INTERNATIONAL RESEARCH JOURNAL OF HUMANITIES AND INTERDISCIPLINARY STUDIES
(Peer-reviewed, Refereed, Indexed & Open Access Journal)
DOI : 03.2021-11278686 ISSN : 2582-8568 IMPACT FACTOR : 5.71 (SJIF 2021)

Improving the Detection of Epileptic Seizure in EEG Signal Using Machine Learning Algorithms

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DOI No. 03.2021-11278686 **DOI Link ::** https://doi-ds.org/doilink/06.2021-91677692/IRJHIS2106038

Abstract:

Epilepsy is a prevalent chronic disorder in humans. Epileptic seizure is most usually executed by specialists with observations made by visual means using signals of Electroencephalography (EEG). The diagnosis of epilepsy using Electroencephalogram (EEG) plays a vital role to aid the patients from epilepsy. Visual Diagnosis of patients suffering from epilepsy would be a time consuming phenomenon and would delay the treatment and would also incur human error. So, a system is proposed for improving the detection of Epileptic Seizure in EEG Signal with the help of Machine Learning algorithms. Inappropriateness of larger data processing and low yield are the most important downside which belong to previous research. Previously, Fourier transform and SVM methods were used to detect epilepsy seizures. In the proposed work the system can be trained by user in ML to achieve accurate results. So, ML approach is much more efficient than previous approach of Fourier or SVM.

Keywords: *Epilepsy, EEG, Epileptic Seizure, Machine Learning algorithms, diagnosis, MATLAB.*

Introduction:

Epilepsy is a chronic disorder, the character peculiarity of which is perennial, gratuitous seizures. Epilepsy is a diapason condition with a wide range of seizure types and dominance assorting from person-to-person. Epilepsy means the dualistic as "seizure disorders." Epilepsy is the fourth most common neurological disorder and affects people of all ages. It is characterized by arbitrary seizures and can cause other health problems. Public misconceptions of epilepsy cause challenges that are often worse than the seizures. Early stage diagnosis of epilepsy is hard to find. Seizure activities can be one of the ways to detect the epilepsy. Electroencephalogram (EEG) is one of the most efficient way of diagnosing epilepsy. In EEG test, the electrodes are attached to the scalp of the brain using a gel type substance to obtain the electrical activity of the brain.

As thorough optical analysis of EEG signal is very gruelling, automatic diagnosis is preferred. Fourier transform has been most often used in initial days of processing of EEG signals. However as EEG signal is a non-stationary signal, Fourier analysis does not give accurate results [3,6]. Most effective time-frequency analysis tool for analysis of transient signal is wavelet transform [1,2].The automated diagnosis or detection of epilepsy can be ramified into preprocessing,characteristic feature abstraction, and categorization. Seizure detection can be classified as either seizure onset detection or seizure event detection. In seizure onset detection the motive is to cognize the initiation of seizure with the least achievable hold off. The intent of seizure event detection is to secernate seizures with the highest realistic exactness.

Patients of epilepsy consume anti-epileptic drugs on a daily note as a remedy. But nearly about a quarter of percentage of them experience frequent seizures. For such patients surgery is the only option, but surgery can be conducted only when epileptogenic focus is known precisely. So, ML would be one of the techniques useful in accurately detecting the seizures. The proposed system detects the epilepsy based on Machine Learning. MATLAB uses GUI to display waveforms which is used in the system to display the EEG waveform.

Recent research have proposed various automated methods for diagnosing epileptic seizure. Fourier spectral analysis is used most commonly for extracting EEG signal assuming that EEG signals are stationary. This allows signal transformation from time domain to frequency domain. But previous literature demonstrated that frequency components of the signals of EEG would alter over time. This states that EEG signals do not have stationary properties. In such a case, time analysis and frequency analysis methods would be useful in eliminating such a predicament. In addition to this, wavelet transform approach for frequency and time domain are appealing for analysis of EEG signals. Fourier transform (FFT) is used for short overlapping sequences that are assumed to be stationary [,7]

Methodology:

Complex low frequency noise such as system interference is suffered by frail and low amplitude signals. So, for epileptic seizure analysis and detection, the EEG signal pre-processing with noise removal is regarded. So, the proposed work employs wavelet threshold denoising method, which has a worthier performance as collated to the Fourier Transform denoising method. The Daubechies wavelet of fourth order is chosen for the better confined estimated performance of non-stationary signals. Using wavelet decomposition and reconstruction five frequency sub- bands of clinical interest are obtained viz., delta, theta, alpha, beta and gamma.

Sub-bands	Frequencies (Hz)
Delta	0-4
Theta	4-8

Alpha	8-16
Beta	16-32
Gamma	32-64

Table 1: Sub-bands with respective frequency range obtained using wavelet decomposition and reconstruction.

From each sub-band in the time frequency domain, the wavelet features of it's better confined properties are extracted. Then a pre-eminent PCA algorithm of the dimensionality reduction is applied on the signals to eliminate insignificant or factitious features. Eventually, various classifiers embracing linear discriminant analysis (LDA), Logistic Regression (LR), K-Nearest Neighbour (KNN), Naïve Bayesian (NB) and SVM are used to recognize epileptic seizures from EEG signals.

Flow Chart of Proposed Work

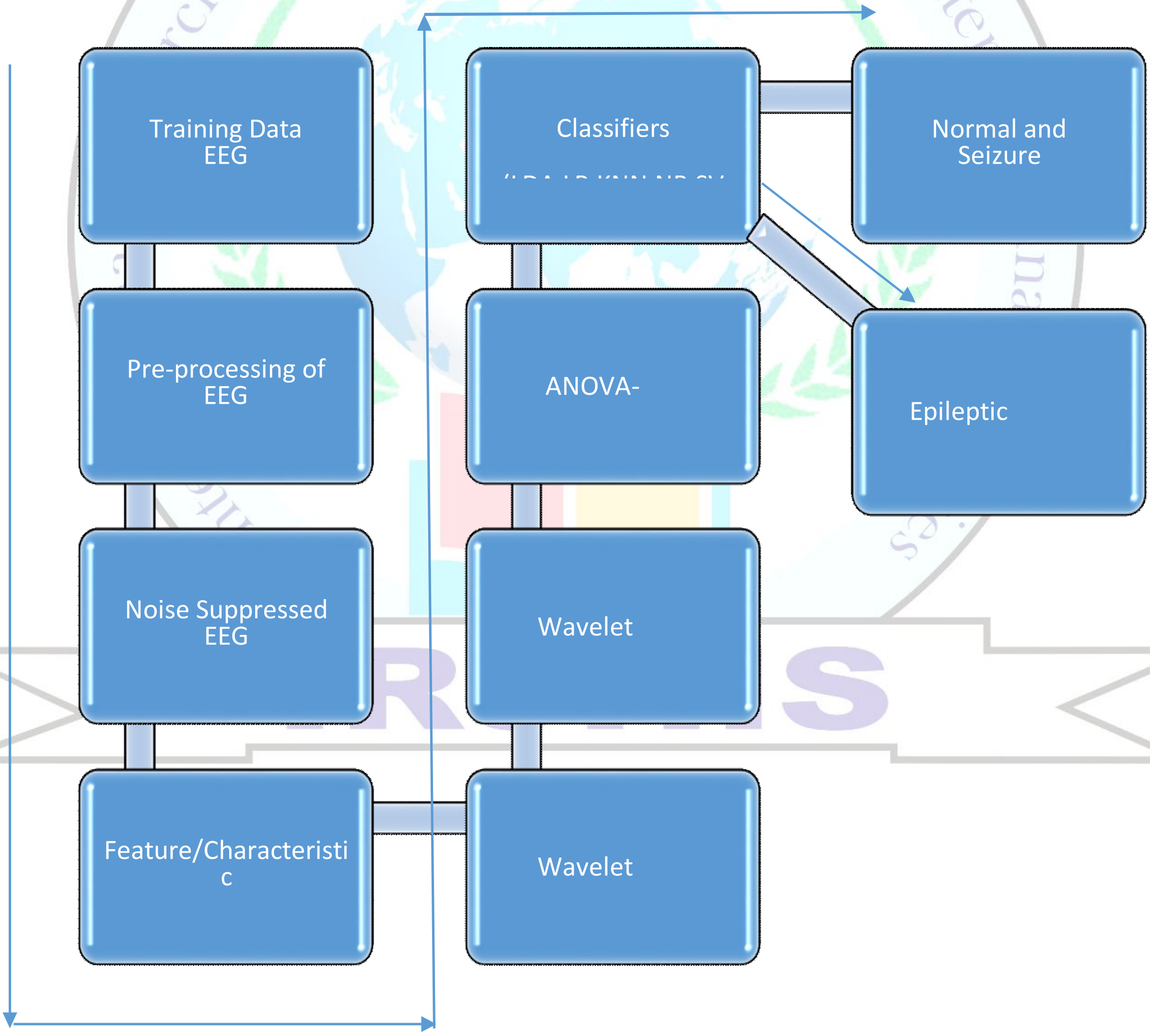


Fig-1

1. Materials:

The EEG signals used in the proposed work are recorded at the Bharti Vidhyapeeth, Sangli, Maharashtra, India. The dataset includes five subsets which are known to be S, F, N, O and Z recorded with same channel amplifier system and a 12-bit analog to digital converter. EEG samples in datasets O and Z are acquired from healthy participants. The samples are collected using external surface electrodes for both close and open eye conditions. The datasets S, F and N are recorded from epileptic patients during seizure as well as seizure free intervals.

2. Signal Pre-processing: Signal Denoising Wavelet Threshold

Normally, anatomical signals are tainted or even contorted by relics. Denoising or eliminating noise is a major key step in signal analysis and pre-processing in medical field. In recent, the automated techniques are used for denoising the signal which are based on the spectrum features and statistical distribution. A superior signal processing results are produced from the analysis in the time-frequency domain. These results include both time as well as frequency components [8-12]. For instance, the signal magnitude to be amplified as larger DWT synergetic is allowed by discrete wavelet transform (DWT), limiting the noise in the entire time-frequency domain. In this manner, the DWT synergetics of the noise are bijou than the desired signals.

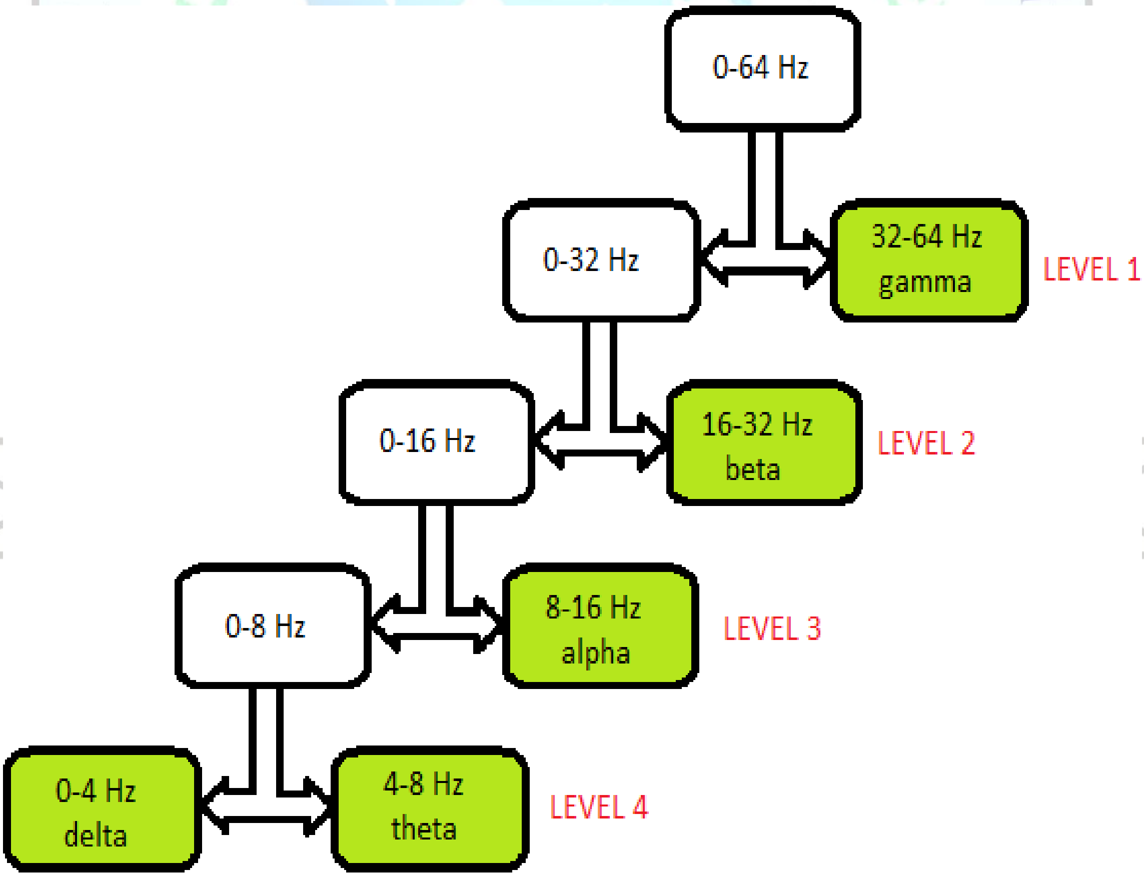


Fig-2

Fig2: Decomposition in 4 levels of EEG Signal from five sub-bands. Five sub-bands are indicated by coloured boxes.

Initially, the indigenous EEG signal (0-64 Hz) is firstly crumbled into higher and lower frequency hunks. Higher frequency part which is detail of signal at first level is 32-64 Hz. Lower frequency part which is approximation of signal at first level is 0-32 Hz. Conjecture of first level signal is further divided into higher frequency and lower frequency which have 16-32 Hz and 0-16 Hz respective frequencies. This is nothing but detail and approximation of second level. The same division into further higher and lower frequency parts continues till we obtain all the required sub-bands. Therefore, in denoising the non-stationary EEG signals, wavelet threshold method can perform well, which is defined using following equation:

$$\lambda = \sigma\sqrt{2logN}$$

$where,\ \lambda = wavelet\ threshold,\ \sigma = Noise\ standard\ deviation, N = Sample\ signal\ length$

It is effectual to embrace the wavelet threshold method to eliminate noise from EEG signal, since the noise buried in EEG signals is in practical, the white noise and has sharpness.

1. Analysis using Wavelet Transform:

Surface Electrodes are connected to the scalp to measure the electrical activity of the brain. For EEG signal feature extraction recently, mathematical tools such as Fourier Transform, Short Time Fourier Transform, Fast Fourier Transform and Wavelet Transform have been introduced. Fast Fourier Transform provides only spectral information in frequency domain and there is information loss in time domain. Short Time Fourier Transform was introduced overcome the problems of Fast Fourier Transform. STFT uses moving window function to represent the signal both in time as well as frequency domain. Due to the complication associated with STFT that it has always a constant size as it does not provide multi-resolution information. In the late 1980's, Wavelet Transform was introduced to overcome the drawbacks of Fourier, Fast Fourier and Short Time Fourier transform. Wavelet transform can be treated as an improved version of Fourier transform working on a multi-scale basis and also is efficient for solving problems related to non- stationary signals. For analyzing time-domain signals, Wavelet transform plays a vital role. Wavelet provides information of both time and frequency within signals as, it is a type of time- frequency analysis. The advantage of using Wavelet transform is that it has a varying window size. This varying window is narrow at high frequencies and broad at low frequencies implying time-frequency resolution in all frequency range. It can be said that it holds multi-resolution properties.

Wavelet Transforms are broadly classified into three categories: continuous, discrete and multi- resolution. In continuous wavelet transform a given signal of finite energy is projected on a continuous family of frequency bands. DWT decomposes the signal into mutually orthogonal set of wavelets. DWT is more efficient in removing redundancy than continuous wavelet transform. This method is perfect for analysing the EEG signal [15-18]. Proposed system uses Discrete Wavelet transform method. In DWT, the EEG signal is divided into small reeds of band. To analyse whether the signal s(t) is progressing and is of high resolution is based of two types of basic function: wavelet and scaling.

$$(t) = \sum_{l=2}^{l} 2\frac{l}{2}\, m_l(\tau)\,(2^l t - \tau) + \sum_{x=0}^{x-1}\sum_{\tau=0}^{\infty} 2\frac{x}{2}\, e_j(\tau)\,\Psi(2^j t - \tau)$$

Where function (t) and (t) are basic scaling functions and mother wavelet respectively. In this expression, first part is approximation of s(t) depending on scaling index and the second part adds additional information using the j scale. When the wavelets are orthogonal then these synergetics are calculated by:

$$m_l(\tau) = \int_{-\infty}^{\infty} (t)\,(2^l t - \tau)\,dt$$

$$e_j(\tau) = \int_{-\infty}^{\infty} (t)\,(2^j t - \tau)\,dt$$

where, m_l and $e_j(\tau)$ $are\ synergetics.$

1. Extraction ofFeatures in time domain, frequency domain and time-frequency domain:

Important frequency information may be omitted if the features are extracted by analysing the EEG signals solely in time domain and vice-versa. Although, the wavelet signal processing technique can abolish such insufficiency and abstract effectual features in the time-frequency domain in a better way. Particularly, a signal can be regarded as linear or non-linear amalgamation of basis function. In time-frequency domain, a function Ψ is formed with finite power, i.e. the basis of function of wavelet used could be finite duration and zero mean. This is satisfied with the following equation:

$$\sum_{N=-\infty}^{\infty} |[N]|^2 < \infty$$

$$\sum_{N=-\infty}^{\infty} [N] = 0$$

$where,\ N = Sample\ signal\ length$

Using the parameter 'b', the wavelet can also be moved over time and using dilation parameter 'a', the wavelet can be scaled using following equation:

$$\Psi_{a,b}[N] = \frac{1}{\sqrt{a}} \quad \frac{(N-b)}{a}$$

To extract faster changes in a better way, narrower wavelets also known as smaller dilation parameter '*a'* can be used while to extract slower changes wider wavelets i.e. with larger dilation parameter '*a'* are more suitable. Through the basis of wavelets, features can be extracted by analysing EEG signals. These features include both time and frequency domain.

By improving the parameters a & b allows an easy computation of the wavelet transform synergetics in the below mentioned formula:

$$\omega_{a,}[n] = \sum_{\tau=1}^{N} x[\tau]\Psi_{a,b}[n-\tau] \qquad 1 \leq n \leq N$$

Where, $[\tau]$ *the sample signal having length of N samples*. Heeded that it is notable to ascertain the wavelet function type and level before pertaining DWT. In the proposed work, for the perfect local features in the time-frequency domain, the DB4 wavelet is utilized, as in the field of non-stationary signal processing techniques, the db4 wavelet's shape and smoothing feature have patronizing estimated execution. Moreover, for clinical use of EEG signal sub- bands, the EEG signals are decomposed into five sub-bands. In the time-frequency domain, the standard deviation and the relative power of the DWT transform synergetics are extracted as features from each of five clinical use sub-bands.

The mean, variance, coefficient of variation and the total variation are extracted in the time domain. In addition to these statistic features in time domain, the mean, minimum, maximum and total variation measures of the DWT transform coefficients are also calculated in order to depict the non-stationary signals in detail. The total variation measure is as follows:

$$V_x = \frac{1 \quad \sum_{n=2}^{N} |[n] - x[n-1]|}{(N-1)max_x - min_x}$$

where, max_x & min_x *are the maximum and minimum of signal x, respectively*

It is necessary to note that, for fast changing signals the value of total variation V_x, is 1 while it ranges between $\frac{1}{(N-1)}$ for slow signals.

Fast Fourier Transform (FFT) is an effectual ordinary practice for signal analysis with different frequencies, in frequency domain, which may not be recognized in the time domain. Constituting the signals' characteristics in the frequency domain, the relative power spectral density approximation by synergetics of FFT is extracted.

Analogous features of time domain, frequency domain and time-frequency domain are examined for the selective power in the epileptic signal categorization using the below mentioned Machine Learning approach.

Stratification and Performance Analysis:

Unnecessary features are eliminated using the principal component analysis (PCA) and analysis of variance (ANOVA) statistical test. The optimal value of principle components p are selected to $10^{-3}(FDR\ adjusted)$. For epileptic seizure stratification, the calculated features are fed into various classifiers. Support Vector machine (SVM) classifier is the most particular and well-known supervised learning method based on finite sample theory [13-17].In small sample cases, traditional classifiers based on the empirical error minimization re prone to generating the over fitting problem, while the SVM is based on the structural risk minimization principle and can ensure a good generalization ability [18-21]. So, initially the efficacy of the selected suitable feature subset is evaluated using radial basis function (RBF) kernel-based SVM (RBF-SVM). Additionally, KNN, LDA, NB, and LR are the four classifiers used to illustrate the efficacy of the proposed stratification framework.

In general, the proposed frame work and stratification performance can be evaluated using statistical measures of the sensitivity (SEN), specificity (SPE) and accuracy (ACC) as follows:

$$SEN = \frac{TP}{TP+FN} \times 100\%$$

$$SPE = \frac{TN}{TN+FP} \times 100\%$$

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$$

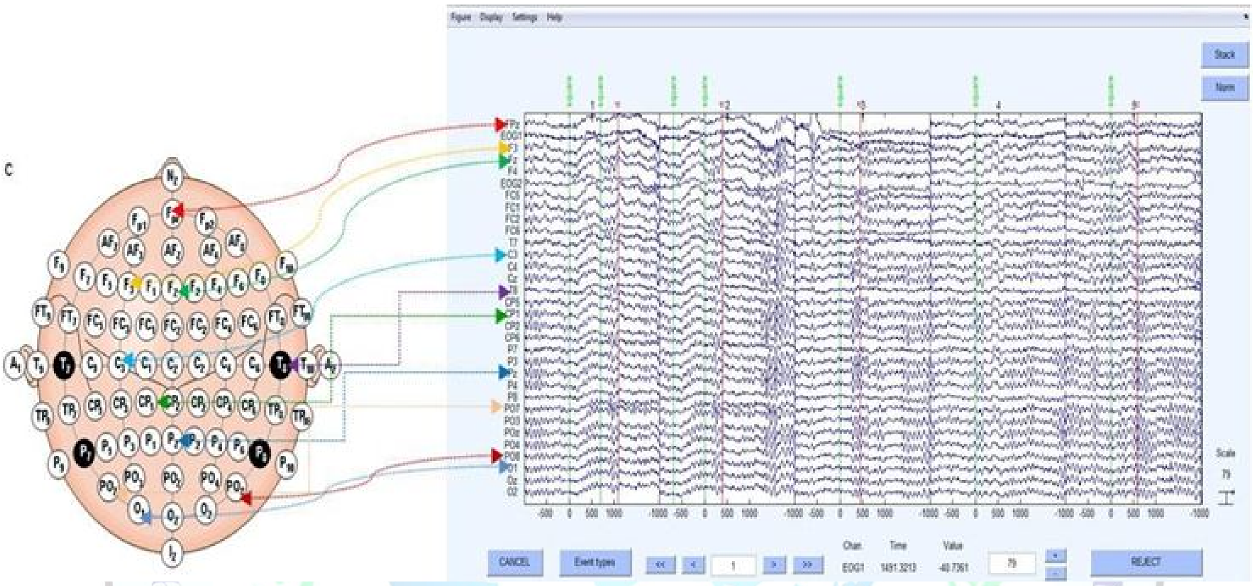
where, TP represents total number of correctly detected true normal events and TN represents true seizure events. FP represents total number of erroneously or delusively normal events and FN represents erroneously or delusively seizure events.

As the training–test strategy, N-fold cross-validation is applied, in order to obtain an unbiased estimation of stratification performance. Idiomatically, the datasets of input are randomly sided into N number of uniform identical parts, where N-1 parts are used for the feature determination and classifier training and the residual part for testing the stratification performance [22-27].

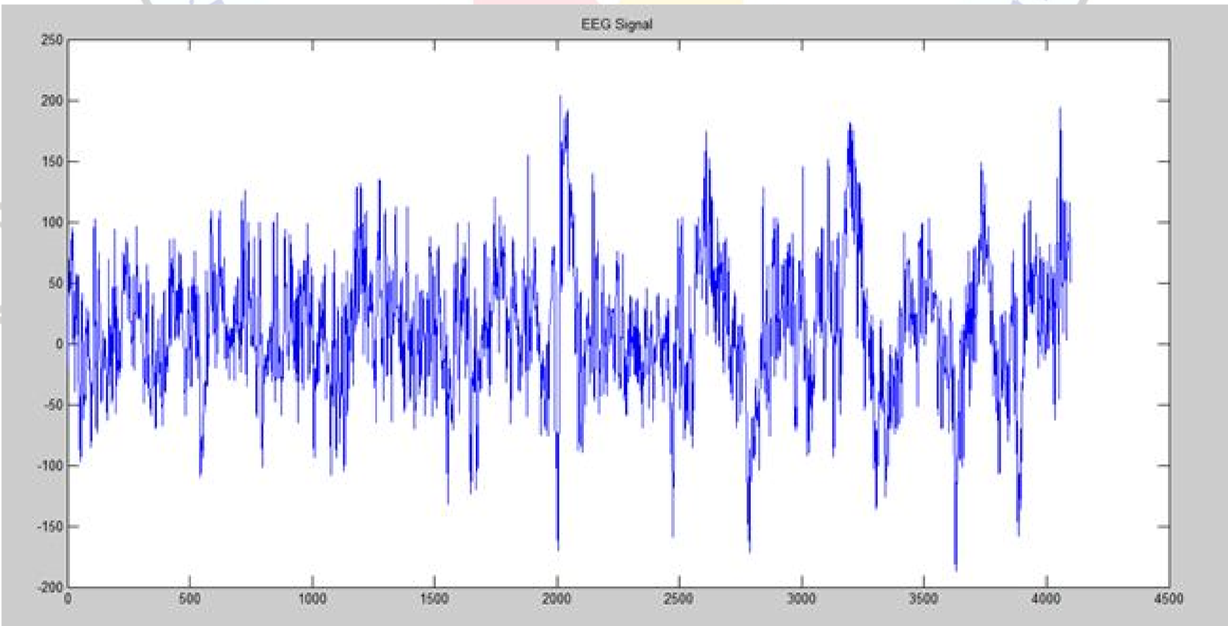
The same procedure is recurred N times, and every time, a distinctive part is left out and tested. Finally, the performance measurement is calculated as the average result across the total testing parts.

Results:

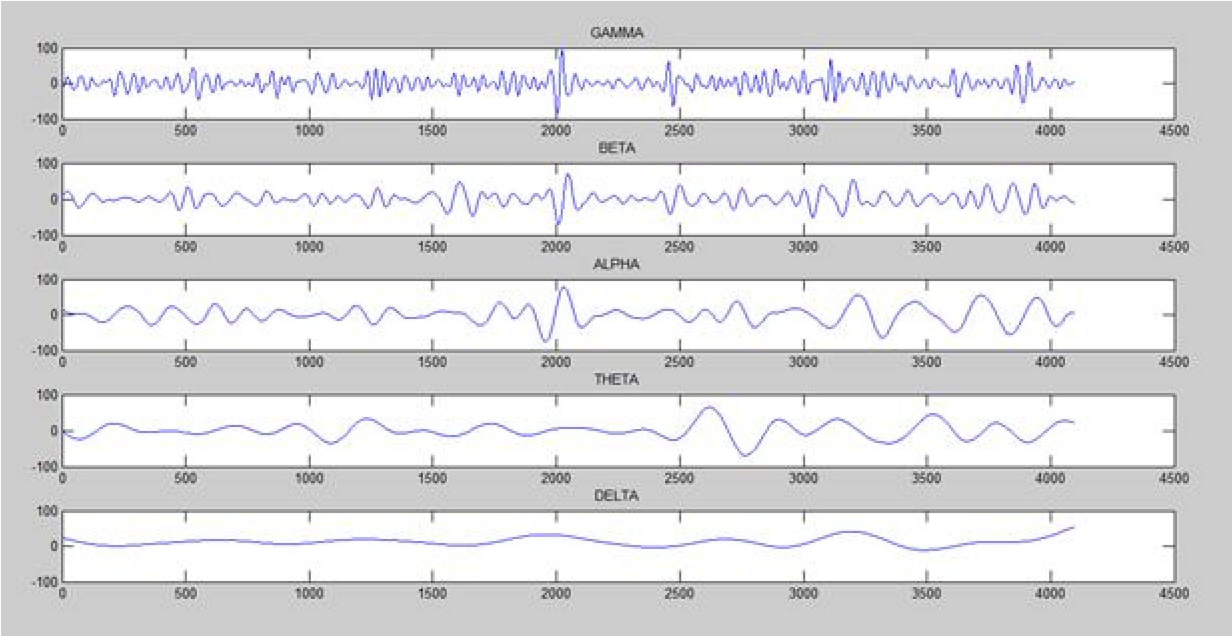
1. **Generation of an EEG Signal with its mapping according to the standard 10 – 20 International System :**



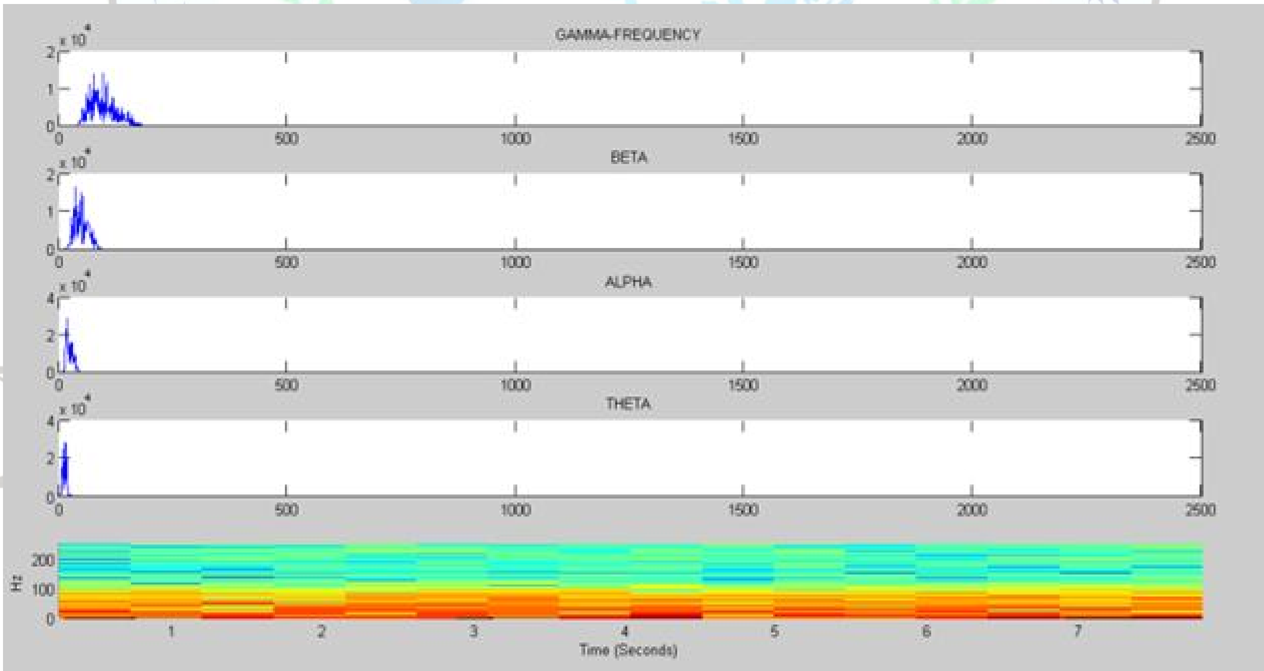
2. **Generation of Raw EEG Signal from single Electrode:**



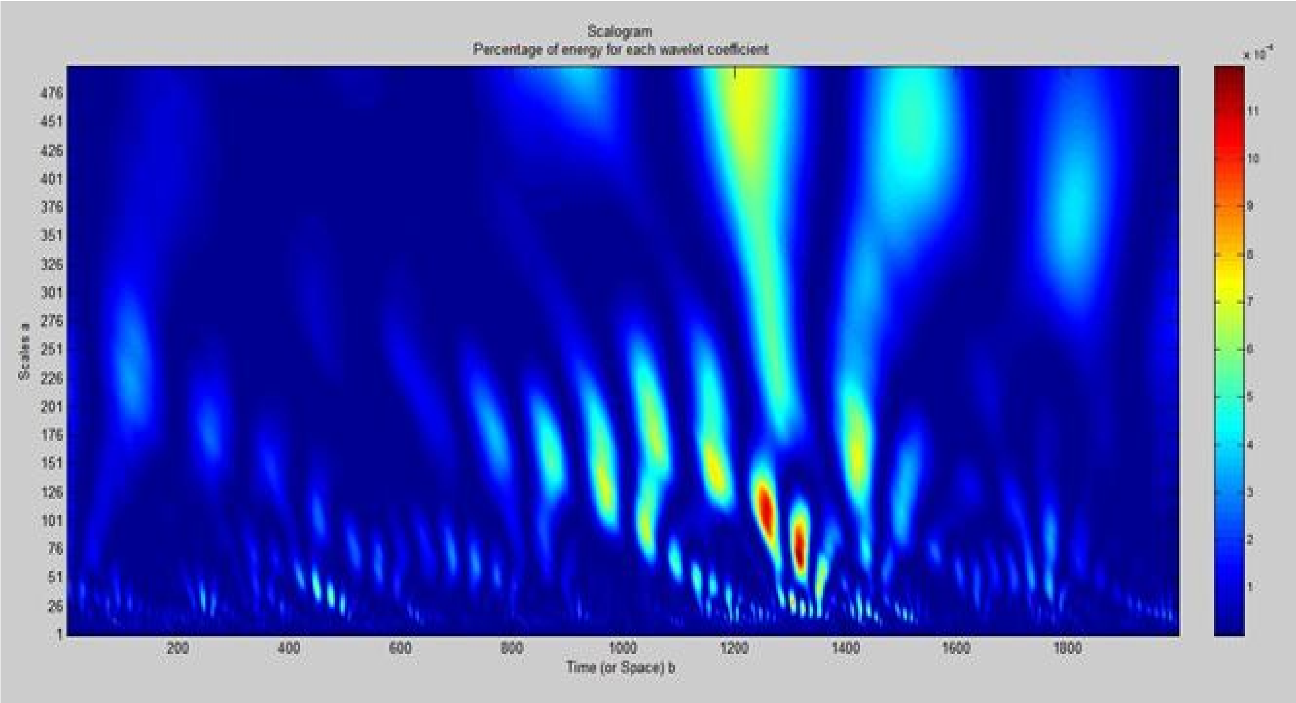
3. **Separation of EEG bands using wavelet functions & spectrogram of the same EEG signal (Continued)**



4. **Separation of EEG bands using wavelet functions & spectrogram of the same EEG signal (Continued)**



5. Use of Wavelet for Observing the Slowing Effect in AD patients.



6. Computation of Power of EEG Signals in various EEG Sub bands:

EEG Band	SAMPLE 1			SAMPLE 2			SAMPLE 3			SAMPLE 4		
	Frontal	Temporal	Parietal	Frontal	Temporal	Parietal	Frontal	Temporal	Parietal	Frontal	Temporal	Parietal
Delta	6.69	1.180	14.11	6.693	3.00	19.21	7.869	6.4803	7.803	34.80	18.50	22.383
Theta	4.83	1..373	15.11	10.11	4.16	23.12	3.906	10.551	16.28	44.56	13.714	19.088
Alpha	3.56	-11.50	3.555	17.05	15.56	35.99	3.843	5.1391	18.82	44.97	13.540	17.749
Beta	1.85	-20.57	3.467	21.01	17.57	35.21	12.15	6.8165	22.40	20.94	21.132	17.509
Gamma	-3.2	-26.67	0.540	21.38	23.6785	45.12	14.68	10.184	37.12	13.12	27.212	16.624

7. Computation of Different complexity measures:

EEG Band/ Feature	Central (C3)				Frontal (F4)				Parietal (P4)				Frontal (F3)			
	ZCR	SC	SR	SE	ZCR	SC	SR	SE	ZCR	SC	SR	SE	ZCR	SC	SR	SE
Sample 1	0.622	0.088	1.992	5.3981	0.0584	0.0863	1.9754	5.2619	0.0553	0.0744	1.9342	5.0385	0.0420	0.074	0.9807	5.0385
Sample 2	0.0012	0.0628	1.9321	5.95343	0.0018	0.0952	1.5423	2.8722	0.0343	0.0021	0.2311	2.0432	0.0143	0.055	0.9876	2.980
Sample 3	0.0916	0.1212	0.987	5.6044	0.0709	0.1102	1.9987	5.5409	0.0229	0.0458	1.9928	4.1449	0.0756	0.1104	0.801	3.9801
Sample 4	0.0100	0.0373	0.1322	3.6440	0.0033	0.0437	0.9921	3.7955	0.0167	0.0363	0.9786	3.6440	0.0032	0.032	0.8878	3.089
Sample 5	0.0033	0.0489	0.0343	3.9189	0.033	0.0443	1.0932	3.9773	0.0200	0.1921	1.0932	6.4532	0.143	0.564	2.323	5.5567
Sample 6	0.0900	0.1249	1.0323	5.7615	0.0967	0.1252	0.9812	5.0921	0.0967	0.1946	1.565	6.4519	0.0367	0.0979	1.3433	5.3064
Sample 7	0.0021	0.0032	0.0054	2.907	0.0034	0.087	0.878	3.0545	0.0212	0.0343	1.0989	3.098	0.034	0.0023	0.879	3.9704
Sample 8	0.0900	0.1178	0.0324	4.897	0.0433	0.1245	0.2432	5.3429	0.0900	0.1245	1.9878	5.4637	0.1100	0.1595	1.9956	5.5765
Sample 9	0.0167	0.1197	0.3432	3.5532	0.0167	0.0175	0.9980	2.8790	0.0367	0.0848	0.8790	4.0177	0.0233	0.0824	1.3432	4.9456
Sample 10	0.0987	0.1526	1.980	6.0060	0.0167	0.0956	1.9878	4.9978	0.1100	0.1900	1.980	6.2752	0.0377	0.1100	1.9801	5.5574
Sample 11	0.0833	0.1417	1.9801	5.980	0.0433	0.1465	NaN	5.9099	0.0833	0.1417	0.6743	5.8690	0.0767	0.917	2.3214	5.0768
Sample 12	0.067	0.1362	0.9802	4.4121	0.043	0.1321	0.8890	4.1765	0.0033	0.0554	1.231	3.8331	0.0033	0.0943	0.9565	4.4555
Sample 13	0.0433	0.0981	1.9322	5.2557	0.033	0.0297	0.9121	3.4978	0.0633	0.0987	1.0213	5.3167	0.0300	0.0637	1.3221	4.6784
Sample 14	0.0900	0.1724	1.0932	6.2905	0.0833	0.1456	0.9912	5.9235	0.1100	0.1808	0.9912	6.2519	0.0833	0.1207	1.923	5.6688
Sample 15	0.0367	0.0756	0.9912	4.9820	0.0500	0.1379	0.9012	3.7781 2	0.0700	0.0732	1.0912	4.7801	0.0500	0.0671	1.0921	4.7075

Outcomes:

1. The developed system can find its application in clinical purposes. It will be useful in diagnosing the disease i.e. Epilepsy Disease.
2. By use of the system, it will be also useful to determine the stage of disease such as Mild cognitive impairment (MCI), Epilepsy, Dementia & Alzheimer Disease.
3. By increasing the overall accuracy of the system (up to 99 %), it will be also useful to determine early diagnosis of the disease.

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