Enhancing Brain MRI Images: Using DC GAN And WGAN For Image Augmentation

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***Abstract*—Generating and detecting MRI images are most beneficial if the illness requires a fast and accurate cure. Concerning the weakness, there have been negative remarks made about DL for violating the privacy of patients. However, it takes a lot of money and time to collect a rich MRI image database to train the model. It has been found out that way too many medical imaging datasets contain imbalanced data, thus making it difficult for the model to find the outliers. Hence, the basic necessity in working with medical images is the process of data augmentation. The regular forms of data augmentation such as rotation, scale, crops, etc. , results in images that look very similar and there isn't a usual variation that is vital in DL algorithms to learn about the characteristics of the images. On the other hand, Generative Adversarial Networks (GAN) have reported the potentiality to generate synthetic data with good generalization to a large image set. It is also important to note that GANs also possess the property of being an cheap in terms of data processing. In this work, we adopted the AGG based on the characteristics of MRI data analysis, and PSNR for the analysis of local information of a source image based on style transfer and multiple GANs for shared information. Style transfer follows aggregation to ensure that the aggregated image is similar to the original images. Then, we perform an analysis of the aggregation and the style transfer and because it drastically reduced the performance, dropped them.**

***Keywords*—cGenerative Adversarial Networks, Synthetic Medical Image Generation, Brain MRI, Data Augmentation.**

I. Introduction

This paper focuses on the importance of true MRI generation in enhancing the proper medical therapies. It is possible to use Magnetic Resonance Imaging (MRI), which is a non invasive method for providing these brain scans. The MRI scans can be used to get important information like for the generation of MRI, shape, size and the growth stage of the brain tumor. For any kind of medical image analysis using deep learning algorithms, a good set of large volumes of data with variation is needed. Nevertheless, the augmentation methods such as scale and rotation of the images where used crop etc. [1] create high data kaggle dataset which have the MRI read the data and generate the MRI images, produce very high correlation images which do not posses the ability to capture feature differences in the source images. Besides, they may shift the pattern useful for according to the dataset size. [2] GAN-based models present good generative features of synthetic contexts with good generalizing capabilities on large data samples. In the present work we implement the style transfer concept using the AGGrGAN model for the reconstruction of a source image and at the same time for extraction of both localized and shared representations of multiple images. [4] We then proceed to ablation study to examine the performance of the generated images (with regard to PSNR and SSIM scores) as well as to assess the effects of the aggregation before style transfer. In our approach for a qualitative analysis, we train a classification network separately on real images and on a combination of real and fake images to assess the authenticity of the images produced by our models. To achieve this, all the experiments have been conducted using Kaggle 2020 dataset only as cited in [5] [6] [7]. Literature review is performed while conducting experiments on Kaggle 2020 dataset Prior works The experimental process is preformed on Experimental results on Kaggle 2020 dataset Next parts of this paper contain descriptions of the Kaggle 2020 structure and the proposed data pre-processing steps. The mathematical description of the internal mechanisms of GAN models is described in the methodology section and further outlines the structure of DCGAN and WGAN architectures, introduces the Aggregation GAN model and style transfer [8].

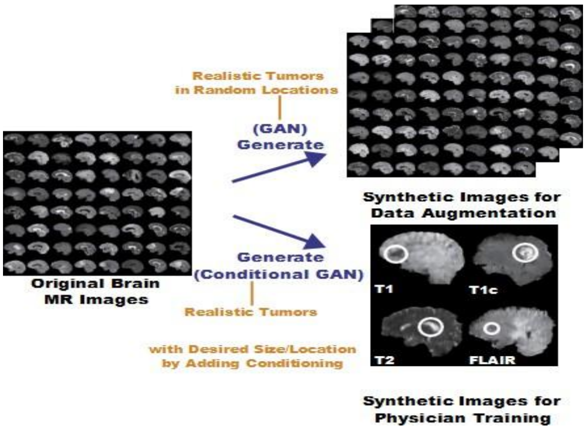

Fig. 1. GAN for Medical Image Synthesis.

The application of the proposed Generative Adversarial Network (GAN) structure in producing synthetic brain MR images is elaborated on in Fig. 1 in terms of their possible implementations. Also, it is beneficial as a way of data enhancement as it provides random but realistic images for classification. Second, it is a better understanding of how this model can look like the images, we wanted to see in the result. For such applications, the generation of the scene images that look realistic but the actual images do not exist is crucial. The results reveal that it is possible to match the generated distributions to the real one where GANbased data augmentation has been deployed; the generalization property of the model. N received 21% better accuracy in estimating eye-gaze compared to the current state of the artitudes. [9] The challenge here is to ask the learners to come up with fabricated multisequence brain MR images that appear real and distinct from the ones provided above. This is especially vital in medical imaging to enhance the dependability utilizing data augmentation in computer-aided diagnosis and physicians in training. [10] Such a development includes Deep Convolutional GAN (DCGAN) and Wasserstein GAN (WGAN) for the usage in image synthesis. These generated images are then screened. [11]

In conclusion, the present paper aims to address the analysis of the essential problem in the application of GANs for generating medical images for its real-life applications related to data augmentation and medical learning for physicians. The utilization of these extended GAN architectures reflects the purpose of our mission of generating authentic images amenable to optimizing generative outcomes and activities relevant to medical practitioners.

II. Literature Review

In this work, we use large and diverse dataset for training deep learning model in medical domain. The use the analysis the data and generate the MRI images using DCGAN and evaluates and effectiveness by comparing the result with those obtain using the augmentation methods. This research is value in medical imagine as the addresses creating synthetic images that can enhance the training of machine learning models for tasks like image segmentation, classification [12] Establish the importance of medical image classification in diagnosis and treatment. Discuss the challenges associated with limited labelled datasets for training robust deep learning models. Introduce the concept of data augmentation and the motivation behind using Deep Convolutional Generative Adversarial Networks (DCGANs) for this purpose [13]. Present the context of medical image generation and its significance in healthcare applications. Discuss the challenges associated with generating high-quality medical images. Introduce the motivation for combining SRGAN and DCGAN to enhance image generation and improve CNN model performance [14]. Noise-to-Image GANs: These GANs generate realistic images from random noise. have used Fully Convolution Network (FCN) as generator and a basic CNN as the discriminator, they have proposed 3D FCN to estimate target image from the corresponding source image, they have used ADNI dataset and have obtained a mean PSNR [15]. In this paper have proposed a GAN based model where ResNet is used as the generator and discriminator is a CNN with five convolutional layers which classify the image as real or fake, they achieved a mean PSNR of 26.6 ± 1.2 for an IRB approved dataset. Shin et al. segmented the overall scans of Alzheimer's Disease Neuroimaging Initiative (ADNI) [16]. It explores methods for simulating brain tumors in magnetic resonance (MR) images. We use these metrics to evaluate the performance of each of the individual GANs and the aggregated image. This type of study is valuable for advancing the development and optimization of segmentation techniques, which arecontext of neuroimaging and brain tumor analysis ensuring visual consistency across different brain lobes. This consistency allows for accurate diagnosis [17]. The CNN models are likely utilized for classification tasks related to brain MRIs. The novelty of the GAN method introduced in the paper would likely be a focal point, The paper would detail how the GAN and CNN components are trained. Training the GAN involves optimizing the generator and discriminator to generate realistic images. Training the CNN involves optimizing the network parameters for accurate classification [18]. The paper aims to perform segmentation on these highresolution images, which involves identifying and delineating different regions or structures within the brain. The novelty of the GAN method introduced in the paper would likely be a focal point, and the results of the method would be compared and discussed in the context of existing techniques for high-resolution image generation and segmentation in brain MRI [18]. A method for generating artificial MRI images using a deep convolutional GAN. GAN-based approach by comparing it with other existing augmentation methods. This research contributes to the exploration of artificial data generation techniques in the context of medical imaging, specifically MRI, which can be valuable for tasks such as training robust machine learning models with limited real-world data [19]. Conditional GAN with 3D Discriminator for MRI Generation of using the Aggregation of the analysis using the CNN and MAE model suggests that the paper focuses on using a Conditional Generative Adversarial Network (CGAN) using the 3d images with a threedimensional (3D) discriminator for the specific task of generating magnetic resonance imaging (MRI) [20]. The discriminator then rates the fake images, while also comparing them to the actual MRI images. The generator adjusts its parameters based on the discriminator's feedback, aiming to create images that appear more authentic realistic images. contributes to the field of image processing and computer vision by exploring the capabilities of GANs in addressing challenges related to image resolution [11]. This paper explains a novel approach for medical image synthesis leveraging context-aware generative adversarial networks (cGANs). during the image synthesis process to produce realistic and clinically relevant medical images. Briefly outlines the importance of medical image synthesis in various applications, such as training deep learning models and augmenting datasets. Highlights challenges in generating realistic mediacla body parts mri images and the need for context-aware approaches [21].In this paper we to quantitatively evaluate our approach we use Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). We use these metrics to evaluate the performance of each of the individual GANs and the aggregated image. These metrics are also used to evaluate the performance after style transfer. In this paper, they have suggested that we use GAN in creating artificial training data for the machine learning activities. The generation of artificial training data may be very beneficial in such scenarios like in case of dealing with imbalanced data set and similar to the function of SMOTE and ADASYN [24].

III. Dataset Description

A. Dataset Composition

The dataset used to train GANs include multispectral contrast-enhanced brain MR images; These images are specifically introduced in Kaggle Multimodal Brain Tumour Image Segmentation Benchmark competition. It speaks of 220 HGG and 54 LGG clinical cases: with all respectively T1, T1ce, T2 and T2ce. The above images are two axial CT scan slices of the brain and each of them contains 240 x 240 x 155 pixels. [23] The Clinical Significance of GANs in MRI Technology Clinical

B. Relevance

In the case of the Argumentation of the dataset, since the GANs for the generation of high quality, real looking MRI images with the help of helps thus it is not very difficult in the identification as well as in the analysis of the training data some of which are many Epochs of 3750*10. of analysis those huge data it takes more than 8 to 10 hr of individual system It may assist in obtaining improved diagnostic expertise and possibly even notion of treatment. reality and a diverse set of examples that can be explained with the help of breathe info about the data explaining envisioned by GANs the general view of the brain anatomy and make all images to match in terms of visuals whether it is lobe or not. Distinctions of this sort are not often met, which helps to achieve the correct diagnosis properly and establish an adequate treatment plan.

IV. Methodology

Creating images for data augmentation, MNIST and CIFAR 10, using GANs within the restricted brain-box [23]. The problem exists because there is limited space that can be provided within the skull, which then becomes a chance as anything which grows can be something that is risky. These can be cancerous, that is malignant, and non-cancerous, that is benign tumours Some of the causes include:The presence of both subtypes can cause the intra cranial pressure to rise and lead to a number of head injuries and even a condition that is life threatening. The class of generative models, which covers deep generative models, are the deep learning models that are capable of specifically solving the following two tasks; estimating the probability distribution of the provided data samples. Some of these applications are that it is capable of filtering data and bringing them down to their bare basics of attributes and also, it is capable of creating new application samples out of different and unique attributes[24]. GANs are used as the adversary of likelihood since the generator network generates samples of data that follows the distribution indicated by the data set. Its objectives include reproducing fluctuations present in the specified dataset. This can be done by incorporating two networks referred to as the generator and discriminator networks[25].

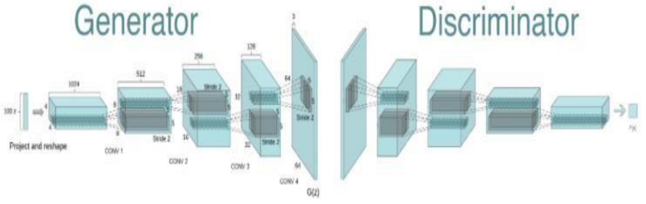

Fig. 2. Basic GAN Architecture.

A. Generator

It is a process where by the generator can take some randomness is as the input and give an image output that will somewhat resemble the input data [26]. Discriminator: In every output image the discriminator receives in its training process, it is also given a real MRI image to verify that the actual image is real. Training Process: Fake images are generated through the role of a generator and then uses those generated images as inputs to the role of the discriminator. The discriminator also assigns scores to the fake images as the fake images will be assessed based on how real they look like compared to MRI images. The generator has to learn about its weightage compared to the discriminator in an attempt to improve the quality of the fake images that it creates so as to impress the discriminator [27]. Performance

B. Improvement

In the end, the generator is improved and tries to come closer to authentic MRI images A , so that it can approximate the MRI scans that it creates progressively In this way As Van Essen et al Moreover, it is noteworthy that the generator approximates the MRI images , but does not reconstruct the images whilst emulating the MRI scans as an analogous process Similarly, it is crucial to mention that the generator comes close to the actual MRI images A to increase the The feedback loop is a way of training the generator to give good quality, convincing MR images; the generator is trained to generate high-quality realistic MRI images. This technology can be used to both discover them and then analyse the more detailed structures of the brain [29].

C. The Minimax setting

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} [logD(x^{(i)}) + log(1 - D(G(z^{(i)})))]$$

The essence is in the value that estimates the distance of generated data distribution from the real data distribution. Here, the discriminator learning process is also anchored on a certain loss function, while the generator also has its own. It is important to understand that the generator wants to optimize the loss function while on the other hand the discriminator wants to optimize it.

D. Testing the Generated sample: Plotting the Distributions

In this test, the output of the generator is compared with the real samples the by visualizing them in the form of histograms. If distributions are complete then it means the generated sample is very much close to the real sampling.

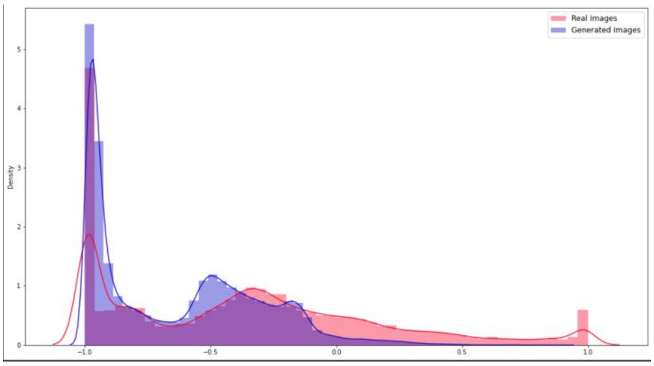

Fig. 3. Graph presenting real images and generated Brain MRI Images.

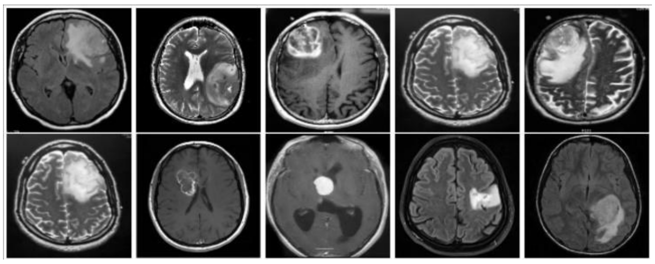

Fig. 4. *Real MRI Image from Brain Dataset.*

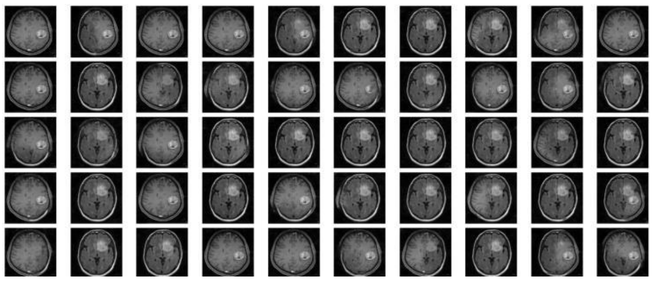

Fig. 5. *DCGAN Generated Images for Brain MRI Dataset.*

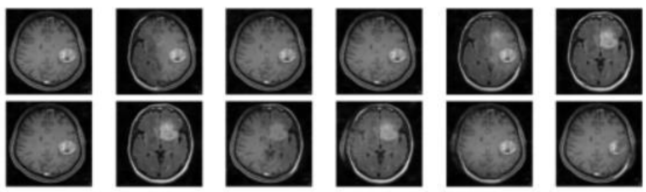

Fig. 6. *WCGAN Generated Images for Brain MRI Dataset.*

"Fig. 4" depicts the actual and augmented images plot to determine what changes occur during the augmentation process. The actual or original of Brain MRI Images are presented as shown in "Fig 4", "Fig. 5" and "Fig. 6" shows the real MR images used to train DCGANs and WGANs resized 256 x 256 sagittal multi-sequence brain MRI scans of HGG patient from Kaggle 2020 training database. Altogether, the generation of new photo-realistic images from scratch using GANs will herald major leaps in clinical practice.

V. Results and Analysis

To quantitatively evaluate our approach, we use Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). We use these metrics to evaluate the performance of each of the individual GANs and the aggregated image. These metrics are also used to evaluate the performance after style transfer. We now formally define these metrics

A. PSNR: (Peak Signal-to-Noise Ratio)

The relationship between the highest intensity value and the existing noise value in an image. With a maximum intensity of 255 in our images, measure of noise. Thus, the PSNR is calculated by assessing the reciprocal of the square root of the MSE.

$$PSNR = 20\log_{10} MAX_f/\sqrt{MSE}$$

B. SSIM: (Structural Similarity Index)

The extent of resemblance between two images, with high SSIM values indicating greatest similarity. When two images are identical, the SSIM is equal to 1. The SSIM is computed using the following formula

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Here, μx and μy are the mean intensity value of both the images, σx and σy are the standard deviation of the intensity values present in both the images. σxy is the covariance between the intensities of both the images. c1 and c2 are constants used to negate the weak denominator effect.

Epoch wise description for 3 epochs of the G loss and D loss with respect to the DC GAN are presented in "Fig. 7,8 and 9".

G_loss = 3.93 D_loss = 0.03

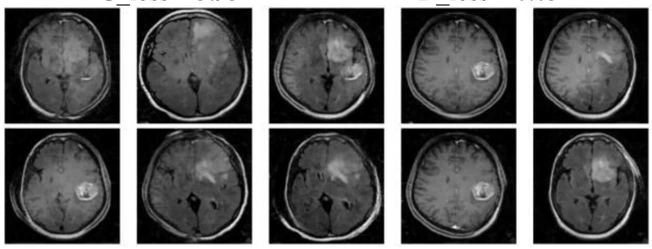

Fig. 7. *Epoch 1 results for DCGAN*

D_loss = 5.8 D_loss = 0.04

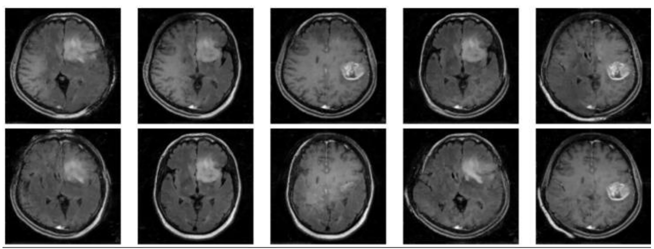

Fig. 8. *Epoch 2 results for DCGAN*

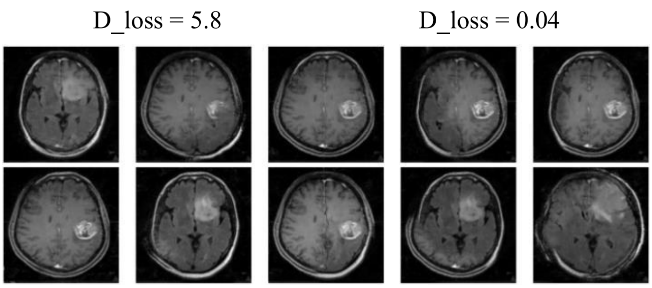

Fig. 9. *Epoch 3 results for DCGAN*

TABLE I. PSNR AND SSIM VALUES FOR THE TRAINED DATA DCGAN AND WGAN.

Model	*T1_PSNR*	*T1_SSIM*	*T2_PSNR*	*T2_SSIM*
DCGAN	20.3	0.69	25.57	0.7
WGAN	19.3	0.6	20.4	0.3

TABLE II. FORMULA FOR THE PSNR, SSIM, G_LOSS AND D_LOSS.

PSNR	$PSNR = 20\log_{10} MAX_f/\sqrt{MSE}$
SSIM	$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$
G_loss	$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} [log\ D(x^{(i)}) + log(1 - D(G(z^{(i)})))]$
D_loss	$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} log(1 - D(G(z^{(i)})))$

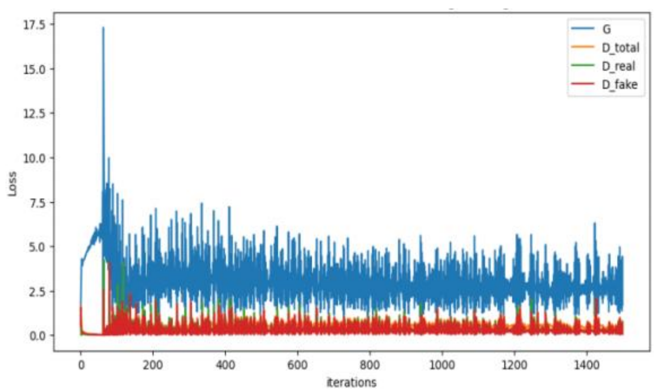

Fig. 10. *Generator and Discriminator losses of DCGAN.*

The epoch-wise description of the G loss and D loss with respect the DCGAN for the third epoch is given by “Fig. 10” The green line depicts the Discriminator loss (D_real) which defines the ability of the discriminator to distinguish between fake MRI images and real images. Meanwhile the blue line represents the generator loss (G) which is in the decreasing trend meaning that the generator is improving on its ability to generate images that resemble real MRI images even more. The red line represent the discriminator loss (D_fake) which also shows a declining trend proving that the function used in discriminator is improving as time goes on with the aim of distinguishing between real and fake image data set. The Orange line (D_total) continues to be low and nearly stable which gives an insight that it performs well in identifying the real from the fake images generated. This shows that the generator and the discriminator are improving their ability during the training process, therefore, GAN has been trained well. Here, it is possible to state that according to PSNR and SSIM results, DCGAN is slightly better than WGAN on creating high quality synthetic brain MRI images.

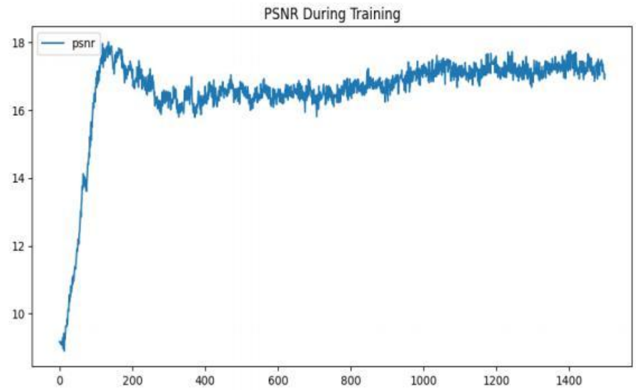

Fig. 11. *PSNR score for DCGAN Generated images.*

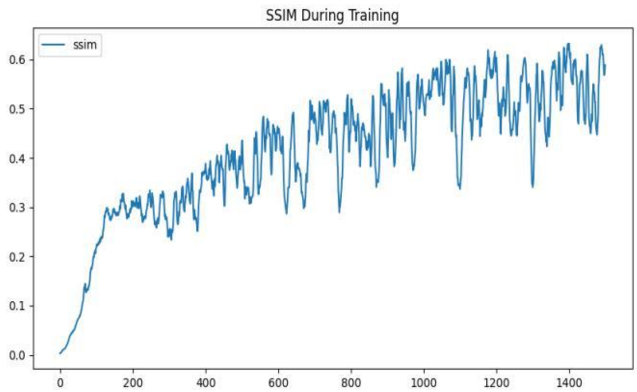

Fig. 12. *SSIM score for DCGAN Generated images.*

The PSNR values and SSIM characteristics of the images generated by DCGAN in training shall be explained and represented. As depicted in “Fig. 11”, there has been an increasing in PSNR of which imply that pixel-wise accuracy of the synthesized image increases with regards to the original MRI images. Therefore from the “Fig. 12” which has been provided the SSIM value increases which show that the structural preservation of the generated image is better. The trends obtained in the data imply that DCGAN can produce high quality synthetic brain MRI images as evident from the following. About the models under consideration, it is possible to note that higher PSNR and SSIM numbers in the respective graphs.

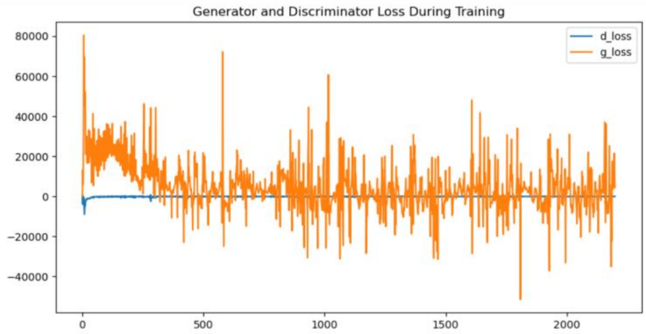

Fig. 13. *Generator and Discriminator losses of DCGAN.*

The training loss of the DCGAN model is displayed in "Fig. 13" where it shows the losses of both the Generator (G) and Discriminator (D). The orange line in the graph stands for the Generator losses (g_loss), which at the beginning of the process shows a sharp reduction and further gentle reduction during the training session. This will also signify a progression on the part of the Generator in terms of coming up with more realistic images. The blue colored lines are for Discriminator losses (d_loss) and these measurements are not very high and are almost constant throughout the epochs indicating that Discriminator has good ability to differentiate between real images and generated images. In total, the declining of (g_loss) show that the proposed model is capable of learning the generator to generate images of good quality

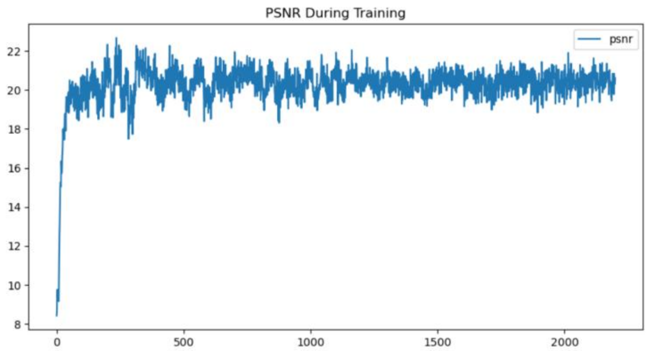

Fig. 14. *PSNR score for WGAN Generated images during training.*

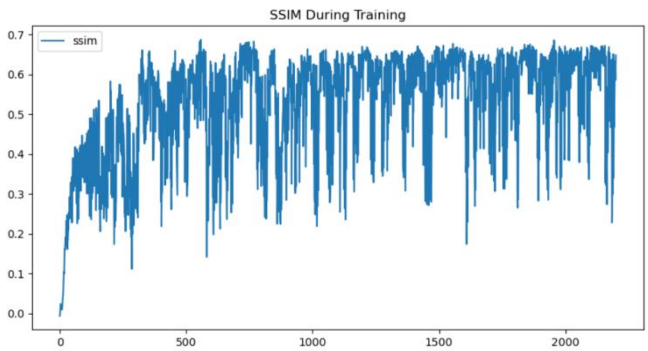

Fig. 15. *SSIM score for WGAN Generated images during training.*

The training curves of the PSNR and SSIM scores of those images that has been synthesized using the WGAN. The PSNR scores also rise gradually as evidenced by the "Fig. 14", therefore, implying that the WGAN is progressively constructing images with improved PSNR to that of the actual MRI images. The same can be observed in the graphical representation of the SSIM scores in "Fig. 15" where increased score show the ability of the models to maintain the structural loyalty of the images. whereas, both of them are significant in measuring image quality that reflects more enhanced scores in these indexes. However, from the presented results, higher PSNR and SSIM values, it should be noted that the DCGAN model is superior to the WGAN model in terms of generating the realistic synthetic MRI image.

VI. Conclusion

In all here, we discussed that for synthesizing rather natural appearing multi-sequence brain MR images, we intended to implement the most advanced deep learning technique in the current world known as Generative Adversarial Network (GAN), specifically Wasserstein GAN (WGAN). From the above tables and the Visual comparison, it can be seen that WGAN has a fairly good ability to generalize the signal; its value function is considerably steep, and even if an experienced physician is told to distinguish between the real and generated images, it will be hard for him or her to do so. The advantage is that it has potential in data augmentation as demonstrated in this paper. for instance DCGAN, in relation to the severity and occurrence of issues such as the low realism in the images generated by the model, mode collapse. Training tends to be done for specific slices of interest to improve the data two kind of images Original and MRI Sequence images are made in medical Imaging. As for admitting that generated samples are not exactly real ones, notwithstanding, confirmed visual likeness of generated samples to real human images by human expertise, discussing the possibility of obtaining a conclusive notion of simulacrum veris by using Classifier Two-Sample Tests (C2ST) in order to determine whether synthetic samples follow the distribution of real ones. This work in future will extend the generation to coronal and transverse images more importantly, it is intended to develop an algorithm for selecting real MRI of the brain from the fake ones. The discourse prioritises the aspect of raw image realism for data augmentation in relation to its possibilities of relevance. As for the concept of creating high resolution image and MRI, it has been talked earlier, and there is some sense that the realism in picture has to be enhanced does not have to be quite right as the quality of data augmentation has to be improved.

VII. Future Scope

As for the future work of this paper we can consider to the generation for the coronal and transverse image, design a classification algorithm for the MRI brain images, distinguish between the real and fake or implement a better quality of data augmentation, applying this technique in other medical images, or to use two-sample tests based on classifiers to verify whether or not that the distribution of the real and synthetic samples are different. Besides the above, the option for exploring transfer learning and multimodal fusion to boost the powers of the GAN model can also be considered. We can also point towards the techniques of attention mechanisms as well as utilizing other strategies to bring the appearance of the images in natural. We can also describe the pattern of generating the MRI pictures real-time and other possibility for the usage of GANs in medical imaging is also inclusive of segmentation as well as registration.

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