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Deep learning based early Diagnosis of Alzheimer's disease using Semi Supervised GAN

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ABSTRACT: Accurate prediction of Alzheimer's disease (AD) plays an important role in preventing the memory deficiency and enhancing the quality of life of Alzheimer's disease patients. For the last decade, neuroimaging was considered as a potential tool for the AD diagnosis. This paper focus on developing a deep learning based end to end model in diagnosing the AD at early stage. The semi supervised Generative Adversarial Network (SSGAN) is designed to automatically classify the presence of AD from Magnetic Resonance Imaging (MRI). By learning from the labeled hippocampus region, a model mapping is built on original image and the segmented result to effectively segments the left and right side hippocampal volume and convolution neural network based feature extraction is applied to extract the deep feature from the segmented area, finally the SSGAN classifier predict the AD. The present study is applied on Alzheimer's disease Neuroimaging Initiative (ADNI) dataset to conduct the experiment. This approach provides the novel deep learning framework for AD detection, which can be utilized for real world patient data to improve the treatment and their quality of life.

KEYWORDS:

Deep learning, Alzheimer's disease, MRI image, Classification, semi supervised GAN, Segmentation

I. INTRODUCTION

AD is the most common cause of dementia that affects 30 million humans worldwide [1]. It is one of the neurodegenerative disease occurs slowly which result in loss of nerve cells. The symptoms start with slight problems in memory and it develops to severe brain damage. Still now there is no cure for this disease and the drugs used by the physicians just slow down the development of AD. Hence early detection of this disease will be the best way to improve the treatment. The Structural imaging modalities of normal, mild cognitive impairment (MCI) and AD is illustrated in fig 1.

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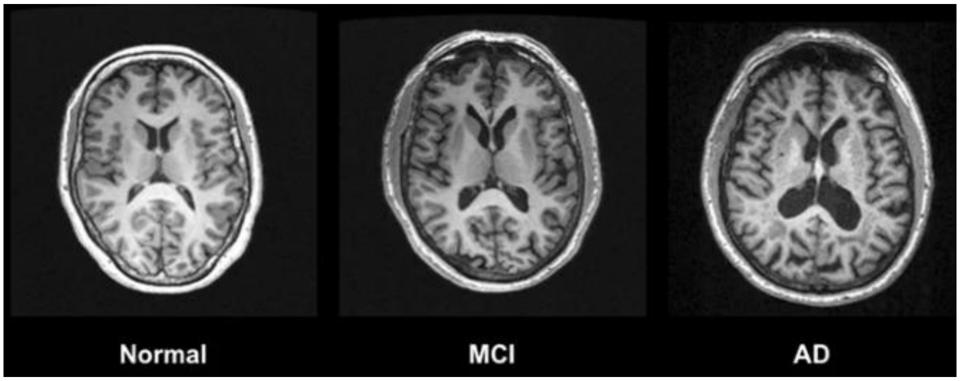

Fig 1: Structural images of MCI and AD compared to a healthy brain [2]

Many researchers have proposed various techniques for AD diagnosis with machine learning [3-4] and deep learning approach [5-6]. The recent studies proved that deep neural network provides best result in medical image analysis [6-7]. However these techniques worked based on the supervised learning architecture and, thus, cannot directly employ subjects with incomplete ground-truth clinical scores for network training.

So Semi supervised based deep learning architecture is proposed for neurodegenerative disease with incomplete ground-truth data. This research is begin with preprocessing the MR image using Gaussian filter and then segments the hippocampal region with u-net framework [8] and then CNN based feature extraction is performed to obtain the deep features for classifier. Eventually the semi supervised GAN classifies the data with generator and discriminator model.

The present study is evaluated on ADNI dataset and compared with prior techniques where stacked auto encoder (SAE) was used as a classifier for AD detection [9]. The prior research applied the multiatlas propagation technique for feature extraction and SAE that reduced the over fitting but increase the difficulty of feature learning. The baseline method achieved the great accuracy for the trained data but low accuracy for test data. The proposed architecture also considered this problem and improves the overall accuracy.

The remaining section of this paper is structured as follows. Section II describes the most relevant studies of AD detection with deep learning techniques. Section III elaborates the details of material used and the proposed methodology. In section IV, the experimental setup, comparison methods, performance evaluation result on ADNI dataset. Section V concludes this research with limitation and possible future research direction.

2. MAGNETIC RESONANCE IMAGING (MRI)

The MRI is most rapidly advancing techniques in imaging that is available and is used for producing the detained sectional images in an imaging plane [10, 21]. The MRI helps to image the human body based on the standard nuclear magnetic resonance. The MRI has many advantages when compared with that of the other modalities in evaluating the knee’s internal architecture. It is a painless and non-invasive method that provides an excellent soft tissue contrast allowing imaging in many planes and also does not incur any radiation dose to that of the patient. The present study utilizes the MRI images to segment the hippocampus to detect the AD. The image segmentation has been defined like a partitioning of images into regions which

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are meaningful for a specific task and is a problem of labeling. This will involve for the detection of a brain tumor from the CT or the MR images. The segmentation is an initial step that leads to image analysis and its interpretation. The goal will be easy to state and achieving may be difficult in terms of accuracy. There are several challenges in the processing of medical image processing [11]:

1. Enhancement and restoration of Image.

2. Accurate and automated segmentation of features in interest

3. An automatic and exact image registration of multimodality.

4. Ordering of an image features.

5. Image feature's computable dimension and clarification of their quantities.

6. Growth of the incorporated systems for clinical areas

The image segmentation is used typically for locating objects of interest and boundaries that make representation of a stack of volumetric images that are more meaningful for analysis that is easier. Traditionally, this is done manually slice by slice needing expert knowledge for obtaining information on boundary for regions of interest [13].

Related Works

This section summarizes the prominent research contributions on the essential domains, namely noise removal, segmentation, machine learning, and deep learning techniques.

Shrestha et al. [14] have compared a few denoising techniques and suggested a unique method for removing impulse noise using the decision-based strategy. These techniques, while suppressing impulse noise, mainly retained image information. Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) of various filtered images depict those techniques' merits. The researchers have also validated the results, esteems with visual perception.

Biswas et al. [15] developed a new noise removal method used with curvelet transform thresholding, combined with the Wiener filter, for the Magnetic Brain Resonance Imaging (MRI). They compared the result with other denoising techniques based on curvelet and wavelet. Peak-Signal-Noise-Ratio (PSNR), Mean Square Error (MSE), and Structural Similarity (SSIM) were used to evaluate the quality of the image. The results of the experiment show that their method shows better results than their competitors.

Mito, R et al. [16] designed a novel method known as pixel-based assessment that comprehensively explored the variations among the voxels, estimate the axonal losses due to Alzheimer's disease and mild cognitive impairment. The authors hypothesized that patients with Alzheimer's disease would display comprehensive functional degeneration.

Kong Z et al. [17] suggested a wavelet-based method to capture the distinct contours. The automatic segmentation of the image can be done using the CNN model with deep learning. The segmented gray and white matter information is quantified to indicate this segmentation technology's ability to quantitatively diagnose cerebral atrophy.

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Awate G et al. [18] proposed a new method for detecting Alzheimer's Disease from MRI using CNN with the Tensor flow using the transfer learning model. This model has classified the various stages of AD. Islam J et al. (2018) designed a new method, namely AD diagnosis, using the ensemble of deep CNN models. These models are used for the clinical dataset to identify the different stages of AD for early diagnosis.

Lee G et al. [19] developed a new system integrating multi-domain longitudinal data. The prediction model for MCI transformation to AD provided accuracy of up to 75% (area under curve (AUC) = 0.83) with only one modality of data separately and this prediction model achieved. The performance by 81% accuracy (AUC=0.86) with incorporating longitudinal multi-domain data. A multi-modal deep learning approach has the potential to identify the subjects at risk of developing AD.

Razavi, F et al.[20] suggested that machine learning methods, particularly deep learning For a smart diagnosis of Alzheimer's disease, were considered helpful for learning raw data features. A two-layer uncontrolled neural network was used at the first stage of learning, scattered faltering, to learn features from raw data directly. Based on the learned features, Softmax regression was used in the second phase to categorize the health status. The technique proposed was validated by Alzheimer's Brain Images datasets.

PROPOSED METHOD

The semi supervised based GAN deep learning technique is used in this research for AD diagnosis. The procedure of the present diagnosis model is described in this section. The overall working procedure of AD detection is illustrated in fig 2. The process start by preprocessing the ADNI MRI data to remove the noise from the image and then segment the hippocampal region, then extract the deep features from the segmented model. Finally the classifier provides the detection result which assist to diagnosis the AD.

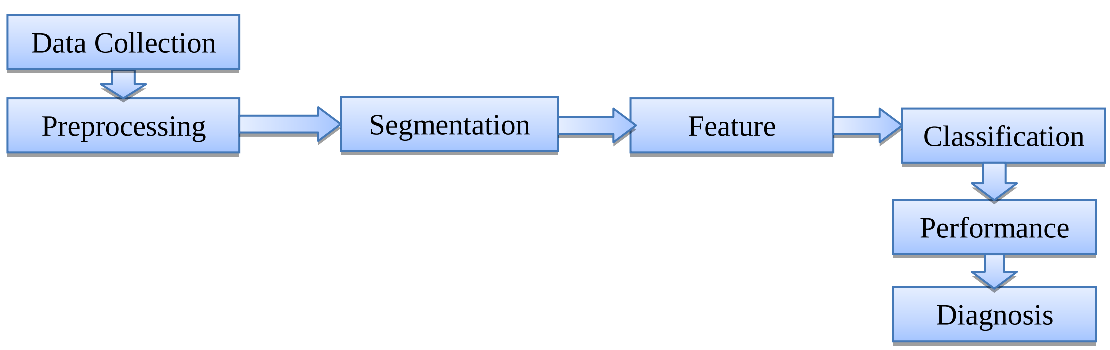

Fig 2 Proposed AD diagnosis System Architecture

PREPROCESSING

Preprocessing is the initial stage of this study. The noise in the MRI images is removed using the Gaussian filter. The goal of any de-noising technique is to remove noise from an image which is the first step in any image processing. The noise in the MRI images is removed using the Gaussian filter. Gaussian filtering has been intensively studied in image processing and computer

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vision. Using a Gaussian filter for noise suppression, the noise is smoothed out, at the same time the signal is also distorted.

SEGMENTATION

U-Net is one of Fully Convolution Network and a network with the U-shaped structure as shown in Fig.3. After extracting feature values while reducing the image size with the convolution layers and the pooling layers, the image size is enlarged with the deconvolution layers and the up-sampling layers. Finally, the same size image as the input image is output. First, learning is performed after inputting the training data to U-Net, and a model for region extraction is constructed. Next, a MRI image of test data is input to the constructed model, and an estimated image by U-Net is obtained.

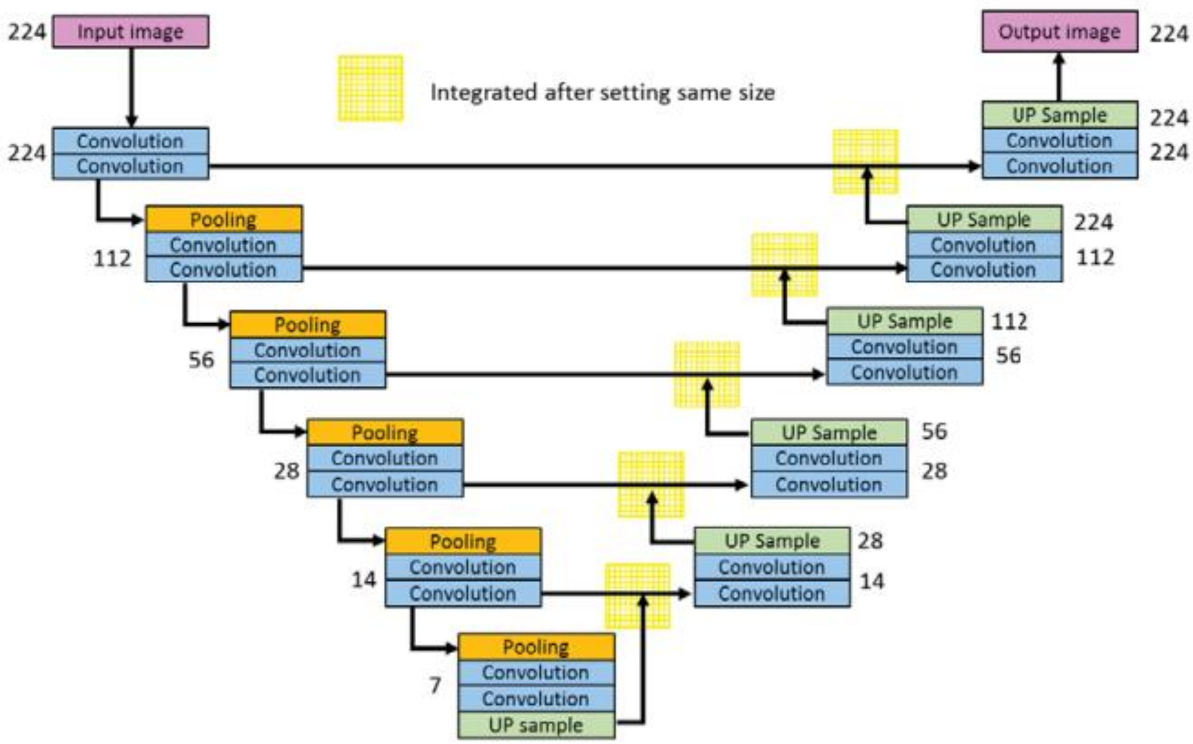

Fig.3 Structure of U-Net Model

FEATURE EXTRACTION

The convolutional neural network architecture is implemented with many layers such as convolutional, ReLu, max pooling. The architecture is inspired by AlexNet as shown in fig. 1. It consists of six layers of Conv2D, ReLu, Max-pooling and fully connected layer. Further layers like dropout added to the network to enhance the performance during training. The dropout layer is activated only during training. The dropout layer randomly drops certain number of neurons during forward pass (input to the function) and remembers the neurons that are left during the forward pass. And only updates the non-dropped during backward pass. The dropout is a feature

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that brings the regularization. The dropout layer makes the model to learn robust features that are independent to the neurons which in turn avoids the overfitting during the training phase.

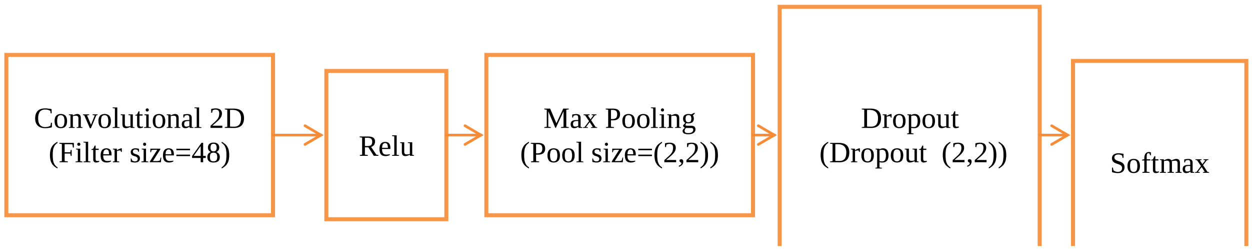

Fig 4 Structure of CNN

Fig. 4 illustrates the implementation of CNN architecture with required layers. This framework includes the repeated layers of Conv2D – ReLu – Maxpooling with various filter size and fit the model to extract the features of extracted hippocampal region. CNN is the recent technology utilized in deep feature extraction which assists to improves the classification accuracy.

CLASSIFICATION

The final stage of the present study is classification which is performed with SSGAN. This section describes the detailed procedure of SSGAN in AD detection.

SEMI SUPERVISED GENERATIVE ADVERSARIAL NETWORKS

The SSGAN based AD classification has two model *Generator (Gm)* and *Discriminator (Dm)*. These two model competete with each other as two player in mix-max game with the function $P(Dm, Gm)$ computed by the equation 1:

$$\min_{Gm} \max_{Dm} P(Dm, Gm) = E_{i \sim k_{data}\,(i)}\left[\log\left(Dm(i)\right)\right] + E_{a \sim k_a(a)}\left[\log\left(1 - Dm\left(Gm(a)\right)\right)\right] \quad (1)$$

Where i represents the input image and a denotes the noise vector. Generator creates a mapping method based on the previous noise distribution $k_a(a)$ to data space $Gm(a)$. Gm and Dm are both trained consecutively where constraints of Gm are adjusted to reduce log(1 $D(G(z))$) and constraints of Dm are adjusted to reduce log($D(x)$). The objective function of GAN is expressed as

$$\min_{Gm} \max_{Dm} P(Dm, Gm) = E_{i \sim k_{data}\,(i)}\left[\log\left(Dm(i|j)\right)\right] + E_{a \sim p_a(a)}\left[\log\left(1 - Dm\left(Gm(a|j)\right)\right)\right] \quad (2)$$

Where j denotes the labeled image that provides the auxiliary information [22]. Prior research [23] showed that GAN benefits the combination of traditional GAN and the loss. In addition the $ls1$ loss improves the performance of the segmentation model. Hence the loss method is defined for generator Ls_{Gm} that can be expressed as

$$Ls_{Gm} = \lambda_1 E_{i \sim k_{data}\,(i)}[\log(Dm(i, Gm(i)) + e)] + \lambda_2 E_{i,j \sim k_{data}\,(i,j)}[\|lm - Gm(i)\|_1] \quad (3)$$

Where i represents is the input image and e denotes the observed number to prevent overflow. lm represents the ground truth Hippocampus labeled images. λ_1 and λ_2 utilized to balance the

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losses with the values of 0.999 and 0.001 respectively. The loss method for discriminator Ls_{Dm} is given as

$$Ls_{Dm} = E_{i,j\sim k_{data}\ (i,j)}[\log(Dm(i,j) + e)] + E_{i\sim k_{data}\ (i)} \log(1 - Dm(i, Gm(i)) + e) \quad (4)$$

The generator and discriminator of AD Classification is optimized by the training process. The Adaptive Moment Estimation (Adam) is utilized for the optimization. The input is the MRI image dataset where as the corresponding labeled MRI image are grounth truth.

IV. EXPERIMENTS

The proposed HC segmentation model with semi supervised GAN architecture was implented with python platform. The keras and Tensorflow library is adopted for executing the deep learning architecture. The publically available HC dataset is used for testing the efficiency of the present segmentation model. The prior deep learning approaches sucn as convolution neural network and generative advers.

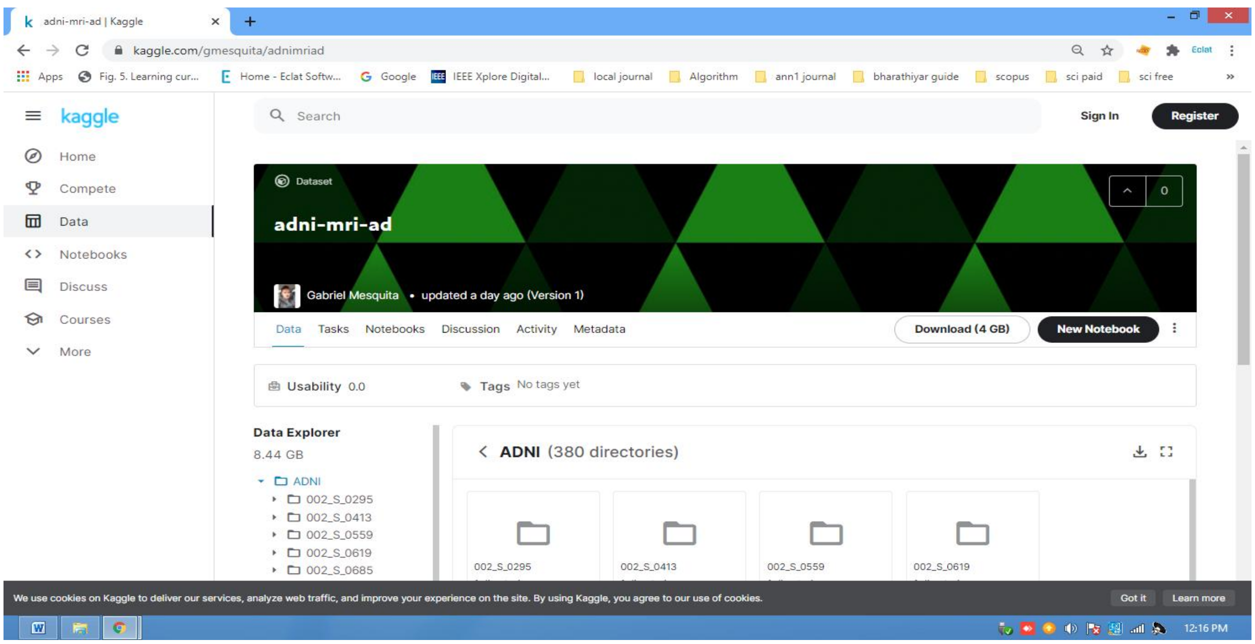

Fig 5 dataset collected from Kaggle data repository

The ADNI dataset is collected from Kaggle data repository. The screenshot of the dataset is shown in fig 5. The Dataset contains 8.44 GB data on brain MRI images. In this study 1000 images are taken for the evaluation 700 images are considered for training and 300 images are taken for testing. The Sample input images are illustrated in fig 6. The input images has the size of 197 x 233 px where the sizes are modified with 100x100 in order to reduce the execution time.

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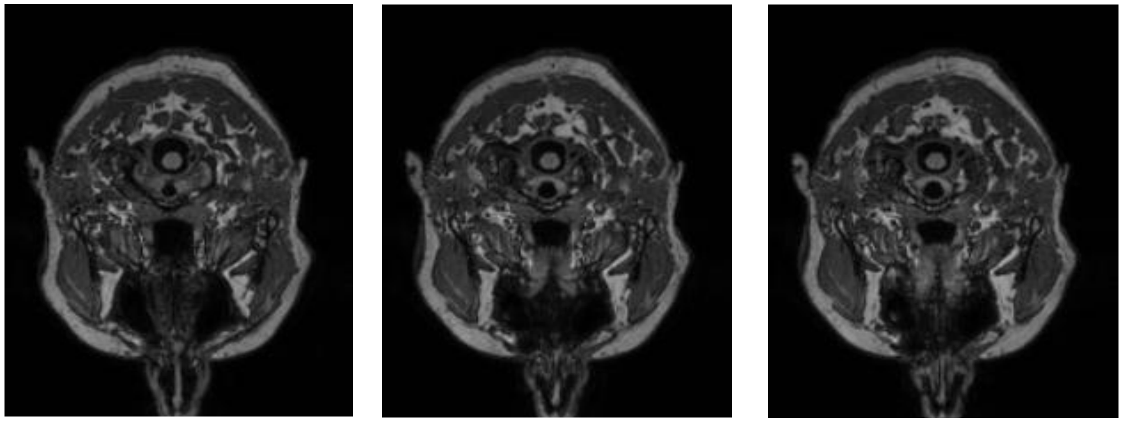

Fig 6 Sample input images

The accuracy and loss of training and the validation is illustrated in fig 7 and 8 respectively. The maximum accuracy 96% accuracy is achieved through this approach. Similarly the loss value is 0.2% which shows the efficiency of the present model.

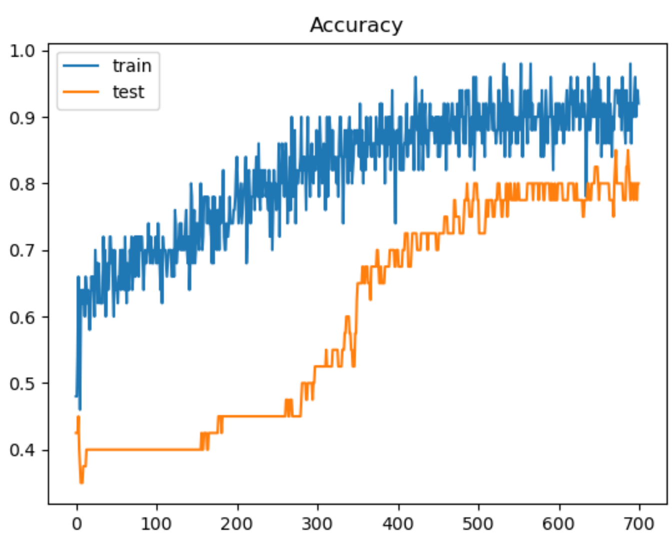

Fig 7 Accuracy on each epoch

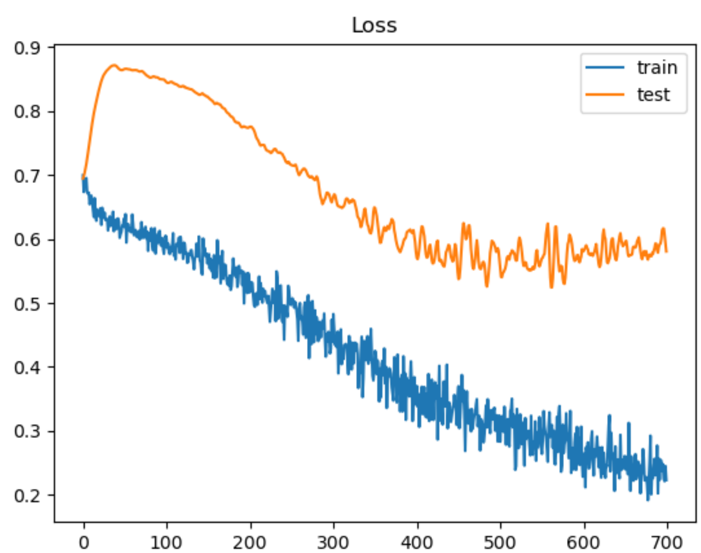

Fig 8 Loss on each epoch

The loss values used in GAN improves the performance by replicating the probability distribution. Above all the experiment conducted with the publically available MRI dataset for AD detection model achieves the efficient result.

Conclusion

In recent years AD is considered as a devastating illness that leads to cognitive deficiency and brain functional weakening. In this study a attempt is made to diagnose the AD in earlier stage based on semi supervised deep learning architecture. In addition the ADNI dataset is used for the evaluation of the present study. The model is start with the preprocessing the noise using

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the Gaussian filter and the hippocampal region is segmented from the brain structure, and then the deep features are extracted from the segmented area. Finally SSGAN is applied to perform the prediction and classification for AD. The experiment was carried out with total of 1000 MRI image and achieved the high accuracy compared to other deep learning model.

In this study only MRI dataset is used for the evaluation. In future this model will tested with more dataset like PET and fMRI etc., in addition this model can be applied for classifying other medical image classification such as breast cancer, tumor detection, liver cancer and kidney cortex, etc.,

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