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Analyzing electroencephalograph signals for early Alzheimer's disease detection: deep learning vs. traditional machine learning approaches

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ABSTRACT

Alzheimer's disease (AD) stands as a progressive neurodegenerative disorder with a significant global public health impact. It is imperative to establish early and accurate diagnoses of AD to facilitate effective interventions and treatments. Recent years have witnessed the emergence of machine learning (ML) and deep learning (DL) techniques, displaying promise in various medical domains, including AD diagnosis. This study undertakes a comprehensive contrast between conventional machine learning methods and advanced deep learning strategies for early AD diagnosis. Conventional ML algorithms like support vector machines, decision trees, and K nearest neighbor have been extensively employed for AD diagnosis through relevant feature extraction from heterogeneous data sources. Conversely, deep learning techniques such as multilayer perceptron (MLP) and convolutional neural networks (CNNs) have demonstrated exceptional aptitude in autonomously uncovering intricate patterns and representations from unprocessed data like EEG data. The findings reveal that while traditional ML methods may perform adequately with limited data, deep learning techniques excel when ample data is available, showcasing their potential for early and precise AD diagnosis. In conclusion, this research paper contributes to the ongoing discourse surrounding the choice of appropriate methodologies for early Alzheimer's disease diagnosis.

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1. INTRODUCTION

In the field of medical diagnostics, there has been a significant focus on the early and accurate detection of Alzheimer disease (AD) through extensive research and innovation. This pursuit has given rise to two closely related and prominent areas of study: deep learning (DL) and machine learning (ML). These approaches offer unique methodologies for analyzing intricate patterns within complex datasets and have shown great potential in facilitating the early diagnosis of AD [1], [2]. Machine learning, which falls under the umbrella of artificial intelligence, encompasses a variety of algorithms that enable computers to learn from data without explicit programming. This technique has been effectively utilized to uncover complex

relationships within medical datasets, enabling the identification of subtle markers that indicate the presence of AD in its initial stages. Conversely, deep learning, a specialized subset of machine learning, utilizes neural networks like human brain structure. Its capacity to automatically extract hierarchical features from raw data has led to significant advancements in the analysis of medical bio signals. This has facilitated the detection of subtle anomalies that might not be discernible through traditional method [3], [4].

In this comparative exploration, the strengths and limitations of both DL and ML in the context of early AD diagnosis are explored. anyone navigates through their respective approaches to data processing, feature extraction, and model construction, shedding light on how each technique contributes to unravelling the intricate puzzle of this debilitating condition. Furthermore, the challenges associated with these methodologies, including data availability, interpretability of results, and model generalization, all of which play pivotal roles in the clinical translation of these innovations. It becomes evident that both DL and ML offer promising avenues for enhancing the early diagnosis of AD [5]. Ongoing research emphasized to explore the utilization of EEG signals in the early detection of AD using ML and DL techniques. Please note that the field of research is rapidly evolving, and there may have been additional studies published since then. Here are some key papers and references that anyone might find useful [6], [7].

A novel architecture for AD detection using electroencephalograph (EEG) signals was introduced by Miltiadous *et al.* [8] in their work titled "Dice-Net: a novel convolution-transformer architecture for Alzheimer detection in EEG signals". This architecture combines convolutional neural networks (CNNs) with transformer components [8]. Similarly, in the study titled " DemNet: A convolutional neural network for the detection of AD and mild cognitive impairment (MCI)," conducted by Billones *et al.* [9] CNN was utilized the diagnosis of AD and MCI. In this research, a modified version of the 16-layered VGGNet was used for the 3-way classification of AD, MCI, and healthy controls [9]. Proposing a method for early AD diagnosis using deep learning, Saleem *et al.* [10] emphasized the significance of utilizing various biomarkers and datasets. A study by Amini *et al.* [11] utilized the time-dependent parameter to extract EEG features from each channel as input for a CNN. Achieving an accuracy rate of 82.30% on a dataset comprising resting-state EEG data from diverse subjects. Amini *et al.* [11] introduced a novel perspective by considering the spatial attributes of EEG in classification of AD. While achieving commendable classification performance, this study lacked a direct comparative analysis of AD versus MCI [12]. The challenge of accurately diagnosing MCI remained unresolved. To address these issues, the authors augmented the EEG data and proposed a one-dimensional convolutional neural network model based on the deep pyramid CNN (DPCNN). This model was designed for the three-class classification of EEG signals at various AD stages [13].

2. METHOD

To facilitate early AD diagnosis, a diverse array of multidisciplinary methods is employed. Firstly, a neurological strategy is employed, entailing the investigation of neurofibrillary tangles, plaques, and gamma-aminobutyric acid as prospective biomarkers. However, given that these investigations are still in their nascent stages, it remains exceptionally challenging to identify reliable biomarkers [14]. Various biological brain analysis procedures using signal or image processing. A method called magnetic resonance imaging (MRI) uses the physical characteristics of the brain's structure to obtain statistical information. Functional MRI (fMRI), which refers to metabolic activity taking place in the brain, gives an intermediate temporal and spatial resolution compared to MRI, which has a high degree of spatial resolution but a poor level of temporal resolution as shown in the Figure 1 [15].

The EEG dataset used in this research was sourced from the Alzheimer's and Related Disorders Society of India (ARDSI) Chaitanya Mental Rehabilitation Centre and Jagruti Rehabilitation Centre in Pune. It involved individuals at various phases of AD and individuals without the condition. Selection criteria involved individuals exhibiting cognitive and behavioral impairment, as confirmed by neurologists through assessments such as the mini mental state examination (MMSE) and clinical dementia rating (CDR), representing distinct age groups and both genders (males (M) and females (F)) from diverse geographic locations. Detailed information about the EEG dataset can be found in Table 1. Each data sample had a duration of 60 seconds.

Raw EEG signals were obtained from patients seated in a dark room. Figure 2 shows EEG signal acquisition system using the EMOTIV EPOC neuro headset with 14 electrodes in Figure 2(a) placed to the scalp with the help of gel as per 10-20 model as shown in Figure 2(b) and acquired EEG signal as shown in Figure 3. These signals were sampled at 128 Hz and wirelessly transmitted to a dongle of desktop system via USB port. Throughout EEG assessments and recordings, subjects were instructed to stay alert, maintain closed eyes, and engage in deep breathing exercises. Any manual identification and isolation of artifacts within the EEG signals, such as instances of eye blinking and muscle movements, were performed.

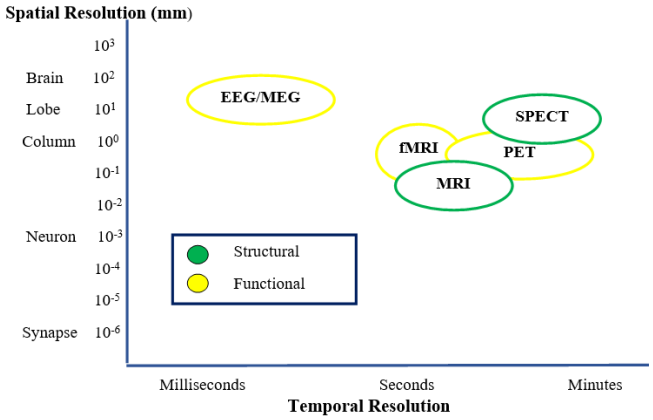
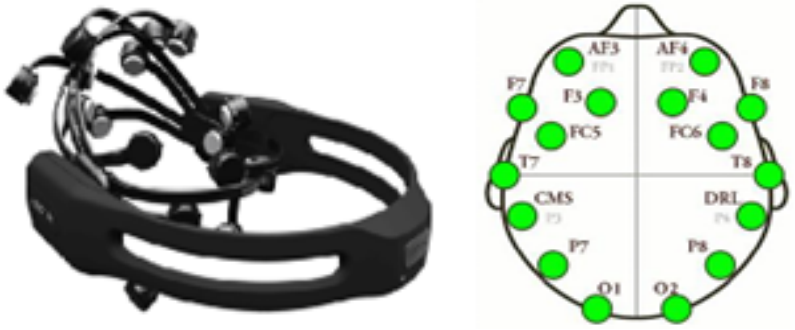


Figure 1. Comparison of several non-invasive and invasive treatments' spatial and temporal resolution

Table 1. Provides comprehensive information regarding the EEG dataset utilized in the research

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



(a) (b)

Figure 2. EEG signal acquisition system (a) EMOTIV EPOC neuroheadset and (b) acquiring electrodes positions as per the 10-20 model [16]

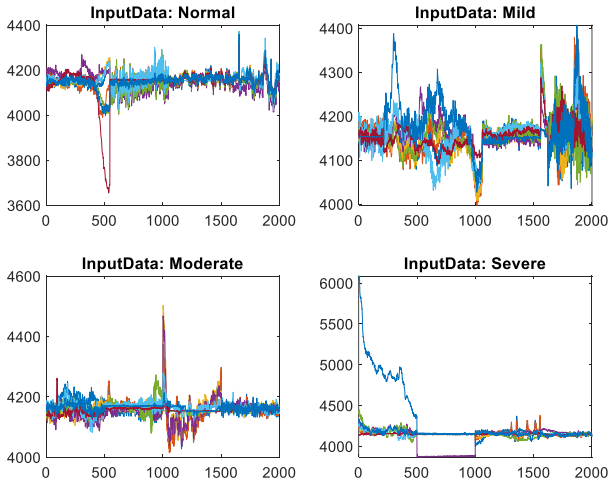


Figure 3. Acquired EEG signals

In contrast to alternative recording methods such as single photon emission computed tomography (SPECT) or positron emission tomography (PET) scans, EEG is commonly utilized due to its inherent simplicity and cost-effectiveness [17], [18]. EEG signals serve various purposes, including applications in brain-computer interfaces (BCIs) and as a diagnostic tool for medical professionals. In the EEG of individuals with AD distinctive abnormalities are often observed, including EEG slowing, a reduction in complexity, and synchronization disruptions. Notably, when EEG signals decelerate, there is an increase in the power of low-frequency components (0.5 to 7.5 Hz), while the power of high-frequency components (7.5 to 30 Hz) decreases [19], [20].

3. METHOD

The system described entails four fundamental steps: EEG signal acquisition, segmentation of the signal through pre-processing, feature extraction from the segmented EEG signals, and finally, classification into distinct phases of AD and normal individual. The initial stage involves preparing the input signal for the next steps EEG analysis. In the second step, EEG data pre-processing is performed to eliminate noise and artifacts such as eye blinking and muscles activity, device power line interference, and additional sources of distortion. The third phase focuses on feature extraction from the pre-processed signals. Lastly, in the classification stage, the signals are categorized into AD stages and normal subjects. The precise functioning of the proposed approach is mentioned in Figure 4.

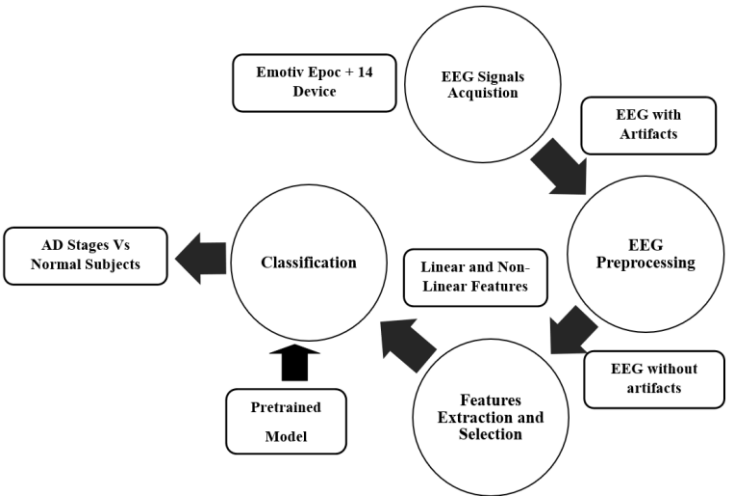


Figure 4. Detailed working approach of the system

The EEG dataset mentioned in the preceding section is further discussed here. Certain critical stages within any algorithm, such as feature calculations, heavily rely on the EEG signal quality. The quality of EEG signals tends to degrade during the acquisition process, potentially introducing various artifacts, as discussed earlier. Consequently, it becomes imperative to perform multiple pre-processing specially wavelet denoising based steps to eliminate these artifacts and enhance signals for further analysis and evaluation.

Zikov utilized the wavelet-based approach to remove artifacts from EEG signal. In this method, continuous wavelet functions known as 'mother wavelets,' like Daubechies, are frequently used to assess signal clarity across various frequencies and time intervals [21]. Essentially, this technique is employed to enhance the EEG signal by reducing noise, as depicted in (1).

$$s(n) = f(n) + \sigma\, e(n) \quad (1)$$

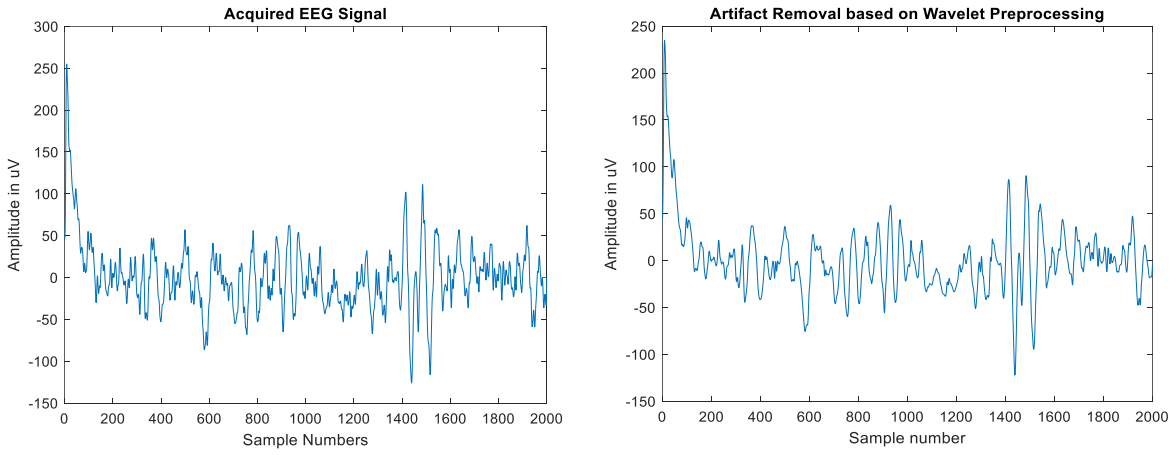
In this study, we utilize three steps in wavelet-based artifact removal from EEG signals decomposition, thresholding, and reconstruction [22]. In this context, 'n' represents the spatial division of the data, $'f(n)'$ denotes the original signal, $'e(n)'$ represents Gaussian noise, and 'σ' is assumed to be one, symbolizing the noise level.

In the context of early diagnosis for various conditions, such as epilepsy, Parkinson's disease and AD, biomedical signal processing plays a pivotal role. These biomedical signals carry crucial information for identifying different disease stages. However, a significant concern arises due to the substantial size of EEG

data, which directly impacts computation time. Moreover, not all portions of EEG data are essential for diagnostic purposes; a substantial portion of it is extraneous. To address this issue, the process of feature extraction is employed to identify meaningful and distinguishing characteristics. Our focus lies on employing spectral-based features, independent component features, and wavelet coefficient features for classification purposes [23]. In our proposed framework, machine learning techniques like decision tree (DT), k-nearest neighbor (KNN) and support vector machine (SVM) and deep learning methods such as MLP and CNN are used for the classification of distinct phases of AD. The EEG dataset is first standardized and then divided into two categories through random partitioning, often allocating one for training and the other for testing purposes [24], [25].

4. RESULT AND DISCUSSION

Within the established framework, the process of data acquisition and pre-processing is carried out. Figure 5 shows sample EEG signal with captured raw EEG in Figure 5(a) and artifact free EEG signal in Figure 5(b). Reliable grouping models are derived from a given research that allows one to place the individual in their respective class like stages of AD and normal. The primary aim of this current research is to investigate whether specific EEG data inputs from participants can distinguish between different stages of AD and normal cognitive function. To distinguish the samples of various phases of AD and normal people as output, this needed a classifier.



(a) (b)

Figure 5. Sample EEG signal (a) captured raw EEG (b) artifact free EEG

4.1. Spectral based features

Several features are discussed in the literature that were used for classification. The classification process involves analyzing multidimensional EEG data signals across different frequency bands [26]. To enhance the raw EEG signals for further analysis, a two-phase approach is employed: EEG acquisition and pre-processing. During pre-processing, unwanted artifacts were eliminated from the signal using wavelet-based algorithms, which allowed us to separate the EEG datasets into alpha, beta, gamma, theta, and delta frequency ranges. The analysis involved determining the power of individual frequency bands for both individuals with Alzheimer's disease and those without the condition, followed by a comparison of these two groups. It was observed that in Alzheimer's patients, the power in the lower frequency bands, specifically delta and theta, increased as the disease advanced from its early stages to the severe stages, while the power in the alpha and beta bands decreased. These variations in relative power indicated a slowing down of the EEG signals, which is a characteristic of AD. In contrast, the power analysis of normal subjects showed higher power in high-frequency bands and lower power in low-frequency bands. To present the results, Figure 6 and Figure 7 illustrated the relative powers of different EEG sub-bands in EEG signals with relative powers of normal subject in Figure 7(a) and relative powers of AD subject in Figure 7(b) [27], [28]. The time-frequency bumps observed in the EEG data signals of AD patients. These bumps are attributed to the slowing effect in the EEG signal caused by neuronal loss in affected brain regions, a phenomenon not observed in individuals without the AD condition.

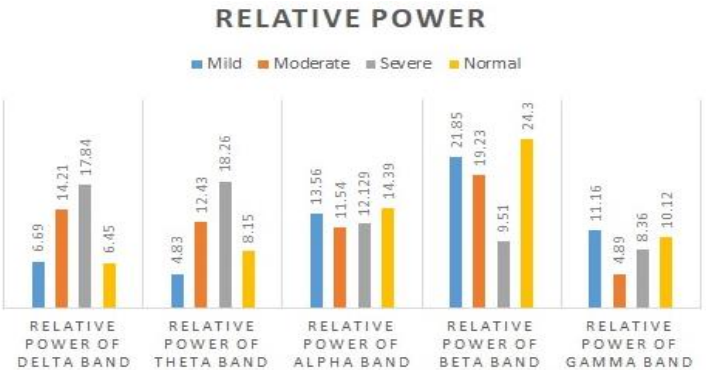
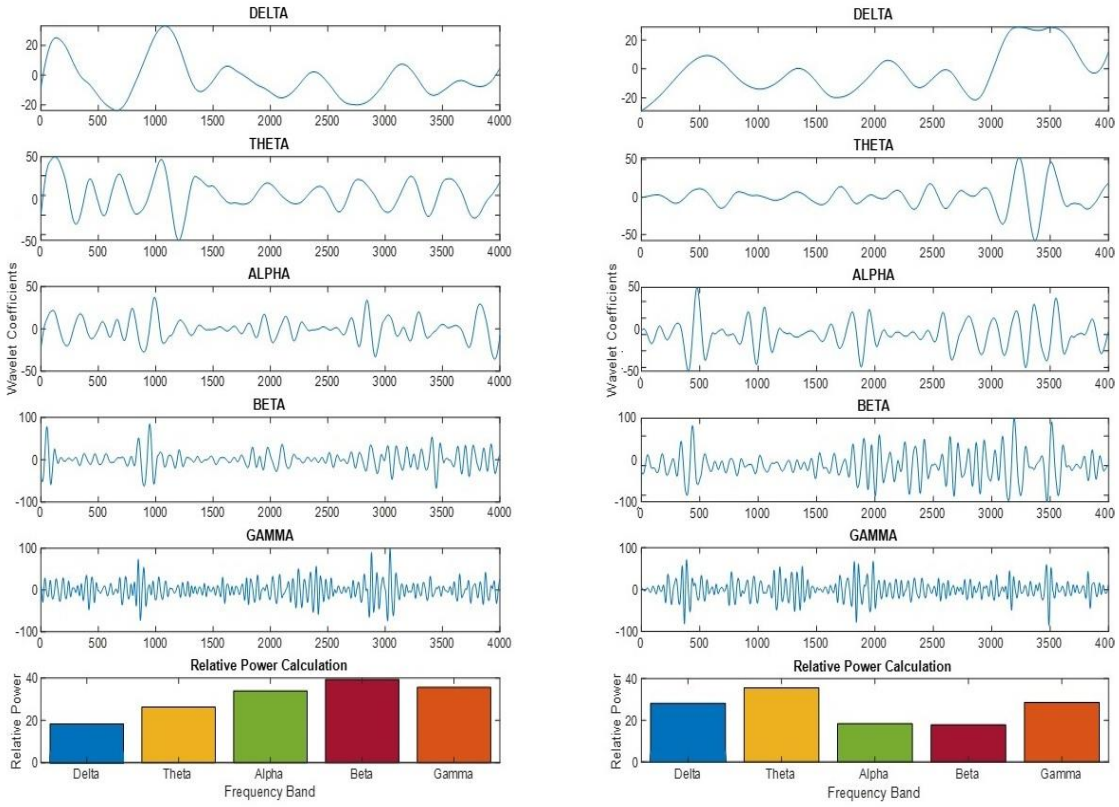


Figure 6. Relative powers of EEG subbands of various individuals



(a) (b)

Figure 7. Relative powers of different sub-bands in EEG signals (a) normal subjects (b) AD subjects

4.2. ICA based features

In this study, ICA is employed to extract features and classify AD stages in comparison to normal subjects. ICA is utilized to enhance early AD detection by integrating conventional feature selection methods. After applying ICA to EEG signals, they are transformed into separate components that provide significant information, as depicted in Figure 8. These components serve as features for the entire length of EEG samples. Notably, the reference channel is not considered in these methodologies.

Figure 8 displays box plots representing ICA features for normal and AD subjects. The interquartile range is notably higher in healthy normal subjects compared to AD stages. This range of variation decreases as AD progresses. The most notable differences can be observed in channels 1 (AF3), 2 (AF4), 7 (P7), and 8 (P8), which are associated with attention, cognitive assessment, verbal abilities, and emotional memory. These aspects are commonly impaired in individuals diagnosed with AD. Additionally, a decrease in motor planning activity is observed in AD subjects as the disease progresses.

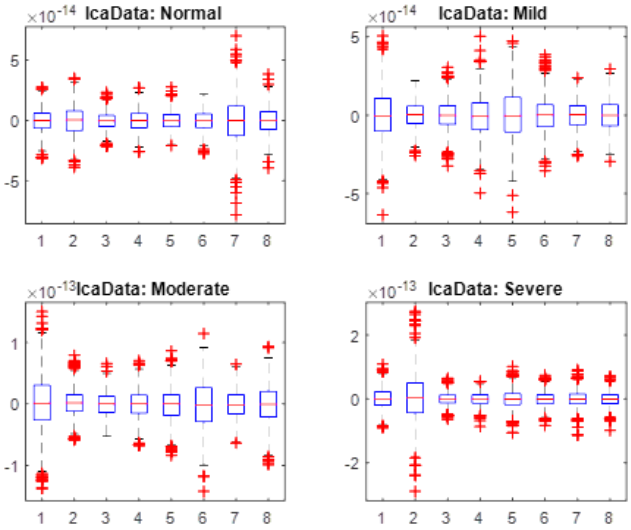


Figure 8. ICA features of the EEG sample of distinct phases of AD and normal individuals

4.3. Wavelet based features

EEG signal analysis plays a crucial role in adopting the appropriate approach for extracting information from signals. A feature represents a quantitative measure that distinguishes between different stages of AD and normal conditions. Specifically, it provides insights or descriptions about specific data points. In this study, the wavelet transform is employed as a technique to extract features from patients, both with and without AD. The application of wavelet transform methods facilitates feature extraction from EEG data. The choice of the wavelet type and the number of decomposition steps is vital in wavelet-based signal analysis. The dominant frequency components of the signal aid in determining the optimal number of decomposition levels. These levels are carefully selected to retain the wavelet coefficients associated with the signal portions that exhibit a strong correlation with the frequencies necessary for signal categorization. The wavelet coefficient values for both AD and normal subjects are presented in Figure 9 and Table 2. It is evident that the wavelet coefficient values are higher for normal subjects, indicating greater EEG complexity in this group. This heightened complexity can be attributed to the increased presence of active neuron cells in the brain. Conversely, for AD subjects, the values in the tables tend to decrease from mild to severe stages, reflecting a reduction in complexity. This reduction is linked to the loss and death of neurons in AD patients, underscoring the diminished EEG complexity in comparison to normal subjects.

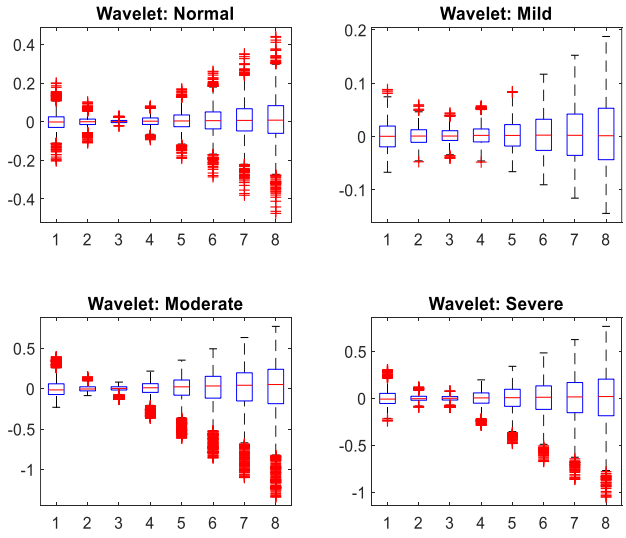


Figure 9. Wavelet analysis features of the EEG sample of distinct phases of AD and normal individuals

Table 2. Wavelet coefficients value of various channel for distinct phases of AD and normal subjects

Sample full length	AF3	F3	T7	P7	P8	T8	F4	AF4
Mild AD subjects								
Mild AD 1	-1.6088	-1.6049	-8.6011	-8.5973	-8.5935	-8.5897	-8.5859	-8.5822
Mild AD 2	-0.0048	-0.0003	0.0041	0.00851	0.01287	0.01721	0.0215	0.02576
Mild AD 3	-0.0048	-0.0003	0.0041	0.00851	0.01287	0.01721	0.0215	0.02576
Mild AD 4	-0.1124	-0.0958	-0.0787	-0.0614	-0.0437	-0.0258	-0.0078	0.01035
Mild AD 5	-0.8209	-0.8383	-0.8334	-0.8057	-0.7594	-0.7009	-0.6351	-0.5639
Moderate AD Subjects								
Moderate AD 1	-2.0778	-5.054	-3.0303	-2.0066	-4.9831	-4.9596	-4.9362	-4.913
Moderate AD 2	-0.041	-0.0132	0.01454	0.04203	0.06929	0.09635	0.12319	0.14979
Moderate AD 3	-0.5047	-0.4379	-0.3706	-0.3032	-0.2357	-0.1687	-0.1024	-0.037
Moderate AD4	-1.3706	-1.2364	-1.0984	-0.9574	-0.8137	-0.6664	-0.5156	-0.3622
Moderate AD 5	-2.0181	-4.0687	-4.0258	-3.8912	-3.6751	-3.4013	-3.0873	-2.7414
Severe AD Subjects								
Severe AD 1	-0.3901	-0.3899	-0.3827	-0.3683	-0.3475	-0.3213	-0.2908	-0.2567
Severe AD 2	0.14742	0.04928	-0.0482	-0.1449	-0.2409	-0.3361	-0.4305	-0.5242
Severe AD 3	1.8176	1.5821	1.3451	1.1074	0.86971	0.63346	0.39972	0.16906
Severe AD 4	-0.0685	-0.0589	-0.0491	-0.0394	-0.0296	-0.02	-0.0104	-0.0009
Severe AD 5	-0.0082	-0.0041	3.0005	0.00412	0.00818	0.01221	0.0162	0.02017
Normal Subjects								
Normal AD 1	-0.3366	-0.3332	-0.3297	-0.3263	-0.3229	-0.3195	-0.3161	-0.3127
Normal AD 2	4.5498	4.0934	3.6243	3.1451	2.6565	2.1563	1.6446	1.1246
Normal AD 3	1.596	11.513	11.429	1.346	01.264	11.182	11.1	11.018
Normal AD 4	-0.2423	-0.2214	-0.1999	-0.1779	-0.1554	-0.1322	-0.1084	-0.0841
Normal AD 5	13.97	1.153	14.006	1.534	0.776	11.815	10.718	9.5113

4.4. Classifier

Some ML techniques are applied for diagnostic accuracy. In this case, samples collected from ARDSI and Jagruti Centre were used in the study mentioned in the previous section. Wavelet based pre-processing is used for removal of noise. Wavelet and ICA based features are extracted which is given to the different three classifiers namely SVM, KNN and DT for the detection of early phases of AD and normal subjects shown in the Figure 10 and the diagnostic accuracy obtained with respect to these classifiers is shown in the Figure 11 and Table 3.

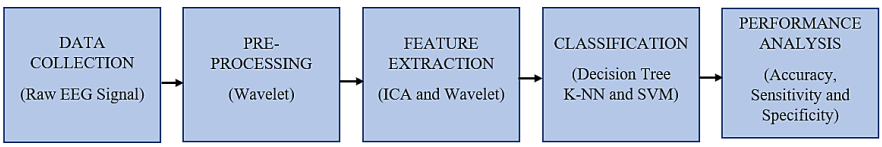


Figure 10. ICA and wavelet-based features used for predicting diagnostic accuracy using DT, KNN and SVM

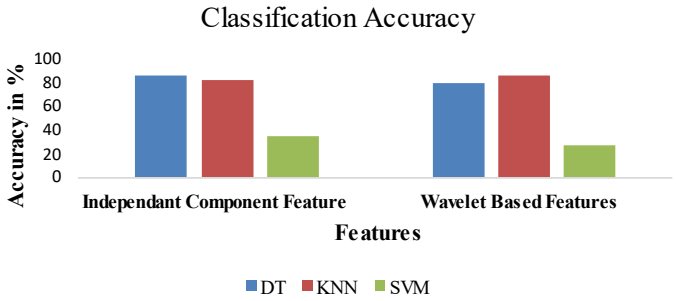
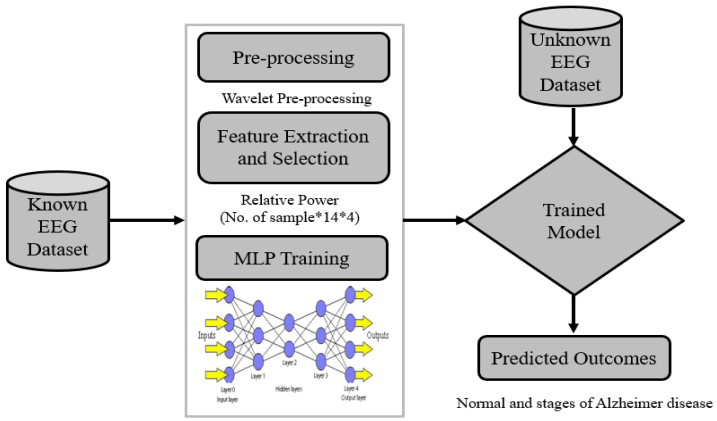


Figure 11. Comparison of accuracy of various classifier based on ICA and wavelet-based features

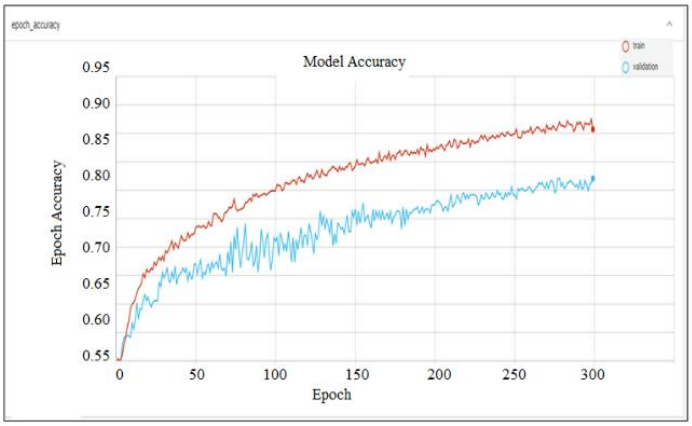
Table 3. Accuracy based on DT, KNN and SVM classifier

Features		Accuracy (%)		
		DT	KNN	SVM
Independent component features	Independent component features	86.47	81.72	34.58
Wavelet based features	Wavelet based features	80.15	85.87	27.58

To improve accuracy, we calculate the relative power of different frequency bands in EEG signals. We have 14 channels per sample, and for each channel, we compute four relative power values, totaling 56 features for each sample. These characteristics are subsequently input into the MLP network, yielding a classification accuracy of 81.65%. Figure 12 shows the use of neural network in analysis process where Figure 12(a) shows the neural network structure for MLP architecture II, Figure 12(b) shows the accuracy across epochs and Figure 12(c) represents the confusion matrix corresponding to MLP architecture II.



(a)



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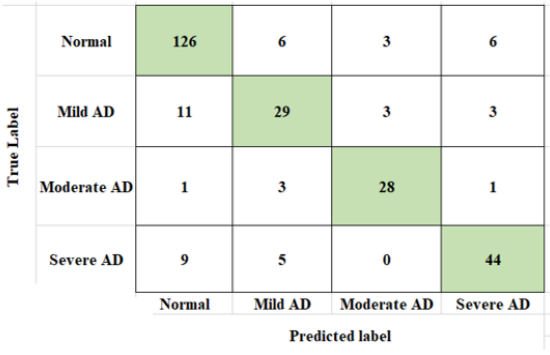
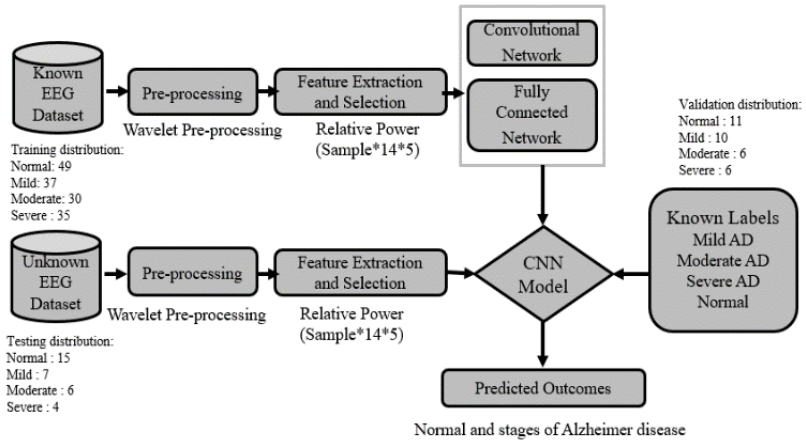


(c)

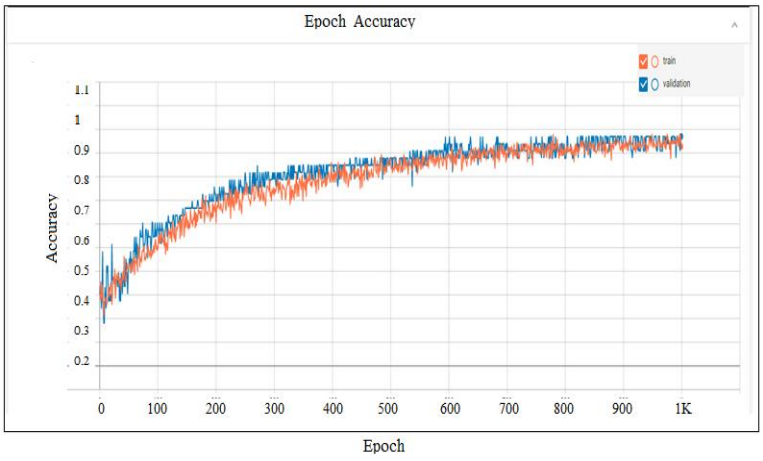
Figure 12. Use of neural network in analysis (a) the neural network structure for MLP architecture II, (b) the accuracy across epochs, and (c) the confusion matrix corresponding to MLP architecture II [26]

The primary objective of this study is to determine if specific EEG signals from subjects exhibit signs of distinct phases of AD or remain within the normal range. To accomplish this, CNN is employed as

the secondary classifier in our research. Within this, relative power values of five sub bands are computed as features for each individual sample, with each sample containing data from 14 channels. Consequently, CNN receives a total of 70 features (14 channels multiplied by 5 features per channel) per input, and its accuracy is evaluated. The CNN architecture I network achieved an accuracy of 93.75%. Figure 13 shows Use of CNN in analysis, where Figure 13(a) shows the neural network structure for CNN architecture I, Figure 13(b) shows the accuracy across epochs and Figure 13(c) shows the confusion matrix corresponding to CNN architecture I. Once more, to enhance accuracy and improve training, the network incorporates the power spectral density (PSD) feature.



(a)



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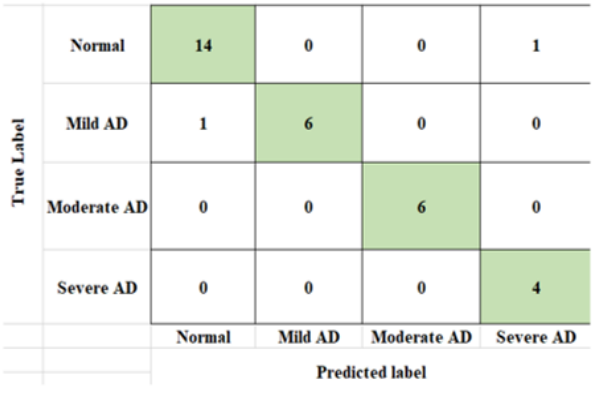
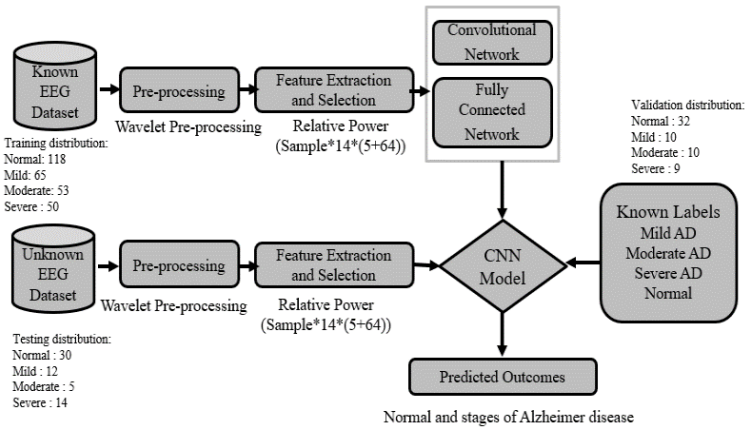


(c)

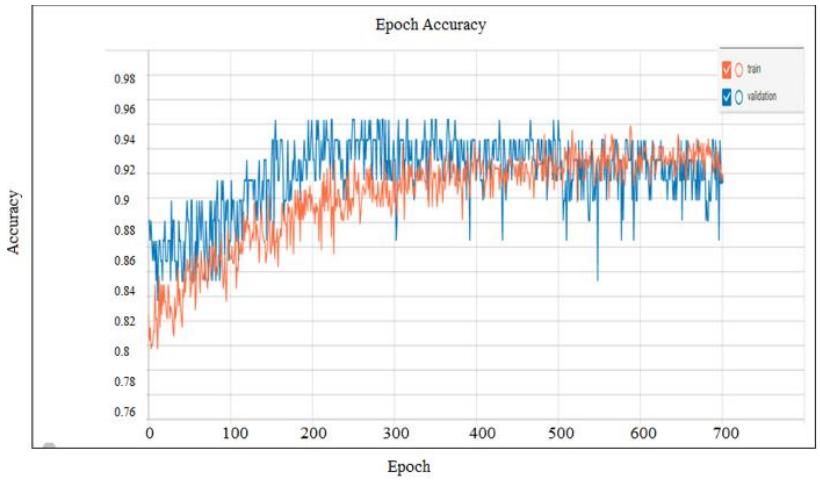
Figure 13. Use of CNN in analysis (a) the neural network structure for CNN architecture I, (b) the accuracy across epochs, and (c) the confusion matrix corresponding to CNN architecture I [26]

Consequently, each channel within this network now encompasses a total of 69 features, comprising 64 PSD features and five relative power features. Consequently, for each individual sample, the cumulative number of features amounts to 966 (14 channels multiplied by 69 features). Figure 14 illustrates the Use of CNN in analysis where the CNN architecture II is shown in Figure 14 (a), which achieves an impressive accuracy rate of 96.72% as shown in Figure 14(b). Figure 14(c) represents the confusion matrix corresponding to CNN architecture II.

The study investigates the effectiveness of deep learning algorithms, specifically the multilayer perceptron model and convolutional neural network, in achieving high accuracy. Upon comparing the study's results with the findings from the existing literature, it is evident that the obtained results are notably strong, as in Table 4.



(a)



(b)

True 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
	Normal	Mild AD	Moderate AD	Severe AD
	Predicted Label			

(c)

Figure 14. Use of CNN in analysis (a) the neural network structure for CNN architecture II, (b) the accuracy across epochs, and (c) the confusion matrix corresponding to CNN architecture II [26]

Table 4. Diagnostic accuracy obtained in current study using various ML and DL techniques

Sr. No.	Pre-processing Techniques	Features	Classifier	Accuracy (%)
1	Wavelet based	Independent component	DT	86.47
2	Wavelet based	Independent component	KNN	81.72
3	Wavelet based	Independent component	SVM	34.58
4	Wavelet based	Wavelet Coefficient	DT	80.15
5	Wavelet based	Wavelet Coefficient	KNN	85.87
6	Wavelet based	Wavelet Coefficient	SVM	27.58
7	Wavelet based	Spectral Based	MLP Arch II	81.65
8	Wavelet based	Spectral Based	CNN Arch I	93.75
9	Wavelet based	Spectral Based	CNN Arch II	96.72

5. CONCLUSION

In conclusion, the analysis of EEG signals for early AD detection presents a significant challenge and opportunity in the field of medical diagnostics. This study investigated the effectiveness of two distinct approaches, namely ML and DL, in tackling this task. DL, a subset of artificial intelligence, has shown remarkable promise in various domains, including image and speech recognition. In the context of EEG signal analysis, DL algorithms, such as MLP and CNN, have demonstrated their ability to automatically learn intricate patterns and features from EEG data or provided features. This enables them to capture subtle abnormalities and nuances that might indicate the presence of early AD. On the other hand, Traditional ML approaches, which encompass a wide range of techniques such as SVM, KNN and DT have also shown promise in EEG-based AD detection. These methods often rely on feature engineering, where domain knowledge is used to extract relevant features from the EEG data.

In comparing the two approaches, it is evident that DL models have the potential to outperform Traditional ML methods in terms of accuracy and generalization. Ultimately, the choice between DL and ML for analyzing EEG signals in early AD detection depends on various factors, including the available resources, dataset size, and the desired level of automation. Combining the strengths of both approaches could also yield promising results, with deep learning models learning intricate patterns and traditional machine learning methods providing interpretability and clinical relevance.

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