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Medical MR Image Synthesis using DCGAN

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Abstract—Generative Adversarial Networks (GANs) have been extensively gained considerable attention since 2014. Irrefutably saying, their most remarkable success has been made in domains such as computer vision and medical image processing. Despite the noteworthy success attained to date, applying GANs to real world problems still posses significant challenges, one among which is diversity of image generation and detection of fake images from real ones. Focusing on the extend to which various GAN models have made headway against these challenges, this study provides an overview of DCGAN architecture and its application as a synthetic data generator and act an a binary classifier, which detects real or fake images using brain tumorous Magnetic Resonance Imaging (MRI) dataset.

Keywords—GAN, medical image processing, synthetic data, brain tumor, MRI.

I. Introduction

Over the past decades, use of deep learning architectures contributed a lot to medical imaging domain. However, availability of sufficient data is a crucial hurdle to the application of these deep networks in medical domain. Even though we have publicly open datasets, many of them are regulated to specific modalities or medical conditions. So, data gathering for deep learning model is still a challenging module to researchers. In order to get rid of this obstacle, some researchers proposed data augmentation techniques to enhance the data sets. In this regard, several data augmentation methods such as rotation, scaling etc for data augmentation have been propounded. Due to its inefficacy in medical domain and over fitting problems in learning processes researchers proposed synthetic data generation methods to expand training sets. By using synthetic data generation methods, newly created images can be added to the available data sets. Thus, along with synthetic data and available open access data, researchers can ensure diversification within the data set and eventually, to enhance the out-turn of machine learning problems. Karras et. al [1] ameliorated generative adversarial networks (GANs), and concede them to spawn realistic human facial images from the existing facial dataset at a resolution of 1024 × 1024 pixels. A multitude of images spawned by the DL model called

Progressive GANs (PG-GANs) are indistinguishable from realistic facial images. Thus, we were inspired by Karras' work and applied synthetic data generation in medical domain with the generation of synthetic brain tumorous magnetic resonance (MR) images for the classification and prediction of brain tumors.

Generative adversarial networks (GANs) satisfied data starvation problem to some extend through its generator model. GANs are a skeleton to enlighten the deep learning models to seizure the training data's distribution so that we can spawn data from that same distribution. GAN model was developed by Ian Goodfellow [2], which comprised of two distinct models training simultaneously called generator denoted by J and *discriminator indicated by L.* The function of the generator is to generate images which pretend as real training images; whereas the role of the discriminator is to act as a binary classifier, ie output a probabilistic value which differentiates whether it is a real image encountered during training or a generated one from the generator model.Generator is stirving to fool the discriminator by spawning fake images on training time, while the discriminator is stirving to flawlessly categorize the actual images from the fake ones. The saddle point of this minmax game is the point at which, generator generates realistic-looking fake image which resembles the training image, and the discriminator correctly predict whether the generator output is real or spawned one with 50% confidence. Most of existing GAN researches can be categorized in terms of objectives such as improvement in training (i.e., to improve GANs performance) and the deployment of GANs for real-life applications.

The working process of GAN is based on a two-player game. Given a distribution$z \sim p_z$, J describes a probability distribution p_g as the distribution of the samples$J(z)$. The intention of GAN model is to study the generator's distribution p_g which approximates the actual data distributionp_r. GAN optimization based on joint loss function with discriminator L and generator J is represented as:

$$\min_J \max_L F(L,J) = E_{x \sim p_r}\,[\log L(x)] + E_{z \sim p_z}\left[\log\left(1 - L\big(J(z)\big)\right)\right] \quad (1)$$

where, $L(x)$ denotes real data and its corresponding generated data is shown as $J(z)$. The discriminator is tuned to increase the probability of output for real image $L(x)$ and is given as $E_{x\sim}p_r$ $[log\ L\ (x)]$ and to reduce the probability of output for generated data $E_{z\sim p_z}\left[log\left(1-L\big(J(z)\big)\right)\right]$. As, J is tuned for generating $J(z)$, the discriminator L returns higher probability output value for $J(z)$.

A Deep Convolutional Generative Adversarial Network (DCGAN) is an extension of GAN with convolutional layers in the discriminator model and convolutional-transpose layers in the generator model, which was instigated by Radford et. al. [3]. In DCGAN, discriminator is comprised of strided convolution layers, batch norm layers, and Leaky ReLU activation functions, whereas generator is comprised of convolutional-transpose layers, batch norm layers, and ReLU activation functions. Figure 1 represents the architecture of DCGAN.

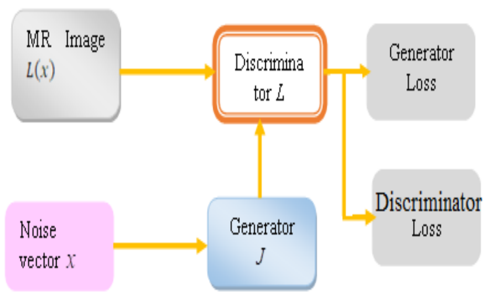

Figure 1. Architecture of DCGAN.

The remaining section of this paper is organized as follows. Section II briefly pinpoints an assessment about existing state of art of synthetic medical MR image generation by GAN architectures. Section III details the feasibility of a DCGAN to spawn brain tumorous MR images and to perform quality assessment of DCGAN generated artificial images using loss function. Section IV concludes the paper with future enhancement.

II. LITERATURE REVIEW

The advancement of deep learning technologies over the past decades have brought numerous breakthroughs in medical imaging diagnosis. The impetus behind this triumph dependent on the availability of big data and its high quality,which is used to train the deep learning models. If the training dataset is small, the neural network model couldn't achieve such a better generalized performance. The main hindrance to gather such a huge collection of labeled data is its expenditure. Moreover, it requires expertise suggestions and valuable time from outstanding experts in the corresponding medical domain. Some of the traditional methods based on probability density function [4], non-linear classification technique [5] produced synthetic data samples.Even though these methods generated synthetic data, but have limited potential to grasp the inherent attributes in the data.

Synthetic data spawning methods are categorized into two major groups. On the one hand, is the model based approach, in which a model is build to capture the features of data and a customized engine renders the data. The model based method is extensively utilized inorder to increase the dataset during training in various applications such as object detection [6], text segmentation [7], brain phantom generation [8] etc. Designing such customized data spawning engine requires depth knowledge of the specific domain and accuracy in model for synthetic data eneration. However, on the other hand, learning based synthetic data spawning approach capture the inherent spatial variability of the data during training. The probability distribution of the actual training data is tacitly studied by the model, and new data is spawned by mimicking the real data. GAN belongs to latter categorization. For synthetic data generation, both supervised [9-10] and unsupervised [11-12] learning are being used.

Medical image simulation and synthesis has gained considerable attention in past decades due to the exponential growth of better machine learning models and optimization algorithms. Shin et al. [13] utilized supervised GAN with and without data augmentation for generating synthetic MR tumor images from respective segmentation masks using BRATS 2015 dataset for 200 epochs on NVIDIA DGX systems. Researchers observed an enhanced throughput with the inclusion of synthetic data on dice score evaluations.

Hu et al. [14] applied conditional GAN to spwan a motion model from a preoperative MR image. Researchers gathered T2-weighted MR images from 143 patients who underake biopsy or focal therapy for prostate cancer. For each patient, 512 finite element simulations were performed, resulting in 72,216 simulated motion data. They claimed that their model can learn convoluted motion straightly from medical image without segmentation, correspondence or other patient-specific information such as tissue properties.

Han et al. [15] introduced a two phase GAN based model to generate realistic brain MR images with and without tumors separately. Researchers claimed that two phse GAN based data augmentation method outperformed the classic data augmentation in tumor detection with sensitivity of 97.48% using BRATS 2016 dataset.

III. ELUCIDATION OF ADVERSARIAL TRAINING ON MEDICAL DATASET

The training of DCGAN is done on the brain MRI tumorous dataset [6]. As a pre-processing, we rescale the images to 64 X 64. All the generator and discriminator model weights are randomly set from a normal distribution with mean value as 0 and standard deviation value as 0.02. The generator is constructed in such a way to convert latent space vector to data space via a pair of strided 2D convolutional transpose layers with 2D batch normalization layer and a relu activation function. The generator model outcome is driven through a tanh activation map to retain it to the data range $[-1, 1]$. Here, the discriminator is designed as a binary classifier which accepts an MR image as input and a sigmoid activation map, which predicts an input MR image is real or fake based on a scalar probability value. Moreover, the discriminator accepts a 64x64 input MR image, processes it through a set of 2DConvolutional layers, 2D batch normalization layer, and LeakyReLU layers.

Table 1: Experimental hyper parameters

Model	Parameters	Settings (values)
DCGAN as binary classifier using brain tumorous MR dataset	Initial Learning rate	0.002
	Momentum	0.1
	Batch size	128
	Optimizer	Adam
	Loss unction	Binary Cross Entropy
	Epochs	20K

The hyper parameters of the network were experimentally finalized inorder to get the convergence of the generator and discriminator loss function during the learnig phase . Adam is the chosen optimizer because of adaptability and computational simplicity. Moreover, the initial learning rate was set as 0.0002, which works well for our work. Inaddition, the mini-batch size was set as 128 for fast learning and computational requirements. Furthermore, Binary Cross Entropy Loss also called Log Loss is the loss function opted here, as it gives the measure of closeness of the predicted and real data distributions and the number of epochs was fixed to 20K. The hyper parameter settings of our experiments are illustrated in Table 1.

IV. EMPIRICAL VALIDATION AND GENERATION OF ARTIFICIAL BRAIN MR IMAGES USING DCGAN

Our research work uses a dataset of tumorous brain MR images to train DCGAN with sufficient images of proper resolution, which was downloaded from KAGGLE. By using DCGAN architecture, we obtained following different results on MRI brain tumor dataset. In figure 2 - (a), (b), (c), (d) , we can visualize the discriminators and generator's losses function during training on different epochs 1K,5K,10K and 20K. And in figure 3, we can visualize a group of real MR images beside a a group of fake MR images from generators after 10K epochs.

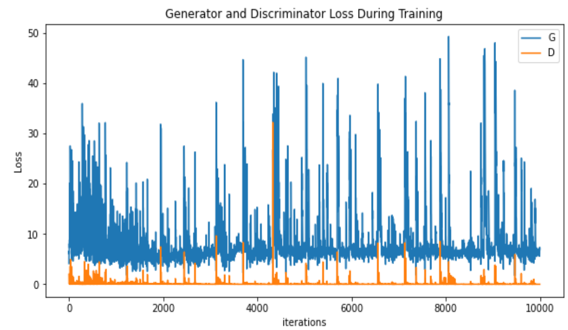

Figure 2. (a) Generator *Vs* Discriminator losses function during training on different epochs 1K.

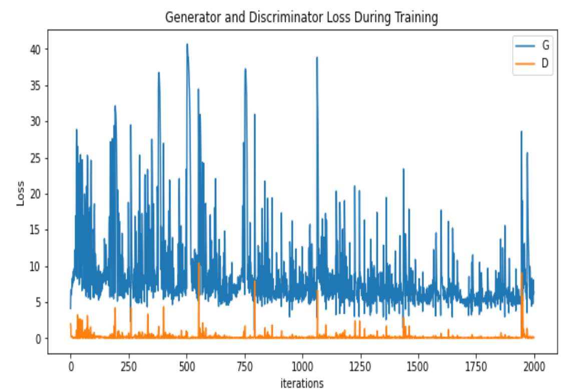

Figure 2. (b) Generator *Vs* Discriminator losses function during training on different epochs 5K.

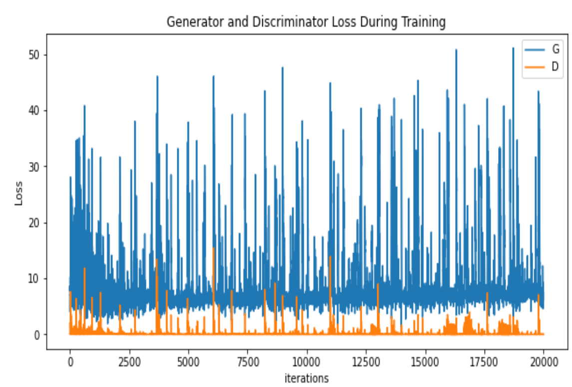

Figure 2. (c) Generator *Vs* Discriminator losses function during training on different epochs 10K.

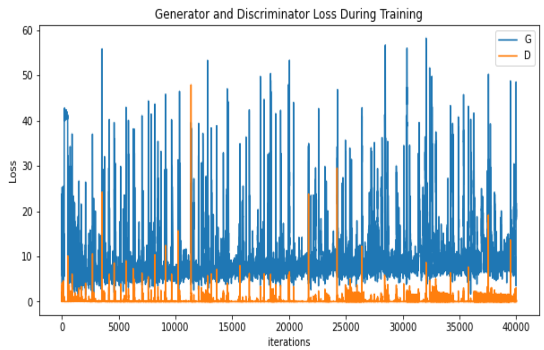

Figure 2. (d) Generator *Vs* Discriminator losses function during training on different epochs 20K

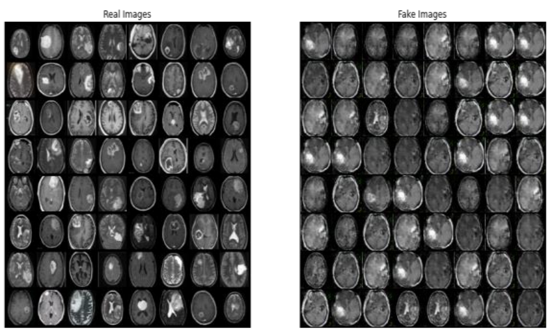

Figure 3. a group of real MR images beside a group of fake MR images from generator model after 20K epochs.

V. CONCLUSION & FUTURE ENHANCEMENT

Our preliminary results show that generator model can output 64×64 synthetic tumorous brain MR images with desired quality and discriminator model can differentiate real and fake MR images accurately with a minimal loss, which further leads to valuable clinical applications such as diagnosis and physician training. We used tumorous MR slices of interest during training to procure desired synthetic brain tumor MR images. Currently this work uses tumorous MR images alone, so we will spawn non tumorous synthetic images and MR images in different sequences in the near future. Moreover, synthetic MR image generation can be used too enhance the training dataset during the classification and progress prediction of brain tumors We reiterate that synthetic data, especially medical data generation, is an auspicious research domain and also an economical approach for the upward growth of automated diagnostic technology.

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