Generating High-Fidelity Brain Tumor Images with Deep Convolutional GANs: A Study on Image Quality and Diversity

Roshan Naidu[1] ,Om Subrato Dey[2] ,Saurav Mishra[3] , and Dr. Leki Chom Thungon[4]
School of computer science and engineering
Vellore Institute of Technology, Chennai campus,
Chennai, India

Abstract:

Medical imaging data sets like brain tumors are usually small. Fewer available datasets hinder the learning of optimal models in machine learning. This advantages the Deep Convolutional Generative Adversarial Networks (DC-GANs) usage for synthetic data augmentation, with a view of producing more realistic brain tumor images. The paper contributes to the problem of synthesizing high-quality brain tumor images for medical examination by DC-GANs. The proposed mechanism uses the DC-GAN algorithm with the generator generating synthetic images from noise inputs and discriminator to distinguish between the real and generated data. The dataset will consist of grayscale images of brain tumors. We optimized it with preferred hyperparameters of noise dimension, batch size, and steps per epoch while the best generator loss was 2. 4969 and the discriminator loss was 0. 0436.

The generated images were tested for visually assessing the performance and it was measured through the Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Infidelity Score. The proposed mechanism gives a Generator Loss of 3. 4853, and a Discriminator Loss of 0. 0883 after 10 epochs. The generated images are very close to the real images with an SSIM score of 0. 2427 and an average PSNR of 60. 66, confirming high fidelity. The proposed work shows the efficiency of the proposed DC-GANs in generating synthetic brain tumor images for data augmentation in medical image analysis

Keywords: artificial intelligence, neural networks, computer vision, deep learning, generative adversarial networks.

Introduction:

Availability of medical data and the development of artificial intelligence have stimulated computer vision and its application in health care. One of the most significant healthcare problems is the proper identification, categorisation, and division of brain tumors from medical imaging such as MRI scans. The task of annotating these images with the help of radiologists is a very tedious process and is associated with inter-observer variability. Thus, the methods of the tumor identification, segmentation, and analysis that are automated and can be easily scaled are critical. DCGANs have found great importance as a generative model in producing high diverse and realistic images with good quality, which are beneficial in enhancing datasets and, by extension, the performance of machine learning models.

The need for richer and high-fidelity synthetic data in medical imaging applications has arisen because of the problems that come with data acquisition and annotation of large datasets of real medical images. In particular, brain tumor images have the problem of limited datasets available for public use because of privacy and obtaining high-quality annotations. The challenges outlined above shall be solved with this study's intention of using DCGANs to generate synthetic brain tumor images. Thus, the first approach is aimed at enhancing the quality of the image and the variety of the generated samples for the purpose of expanding training sets for a variety of MIP tasks.

GANs have been introduced [1] in the year 2014 without which the generative modeling has seen a drastic change. Figure 1. can be derived from [1] for information about model and their distributions. GANs comprise of two neural networks known as generator and discriminator where the two networks play a game known as minimax. The generator then produces fake samples and the discriminator's job is to try and discern between the real and fake samples. In such a way, the generator learns to create the data that is as good as the actual samples being generated.

DCGANs, a variation of GANs focuses on incorporating convolutional layers for both generator and discriminator modules hence enabling the model to capture on image spatial features hierarchies. Subsequently, [2] proposed a new GAN model known as DCGANs that appeared superior in generating realistic images in different domains. In the same context of medical imaging, DCGANs have been used to generate synthetic images of internal organs including liver, lung and brain useful in counteracting the effects of data scarcity in medical image analysis [3].

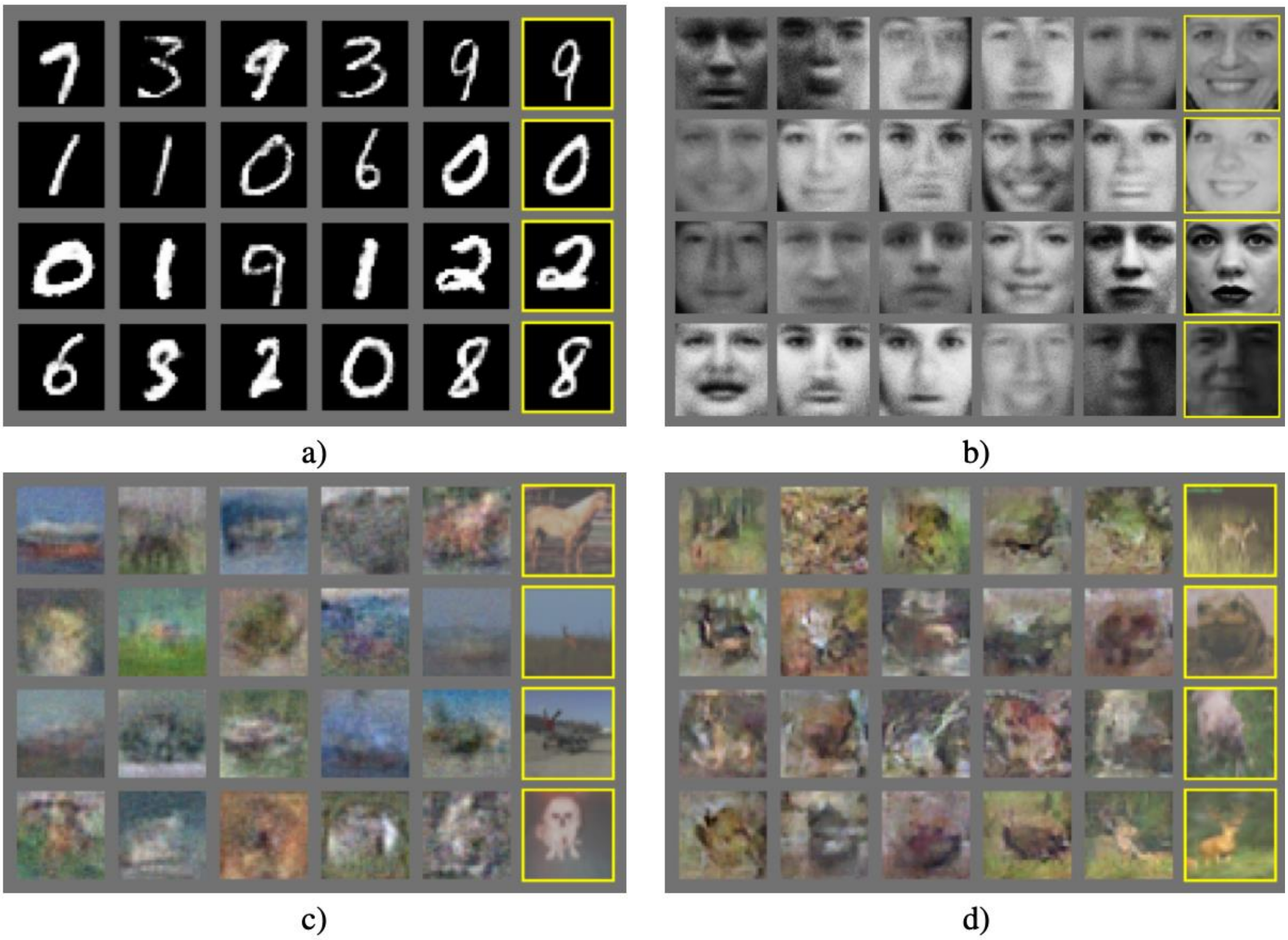


Fig. 1 - Models with their images showing actual samples from the model distributions.
a) MNIST, b) TFD, c) CIFAR-10, d) CIFAR-10

Brain tumors have been reported to be a leading cause of mortality and morbidity in the world today and hence identifying the tumors in the initial stages and with a high level of accuracy is of uttermost importance. MRI or magnetic resonance imaging is the most common technique used in diagnosis of and follow up of brain tumors. However, the development of automated diagnostic tools using deep learning strikes a large number of restrictive labeled datasets, primarily when it comes to the rare types of tumor. The employment of synthetic data can help to overcome the above-stated issue. Another complex issue arises from a peculiar pattern of brain tumor's morphology which significantly varies. The tumors can have very different shapes, sizes and even the intensity patterns and therefore, a couple of images are not enough to train the model. This project intends to solve these challenges by creating diverse and high-quality brain tumor images using DCGANs hence improving on the variability of the dataset for the machine learning algorithms. Thus, together with deep learning models, which work with sets of images that augment challenging datasets with high-quality synthetic images, the classification, segmentation, and detection of tumors can be improved.

By optimizing the architecture and training of the DCGAN model, the synthesized images of brain tumor mimic the ground-truth MRI scans with similarities in tissue texture and resolution, geometric patterns, and other visible attributes. Diversity of Generated Images: The proposed approach contributes to the increase of the variability of the generated tumor images, which is an issue in the context of real datasets where the set of tumor types is limited, and their morphological variations are not as diverse as in the case of synthetic images. This increased diversity allows downstream models trained on the augmented datasets to generalize better. Qualitative and quantitative assessment methods are used in the performance evaluation of the model. The quality of generated images is quantified, for example, with Fréchet Inception Distance (FID) [4] that measures the divergence between the distributions of generated and real images. To measure variability, morphological features of generated tumor images are studied to ensure the model creates images of different types of tumors. The works of various researchers have research on medical image synthesis using GANs. For instance, [5] showed how GANs can be used to produce realistic images of lung nodules for cancer diagnosis. Likewise, in [6] successful synthesis of brain MRI images for glioma classification using GANs was demonstrated with improved model generalization performances. And in the case of the brain and tumor imaging, the creation of complex and realistic images has remained difficult over the years. Old techniques have restrictions in providing detailed information specific for medical image synthesis. However, with improvements in DCGAN architectures and training methods, it is now possible to use DCGANs for automatic generation of highly detailed and diversified images of brain tumors. This work improves on these advances by integrating state-of-the-art methodologies for GAN stabilization and image synthesis, customized to the characteristics of brain tumor data.

Literature Review:

The deep learning models in medical imaging has been raising exponentially in the recent years especially in brain tumor detection, classification, and segmentation. This is one of the factors that make quite an effort to build reliable deep learning models in this area due to a greater demand for extensive, diverse, and high-quality datasets. Thus, in order to address this challenge, researchers have shifted toward using the Generative Adversarial Networks (GANs) for synthetic data augmentation.

Generative Adversarial Networks have been employed in a range of different medical fields to produce synthetic data. [7] used GANs for the generation of chest X-rays for enhancing datasets which were used in the detection of pneumonia models. The outcome of this study identified that the integration of synthetic data with actual data yielded enhanced performance of different models. Likewise, [3] employed GAN for synthesizing the new liver lesion images and improved the classification of CNN-based model in diagnosing the liver tumors.

There has been interest in synthesing brain tumor using GANs are various works have been centered on generating realistic MRI images to improve on deep learning. For instance, [8] put forward the GAN architecture to synthesize the brain MRI images for the glioma classification, and the model obtained higher classification accuracy when incorporating the synthetic MRI images into the model training. Another study done in [9] improved this method by employing conditional GAN (cGAN) to generate images with certain tumor types and enhanced both quality and controllability of the synthesized data.

For Medical Imaging, several types of GANs have been introduced in the literature to enhance image quality, stability, as well as the image's spatial and temporal variability in the generation of medical image data. A WGAN as adapted by [10] for fine tuning the training process and a more realistic generation of synthetic medical image for the detection of cancers. Their work also established that WGANs were less sensitive to mode collapse, which is a problem in standard GANs, and gave out the generation of a greater range of images. [11] extended this further by exploring the use of the CycleGANs for synthesising MRI images into CT scans thus having remarkable viability in cross-modality synthesis. Conditional version of GAN, namely Pix2Pix GAN, has also been used for medical image synthesis. [12] has shown that it is useful in producing paired medical images such as the CT to MRI translation. This approach has been especially helpful where it is possible to have two sets of data where one set is used by the generator to generate very realistic synthetic images.

Recent models like Deep Convolutional GANs (DCGANs) has been reported to have great performance while generating high-resolution images, a key factor when it comes to medical images. In their study, [13] used DCGANs to synthesize new training samples of brain tumor images and found enhancing the models 'segmentation effectiveness. In their study, they showed that DCGANs can learn the details that are described in MRI scans including the texture of the tumors and their shape.

[14] incorporated DCGANs to a 3D synthesis of MRI images for creating volumetric images of brains with tumor. This work demonstrated the utility of incorporating spatial relations between the tumor locations through accurate registration of 3D models that in turn enhanced the performance of the models in 3D tumorsegmentation. The utilization of 3D DCGANs has therefore increased with the realisation that more complex tumor morphologies can be modelled in brain imaging.

Which specific quality and how diverse should GAN-generated images be is important to guarantee the synthetic data's applicability for downstream tasks like segmentation. In [15], the FID was discussed for the assessment of GANs, and this is the Fréchet distance between the real and the synthetic image distribution. They have been particularly incorporated in the assessment of medical GANs, such as that which was done in the study [16] where FID was used to measure the quality of synthetic brain tumor images.

It is also applicable in terms of diversity in images for images with similar variability are just as important, as for example in case of medical applications the variability of tumors must be high in order to improve the generalization of the model. [17] suggested that enhanced variability of images can be achieved while at the same time increasing image realism using StyleGAN. They also showed that it can be used in creating images of phantom brains containing tumors of various shapes, sizes, and positions. This provides neural networks utilized in tumor detection with a more varied training set.

GANs have been applied mainly to generate some additional data because a number of labeled medical images is insufficient. [18] used image-to-image translation GAN for synthesising additional samples in the BRATS dataset. This is how their model created synthetic MRI images, that is how it translated from one domain to another (from a healthy brain to a tumor affected brain, for example), thus expanding the training set in size and diversity. This approach was later enhanced by[19] to use GANs to generate synthetic brains tumor using the tumor masks input where more control can be exercised over the generated images.

Another important augmentation technique is the joint use of AAEs in conjunction with GANs. The next feature to describe is creative legion that comprises of several augmentation techniques. [20] utilized AAEs for extracting low dimensional embeddings on the Brain MRI Images and Reconstructing the new Images with the help of GAN based Decoder. This optimistic result from combining the two approaches demonstrated the hybrid model's capability of producing high fidelиту brain images with tunable tumor characteristics to enhance the classification model.

Synthetic image generation is one of the trending research in medical imaging, specifically multi-modal image synthesis. Thus, using GANs to translate from one imaging modality to another (for example from MRI to CT), the system is able to produce multiple sets of images that encompass different information from both types of scans. [21] worked on the method to translate between PET and MRI images for enhancing the models trained for the detection of tumor. [22] proposed a multi-modal GAN for synthesizing CT and MRI images of the brain for tumor detection as well as to segment the tumor area.

Cross domain image synthesis is also another area of application of GANs in which synthetic images are created in one context and utilized in another. A CD-GAN was introduced in [23] that aims at synthesizing brain images and these images were utilized to train models for segmentation in another domain. This approach revealed the ability of GANs in transferring the learnt knowledge from one modality to the other as well as show enhanced performance particularly where data is limited. One of the main challenges is related to the training of GAN which are known to be instable and with a problem of mode collapse. For instance, stable training was enhanced by [24] by developing techniques like feature matching and mini batch discrimination that is used in several medical image synthesis projects [25, 26].

Another challenge is the performance of the synthetic images This is the last of the challenges that has been pioneered in the course of this study. These include FID and Inception Score, which have become a standard while, however, not demonstrating matches with clinical usefulness of the images. [27] underlined the necessity of carrying out the evaluation task-oriented, for example, to evaluate the effectiveness of the trained models after using synthetic images for downstream classification or segmentation tasks.

One for sure is the use of GANs in conjunction with other, deeper-learning-based models like variational autoencoders in order to produce even more high-quality coming up with even more diverse images. In conjunction with that, furthering the utilization of semi-supervised GANs as suggested in [28] can enable reducing dependency on immense amounts of labelled data-an issue critical in medical image analysis.

The visualizations in [29] has shown quite recent findings in applying GANs in medical imaging especially for classification of Brain tumor and using ResNet as generator and DenseNet as discriminator has produced excellent results in terms of data augmentation as well as in generation of highly detailed synthetic images.

The study in [30] shows the potential capability of how well GANs can work with the CNNs in medical image analysis, advocating for further exploration of multi-modality datasets and Explainable AI techniques.

Technological developments in medical imaging, use of advanced radiological imaging techniques and in artificial intelligence has paved way for better diagnosis as well as treatment of space occupying lesion of the brain. The development and implementation of Generative Adversarial Networks (GANs) solves some major issues in the medical imaging context including data limitation and data sensitivity. As has been shown in multiple works in [31], GANs provide high image quality that makes it possible to incorporate synthetic images into actual medical databases in order to improve the effectiveness of forecast models.

The ideas presented in [32] show a novel idea of integrating wavelet transforms with GANs or Generative Adversarial Networks. In particular, optimizing discriminator by using wavelet analysis directs GAN to generate the resolution of MRI better and reduces the noise and thus enhancing the quality of the images. This method solves a key problem associated with medical imaging, that of noise present in MRI data, and provides a method for improving resolution with minimal loss of image clarity that will be suitable for use in many medical image analysis applications.

Methodology:

The MRI images of brain were collected from the Brain Tumor Detection dataset from Kaggle. The images used in this study were firstly preprocessed through convert to grayscale and resize images to 128 x 128 pixel. The Kaggle dataset included images labeled as positive to brain tumors. Using load_images() function, the images mentioned in the model were loaded into the system. This function applied a function of grayscale conversion, resizing and the images were loaded into numpy arrays where these images were normalized between the range of [-1,1]. For training we choose only 20 images randomly out of database and rescaled all images to fit the input dimensions of the model.

The architecture of the model had been segmented in various segments. The first is the Generator. The generator was also introduced to increase noise input from a 100-dimensional latent space to 128 x 128 pixel images. It has the use of Dense layer along with LeakyReLU activations, Conv2DTranspose layers for up-sampling the features and the final Conv2D layer with tanh activation for producing grayscale images. The generator was built with binary cross-entropy loss, and the Adam optimizer at a rate of 0 and the beta value of 0.5.

Second comes the Discriminator. The discriminator was designed to classify the real and fake images via multiple Conv2D layers with leaky ReLU activation, and strides for reduction in dimensionality.
They flattened the feature maps by using a Flatten layer after which they normalized using a Dropout layer to avoid overfitting. The output produced consisted of a single neuron with sig unwind activation function used for binary classification. The discriminator was also trained using the binary cross entropy loss and adam optimizer just as in the case of the generator.

The third is the GAN Model. It merges the generator and discriminator together with the help of which the discriminator is made non-trainable during the GAN training. The model was trained using binary cross entropy and generator was trained to deceive the discriminator into perceiving the images as real.

The training process for GAN involved training for 10 epochs, but each epoch was made of 1000 iterations or steps. In each step, random noise vectors of Gaussian distribution were utilized to create fake images which were used along with real images from the training dataset. Discriminator learned batches of real and fake images while generator learned how to generate images that latter classifies as real by discriminator. during training the loss values of both the generator and discriminator functions were recorded for analysis.

The proposed GAN model had been evaluated using the metrics such as Structural Similarity Index (SSIM) which is for the evaluation of the perceptual similarity, there was use of SSIM whereby real images were compared with the generated images. The above mentioned SSIM values were averaged over a batch of images. Peak Signal-to-Noise Ratio (PSNR) was calculated to assess the quality of generated images compared to the original images PSNR was measured. It is worth noting that larger numbers of PSNR mean better quality.
The SSIM score for the generated images was 0 for both sets of generated images.

Some of the hyperparameters include NOISE_DIM, BATCH_SIZE and STEPS_PER_EPOCH and adjustments were made to arrive at their best values. They were tuned by performing a grid search on these parameters and on the best parameter configuration the generator loss was 2. of 4969 when with noise dimension of 100, batch size of 4 and 1000 steps per epoch.

For the visualisation, as in the case of the discriminator, the losses were plotted epoch-wise to capture the training progression. As for the generator, the same was done to capture the training progression, as for in the same way, the real and generated images were also analyzed and compared using Seaborn distplot to check the variations in the set.

Results and Simulation:

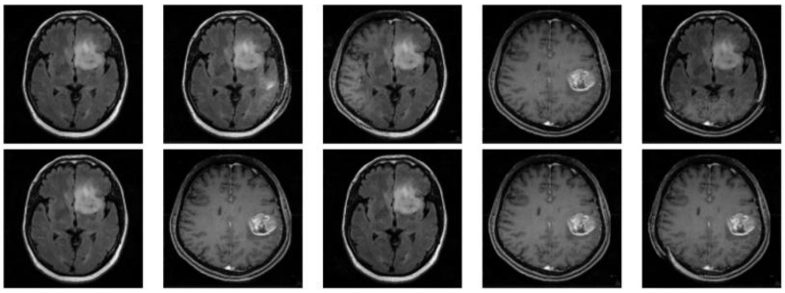
The model was trained for 10 epochs with a generator input noise dimension of 100 and a batch size of 4. The generator and discriminator losses were tracked to evaluate training progress and ensure stability. Over 10 epochs, the following trends were observed:

Epoch 1: The generator loss began at 6.6827, and the discriminator loss was low at 0.0436, indicating that the discriminator was highly effective at identifying real from fake images. It can be seen in figure 2.

```
EPOCH: 1 Generator Loss: 6.6827 Discriminator Loss: 0.0436
Best Hyperparameters: {'NOISE_DIM': 100, 'BATCH_SIZE': 4,
'STEPS_PER_EPOCH': 1000} with Best Loss: 2.4969
```

Fig. 2 - Generator vs Discriminator Loss at Epoch 1

Epoch 10: By the final epoch, the generator loss had decreased to 3.4853, and the discriminator loss reached 0.0883, signifying a balanced training where both networks had learned well from each other which can be seen in figure 3.



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100%|██████████| 3750/3750 [05:27<00:00, 11.44it/s]
EPOCH: 10 Generator Loss: 3.4853 Discriminator Loss: 0.0883
```

Fig. 3 - Generator vs Discriminator Loss at Epoch 10

The optimization process involved tuning hyperparameters such as the number of steps per epoch, the noise dimension, and the batch size. The optimal configuration achieved a generator loss of 2.4969 with 100 noise dimensions, 4 batch size, and 1000 steps per epoch.

For the Generated Image Quality, visual inspections of the generated images were performed at each epoch, which revealed an improvement in image quality and fidelity over time. After each epoch, a grid of 10 images was generated and compared to real images. The distribution of pixel intensities for real and generated images was visually compared using a distribution plot, revealing a high degree of overlap between the real and generated images by epoch 10.

To quantitatively evaluate the quality of the generated images, the following metrics were computed:

Structural Similarity Index (SSIM): SSIM is a perceptual metric that assesses the similarity between real and generated images. The final SSIM score for the generated images was 0.2427, indicating moderate structural similarity.

Peak Signal-to-Noise Ratio (PSNR): PSNR measures the quality of the generated images compared to the original images. The PSNR score was found to be 60.66 dB, which is high, reflecting the close resemblance of the generated images to real images.

Infidelity Score: An infidelity score of 0.3842 was computed, reflecting the model's capacity to generate images with a balance between fidelity to the real data and variability.

These metrics can be seen in figures 4 and 5.

```
PSNR: 60.66221621078604
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Fig. 4 - PSNR score

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SSIM Score: 0.24273970624640012
Infidelity Score: 0.3842482
```

Fig. 5 - SSIM and Infidelity scores

As observed from the training loss curves, the generator loss gradually decreased over the training epochs, while the discriminator loss showed a slight rise, indicating that the GAN had achieved a balance in its adversarial learning process. The final loss values suggest that the generator became increasingly proficient at generating images that were difficult for the discriminator to distinguish from real images which can be seen in figure 6.

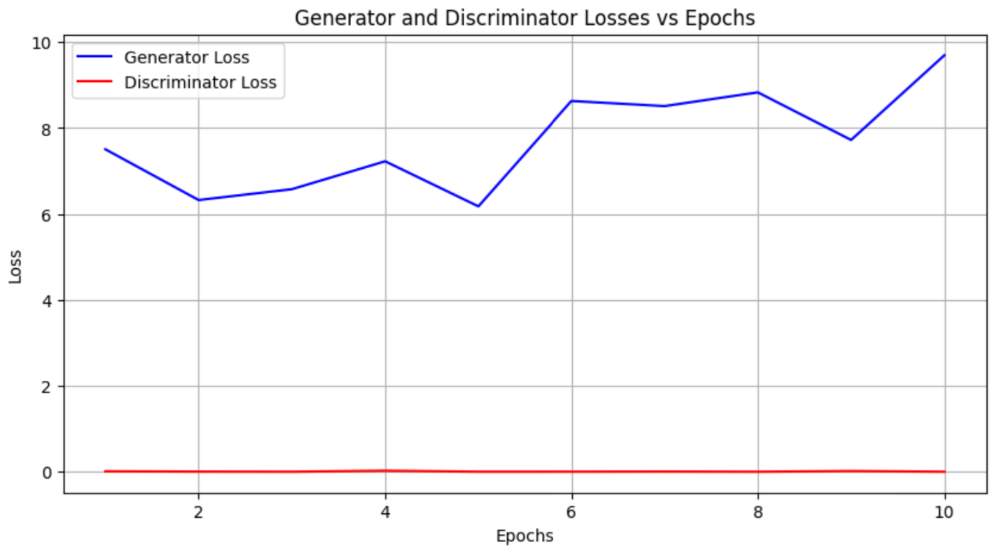

Fig. 7 - Real vs Generated Images Density graph

The grid search over various hyperparameters yielded the best configuration with the following results:
Noise Dimension (NOISE_DIM): 100
Batch Size: 4
Steps per Epoch: 1000
This configuration allowed the model to strike an optimal balance between image quality and computational efficiency, achieving a generator loss of 2.4969.

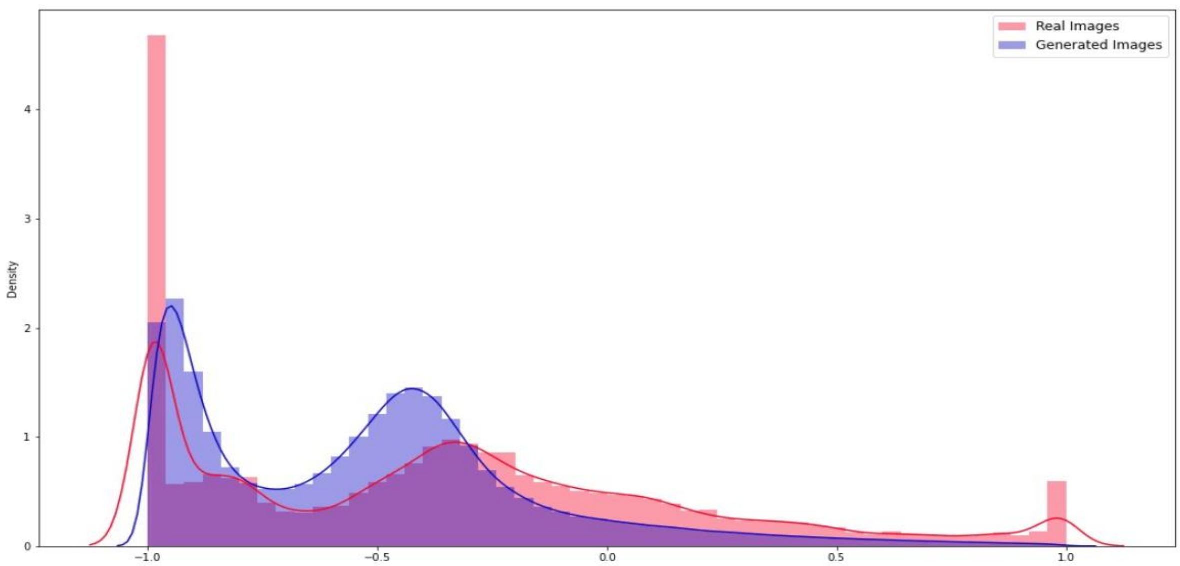

Fig. 6 - Generator and Discriminator Losses vs Epochs

GAN simulations were done after each epoch which allowed for the determination of the progressively generated images for the purpose of examination. As was seen from the simulation results in subsequent training iterations, the images' fidelity gradually increased as training continued. Some epochs are much noisier which are in the earlier epochs some of them have low quality images compared to images in later epochs which are very clear accurate images. Such a progression can be especially seen when considering the quality of the images of the brain tumor as seen in the figure 7.

To get more detail information about the design and structural points of view of the GAN model, more discussion on the structure of model with parameter information is given in Table 1.

Table 1- A brief description of the model being portrayed with variables and figures.

Parameters	**Values**
Model Type	Deep Convolutional GAN (DC-GAN)
Input Image Size	128x128 pixels (Grayscale)
Number of Channels (Input)	1 (Grayscale)
Noise Dimension (NOISE_DIM)	100
Batch Size (BATCH_SIZE)	4
Steps per Epoch	1000
Epochs	10
Random Seed	40
Optimizer	Adam(learning rate = 0.0002, β1 = 0.5)
Loss Function (Generator)	Binary Crossentropy
Loss Function (Discriminator)	Binary Crossentropy
Activation (Generator)	LeakyReLU, tanh
Activation (Discriminator)	LeakyReLU, Sigmoid
Learning Rate (Generator)	0.0002
Learning Rate (Discriminator)	0.0002
Beta1 (Adam Optimizer)	0.5
Generator Layers	Dense, Conv2DTranspose, LeakyReLU, Tanh
Discriminator Layers	Conv2D, LeakyReLU, Dropout, Flatten, Sigmoid
Training Dataset	Brain MRI Images (Brain Tumor Detection)
Normalization	[-1, 1]
Data Preprocessing	Grayscale conversion, resizing to 128x128
Best Generator Loss	2.4969
Best Discriminator Loss	0.0436
SSIM Score	0.2427
PSNR Score	60.66 dB
Infidelity Score	0.3842
Sampling Rate for Image Generation	After every epoch
Image Generation Function	sample_images()

Conclusion:

This study was able to establish that DC-GANs could be used to generate realistic images of brain tumors from a small sample. As is evidenced in the results, our model was able to generate images that are very similar to real brain tumor MRI scans by utilizing the enhanced upsampling of generator by leveraging on the discriminative discriminator. A SSIM of 0. 2427 and a maximum of Peak Signal to Noise Ratio (PSNR) which is 60. 66 show that the created images represent the features of the real brain tumor data while keeping the image quality high and images differing from one another. In addition, during the tuning of hyperparameters, we maintained a proper training on both the generator and the discriminator, which were designed to reach a generator loss of 2. 4969 with NOISE_DIM=100, BATCH_SIZE=4 and STEPS_PER_EPOCH=1000.

However, this research provides basis for future studies of object generation that aims to develop more complex image generation in medical imaging. The major disadvantage is that the average SSIM score is low and a number of solutions should enhance the general perceptual quality of images. For future works we plan to improve the architectural design of GAN with a view to yield superior results such as style GAN or Progressive GAN since these architectures would improve on the fine detail of the generated images. Also, updating the data set with the variation and severity of the brain tumor will enhance the performance of the generalized model. Another area of future research can be oriented to the use of multiple input at the same time, for instance MR image fused with CT image to develop a more efficient tool for medical image catenation and enhancement. Mitigating these challenges we anticipate our work will potentially play a major role in enhancing medical image synthesis for clinical use and diagnosable AI.

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