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Diagnostic Classification of Alzheimer Disease using EEG signal

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Abstract:
Alzheimer's disease (AD) plays an important role in the medical image processing. It is an irreversible neurodegenerative dementia that often occurs at the age of 65. It is a kind of memory loss that related with thinking and behavior of people's day to day lives. Therefore, the researchers are taking more efforts to find proper treatment and improve the quality of patient's life. This paper organize totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive normal are analyzed with 1 K Hz and 2 K Hz. From the results, it can be measured that AR pole tracking with 15th order using FBNN reported the highest classification accuracy of 97.5 per cent with specificity 97%, sensitivity 94% and F measure 91%.

Keywords: *Alzheimer's disease (AD) Neuroimaging Initiative (ADNI) Hippocampal Unified Multi Atlas Network (HUMAN).*

I. Introduction

Brain is one of the important and complex organs in our human body which is located at the center of the nervous system. It consists of several billons of cells to communicate trillion connections like synapses.[1] The brain includes some major task such as visualization, thinking, language processing, emotional response and learning. As it locates at the center of the nervous system, is there any abnormal behavior inside the cells it may affect our entire functionalities of the body which leads to Alzheimer's disease (AD). It is otherwise known as dementia that occurs often at the age of 65. It is a kind of memory loss with improper thinking and behavior, also in current progress there is no treatment for dementia. Thus, the experts are taking more effort to find the proper treatment and improve the quality of patient's life. To achieve this, some of the automatic development was progressed for the early detection of AD[2]. It is one of the top 10 diseases in America that affects more than 5 million people of Americans and it may exceed up to 16 million people in 2050. The Alzheimer's disease was developed in the plaques and tangles of the brain, which leads to block the communication among the nerve cells, reduce its function and respective cells will die. Hence, the death of the nerve cells and distraction may cause memory failure and problem of changes in personal and daily activities[3] . This paper represents the review about various algorithms and representation of Alzheimer's disease (AD). Further, it organize totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive model using Feedback Neural Network

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(FBNN). Finally, the results and graph are shown as below with accurate results[4].

II. Literature review

In recent reviews, the segmentation based on different methods of aspects and it can be concluded in different ways. Following that, Pier rick Coupe, et.al proposes methods of segmentation in life span analysis of brain trajectory using inferred models in AD that exhibits the early divergence between normal and pathological models[5] . Jose Vicente Manjon, et.al, contributes some segmentation results using tissue classification in TMS method. It highlights the biomarker key in AD, temporal lobe atrophy are the early path physiological event that associated with early life of patients risk factors [6].

The MRI images are used to detect the Alzheimer's disease with the help of Neuroimaging Initiative (ADNI) dataset which obtains high accuracy with new biomarker images [9]. The following results are evaluated by ADNI datasets and determine the ability of the suggested biomarker with SVM algorithm for better results . Then the limitations of previous analysis of neuroimaging in biomarkers were concluded in .

The evolution of brain Atrophy subtypes includes all types of segmentation methods that predict long-term cognitive decline and future clinical syndrome of Alzheimer's disease . Frank de Vos, et.al, proposes anatomical measurements of MRI to increase the classification of AD into two different methods for combining the different measures of features . The measure of all weighted combination is better than concatenated combination. These results may be to concatenate with the study of early diagnosis AD and other neurodegenerative diseases.

Jorge Samper- Gonzalez, et.al, describe the results which accessed by applying classifiers to trained ADNI to AIBL&ASIS datasets using Machine learning and feature extraction . The diagnosis of Alzheimer's disease based on Hippocampal Unified Multi Atlas Network (HUMAN) algorithm with ADNI database. It results showed the (specificity ~ 0.75 ± 0.04) greater than (sensitivity 0.52 ± 0.07) with the help of hippocampal volumes and the segmentation algorithm is stable and precise to identify the disease . Weihao Zhang,et.al, proposes a identification of AD and mild cognitive impairment using constructed networks based on morphological features of AD with ADNI database. This shows the particular improvement for calculating patient's datasets with AD (or) MCI from NC subjects with accurate results of 96.37% & 96.42 % .[7]

Kilian Hett, et.al, proposes a classification of Alzheimer's disease using Multimodal Hippocampal Subfield Grading based on patch-based grading (PBG) methods. It supports Multi modal patch-based grading (MPBG) applied on T1w and MD; it gives same results when it compared to the performances of two modalities. [8] Then the classifier performances are gained by separate feature extraction using SVM algorithm . Further, the similarity of pattern analysis estimated with patch-based grading strategy by voxel-based morphometry (VBM). This graph modeling method based on intra-subject variability between the structures grading [8].

Diana Lorena Giraldo Franco , et.al, proposes the early detection of Alzheimer's disease using Nonnegative Matrix Factorization (NMF) for Morphometric Data Fusion . The cognitive behavioral and olfactory tests was implemented for 27 cognitively normal (CN), 15 AD subjects and 21 MCI . This is the prominent atrophy in the POC and hippocampus which is used to find both MCI and AD subjects, and then it correlated with behavioral measurements without significant differences in cognitive and olfactory performance, hippocampal, POC volume and POC activation. Following, the

interneuron olfactory tests can be related with Alzheimer's disease using ADNI database and this results are obtained from these olfactory tests through AD progression.

The odor identification screening enhances the diagnostic classification in Incipient Alzheimer's disease. It is used for screening tool which gives more information that relevant to clinical assessments of AD and MCI. It includes the person those who are at highest risk to convert in to AD . Further, the symptoms of modeling and prediction of Alzheimer's disease was proposed using ADNI database .

Anja Soldan, et.al, compares the relevant information about Medial Temporal Lobe Atrophy, Cognitive Reserve and APOE Genotype in Preclinical AD was contributed using ADNI database. The relation between the MTL atrophy using MRI measures, APOE genotype, and CR level are onset in a particular time of clinical symptoms with of individuals large sample that are cognitively normal at baseline . The pre symptomatic atrophy of autosomal dominant was proposed using MRI datasets in AD. Here, the Genotyping was performed to determine the presence of an AD mutation for each at risk participant. The odor identification screening enhances the diagnostic classification in Incipient Alzheimer's disease. It is used for screening tool which gives more information that relevant to clinical assessments of AD and MCI. It includes the person those who are at highest risk to convert in to AD . Further, the symptoms of modeling and prediction of Alzheimer's disease was proposed using ADNI database[9] .

Kilian Hett, et.al, proposed the Adaptive Fusion of Texture-Based Grading in the application of detection of AD detection with regions of interest (ROI). In order to validate the improvement the results are compared and obtained with our framework using raw intensities (T1-w grading). Then the classification step involves the distribution of weak classifiers to get a better discriminate pathology stages

III. Data Collection

In this study, data set was acquired through auditory oddball paradigm to analyze the Alzheimer disease. The dataset used in this research work consist of totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive normal. Three different types of auditory signals were stimulated with 1 K Hz and 2 K Hz. Duration of the presentation of the stimuli is 30 minutes. 16 channel EEG is used to acquire the signal along with the sampling frequency of 256 Hz. The evoked potential response signals were averaged and classified with AD and Cognitive normal. [10]

IV. Feature Extraction

Parametric Function

Parametric modeling is a mathematical model that estimates the values of zeros and poles, which provides additional insight about the dynamics of EEG signal more directly. Further, it is also very useful in finding the transition between the normal AD and abnormal AD states. Autoregressive (AR) modeling is a parametric model that can be used to quantify the boundary limits between the AD and non AD transition states of a subject. [11]

Step 1: Let T = { }. where T is a null set or a measure-zero set.

Step 2: For channel c = 1, 2, 3, ..., 19, do steps 3-10

Step3: Consider the EEG signals recorded for 10 seconds from each channel 'c' $x_i^c, i = 1, 2, 3, \ldots, 2560$

Step 4: Normalize the AEP signals using Equation (1)

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$$xn_i^c = \frac{0.8\left(x_i^c - x_{min}\right)}{\left(x_{max} - x_{min}\right)} + 0.1, i = 1, 2, 3, \ldots, 2560. \quad (1)$$

where,

xn_i^c is the normalized data value,

x_i^c is the data to be normalized,

x_{min} is the minimum value from EEG data,

x_{max} is the maximum value from EEG data.

Step 5: For the normalized EEG signals, formulate the AR model for the given order (k) and relation $d(z)$ from Equation $d(z) = 1 + \sum_{k=1}^{p} a_k z^{-k}$

Classification

The feedback neural network consists of arbitrary functions of neurons which have feedback interactions among different layers, but it is suitable for simple set of neurons.[13] It consists of many feedback connections between the neurons. It is a dynamic network even at evolve in either continuous or discrete time. In general, the fig.1 shows the basic structure of a single-layer feedback network (or) Hopfield network. The loops are introduced in the network to guide their signals from one direction to another direction. Further, this network gives an impression in the input of earlier derived algorithms, and then FBNN will change repeatedly till it attains the state of equilibrium point. When the input of the network is changed then a new equilibrium will be farmed. The architecture of FBNN also referred as interactive or recurrent neural network which is often used to determine the feedback connections in a single layer organization. After, the feedback loops are allowed in networks that are used in content addressable memories.

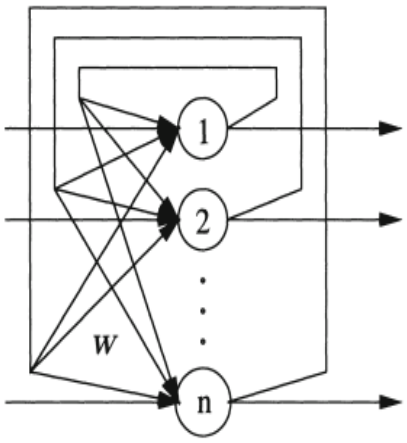

Fig. 1 Diagram of Feed Back Neural Network (FBNN) [30]

V. Result and Discussion

In order to develop a generalized neural network model, the training samples are randomly selected from the total samples and a neural network is trained. 60% of dataset has been used for training the neural network and the remaining 40% of dataset has been used to test the performances of the neural network.[12,13]

Parametric Feature	Accuracy (%)	Sensitivity (%)	Specificity (%)	F measure (%)
AR Pole Tracking with 5th order	87	90	88	84
AR Pole Tracking with 10th order	91	93	91	88
AR Pole Tracking with 15th order	97.5	97	94	91
AR Pole Tracking with 20th order	95	93	95	94

Table 1: Classification results of Feedback neural network

Four intelligent classification designs are studied using the FBNN for three distinct hearing frequencies name 1 and 2 K Hz. Using feature extraction algorithms, four independent spectral features are extracted for distinct hearing

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frequencies. For each hearing frequency, using the same spectral energy features extracted from the 16 channels, a neural network model was developed to distinguish the normal and abnormal AD states. While developing this model the same spectral band feature is extracted from each channel and fed as input to the network model. The developed neural network model has 16 input neurons and an output neuron. Through simulation the number of hidden neurons is chosen. First, using too many neurons in the hidden layer results in over fitting and using few neurons in the hidden layer results in under fitting. The hidden neurons and output neurons are activated using log sigmoid activation functions. Training is conducted until the average error falls below 0.01 or reaches a maximum epoch limit of 10000. Testing error tolerance is set at 0.1. For each trial, the network is trained for ten times using the dataset and the classification performance is observed. [14]

From the Table 1, it can be observed that AR pole tracking with 15th order using MFNN reported the highest classification accuracy of 97.5 per cent and the AR pole tracking with 5th order using FBN reported the lowest classification accuracy of 88 per cent. It was also noted that AR pole tracking with 15th order using FBNN has obtained specificity 97%, sensitivity 94% and F measure 91%. From the Table 1, it indicates that AR pole tracking with 5th order using FBNN has obtained specificity 90, sensitivity 88% and F measure 84%.

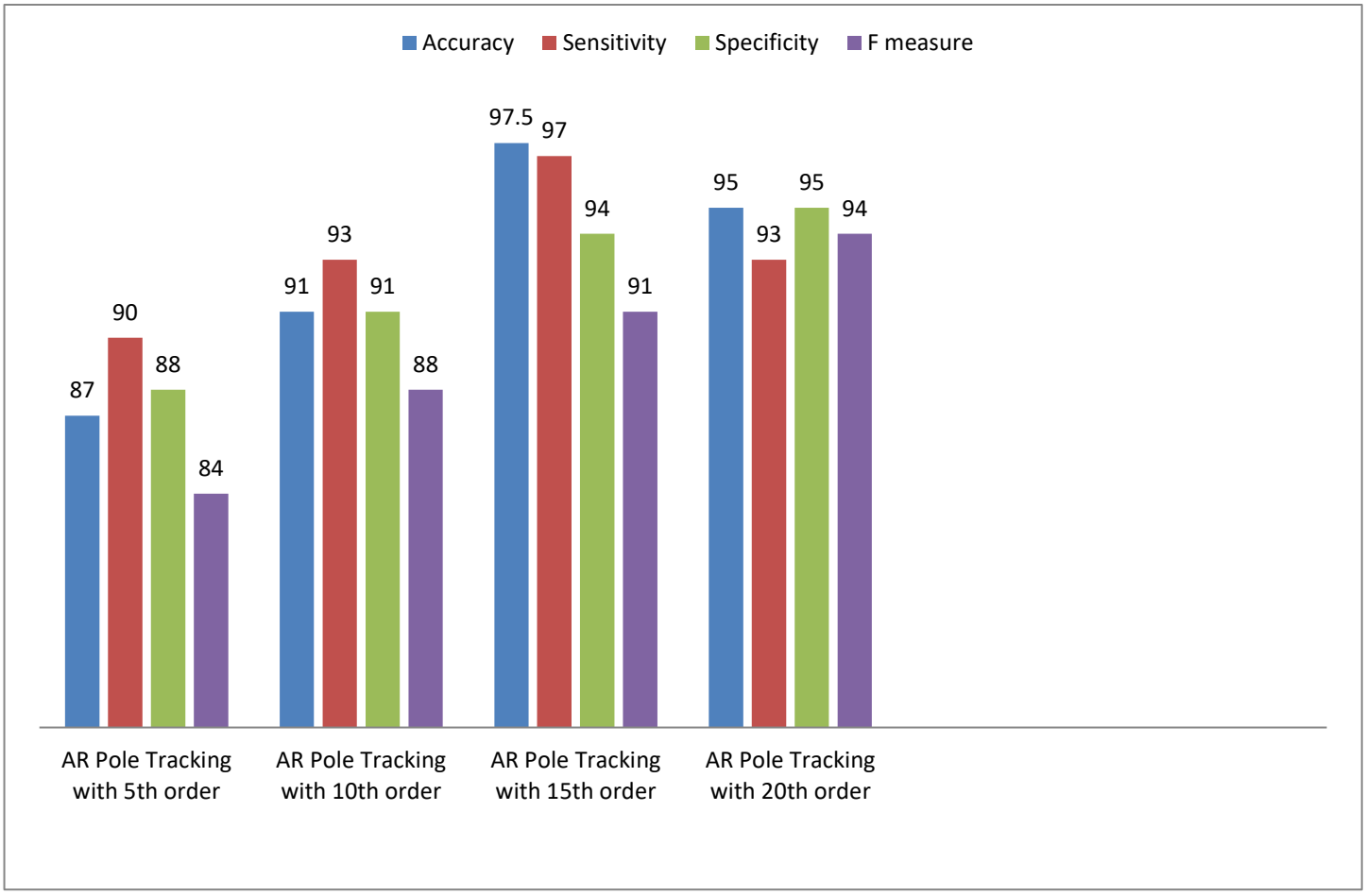

Fig. 2 Performance analysis of EEG signals using FBNN

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The performance analyses graph is shown in Fig.3. It observes the values of accuracy, sensitivity, specificity and F measure which obtained from the parametric feature of Feedback Neural Network (FBNN).[15]

VI. Conclusion:

Alzheimer's disease (AD) is otherwise known as Dementia which is most vulnerable disease in our human brain. Totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive normal are analyzed with 1 K Hz and 2 K Hz. From the results, it can be measured that AR pole tracking with 15^{th} order using FBNN reported the highest classification accuracy of 97.5 per cent with specificity 97%, sensitivity 94% and F measure 91%.

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