RESEARCH ARTICLE | DECEMBER 05 2023

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AIP Conf. Proc. 2916, 020013 (2023)
https://doi.org/10.1063/5.0179925

Deep Learning Method for Early Alzheimer Disease Diagnosis Based on EEG Signal

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Abstract. Alzheimer disease in its early stages, often known as a kind of dementia, is one of the major causes of death worldwide. It is a neurodegenerative illness in which brain electrical activity called electroencephalograph (EEG) slows down relative to that of healthy people. In the literature, a number of biomarkers are explored for detecting these EEG irregularities in signal. The EEG signals that record brain's small electrical signal activity are highlighted in the current scientific study. EEG signals are utilized to diagnose Alzheimer disease based on relative power features. The wavelet transform is used for the denoising the EEG signal to increase the superiority of the signals. Multilayer perceptron and convolutional neural network were incorporated to learn the various features based on power for different stages of Alzheimer disease and normal people and achieved better results were compared to those found in the literature. The presented methodology gives the 96.72% accuracy on the real time database which is used in the study. As a result, the use of deep learning algorithms in clinical evaluation gives a baseline for investigation numerous neurological illnesses such as epilepsy, brain tumors, Alzheimer's disease, and many other.

Keyword. Alzheimer Disease (AD), Convolutional Neural Network (CNN), Deep learning method, Electroencephalogram (EEG), Multilayer Perceptron (MLP), Relative Power.

INTRODUCTION

In present society, Alzheimer disease (AD) is a neurological disorder and particularly the regular type of dementia. It directly influences on the human behavior and subjective deficit. AD is the sixth most significant reason of death for carrying with its generous social and individual cost. 100 years back, AD discovered by Alois Alzheimer, but research in AD's symptoms, causes, risk factors and momentum are going on rapidly in the last 30-40 years. As per the health care survey, AD is now the costliest disease after cancer and cardiovascular disease leading towards the cause of death [1][2]. AD normally caused due to the loss of neuron in the brain and finally damaging nerve cells. Damaged neurons are not extensively or any further extent characteristic well and afterwards it can die. Once, lost the neuron, other neurons cannot replace the dead neurons. By the time, the brain parts get smaller in size noticeably, affecting with all of its abilities and finally damaged the brain [3][4]. Since 2015, 46.5 million peoples have suffered from the first stage of AD called mild AD worldwide. This count will boost up to and 135.5 million in 2050. In developing countries such as India, China even now, 62% of peoples with dementia live, however, by the end of this year rise to 71%. In truth, the suffering of AD is projected to almost double in the next two decades [5]. At the beginning, the EEG has been viewed with great interest as it is the sole technology that allows direct observation of the brain. We are not surprised by the use of nonstationary EEG signals for the investigation of any brain disorder because the EEG provides a prompt interface. As a result, EEG signals have been utilized therapeutically to check brain function [6]. The neuroimaging approaches for the diagnosis of AD are widely accepted. In this case, the diagnosis of Alzheimer based on these neuroimaging tools are visually identifiable

Applied Data Science and Smart Systems
AIP Conf. Proc. 2916, 020013-1–020013-11; https://doi.org/10.1063/5.0179925
Published by AIP Publishing. 978-0-7354-4733-2/$30.00

rather it's very difficult in the tool which is based on EEG signal. EEG has emerged as an important tool for early detection of AD. The AD-patient EEG signal shows functional changes in the brain cortex like EEG slows down. While similar findings have been described in the literature several times, they are not visible due to the diversity in Alzheimer's disease patients. As a result, any of the identified effects is utilized to improve the accuracy of diagnosing AD in its early stages. The main problem faced by the neurologist consists in distinguishing the phases of the AD from changes in memory and thought, particularly normal, mild and moderate, since the slight EEG changes occur between normal, mild and moderate. In the light of clinical data, a neurologist interprets EEG findings. In such diagnosis, the percentage of human error is varying according to the skillset of the neurologist. In order to increase the accuracy of biomarker, deep learning is used to diagnose the Alzheimer disease. These AI classifiers save time and it is faster than the clinician.

Different neuroimaging techniques, including as positron emission tomography (PET), magnetic resonance imaging (MRI), and single-photon emission computerized tomography (SPECT), have proved effective in detecting Alzheimer disease at an early stage. However, the primary issue with PET and SPECT is that they present radiation hazards, and the main issue with MRI is that it generates a lot of noise during processing since it uses a lot of electric current. So, in addition to all of these neuro-imaging techniques, EEG is one of the commonly utilized techniques for Alzheimer disease diagnosis. Other drawbacks include their high expenditures, which are often time-consuming and inconvenient. Table 1 compares several techniques for AD diagnosis [26]. Table 2 provides a summary of the literature review on the EEG neuroimaging method for Alzheimer disease diagnosis.

TABLE 1. Comparison of Different Neuroimaging Techniques.

Parameter	MRI	PET	SPECT	EEG
Risk of Radiation	Yes	Yes	Yes	No
Time Resolution	Superior	Superior	Superior	Reduced
Temporal Resolution	Reasonable	No	No	High
Cost	Expensive	Expensive	Expensive	Affordable
Portability	No	No	No	Yes
Biomarker	Indirect	Indirect	Indirect	Direct

TABLE 2. Diagnosis of Alzheimer Disease by EEG Biomarker Literature Summary.

Sr. No.	Authors	Method used	Accuracy (%)
1	D. Puri et al [7]	Spectral Entropy (SE) and Kolmogorov Complexity (KC) features based on SVM	95
2	D. Pirroneet et al [8]	Supervised machine learning method	75
3	M. Amini et al [9]	Time dependent based features and CNN Deep learning method	89.14
4	M. Ouchani et al [10]	Complexity based	93.3
5	S. Nobukawa et al [11]	Complexity and Synchronization of Electroencephalography	92
6	M. Ismail et al [12]	Deep Neural Network	92.52
7	S. Simons et al [13]	Fuzzy Entropy EEG analysis	90.21
8	P. Goli. et al [14]	Elman Neural Network	87.2
9	A.Rakshit. et al[15]	Multiracial Detrended Fluctuation Analysis	86.54
10	S. Nazari et al [16]	K- Neural Network	94

MATERIAL AND METHOD

The EEG database utilized in this study was obtained from the Alzheimer's and Related Disorders Society of India (ARDSI) Chaitanya Mental Rehabilitation Centre and Jagruti Rehabilitation Centre in Pune, and included patients at various stages of Alzheimer's disease (AD) as well as healthy people. People with cognitive and behavioral function deterioration validated by neurologists on the basis of Mini Mental State Examination (MMSE) and Clinical Dementia Rating (CDR) criteria from various age categories, including males (M) and females (F), and from diverse places were included. Table 3 contains information on the EEG database. Each sample has a length of 60 seconds.

TABLE 3. Details Information About Collected EEG Dataset Used in the Study.

Variable	Total	Mild AD	Moderate AD	Severe AD	Normal
Number of patients	89	19	16	21	33
Gender	72 M and 17 F	15 M and 4 F	10 M and 6 F	18 M and 3 F	29 M and 4 F
Number of samples	712	152	128	168	264
Age group	63-91	65-82	65-86	74-91	63-81

Acquiring the raw EEG signals by seating the patients on the chair in the dark room. After that, 14 electrodes Emotiv Epoc neuro headset device as shown in the figure 1 attached to the sculp by using gel at different positions, as per the international 10-20 system [25]. Signals are tested with sampling rate 128 Hz and sent to the dongle through the wireless connection, which is connected to the USB port of personal computer and used as a receiver. During EEG inspections and recordings, subjects were awake and relaxed with closed eyes and deep breathing. The artifacts present in EEG signals such as eye blinking and muscle movement has been extracted manually.

FIGURE 1. Emotiv EPOC Neuroheadset.

When compared to other recording techniques like SPECT or PET scans, EEG is frequently employed because of its inherent simplicity and inexpensive cost [17][18]. EEG signals are used in brain computer interface (BCI) applications and as a diagnostic tool for doctors. Typical anomalies such EEG slowness, complexity reduction, and synchronization loss measures are visible in the EEG of AD patients. The power of low frequencies (0.5 to 7.5 Hz) increases when EEG signals slow down, whereas the power of high frequencies decreases (7.5 to 30 Hz) [19][27].

METHODOLOGY

For early AD diagnosis, a variety of multidisciplinary techniques are used. The first is a neurological approach that includes neurofibrillary tangles, plaques and gamma-aminobutyric acid as neurobiological and neurochemical biomarkers. Since these trials are only in the early stages, so, it is very tough to consider good biomarker. Physical changes in the brain occur due to AD's physiological changes. MRI or EEG can track these changes, and can be used as visual biomarker. The other approach is analytical models for anatomical and functional brain images; these approaches are commonly used in AD diagnosis. Neurologists, on the other hand, are unlikely to diagnose AD solely based on a brain scan. This may be attributed to a lack of sensitivity for different stages of AD, making it impossible to improve accuracy even with advanced technologies. Furthermore, these imaging techniques have some disadvantages discussed in table 1. Most recently, researcher focused on the EEG biomarker for the diagnosis of AD as EEG studies show comparable sensitivity and specificity in comparison to imaging.

The EEG dataset used in the study is already discussed in the previous section. Some specific stages in any algorithm like feature extraction and selection relies extensively on the superiority of the signal acquired at the input. The superiority of EEG signals worsens during acquisition method. The EEG acquisition method may additionally consist of certain artifacts due to the machine power lines interferences and the subject activities such as eye blinking, muscle activity. As a result, numerous pre-processing steps are essential to get rid of those artifacts and to improve the EEG signals for in addition exam and evaluation. In this study, wavelet denoising techniques is used for removal of the artifacts. Zikov utilized the wavelet transform to eliminate the artifacts from EEG signals. The continuous wavelet capacities are called as mother wavelets. Mother wavelet such as Daubechies are used in biomedical signal processing for examining the resolution at various frequencies and time basically [20] the noisy EEG signal represented in equation

$$s(n)=f(n)+\sigma e(n) \tag{1}$$

Here n is similarly space divided, $f(n)$ is original signal, $e(n)$ is gaussian noise and σ is assumed to be one represent the noise level. Elimination of artifacts from the EEG signals in wavelet required three steps like decomposing, thresholding and reconstruction [21].

Biomedical signal processing helps in early detection of various diseases like Parkinson's disease, epilepsy and Alzheimer disease. The importance of bio signals is increased as these signals contain vital information to recognize the different stages of the disease. Be that as it may, the real worry here is large EEG data size signals which reflect on the computation time. In addition, few EEG data, not all, in the signals are required for diagnostic purposes as a substantial segment of EEG data is unessential. For this reason, features extraction task is executed to find significant and discriminative features. In this study, spectral based features like relative power and power spectral density are used for the classification. In our proposed framework, we have utilized multilayer perceptron and convolution neural network for the classification of different stages of Alzheimer disease. EEG dataset is normalized and randomly divided into two classes. Normally one class is provided for the training and other class is used for the testing purpose [22][23].

An enhancement of a feed-forward neural network is a multi-layer perceptron (MLP). The input layer, the output layer, and the hidden layer are the three layers that make it up. The input layer receives the input signal that has to be processed. Prediction and classification are examples of jobs that fall under the output layer's purview. An arbitrary number of hidden layers added between the input and output layers make up the MLP's true computational engine [24]. Each layer is denoted by the formula

$$y = f\,(WxT + b) \tag{2}$$

Where x is the input vector, which can also be the output of the preceding layer, b is the bias vector, f is the activation function and W is the collection of parameters, or weights, in the layer. Convolutional neural networks (CNNs), which process input in a grid-like manner, are extensively used feed-forward neural networks for signal analysis. It is sometimes referred to as a ConvNet, as seen in Figure 2. Use of a convolutional neural network allows for the recognition and classification of signals into the proper classifications. Convolution neural networks include multiple hidden layers that help with the extraction of visual information [23]. There are four key levels in CNN. Layers include Convolution, ReLU, Pooling, and Fully Connected.

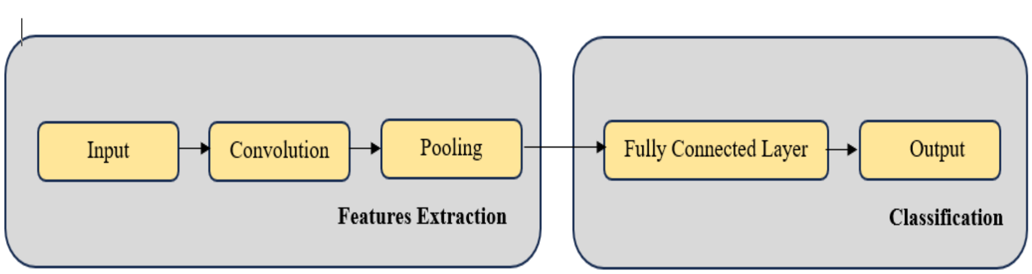
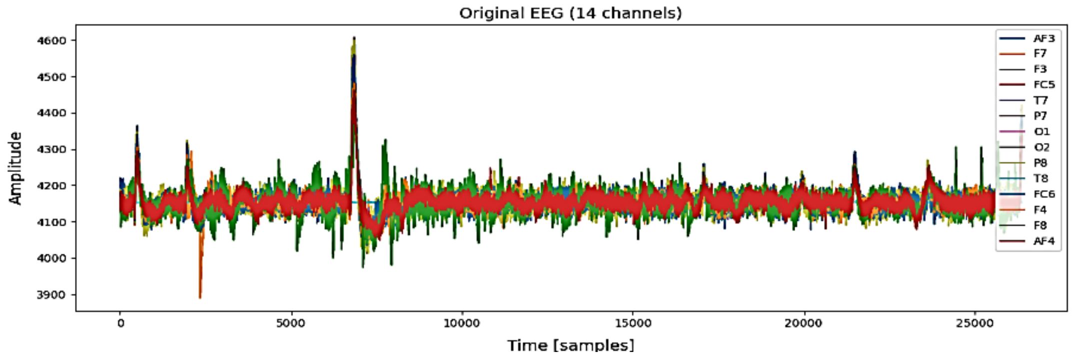


FIGURE 2. Convolutional Neural Network.

RESULT AND DISCUSSION

In the decided framework, acquisition, pre-processing and feature extraction are executed as shown in the figure 3.



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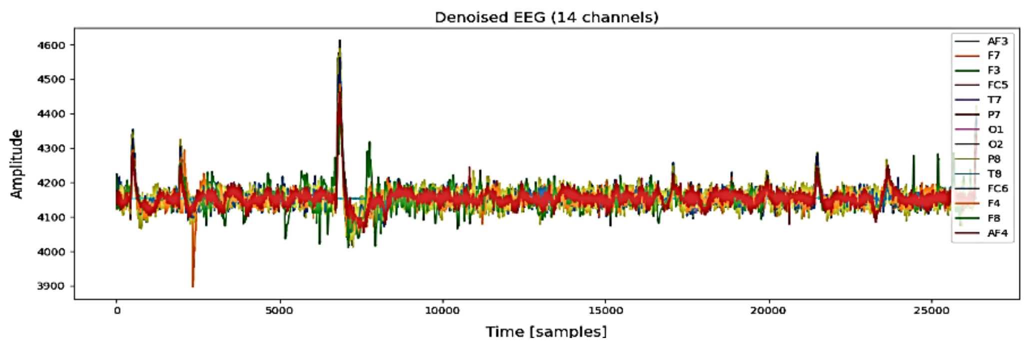

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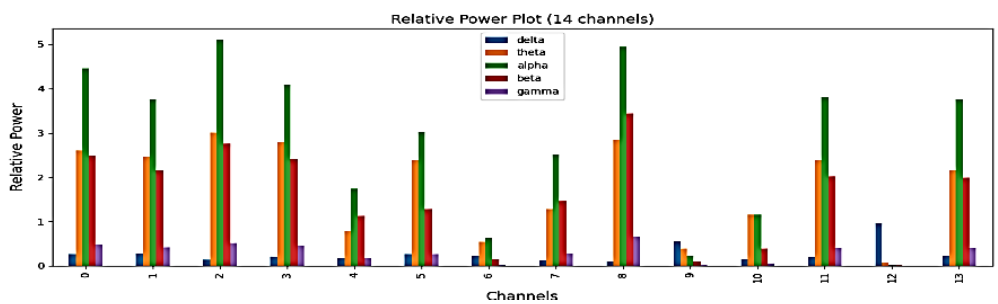
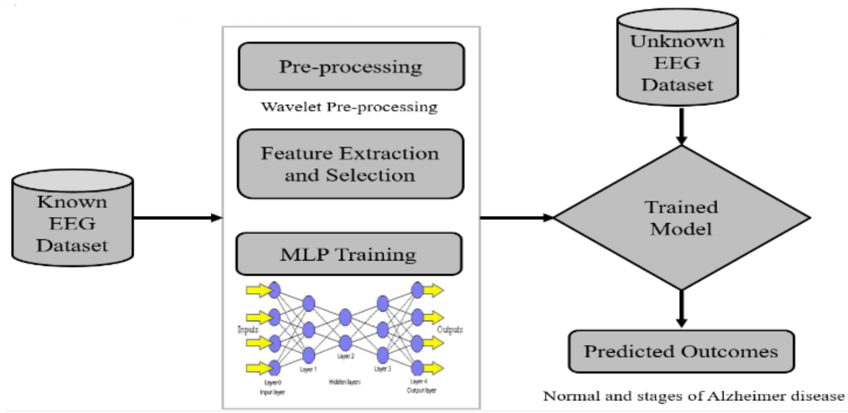


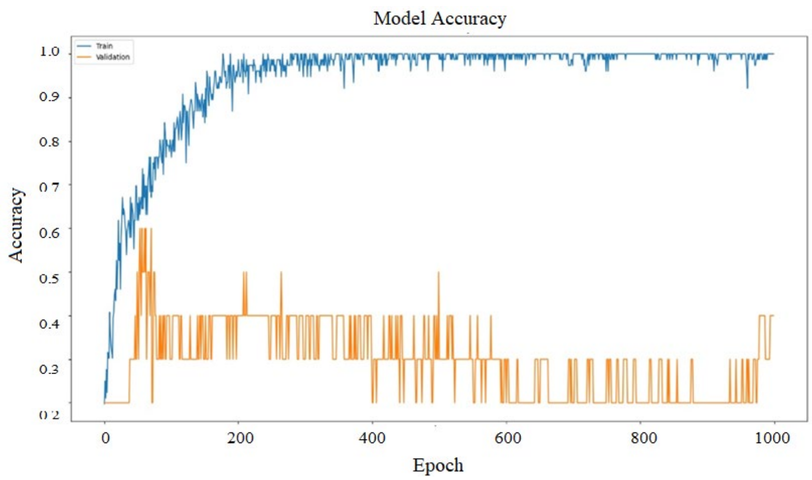
(c)

FIGURE 3. (a) Acquired EEG Signal (b) Denoised EEG Signal (c) Relative Power of EEG Signals.

EEG signal are acquired with the help of the Emotiv Epoc neuroheadset. Acquired EEG signal for the subject suffering from the Alzheimer disease as shown in the figure 3(a). Preprocessing technique like wavelet is used for the denoising the EEG as shown in the figure 3(b) and then calculates spectral based feature like relative power as shown in the figure 3(c). Deep learning is a form of machine learning and artificial intelligence (AI) that imitates the way individuals learn particular types of information. Data science, which also includes statistics and predictive modelling, is essential for deep learning. Deep learning has the advantage that the feature set is generated by the program independently. Unsupervised learning is often more accurate and faster than supervised learning. The MLP network produces an overfit model that is inappropriate for testing when different EEG data from various phases of AD and normal are input into it, as illustrated in figure 4.



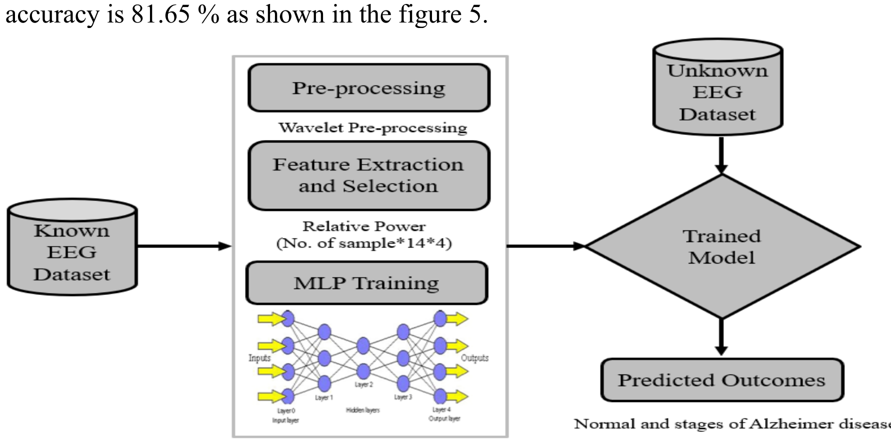
(a)



(b)

FIGURE 4. (a) MLP Architecture I Network (b) Epoch Accuracy

In order to increase the accuracy, relative power of different band present in EEG signals are calculated. During EEG signal acquisition, 14 channels are available per samples. Here, four relative powers calculated for each channel so total features for each sample are (14*4) = 56. These features are given to the MLP network. After classification the accuracy is 81.65 % as shown in the figure 5.



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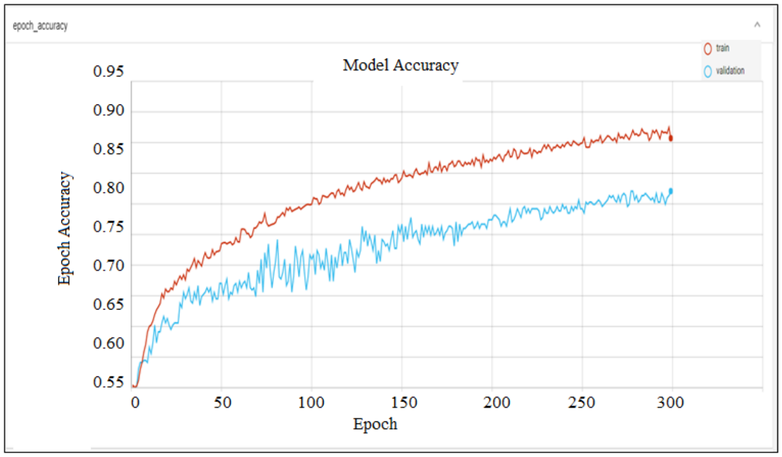
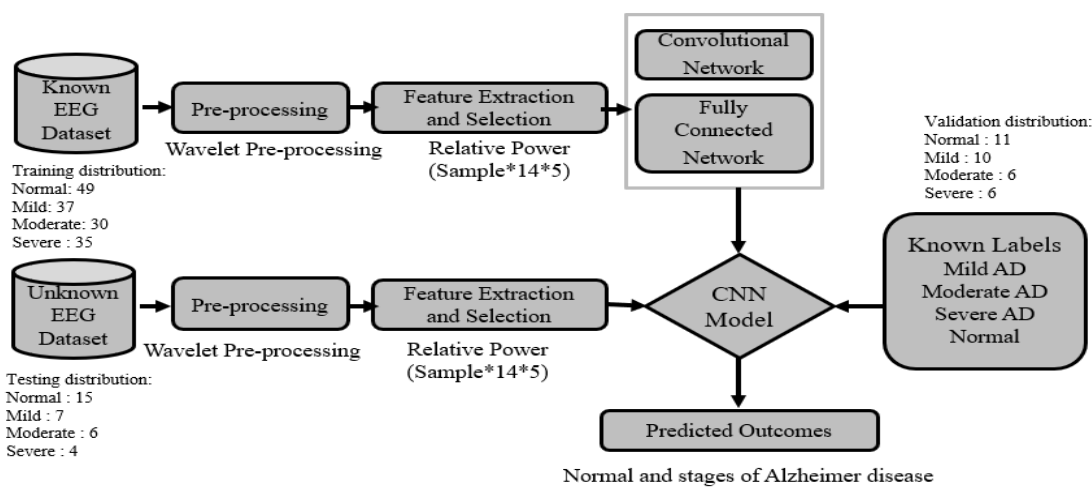


(b)

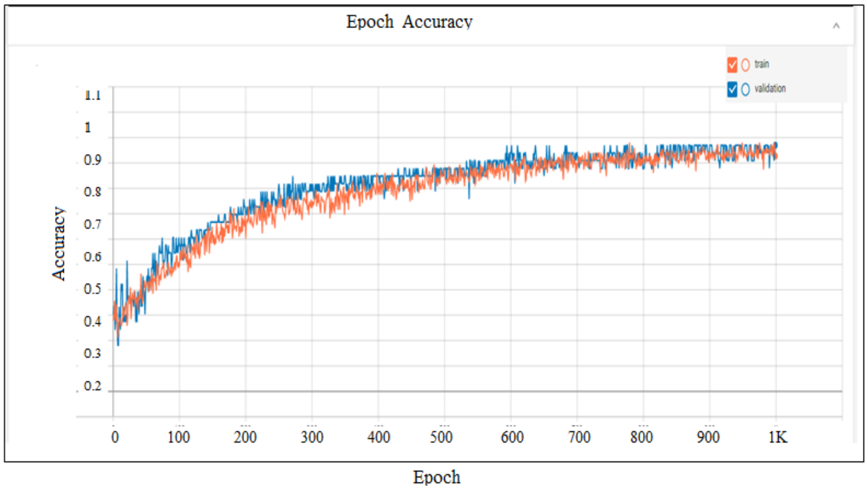
True Label \ Predicted label	Normal	Mild AD	Moderate AD	Severe AD
Normal	126	6	3	6
Mild AD	11	29	3	3
Moderate AD	1	3	28	1
Severe AD	9	5	0	44

(c)

FIGURE 5. (a) MLP Architecture II Network (b) Epoch Accuracy (c) Confusion Matric for MLP Architecture II



(a)



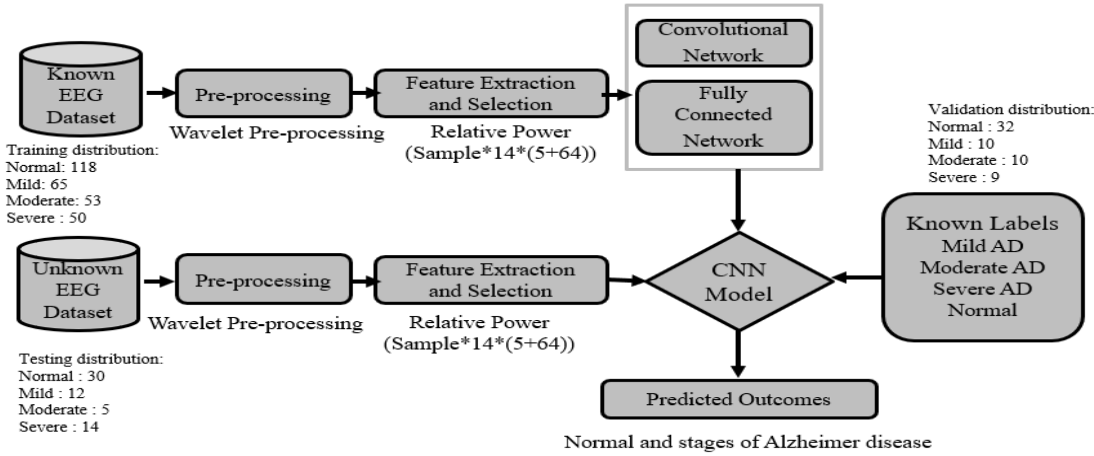
(b)

True Label	Normal	Mild AD	Moderate AD	Severe AD
Normal	14	0	0	1
Mild AD	1	6	0	0
Moderate AD	0	0	6	0
Severe AD	0	0	0	4
	Predicted label			

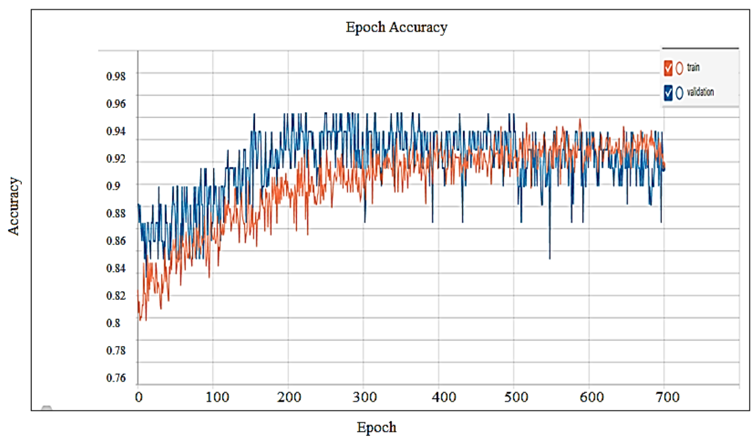
(c)

FIGURE 6. (a) CNN Architecture I Networks (b) Epoch Accuracy (c) Confusion Matrix

The main objective of the present study is to diagnose whether the certain input EEG signals of the subjects are suffering from various stages of AD or normal. So, second classifier used in this study is convolutional neural network. In this network, five relative powers are calculated as features for each sample and all samples have 14 channels. So, Total features are provided to the CNN are 70 (14*5) per channel and calculate the accuracy.93.75 % accuracy is obtained for the CNN architecture I network as shown in the figure 6



(a)



(b)

True Label		Predicted Label			
		Normal	Mild AD	Moderate AD	Severe AD
	Normal	29	1	0	0
	Mild AD	1	11	0	0
	Moderate AD	0	0	5	0
	Severe AD	0	0	0	14

(c)

FIGURE 7. (a) CNN Architecture II Networks (b) Epoch Accuracy (c) Confusion Matrix

Again, for increasing the accuracy and for good training, power spectral density feature is added in the network. So total features in this network for each channel is 69 (64 power spectral density and 5 relative power). So, for each sample, total features are 966 (14 channel * 69 features). The obtained accuracy for the CNN architecture II is 96.72 % as shown in the figure 7. we shifted the deep learning algorithm especially multilayer perceptron model and convolutional neural network for getting the good accuracy. After comparing the obtained results in the given study with the literature survey, the obtained result are comparatively so good which is summarized in the table 4.

TABLE 4. Diagnostic Accuracy Obtained in the given Study using Multilayer Perceptron (MLP) and Convolution Neural Network (CNN) Classifier Compared with the Literature Survey

Sr. No.	Author	Algorithm	Accuracy (%)
1	D. Puri et al [7]	Support Vector Machine	95
2	D. Pirroneet et al [8]	Supervised machine learning	75
3	M. Amini et al [9]	Deep Learning Algorithm	89.14
4	M. Ouchani et al [10]	Complexity features	93.3
5	S. Nobukawa et al [11]	Complexity based Synchronization features Electroencephalography	92
6	M. Ismail et al [12]	Deep learning Network	92.52
7	Proposed Methodology	Multilayer Perceptron I	45
8	Proposed Methodology	Multilayer Perceptron II	81.65
9	Proposed Methodology	Convolutional Neural Network I	93.75
10	Proposed Methodology	Convolutional Neural Network II	96.72

CONCLUSION

The diagnosis of Alzheimer based on these neuroimaging tools are visually identifiable rather it's very difficult in the tool which is based on EEG signal. EEG has emerged as an important tool for early detection of AD. The AD-patient EEG signal shows functional changes in the brain cortex like EEG slows down, reduced the complexity in EEG signal and perturbation in synchrony measure. The main problem faced by the neurologist consists in distinguishing the phases of the AD from changes in memory and thought, particularly normal, mild and moderate, since the slight EEG changes occur between normal, mild and moderate. In order to increase the accuracy of biomarker, artificial intelligence is used to classify the AD and find the early stage of AD called mild AD. The actual purpose of behind introducing AI to this space as AI is machine intelligence that enable computer to perform such intellectual task such as problem solving and decision making. The main aim of AI is to make task automated. Not all, but most of the task which reduces human effort and time with more accuracy. Finally, by comparing the classification performances in term of accuracy based multilayer perceptron and convolution neural network, 96.72 % accuracy is achieved.

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