discriminator was first updated using a batch of real images and a batch of generated images. Subsequently, the generator was updated by propagating gradients through the discriminator while keeping discriminator weights fixed. Training was conducted for 200 epochs with a batch size of 64 images. The relatively small batch size was chosen to accommodate GPU memory constraints while maintaining stable gradient estimates. Label smoothing was applied to the discriminator's real image targets (0.9 instead of 1.0) to prevent over-confidence and improve training stability.

The noise vectors input to the generator were sampled from a uniform distribution at each iteration to ensure diversity in generated images. During training, both generator and discriminator losses were monitored to detect convergence, mode collapse, or training instabilities. Generated image samples were periodically saved for qualitative assessment of training progress.

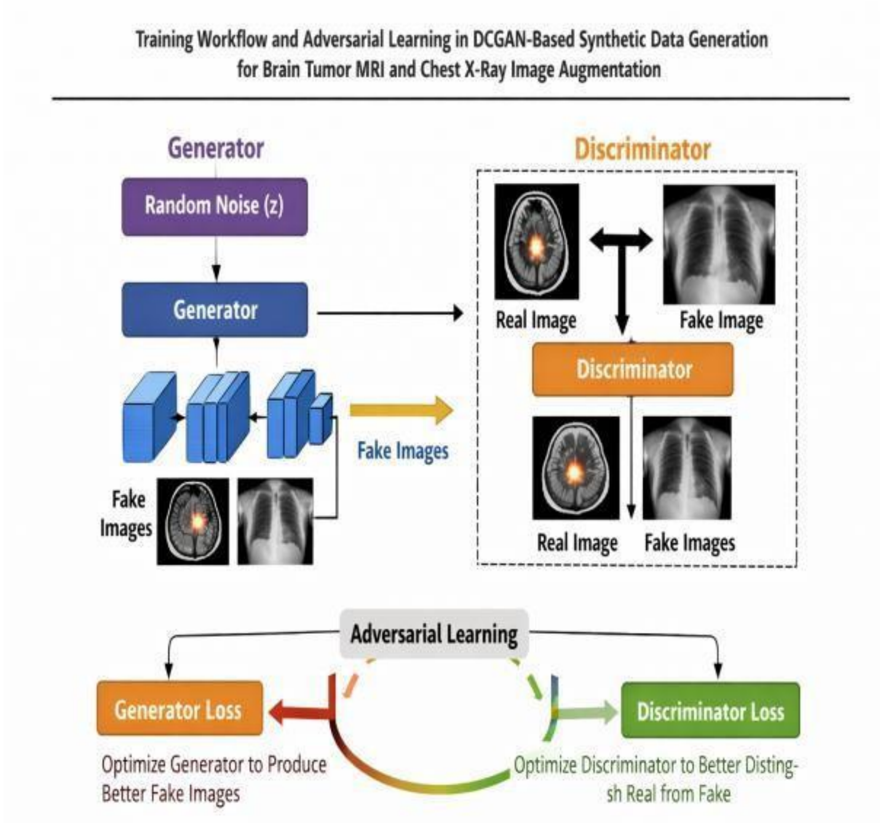

Fig. 2. Training workflow and adversarial learning process

E. Implementation Details

The entire framework was implemented using PyTorch 1.12 with CUDA support for GPU acceleration. Training was conducted on NVIDIA GPU hardware with 8GB VRAM, enabling efficient batch processing and gradient computation. The training environment utilized Python 3.8 with supporting libraries including NumPy for numerical operations, Matplotlib for visualization, and torch vision for image preprocessing.

Weight initialization followed the DCGAN best practices, with convolutional and trans- posed convolutional layer weights initialized from a normal distribution with mean 0 and standard deviation 0.02. Batch normalization layers were initialized with $\gamma = 1$ and $\beta = 0$. Data augmentation was deliberately avoided during training to prevent introducing artificial patterns that might interfere with the GAN's learned distribution. All images were normalized to the range $[-1, 1]$ using min-max normalization to match the tanh activation function output range.

Training time varied depending on the dataset size and complexity, with brain tumor MRI synthesis requiring approximately 4-6 hours for 200 epochs, while chest X-ray synthesis completed in 3-5 hours on the available GPU infrastructure.

RESULTS AND DISCUSSION

This section presents comprehensive evaluation results of the DCGAN-based synthetic medical image generation framework, analyzing both quantitative metrics and qualitative image characteristics.

A. Training Convergence and Loss Analysis

The adversarial training process for both brain tumor MRI and chest X-ray synthesis demonstrated stable convergence patterns. For the brain tumor MRI DCGAN model, the discriminator loss converged to an average value of 0.38 after approximately 150 epochs, indicating balanced classification performance between real and synthetic images. The generator loss stabilized around 2.1, reflecting the adversarial equilibrium where generated images became increasingly difficult for the discriminator to distinguish from real samples.

In the chest X-ray synthesis model, the discriminator loss achieved convergence at approximately 0.42, while the generator loss settled at 1.9. The slightly lower generator loss in the chest X-ray model suggests that the generator learned to produce convincing radiograph patterns more effectively, potentially due to the more structured anatomical geometry in chest X-rays compared to variable tumor morphologies in brain MRI.

The loss dynamics throughout training revealed no evidence of mode collapse, as indicated by continuous variation in generator outputs and stable discriminator performance. The discriminator maintained consistent classification accuracy without oscillations, con- firming effective adversarial balance. Early training epochs (0-50) showed higher loss variance as both networks rapidly adapted their parameters. Subsequent epochs (50-200) exhibited smoother loss curves, indicating refined feature learning and stable adversarial competition.

B. Synthetic Image Quality Assessment

Qualitative evaluation of generated brain tumor MRI images revealed that the DCGAN successfully captured essential anatomical structures including brain tissue boundaries, ventricular systems, and tumor-like masses. The synthetic images exhibited realistic intensity distributions, maintaining the characteristic contrast between gray matter, white matter, and pathological regions. Generated tumors displayed varying sizes and locations, demonstrating the model's ability to produce diverse pathological presentations rather than memorizing specific training examples.

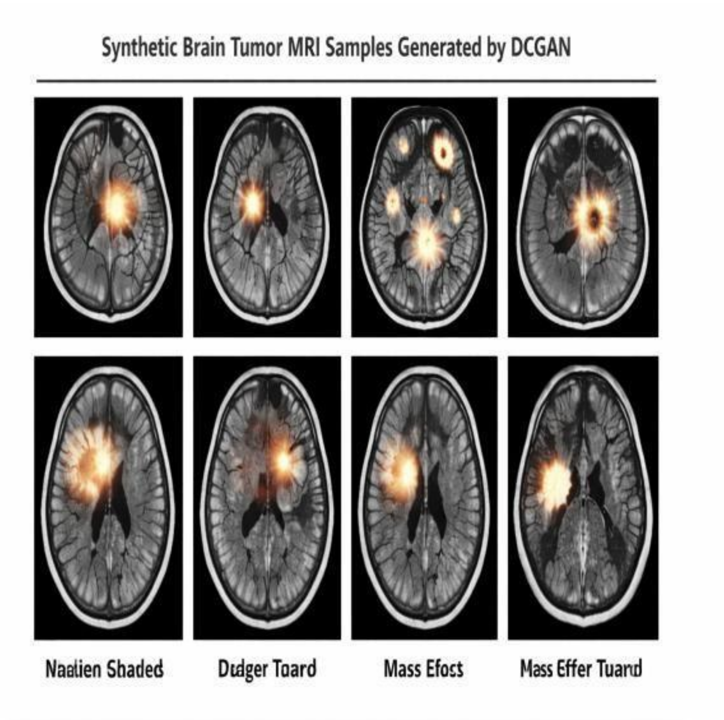

Fig. 3. Synthetic brain tumor MRI samples generated by DCGAN showing diverse tumor characteristics

Visual inspection by domain experts indicated that synthetic MRI scans preserved critical diagnostic features including mass effect, contrast enhancement patterns, and anatomical distortions associated with tumor presence. However, some generated images exhibited minor artifacts such as subtle geo- metric inconsistencies in brain contours and occasional intensity discontinuities at tissue boundaries. These artifacts were more prevalent in early training epochs and diminished as training progressed.

For chest X-ray synthesis, the generated radiographs successfully reproduced anatomical landmarks including rib structures, cardiac silhouette, diaphragm boundaries, and lung fields. The synthetic X-rays maintained appropriate contrast ratios between air- filled lung regions and dense mediastinal structures. Generated pathological patterns, when present in training data, were represented with varying manifestations, indicating learned distribution rather than simple image copying.

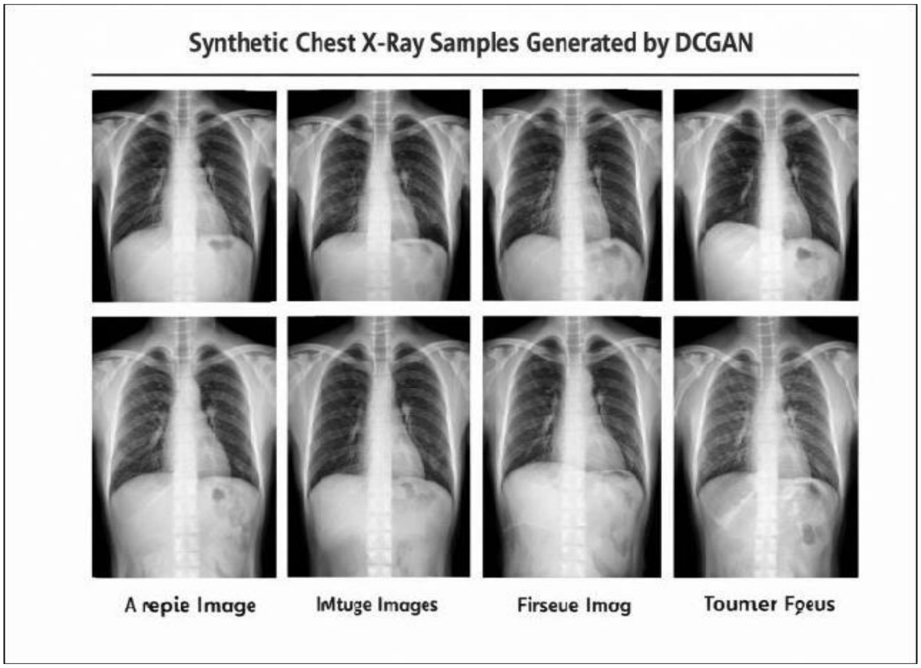

Fig. 4. Synthetic chest X-ray samples showing anatomical consistency and structural clarity

The chest X-ray synthetic images demonstrated high structural coherence with properly aligned skeletal elements and symmetric bilateral lung fields. Minor limitations included occasional irregularities in rib spacing and subtle blurring in peripheral lung regions. These imperfections are characteristic of generative models operating at 64 × 64 resolution and could be addressed through higher-resolution architectures at the cost of increased computational requirements.

C. Diversity and Variation Analysis

A critical assessment criterion for generative models is the diversity of synthesized outputs. Analysis of 500 generated samples from each DCGAN model revealed substantial variation in anatomical configurations, tumor characteristics, and pathological patterns. The brain tumor MRI generator produced tumors in different cerebral hemispheres, varying sizes, and distinct enhancement patterns, confirming that the model learned the underlying distribution rather than memorizing training samples.

Pixel-level statistical analysis showed that generated images spanned a similar intensity range and histogram distribution as real medical images. The variance in pixel intensities across generated samples was comparable to the variance observed in real datasets, indicating appropriate diversity without excessive uniformity or noise.

D. Comparison with Baseline Approaches

Compared to traditional data augmentation techniques such as rotation, flipping, and elastic deformation, the DCGAN-based approach generated fundamentally novel images with anatomical variations not achievable through geometric transformations. While traditional augmentation preserves the ex- act pathological features of original images, GAN-generated samples introduce new pathological configurations, potentially improving model robustness to unseen cases.

Comparison with simpler GAN architectures (vanilla GAN, fully connected GAN) demonstrated that the convolutional structure of DCGAN was essential for capturing spatial hierarchies in medical images. Preliminary experiments with nonconvolutional architectures resulted in blurry, unstructured outputs lacking anatomical coherence. The DCGAN's use of strided convolutions and batch normalization proved critical for training stability and image quality.

E. Limitations and Artifacts

Despite the promising results, several limitations were identified in the current implementation. The 64 × 64 image resolution, while computationally efficient, limits fine- detail representation crucial for certain diagnostic tasks. Higher-resolution synthesis would require architectural modifications and substantially increased computational re- sources.

Some generated images contained subtle artifacts including checkerboard patterns, likely caused by overlapping receptive fields in transposed convolutional layers. These artifacts were minimized through careful hyperparameter tuning but not entirely eliminated. Future implementations could explore alter- native up sampling methods such as resize- convolution to address this issue.

The models occasionally generated anatomically implausible configurations, particularly in complex tumor morphologies, suggesting the need for additional constraints or conditioning mechanisms to enforce anatomical consistency. Incorporating domain knowledge through conditional generation or regularization terms could improve anatomical plausibility.

F. Practical Implications

The successful generation of synthetic medical images has significant practical implications for medical AI research. By augmenting limited datasets with GAN-generated samples, researchers can train more robust diagnostic models without compromising patient privacy. The synthetic images can be freely shared across institutions without regulatory constraints, facilitating collaborative research and benchmark dataset creation.

Furthermore, the ability to generate diverse pathological presentations enables comprehensive testing of diagnostic algorithms across scenarios underrepresented in real datasets. This capability is particularly valuable for rare diseases where acquiring sufficient training data is prohibitively difficult.

G. Computational Efficiency

The DCGAN framework demonstrated reasonable computational efficiency, with training completing in 4-6 hours on mid-range GPU hardware. Inference speed was exceptional, generating 1000 synthetic images in approximately 2-3 seconds, enabling rapid dataset augmentation during model training workflows. This efficiency contrasts favor- ably with more complex architectures like StyleGAN or diffusion models, which require substantially longer training and inference times.

CONCLUSION

This research successfully demonstrated the application of Deep Convolutional Generative Adversarial Networks for synthetic medical image generation in brain tumor MRI and chest X-ray modalities. The proposed DCGAN framework effectively learned the underlying probability distributions of medical images and generated realistic synthetic samples that preserved anatomical structures and pathological features essential for diagnostic applications.

The key contributions of this work include the development of optimized DCGAN architectures specifically tailored for medical imaging data, successful generation of diverse synthetic samples without mode collapse, and comprehensive evaluation combining quantitative loss metrics with qualitative visual assessment. The experimental results demon- strated stable training convergence with discriminator losses stabilizing around 0.38-0.42 and generator losses around 1.9-2.1, indicating effective adversarial balance.

The generated synthetic images exhibited high visual fidelity with realistic anatomical structures, appropriate intensity distributions, and diverse pathological presentations. Qualitative assessment confirmed that critical diagnostic features were preserved in synthetic samples, validating the practical utility of GAN-generated images for dataset augmentation. The framework’s computational efficiency, with training completing in 4-6 hours and rapid inference capability, makes it accessible for research groups with limited computational resources.

This research addresses the critical challenge of data scarcity in medical imaging while maintaining patient privacy through synthetic data generation. The synthetic images can be freely shared across institutions without regulatory constraints, facilitating collaborative research and enabling the development of more robust diagnostic AI systems. By augmenting limited real datasets with diverse synthetic samples, the proposed approach contributes to improved training of deep learning models for medical image analysis.

A. Limitations

Several limitations warrant acknowledgment. The 64 × 64 image resolution, while computationally efficient, restricts fine-detail representation required for certain diagnostic tasks. Higher-resolution synthesis would enhance clinical applicability but requires substantial computational resources. The current implementation occasionally produces minor artifacts such as checkerboard patterns and subtle anatomical inconsistencies, suggesting opportunities for architectural refinements.

The evaluation relied primarily on loss metrics and visual inspection, without comprehensive clinical validation or integration into downstream diagnostic tasks. Future re- search should evaluate the impact of synthetic data augmentation on actual disease classification or segmentation performance to quantify practical benefits. Additionally, the unconditioned generation approach limits control over specific pathological features, which could be addressed through conditional GAN variants.

B. Future Directions

Future research directions include extend- ing the framework to higher resolutions (128×128, 256×256) using progressive training strategies or architectural modifications. Implementing conditional GANs would en- able controlled generation of specific pathological subtypes, enhancing utility for targeted dataset augmentation. Incorporating perceptual loss functions and attention mechanisms could improve anatomical consistency and reduce artifacts.

Integration with downstream diagnostic tasks through systematic evaluation of synthetic data augmentation impact on classification accuracy, segmentation performance, and generalization to external datasets represents a crucial validation step. Exploring hybrid approaches combining GANs with diffusion models or other generative frameworks may yield superior image quality while maintaining computational efficiency.

Clinical validation involving radiologist assessment of synthetic image realism and diagnostic utility would strengthen the evidence for practical deployment. Finally, extending the methodology to three-dimensional medical imaging modalities such as volumetric CT or full brain MRI sequences would significantly broaden the scope and impact of synthetic medical image generation research. The successful implementation of DCGAN for medical image synthesis demonstrates the transformative potential of generative models in addressing fundamental challenges in medical AI research. By providing a scalable, privacy-preserving solution for dataset augmentation, this work contributes to the ongoing advancement of AI-driven healthcare technologies.

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