NEURAL NETWORK IN DIAGNOSIS OF ALZHEIMER'S FROM ELECTROENCEPHALOGRAPHY

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***Abstract :** Alzheimer's disease (AD) is an irreversible, progressive brain disorder that slowly destroys memory, thinking skills, and eventually the ability to carry out the simplest tasks. Recent estimates indicate that the disorder may rank third, just behind heart disease and cancer, as a cause of death for older people. Early diagnosis of AD helps to ensure prescription of the medications when they are most useful. Early diagnosis of AD also allows prompt treatment of psychiatric symptoms such as depression or psychosis. Early diagnosis raises the chance of treating the disease at a nascent stage, before the patient suffers permanent brain damage. The purpose of the project is to assist neurologist in detecting and monitoring the Alzheimer's diseases at the early stage by analyzing the EEG recordings. The project proposes the classification of EEG signal of patients suffering from Alzheimer's diseases in the early stages using artificial neural networks. The classification is carried out by identifying the abnormalities of EEG signal. Different types of neural networks are used for classifying the EEG signals into 2 classes (Alzheimer's or Normal) and this neural networks are compared with the parameter classification accuracy to predict which neural network model is best for classifying EEG signal. The input for the classifier is a vector which contains the features. The features relevant for distinguishing Alzheimer's patients EEG is extracted from the EEG Signal. The Discrete Wavelet Transform (DWT) is employed for extracting features from EEG. Use of wavelet transform for the feature extraction, which is faster and enables better resolution and high performance for representation and visualization of the abnormal activity in EEG than other methods. The db4 wavelet selected enables it appropriate for detecting changes in EEG signals because of its smoothing feature. The Feed-forward neural network (FNN), Block based neural network (BBNN) and Convolutional neural network (CNN) are used as classifiers and a comparative study is conducted to choose best classifier.*

***Index Terms** - Alzheimer's disease, FNN, BBNN, CNN, EEG, Features.*

I. INTRODUCTION

Alzheimer's disease serves as sixth-leading cause of death in the United State. Only fewer than 50 percent of people with Alzheimer's disease get to the stage of diagnosis [1]. AD is a progressive neurodegenerative disease of brain resulting in the gradual diminish of a person's memory and Intellectual abilities, judgmental abilities, interactions, and carry out daily activities of life [3,4]. It affects more than 10% of Americans over age 65; nearly 50% of people older than 85. It is estimated that the prevalence of the disease will triple within the next 50 years. While no known cure exists for Alzheimer's disease, a number of medications are believed to delay the symptoms or cause of the disease.

The progression of the disease can be categorized in four different stages. The first stage is known as Mild Cognitive Impairment (MCI), and corresponds to a variety of symptoms- most commonly memory loss - which do not significantly alter daily life. The next stages of Alzheimer's disease are characterized by increasing cognitive deficits, and decreasing independence, and a complete deterioration of personality.

Diagnosis of MCI and AD is important for several reasons such as: A positive diagnostic gives the patient and his family time to plan for the future needs and care of the patients. A negative diagnostic may ease anxiety over memory loss associated with aging.

The traditional method used to identify Alzheimer is massively dependent on the visual analysis of the EEG recordings by the trained professionals. This procedure is very costly as well as tedious task to review a 24 hour continuous EEG recording, particularly if the number of EEG channels is large. Moreover, the detection of Alzheimer by visual scanning of a patient's EEG data usually collected over a few days is a tedious and time consuming process. In addition, an expert may need to analyze the whole EEG recordings, in order to detect Alzheimer activity [2]. As complete visual analysis of EEG signal is very difficult, automatic detection is preferred. A reliable automatic classification and detection system would ensure an objective and facilitating treatment and significantly improve the diagnosis of Alzheimer as well as long-term monitoring and treatment of patients. Automating the detection of Alzheimer is valuable for assisting neurologists to analyze the EEG recordings, and could also offer solutions for closed-loop therapeutic devices such as implantable electrical stimulation systems. Therefore, there is a strong demand for the development of such automated systems, due to both huge amounts and increased usage of long-term EEG recordings for proper evaluation and treatment of neurological diseases, including Alzheimer. The possibility of the expert misreading the data and failing to make a proper decision would also be narrowed down. The automated diagnosis of Alzheimer can be subdivided into signal acquisition, pre-processing, feature extraction, and classification. In Alzheimer detection the purpose is to recognize the starting of Alzheimer with the shortest possible delay. The purpose of Alzheimer detection is to identify Alzheimer with the highest possible accuracy.

Monitoring brain activity through electroencephalographic (EEG) data has become a successful means for detecting seizure. This involves identifying sharp, repetitive waveforms in the EEG data that indicate the onset of seizure. These signals are easily recognizable against low amplitude, random background characteristic of normal brain activity.

The objective of the proposed work is to develop a new method for automatic detection and classification of EEG patterns into two category normal and Alzheimer's patient using Neural Networks and wavelet feature extraction method.

Careful analyses of the EEG records can provide valuable observation and better understanding of the activities causing Alzheimer disorders. The detection of Alzheimer discharges in the EEG is an important component in the diagnosis of Alzheimer. In this work, a novel approach towards the automatic Alzheimer detection and classification based on BBNN using Wavelet transform is employed. BBNN is not so far used to classify a non-stationary signal. The BBNN is a two dimensional array of blocks which are connected to each other. The structure of each block depends on the count of both input and output signals. The input of the BBNN is a vector which contains the features extracted from the EEG signal. The feed forward neural network and convolutional neural network where also introduced as classifiers. The feed forward neural network is the simplest form of artificial neural network and the convolutional neural network is a part of deep learning concept. EEG signals are classified as normal (healthy) signals or as Alzheimer signal. Wavelet transform is particularly effective for representing various aspects of non-stationary signals such as trends, discontinuities and repeated patterns where other signal processing approaches fail or are not as effective. Through wavelet decomposition of the EEG records, transient features are accurately captured and localized in both time and frequency context.

This paper is organized as follows: Section II describes the concept of EEG and its relevance. The details of dataset used are also described in this section. Preprocesing of EEG data and method used for extracting features are also included in this section. Section III describes the basic concepts of classifiers i.e. feed forward, convolutional and block based neural networks. Section IV proposes the working of the proposed systems with the three classifiers and at the end in Section V the conclusions of this research will be presented.

II. EEG SIGNAL

The EEG was originally developed as a method for inspecting state of mind. Clinical applications soon became visible, most notably in Epilepsy and other brain disorders. Now diagnosis of Alzheimer's disease using EEG signal also employed in clinical. Caton reported the first recordings of the brain electrical activity in 1875 which uncovered brains of monkeys. In 1929, the first measurements of brain electrical activity in humans were reported by Hans Berger [6]. Since then, the EEG signal has been utilized to clinically evaluate neuron's behavior and functional states of the brain such as different stages of wakefulness; sleep or metabolic disturbances [7].

The EEG signal consists of potential differences on the scalp caused by the electrical activity of neurons in the brain. It is measured with electrodes placed on various positions on the head. The name and location of these electrodes are specified by the international 10/20 system [8]. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The `10' and `20' refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. Fig.1 shows the clinically recorded EEG signal of Alzheimer's patient.

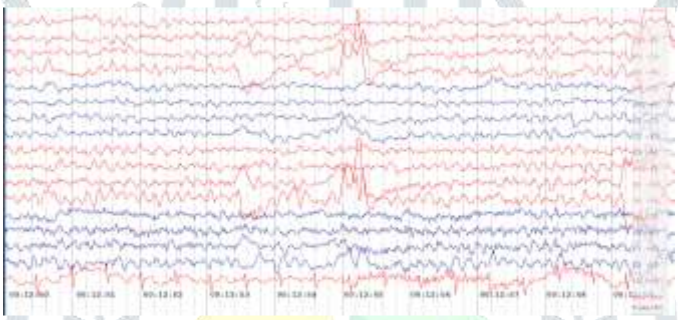

Fig.1.EEG Signal recording of Alzheimer's patients

Data set

An EEG dataset, which is available online and includes recordings for both healthy and Alzheimer subjects, is used. The dataset includes 2 subsets (denoted A and B) each containing 100 EEG segments, with one having a duration of 23 second. The subsets A have been acquired using surface EEG recordings of healthy volunteers with eyes open. The subset B contains abnormal activity which cause due to the presence of Alzheimer's disease. All EEG signals were recorded with the same amplifier system, using an average common reference. The data were digitized at 173.6 samples per second using 12 bit resolution and they have the spectral bandwidth of the acquisition system, which varies from 0.5Hz to 85 Hz.

Preprocessing

In biomedical signal processing, it is crucial to determine the noise and artifacts present in the raw signals so that their influence in the feature extraction stage can be minimized. EEG recordings have a wide variety of artifacts, which may occurred due to technical or physiological reason [16]. The preprocessing stage attempts to eliminate these artifacts without losing relevant information. Noise of technical origin depends on the acquisition settings, which are related to the type of EEG (scalp or intracranial), including gain (vertical resolution), cut-off frequencies of high-pass and low-pass filters, characteristics of the notch filter, and sampling rate [17].

In this work, cut-off frequency of high-pass and low pass filters are kept to 70Hz and 1Hz respectively and the notch filter is said to cut-off frequency 50Hz to remove the artifacts from the EEG signal.

Feature Extraction

Feature extraction is done using discrete wavelet transform. In feature extraction using wavelet transform, the pre-processed signals undergo wavelet decomposition. Fig.1 illustrates the DWT sub band decomposition.

Wavelet decomposition generates different wavelet coefficients on each level, which are considered as features for the signal. The EEG signal from the pre-processing phase undergoes wavelet transformation for the initial level and high frequency components called `details' and low frequency components called `approximations' are generated.

On next level of wavelet decomposition, the approximations in the previous level are transformed in to next level approximations and details. The process is continued up to desired levels of decomposition.

MATLAB enables function for performing multi-level one-dimensional wavelet analysis using a specific wavelet in its Wavelet Toolbox.

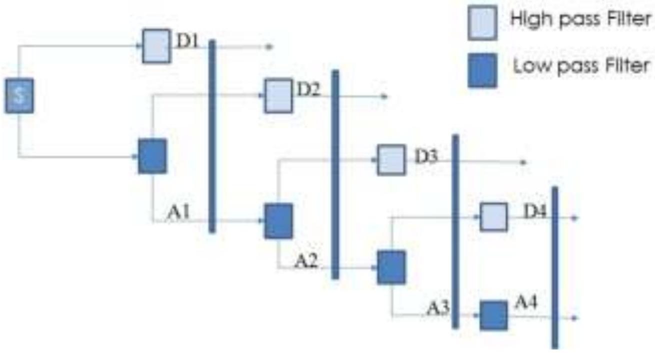

Fig.2 DWT sub band decomposition

III. Neural Network as Classifier

Artificial neural networks are computational models which work similar to the functioning of a human nervous system. There are several kinds of artificial neural networks. These type of networks are implemented based on the mathematical operations and a set of parameters required to determine the output. In this work, three types of neural networks are used as classifier.

A. Feed Forward Neural Network

This neural network is one of the simplest form of ANN, where the data or the input travels in one direction. The data passes through the input nodes and exit on the output nodes. This neural network may or may not have the hidden layers. In simple words, it has a front propagated wave and no back propagation by using a classifying activation function usually.

Below is a feed forward network used in this paper. Here, the sum of the products of inputs and weights are calculated and fed to the output. The output is considered if it is above a certain value i.e. threshold (usually 0) and the neuron fires with an activated output (usually 1) and if it does not fire, the deactivated value is emitted (usually -1).

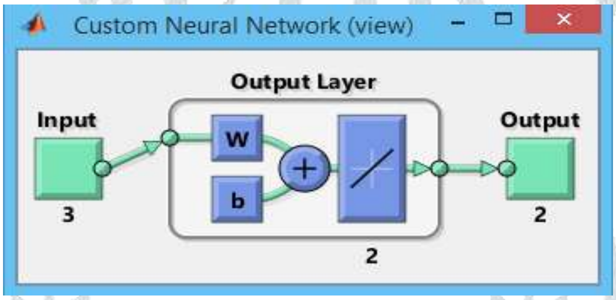

Fig.3 Feed forward neural network

B. Block Based Neural Network

Block-based Neural Network is represented by a structure of blocks in two dimensions. Each block is a small neural network with one input layer and one output layer (without any hidden layer). There are four neighboring blocks around each block and it is connected to them with signal flows. In other words, the outputs of each block are connected to the inputs of the neighbor blocks. The first block and the last block in each row are also connected to each other. The overall construction of network and internal structure of all blocks are determined simultaneously by following the signal through the network blocks.

Fig. 4 represents the BBNN structure by size of m by n where m and n are count of rows and columns, respectively. Each block is labeled as B_{mn} that specifies the block position i.e, B_{mn} is the block at m^{th} row and n^{th} column. The vector x is the input to the blocks and vector y is the output. The BBNN can contain zero or more middle layers. BBNN can widen by adding extra blocks because of its modular property.

There is no build-in function available yet for BBNN in MATLAB. In this work, each block is constructed as feed forward network without any hidden layer.

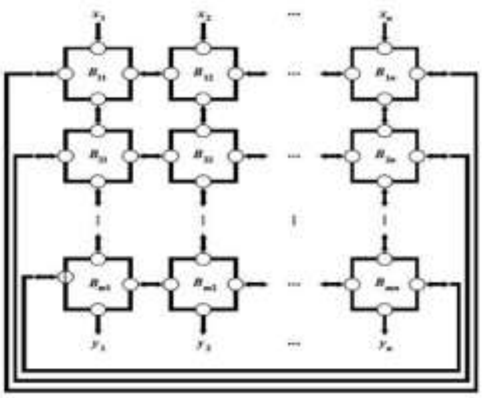

Fig.4 Block Based Neural Network

C. Convolutional Neural Network

Convolutional neural networks are similar to feed forward neural networks, where the neurons have learn-able weights and biases. Its application has been in signal and image processing which takes over OpenCV in field of computer vision. Computer vision techniques are dominated by convolutional neural networks because of their accuracy in image classification. Here the convolutional neural network is used for classifying EEG signal. Fig. 5 represent convolution neural network with 2 encoders and 1 softmax layer.

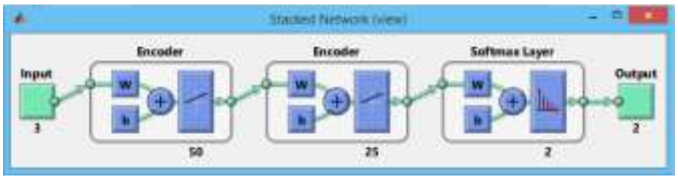

Fig. 5 Convolutional Neural Network

A CNN is composed of a stack of convolutional modules that perform feature extraction. Each module consists of a convolutional layer followed by a pooling layer. The last convolutional module is followed by one or more dense layers that perform classification. The final dense layer in a CNN contains a single node for each target class in the model with a softmax activation function to generate a value between 0–1 for each node. Interpretation of the softmax values for a given signal as relative measurements of how likely it is that the image falls into each target class.

IV. Proposed Methodology

Recent estimates indicate that the Alzheimer's disorder may rank third, just behind heart disease and cancer, as a cause of death for older people, affecting more than 50 million patients around the world. A significant way for identifying and analyzing Alzheimer activity in humans is by using Electroencephalogram (EEG) signal. In this work, EEG signals will classified as normal (healthy) signals or as Alzheimer signal using an automated system using Neural Network. Once the EEG signals are analyzed, the features will be extracted using Discrete Wavelet Transform (DWT) and from the selected features, a BBNN is trained for and on the basis of training samples, test samples are classified accordingly. The parameters of BBNN are optimized using PSO algorithm. Based on this, the class of the input signal is predicted using BBNN. Finally, the performance parameters such as classification accuracy, specificity, sensitivity of the automatic classification system for the EEG signals proposed, will be measured and performance of the system will be evaluated.

The proposed method is automatic and hence it is not subjective and thereby eliminates the need for the visual inspection based method which is subjective. Moreover, the proposed method offers better performance than the existing visual inspection based method of EEG signal classification. An EEG signal is analyzed and fed to a classifier. The input signal received by the classifier, uses it for classifying on the basis of input signals received during the training phase. Proposed system uses a novel classification method using Block Based Neural Network and the parameters are optimized using Particle Swarm Optimization (PSO). The proposed system has five stages Signal Acquisition, Preprocessing, Feature Extraction, Feature Selection and Classification. The proposed architecture is shown in Fig. 6 It shows how each of the phases is related with its predecessor phases.

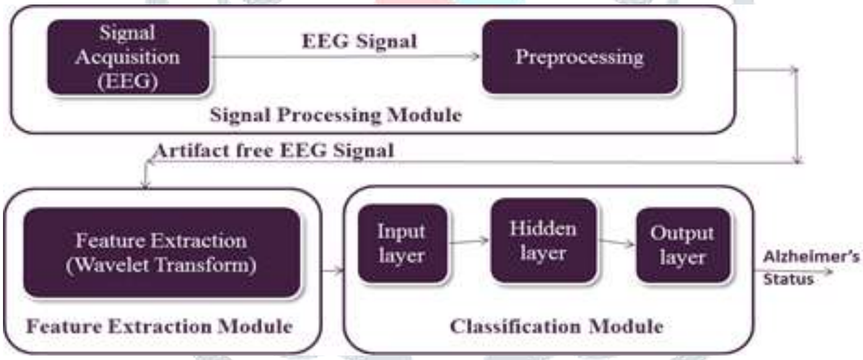

Fig. 6 Proposed System Architecture

In the Signal Acquisition phase, An EEG dataset, which is available online and includes recordings for both healthy and Alzheimer subjects, is used. The dataset includes 2 subsets (denoted A and B) each containing 100 single-channel EEG segments, each one having 23.6 second duration. The subsets A has been collected surface EEG recordings of healthy person on awake. The subset B contains EEG signal of Alzheimer's effected person. All EEG signals were recorded with the same amplifier system, using an average common reference. The data were digitized at 173.6 samples per second using 12 bit resolution and it utilizes spectral bandwidth of the acquisition system. EEG signal consists of the various types of artifacts. These include cardiac artifacts, electrode artifacts, external device artifacts, muscle artifacts and ocular artifacts.

The proposed system focuses on removal of artifacts or noise caused due to eye blinks, eye movements, heartbeat, muscular movement and power line interferences. For this purpose, the EEG recordings healthy subjects (set A) and Alzheimer subjects (set B) in the dataset are preprocessed separately. Initially, the total 100 instances of the set A are subjected to preprocessing by considering each one individually. For each instance, the artifacts are identified and are removed using a low pass filter setting cut off frequency to 40 Hz and stop band frequency to 50 Hz. Similarly, the 100 instances of set B are subjected to preprocessing and the above mentioned steps are performed.

In Feature Extraction phase, after obtaining artifact free signals from the preprocessing phase, necessary features are extracted from EEG signals. The wavelet transform for feature extraction enables better resolution and high performance for representation and visualization of the Alzheimer activity than other methods. The proposed method is designed with using a Discrete Wavelet Transform for the process of feature extraction. Thus, proposed method is designed with using a Daubechies 4 (db4) wavelet since its smoothing feature makes it more appropriate to detect changes of EEG signals.

Feature Selection is employed to reduce the dimension of feature vector while preserving the relevant information of the original data. The wavelet coefficients generated as a result of wavelet decomposition on different levels denotes the features extracted at that level. Proposed method focuses on wavelet coefficients in the significant sublevels.

The classification phase consists of training the neural networks with the selected features which is extracted in the previous phase and testing the neural network to classify EEG signal into 2 categories (Alzheimer's and Normal). Training is performed so that new incoming

EEG signals will be classified into Normal and Alzheimer's categories. The EEG signal is classified with all the three neural networks mentioned in the Section III and best accuracy obtained when classified with convolutional neural network.

IV. CONCLUSION

Accurate automated Alzheimer detection remains an important challenge and a critical step in removing the uncertainty associated with when Alzheimer will occur and further the understanding of Alzheimer and its causes. In the proposed method, the EEG signals have been classified in 2 classes. A classification system for this purpose makes use of a Block Based Neural Network, Feed forward Neural Network and Convolutional Neural Network. Result shows classification with CNN provide best accuracy when compared to BBNN and FNN.

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