Enhancing Brain Tumor Diagnosis with Generative Adversarial Networks

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***Abstract*—Advancements in medical technology have brought a significant change in healthcare by enabling accurate diagnosis and personalized treatments. However, machine learning algorithms' achievement in medical image analysis depends on the amount and quality of available data. Data augmentation, which is a process to diversify the data set, has emerged as a crucial tool to address the medical image shortage. A new method has been presented in this paper to enhance brain tumor MRI images using Generative Adversarial Networks (GANs). It was trained using pre-processed images, where a generator creates images from random noise and a discriminator distinguishes real from generated images. The post-processing involved clamping and smoothing to ensure pixel values and visual quality. The quantitative evaluations of the method included a Structural Similarity Index (SSIM) for image similarity, and a high pixel accuracy of 86%, along with Intersection over Union (IoU) for segmented image quality assessment and we added the generated image to a pretrained model which had an accuracy of 62% and we improve it to 91% by adding some generated images.**

***Index Terms*—Generative Adversarial Networks, MRI, Brain tumor, data augmentation.**

I. Introduction

The integration of medical and artificial intelligence heralds a new era in diagnosis and treatment. Diagnostics has advanced with the introduction of advanced imaging techniques such as MRI,CT,and ultrasound. These technologies provide an unprecedented estranging of the human body, helping diagnose diseases, track treatment success, and guide surgical interventions [1]. On the other hand, the success of machine learning algorithms in medical image analysis depends on access to large, diverse, and well-annotated data. The convergence of healthcare and artificial intelligence has ushered in a new era of diagnosis and treatment. With the introduction of advanced imaging technologies such as MRI, CT, and ultrasound, diagnosis has advanced significantly [2]. These technologies provide unprecedented insight into the human body, assisting us in diagnosing diseases, monitoring treatment efficacy, and performing surgeries. The success of machine learning algorithms in medical image analysis, on the other hand, is dependent on access to large, diverse, and well annotated data sets [3].

It is commonly known that in order to successfully train a machine learning system for medical image interpretation, a significant volume of data must be available. Inadequate variability or a severe class imbalance in the data cause poor classification performance. Abnormal findings in the field of medical imaging are generally considered rare occurrences. Our work focuses on brain tumor diagnosis and is conducted at the intersection of medical imaging and artificial intelligence in healthcare. This area has experienced rapid expansion because of the potential to greatly enhance patient care and diagnostic accuracy [4]. In addition to increasing the accuracy of tumor detection in this field, the use of advanced machine learning technology facilitates early intervention, which is essential for improving treatment outcomes [5].

The previous researches on this field was primarily focused on using Convolutional Neural Network (CNN) for analysing medical images like MRI scans. These studies have been instrumental in establishing a robust foundation for the application of deep learning techniques in medical diagnostics. These CNN models have proved remarkably successfully in this field by identifying complex and subtle patterns which are characteristic of these tumor in medical images. Existing models have achieved significant milestones, including high accuracy rates in distinguishing between malignant and benign tumors. These models typically utilize neural network architectures and advanced feature extraction methods for analyzing MRI scans. Despite their success, they often face challenges like limited dataset diversity and potential overfitting [3]. A major drawback of current approaches is their reliance on extensive, well-annotated medical datasets, which are often not readily available [4].

To overcome this problem we propose a Generative Adversarial Network (GAN) model to create artificial images .This offers a novel approach to enhancing data and also functions as a useful technique for data anonymization. This provides a low-cost automatable supply of diverse information that may be added to the training set. One active field of generative model learning research is Generative Adversarial Networks, or GANs. Across a range of tasks, including image synthesis, image transformation, superresolution text to image, video captioning, picture dehazing, domain adaptability, and anomaly detection GAN has demonstrated impressive performance. Using the limited number of training samples, GAN seeks to discover the underlying data distribution. But it's common knowledge that gathering data may be very costly in many fields, like medical imaging. For this reason, data augmentation which has been effectively used for a variety of deep learning-based discriminative tasks might be taken into consideration for GAN training.

In our approach we have successfully generated 20,000 images from 200 MRI scans using GAN model. This method of data augmentation By generating these additional images, we significantly enhance the diversity and volume of data available for training, thereby improving the potential of machine learning models to accurately interpret medical images. This innovative approach demonstrates the potential of GANs in overcoming one of the major hurdles in medical image analysis, paving the way for more advanced diagnostic tools and treatment planning strategies.

II. Literature Survey

Generative adversarial networks for imputing missing data for big data clinical research"[1] investigates the use of Generative Adversarial Imputation Nets (GAIN) to deal with missing data in large clinical datasets. This paper [2] investigates the impact of the development of brain segmentation using MRI scan data. In order to diversify training datasets in convolutional nets, authors employ different boosting techniques like translation, rotation and Gaussian noise. This study [3] presents a new method combining brain tumour and tractography feature extraction from magnetic resonance imaging images to predict the overall survival of glioma patients. The article [4] includes a deep learning approach that can be applied to diagnosing brain diseases, even though it is mainly focused on the diagnosis of heart disease. To achieve full and robust segmentation of cardiovascular lesions in magnetic resonance imaging, the method set out below is based upon 3D spatial data as well as a new mechanism for propagation

The authors of the study [5] are looking at how Artificial Neural Network + ANs could be used to create a Synthetic MR image. By developing realistic, high-quality MRI scans that may be used to improve existing knowledge, this research is aimed at addressing the lack of medical knowledge. The paper suggests that, in future medical tasks, images produced by GANs may improve the functionality of neuronitis networks. A novel method [6] to generate brain tumor images from standard MRIs is introduced, which addresses the problem of insufficient data on patients for efficient Deep Neural Network training when it comes to image analysis. In this paper [7] they offered a novel approach-called TumorGAN that uses unpaired adversial to create picture segmentation pairs. In order to boost the discriminator's performance and increase the excellence of the image tha are generated, they included a localized perceptual loss. Lastly, they validated TumorGAN's effectiveness using the BraTS 2017 public brain tumor data collection. Paper [8] and data augmentation improved accuracy by 6% (p¡0.05). FLAIR sequence was effective in detection.

The paper (referenced as [9]) proposed an autonomous data augmentation method employing generative adversarial network architecture to generate images of higher quality , making it easier for DL systems to be trained more effectively with less amount of preprocessed data. Using a level set formulation and geodesic active contour, the tumor has been segmented. The suggested method has been verified using various modes of brain magnetic resonance imaging data from the BRATS2013 datasets. This article [10] highlights the importance of data development in overcoming the challenges of limited and inequitable health data. More importantly, data augmentation to develop detailed and robust models is well established and widely used in medical image analysis. The model defined in [11-12] hides the principle image from the regular content. The performance of the proposed technique is in comparison to the prevailing improvement approach by way of testing on two overlapping underwater snap shots. The version's overall performance is evaluated using metrics along with suggest square errors and optimization of the ADAM optimizer. The have a look at by means of Tsehay Admassu Assegie et al [13]., published inside the IAES global magazine of synthetic Intelligence in 2022, delves deeper into this issue.

Improving the general capabilities of deep neural networks is crucial, especially in situations where good location information is scarce. that is specifically [14] the authors reviewed submissions to the Multi-modal brain Tumor Segmentation undertaking (BraTS 2018), a yardstick for brain tumor analysis and segmentation technology. .A study (referenced as [15]) conducted a classification of individuals based on one of the 16 Myers-Briggs personality traits. The effectiveness of this approach can be improved by using data augmentation techniques. Research studies with automatic machine learning (Auto-ML) [16], which uses genetic algorithms to optimize the model, can be compared to the concept of data augmentation in the analysis of brain tumour information.

III. METHODOLOGY

In our study, we propose a novel approach for enhancing the diagnosis of brain tumors using Generative Adversarial Networks (GANs), leveraging a rich dataset of brain MRI images. The methodology encompasses several key phases, each designed to optimize the effectiveness of the GAN in generating high-quality, diverse medical images for improved diagnostic capabilities.

A. Dataset

We used the dataset, "Brain MRI Images for Brain Tumor Detection," available on Kaggle, is a significant compilation of brain MRI images used for the detection of brain tumors. This dataset, comprises MRI scans with a specific focus on brain tumor presence [22]. It includes images labeled as 'yes' for scans indicating tumors and 'no' for normal scans, providing a binary classification framework essential for training and evaluating machine learning models, particularly in the field of medical image analysis.

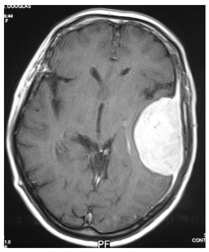

Fig. 1. Tumorous Brain MRI Image

The shows 'yes' category contains images of patients diagnosed with a brain tumor, while the 'no' category comprises scans of patients without tumors. The Fig 1 is a sample image of tumorous brain where the white part represents the tumor and the Fig 2 is the sample image of non tumorous brain. This dichotomy facilitates the development and testing of algorithms aimed at tumor detection, making the dataset a valuable resource for researchers and practitioners in medical imaging and machine learning.

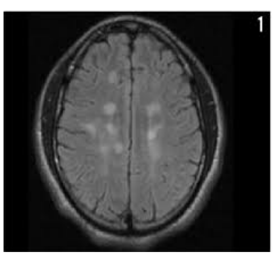

Fig. 2. Non Tumorous Brain MRI Image

B. Pre-Processing

Data Acquistion and Pre-Processing during the initial stage of the project, we obtained images from a local directory. To ensure that the images were consistent in format and scale, we implemented a Pre-Processing pipeline. This pipeline protected resizing every photograph to a widespread size of 64x64 pixels, converting the images to grayscale, and normalizing them with pixel values among zero and 1. This pipeline was crucial for effective training of neural networks. To get a much deeper understanding of the dataset and validate the Pre-Processing steps, we visually analyzed a subset of the Pre-Processed images using a 4x8 grid.

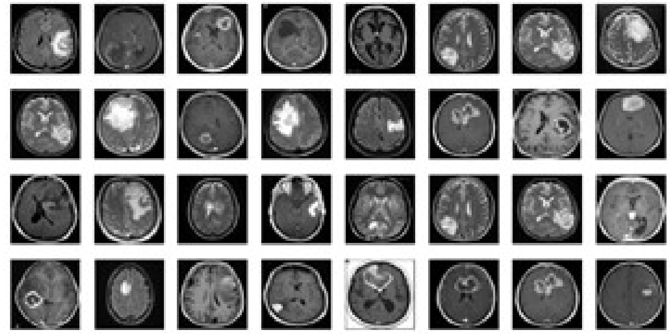

Fig. 3. Pre-Processed Image

C. GAN Model Architecture

The GAN model forms the core of this methodology, comprising of two components: the Generator and the Discriminator. The Generator is trained to convert a random noise vector from the latent space into a plausible 2D image that mimics the distribution of the real images in the dataset.The Fig.4 shows the overall architecture of our model

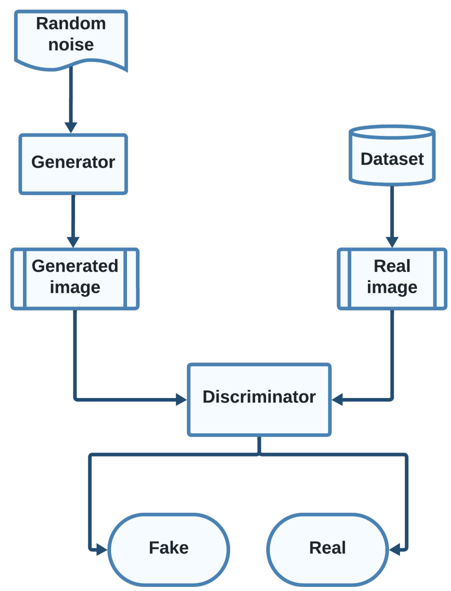

Fig. 4. GAN Architecture

This process is iterative and relies on back-propagation and gradient descent methods to refine the generated images. Linear layers are used in the Generator, with the tanh activation function, to produce image outputs within the [-1, 1] range. Meanwhile, the Discriminator features linear layers that end with a sigmoid activation function, providing a probability estimate of the input image's authenticity.

D. Training Loop

The model is trained multiple times during the training process. These training sessions are called epochs and they have a predetermined number of iterations. In each epoch, the

Generator creates images using random noise. These images are then evaluated by the Discriminator, which provides feedback and calculates a loss for the Generator. At the same time, the Discriminator evaluates both real and generated images (as shown in Figure 1) and calculates its own loss. Optimization with ADAM Adam optimizer is used to change the generator and discrimination during this process. The optimizer calculates the slope of the loss with the model parameters (generator or splitter) and then adjusts the parameters using the following steps:

- Calculate the gradient of the loss based on the sample parameters:

$$d_t a = \nabla L_{\text{Generator}}(\theta) \tag{1}$$

- Update the first time estimate m_t and second time estimate v_t of each parameter using Adam's best model.

$$m_t = \beta_1 \cdot m_{(t-1)} + (1 - \beta_1) \cdot \Delta \text{VL\_Generator}(\theta) \tag{2}$$

$$v_t = \beta_2 \cdot v_{(t-1)} + (1 - \beta_2) \cdot (\Delta \text{VL\_Generator}(\theta))^2 \tag{3}$$

m_t denotes the first moment estimate and v_t denotes the second moment estimate.

$$\hat{m}_t = \frac{m_t}{(1 - \beta_1^t)} \tag{4}$$

$$\hat{v}_t = \frac{v_t}{(1 - \beta_2^t)} \tag{5}$$

- Correct the difference between the first and second estimates by calculating m_hat_t and v_hat_t.

$$\theta = \frac{\theta - \alpha \cdot \hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{6}$$

- Use the corrected first and second time estimates to adjust the parameters of the model.

The formulas used in the Adam optimization tool are different. The symbol θ represents the sample parameter, α is the learning rate, β_1 and β_2 are the exponential decay rates for the moment estimates, and ε is a small scalar used to prevent division by zero. It is a powerful tool for training generators and discriminators in GANs. It uses past gradients to adjust the learning rate of each parameter, which helps improve the training process.

E. Post Processing

While generating images, it's common to encounter noise or artifacts. To address this, we take each generated image and clamp it within the range of [0, 1]. This helps reduce pixel-wise artifacts and creates a smoother appearance. To further enhance the quality of the images, we apply a Gaussian kernel for smoothing. This process ensures that the generated images are visually appealing and of high quality. Once generated and smoothed, the images are stored in a designated directory. Each image is given a unique name depending on the epoch of generation. We also integrated a transformation pipeline to resize the images to 256x256 pixels, ensuring compatibility with other applications or studies that require higher resolution.

IV. RESULTS AND DISCUSSIONS

The training process uses GAN model to create artificial images. To do so, we first loaded and resized the images to the desired dimensions. Afterward, we converted them into greyscale and normalized them. Additionally, to ensure that the pixel values were within the acceptable range, we clamped the images during their creation.

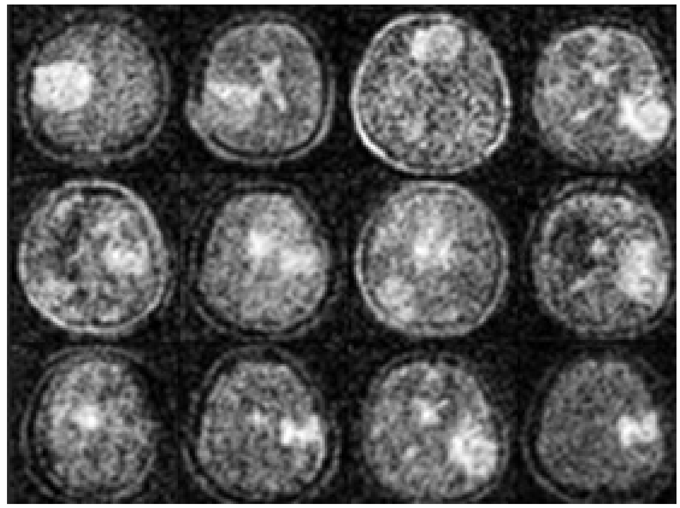

Fig. 5. Generated Images using GAN

The images in Fig 5 are the generated using GAN this image is then used as input for ESRGAN which improves the resolution the image which is showed in Fig 6.

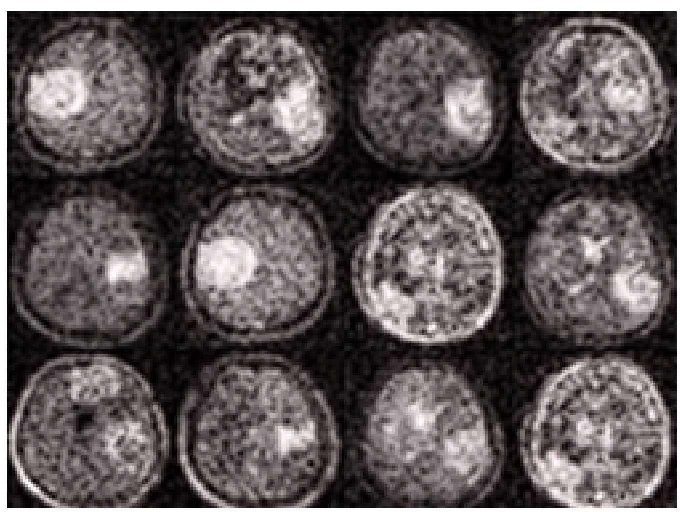

Fig. 6. Enhanced Images using ESRGAN

The metric used to evaluate the similarity is the Structural Similarity Index (SSIM). The SSIM fee degrees between 0 and

1, with 1 indicating identical photographs and a rating close to 0 indicating big differences. The highest similarity index which we got was 0.86 and the average index with noise is 0.74.The Fig 7 shows a result of SSIM score of few images which where generated.

Real Image	Generated Image	SSIM Score
79.jpg	100400_8042.png	0.8674527
Y54.jpg	105200_8416.png	0.8343
y323.jpg	107600_8610.png	0.8250097
44.jpg	10000_804.png	0.80703839
Y182.JPG	10400_863.png	0.74691837

Fig. 7. SSIM score of generated image to real image

Then we added our image to a CNN model trained on 50 images of both tumorous and non tumorous which had an accuracy of 62% showed in Fig.8

	precision	recall	f1-score	support
no	0	0	0	19
yes	0.62	1	0.77	31
accuracy			0.62	50
macro avg	0.31	0.5	0.38	50
weighted avg	0.38	0.62	0.47	50

Fig. 8. Accuracy before adding generated image

We added 200 images of both tumorous and non tumorous images and trained the same model and improved the accuracy to 91% as showed in Fig.9.

	precision	recall	f1-score	support
no	0.2	0.05	0.08	219
yes	0.93	0.98	0.95	235
accuracy			0.91	454
macro avg	0.56	0.52	0.52	454
weighted avg	0.87	0.91	0.89	454

Fig. 9. Accuracy after adding generated image

V. Conclusion and Future work

Accurately analyzing medical information using deep learning methods can be a challenge with limited available medical images. Classifiers that rely heavily on large datasets may struggle when classifying or segmenting data from smaller datasets. In such cases, generating synthetic images that are compatible with the original medical images can be incredibly useful. This approach highlights the potential of creating synthetic medical images and suggests that it could offer numerous opportunities in the field of medical imaging. Moreover, these methods can help lower expenses related to preparing the original medical data. We plan to apply our model in different clinical imaging domains with constrained sample images.

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