PROJECT ABSTRACT

Brain tumors are one of the leading causes of death globally. Early detection and accurate diagnosis of brain tumors can significantly increase the chances of survival and improve patient outcomes. In this project, we propose a brain tumor prediction model that utilizes a combination of RESNET50 and DCGANs (Deep Convolutional Generative Adversarial Networks). RESNET50 is a popular deep neural network architecture known for its excellent performance in image classification tasks. On the other hand, DCGANs are generative models that can generate realistic images based on a given input. By combining these two models, we aim to create a more robust brain tumor prediction system that can accurately identify brain tumors in medical images.

We will train our model using a large dataset of brain MRI scans, comprising both tumor and non-tumor images. We will use the RESNET50 architecture as the backbone of our model, which will extract features from the input images. The extracted features will then be passed to the DCGAN, which will generate synthetic tumor images to augment the original dataset. We will use the augmented dataset to train the RESNET50 model in a supervised learning setting. We will evaluate the performance of our model using various metrics such as accuracy, precision, recall, and F1 score. Our proposed brain tumor prediction model is expected to improve the accuracy and reliability of brain tumor detection, leading to earlier diagnosis and better treatment outcomes. Additionally, our approach of combining supervised and unsupervised learning techniques may have broader applications beyond medical imaging.

CONTENTS

1. INTRODUCTION

Brain tumor is a highly prevalent and fatal disease that has impacted countless lives worldwide. It involves the growth of cancer cells in the brain tissue and is responsible for over 100,000 diagnoses each year globally. Despite ongoing efforts to combat the complexities of this disease, the prognosis for brain tumor patients remains poor. Accurate identification of the specific type of brain abnormality is critical for effective treatment, and computer-aided diagnosis (CAD) systems have been used to improve precision and reduce diagnostic errors. The main objective of computer vision is to provide reliable output in the form of an estimated diagnosis to aid medical professionals in image analysis and reduce the time required for image interpretation.

Medical advancements have greatly improved the accuracy and reliability of diagnosis, but the segmentation of MR images for tumors presents a significant challenge. Identifying tumors in specific regions of the brain without relying on picture intensities further complicates computerized detection and segmentation. To address this issue, many researchers have utilized Convolutional Neural Networks (CNN) in medical image processing. We aimed to develop a model that could efficiently and accurately classify tumors in 2D Brain MRI images. Although a fully-connected neural network is capable of detecting tumors, we chose to utilize a CNN due to its parameter sharing and sparse connections.

2. BACKGROUND STUDY

We give a quick overview of the various clustering approaches that have been proposed from 2002 to 2018 in the background study. We have read a number of studies, each of which takes a different tack when it comes to parameter segmentation. The following lists the summary of each paper.

Dr. M. Karnan and A. Sivaramakrishnan International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013, "A Novel Based Approach for Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques." The image in the study was finalised utilising the Fuzzy C approach grouping algorithm and histogram equalisation, and it projected an effective and creative discovery of the brain tumour location. Using primary factor assessment to lower the size of the wavelet coefficient allows for the disintegration of images. The predicted FCM clustering technique successfully removed the tumour from the MR images.

Improved Edge Detection Algorithm for Brain Tumor Segmentation by Asra Aslam, Ekram Khan, and M.M. Sufyan Beg, Procedia Computer Science, Volume 58, 2015, Pp. 430 M. A detection employing increased edge technique for brain tumor segmentation that primarily relied on Sobel feature detection was given by M. Sufyan et al. Their work here links the binary thresholding operation to the Sobel technique and uses a secure contour process to excavate various extents. Following the completion of that procedure, cancer cells are removed using intensity values from the resulting image.

Devkota, B. & Alsadoon, Abeer & Prasad, P.W.C. & Singh, A.K. & Elchouemi, A. (2018). Image Segmentation for Early-Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Science. According to B. Devkota et al., morphological procedures are utilised to detect abnormal tissues using a computer-aided detection (CAD) method. The morphological opening and closure operations are chosen among all segmentation methods because they need less processing time while being the most effective at removing tumour areas with the fewest flaws.

K. Sudharani, T. C. Sarma and K. Satya Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using a K-NN technique," 2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kumaracoil, 2015, pp. 777-780. DOI: 10.1109/ICCICCT.2015.7475384. To locate and contain the fully hysterical section within the aberrant tissues, K. Sudharani et al. applied a K-nearest neighbour technique to the MR images. Although the process for the suggested work is slow, it provides beautiful results. The sample training step is what determines accuracy.

M. Kumar and K. K. Mehta, "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method," International Journal of Computer Technology and Applications, ISSN: 2229 6093, Vol. 2, Issue 4, PP. 855859 August 2011. In this study, Kumar and Mehta proposed the texture-based approach. If the boundaries of the tumour tissue are not sharp, they highlighted the effects of segmentation. Due to the edges, the performance of the suggested technique can produce unexpected results. The seeded region technique and texture evaluation were carried out in the MATLAB environment.

Mahmoud, Dalia & Mohamed, Eltaher. (2012). Brain Tumor Detection Using Artificial Neural Networks. Journal of Science and Technology. Artificial neural networks were used in a model by Dalia Mahmoud et al. to identify tumours in brain scans. They used Artificial Neural Networks to build a computerised recognition system for MR imaging. When the Elman community was incorporated into the recognition system, it was found that the period of time and accuracy level were high when compared to other ANNs systems. The sigmoid property of this neural community increased the level of tumour segmentation accuracy.

"Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks" by Alec Radford, Luke Metz, and Soumith Chintala, in Proceedings of the International Conference on Learning Representations (ICLR), 2016.This paper introduced the DCGAN architecture, which is a modification of the standard GAN architecture with deep convolutional neural networks. The authors showed that DCGANs can learn to generate high-quality images across a range of datasets, including MNIST, CIFAR-10, and ImageNet.

"Progressive Growing of GANs for Improved Quality, Stability, and Variation" by Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen, in Proceedings of the International Conference on Learning Representations (ICLR), 2018.This paper proposed a new technique for training GANs called "progressive growing," which involves gradually increasing the size of the generated images and the complexity of the network architecture during training. The authors showed that this approach can lead to improved image quality, stability, and variation compared to traditional GAN training methods. They also demonstrated that DCGANs can be used as the base architecture for progressive growing.

"Generative Adversarial Networks" by Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, in Proceedings of the Conference on Neural Information Processing Systems (NIPS), 2014.This paper introduced the GAN architecture, which is a framework for training generative models using a two-player game between a generator and a discriminator. The authors showed that GANs can learn to generate realistic images, and they demonstrated their effectiveness on several datasets, including MNIST and CIFAR-10.

"Improved Techniques for Training GANs" by Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen, in Proceedings of the Conference on Neural Information Processing Systems (NIPS), 2016.This paper proposed several techniques for improving the training of GANs, including the use of different loss functions, regularization techniques, and architectural changes. The authors showed that these techniques can lead to more stable and effective GAN training, and they demonstrated their effectiveness on several datasets, including CIFAR-10 and LSUN. They also introduced a new metric for evaluating GANs called the "inception score," which measures the diversity and quality of the generated images.

3. RESEARCH GAP FINDINGS AND OBJECTIVE

3.1 Research Gap Findings

We have determined from the research analysis that conventional algorithms are very effective at determining the initial cluster size and cluster nodes. Pixel classification becomes difficult if these clusters change with different initial inputs. The cluster centroid value is chosen at random in the widely used fuzzy cluster mean technique. Due to this, it will take longer to find the ideal solution. Radiologists must manually segment and evaluate MRI brain images, and the segmentation is done using machine learning techniques, which have lower accuracy and processing speeds. In areas where accuracy is low, a lot of neural network algorithms have been used to classify and identify tumours. The segmentation and detection algorithms are what determine how accurate the detection is.The image accuracy and quality are currently lower in an existing system. A significant number of prior studies that utilised Classification DNN and Segmentation Fuzzy C, Residual Network ResNet, RNN, and VGG-16 have a number of flaws.

3.2 Objective

The suggested method for detecting tumours from MRI images works well. The proposed method employs a variety of classifiers. The suggested system must have the ability to process MRI, multislice sequences, and accurately bound the tumour area from the pre-processed image using morphological operations and skull stripping. Our research suggests that CNN model is most effective at identifying brain tumours from MRI images. The prior models are not up to par to be medically approved, so we aim to significantly improve the prior models using new approaches or by incorporating features from the prior models into our new model.

4. PROPOSED ALGORITHM / MODEL

At first, the required packages are imported. Then the folder where the dataset is stored is imported. Image reading is done after that it is labelled (such as 0 non-tumour and 1 for tumour image) and then the images are stored in the data frame (refer to Fig. 4.3 and Fig. 4.4).

We have used DCGANs, or Deep Convolutional Generative Adversarial Networks which is a type of neural network architecture that are specifically designed to generate images. The basic idea behind a GAN is to have two neural networks: a generator network and a discriminator network. The generator network generates new images, while the discriminator network tries to distinguish between the generated images and real images.

Then, the dataset is imported and pre-processed by resizing the images, normalizing the pixel values, and converting them into a tensor format. Then, the generator and discriminator models are defined. The generator model is typically made up of convolutional and transpose convolutional layers, with batch normalization and ReLU activations. The discriminator model is also made up of convolutional layers with batch normalization and LeakyReLU activations. The models are compiled and trained using a combination of binary cross-entropy loss and the Adam optimizer. The proposed algorithm for DCGAN is represented with the help of flow-chart (refer to Fig. 4.1).

We then set the input shape of the images to (224, 224, 3) as required by the ResNet50 model. We then set up two instances of the ImageDataGenerator class with advanced image augmentation. The train_datagen object is configured to perform rotation, width and height shift, shear, zoom, and horizontal flip augmentations, and the valid_datagen object is set up to only rescale the pixel values of the images. The data was split into 2 parts, namely training and validation. Then we load the ResNet50 model from Keras, remove the top layer, and freeze the pre-trained layers. We then add a custom output layer consisting of a Flatten layer followed by a Dense layer with a sigmoid activation function.

We compile the model with the Adam optimizer, binary cross-entropy loss, and accuracy metric. We then set up the training and validation sets using the flow_from_directory() method of the ImageDataGenerator objects. Finally, we train the model using the fit() method.

ResNet50 is a pre-trained model made up of a series of convolutional layers, pooling layers, and fully connected layers. The network is trained using a combination of cross-entropy loss and the stochastic gradient descent optimizer containing features like :-

Conv2D - Keras Conv2D is a 2D Convolution Layer, this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.

ReLU - The rectified linear unit (ReLU) is one of the most common activation functions in machine learning models. As a component of an artificial neuron in artificial neural networks (ANN), the activation function is responsible for processing weighted inputs and helping to deliver an output.

MaxPooling2D - Keras MaxPooling2D is a pooling or max pooling operation which calculates the largest or maximum value in every patch and the feature map. The results will be down sampled, or it will pool features map which was highlighting the most present feature into the patch which contains the average feature presence from the average pooling. The max pooling is found to work well in average pooling for vision tasks.

Dropout - Dropout refers to data, or noise, that's intentionally dropped from a neural network to improve processing and time to results.

Flatten - Flattens the input. Does not affect the batch size. If inputs are shaped (batch,) without a feature axis, then flattening adds an extra channel dimension and output shape is (batch, 1).

Dense - The tf.layers.dense() is an inbuilt function of Tensorflow.js library. This function is used to create fully connected layers, in which every output depends on every input.

The proposed algorithm is represented with the help of a flow chart (refer to Fig. 4.2).

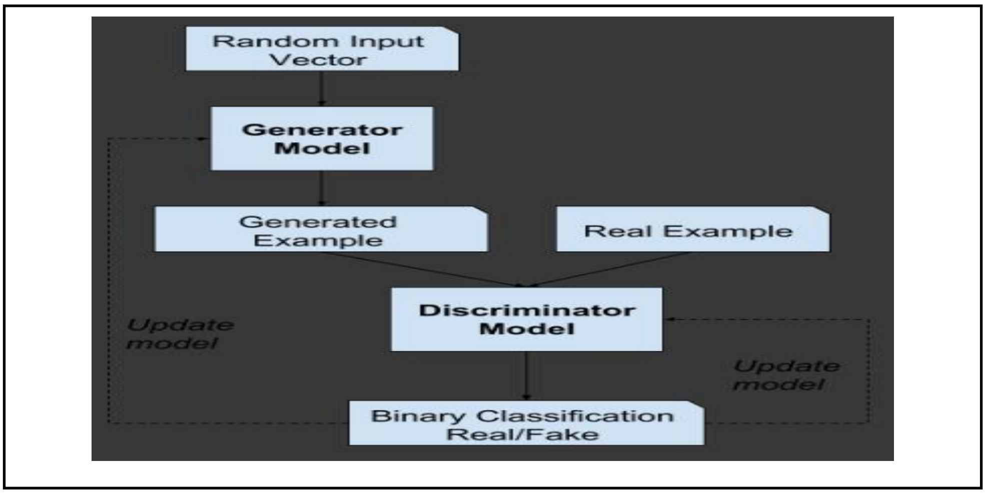

Fig. 4.1 : Algorithm for DCGAN

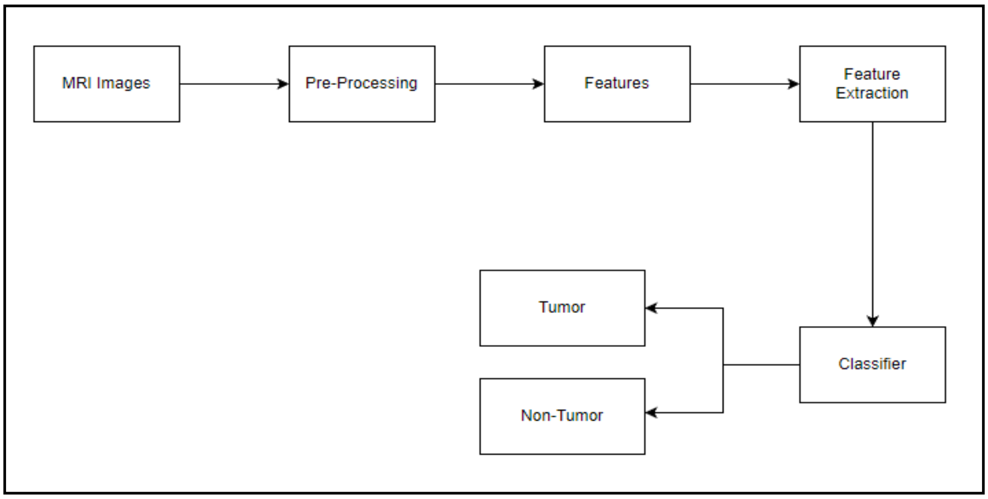

Fig. 4.2 : Flow chart of the proposed work

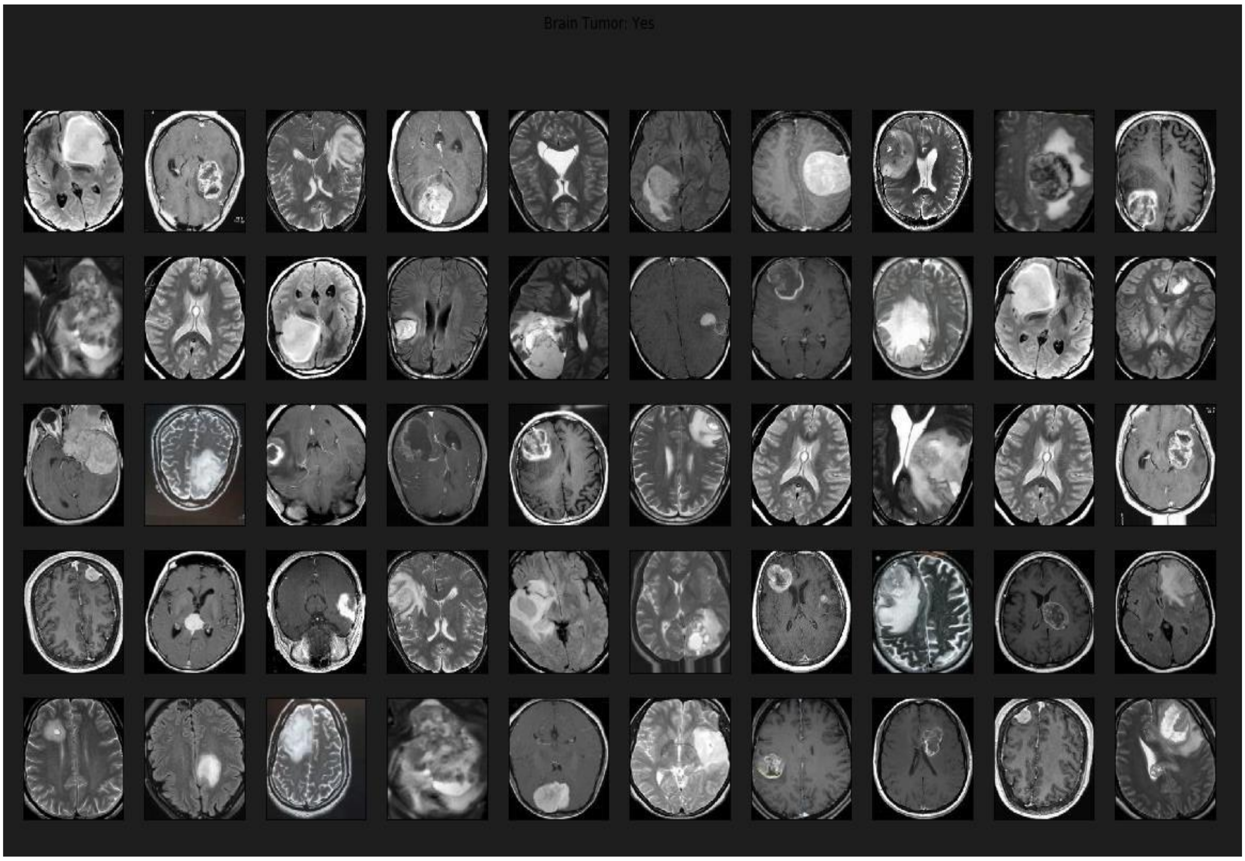

Fig. 4.3 : MRI Images Containing Brain Tumor

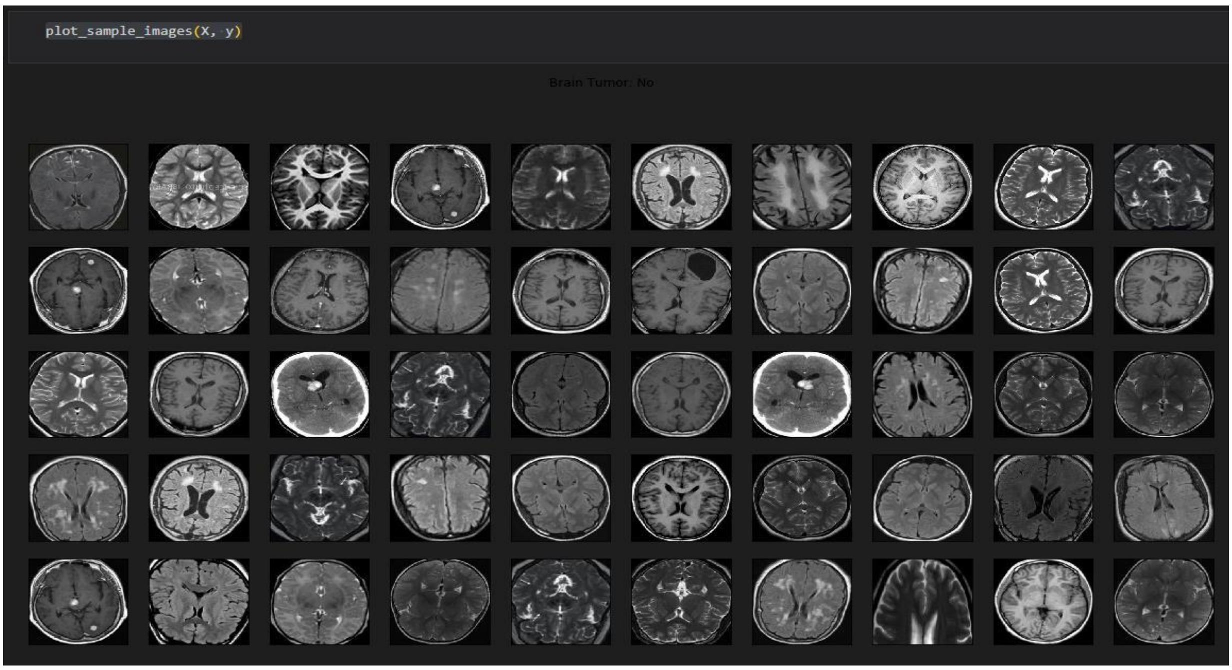

Fig. 4.4 : MRI Images Not Containing Brain Tumor

5. RESULT ANALYSIS

Using the Generative Adversarial Networks (GANs), synthetic images generated (refer to Fig. 5.3) were adequate as is represented by the graph (refer to Fig. 5.2). When the model is applied to the testing data set for 100 epochs, a validation accuracy of 84.85% is obtained and the validation loss is around 0.47 which kept decreasing with the number of epochs as our model is fitting really well with the data (refer to Fig. 5.1). We have obtained an accuracy of 91.78% with a loss of 0.19. Due to the massive size of the dataset (around 3200 images), we get better results as the epoch increases.

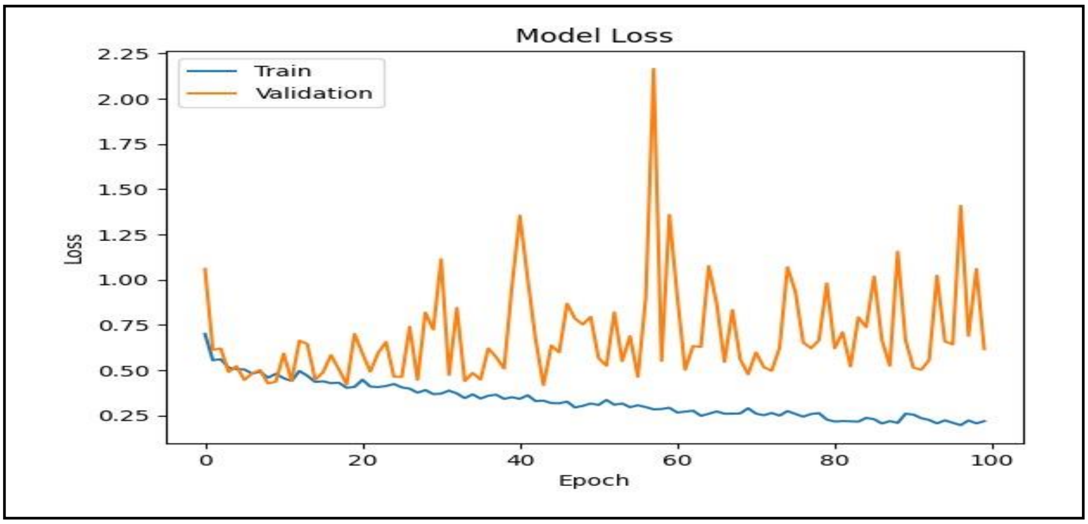

Fig. 5.1 : Model Loss Curve

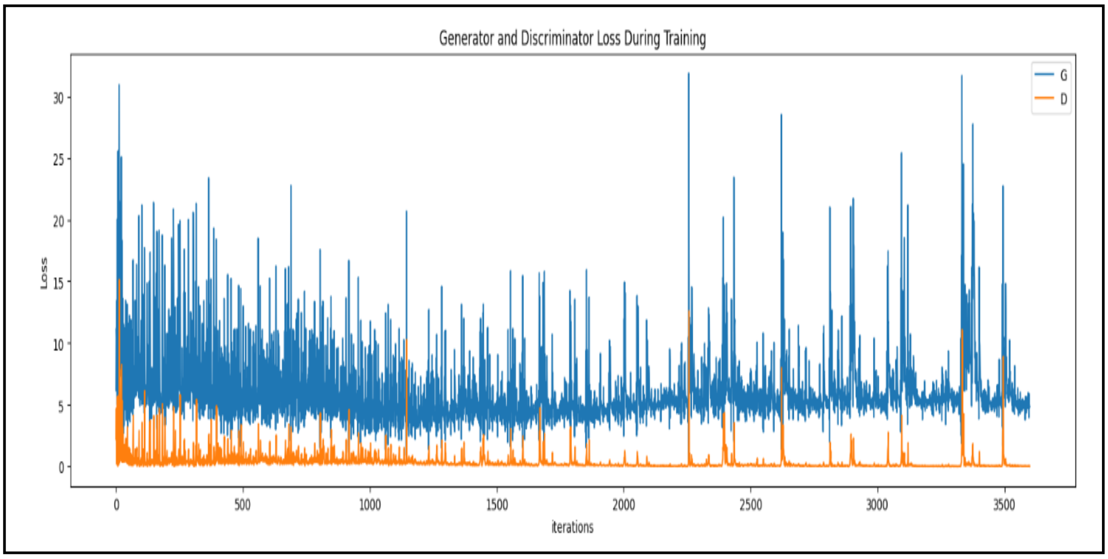

Fig. 5.2 : Generator and Discriminator Loss During Training

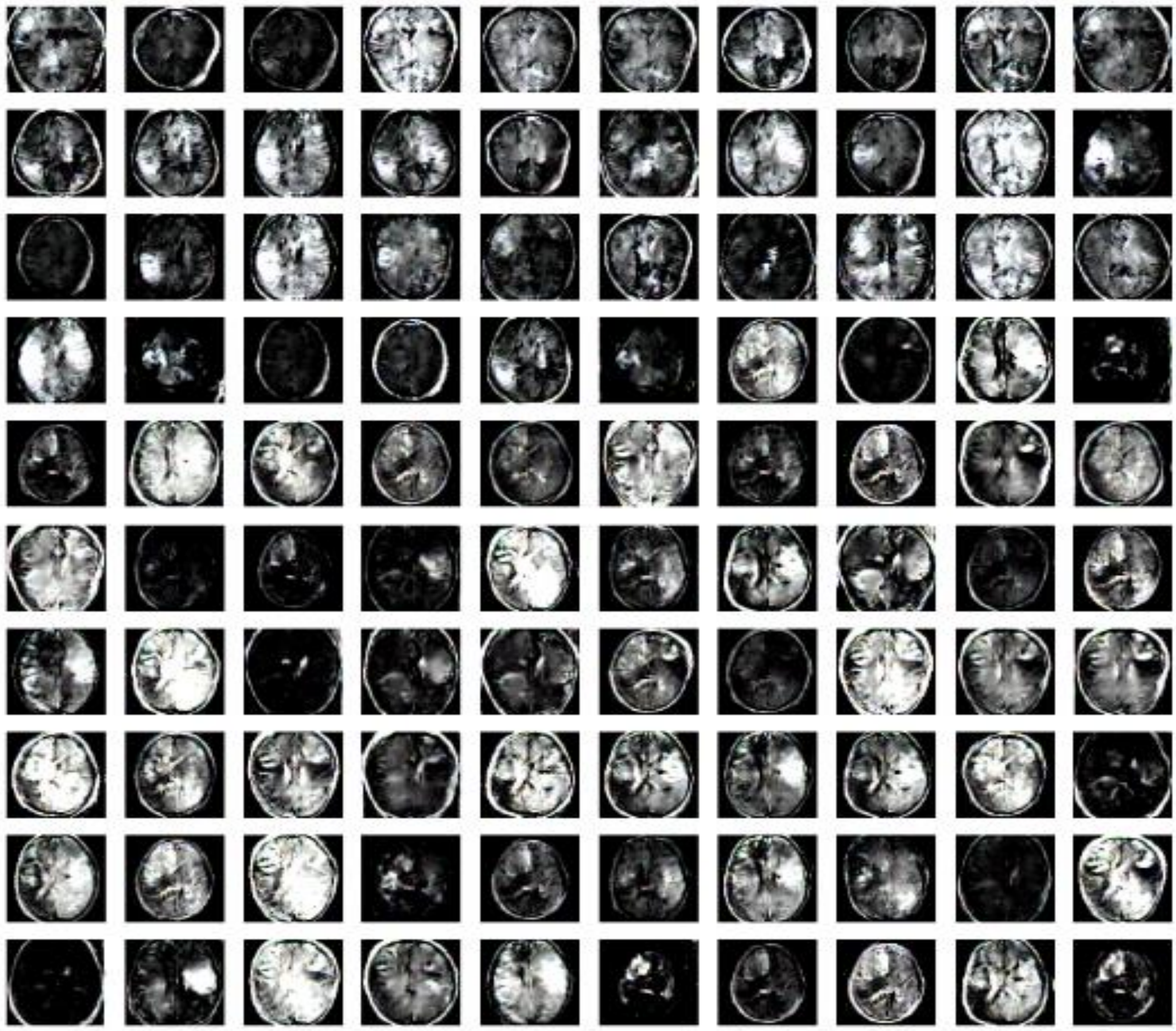

Fig. 5.3 : Synthetic Images Generated By DCGANS

Reference

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