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Optimized feature extraction process to identify the seizure using feature fusion technique

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Abstract

Epilepsy is a brain disorder that results in seizures; in general seizure is a suddenly occurring uncontrollable electrical disturbance in the brain. These disturbances in the brain can lead to changes in behaviour, feelings, movements, etc. It is highly essential for the patients suffering with epilepsy to be diagnosed and treated. The normal detection of epilepsy is done using EEG signals which are time consuming. This paper aims at proposing a methodology to diagnose epilepsy by the use of EEG signals by establishing a correlation between statistical calculations and EEG signals. A various set of features are applied to the epilepsy and non-epilepsy dataset. Features such as time domain frequency which include mean, skewness, variance, kurtosis, standard deviation, approximate entropy, zero crossings, power spectrum and frequency domain features that include signal energy and total signal area, average DWT coefficient, signal relation features and human brain graph features. Further, considering these features, feature fusion and optimiziation aka FFO is carried out which helps in analysing the features in optimal way for further classification. Moreover, feature fusion and its optimization helps in exploring the new features that helps in enhancing the distinguish between classes.These features help diagnosis of the brain disorder in a very time efficient manner with higher accuracy. In this paper, we propose a feature fusion methodology for the most efficient working of the system.

Keywords- Epilepsy, Feature extraction,

1 Introduction

Epilepsy is a disorder that causes the activity of the nerve cell to be disturbed resulting in seizures. It is the second most commonly occurring neurological disorder [1]. The occurrence of epilepsy is due to genetic disorders or a brain injury such as a stoke or a trauma . A seizure occurs during epilepsy when the electrical connections in the brain are scrambled and there are sudden outbursts of the electrical activity in the brain. A seizure results to various changes in a person some of them include behavioural, emotional, physical movement, etc. Among the total population of the world, around 1% are affected by epilepsy and 30% of epilepsy patient encounter resistance to drugs during the course of their medical treatment [17]. Medical failure results in the need for surgery which aims as the lesson removal that causes the misfire in the neuron [2]- [4]. It is essential to diagnose and recognise this disorder to prevent major seizure in the patient suffering from this disease. The normal diagnosis of epilepsy is done using electroencephalogram (EEG). An EEG is a test that is done to measure the electrical activity in the brain. The early prediction of epilepsy can help improve the standard of living in many patients that are affected with epilepsy. The quality and standard of life of a patient suffering with epilepsy increases when early diagnosis takes place as there is also a reduced resistance to medication [5].

EEG is used for the diagnosis of many other disorders of the brain other than epilepsy which include brain tumours and sleep disorders. EEG is a method of electrophysiological monitoring which is done by applying a number of electrodes to the scalp, it records the electrical activity that is carried out in the brain. In this paper, we are aiming at establishing a correlation between EEG signals as well as statistical parameters [6]. There are several features that are extracted using these two groups of datasets. The features that are extracted include time domain features that include mean, variance, skewness, kurtosis, standard deviation, zero-crossing, peak-to-peak voltage and frequency domain features that include total signal area, signal energy and frequency DWT features, signal relational features that include cross-correlation, decorrelation and human brain graph features that include clustering coefficient, local efficiency, betweenness centrality, eccentricity, global efficiency, global diameter, global radius and global characteristic path. The variation of all these features that occur among a normal person and a person affected with seizure is observed [7]- [10]. The combination of feature extraction along with the statistical calculation that is used in this paper helps diagnosis in a shorter span of time efficiently.

The figure 1 shows the entire process flow of the work carried out in this paper. The signals are initially collected and segmented. This segmentation occurs at definite time intervals this makes the EEG signal value more accurate. After the required segmented signals are identified, the features that are required for the detection of epilepsy from the signals are extracted. Statistical measurements along with the EEG signals are both combined for feature extraction. The datasets that are used in this proposed work include two parts: a normal person and a person affected with seizure. The features that are extracted are combined, feature fusion is done for better results [11].

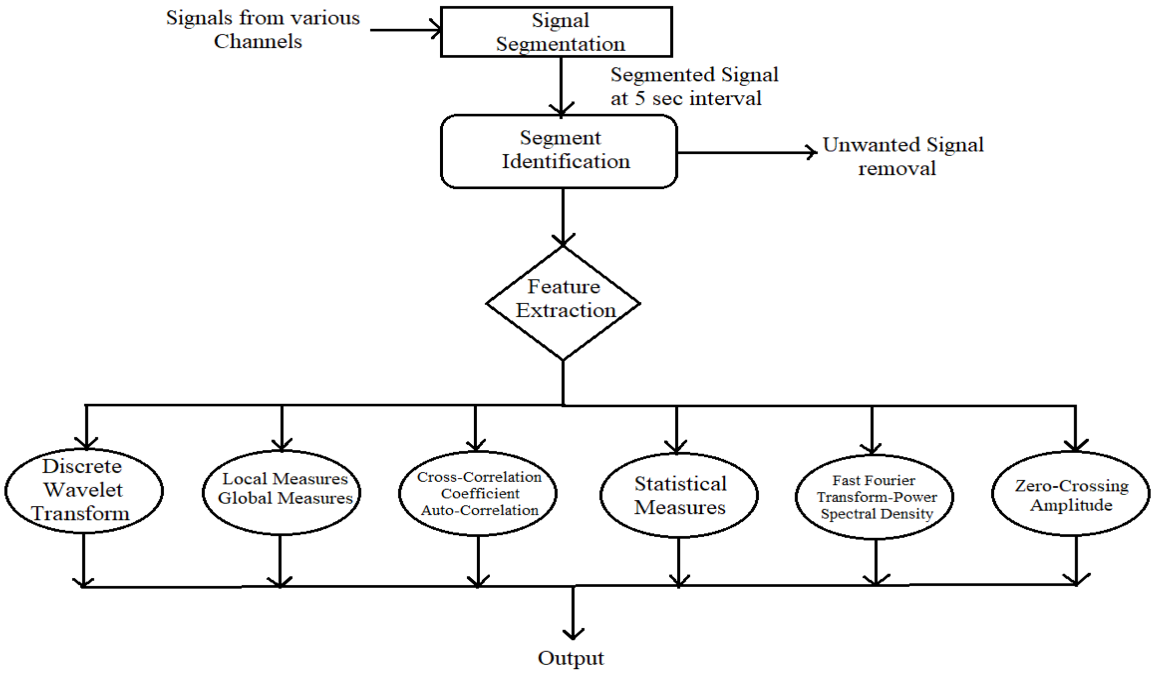


Figure 1: Typical EEG Feature Extraction

The use of entropy and energy band in the feature extraction phase for detection of epilepsy using EEG signals are studied in [12] [13]. Segment length and frequency band are the statistical calculations that are needed in the proposed work of this paper. An MIT dataset is used here for the epilepsy detection where the features of EEG are extracted using common spatial patterns. the neurological brain disorders can be automatically detected using the proposed system. This helps doctors and technicians to diagnose the disorders quicker and more efficiently; it also uses common spatial patterns of EEG for detection of epilepsy, here artificially preictal signals of EEG are generated after which feature extraction takes place. This paper also uses time domain and frequency domain features for its proposed methodology. The use of these features helps increase the overall accuracy while it reduces the training time. A dataset obtained from 23 patients is used to produce results. The technique of combining EEG signals along with statistical parameters to perform classification and feature extraction is adopted in this proposed paper.

The importance of EEG signal recognition is extremely vast as it helps in epilepsy detection. The detection can be performed by maximizing the mean and the loss which is sparsely found in the EEG signals [14]. The application of Discrete Wavelet transform (DWT) for the detection and diagnosis of epilepsy for the extraction of frequency domain features is applied [15]. Spectral entropy and dominant frequency are the features that are obtained after performing DWT on the EEG signal. This is done in order to select the most prominent features; this helps is a better detection between a normal person and patients that are affected with epilepsy [15]. For a proper evaluation of the accuracy of time-frequency domain features done using various combinations of the datasets available. Digital signal processing is observed, this enables a more accurate and precise diagnosis of the disorder. The transfer of technology from computer vision to machine learning has made enormous advances in the field of biomedical science. This increases the precision and reliability of the performance. The result in an unwanted noise. The methodology applies also helps in dropping out the unwanted features as to reduce the load on the system making it work faster and more efficient.

1.1 Motivation and contribution of research work

The increase in the number of epilepsy patients globally and the effect it has on them requires new and more improved methodologies to be developed for their better livelihood. The diagnosis and detection of epilepsy at the early stages causes better treatment and lesser resistance to drugs during the course of the treatment. The normal detection of this disorder is done using EEG signal that are diagnosed manually, this is a time-consuming process. Hence, it is essential to detect this disorder automatically. The combined use of EEG signals along with statistical parameters leads to a more accurate detection. The features that are extracted are combined and used with a CNN model for a precise and accurate detection; moreover, considering the above motivation, this research work has following contribution.

- At first, different features are analysed and outcomes of same are observed thoroughly; further considering the eminent feature, feature fusion is carried out.
- Feature fusion process helps in optimizing the feature extraction of EEG signal along with the statistical parameter.Further, considering these features, feature fusion and optimiziation aka FFO is carried out which helps in analysing the features in optimal way for further classification.
- Moreover, feature fusion and its optimization helps in exploring the new features that helps in enhancing the distinguish between classes.
- Moreover, this research works also performs the evaluation of each feature individually that can further help in learning the deep features for seizure detection.

This particular research work is organized such that first section discuss about the background of the epilepsy, further various feature extraction process and their characteristics are discussed. Mroever, second section ends with the research motivation and contribution. Second section of the research discuss the various existing methodologies along with their shortcoming. Third section focus on deesinging the mathematical model of various feature along with feature fusion and optimization for optimal feature extraction. Performance evalution is carried out in fourth section where different features are evaluated with normal person and person with seizure.

2 Literature Survey

In the classification of epileptic signal, there is an accurate detection at the preictal stage done in a reasonable duration of time before the onset seizure becomes vital to taking precautions or interventions. An extremely early prediction could be the cause leading to anxiety and an extremely late prediction may forfeit the chance of precaution. Considered by conventional studies as preictal one hour before ictal state the time duration is very long for an accurate and proper prediction.

The prediction of the preictal state has been studied recently in [16] – [18], in which the one-hour preictal EEG signals are split up into fine and small segments along with a multi category classification with minimal resolution for time-scale which is smaller than one hour. This has been formulated for the prediction of preictal state. A novel representation of EEG has been presented in [17] by the use of wavelet packet based on decomposition sub band energy ratio and the entropy features (WPFs), in which the RF algorithm (RF+WPFs) have been applied for the seizure and for prediction of preictal state. The classification rate in the epileptic database of CHB-MIT is achieved in [17] while segmenting the preictal into fine resolution along a 20-minute scale. Including the interictal, three preictal and ictal phases that is proposed in [17] there is a classification problem that is five categories. However, a more enhanced classification method of epilepsy has been proposed in [18] which is done by the combination of CNN used for feature learning with classifier learning done by SVM (CNN+SVM). In this a mean of amplitudes of the sub band spectrum (MAS) from five of the representative rhythms have been extracted for the representation of a multichannel EEG. An 86.25% average accuracy was obtained by the improved performance from the epileptic database of CHB-MIT. Specifically, for three phases of preictal, the average classification rate as depicted in [18] for CNN+SVM was 78.53% which provides a 1.8% increment over RF+WPFs [17].

An epilepsy diagnosis model is developed in [19] with the use of DWT, it also uses the principle of minimum entropy along with Associative Petri Net (APN) technique. The authors have concluded that the results generated by the G-mean, precision rate, APN diagnosis model accuracy and F-measure are better than the results that are provided by the machine learning models that include “neural networks, decision tree, Bayes Net (BN) and SVM”. The combination of the APN and MEPA methods have accurately determined if patients have or don’t have epilepsy. APN model has obtained a 99% precision rate and 90.33% value of negative prediction. The method that is proposed in [20] shows epileptic seizures detection by the use of 54 DWT mother wavelets for extraction of statistical features such as “Skewness, Shannon Entropy, Average power (AVP), Mean Absolute Value (MAV), Max, Mean, Standard Deviation (SD), Min, Variance, Kurtosis, Energy and Normalized SD” from the EEG signal. Furthermore, the reduction of feature space and selection of relevant features is done using a

Genetic Algorithm (GA). Machine Learning classifiers including ANN, KNN, NB and SVM are used for classification of the EEG signal to non-epileptic or epileptic. After the evaluation of these metrics, high accuracy has been obtained by ANN classifier along with the other combinations of datasets and this outperforms other classifiers. [21] introduces a technique of seizure recognition that is effective for epilepsy on the basis of Stockwell Transform (S-transform) and bidirectional long short-term memory (Bi-LSTM) neural networks for EEG recordings that are intracranial. Evaluation based on event and segment to evaluate signals has been done. Resulting in which the authors have obtained 98.09% sensitivity, 98.69% specificity, 96.3% sensitivity and 0.24/h false detection rate respectively. In [22] includes a framework which has two parts. The signal intensity is calculated in the first part for every data point, that enables the autoregressive moving average (ARMA) model used in characterizing dynamic behaviour for the time series of EEG. Secondly, pattern recognition technique has been used as a classification method and has an accuracy of 93% and 94% respectively. During this work, 0.317s of execution time was attained for the SVM model. A method that is based on extraction of training the EEG signals from epileptic characteristic waves in [23]. A set of the wavelets have been constructed for performing CWT on recorded signal of EEG. CWT coefficient matrices have data fusion applied to it that correspond to the wavelets that are multiple constructed which help determine the boundaries of the seizures. A system that is based on DWT analysis has been developed in [24] having EEG signals that use non-linear and linear classifiers for the detection of epileptic seizures. Statistical features are classified using Naïve Bayes and KNN classifiers that are obtained through DWT having accuracy of 100%. A system has been developed by the authors in [25] for the detection of epilepsy by the use of TF entropy features where S-Transform is used having 86% accuracy. Wavelet packet transform (WPT) has been introduced in [26] where the wavelets having links between them and the multi-resolution approximation has been explained. As various techniques for the detection of epilepsy in the EEG signals has been discussed, mostly used are S-transforms, entropy principle, ARMA models, basic analysis of CWT DWT and Bi-LSTM for performing tasks of feature extraction. Since all of these methods increase the computational complexity, features extracted do not appropriately select because of the feature dimensionality. Classification complexity becomes rigid due to the increase of the feature dimensionality. For these drawbacks to be overcome, extra work has to be performed on the dimensionality reduction of the epileptic features for obtaining better results.

3 Proposed Methodology

In this section, the detailed calculation of the statistics for every feature is provided. This shows the relation between the EEG signals and the statistical calculations. For every feature that is described, value of every sample is denoted as w_j every sample is represented as j and number of samples in EEG signal is given as *M.*

3.1 Features of frequency domain

Frequency analysis (energy estimation) has been performed on EEG signal that is digitized by the use of Welch's method with 32-data point Hanning window, allowing the analysis of features in frequency domain and calculate features Case1, case2, case3 , case4 and $mean_{freqn}$.Obtained through Fourier transform, the signal has a power spectrum R_x where the complete power of signal is computed by the use of equation 1.

$$O_{whole} = \sum_{j=1}^{M} R_w(j) \quad (1)$$

The power spectrum is denoted as $R_w(j)$at bin j, from R_w and $O_{whole}$of signal, the estimation of these features is done as follows:

$$mean_{freq} = \left(\sum_{i=1}^{M} R_w(j).spec_{freq}\right)^{-1} \sum_{j=1}^{M} R_w(j) \quad (2)$$

Where the mean frequency is denoted as $mean_{freq}$and the spectrum frequency at bin j is denoted as $spec_{freq}$.

Case1: Is the frequency at which 20% of the complete power of R_x*(P20)* is as given below.

$$O_z = \sum_{j=1}^{M} R_w(j \times \delta freq) \leq 0.2 \times O_{whole} \quad (3)$$

*Case2:*50% Frequency, It is called as median frequency. This frequency divides the area R_x equally into two parts.

$$O_z = \sum_{j=1}^{M} R_w(j \times \delta freq) \leq 0.5 \times O_{whole} \quad (4)$$

Case3: 80% Frequency: At this frequency 80% of the complete power R_x *(P80)* is as given below.

$$O_z = \sum_{j=1}^{M} R_w(j \times \delta freq) \leq 0.8 \times O_{whole} \tag{5}$$

Case4: 95% Frequency: At this frequency 95% of the complete power R_x *(P95)* is as given below.

$$O_z = \sum_{j=1}^{M} R_w(j \times \delta freq) \leq 0.95 \times O_{whole} \tag{6}$$

3.1.1 Analysing the EEG signal through different bands

In every band of wave frequency, the signal has been filtered. This was used most commonly for the EEG signal study $(\alpha, \beta, \gamma, \delta)$used for calculation of the features for bands of these frequencies. The spectrum power of every band was calculated after filtering the signal $\left(R_{w\alpha}, R_{w\beta}, R_{w\gamma}, R_{w\delta}\right)$ that have been obtained using Fourier transform. From the signal spectrum of every band, the power of every band was calculated according to the equation 1, that generate features such as:

$$\begin{gathered} \alpha = \sum_{j=1}^{M} R_{w\alpha}(j) \\ \gamma = \sum_{j=1}^{M} R_{w\gamma}(j) \\ \beta = \sum_{j=1}^{M} R_{w\beta}(j) \\ \delta = \sum_{j=1}^{M} R_{w\delta}(j) \end{gathered} \tag{7}$$

3.1.2 Power Spectrum square

This feature's value has been obtained using quadratic sum of power

$$D = \sum_{j=1}^{M} R_w(j)^2 \tag{8}$$

$\alpha', \beta', \gamma', \delta'$ are the few feature which are computed for each band; these features listed above are calculated with respect to equation 8, using the EEG signal that is filtered from every band through the spectrum. Each feature has been defined below:

$$\begin{gathered} \alpha' = \sum_{j=1}^{M} R_w(j)^2 \\ \beta' = \sum_{j=1}^{M} R_{w\beta}(j)^2 \\ \gamma' = \sum_{j=1}^{M} R_{w\gamma}(j)^2 \\ \delta' = \sum_{j=1}^{M} R_{w\delta}(j)^2 \end{gathered} \tag{9}$$

3.2 Time Domain Features

A. Root Mean Square Value (RMS)

RMS is defined as the square root of values of instantaneous signal that is average squared and it is calculated using the equation

$$w_{root\_ms} = \left(\frac{1}{M} \sum_{j=1}^{M} w_j^2 \right)^{-1} \qquad (10)$$

B. Zero Crossings (ZC)

Counting the number of times that the waveform crosses zero leads to obtaining ZC. It is essential to include threshold (ϱ) for calculating zero crossing for reducing noise induced. Considering two consecutive samples w_j and w_{j+1} the zero crossing counting increases if the following equation are satisfied

$$\{w_j < 0 \; ew_{j+1} \; is \; greater \; than 0\} and \; [w_j - w_{j+1}] \; is \; greater \; than \; \varrho \qquad (11)$$

C. Variance

The measurement of the Statistical dispersion is called as variance. This indicates the variability degree in some situations. This is calculated by equation 20 by adding the squares of differences between the observed value and the average value.

$$U = \sum_{i=1}^{M} \frac{(w_j - \bar{\bar{w}})^2}{M-1} \qquad (12)$$

Where $\bar{\bar{w}}$ denotes the average value of the EEG signal

D. Standard Deviation

Standard Deviation is the square root of Variance. It is calculated using the following formula:

$$SD = \left(\sum_{j=1}^{M} \frac{(W_j - \bar{\bar{W}})^2}{M-1} \right)^{\frac{1}{2}} \qquad (13)$$

E. Kurtosis

Kurtosis is the calculation done to determine the degree for flatness of any distribution, determining if it is tapered or flattened comparatively to the pattern normally characterized. The higher the value of kurtosis more is the presence of values which are distant from the average Kurtosis has been defined as follows:

$$B = \sum (x_i - \bar{\bar{x}})^4 (SD)^{-4} \qquad (14)$$

F. Skewness

Skewness is basically used to verify and calculate data symmetry that indicated the variable distribution probability, the skewness value is as defined below:

$$\zeta = \sum_{i=1}^{M} (W_j - \bar{\bar{W}})^3 ((M-1)(SD)^3)^{-1} \qquad (15)$$

G. Approximate Entropy

It is used to statistically measure the quantifiable variability and regularity of finite time signal; the activity performed by the cortical pyramidal cells are measured by the entropy that describes complexity, uncertainty degree and irregularity of EEG signal. Time domain was used to calculate the entropy of EEG signal. Consider a sequence of given signals with M as samples $(w(1),w(2),\ldots\ldots w(M))$, is essential for determining two values to calculate the approximate entropy: a pattern size composed of ($\mathbb{A}$)elements and similarity criterion ($\mathbb{B}$)or the tolerance to compare the patterns. Therefore, two patterns have been considered that are similar when their differences are smaller than $\mathbb{B}$.The application of entropy for EEG signals has a value of w (standard size) that is equal to two and has the value of μ (criterion of tolerance or similarity) that equals 0.2* $SD(R(w))$, where the standard deviation of $R(w)$ is denoted as $(R(w))$. Set of all the patterns contained in the spectrum of power denoted as Rw and $M_w(SD)$ denotes the count of similar patterns, the possibility to find the average of every value that is calculated. Therefore, $M_w(\sigma)$ is used for the measurement of frequency or regularity of pattern similarity to the given standard. This allows the entropy to be defined approximately.

$$\chi(\mathbb{A},\mathbb{B},R(w)) = \ln\left[\frac{M_w(\mu)}{M_{w+1}(\mu)}\right] \tag{16}$$

3.3 Graphical Features

In case of each subjects, brain network over the time was monitored considering the various graph over the time i.e. clustering coefficient, global and local efficiency.

3.3.1 Global efficiency

Let's consider any path length parameter i.e. c_{jk} among the node pair i.e. j and k which is elaborated as the minimal edges that requires traversal from j to$k$. Further, characteristic path length is defined as the average length among entire node pair that can be further measured through below equation.

$$K = m^{-1}(m-1)\left(\sum_{i,j\ bleongs\ to\ M\ where\ j\ is\ not\ equivalent\ to\ k} c_{jk}\right) \tag{17}$$

Further, due to limitation of characteristics path, we can find the node pair efficiency and computed as:

$$K = m^{-1}(m-1)\left(\sum_{i,j\ bleongs\ to\ M\ where\ j\ is\ not\ equivalent\ to\ k} 1/c_{jk}\right) \tag{18}$$

3.3.2 Clustering coefficient

Clustering coefficient of any graph B_j can be defined as the existing edges fraction among the nearer node to j and computed as:

$$B_j = 2r_j\left(l_j(l_j-1)\right)^{-1} \tag{19}$$

Where l_j indicates the node degree; r_j indicates the edges number, further mean can be computed as:

$$B = (m^{-1}) \sum_{j\ belongs\ to\ M} B_j \tag{20}$$

3.3.3 Cross correlation

Cross correlation is defined as the similarity index among the two distinctive series as the displacement function of one related to the other. Let's consider a pair of series $y(u)$ and $z(u)$ then cross correlation is computed as:

$$B_{yz} = \sum_{s=1}^{m-v} \left(y(u)(SD_y)^{-1}\right)\ (y(s+v)(SD_z)^{-1}) \tag{21}$$

In above equation, SD_y and SD_z are the standard deviation, v indicates the lag range; Decorrelation is the process of reducing correlation or auto-correlation among a set of signals while preserving other aspects of it

3.4 Feature fusion and optimization

Feature fusion is the process where above discussed feature are fusion in the process to enhance the feature extraction; in this section of the research optimization along with fusion is carried out through designed algorithm. Feature Fusion and optimization is method that has been applied for the dimensionality reduction of the data and classification, assuming the classes or groups have been linearly separable and if there is a possibility for new features to be estimated that are designed approximately to the axes that make the reparability maximum between classes. This study uses a technique to estimate the value of proposed approach which focuses on the relationship among aging and postural control by the use of Algorithms for search method for solving the problems on optimization. This justifies the applicability of context proposed in this research which is between aging and EEG. The FFO method consisted of the following steps:

Table 1FFO(Feature Fusion and optimization)

Step1:	Data Representation (C_n) within a space having angular coordinated that are multidimensional in which number of features is denoted as n, radius denoted as r and the angle is θ as depicted in the equations. $$r = (B_1^2 + B_2^2 + B_3^2 + \cdots + B_n^2)^{-1}$$ $$\Xi = \{\Xi_1, \Xi_2, \Xi_3, \dots, \Xi_{m-1}\}$$ $\Xi_1 = \tan^{-1}(\frac{B_1}{B_2}),\ \Xi_2 = \tan^{-1}\left(\frac{B_3}{(B_1^2+B_2^2)^{-1}}\right)$ $$\Xi_{n-1} = \tan^{-1}\left(\frac{B_3}{(B_1^2 + B)^{-1}}\right)$$
Step2:	Data projection is done in a specific axis as depicted in equation which results in single scalar p or new characteristic. $$FFO = 100.r.cos(\Xi_1 + \hat{\Xi}1).cos(\Xi_2 + \hat{\Xi}2)\dots\dots\dots cos(\Xi_{n-1} + \hat{\Xi}_m - 1)$$ Where $\hat{\theta}$ denotes the angles of rotation that causes class separability to maximize.
Step3:	implementation starts by defining the initial variable $\hat{\theta}_0$ which is created by sampling imaginary axes, whose values ranged 0 to 2π
Step4:	By the use of a set of projections for calculating accuracy estimator D_a as given, ς denotes the count of classes, $\overline{w}_j$ and $SD_{w_j}^2$ are the values of mean and variance of jth class respectively. $D_a = \sum_{j=1}^{\varsigma-1}\sum_{k=j+1}^{\varsigma}\left\lvert\frac{\overline{W}_j - \bar{x}_j}{\sqrt{SD_{w_j}^2 + Sd_{w_k}^2}}\right\rvert$, a=1,2,…..,m
Step5:	To calculate the value of D_2, which indicates the fitness function of GA for every imaginary axis that results in vector *Vec*, as given. $\psi = \begin{bmatrix} D_a = 1 \\ D_a = 2 \\ \vdots \\ D_a = m \end{bmatrix}$
Step6:	By selecting the technique of roulette wheel, a method of sampling with common replacement is used for random selection of individuals from a generation for building the basis for the further generation.
Step7:	Descendants of three generations ($\hat{\Xi}_{child1}$, $\hat{\Xi}_{child2}$ and $\hat{\Xi}_{child3}$) according to the below equations . In this only the topmost two offspring have been selected in regard to the values of their fitness function (E_Z). $\hat{\Xi}_{child1} = 1.5\hat{\Xi}_{parent1} - 0.5\,\hat{\Xi}_{parent2}$ $\hat{\Xi}_{child2} = 0.5\hat{\Xi}_{parent1} + 0.5\,\hat{\Xi}_{parent2}$ $\hat{\Xi}_{child3} = 0.5\,\hat{\Xi}_{parent1} + 1.5\,\hat{\Xi}_{parent2}$
Step8:	Some individuals of L change randomly that results in new population ($\hat{\Xi}_c$).
Step9:	The location of imaginary axis ($\hat{\Xi}$) such that it maximizes the class separation and relevance of features used for analysis.
Step10:	The process is repeated for each available feature. Considering the feature as irrelevant for discrimination whenever there is a difference between D_a and D_a^{new} which is lesser than 1% of the D_a value.

Moreover, consideirng the feature fusion different features can be explored and further optimization is carried out for dimensionality reduction and classification of the data; also through the above steps, this research aims to idenitfy the novel features.

4 Performance Evaluation

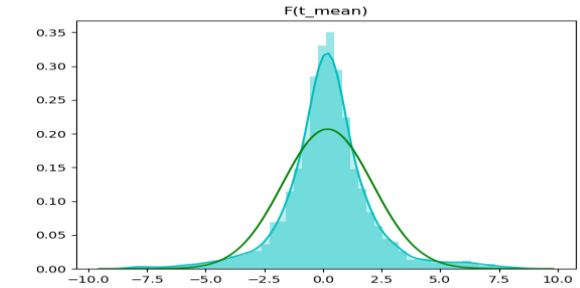
The integration of the graphs, FDS, TDS and correlation form the proposed system. The detection of epilepsy is done with the help of EEG by taking the dataset from CHB-MIT as without seizure and seizure data that is used for the process of feature extraction. This part of the review is mainly aimed at identifying the difference between the seizure and non-seizure patients with the feature extraction resulting in increased speed and decreased time. These features indicate the difference between seizure and non-seizure patients, the non-seizure is indicated by blue graphs and the seizure is indicated by green graphs.

4.1 Resulting Values of Time Domain Features (TDS)

There is a significant difference that has been observed during feature extraction. Time Domain features include attributes such as mean, kurtosis, variance, skewness, peak2peak voltage, zero crossing and total area.

4.1.1 Root Mean Square Value (RMS)

RMS is defined as the value of the square root of the instantaneous signal that is average squared.



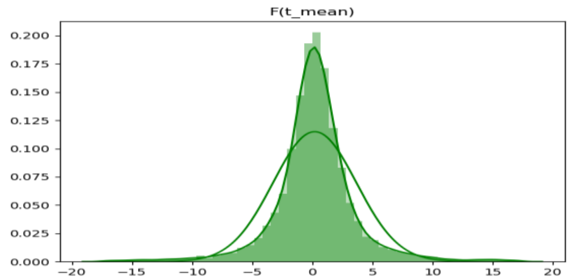
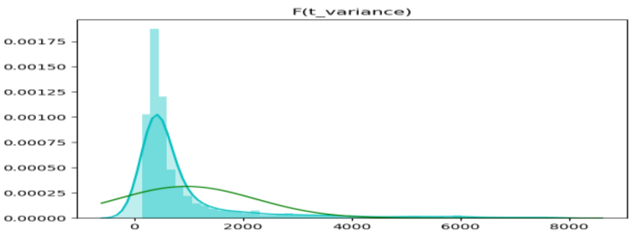


Figure 2.1 (a) Mean of a normal person Figure 2.1 (b) Mean of a seizure patient

4.1.2 Variance

The measure of the statistical dispersion is termed as variance which is used to indicate the variability degree.



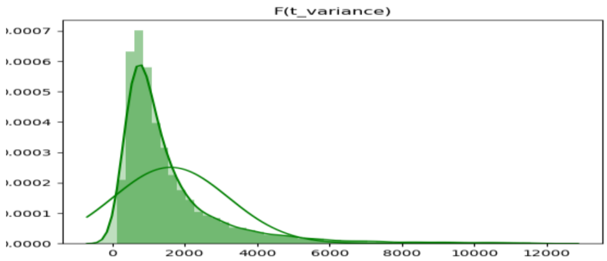
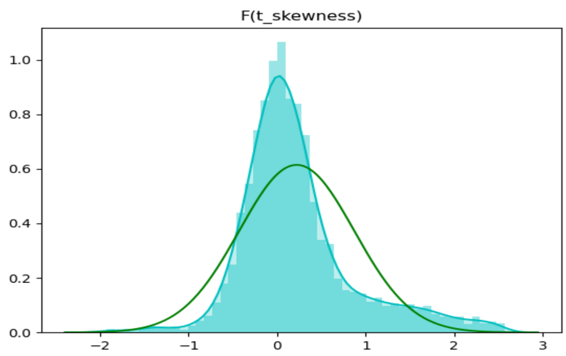


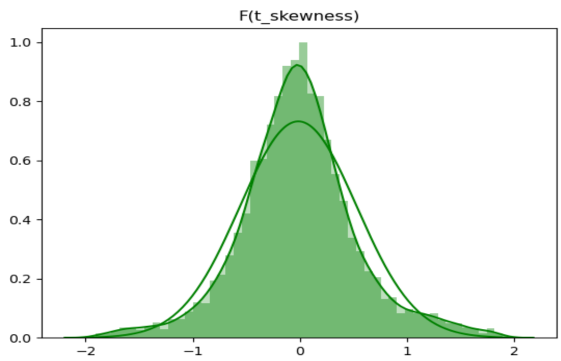
Figure 2.2 (a) Variance of a normal person Figure 2.2 (b) Variance of a seizure patient

4.1.3 Skewness

Skewness is used to indicate the data symmetry that is indicated by the variable distribution probability.

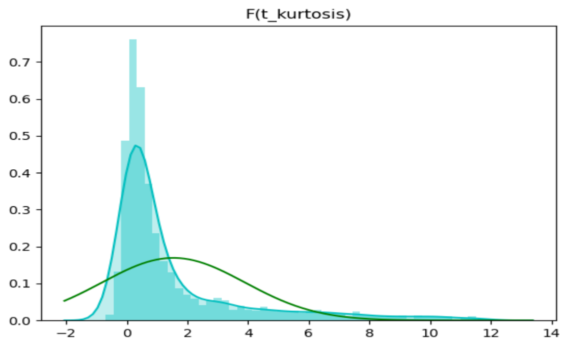
Figure 2.3 (a) Skewness of a normal person Figure 2.3 (b) Skewness of a seizure patient





4.1.4 Kurtosis

The degree of flatness for any distribution is done by the calculation of kurtosis.



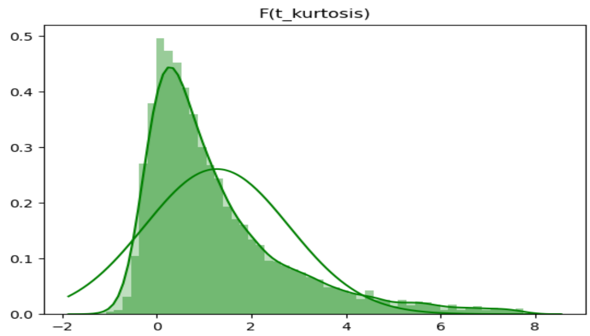
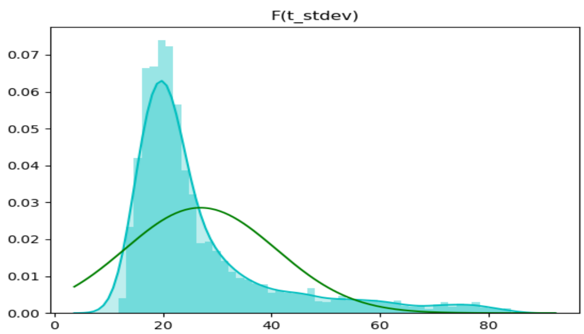


Figure 2.4 (a) Kurtosis of a normal person Figure 2.4 (b) Kurtosis of a seizure patient

4.1.5 Standard Deviation

Standard Deviation is defined as the square root of Variance.



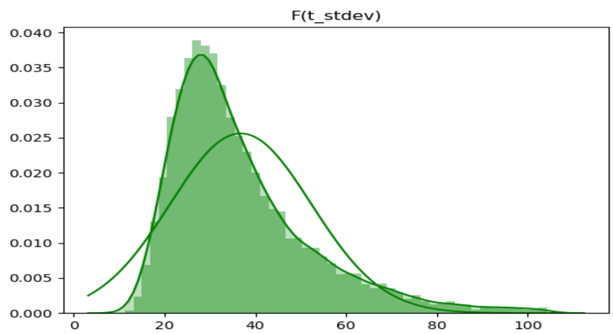
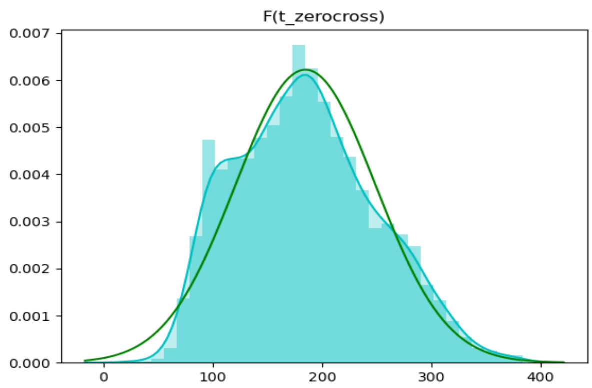


Figure 2.5 (a) Standard deviation of a normal person Figure 2.5 (b) Standard deviation of a seizure patient

4.1.6 Zero Crossing

Counting the number of times that the waveform crosses zero obtains Zero Crossing.



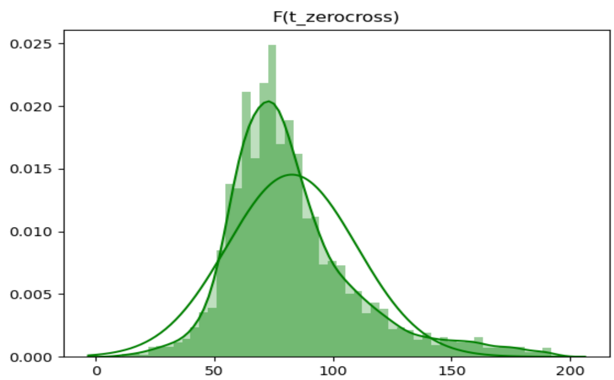


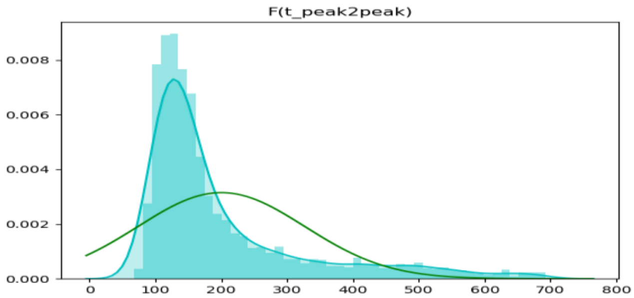
Figure 2.6 (a) Zero Cross of a normal person Figure 2.6 (b) Zero Cross of a seizure patient

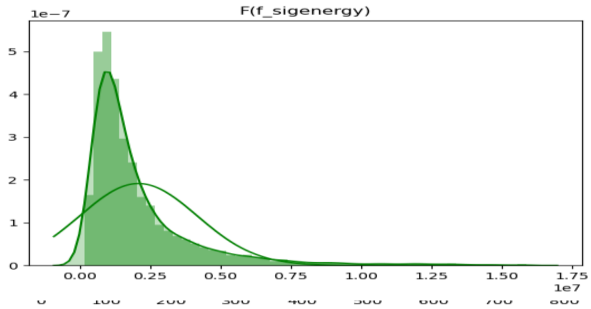
4.1.7 Peak-to-Peak Voltage

This is defined as the distance between the least negative amplitude to the most positive amplitude.

Figure 2.7 (a) Peak2peak Voltage of a normal

Figure 2.7 (b) Peak2peak Voltage of a seizure patient





Resulting Values of Frequency Domain Features (FDS) Frequency analysis also known as energy estimation has been performed on EEG signal that is digitized by the use of Welch's method with 32-data point Hanning window, allowing the analysis of features in frequency domain.

4.1.8 Total Signal Area

Total Signal Area represents the total area under the curve of the graph.

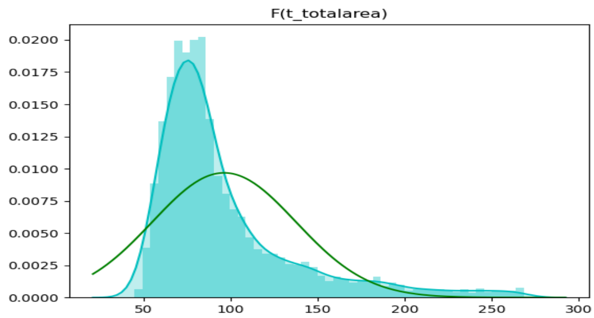


Figure 2.8 (a) Total Signal Area of a normal person

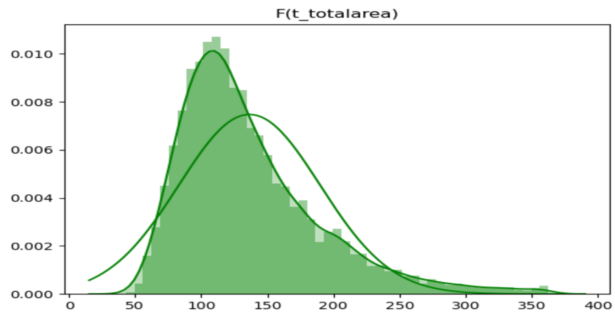


Figure 2.8 (b) Total Signal Area of a seizure patient

4.1.9 Energy Packet

Energy packets are particles of light that are like packets which are called as photons.

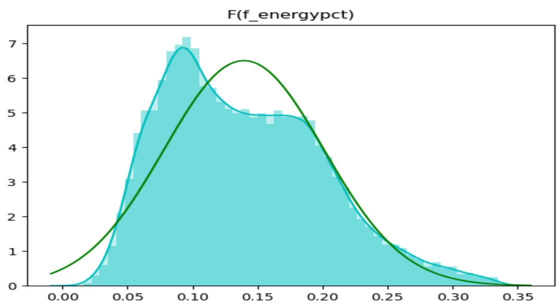


Figure 2.10 (a) Energy Packet a normal person

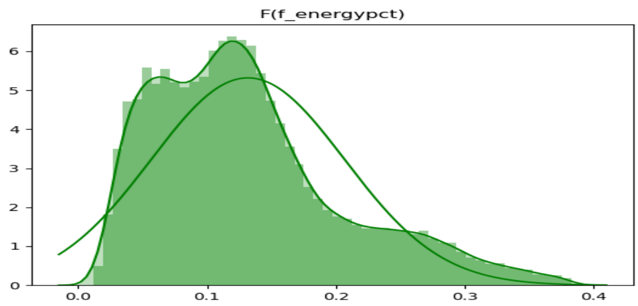


Figure 2.10 (b) Energy Packet of a seizure Person

4.2 Resulting Values of Frequency DWT Features

DWT is the discrete wavelet transform which is defined as a transform which decomposes any signal into various sets, in which each set is a series of time coefficients that describes the evolution of time of the signal.

4.2.1 Average DWT Coefficient

The discrete wavelet transform coefficient indicates the correlation degree between the wavelet function at various instances of time and the signal that is analysed.

Figure 2.11 (a) Average DWT Coefficient seizure

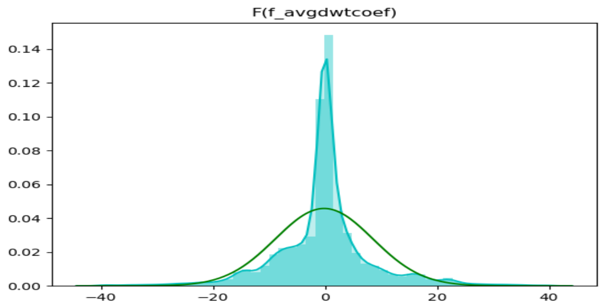
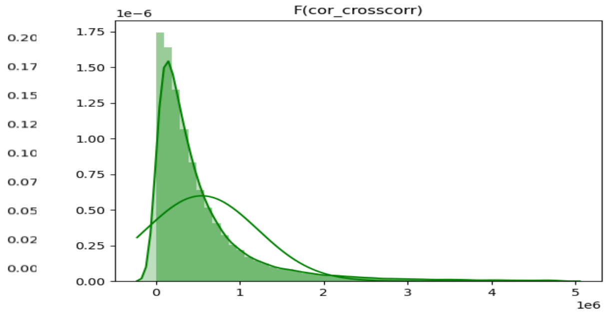


Figure 2.11 (b) Average DWT Coefficient normal person



Resulting Values of Signal Relational Features

The signal relation diagram is used to graphically represent the relation present between quantity models.

4.2.2 Decorrelation

Decorrelation is the process of reducing correlation or auto-correlation among a set of signals while preserving other aspects of it.

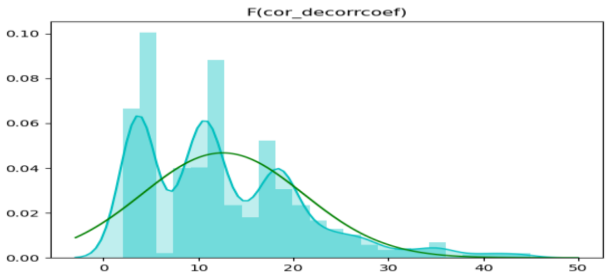


Figure 2.13 (a) Decorrelation of a normal person

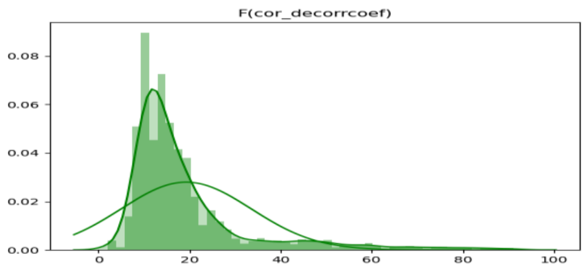


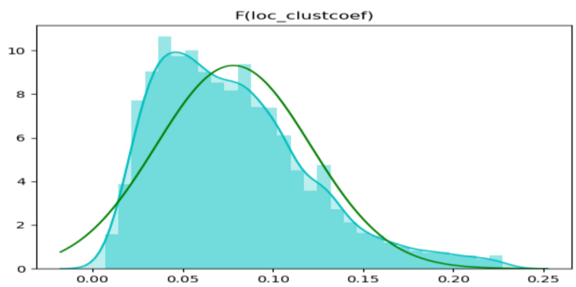
Figure 2.13 (b) Decorrelation of a seizure patient

4.3 Human Brain Graphic Features

4.3.1 Clustering Coefficient

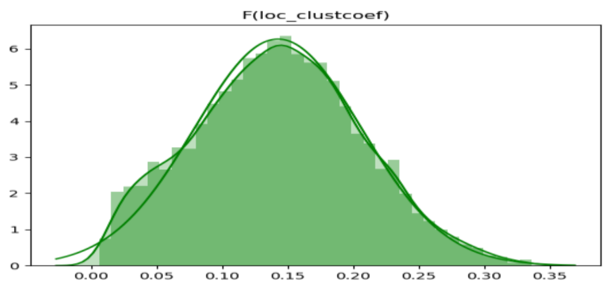
Clustering Coefficient is the measurement of the degree in which the nodes cluster together in a graph.

Figure 2.14 (a) Clustering Coefficient of



a normal person

Figure 2.14 (b) Clustering Coefficient of a



seizure patient

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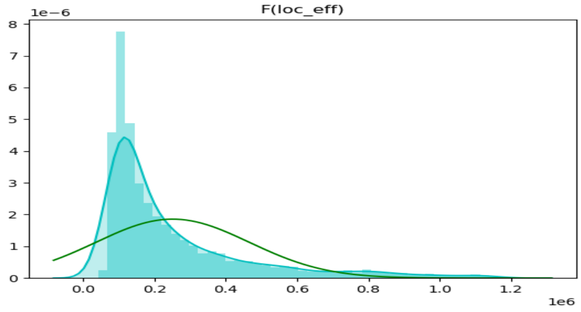
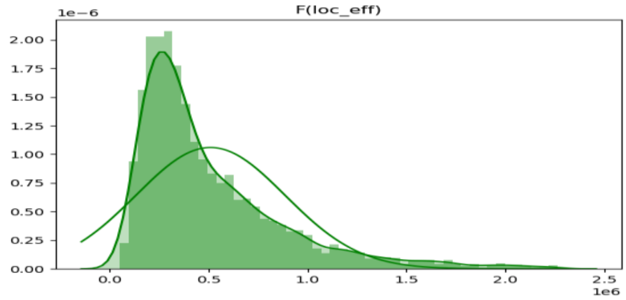
4.3.2 Local Efficiency

It is the measurement of the average information transfer efficiency within local subgraphs. Figure 2.15 (a) Local Efficiency of a Figure 2.15 (b) Local Efficiency of a



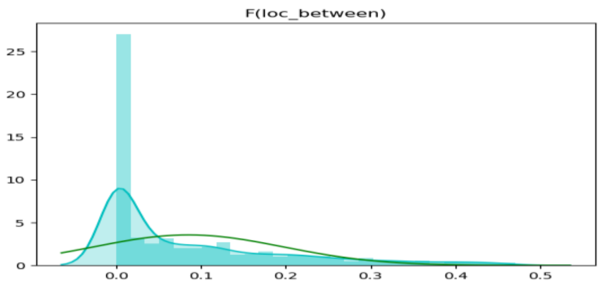


normal person

seizure patient

4.3.3 Betweenness Centrality

In a graph, it is the measurement of the centrality based on the shortest path.



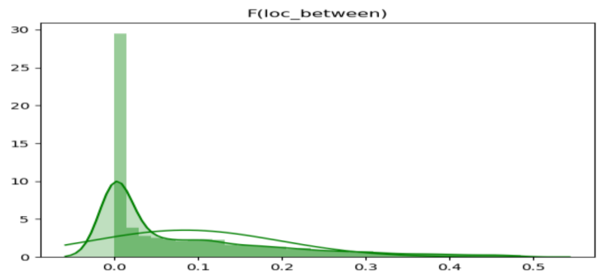
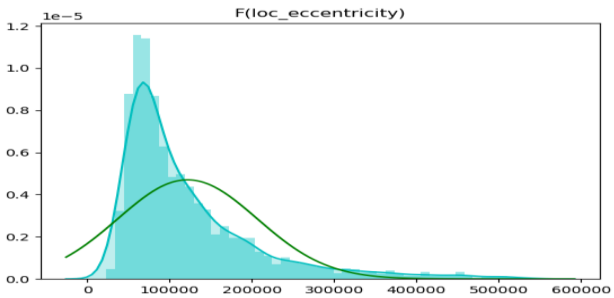


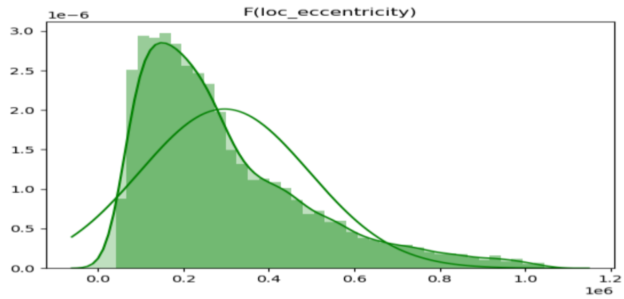
Figure 2.16 (a) Betweenness Centrality of a normal person Figure 2.16 (b) Betweenness Centrality of seizure

4.3.4 Eccentricity

Eccentricity of a graph is defined as the maximum distance of a particular vertex from the other vertices.

Figure 2.17 (a) Eccentricity of a normal person Figure 2.17 (b) Eccentricity of a seizure patient





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4.3.5 Global Efficiency

Global Efficiency is defined as the measurement of efficiency of transfer of distant information in the network.

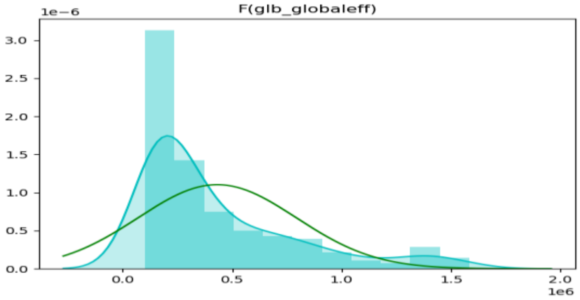


Figure 2.18 (a) Global Efficiency of a normal person

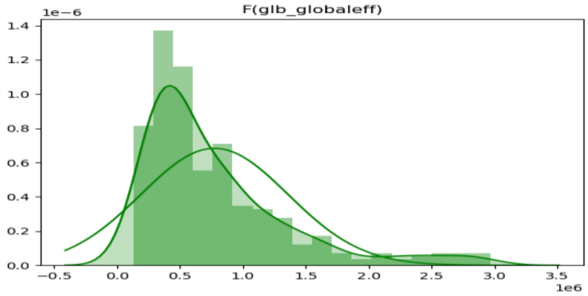


Figure 2.18 (b) Global Efficiency of a seizure patient

4.3.6 Global Diameter

It is referred to as the maximum eccentricity that is present for any vertex in the graph.

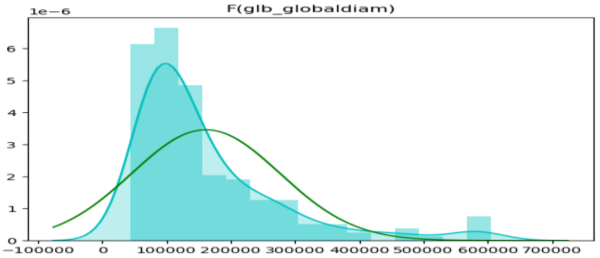


Figure 2.19 (a) Global Diameter of a normal person

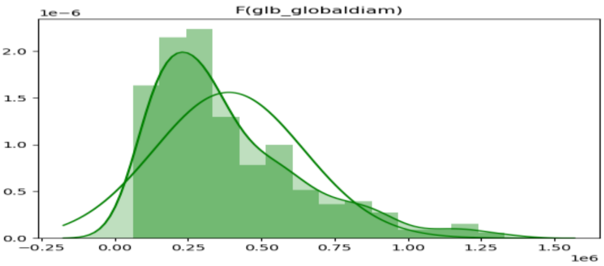


Figure 2.19 (b) Global Diameter of a seizure patient

4.3.7 Global Radius

It is the minimum eccentricity of graph of any vertex in the graph.

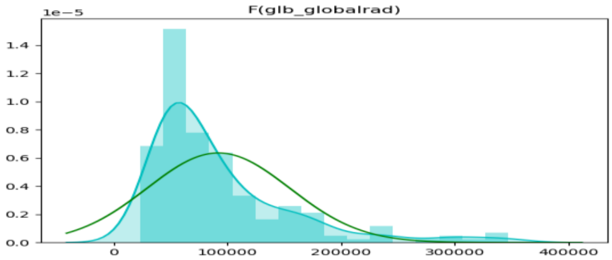


Figure 2.20 (a) Global Radius of a normal person

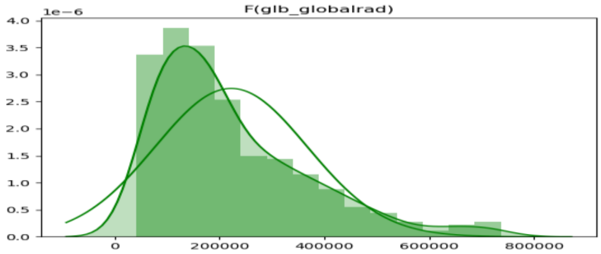
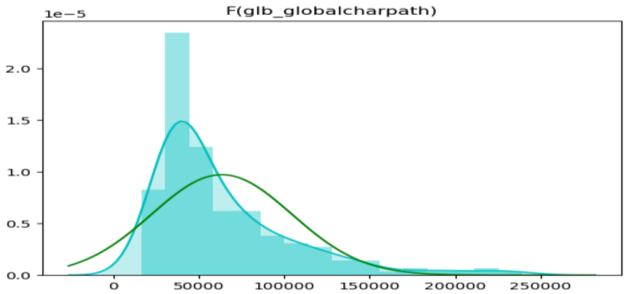


Figure 2.20 (b) Global Radius of a seizure patient

4.3.8 Global Characteristic Path

It is also called as average path length which is defined as the average number of steps taken along the shortest paths for the network of nodes.



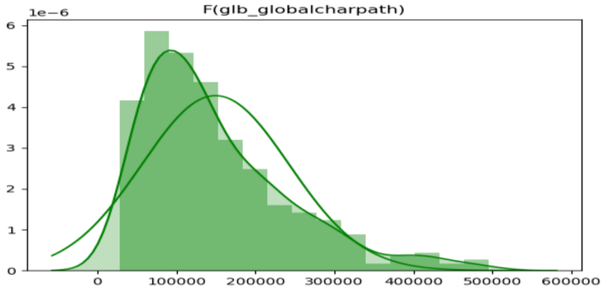


Figure 2.21 (a) Global Characteristic Path of   Figure 2.21 (b) Global Characteristic Path normal path of a seizure patient

Conclusion

A seizure occurs during epilepsy when the electrical connections in the brain are scrambled and there are sudden outbursts of the electrical activity in the brain. A seizure results to various changes in a person some of them include behavioural, emotional, physical movement, etc. Among the total population of the world, around 1% are affected by epilepsy and 30% of epilepsy patient encounter resistance to drugs during the course of their medical treatment. There exist two sets of data: EEG signals of a normal person and EEG signals of seizure affected patient. The detection of seizure with different features are carried out in this research work. Further, considering these features, feature fusion and optimiziation aka FFO is carried out which helps in analysing the features in optimal way for further classification. Moreover, feature fusion and its optimization helps in exploring the new features that helps in enhancing the distinguish between classes. Future scope of this research is to classify using convolutional Neural Network and predict the seizure.

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