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Visualization of Progression from MCI to AD in MRI Images

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Abstract:
Memory problems are one of the first signs of cognitive impairment. Difficulties with movement and problems with the sense of smell are some factors related to mild cognitive impairment (MCI), most often in older adults with MCI or at a greater risk of developing Alzheimer's disease (AD). Signs and symptoms may vary from person to person, so it is difficult for the researchers to diagnose the early changes in the brain with MCI vs. cognitively normal people who are at greater risk of developing Alzheimer's disease. Imaging techniques are noninvasive; MRI (magnetic resonance imaging) is the first step in the diagnosis of a brain condition and helps to visualize the structure and function of the brain. Machine learning methods along the MRI imaging process have the highest accuracy rate in achieving the classification of brain abnormalities. This research methodology proposes automated feature extraction using an equilibrium optimization algorithm with a deep learning process for the given MRI images. The goal of the proposed algorithm is to recognize and classify brain abnormalities and differentiate between cognitively normal, MCI, and Alzheimer's disease using the deeper belief network (DBN). The experimental evaluation of the tested data on structural brain MRI images uses the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset.

Keywords: (MCI)Mild Cognitive Impairment, (AD)Alzheimer’s disease, (MRI) Magnetic resonance imaging, Equilibrium Optimization Algorithm, Deep learning, (DBN)Deep Belief Network, (ADNI)Alzheimer's Disease Neuroimaging Initiative.

INTRODUCTION

Recently, an Alzheimer's Disease International (ADI) report stated there are 5.2 million people in America impacted by Alzheimer's disease, and the numbers are expected to reach 10 million within 2050 [5]. The neurons in the brain cells, which are responsible for memory, language, and thinking problems, are damaged. So, the first symptom of Alzheimer's disease is memory loss, which is considered to be the main cause of dementia [6]. Alzheimer’s patients, compared with normal patients, will have a change in brain shape; this is visible using MRI studies since some neurons in the affected brain parts are affected or reduced. Alzheimer’s disease is also called mild cognitive impairment because the symptoms of the initial stages are normal, but when the damage is severe, it is called Alzheimer’s disease. According to various studies, the conversion rate from MCI to AD in patients is high; this is due to the development of atrophy in certain brain parts (the hippocampal region) [Figure 1]. This neurological disorder is a progressive disease, which means that over time, the ability to think and carry out even simple tasks of day-to-day activities will become more difficult. In the early stages of dementia, the hippocampus region of the brain

suffers brain damage, resulting in short-term memory loss and disorientation; in the advanced stages of dementia, the brain cells in the hippocampus region shrink, and the patient is completely reliant on others to perform daily tasks.

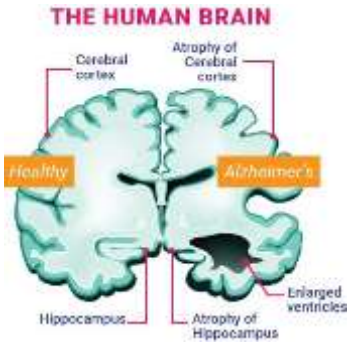


Figure:1 The progression of MCI to AD

People over the age of 60 are more likely to be affected. Alzheimer's disease is difficult to diagnose because early symptoms are frequently misdiagnosed as normal ageing problems. Since there is no cure for dementia, early detection and timely diagnosis are the only solutions to this irreversible disease.
The study work for the detection of Alzheimer's disease is based on a computer vision approach using image data with a 3D volume where the brain image is obtained from MRI. Various research papers have been done already to detect MCI, AD, and normal healthy control by categorizing the changes that occur in the brain volume and shape. Lama et al. compared the diagnosis process using structural magnetic resonance imaging (sMRI) for discriminating brain changes in their paper work. Biju et al. compared the segmentation images of MRI for AD, CN, and MCI. [14] In another approach, the ROI features are determined using a convolutional neural network with sMRI and fMRI modalities. This paper explains the positive and negative cases by measuring the white matter ratio. Researchers in this era are constantly striving to achieve highly affordable models with accurate algorithms for solving complex healthcare problems in order to assist medical practitioners. Machine learning techniques, especially deep learning-based convolutional neural networks (CNN), are used to improve the process of detection and classification of Alzheimer's disease. Medical imaging techniques are highly precise in the diagnosis of MCI and identify the early stages of AD.

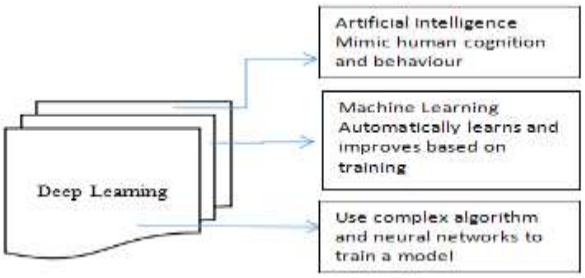


Figure : 2 Definition of AI, ML, DL

This study develops an equilibrium optimization algorithm with deep learning [12] for the given MRI images. Magnetic resonance imaging (MRI), the most widely used imaging model that differentiates

between MCI, AD, and other neurological disorders, The existing research, starting with diagnosing with imaging modalities, follows almost the same steps as pre-processing, segmentation (region of interest), feature extraction, future selection, and finally classification. However, overcoming the challenges and limiting the drawbacks is the main goal. Therefore, in this paper, we propose deep learning-based binary classification and detection of Alzheimer's disease. This technique begins with two stages: 1) Denoising using filtering-based noise elimination 2) U-Net segmentation-based skull stripping Besides, for feature extraction, the Squeeze Net Equilibrium Optimization Algorithm is used, and the Deep Belief Network is applied for brain disorder classification. The final outcome of this proposed technique is evaluated using brain MRI scans from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. For achieving a good extraction of features, use the Finer-DBN framework. The main goal of this paper is to detect Alzheimer's disease in positive cases with an effective and efficient running time and formulation.

RELATED WORKS

This section carries the source findings of early MCI and various AD publications searched using Google Scholar. Earlier in 1910, clinical psychiatry discussed the deaths of subjects due to brain diseases—one-third of the cerebral cortex with a sudden burst of neurofibrils—and some of them were denoted as the cause of severe malnutrition, indicating the ambiguous clinical definition.

The name Alzheimer's was given by German psychiatrist Alois Alzheimer in 1906. As the cause of brain damage, he described a brain disorder with some plaques and neurofibrils in the brain parts. In 1998, some researchers and scientists around the world concluded that shrinking all the damaged parts was the cause of the symptoms of early MCI or AD. Dr. Gerber from the neurobiology department of Planck's University researched amyloid plagues in 1997; this led to the seriousness of the study of MCI [27]. In those studies that mentioned disease prediction using new methodologies and expected a high accuracy rate, various brain imaging techniques were used to identify Alzheimer's. Here are some of the most important real-time imaging modules:

MRI (Magnetic resonance imaging) [28–29] MRI is the most commonly used technique for producing high-quality, high-resolution 3D images of the brain's structure and function; thus, the topography of the brain as well as the visual cortex are studied .SPECT (single photon emission computed tomography) On comparing SPECT with MRI, the first mentioned technique is more economical and mentions the examination of cerebral cortex blood flow [30]. PET (positron tomography) tracing is used for AD diagnosis to visualize certain functional activities of the brain like remembering, visualizing, working, etc. These activities are analyzed using radioactive spheres, which may have some negative impacts on the patients in the future. Biomarkers of AD [31] Biomarkers are used for precise measurements of certain special properties, like identifying AD neuropathology; these are reliable, non-invasive methodologies. There are three kinds of biomarkers for describing AD: genetic, biochemical, and neuroimaging.

Machine learning is the fastest method that is used to predict disease using a computer vision approach. The transition-based approach to the computer vision approach has improved the prediction and determination of the disease by avoiding human error by the medical practitioner, which may be helpful in cases of earlier diagnosis. [32] In Haller et al., the author examined early MCI in a variety of subjects in the study work. The SVM (support vector machine)[33] machine learning process is used for initial disease area segmentation using the ROI from image classification and the classic texture description. Nowadays, deep learning paves the way for a new era in the world of artificial intelligence in determining the positive and negative cases and in training, tuning, and testing methodology. [34] Deep learning uses

two architectures to understand sound, text, and image: "generative architecture" and "discriminative architecture." Deep neural networks use the bio imaging datasets with data augmentation because the documentation process has a well-known procedure in the initial stage of processing the image, like translating and rotating the input. Very recently, generative advisory networks have been used to blend and modify the image by comparing it with the basic one. [30] [31]: For this training of data, it is essential. Most of the research work uses deep neural networks, which tend to achieve high accuracy and reduce the computational cost. [32] SVM-based research is commonly used to classify normal control, MCI, and Alzheimer's disease coup et al.[33]. Mentions characteristics that can be used to differentiate MCI, such as the volume of the left and right hippocampus regions, the thickness of the left precuneal cortical, the anterior part of the parahippocampus, and the temporal region of the left superior brain.Wolf et al., Basia et al., and Liu et al. mention the subjects and compare the data to the total number of healthy controls, Alzheimer's disease cases, and mild cognitive impairment cases.

METHODOLOGY

Alzheimer's disease is a progressive neurological disorder that starts from Mild memory loss gradually erodes one's ability to carry on a conversation and respond to their surroundings; it is the second most feared disease after cancer. Since there is no cure for AD, earlier identification will have prospective benefits. Usually, the first stage of the diagnosis will be based on the information provided by a clinical examination using brain imaging techniques. Noninvasive visualisation of brain images is generally divided into two types: 1) structural image 2) functional imaging.

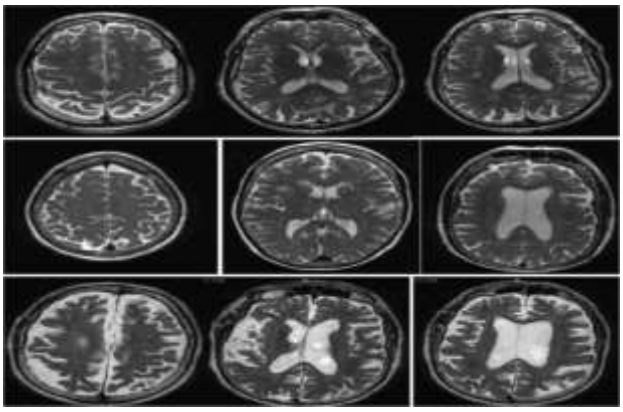
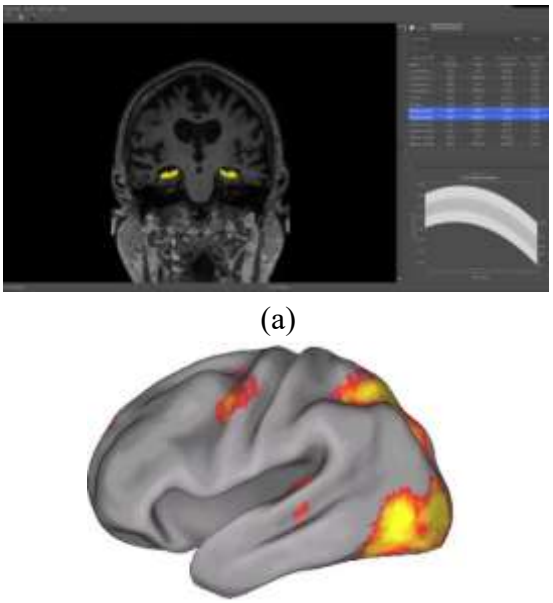


Figure: 3 Example of Brain MRI images (cross-section) of CN; MCI (middle row); AD (bottom row) CN = Cognitive Normal; MCI = Mild Cognitive Impairment; AD = Alzheimer's disease

Structural imaging [8] gives brain structure, including neuronal connections, synapses, etc. The activity of the brain is visualized in functional imaging. In this paper, we evaluate magnetic resonance imaging (MRI) technique images because MRI produces high-quality, high-resolution 2D and 3D images of the brain. The experimental evaluation of training and testing is processed using MRI scans from the Alzheimer's disease Neuroimaging Initiative (ADNI) dataset. Initially, during the data acquisition and preprocessing stages, bilateral filtering-based noise elimination is combined with U-Net segmentation-based skull stripping to denoise the raw image acquired from MRI scans in the ADNI dataset. The normalization is performed in the denoised image, which has a mean value of 0.1 percent. The high intensity level is selected for intensity normalization. The high-dimensional issue is overcome using the feature selection method. Feature extraction is applied using Squeeze Net's equilibrium optimization

algorithm.



(a)

(b)

Figure: 4 (a) & (b) Brain area in older controls and AD of sMRI and fMRI from ADNI datasets
[sMRI= Structural Magnetic Resonance Imaging;
fMRI=Functional Magnetic Resonance Imaging]

To extract coarse- and fine-grained features, this method implements the finer deep belief network (finer DBN) alongside a tensor flow network using an MCI-based recognition framework for dementia. This structure is composed of multiple staked ConvRBM modules. The parameters are fixed, and the first ConvRBM with normalized datasets is trained. The output of the first module is used as the input for the second, and the layer-wise training process is used to obtain reconstructed data by minimizing error, and finally, the proposed model uses the RBF kernel in SVM for disease classification.

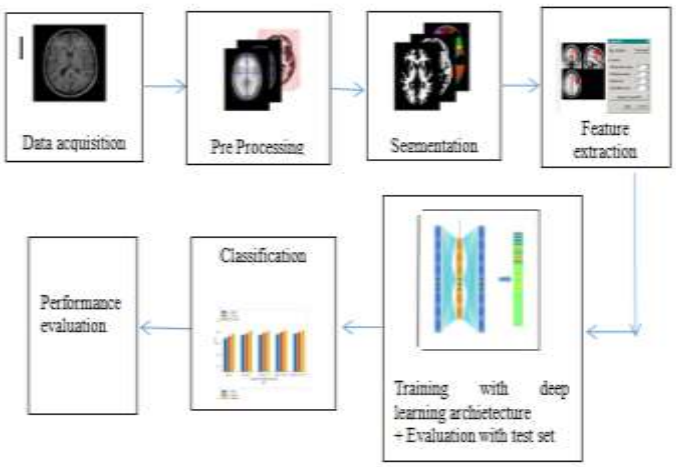


Figure: 5 Research workflow

A. DATA ACQUISITION AND PREPROCESSING

Data Collection: Alzheimer's disease is an irreversible disease that will not be visible for years, but detecting MCI in its early stages is critical for Alzheimer's disease diagnosis The initial identification

process is supported by two major sources: neuroimaging and biomarkers. In the proposed methodology, training datasets are obtained from the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) project, which provides information regarding the structure and functional data of the brain.
The ADNI study started in 2004 and contains four phases: ADNI-1, ADNI-GO, ADNI-2, and ADNI-3.

1) ADNI 1- started in 2004(5 years)

a. Objective - Biomarkers used to examine stages of Alzheimer's disease detection and further growth of the disease.
b. Study- 200 elderly controls,400 MCI,200 AD subjects with their brain scans and genetic history

2) ADNI GO - started in 2009 (two years)

a. Objective - detection of AD at early stages
b. Study - 200 new EMCI subjects

3) ADNI 2 - started in 2011 (five years)

a. Objective - to identify and analyse cognitive impairment
b. Study - along with existing it includes 150 healthy controls, 100 yearly MCI, 150 late MCI, 150 AD subjects.

4) ADNI -3 - started in 2016 and continues in exploring clinical, cognitive, imaging, biochemical biomarker characteristics of AD.

a. Study - ADNI 3 includes 59 research centers with the previous data, they added 133 normal controls, 151 MCI, 87 AD participants.

Image preprocessing:
In this methodology, the ADNI images were obtained for performance evaluation, but before they were actually functional, they underwent certain free processing steps. The automation of the augmentation process starts with loading and resizing the images; the images are also preprocessed using the VBM8 Toolbox in SPM8, and the outcomes are performed in MATLAB 2010b. The combination of structural MRI with the execution module has a single modality known as multifeatured kernel discriminant dictionary learning, which achieves a higher accuracy rate in classifying AD, CN, and MCI than other similar discriminant dictionary learning techniques.
For converting the image into a series of numbers, see numpy. The dataset is fed into the convolution block after an array (input) is used. Convolution block hashing components aid in the extraction of features for disease diagnosis and classification. The components are convolution, ReLU (Rectified Linear Input Unit), and some pooling components. The convolution block identifies the Hippocampus region of the brain, and its shrinkage represents Alzheimer's disease.

B. NORMALISATION

The rate of change in the pixel intensity values is known as "normalization." Generally, normalization is also called "dynamic range of expansion," "contrast stretching," and "histogram stretching." Intensity normalizations may have some problems that occur when the peak intensity input values are combined with the noise for the given image. From the paper [27], the intensity normalization of the proposed method has a mean value of 0.1% voxels with high intensity levels for the selected pixels; this will possibly avoid errors in the denoised image. The intensity is applied based on the mean value of a group of voxels with high intensity values.

C. FEATURE SEGMENTATION

Before applying the proposed method, image to signal conversion takes place using a mathematical reshape function, where 2D or 3D images are converted into 1D vector images. In this methodology, the

U-Net image segmentation tool is used because of its high utility in the medical imaging community. The basic structure of U-NET has two paths: a contracting path and an expansion path. The contracting path is very similar to the convolution neural network and gives classification outcomes, whereas the expansion path has classification outcomes along with high resolution, then finally passes to the convolution layer to get the segmented image with the ROI (region of interest).

U-net architecture

The contracting path of U-NET architecture typical CNN architecture each block consists of two successive 3x3 convolutions with its activation unit, pooling layer and ReLU, The expensive path up samples 2x2 up convolution [17]. Finally, additional 1 x 1 convolution is applied so reduce the feature map and crop the segmented image. The cropping is important since the pixel shows the edges with least amount of contextual information. Final result in resembling the U-shaped network allows the segment object and avoid overlapping area.

The network energy function is formulated as,

$$E = \sum_{W(X)\log pk(x)}(x)$$

Where, pk is the pixel-wise SoftMax function, for the final feature map this above formula is applied and defined as, $p_{k=\exp(ak(x))/\sum_k \exp(ak(x)')}$

and ak denotes the activation in channel k.

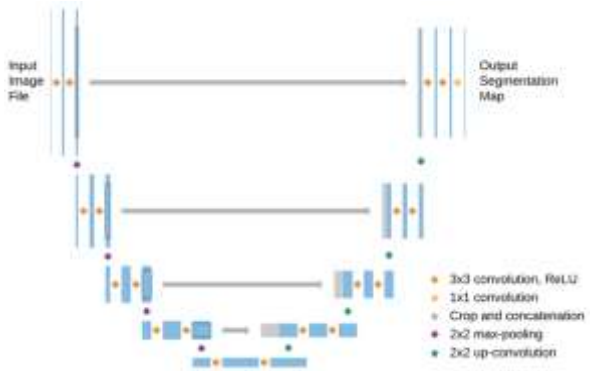


Figure: 6 Basic U-Net architecture

The primary task of U-NET model is to show and separate the outline of the object for the given input image.

D. FEATURE EXTRACTION

This step in feature extraction undergoes decomposition using the ADNI dataset. To carry out decomposition for the selected images, a high intensity level is used for differentiating among the selected pixels. The processing time of three-dimensional images is higher, and the memory size is very large when compared with two-dimensional images. For example, for the 120 selected images, the number of extracted features will be more or less 2122945 pixels.

This study work is used to minimize the large dimensionality in the given 3D images, after which this image has a reduced number of pixels. However, extracting the most important features while ignoring the unnecessary ones improves the classifier's performance.

For processing, the feature extraction of the input image is outlined as follows as,

Initially, the acquired image from the ADNI project dataset is divided into two categories, the first sets has demented (abnormal or positive case) group and the other has non demented (normal or negative) group.

calculating the mean for each group

Assume, μ1 and μ2 as the mean value of first and second group

$\mu_{1=\frac{1}{n}*\sum_{i=lz}^{n} xi}$, $\mu_{2=\frac{1}{m}*\sum_{j=lz}^{m} xj}$,

---- (1) & (2)

Where, n & Xi represent the number of images in first group - m &Xj represents the number of images in the second group

μ1 μ2- repeation of each feature in first and second group.

calculating standard deviations for each group

$$\sigma 1 = \sqrt{\frac{\sum_{i=1}^{n}(xi-\mu 1)2}{n-1}}, \quad \text{----- (3)}$$

Where σ1, xi n and μ1 represent as the value of first group

$$\sigma 2 = \sqrt{\frac{\sum_{i=1}^{m}(yj-\mu 2)2}{m-1}}, \quad \text{----- (4)}$$

Where σ2, yj n and μ2 represents the value of second group.

w denotes the weight of each feature and the value is calculated for both the groups. Difference between mean (1) & (2) is divided by multiplying the standard deviation (3) & (4) along with it.

$$w = \frac{|\mu 1-\mu 2|}{\sigma 1*\sigma 2} \quad \text{----- (5)}$$

w percent is calculated as,

$$w_{percent} = 100 * \frac{w}{\sum_{i=1}^{N} w1} \quad \text{------ (6)}$$

$i = 1,2, \ldots . N$ features Where, wi represents the summation of all features. The sample database with cross-validation is done by randomly choosing the 10- folds and the loop is repeated.

Cross validation

This technique is used for validating the performance of input data by training and testing the previously given subset of the input datasets. Training and testing the model with the already-trained datasets are mostly used to check the statistical model on an independent dataset. In machine learning algorithms, the cross-validation technique is used for testing the stability of the given model. Here are some basic steps in the cross-validation methodology:

1. Reserve a subset for validation.
2. Train the model using a training dataset.
3. Evaluate the model's performance; if the model performs well with the validation set, then proceed further.

In our paper work, a "fold" working model is used, and the datasets are divided into equal-sized subsets. K-1 is trained, then other folds are tested, and the loop is repeated K times. Hence, k denotes the size of the training set. After validation, one data point is left out, which is known as LOOCV (Leave One Out Cross Validation).

E. CLASSIFICATION

The proposed novel method uses the Finer DBN model combined with a dementia recognition framework. The Finer DBN model categories fMRI data using the layer activation method along with learned activation maps that can be easily interpreted. The first layer in the higher order levels of the DBN structure shows active brain spot feature extraction; the extracted feature spots are larger than the reconstructed data. Occipital lobe and left prefrontal lobe function play a vital role in the classification of dementia recognition in the brain region, and dementia in the brain structure has different stages. Biomarkers are

used to mark the differentiation of every stage of dementia exactly in the right hippocampus region.
The basis of Finer-DBN is the RBM (Restricted Boltzmann Machine). RBM consists of two layers, namely, a visible layer and a hidden layer. Finer-DBN is a deep learning model with cascade structures, which are the combination of multiple ConvRBM modules. As mentioned earlier, the ConvRBM modules of the first module's output are the input for the second module. This novel approach uses the dual branch structure with a 1D convolution branch. This 1D branch is more compatible with the input data; however, the main focus during feature extraction is to ensure that the stubble information is not lost during the process. The basic principle behind using Finer-DBN is the maximum likelihood estimation principle, which is more attractive for model interpretability.
Once the Finer-DBN training is completed, SVM is used for the classification of Alzheimer's disease. Support vector machines with RBF kernels are dependent on hyper parameters. In recognizing a novel framework for dementia disease Accuracy, sensitivity, and specificity scores were calculated with 10-fold cross-validation. The following are the specific definitions that are used for evaluation:
Positive Samples - classified as NC
Negative Samples - classified as MCI or AD

- False +ve (FP): Number of patients correctly labelled with +ve samples
- False -ve (FN): Number of patients incorrectly labelled with -ve samples
- True +ve (TP): Number of patients correctly labelled with +ve samples
- True -ve (TN): Number of patients incorrectly labelled with -ve samples

The following formulas for Accuracy, Specificity, Sensitivity is defined using the above functionalities,

- Accuracy(A) = TP + TN / FP+FN+TP+TN
- Specificity (Sp) = TN / TN + FP
- Recall (Re) = TP/ TP+ FN
- Fscore = 2X (PXR)/P+R

RESULTS AND CONCLUSION

In this study, standardized procedures were followed. For training and testing, datasets for 334 subjects are taken from the online, open-source Alzheimer's Disease Neuroimaging Initiative (ADNI) project to get the classification of normal, MCI, or AD. The volume of each subject is discarded before the preprocessing step; however, some of the volume reminders in the subject are used to perform outlier detection, motion estimation, direct segmentation, normalizations, etc. All subjects' normalized procedures were carried out in a 152-square-foot space with a spatial resolution of 2 mm at the Montreal Neurological Institute. The information on Table 1 represents the normal group of subjects' data that are acquired from ADNI datasets.

Information from ADNI project Dataset denotes demographic,clinical features of CN,MCI and AD

	CN	AD	c-MCI	s-MCI	P AD vs HC	P c-MCI vs HC	P s-MCI vs HC	P AD vs c-MCI	P AD vs s-MCI	P c-MCI vs s-MCI
N	352	294	253	510						
Men/women [Gender]	167/185	158/136	151/102	287/223						
Age [Mean ± Standard Deviation]	74.53 ±6.16	75.13±7.75	73.80±7.35	72.33±7.68	1.00	1.00	<0.001	0.20	<0.001	0.05

Values are numbers or means ± standard deviations (range). *P* values refer to ANOVA models, followed by post-hoc pairwise comparisons (Bonferroni-corrected for multiple comparisons), or Chi-squared test.

AD = Alzheimer's Disease; CN = Cognitive Normal; MCI = Mild Cognitive Impairment (c = converters; s = stable);N = Number.

Table: 1 Standardized dataset from ADNI project

For the recognition results in the proposed method to be evaluated on the ADNI database with a 10-fold cross-validation strategy, the classification task for the given dataset is specifically performed using the binary classification, i.e., CN vs. eMCI, NC vs. AD, eMCI vs. AD.

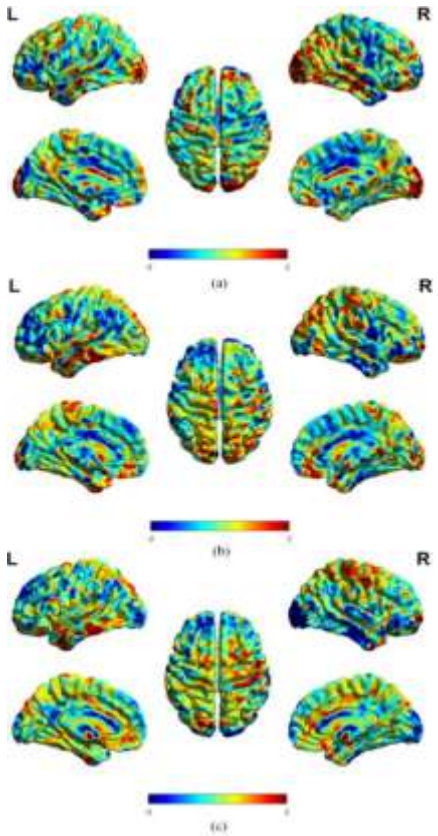


Figure: 7 ADNI data of Neurological disorder of brain maps. (a) CN vs eMCI, (b) CN vs AD. (c) eMCI vs AD

Typically, for this type of classification task with so much imbalanced data, a random sample is chosen from another category to evaluate the test and try the model. The test process was performed 10 times to get the average along with the relatively fair result. Finer-DBN employs the same training hyper parameters; the learning rate of 0.001 has an impact on model prediction results.

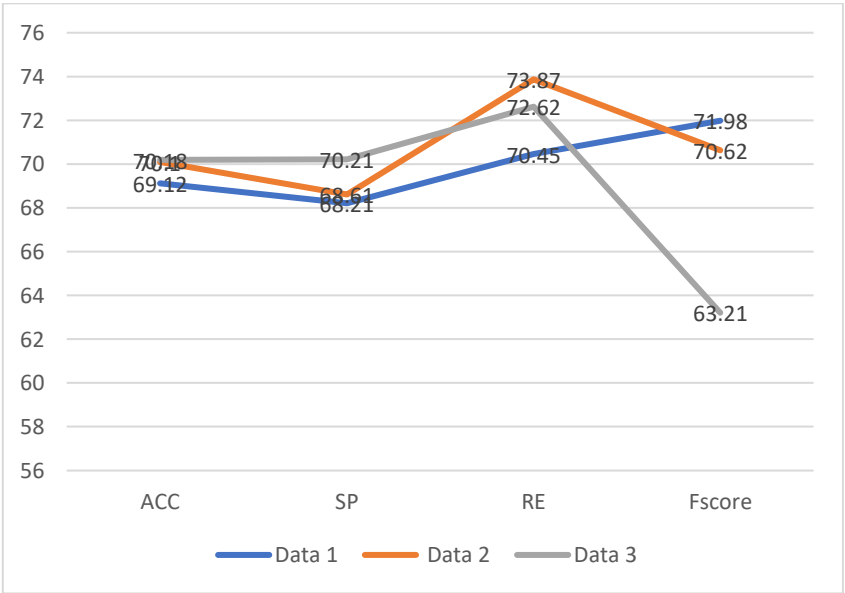


Figure: 9 Performance comparison of Training and Tested values (ADNI Dataset)

ACCURACY	SPECIFICITY	RECALL/SENSITIVITY	Fscore
$\frac{TP}{TP+FP}$	$\frac{TN}{TN+FP}$	$\frac{TP}{TP+FN}$	$\frac{2X(PXR)}{P+R}$
69.12	68.21	70.45	71.98
70.1	68.61	73.87	70.62
70.18	70.21	72.62	63.21

Table: 2 Statistically Derived Parameters

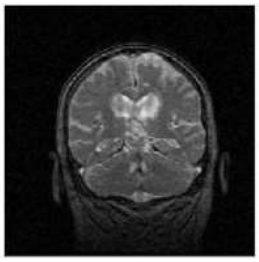


Figure: 10 Original image with denoising

Figure: 11 Extracted features of TEST POSITIVE case

The reason for using this structure and this proposed methodology is explained using three main steps:

a. The trained data input in the first layer is a brain volumetric signal (vector); hence, the input form of data has a 1D convolution structure.
b. Nowadays, convolutions are widely used for feature extraction from the given processed image because they are compatible in nature. Our work focuses primarily on ensuring that the size of input and output data is consistent; this will prevent important information from being lost during processing.
c. The Finer-DBN framework is optimized by the maximum likelihood estimation principle. Following the execution process, the primary goal is to obtain feature volumetric data. To obtain the feature from normal subjects, we use the compress and recover option for the volumetric data, so that some potential negative subjects with abnormal data can be detected. Various previously proposed studies agree that the clustering coefficient shows a higher accuracy rate in categorizing neurological disorders. Our methodology achieves this directly, as it clearly denotes whether the given sample is from a normal or abnormal subject.

DISCUSSION AND FUTURE WORK

In this paper, the classification of positive cases in Alzheimer's disease is presented based on the Finer DBN model and the image modality, and the source of data for AD detection is taken from the ADNI project, which is publicly available, and some sources of the data are taken from the AD detection articles.

The increasing demand for ML and DL methods attracts researchers because of their high potential, and approaches to brain diagnosis with verified predictions, new techniques, updated models, and explainable diagnosis by the medical practitioner and medical experts in real time are highly negligible. In the case of quality training and the availability of data resources, artificial intelligence-based diagnosis is a significant technique. Multi-dimensional collaboration among the scientists and the researchers is beneficial for enhancing the quality of brain-related treatments, and this collaboration may solve the scarcity of medical data in the world. To avoid this, the image for each and every even piece of data is trained separately with their parameters for deep learning technique-specific model training and for detecting one type of brain disorder that may not work well with other types, so that a small change can trigger a performance with the expected output. Privacy plays an important role, and the patient's legal rights over their personal information and medical diagnosis should be protected. The security concern of protecting the patients' sensitive information should be protected in future work. The potential increase in the risk of medical data breaches should be avoided, and algorithms for identifying various brain disorders should be followed. The inclusion of an artificial intelligence model that transforms clinical practice into a diagnosis of a patient in real time with a model of interest provides the result with a small variance. In future work, large-scale medical data management, resource efficiency, security, and privacy also need to be addressed.

ACKNOWLEDGEMENT

In this paper work the image and the datasets which are used for training and testing process are obtained from ADNI (Alzheimer's Disease Neuroimaging Initiative) Database (www.loni.ucla.edu/ADNI)As such, the investigators within XIA et al.: RECOGNITION OF DEMENTIA BIOMARKERS WITH DEEP FINER-DBN 1935.www.loni.ucla.edu/ADNI/Collaboration/ADNI_Authorship_list.pd ADNI investigators list are found using the above link

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