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Development of Alzheimer Disease Classification System using FBNN

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Abstract: Alzheimer's disease (AD) plays an important role in the medical signal processing using EEG signals. It is an irreversible neurodegenerative dementia that often occurs at the age of 70. 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 suitable diagnosis methods to improve the quality of AD patient's life. This paper totally organize 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 observed that Box counting fractal feature with 20 orders using FBNN reported the highest classification accuracy of 90 per cent and the Box counting with 5th order using FBNN reported the lowest classification accuracy of 78 per cent.

Keywords: *Alzheimer diseases, Fractal features, neural network*

I. INTRODUCTION

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. Then the classifier performances are gained by separate feature extraction using SVM algorithm [1]. 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 [2].

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 [3]. 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 [4]. 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 [5]. 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 [6]. WeihaoZhang,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].

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 [8]. Further, the symptoms of modeling and prediction of Alzheimer's disease was proposed using ADNI database [9].

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 [10]. 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 [11]. 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 [12]. 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 [13]. 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 [14]. 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 [15]. WeihaoZhang,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 % [16].

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. Then the classifier performances are gained by separate feature extraction using SVM algorithm [17]. 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 [18].

II. 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.

III. FEATURE EXTRACTION

Box-counting method employs the self similarity property to compute the FD values and it is the most commonly employed method used to compute the FD values.

To extract the fractal features, the following algorithm is employed:

Step 1: Using EEG protocol, EEG signals are recorded for 10 seconds.

Step 2: For each trial, the recorded EEG signals consist of 10 frames (2560 samples) such that each frame has 256 samples.

Step 3: For step sizes k = 1, 2, 3,...,4, $\log_2(L\text{-}1)$, compute the total number of boxed required to cover the AEP signals using Equation

Step 4: Apply the least squared fitting line to the log-log plot of *N(r)* versus *1/r* using Equation (1). The slope of the straight line is taken as an estimate of the box-counting fractal dimension.

Step 5: Repeat steps 2 to 4 for all the EEG signals recorded while performing the trails

Step 6: A fractal feature dataset features along with its associated target values are formulated, and this dataset is named as EEG box-counting fractal feature (AEP-HPR-BFF (L)) database.

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.

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)

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

(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

$$d(z) = 1 + \sum_{k=1}^{p} a_k z^{-k}$$

IV. 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. 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

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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.

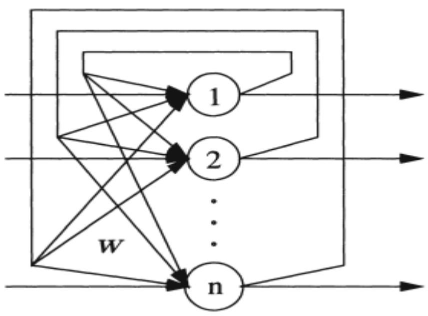

Fig. 1 Diagram of Feed Back Neural Network (FBNN) [30]

V. RESULTS 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. 40% of dataset has been used for training the neural network and the remaining 60% of dataset has been used to test the performances of the 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 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.

Table 1: Classification results of Feed forward neural network

Fractal Feature Number of boxes	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F measure (%)**
N=5	81	85	83	80
N=10	86	81	84	79
N=15	91	92	94	90

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

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error falls below 0.06 or reaches a maximum epoch limit of 600.

From the Table 1, it can be observed that Box counting fractal feature with 15 orders using FBNN reported the highest classification accuracy of 91 per cent and the Box counting with 5th order using FBNN reported the lowest classification accuracy of 78 per cent.

It was also noted that Box counting fractal feature with 20 order using MFNN has obtained specificity 94%, sensitivity 92% and F measure 90%. From the Table 1, it indicates that Box counting fractal feature 5th order using FBNN has obtained specificity 83%, sensitivity 85% and F measure 80%.[19].

V. 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. It was also noted that Box counting fractal feature with 20 order using FBNN has obtained specificity 94%, sensitivity 92% and F measure 90%. From the results it can be interpreted that, box counting fractal feature is suitable for Classification of AD patients.

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