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ENHANCING BRAIN MRI QUALITY: FROM NOISE REDUCTION TO IMAGE SYNTHESIS USING GENERATIVE ADVERSARIAL NETWORKS

Velivela Gopinath, Kamini Sri Harshitha Santoshi, Chandaluri Sai Pavan, Daggula Mahesh,
Kaja Syamala Sri Lakshmi Ramya
Department of Information Technology,
Sir C R Reddy College of Engineering, Eluru,

Abstract: **Convolutional Neural Networks (CNNs) excel in computer-assisted diagnosis, given sufficient annotated data. However, scarcity and fragmentation of medical imaging datasets limit model performance. Generative Adversarial Networks (GANs) address this challenge by creating realistic additional training images to complement existing datasets. Although previous studies explored noise-to-image or image-to-image GANs separately, the potential synergy of combining both approaches remains largely unexplored. Here, we propose a novel two-step GAN-based data augmentation (DA) method for enhancing brain MRI datasets, covering both tumor-inclusive and tumor-exclusive scenarios. Firstly, Progressive Growing of GANs (PGGANs) generates high-resolution MRI images with diverse characteristics. Subsequently, Multimodal UNsupervised Image-to-image Translation (MUNIT) further refines texture and shape of PGGAN-generated images, aligning the images closely with real MRI scans. Our approach significantly improves CNN-based diagnosis across various medical imaging tasks, demonstrating its effectiveness with limited and fragmented datasets.**

Keywords: **Generative Adversarial Networks (GANs), Data Augmentation, Synthetic Image Generation, PGGANs, MUNIT, Brain Magnetic Resonance Imaging**

I. INTRODUCTION

Medical imaging, particularly Magnetic Resonance Imaging (MRI), plays a pivotal role in diagnosing and monitoring various neurological conditions, including brain tumors. Deep learning techniques have shown remarkable success in automated tumor detection from MRI scans. However, their performance heavily relies on the availability of diverse and representative training data. Traditional data augmentation methods such as rotation and flipping are limited in capturing the complex variations present in MRI images.

To address this challenge, we propose a novel approach for brain MR image augmentation specifically tailored for tumor detection. Our method leverages the power of Generative Adversarial Networks (GANs), specifically combining Noise-to-Image (N2I) and Image-to-Image (I2I) architectures. This integration aims to generate synthetic images with enhanced diversity and realism, thereby enriching the training dataset and improving the generalization capability of tumor detection models. In this paper, we present the rationale behind our approach, discuss the underlying methodologies of N2I and I2I GANs, and outline our experimental setup and results. By augmenting the training data with realistic synthetic images, we aim to enhance the robustness and performance of tumor detection models, ultimately contributing to more accurate and reliable diagnoses in clinical practice. However, by merging noise-to-image and image-to-image GANs, research has achieved even greater performance improvement.

(i) Initially, low-to-high resolution noise-to-image GANs, such as Progressive Growing of GANs (PGGANs), generate a diverse set of realistic images, assisting in data augmentation (DA).

(ii) Subsequently, Multimodal UNsupervised Image-to-image Translation (MUNIT) refines the texture and shape of the images generated by PGGANs to better match the distribution of real images. MUNIT combines various GANs utilizing a GAN loss focused on DA. Instead of training a single complex GAN system from scratch, we employ a two-step approach, leveraging an ensemble generation process from multiple state-of-the-art GAN algorithms to enhance performance.

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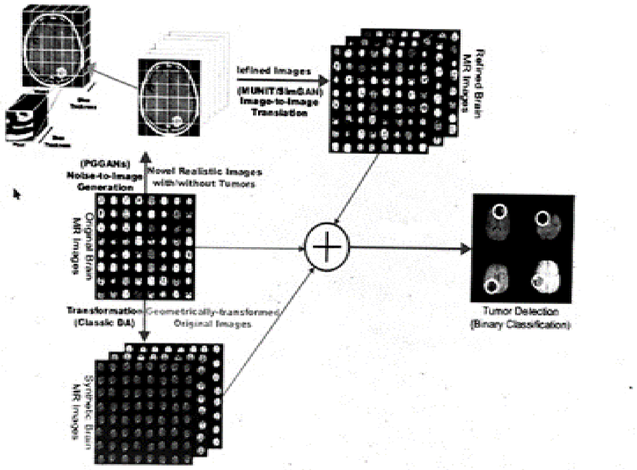

Figure1:Better tumor detection can be achieved by combining noise-to-image and image-to-image GANs: the PGGANs independently produce several realistic brain tumor/non-tumor MR images, the MUNIT independently refines them, and the binary classifier uses them as extra training data.

II. GENERATIVE ADVERSARIAL NETWORKS

The passage discusses the challenges and advancements in utilizing Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) for image generation and augmentation, particularly in the realm of medical imaging. VAEs often yield blurred samples due to their reliance on a single objective function for reconstruction. GANs have transformed image generation by employing a two-player objective function, where a generator aims to create realistic images to deceive a discriminator, thereby ensuring diversity in generated outputs. Despite their progress, GANs face hurdles like mode collapse, particularly when generating high-resolution images.

1. **Multi-Stage GANs**:

To overcome challenges, multi-stage GAN models like PGGANs have been introduced. PGGANs employ a progressive training approach, transitioning from low to high resolution, to generate realistic images.

2. **Image-to-Image GANs**:

These GAN variants are instrumental in producing images with specific textures or shapes. Notable examples include MUNIT.
MUNIT facilitates image translation using both GANs and VAEs.

III. LITERATURE SURVEY

The paper "Brain tumor segmentation with deep neural networks" by M. Havaei et al. (2017) utilizes deep neural networks (DNNs) for accurate segmentation of brain tumors from medical imaging data, as published in Medical Image Analysis. This research significantly advances the field of medical image analysis by demonstrating the effectiveness of DNNs in improving the accuracy of brain tumor segmentation, which holds promise for enhancing diagnosis and treatment planning in neurology and oncology.
The paper "USE-net" by Rundo et al. (2019) introduces a new neural network architecture for prostate zonal segmentation in MRI datasets. By incorporating squeeze-and-excitation blocks into the U-Net model, it improves accuracy in segmenting prostate zones. This research advances medical image analysis, particularly in prostate cancer diagnosis and treatment planning.
The paper "Deep learning applications in medical image analysis" by J. Ker et al., published in IEEE Access in 2018, surveys the use of deep learning techniques in the field of medical image analysis. It covers a wide range of applications, including image classification, segmentation, and disease detection, highlighting the significant impact of deep learning on improving accuracy and efficiency in medical imaging tasks. This comprehensive review contributes to the understanding and advancement of deep learning methodologies in medical research and healthcare practice.

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Table 1: Analysis of Literature review

S.No	Author Name	Algorithms used	Advantages	Disadvantages
1.	M. Havaei et al. (2017)	Deep Neural Networks	High accuracy	Overfitting, Model Complexity
2.	Rundo et al. (2019)	USE-net	Better Feature Representation	Deployment Challenges
3.	J. Ker et al. (2018)	Convolutional Neural Networks	Automated analysis, Feature Learning	Data Dependency
4.	I. Goodfellow et al. (2014)	Generative Adversarial Networks	Versatile Generative model, High Quality Image Generation	Sensitive to Hyper parameters
5.	X. Yi et al. (2019)	GAN, Generative model	Improved Diagnosis and Treatment	Data Quality and Quantity
6.	Ronneberge et al. (2015)	U-Net	Accurate Biomedical Image Segmentation, Fast Inference Speed	Limited Conceptual Information

The paper "U-Net" by Ronneberger et al. (2015) presents a convolutional neural network architecture designed for biomedical image segmentation, introduced at the MICCAI conference. The U-Net model utilizes a symmetric encoder-decoder structure with skip connections, enabling accurate segmentation by preserving spatial information. Widely adopted in medical imaging, U-Net has demonstrated superior performance in tasks such as cell detection and tumor segmentation.

The paper "Generative adversarial nets" by I. Goodfellow et al., presented at the Advances in Neural Information Processing Systems (NIPS) conference in 2014, introduces Generative Adversarial Networks (GANs). This seminal work proposes a framework where two neural networks, the generator and discriminator, engage in a game: the generator produces synthetic data samples to fool the discriminator, which learns to distinguish real from generated samples. GANs have since become a cornerstone in the field of generative modelling, with applications ranging from image generation to data augmentation and unsupervised learning

The paper "Generative adversarial network in medical imaging: A review" by X. Yi et al., published in Medical Image Analysis in December 2019, provides a comprehensive review of the application of Generative Adversarial Networks (GANs) in medical imaging. This review paper covers various aspects of GANs in medical imaging, including image generation, data augmentation, image-to-image translation, and domain adaptation. By summarizing the latest advancements and challenges in using GANs for medical image analysis, this review contributes to a deeper understanding of GAN-based techniques and their potential impact on improving diagnosis, treatment, and research in the medical field.

IV. PROPOSED SYSTEM

The proposed system aims to integrate Noise-to-Image and Image-to-Image Generative Adversarial Networks (GANs) for brain MRI image augmentation to enhance tumor detection accuracy. Initially, a comprehensive dataset of brain MRI scans, including tumor and non-tumor cases, will be collected and pre-processed for standardization.

Subsequently, two branches of GANs will be employed: one to generate synthetic MRI images from noise, and the other to augment real MRI images by introducing variations in tumor characteristics. These GANs will be jointly trained to optimize the synthesis and augmentation processes while preserving important features of the MRI scans. The augmented dataset will then be utilized to train tumor detection models, potentially leading to improved sensitivity and specificity in diagnosing brain tumors.

Overall, this proposed system seeks to leverage GAN-based image augmentation techniques to enhance the accuracy and reliability of tumor detection in clinical brain MRI analysis.

Key Elements of the Proposed Approach:

i. PGGANs based Image Generation: PGGANs can effectively generate realistic images, aligning well with common CNN architectures' input sizes.

ii. MUNIT Refinement: MUNIT enhances the texture and shape of PGGAN-generated images, bringing them closer to the real image distribution

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4.1 PGGANs

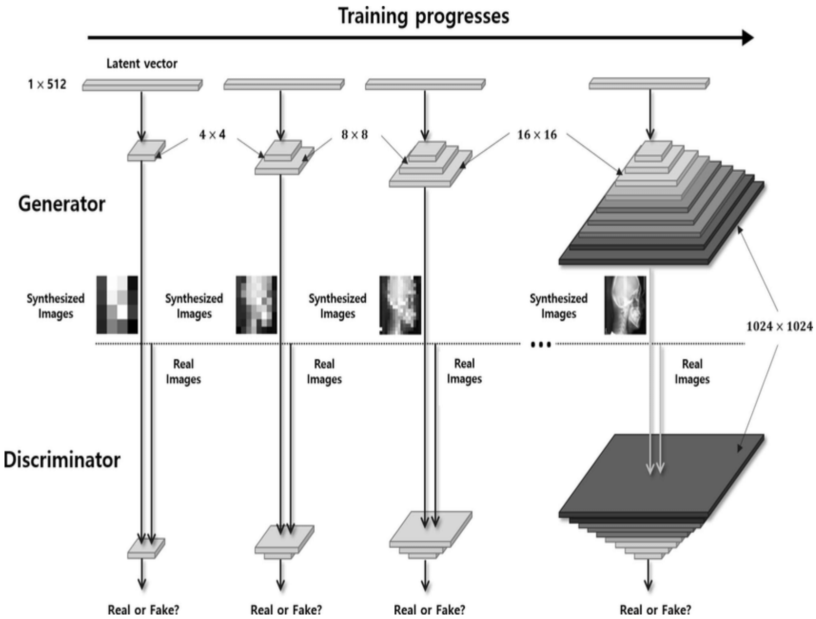
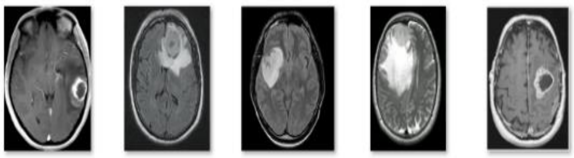


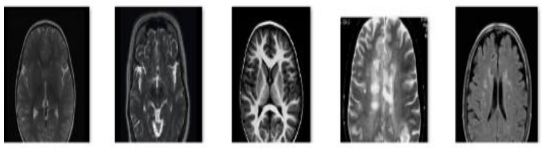
Figure2:Conceptual Architecture of PGGAN

It is a GAN training technique that gradually expands a generator and discriminator by adding new layers of model features as training goes on, starting with low resolution solutions.
The PGGAN is used in this work to synthesize realistic/diverse brain MR imagestumor/ non-tumor pictures are generated and trained independently.

4.2 MUNIT Refinement
MUNIT is an image-to-image GAN that extends UNIT by introducing a stochastic model to enhance the realism and diversity of PGGAN generated images. It combines autoencoding and translation capabilities and represents continuous output distributions, allowing for more varied and realistic results.



(with Tumor)



(without tumor)
Figure4: Example real MRI images for PGGAN Training

4.3 Data Collection and Preprocessing:
The system would start by collecting a large dataset of brain MRI images, including both tumor and non-tumor cases. These images would then undergo preprocessing steps to normalize intensity values, standardize orientations, and potentially segment the tumor regions for further analysis.

V. EXPERIMENTAL RESULTS

PGGANs contribute to improving the quality and realism of the pixel scans generated from brain MRI data by utilizing a deep learning framework. Specifically, PGGANs are trained on a large dataset of MRI scans to learn the underlying patterns and structures present in the images. Through progressive training, the PGGAN model gradually grows in

depth and resolution, allowing it to capture finer details and nuances in the MRI scans.
Once trained, the PGGAN model can generate synthetic pixel scans that closely resemble real MRI scans. These generated pixel scans exhibit high-fidelity textures, anatomical details, and spatial characteristics, making them suitable for various applications in medical imaging.

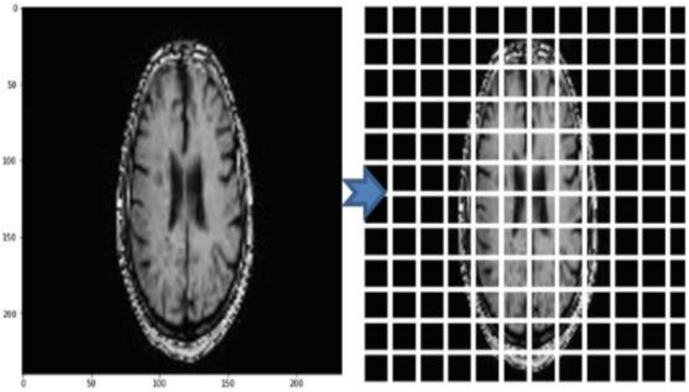


Figure5:PGGAN generated images in Pixels

By leveraging PGGANs, the process of converting brain MRI scans into pixel scans is enhanced in the following ways:

1. Improved Realism: PGGANs generate pixel scans with enhanced realism, capturing subtle variations and nuances present in real MRI scans. This realism is essential for accurate interpretation and analysis by medical professionals.
2. Texture Generation: PGGANs can generate synthetic textures and anatomical details that closely resemble those observed in real MRI scans. This capability enhances the visual quality and fidelity of the generated pixel scans.
3. Data Augmentation: PGGANs can be used to augment existing MRI datasets by generating additional synthetic scans.

These augmented datasets help improve the robustness and generalization performance of machine learning models trained on limited MRI data
Overall, MUNIT serves as a powerful refinement technique for PGGAN-generated pixel images, enhancing their realism, diversity, and adaptability to different imaging modalities or styles. By leveraging unsupervised multimodal translation, MUNIT contributes to the generation of high-quality and versatile MRI images, advancing the capabilities of medical imaging research and practice.

VI. CONCLUSION

The utilization of PGGANs and multi-stage noise-to-image GANs has shown promising results in generating realistic and diverse brain MRI images, both with and without tumors. These GAN-generated images exhibit characteristics that complement traditional data augmentation methods, particularly in capturing local tumor features with minimal overlap between tumor and non-tumor regions. By combining these GAN-generated images and refining them with MUNIT image-to-image GANs, we can significantly enhance tumor detection sensitivity and improve model generalization by replacing missing data points and addressing data imbalances.
Furthermore, the ensemble generation process from different GAN algorithms, coupled with the texture and shape refinement by MUNIT, contributes to better discrimination ability and fills the distribution gap in real tumor image data. While GAN-generated images may contain artifacts, discarding them without pre-training has been shown to enhance data augmentation performance.
Overall, the proposed two-step GAN-based data augmentation method has the potential to reduce the reliance on annotated images for medical imaging tasks. Beyond classification, this approach may also benefit object detection and segmentation tasks. Additionally, there are promising prospects for its application in various other medical domains.
In order to achieve this, we may build upon a preliminary study on a three-player GAN for classification [52] to generate only difficult-to-classify samples in order to improve classification. Additionally, we could (i) explicitly model deformation fields/intensity transformations and (ii) utilize unlabelled data during the generative process to effectively capture the real image distribution. Our ultimate goal is to design a new end-to-end GAN loss function that explicitly optimizes the classification results rather than maintaining diversity while optimizing visual realism.

Conflict of interest
All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or

materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

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