A Deep Learning-based Semi-Supervised GAN to detect Alzheimer's illness efficiently

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3 authors:

Saravanakumar Subramanian
Kalasalingam Academy of Research and Education

T. Saravanan
GITAM University

Thillaiarasu Nadesan
REVA University

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S. Saravanakumar
Department of CSE
St. Martin's Engineering College,
Secunderabad, India
sar112113118@gmail.com

T. Saravanan
Department of CSE
St. Martin's Engineering College,
Secunderabad, India
tsaravcse@gmail.com

N.Thillaiarasu
School of Computing and Information Technology
Reva University,
Bengaluru, India
thillai888@gmail.com

Abstract— Alzheimer's disease (AD) prediction accuracy is crucial for minimizing memory loss and enhancing Alzheimer's disease patients' quality of life. Neuroimaging has been explored as a possible method for diagnosing Alzheimer's disease for the past decade. The goal of this study is to create a deep learning-an alzheimer's disease assessment from beginning to finish ahead of schedule on. The semi-supervised deep learning algorithm is a adversarial network generatively designed to detect the presence of Alzheimer's disease in magnetic resonance imaging data automatically. This model is mapped on the original representation and the semi-supervised Generative Adversarial Network classifier predicts the AD, the segmented result is used to efficiently partition the left and right-side hippocampal volume, and the deep feature from the segmented area is derived with convolution computational intelligence morphological operations. The current study uses the alzheimer's disease uses the dataset of neuroimaging initiative to perform the experiment. This method presents a revolutionary deep learning framework for detecting alzheimer's disease that can be used to patient data from the adult situation to improve medicine and standard of living.

Keywords—Alzheimer's disease, Classification, Segmentation, MRI image, Semi - Supervised GAN.

I. Introduction

Alzheimer's disease is one of the most communal reasons of dementia, affecting 30 million people globally [1]. It is a neurodegenerative disease that progresses lightly and results in the loss of nerve cells. Minor memory issues are the first indication, which progresses to serious brain affect. There has been presently no cure for dementia, and the medications that doctors prescribe simply slow the progression of the disease. As a result, the most effective strategy to improve treatment will be to discover the condition early. Figure 1 depicts the structural normal, mild cognitive impairment, and alzheimer's disease imaging modalities

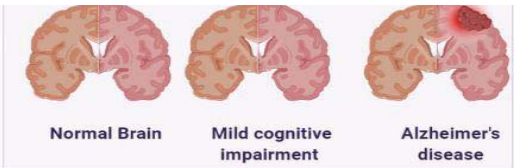

Fig. 1. Alzheimer's disease structural characteristics compared to a healthy brain

Many researchers have proposed various techniques for detecting alzheimer's disease using machine learning [2] and deep learning [3]. Recent research has shown that deep neural networks produce the best results in the analysis of medical imaging [4]. However, because these techniques were developed using the supervised learning architecture, they cannot be directly applied to topics with incomplete ground-truth medical scores for network exercise.

As a result, a semi-supervised deep knowledge architecture based on incomplete ground-truth data is proposed for neurodegenerative disease. This study begins with MR image preprocessing the with a Gaussian filter, followed by segmenting the hippocampal area with the u-net Finally, featured on CNN To gather deep information, extraction is carried out features for the classifier [5]. Finally, the semi-supervised generative adversarial network uses a generator and discriminator type to classify the data.

The current investigation is measured on the ADNI dataset and investigated to period leading up methodologies that used the stacked auto encoder as a classifier for detecting Alzheimer's disease [6]. For feature extraction and SAE, the prior study employed the multi atlas propagation strategy, which decreased interpolation, however, made pattern detection more difficult. The standard procedure produced excellent results for trained data but poor results for test data. This is taken into account in the suggested architecture, which increases overall accurateness.

The rest of this paper is organized as follows. Section II discusses the most recent studies on Alzheimer's disease detection using deep learning methods. Section III goes over the specifics of the techniques used and the proposed System. Section IV describes the investigational and the ADNI dataset used to create the setup, comparison methodologies, and performance evaluation results. Section V concludes this study by discussing limitations and potential future research directions.

II. Magnetic Resonance Imaging

Magnetic reverberation imaging is a rapidly evolving imaging technique that produces interned sectioned images in an imaging level [7]. The magnetic resonance imaging which is based on nuclear magnetic resonance, aids in imaging the human body. When evaluating the internal architecture of the knee, MRI has many advantages over other modalities. It's a pleasant, non-invasive procedure that produces good soft tissue contrast and allows imaging in many planes while exposing the patient to no radiation. The current work segments the hippocampus using MRI scans in order to diagnose alzheimer's disease is a type of dementia.

Image segmentation is a labelling problem that involves splitting images into parts that are significant for a certain task.

This will include using CT or MR scans to detect a brain tumour. The process of segmentation is the initial step toward Image interpretation and analysis. The aim will be simple to state, but attaining it with precision will be tough. The processing of medical images presents a number of difficulties [8]:

1. Image acquisition and reconstruction.
2. Specialty categorization that is accurate and automated
3. A multimodal image registration system that is both automatic and precise.
4. The features of an image are ordered.
5. The image has a computable dimension and their quantities are clarified.
6. Development of integrated systems for clinical applications

for finding objects of interest, image segmentation is widely utilized [9]. and boundaries that allow for more meaningful representation of a stack of volumetric images for easier analysis. Obtaining boundary information for regions of interest is traditionally done manually, slice by slice, and requires specialist knowledge [10].

III. Related Works

This section highlights significant research contributions in the areas of noise reduction, segmentation, machine learning, and deep learning techniques.

Using a decision-based strategy, Biswas et al. [11] analyses many denoising strategies and presented a novel method for reducing impulse noise. These approaches primarily kept image information while decreasing impulsive noise. The benefits of those approaches are demonstrated by the mean different filtered Images of absolute error and optimum detection sensitivity. The findings have also been confirmed by the researchers, who are experts in the field of cognitive awareness

Mito R et al. [12] developed a new approach for background subtraction approach for MRI that employs curvelet transform thresholding in combination with the Wiener filter (MRI). They compared their findings to those of other curvelet and wavelet-based denoising methods. The image's quality was assessed using Optimal sensor efficiency, mean absolute error, and functional relationship are all things to think about. The experiment's findings reveal that their method outperforms that of their competitors.

Kong et al. [13] created a new pixel-based technique-based evaluation, which looked into the differences between voxels and calculated the axonal losses induced by alzheimer's disease and moderate cognitive impairment. Patients with alzheimer's disease, the authors hypothesized, would have total functional deterioration.

To capture the distinctive contours, A curvelet approach was developed by Awate G et al. [14]. The CNN model with deep learning can be used to conduct automatic image segmentation. The capacity of this segmentation technology to quantitatively identify brain atrophy is demonstrated by the quantification of segmented grey and white matter information.

Lee et al. [15] developed a novel technique for diagnosing hypertension from MRI by combining a classifier with a Tensorflow backend and employing the transfer learning approach. This paradigm is used to categorise the various stages of Hypertension. Razavi et al. [16] used an ensemble of deep Convolutional networks to develop a new technique for detecting hypertension. This representations are used in the medical dataset to identify the various phases of vascular dementia in order to achieve an early diagnosis.

Saravanan et al. [17] devised a novel method that incorporates multi-domain longitudinal data. Using only one modality of data individually, the prediction model for MCI transformation to alzheimer's disease displayed an accuracy of up to 77 percent (area under curve = 0.85). The performance improved by 81 percent (area under curve =0.86) when longitudinal multi-domain data was included. A multi-modal deep learning method offers the ability to detect those at risk of alzheimer's disease.

Machine learning algorithms, particularly deep learning, were useful for learning raw data features for a smart diagnosis of alzheimer's illness. A two-layer uncontrolled neural network was used to learn features from raw input directly at the first stage of learning, dispersed faltering. In the key process, Convolution layers extrapolation was used to categories the medical problem based on the learnt features. Statistics of alzheimer's brain scans were used to verify the theoretical technique.

IV. The Proposed Methodology

The semi-supervised GAN deep learning technique is utilised to identify Alzheimer's disease in this research. This section explains how the current diagnostics model works. The complete working technique for detecting Alzheimer's disease is depicted in Figure 2. The approach begins with noise removal from the ADNI MRI data, followed by segmentin the hippocampus region and extracting the the segmented model's deep characteristics. Next, there is the classifier generates detection findings that aid in alzheimer's disease diagnosis.

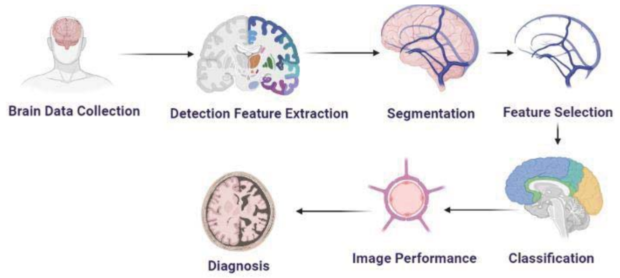

Fig. 2. Parkinson's Disease Diagnosis Process

A. Feature extraction

Filtering is the very first level of this investigation. The Gaussian filter is used to eliminate noise from magnetic resonance imaging images. Any non - self technique's goalis the initial step in the process of removing noise from an image either computer vision process. The Gaussian filter is used to eliminate noise from magnetic resonance imaging images. Gaussian filtering has gained a lot of interest in image processing and computer vision. The signal is distorted, but the noise is smoothed out using a for noise reduction, use a Gaussian filter.

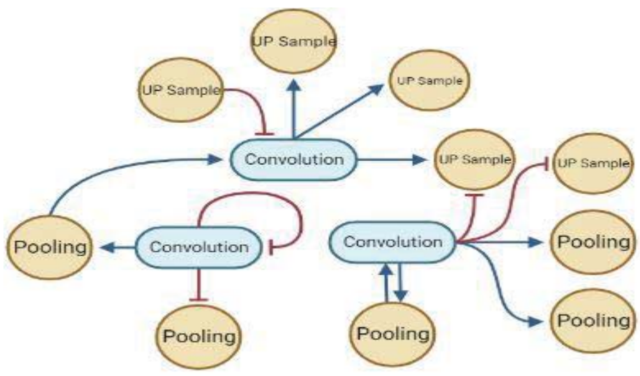

Fig. 3. U-Net Model Architecture

B. Segmentation

As depicted in Fig.3, U-Net is a Completely Convolutional Network with a U-shaped structure. The picture size is increased with After extracting feature values, deconvolution and up sampling layers are used to reduce image size, whereas convolution and pooling layers are used to reduce image size. Finally, the size of the output image is the same as the size of the original image. The learning process begins once the training data is sent into U-Net is created, and a region extraction model is created. After that, an MRI picture of test data is fed into the created model, and U-Net produces an estimated image.

C. Feature Extraction

Many layers, including convolutional, ReLu, and max pooling, are used to implement the convolutional neural network architecture. The architecture is based on Alex Net, as shown in Fig. 1. ReLu, Conv2D, Max-pooling, and a completely connected layer are among the six layers. To improve training performance, additional layers such as dropout, are additional to the network. Only during exercise is the attrition layer active. During the forward pass (input to the function), the attrition layer removes a random number of neurons, and the neurons that remain after the forward pass are remembered. During the backward pass, only non-dropped items are updated. Pooling layer is a feature that promotes batch normalization. The dropout layer tells the model to look for neuron-independent robust traits, preventing overfitting during the training phase.

To extract the features of the extracted hippocampus region, this framework employs multiple layers of Conv2D – ReLu – Maxpooling with variable filter sizes. CNN is a revolutionary deep feature extraction technology that helps increase grading specificity.

D. Categorisation

The proposed poll's segmentation stage is completed using SSGAN. The SSGAN detection process is detailed in this section.

E. Generative adversarial Networks with Semi-Supervision

There are two models for AD classification based on SSGAN: Generator (Gm) and Discriminator (D) (Dm). Using the function P (Dm, Gm) derived by the equation, these two models compete like two players in a mix-max game.

$$\text{Min max}\sum_{i+kdata}[\log Dm(i))] + \log 1 - Dm(Gm(a))] \quad (1)$$
Gm Dm

The input image is denoted by i while the noise vector is indicated by a. Generator produces a mapping technique for data space Gm a based on the prior noise distribution ka a. Both Gm and Dm are Gm's restrictions were adjusted to minimize the training timeDm's restrictions and log(1 D(G(z)) have been changed to minimize log(D(x)). GAN's objective function is as follows:

$$\text{Minmax}\sum_{i+kdata}[\log Dm(i))] + \log 1 - Dm(Gm(a/j))](2)$$
Gm Dm

Where j refers to the labeled image that contains the auxiliary data [22]. GAN advantages the combination of traditional GAN and the loss, according to previous research [23]. In addition, the ls1 loss increases the segmentation model's performance. As a result, the loss technique for generator LsGm is defined, which may be represented as

$$Lx_iGm = \sum_{i+kdata}[\log Dm(i))] + \log 1 - Dm(Gm(a/j))](3)$$

To avoid overflow, i denotes the input picture and e denotes the observed number. The ground truth Hippocampus labeled images are represented by lm. With values of 0.999 and 0.001 respectively, 1 and 2 were used to offset the losses. The discriminator LsDm's loss mechanism is as follows:

$$Lx_iGm = \sum_{i+j,kdata}[\log Dm(i))] + \log 1 - Dm\left(Gm\left(\frac{a}{j}\right)\right) + e](4)$$

The training approach optimizes the AD Classification generator and discriminator. For the optimization, Adaptive Moment Estimation (Adam) is used. The MRI image dataset is the input, whereas the associated labelled MRI picture is the ground truth.

V. EXPERIMENTS

The proposed HC segmentation model was implemented in Python using a semi-supervised GAN framework. The deep learning architecture is implemented using the keras and Tensorflow libraries. The efficiency of the current segmentation model is tested using the publicly accessible HC dataset. Prior deep learning methods included convolutional neural networks and generative adversarial networks. Figure 5 illustrates a dataset obtained from the Kaggle data source.

On Kaggle's data archive, the ADNI dataset was discovered. Figure 5 depicts a snapshot of the dataset. The dataset contains 8.49 GB of data from MRI scans of the brain. A total of 1000 images were taken for this study's evaluation. 700 images are used in the training process, whereas 300 images are used in the testing process. Figure 6 shows some examples of input images. The input photos are 197 x 233 pixels; however, the sizes have been changed to 100x100 to reduce the execution time.

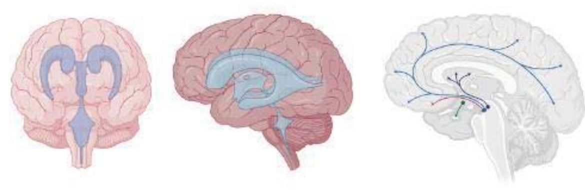

Fig. 4. Input image thumbnails

Figures 7 and 8 show the accuracy and loss of training and validation, respectively. With this method, you can achieve a maximum accuracy of 97 percent. Similarly, the model's efficiency is demonstrated by the loss value of 0.3 percent.

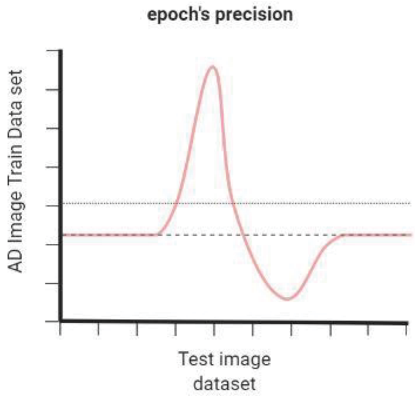

Fig. 5. With epoch's precision

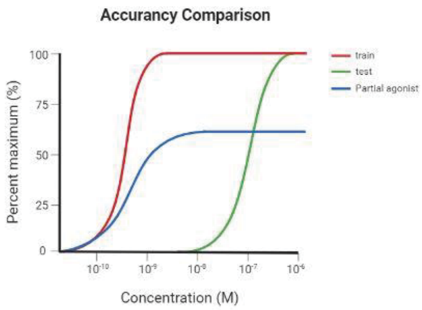

Fig. 6. With epoch's decline

By repeating the probability distribution, the loss values used in generative adversarial network increase performance. Then there's the alzheimer's disease detection model experimented with using a publically available MRI dataset yielded a successful outcome.

VI. CONCLUSION

Alzheimer's disease has come to be viewed as a terrible illness that causes cognitive deficiencies and degeneration in brain function in recent years. This work uses a semi-supervised deep learning architecture to try to diagnose Alzheimer's disease earlier. In addition, the current work is evaluated using the ADNI dataset. The model starts by filtering the noise with a Gaussian filter, then segmenting the hippocampal region from the central nervous system and extracting key characteristics of the divided area. Finally, semi-supervised Generative Adversarial Network is utilized to diagnose and forecast alzheimer's disease. The only dataset used in this study for evaluation was an MRI dataset. This model will be tested with more datasets in the future, including PET and fMRI, and it might be used to identify other medical images breast cancer, tumour detection, liver cancer, and renal cortex are just a few examples.

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