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Significance of Spectral & Wavelet features in diagnosis of Alzheimer's Disease

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***Abstract*—** Alzheimer Disease is one of the leading neuro-degenerative diseases. It is the most expensive disease in the modern society which is characterized by cognitive, intellectual as well as behavioral disturbance. Due to this, the early diagnosis of the disease is essential. Electroencephalography can be used as standardized tools for diagnosis of Alzheimer Disease. This paper discusses the important aspects of Electroencephalography & spectral & wavelet based features for early diagnosis of Alzheimer's disease. This paper discusses the use of the different spectral based features such as Relative EEG power in various bands of EEG signal. In this study, it is observed that the EEG of the Alzheimer patients slows down & the EEG of the AD infected patients is less complex as that compared to the Controlled patients. In present research work, classification accuracy of 96% is achieved by use of K nearest Neighbor classifier by combination of Spectral & Wavelet based features. EEG can be therefore used as the tool for the early & automated diagnosis of Alzheimer disease.

***Keywords*—** Alzheimer Disease, Dementia, EEG, Spectral features, Wavelet features, K nearesst neighbor classifier

I. INTRODUCTION

Alzheimer disease is one of the Neuro-degenerative diseases which are found to be complex in the present scenario. It is the common form of dementia and by the time it affects the brains cells [1, 2]. Alzheimer Disease is a chronic Neuro-degenerative disorder that has ranked as third most expensive disease and sixth leading cause of death in United States. It is neurodegenerative disorder characterized by rapid impairment of memory and some other cognitive functions, which are mainly associated with the behavioural disturbances and finally leads to total dependency [3]. An important research is to identify the neuroanatomical basis of cognitive impairment in Alzheimer disease (AD).The need of research is to understand the changes taking place related to the cognitive impairment and the progression of AD in the brain structure [4]-[7]. There exist different techniques for diagnosis of Alzheimer Disease & other neurodegenerative diseases such as Epilepsy, Brain Stroke, and Parkinson's Disease etc. Different neuroimaging methods such as MRI (Magnetic Resonance Imaging), SPECT (Single Photon Emission Computerized Tomography), and PET (Positron Emission Tomography) are used today for diagnosis of neural diseases. Imaging has a key role in medical diagnosis, education and non-invasive therapeutics. The new scientific and technological advances boost the complex issues of diseases such as Alzheimer, Epilepsy and many more. Computer Aided Diagnosis (CAD) is a general tool used for a variety of applications such as to diagnose the disease in medical applications. CAD helps the physicians, researchers in diagnosing the disease in less time by identifying the patterns, making fewer efforts. Non-neuroimaging methods such as EEG, Biomarkers are also used today for AD diagnosis. Electroencephalography (EEG) is one of the tools which can be used for early diagnosis of Alzheimer disease. The Electroencephalogram (EEG) basically reflects the electrical activity of large number of cortical neurons which is mainly associated with the neural information processing of brain regions [8]. In present scenario, there is no significance of objective method based diagnosis of Alzheimer Disease but the use of EEG as a diagnostic tool continues to be challenging part in current studies. Focusing on previous studies obtained in literature, none of the existing systems are not clinically or analytically validated. Due to such reasons, the systems require significant improvements.

In present study, our aim was to investigate and observe the effects of different wavelet & spectral based features on EEG signals of both Alzheimer Disease & Normal patients. In literature, it is observed that Spectral Based features such as EEG Relative Power, Magnitude Square Coherence, Phase Synchrony & EEG amplitude modulation Energy are widely used which plays a significant role in AD diagnosis giving accuracy of about more than 80%. In our proposed research work, our goal was to improve the diagnostic accuracy for classification between two groups. In further part of the paper we discuss the role of the different non – linear features used for early diagnosis of Alzheimer disease.

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II. METHODS

EEG is one of the well-known modality for measuring the electrical activity generated by neurons of the cortex in brain regions. The EEG signals (Bioelectric signals) are recorded noninvasively through a set of electrodes placed on the scalp of human brain according to international 10-20 systems. EEG is now not only treated as key diagnostic tool for neurologists but it is more widely used in Brain Computer Interface (BCI) applications. The use of EEG in the early diagnosis of Alzheimer disease is supported by typical abnormalities observed in the literature [8] [9] [10]:

a) *Slowing:* The slowing effect in EEG signals of Alzheimer patients is associated with the increase of relative power of the low frequency bands (Delta, 0.5-4 Hz, & Theta, 4-8 Hz), along with reductions in power in high frequency bands (Alpha, 8-12 Hz & Beta, 12-30 Hz).

b) *Reduced Complexity*: Reduced Complexity is measured by use of different non-linear features such as Information Theory & other signal processing measures. The non-linear measure shows the increase in regularity in EEG signals of Alzheimer patients.

c) *Loss of Synchrony measures*: Synchrony measures obtained from EEG signals may be significantly affected by brain events other than changes of synchrony, and by choices (like the reference electrodes) that necessary have to be made during the analysis. Several of the Synchrony measures can be applied such as the Pearson Correlation Coefficient, Magnitude and Phase Coherence, Granger Causality, Phase Synchrony etc. Some typical measures includes Coherence, Granger Measures, state space based synchrony measures, Phase Synchrony (PS) and stochastic event synchrony measures. All these measures seek to quantify the relationships between two or more signals.

The diagnosis of Alzheimer disease using EEG signals is followed by suitable methodology. Initially, EEG signal from patient is acquired through the EEG electrode. Basically, 10-20 electrode placement system is used for acquiring of EEG signal. Nowadays, a special electrode cap is available in market, which is normally used for electrode placement on patients head. The acquired signal is pre-processed to obtain the noise free signal. This is done in order to remove certain artefacts available in signal. Different pre-processing techniques are used for signal processing such as Independent component analysis (ICA), Wavelet denoising, Blind source separation (BSS) etc. By using suitable feature extraction methods, various algorithms are used for differentiating the signal. The features extracted are given as the input for classification. Various classifiers are available in domain of pattern recognition & machine learning. Linear Discriminant Analysis, Support vector machine are some of the classifiers that can be used for diagnosis [8]. The fig.1 shows the methodology used for early diagnosis of AD using EEG signals. In this way, EEG can be used as a tool for diagnosis of Alzheimer disease. Along with this, the EEG signals of Temporal, Frontal, Central & Parietal lobes of both normal & Alzheimer disease patients were taken into the consideration for study.

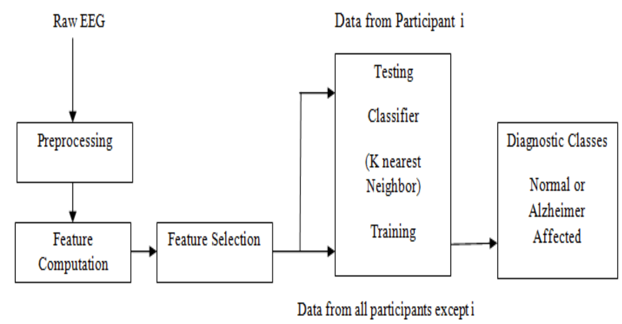

Fig.1 Block Diagram of the Proposed System

III. DATA COLLECTION & SUBJECTS INVOLVED

Relevant Data used in the study was obtained from Smt. Kashibai Navale General Hospital & Research Centre, Pune (India) & Jagtap Clinic & Research Centre, Pune consisting of both Alzheimer patients, Dementia & control patients. Patients were selected from consecutive, community residing elderly persons 60-80 years of age with the report of cognitive decline as well as behavioural functioning. The diagnosis of the patients was made by experienced neurosurgeons, neurologists based on *Mini Mental State Examination (MMSE) and Clinical Dementia Rating (CDR)*. Resting awake multi channel EEG recordings (24 channel electrode) were obtained from 100 participants separated into 2 groups. The first group was consisted of 50 subjects; 30 males & 20 females (mean age: 60 years) giving indication of functional cognitive & behavioural decline. The second group consists of 50 participants of normal subjects consisting of 35 males & 15 females (mean age: 60.5 years), giving no indication of functional cognitive decline. In addition to the AD cohorts, an additional criterion was the presence of functional, behavioural & cognitive decline over the previous 6 months. Patients belonging to the abnormal group were also checked for different diseases such as diabetes, kidney disease, thyroid disease lung & liver disease or vitamin B12 deficiency, as these can also cause cognitive decline. The EEG recordings and the study was approved from Ethical committee of the hospital & the participants.

EEGs were recorded from RMS (Recorders & Medicare systems Private Limited) EEG machine with 12 bits resolutions and sampling rate of 1024Hz. Impedance was maintained below 10Mohms and the electrodes (Referential Montages) were placed according to the International 10-20 systems. Biauricular referential electrodes were also attached as recommended by American EEG Society. The Power grid interference was eliminated by low pass filtering. As there is

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evidence of an interhemisperic disconnection in AD & dementia, a virtual hemisphere bipolar montage is also taken into consideration. The obtained signals are also termed as ‘Bipolar signals’. The Bipolar signals recorded in the study & taken into the consideration are Fp1-Fp2, F3-F4, F7-F8, C3-C4, T3-T4, P3-P4, T1-T6, O1-O2,. During EEG examination & recordings, patients were awake and relaxed with eyes closed. The artefacts of EEG signals such as muscle activity & eye blinking were removed manually.

IV. PRE-PROCESSING

In proposed research work, EEG signal is acquired using EEG electrode cap. But, at the time of acquiring the signals, the signal is contaminated with different noise artefacts. These artefacts are mainly associated due to the power line interference, muscle activity of the patients & eye blinking effects. To obtain the noise free signals, pre-processing of the signal is necessary since signal containing noise may lead to false diagnosis of the patient In present work, Independent analysis (ICA) method is used for signal Denoising. In such a case, first aim is to search a method to separate out significant components from background mental activity & noise. As per the literature review; different algorithms are applied to biomedical signals considering the EEG signal, one of the most popular classes of algorithm is the Independent Component Analysis (ICA). It is one of the effective tools which can be used for obtaining noise free signal. The important use of ICA technique is to perform the dimensionality reduction & separate the relevant information of the signal. In this case, aim is to separate out the information from various lobes of the patient EEG signals consist of high dimension data, in such cases ICA helps out for obtaining noise free signals. ICA is general purpose statistical technique in which observed random data are linearly transformed into components which are maximally independent from each other, and simultaneously have “interesting” distributions [10] [11] [12]. In general, mathematical formulation of Independent Component Analysis is given by,

$$x = As + n \,\ldots\ldots\ldots\, (1)$$

where **A** is *mixing matrix*, **x** is sensor vector, **s** is source vector and **n** is noise, which is to be eliminated by filtering [11] [12].

It is also assumed that the component variables used are statistically independent from each other. We have also assumed that the independent components must have Non - Gaussian components.

V. FEATURE EXTRACTION

The There exist different features for diagnosis of Alzheimer disease in literature. Features play a significant role in automated diagnosis of Alzheimer Disease. In this paper, we have incorporated the use of wavelet & spectral based features for diagnosis. The following sections discuss the role of Spectral & Wavelet based methods for diagnosis.

1) Spectral Based Features:

Several research findings have shown the changes in the EEG power spectra due to AD. It consists of increase in the delta & theta band powers, together with a decrease in alpha & beta band powers, thus suggesting a “Slowing of the EEG signal” [9][13][14][15]. In this paper, Spectral power features present in each of the five conventional EEG frequency bands is measured, namely: 0.1 – 4 Hz (delta), 4 – 8 Hz (theta), 8 – 12 Hz (alpha), 13 – 30 Hz (Beta) and 30 – 100 Hz (gamma) [16]. The above of the five spectral power features can be computed for per epoch for different 20 EEG electrodes and 8 bipolar channels. In this present study, we have computed the same for EEG electrodes such as T3 (Temporal), F3 (Frontal), C3 (Central) & P4 (Parietal) respectively. Thus, Spectral Power based features plays a significant role in diagnosis of Alzheimer Disease.

The algorithm used for the computation of Power features in each sub band of EEG signals is given below.

Step.1: Load the EEG signal of any electrode.
Step.2: Declare the Sampling Frequency (fs) & obtain the length of the EEG signal (N).
Step.3: Declare the Wavelet decomposition Function (Daubechies wavelets).
Step.4: Obtain different EEG bands (from 0.5-30 Hz).
Step.5: Obtain the frequencies of EEG Bands Using detrend & FFT functions.
Step.6: Compute the Power in each Bands of EEG signal using the Power Density function (PSD).
Step.7: Stop.

From above algorithm, it gives the idea of calculating the Power in each sub bands of each signals from specific electrode. Firstly, the filtered EEG signal is decomposed into the various bands using the wavelet decomposition tool. In this, “Daubechies” mother wavelet is used for decomposing the EEG signal into different five sub bands. The reasons behind use of Daubechies wavelet is (i) they possess wide smoothing characteristics (ii) they are well understood & (iii) the changes in the EEG signals are easily seen [17]. The EEG is decomposed using “db2” Daubechies wavelet at level decomposition 5. Accordingly EEG signals into five bands with following frequencies Delta (0.5 – 4 Hz), Theta (4 – 8 Hz), Alpha (8-13 Hz) & Beta (13-30 Hz) is obtained. Further, the Power in each sub bands of EEG signal is computed by means of Power Density function. The following figure shows the classification of EEG signal in various bands.

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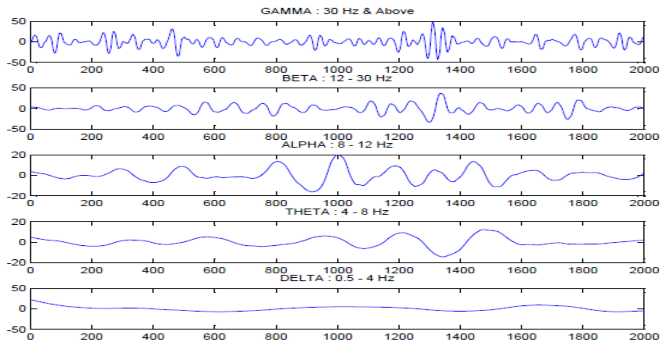

Figure 2. Classification of EEG signals into different sub bands.

The assessment of spectral characteristics of the EEG activity is based on the power spectral density (*PSD*) of each EEG epoch, which is computed as the Fourier transform of its autocorrelation. The *PSD* is normalized by the total power in the considered broadband (1Hz to 40Hz) to obtain a normalized *PSD* (*PSDn*):

$$PSD_n(f) = \frac{PSD(f)}{\sum_{f=1Hz}^{40\,Hz} PSD(f)} \quad .... (2)$$

The above equation is used for calculating the power in each band of the EEG signals.

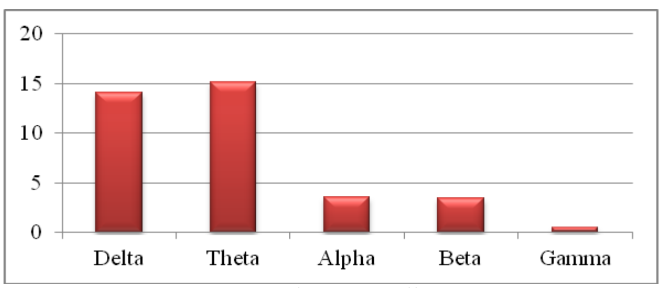

Figure 3. Computation of Power in different EEG bands in EEG signals of Alzheimer patients.

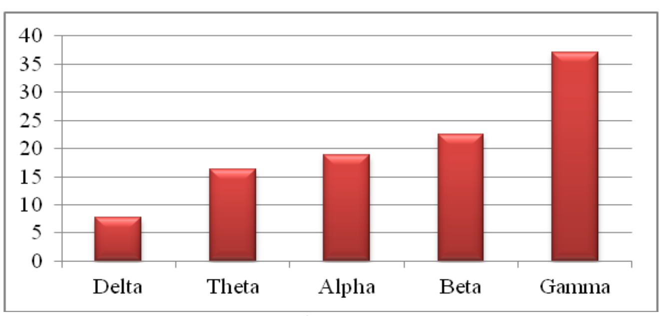

Figure 4. Computations of Relative Power in EEG sub bands in Normal patients.

In the above fig.6 & fig.7, it is observed that power in low frequency bands of Alzheimer infected patients is increased whereas it is reduced in high frequency bands. Thus, spectral based feature helps out in diagnosis of AD. Thus, it shows that slowing effect is observed in the EEG signals of Alzheimer's disease patients.

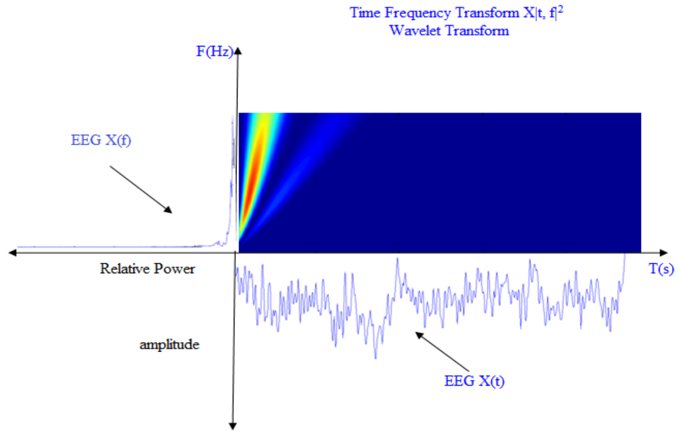

Figure 5. Practical results obtained for Slowing of the EEG signal in Normal subjects: EEG signal, shown in time-domain x (t), Frequency domain X (f), and time-frequency domain |X (t, f) |.

The above fig.8 & fig.9 shows the time frequency bumps observed in the EEG signal of the Alzheimer's disease patients. In case of AD patients, the EEG signal shows the slowing effect due to the neuronal loss observed in the brain regions; but this phenomenon is not observed in case of normal subjects. Dauwels et al. [9] has already justified this concept in his paper.

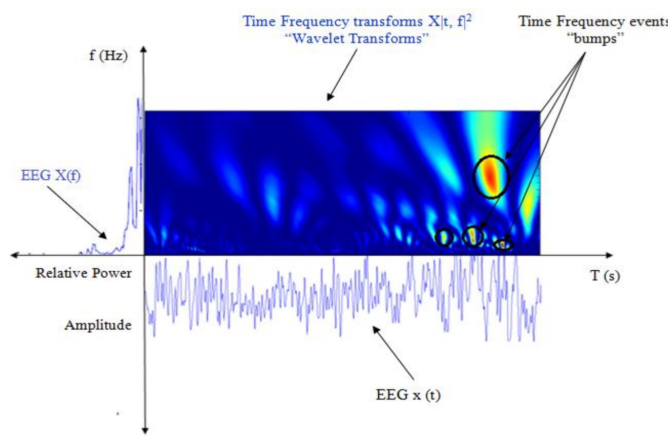

Figure 6. Practical results obtained for Slowing of the EEG signal in AD patients: EEG signal, shown in time-domain x (t), Frequency domain X (f), and time-frequency domain |X (t, f) |.

But in this study, bumps exhibited in EEG signals of our database are observed. Relative EEG power is also computed. Time – frequency maps of EEG signal of Alzheimer patient is quite sparse. Most energy is contained in specific regions of time frequency maps which are called as "bumps". It is observed that transient oscillations in the EEG signals of MCI & Alzheimer's disease patients occur more often at low frequencies as compared to the normal subjects. This is the signal of severe Alzheimer disease; in which the signal exhibits slowing effect. Thus, cognitive deficits are tremendously affected in this stage. The above figure also shows the time-frequency representation using

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wavelet transform; along with it the relative power is also calculated which is decreased in delta & theta bands in case of Alzheimer's disease patients. These bumps are not observed in case of Normal patients since they do not exhibit slowing effect.

2) Wavelet Based Features

In previous section, EEG signal decomposition is computed by means of wavelet technique. In present research work, EEG signal is decomposed at five levels for separating the signal in different bands of frequency. In such a case, for certain coefficients mean & variance for those particular coefficients are calculated. In case of AD patients, it is noticed that the value of mean & variance decreases as compared to those Normal patients. Mean & Variance are given by,

$$Mean = \frac{1}{n}\sum_{i=0}^{n-1} x_i \,, i = 1 \ldots N \text{ .... (3)}$$

where x_i's are the computed coefficients of the signal at each sub-band, n is the number of coefficients at each band & N is the number of band.

Similarly, Variance is calculated by using following formula,

$$Var(X) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2 \text{ .... (4)}$$

Where μ is the expected value. The above calculated values of mean & variance is taken for classification purpose.

VI. Results

After computations of the above features, the significant results were obtained clearing out our proposed hypothesis. Spectral based feature i.e. Relative EEG Power & Wavelet based features such as mean & variance were computed for certain electrodes of EEG signals as discussed above. In proposed research work, the use of K nearest neighbor (k-NN classifier) is incorporated for classifying the data. Based on database available for computation, 50 % of the data was trained & remaining 50 % data was left out for testing purpose. The computed values for different features used in different electrodes are used for training & testing purpose.

Based on above values computed, we have used K nearest Neighbor classifier for classifying the EEG data between two group's i.e. Normal v/s Alzheimer patients. K-NN is a simple, intuitive & efficient method of classification used by researchers & scientists for classifying signals. This classifier makes a decision on comparing a newly labeled sample (testing data) with the baseline data (training data). For the given set of input values, it finds the k (closest neighbourhood) in training dataset and assigns a class which appears frequently in its neighbourhood. In similar manner, the algorithm for k-NN can be given as:

i. The k-nearest neighbor classification is performed by using a training data set which contains both the input and the testing variables which are to be classified

ii. Then test data which only contains input variables is compared with reference set of values.

iii. K-NN classifier works with k patterns, the distance of unknown 'k' determines its class, by considering nearest neighbor points. The value of K can be varied.

iv. Majority voting scheme where class gets one vote for each instance in neighbourhood samples is classified accordingly.

v. The given target data is then said to be classified.

The Classification output of the K Nearest Neighbor classifier is shown below.

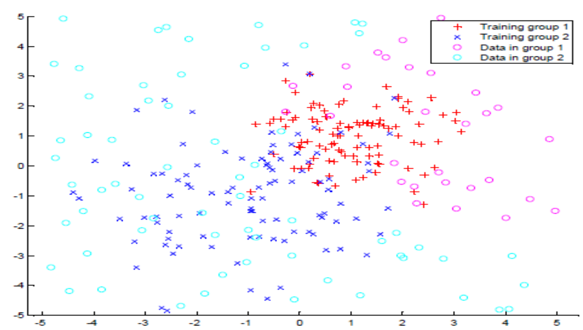

Figure 7. Classification of K Nearest Neighbor Classifier for classifying the testing Data into two groups.

In K Nearest Neighbor classifier, we have to specify the value of K for classification. Default value of K is equal to 1. But, to obtain more accuracy we can vary the value of K from 1 to 10. We have used default value K=1 in our study. Based on the features calculated & classifier used, we have calculated the accuracy of classification based on following terminology [18].

Accuracy = (TP + TN) / (TP + TN + FP + FN).

Sensitivity = TP / (TP + FN).

Specificity = TN / (FP + TN).

Where,

TP stands for True Positive (AD individuals correctly classified), TN stands for True Negative (NC individuals correctly classified), FP stands for False Positives (NC individuals misclassified), FN stands for False Negative (AD individuals misclassified) [18].

In our study, we have trained 50 EEG signals from Temporal, Frontal, Parietal & Central electrodes randomly. Out of which remaining 50 EEG signals were left out for testing comprising of both Normal & Alzheimer Affected persons. The following results were obtained after testing,

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1. Total number of Correctly Identified AD individuals (TP) = 24.
2. Total number of Correctly Identified Normal individuals (TN) = 24.
3. Total number of misclassified AD individuals (FN) = 01.
4. Total number of misclassified Normal individuals (FP) = 01.

Correspondingly, we have obtained the following results after calculating the values,

Accuracy = (TP + TN) / (TP + TN + FP + FN) = 24 + 24 / (24 + 24 + 01 + 01) = 48/50 = 96 %

Sensitivity = TP/ (TP + FN) = 24/ (24 + 01) = 24/25 = 96%.

Specificity = TN / (FP + TN) = 24 / (22 + 03) = 24/25 = 96%.

Table.1 Results indicating the Accuracy obtained in the research work using KNN classifier

Accuracy	Sensitivity	Specificity
94%	92%	96%

The table.1 shows the accuracy obtained in present research work.

VII. CONCLUSION & RESEARCH CHALLENGES

On the basis of the above results & features used, we have evaluated different features for EEG based diagnosis of Alzheimer disease by using EEG signals. The aim of these features was to observe and study them if they carry any diagnostic useful information In medical terminology, it is signified that AD affects the neuronal activity of the patients. In this study, we evaluated the spectral & wavelet based features for AD diagnosis. From the above calculated features values, it is observed that power in low frequency bands increases & Power in high frequency bands is decreased in case of Alzheimer disease patients. The above used features show decreased features values for AD patients, which practically confirm our obtained results as discussed in literature. The difference in the wavelet based features values among two groups are small, but indicates its significance on the different electrodes of EEG. The AD group features consists of lower values, suggesting that AD subjects tends to be less complex. The features used carry relevant information in the central, parietal, temporal & frontal lobe of the human brain as per the guidelines of American EEG society. This reduced complexity occurs due to the appearance of the neurofibrillary plaques & tangles. Mean & variance values of wavelet coefficients were also lower for Alzheimer patients in the frontal & temporal lobes. It is observed that there exists a higher amount of spectral content in higher frequencies for controlled group. This is predicted as the high level of complexity in controlled subjects.

Future work in this study includes the automated diagnosis & classification of EEG data using various classifiers such as Support Vector Machines [19], Random Forest [20] and many more; and to use automated artifact removal techniques to increase the diagnostic accuracy for distinguishing between AD & controlled group. In this study, investigation of Spectral & Wavelet based features is done for automated diagnosis of AD. It is to highlight that when we combine these features together with one another they provide more diagnostic information & increases the diagnostic accuracy. In this way, we can conclude that the above combination of Spectral & Wavelet features can be effectively used for AD diagnosis using EEG signals.

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REFERENCES

[1] Mattson M., “Pathways towards and away from Alzheimer’s disease”, *Nature*, Vol. 430, pp. 631–639, Aug.2004.

[2] Meek P.D., McKeithan K., and Shumock G.T.,”Economics considerations of Alzheimer’s disease”, *Pharmacotherapy*, Vol. 18, pp.68–73, March-April 1998,

[3] World Health Organization and Alzheimer’s disease International (2012) Dementia: a public health priority, Technical report.

[4] De Carli C, Kaye JA, Horwitz B, Rapoport SI., “Critical analysis of the use of computer-assisted transverse axial tomography to study human brain in aging and dementia of the Alzheimer type*”, Neurology*, Vol .40 ,pp. 872–83, 1990.

[5] D. Fo¨rstl H, Kurz A., “Clinical features of Alzheimer’s disease.” *Eur ArchPsychiatry Clin Neurosci*, Vol.249, pp.288–90, 1999.

[6] Bianchetti A, Trabucch M., “Clinical aspects of Alzheimer’s disease” *AgingClin Exp Res*, Vol 13, pp. 221–230, 2001.

[7] Béatrice Duthey, A Public Health Approach to Innovation‖, Update on 2004 Background Paper written by SaloniTanna, February 2013.

[8] Kulkarni N. (2019) EEG Signal Analysis for Mild Alzheimer’s Disease Diagnosis by Means of Spectral- and Complexity-Based Features and Machine Learning Techniques. In: Kulkarni A., Satapathy S., Kang T., Kashan A. (eds) Proceedings of the 2nd International Conference on Data Engineering and Communication Technology. Advances in Intelligent Systems and Computing, vol 828. Springer, Singapore

[9] Justin Dauwels, Francois Vialatte, and Andrzej Cichocki, “Diagnosis of Alzheimer’s disease from EEG Signals: Where Are We Standing?” *Current Alzheimer Research*, Vol. 7 Issue 6, pp. 487-505, September 2010. .

[10] Andrzej Cichocki, Sergei L. Shishkin, ToshimitsuMusha, Zbigniew Leonowicz , Takashi Asada, Takayoshi Kurachi, “EEG filtering Based on blind source separation (BSS) for early detection of Alzheimer’s disease‖, *Clinical Neurophysiology*”, Vol 116, No.3, pp.729-737, March 2005.

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[11] Aapo Hyvarinen, Erkki Oja, "Independent Component Analysis: Algorithms & Applications", *Journal of Neural Networks*, Vol. 13, Issue.4, pp.411-430, 2000.

[12] Co Melissant, Alexander Ypma, Edward E.E. Frietman, Corn elis J.Stam, "A method for detection of Alzheimer's disease using ICA enhanced EEG measurement", *Artificial Intelligence in Medicine*, Vol. 33, No.3, pp. 209-222, March 2005.

[13] Jaeseung Jeong, "EEG dynamics in patients with Alzheimer's disease", *Artificial Intelligence in Medicine*, Vol 33, Issue 1 pp. 209-222, 2005.

[14] Simon-Shlomo Poil, WillemdeHaan, Wiesje M.vAnder Flier, HuibertD.Mansvelder Philip Scheltens and KlausLinkenkaer-Hansen, "Integrative EEG biomarkers predict progression to Alzheimer's disease at the MCI stage", *Frontiers in Aging Neuroscience*, Vol.5, Oct 2013, pp. 1-6, Article ID 58.

[15] Raymundo Cassani, Tiago H. Falk, Francisco J .Fraga, Paulo A. M. Kanda and Renato Anghinah, "The effects of automated artifact removal algorithms on electroencephalography-based Alzheimer's disease diagnosis", *Frontiers in Aging Neuroscience*, Volume 6, Article 55, pp. 1 – 13, March 2014.

[16] Kulkarni N, Bairagi V, "EEG-based diagnosis of alzheimer disease: a review and novel approaches for feature extraction and classification techniques", Academic Press, Cambridge, 2018.

[17] Parham Ghorbanian, David Devilbiss, "Identification of Resting & Active State EEG features of Alzheimer's Disease Using Discrete Wavelet Transform*", Annals of Biomedical Engineering, The Journal of Biomedical Engineering Society*, Vol.41, No. 6, pp.1243-1257, June 2013.

[18] Andrea Rueda, Fabio A. Gonzalez, "Extracting Salient Brain Patterns for imaging based Classification of Neurodegenerative Diseases", *IEEE Trans. Med. Imaging*, Vol. 33, No.6, pp. 1262-1274, June 2014.

[19] R. Viswanathan, K. Perumal, "*Segmentation Technique to Detect the AD in Hippocampus Shape using Region Growing in Support Vector Machine*", International Journal of Scientific Research in Computer Science and Engineering, Vol.6, Issue.1, pp.56-59, 2018.

[20] Meenu Shukla, Sanjiv Sharma, "*Analysis of Efficient Classification Algorithm for Detection of Phishing Site*", International Journal of Scientific Research in Computer Science and Engineering, Vol.5, Issue.3, pp.136-141, 2017

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