VISVESVARAYA TECHNOLOGICAL UNIVERSITY

BELAGAVI-590018, KARNATAKA

PROJECT REPORT ON

"AUTOMATED FOCAL EEG SIGNAL DETECTION USING ARTIFICIAL NEURAL NETWORK"

Submitted in partial fulfillment of the requirement for the award of the degree of

Bachelor of Engineering
In
Electronics and Communication Engineering

For the academic year 2019-20

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CERTIFICATE

This is to Certify that the dissertation work **"Automated Focal EEG Signal Detection using Artificial Neural Network"** carried out by **Prakhar Jain, Pratyush Banke, Priyanshu Sinha and Rajnish Kr. Shah** having **USN: 1CR16EC111, 1CR16EC115, 1CR16EC119, 1CR16EC124** respectively are bonafide students of **CMRIT** in partial fulfillment for the award of **Bachelor of Engineering** in **Electronics and Communication Engineering** of the **Visvesvaraya Technological University, Belagavi,** during the academic year **2019-20**. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said degree.

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ACKNOWLEDGEMENT

We take this opportunity to express our sincere gratitude and respect to **CMR Institute of Technology, Bengaluru** for providing us a platform to pursue our studies and carry out our final year project.

We take great pleasure in expressing our deep sense of gratitude to **Dr. Sanjay Jain,** Principal, CMRIT, Bangalore for his constant encouragement.

We would like to thank **Dr. R. Elumalai,** Professor and Head, Department of Electronics and Communication Engineering, CMRIT, Bangalore, who has been a constant support and encouragement throughout the course of this project.

We express our sincere gratitude and we are greatly indebted to **Dr. Binish Fatimah, Associate Professor,** Department of Electronics and Communication Engineering, CMRIT, Bangalore, for her invaluable co-operation and guidance at each point in the project without whom quick progression in our project was not possible.

We are also deeply thankful to our project guide **Mr. Manjunath V. Gudur, Assistant Professor,** Department of Electronics and Communication Engineering, CMRIT, Bangalore, for critically evaluating our each step in the development of this project and provided valuable guidance through our mistakes.

We also extend our thanks to all the faculty of Electronics and Communication Engineering who directly or indirectly encouraged us.

Finally, we would like to thank our parents and friends for all their moral support they have given us during the completion of this work.

ABSTRACT

The electroencephalogram (EEG) signals are obtained from the electrical activity that goes on the brain and contain a lot of information with respect to any activity performed by an individual. These signals are affected by even a minute action performed by an individual or even a thought of the individual. In this report, we present a methodology for successful detection of epileptogenic (focal) and non-epileptogenic (non-focal) areas in the brain to treat the patients suffering from epilepsy that occur due to irregular electrical activity in the brain.

In this approach, we used deep neural network to identify the areas affected by epilepsy. The EEG signals from the brain are first recorded and then decomposed into various sub-bands using Fourier Decomposition Method (FDM). Then, the several features are calculated from each of these sub-bands and the features which statistically provide the best results are then selected for further processing. These selected features are then fed to the neural network where the final classification of the EEG signals into focal and non-focal are carried out. After classification the accuracy, sensitivity and specificity of these segmented signals are calculated.

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Chapter 1

INTRODUCTION

EEG signals has been used for a long time to study the brain's electrical activity as it is highly reliable and also helps in diagnosis of brain related disorders efficiently.

The Electroencephalogram (EEG) signals are stimulated whenever there is some electrical impulses or information exchange takes place among neurons. Whenever excessive electrical discharges of brain cells occurs it is called as seizure, and when the seizures are recurrent they are termed as epilepsy.

The recurrent seizures which occurs in epilepsy is a neurological disorder of the brain which cannot be cured by medicines and requires surgery. The excessive neuron activity in the brain causes irregular firing of neurons. Various pre-surgical techniques are used for detection of epilepsy such as MRI,PET etc., however they are generally not preferred over EEG as the accuracy levels of these methods are only 50% -80% which proves inadequate, thereby making them inappropriate to continue with epileptic surgery.

The EEG signal though non-linear consist of various rhythms that respond to any brain activities. According to observations the non-focal i.e. the unaffected EEG signal's behaviour is less rhythmic and more chaotic as compared to the focal EEG signal. It is further observed that the delta rhythm of focal epileptic patient is asymmetric in nature, and to visually analyze these EEG signals becomes very complex and error prone.

Chapter 2

LITERATURE SURVEY

2.1 Title: Non-randomness, Non-linear, and non-stationarity of electroencephalographic recordings from epilepsy patients.

In this paper, the intracranial EEG recordings from five epilepsy patients is taken and all of those patients had longstanding pharmacoresistent temporal lobe epilepsy and epilepsy surgery was to be carried on to them. However, the studies did not allow for unambiguous localization of the brain areas which had seizure onset zone i.e. the origin of the seizures.

Extracranial reference electrodes were also placed between 10/20 positions Fz and Pz was used. The EEG signals were recorded with around 64 channels and sampled at 512 or 1024 Hz.

The signals were digitally band-pass filtered between 0.5Hz and 150Hz using a fourth order butterworth filter and were sampled at the rate of 1024 Hz. Here the signals which were sampled at 1024 Hz are down-sampled to 512 Hz before analyzing it further.

In this method, 3750 pairs which are simultaneously recorded are separated into signals x and y (x is the focal EEG signal and y is the neighbouring signal) from the pool of all signals measured at focal EEG signal. The signal pairs are randomly selected and these recordings are divided into time windows with window size of 20 seconds corresponding to 10240 signals.

For analyzing each signal pair, one patient is randomly selected of the five patients whose EEG signals were recorded and from the selected patient, the channel for signal x and for signal y are randomly selected as well. If the signal pairs contained any prominent contaminations then it was excluded. However, the noise at 50 Hz is considered moderate and was not used for exclusion of the signal.

2.2 Title: Classification of Focal and Non-focal EEG signals using ANFIS classifier for Epilepsy Detection

In this paper, a computer aided automatic detection and classification method for focal and non-focal EEG signal is used for the localization of the epileptogenic area which is an essential practice to detect and treat epilepsy. The decomposition of the signal is carried out by Dual Tree Complex Wavelet Transform (DT-CWT) and the features are calculated using the decomposed co-efficients. The Adaptive Neuro Fuzzy Inference System (ANFIS) classifier is used here to train and classify the features.

The EEG signal acquisition of epileptic seizures were collected from open database available at the University of Bern. In the study, 50 Focal and 50 Non focal pairs of EEG signals were randomly chosen from a database of 750 focal and 750 Non focal EEG signals obtained from adjacent channels, each signal with a pair of two EEG signals x and y.

The proposed system consists of the following stages as complex wavelet transform, Feature Extraction, and classification. The ANFIS(Adaptive Neuro Fuzzy Inference System) classifier is also used in learning mode to train the focal and non focal EEG signal.

After recording the trained signals the trained pattern is used to classify the focal and non-focal signals in ANFIS classification.

The frequency components of an EEG signal change whenever and epileptic seizure occurs. The change observed in the frequency components needs to be quantified for obtaining useful information for classification and extraction of different frequency features was done using Fourier Transform.

Proposed Method:

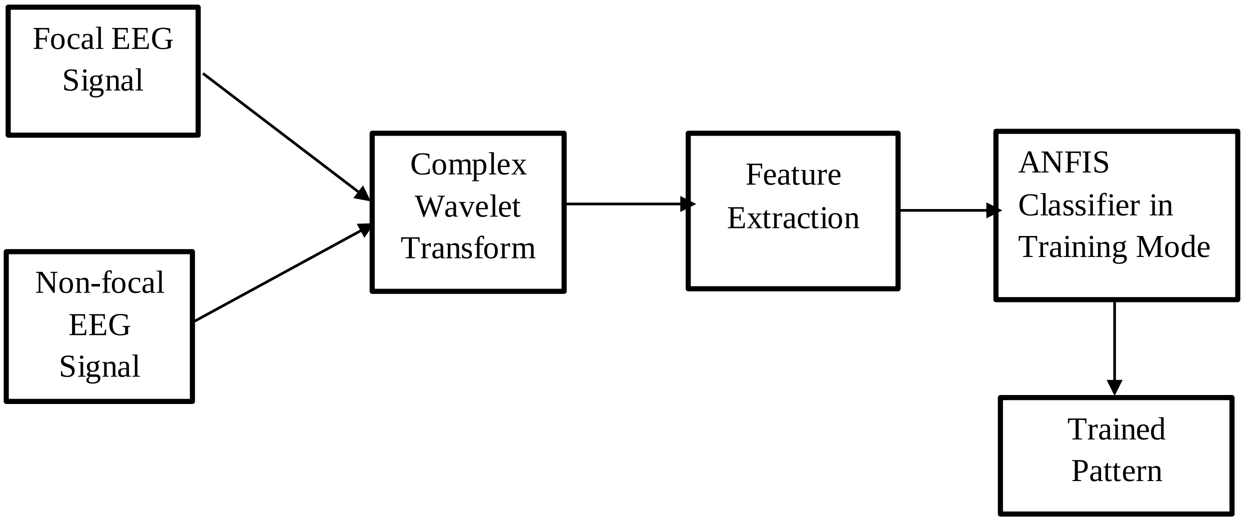

Fig. 2.2.1 Methodology

To achieve the decomposition of the signal into sub-band signals at various time scales, the Complex Wavelet Transform is being used. However, during DWT if there is a small change in the input signal it may cause large changes in its wavelet coefficients. Thus, Dual Tree Complex Wavelet Transform (DT-CWT) is used in this paper for perfect reconstruction of the signal.

The co-efficients obtained after Complex Wavelet Transform are used as feature sets for improving the classification and accuracy of the system the mean and standard deviation are computed from transformation coefficients obtained. The mean and standard deviation are represented by the following equations:

$$\text{Mean} = \frac{\sum \text{Low pass band coefficients} + \sum \text{High pass band coefficients}}{\text{Number of decomposition levels}}$$

$$\text{Standard Deviation} = \frac{1}{n} * \text{std}_{\text{low-pass-coefficients}} + \text{std}_{\text{high-pass-coefficients}}$$

The average accuracy achieved for automatic EEG signal classification is about 99%. The proposed method used in this article was able to achieve 98% sensitivity, 100% specificity, 99% accuracy, 100% positive predictive value, 98.03% negative predictive value, and 98.04% Matthews's correlation coefficient.

2.3 Title: Focal and Non-focal Epilepsy detection using EEG signals via Empirical Mode Decomposition(EMD)

In this approach, Empirical Mode Decomposition is applied to decompose the EEG signals into finite and a small set of amplitude and frequency modulated oscillating components known as IMFs (Intrinsic Mode Functions).After obtaining these IMFs, they are operated upon individually for further analyzing of the signal.

This approach is used for localization and isolation of the epileptogenic area for pre-surgical analysis of the affected area. For the discrimination of focal and non-focal epilepsy the average sample entropy of Intrinsic Mode Functions (IMFs) is taken into consideration and along with this entropy the average variance of instantaneous frequencies of IMFs is also used. Both sample entropy and instantaneous frequency are a part of the signal processing approach for differentiation.

The EMD is employed for decomposition as the EEG signals are non-linear and non-stationary. The EMD decomposes these EEG signals into a finite small set of amplitude and frequency modulated oscillating components called IMFs. The EMD produces smooth envelopes of a non-linear and non-stationary signal. These envelopes are characterized by the local minima and local maxima of the sequence and subtraction is done of mean of these envelopes from original sequence to obtain IMFs. The IMFs obtained are a set of narrow-band and symmetric functions in nature.

For this approach, first all the IMFs of x and y signals for focal as well as non-focal signals are found and then for each of the x-signal of the focal signal quantization is performed. Similarly, this quantization operation is also performed for y-signal of the focal signal. The quantization is then performed for the x and y signal of the non-focal signal as well.

Now, the energy for the modified x-signal is calculated by multiplying each point by its absolute value and summing the energy of all points. The square root of this energy is calculated and is used to divide each value of the modified x-signal. This is considered the first part of the resultant pair of signals (focal one).

$$E = \sum_{i=1}^{i=t}(\mathrm{m(i)} * \mathrm{m\ (i)})$$

The values obtained in the above step are multiplied and subtracted with corresponding values of y-signal of focal signal. Now, the energy and also the square root of the values obtained is calculated.

$$E2 = \sum_{i=1}^{i=t}[\{\mathrm{m2(i)}\ (\ 1 - \frac{m1(i)}{sqrt(E)})\ \}\ \hat{}2]$$

Each value obtained after subtraction in the last step is divided by the values obtained after finding the square root of the energy. The result derived here is the second part of the resultant pair of signals (focal one) and is used for comparison between the focal and non-focal signals. These steps are also employed for non-focal part of the signal as well.

After all IMFs of both signals were made to undergo the whole procedure above, it was found that the eighth IMFs gave the most promising results, accurately differentiating the focal EEG signals from the non-focal ones. The graphical results obtained is as follows:

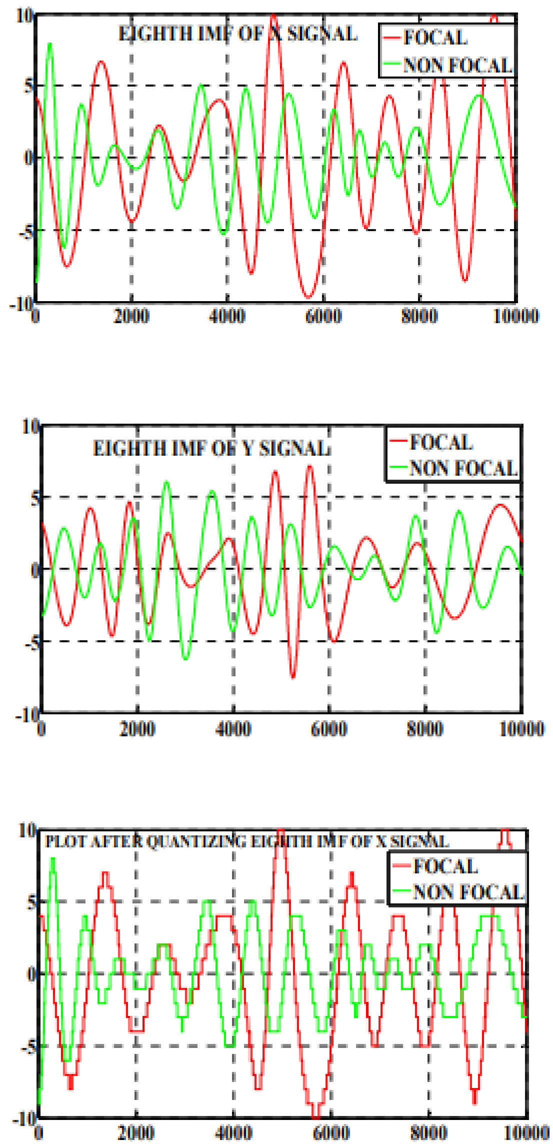

Fig. 2.3.1 Plot after quantizing x-signal values

2.4 Title: Classification of focal and non-focal EEG signals using neighbourhood component analysis and machine learning algorithms.

In this paper, Computerized Automated Focal Epileptic Seizures i.e. CADFES tool is introduced for the study of EEG signals. A lot of features were used and a set of 28 features were extracted from time, frequency and statistical domain and significant features were selected after extraction by the help of Neighborhood Component Analysis (NCA). The classifiers used here consists of support vector machine (SVM), K-nearest neighbor (K-NN), random forest and adaptive boosting (Ada-Boost) which are used to analyze the overall performance of the system. These classifiers are mostly used because of their learning ability and adaptability.

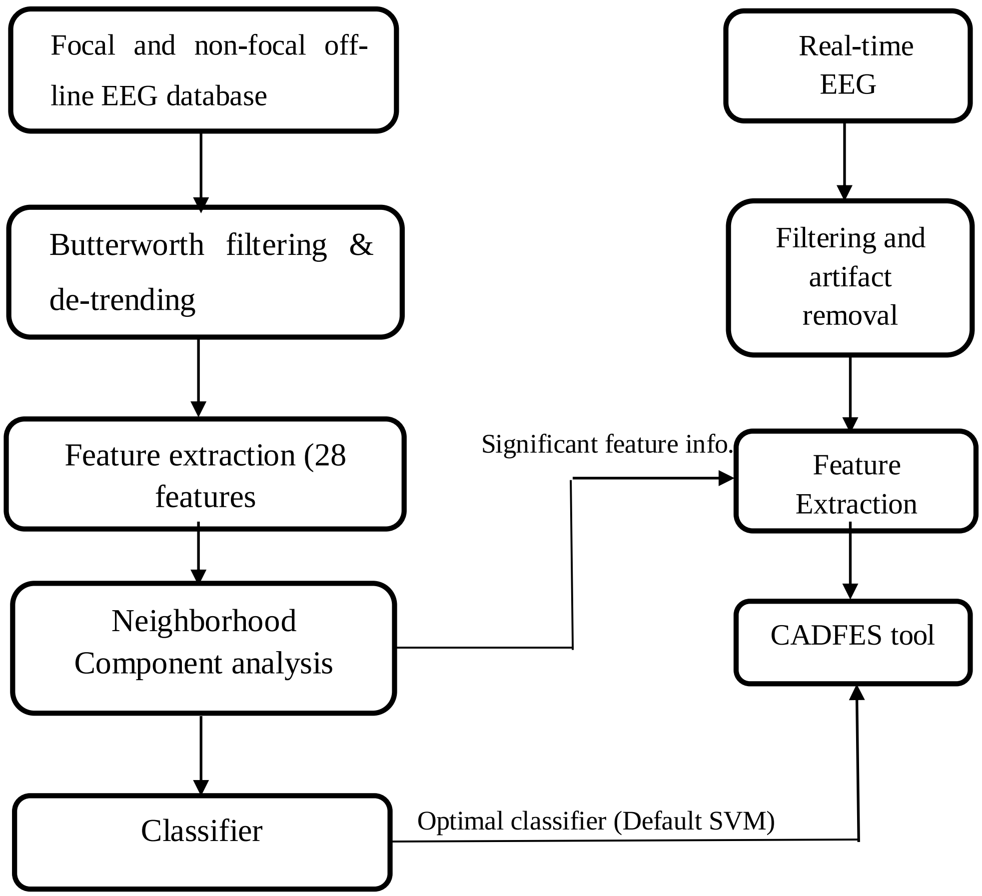

Fig. 2.4.1 Methodology

For preprocessing, the EEG signals with frequency range from 0.5 to 60 Hz are preserved as this range preserves the vital information in the signal. Then the EEG signal was passed through the Butterworth low pass filter after which detrending is applied. Following the detrending 28 features were extracted with segmentation lengths of 2s, 5s and 10s.

The features are then extracted and selected according to their performance and accuracy. The features are selected using the neighborhood component analysis (NCA).

Classifiers such as SVM and K-NN are used for EEG pattern classification to discriminate binary classes and random forest and Ada-boost classifiers are used for seizure classification.

All the classifiers were trained using seven significant features which were selected using the NCA algorithm. The CADFES tool analyzes EEG signal with the segmentation length of 10s to classify as “Focal” and “Non Focal” EEG.

Experimental results showed sensitivity, specificity, accuracy, positive predictive rate, negative predictive rate, and area under the curve with accuracy and performance as follows 97.6%, 94.4%, 96.1%, 92.9%, 98.8% and 0.96 using the SVM classifier.

2.5 Title: Discrimination of Focal and Non-focal seizures from EEG signals using Sliding Mode Singular Spectrum Analysis(SMSSA)

In this paper the approach is based on Sliding Mode Singular Spectrum Analysis which is basically a decomposition and reconstruction algorithm. SMSSA is a spectral estimation method which is data dependent and time-frequency approach. This method is the extension of SSA and automated SSA approaches for the decomposition of non-stationary signals.

For the discrimination of EEG signals in Focal and Non Focal signal, at first directly EEG signal or sub band signal is extracted from EEG using decomposition approaches and then it is fed into the deep learning model.

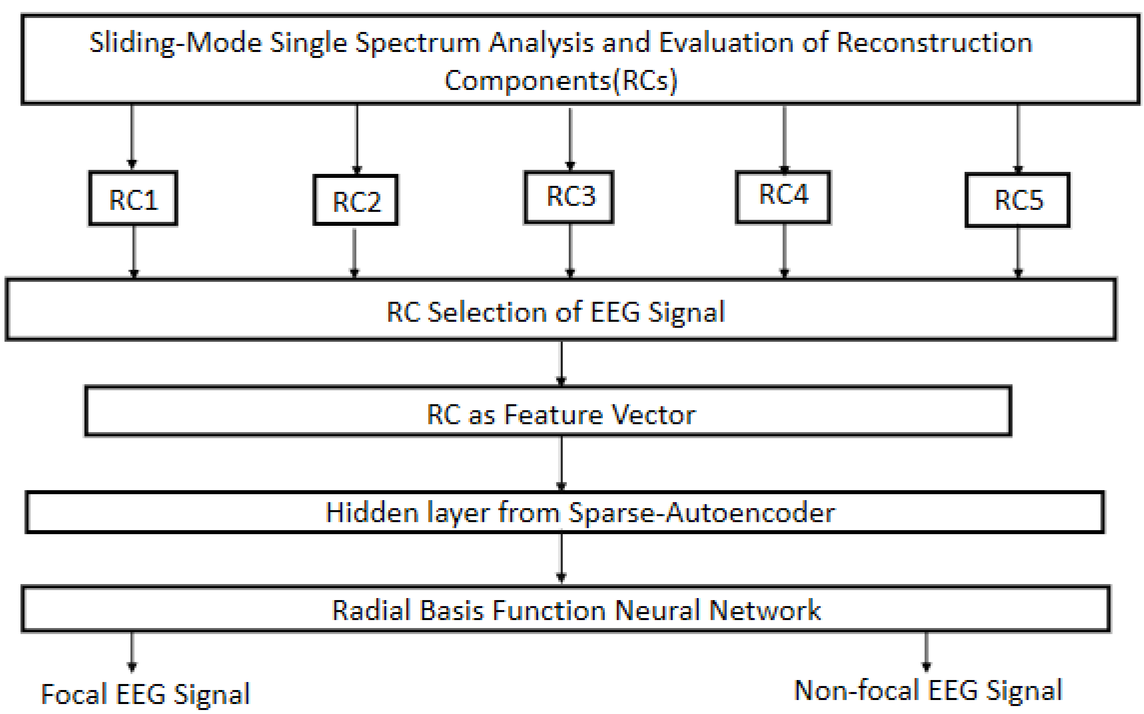

Fig 2.5.1 Methodology

SMSSA assigns number of RCs to each sample of the analyzed signal as prior for the decomposition. After getting the RCs (Reconstruction Component) by the decomposition of EEG signal, learnable features are then extracted from each RCs using Deep Learning techniques for the classification of Focal and Non-Focal Classes. The SAE-RBFN classifier is used for the classification of RCs, this Radial Basis Function is basically an artificial neural network, and this uses radial basis function as an activation function. The linear combination of radial basis function of the inputs and neurons parameter defines the output.

After extraction and classification it is found that the information of EEG signal is captured correctly by the RCs. Out of the five RC component the RC3 component has the higher performance with an accuracy of 99.11%. The sparse auto-encoder is responsible for extracting the learnable feature vector from the RCs of the EEG signal and it is found that these features have effectively captured the information required for the classification of Focal and Non Focal types.

2.6 Title: Classification and Discrimination of Focal and Non-focal EEG signals based on deep neural network

In this paper, the classification of focal and non-focal eeg signal is carried out using a deep neural network (DNN) model. For feature extraction the Convolution Architecture (Caffe) framework with three different models LeNet, AlexNet, and GoogLeNet are applied, where the DNN is trained with different training epoch values (TEs) is used to discriminate between the signals.

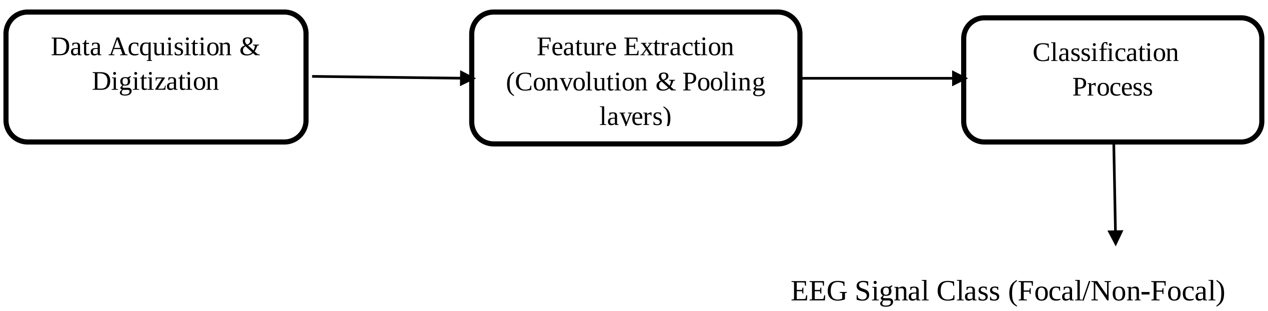

Fig. 2.6.1 Methodology

The data is obtained from the public available database online which had 3750 focal and non-focal pairs each. Feature extraction is done using convolution and pooling layers, while the classification process is executed using fully connected and soft-max classifier.

Caffe framework consists of multiple training stages which are stacked above each other. These training stages are utilized to abstract the data features hierarchically as they are one above the other.

Classification accuracy result is 100% for LeNet model at TE=2, for AlexNet the accuracy reaches to 100% at TE=5, and finally, GoogLeNet touches an accuracy of 100% at TE=10.

2.7 Title: Classification of focal and non-focal EEG signals in VMD-DWT domain using ensemble stacking

In this paper, focal and non-focal EEG signals are analyzed in variational mode decomposition (VMD) and discrete wavelet transform (DWT) domain and features such as refined composite multi-scale dispersion entropy, refined composite multi-scale fuzzy entropy, and autoregressive model (AR) coefficients are extracted in VMD, DWT and VMD-DWT domain. A feature reduction algorithm based on neighborhood component analysis is used to reduce the model complexity and select the features with the highest discriminating abilities.

To improve the classification accuracy of the system the ensemble stacking approach is employed. It is observed that the stacking configuration greatly improves the accuracy as compared to a standalone classifier.

The database used is the Bern-Barcelona Database which consists of 3750 pairs of focal and non-focal signals each. In this method, first the EEG signal is split into segments namely x segment and y segment. The x segment of the signal is obtained from the focal channel and y segment is obtained simultaneously from the neighboring focal channel. Similarly, these x and y segments are obtained from the non-focal channel and its neighboring channel simultaneously. Three feature sets are then extracted from the EEG data which are Refined Composite Multi-scale Dispersion Entropy (RCMDE), Refined Composite Multi-scale Fuzzy Entropy (RCMFE) and Autoregressive (AR) Model Coefficient. They are given as follows:

$$\text{RCMDE}(x) = -\sum_{\bar{\wedge}=1}^{c^m} (p(\bar{\wedge}_{v_0 v_1 \ldots v_{m-1}}) \ln p(\bar{\wedge}_{v_0 v_1 \ldots v_{m-1}})$$

$$\text{RCMFE}(x) = \ln \frac{\phi^{m+1}}{\phi^{m}}$$

$$r_x(m) = \frac{1}{N}\sum_{n=0}^{N-1-m} x(n)x(n+m) \quad \text{for } m \geq 0$$

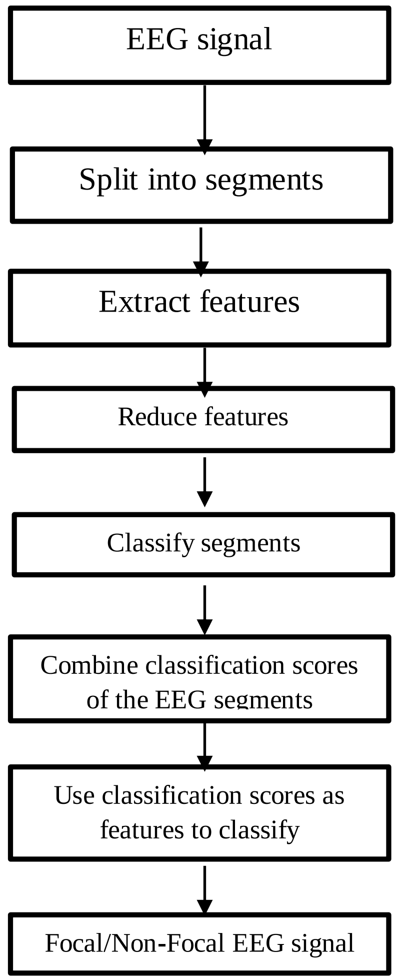

Fig 2.7.1 Methodology

Generally, the feature extraction is done in a single domain but here it is performed in three different domains which are VMD, DWT and VMD-DWT. For reducing the features, the reduction technique is known as Neighbourhood Component Analysis (NCA). NCA performs feature selection with regularization to learn feature weights for maximization of leave-one-out accuracy.

The ensemble stacking approach is employed to classify focal and non-focal EEGs from the reduced feature set. In this regard, a two-stage classification is considered where the features are first fed into a first stage classifier and the scores of the classifier are then used as features for the second stage classifier. The classifier scores are according to these classification scores are combined.

For the purpose of classification, 20% of the data are chosen randomly for training and the rest are used for validation. The EEG signal is segmented into 10 segments and the features of each 10 segment are fed into the first stage classifier.

For each segment, the classifier gives a score for each class indicating the likelihood of the segment to be classified into a particular class. Since we have 2 class classification problem, we have 2 scores for each sample. Thus, we now have a vector of 20 scores for each EEG signal. This is used as the feature vector for the second stage classifier.

Significant improvement in the ROC curve is observed for the stacked classifier. The area under curve of the standalone classifier is .958 where the AUC of the stacked classifier is .989. The accuracy of the standalone classifier is 91.3%, in contrast the accuracy of the stacked classifier is 95.2%, an improvement of accuracy by more than 3%.

2.8 Title: A novel approach for automated detection of focal EEG signals using empirical wavelet transform.

This paper aims at identifying the area linked to focal epilepsy and to decompose the EEG signals into rhythms by Empirical Wavelet Transform (EWT) technique. In this approach, the focal and non-focal signals are distinguished by computing the area of two-dimensional (2D) Reconstructed Phase Space (RPS) plots of EEG signal rhythms.

Empirical Wavelet Transform (EWT) has been proposed for the analysis of non-stationary signals because it designs a family of adaptive wavelets capable of representing different components of a signal and it also helps to find the rhythms of focal and non-focal groups of EEG signals. Rhythm separation here is a one-step process thus it has a very simple implementation.

The database used here is the Bern-Barcelona EEG signals database out of which one small and one large dataset is considered with 200 and 3000 signals respectively with equal number of focal and non-focal signals in both these datasets

Firstly, the EWT is used to decompose the EEG signal into rhythms by a simple procedure involving Fast Fourier Transform (FFT) and reconstruction of the sub-band signals to obtain rhythms. Then rhythm separation is performed using empirical wavelet transform which involves obtaining the frequency components using FFT, mode extraction through proper segmentation and wavelet and scaling coefficients obtained and sub-bands reconstructed.

The reconstructed phase space (RPS) is a very convenient method to find the nonlinear features from the stabilogram signal. The RPS plot is obtained after rhythm separation and then two-dimensional (2D) projections of reconstructed phase space (RPS) of each rhythm are obtained. The logarithmic area of the two-dimensional (2D) RPS projections is computed using central tendency measure (CTM).These computed features are subjected to statistical analysis.

Kruskal–Wallis statistical test is performed for each CTM value to find the clinical significance of these extracted features.

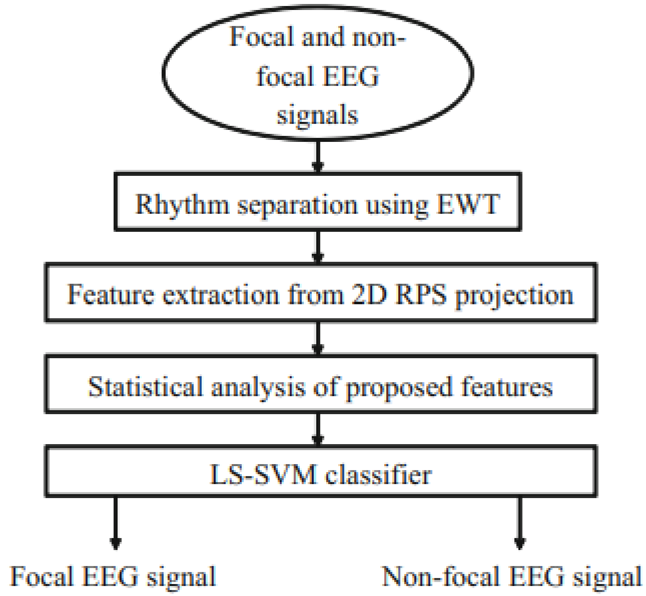

Fig. 2.8.1 Methodology

The logarithmic area computed from the 2D projection of RPS is fed as input to the least-squares support vector machine (LS-SVM) for classification of EEG signals into focal and non-focal categories. The support vector machine (SVM) and its least-squares version has proven to be reliable classifiers for focal EEG signals detection. The LS-SVM is formulated as the least-squares form of SVM. LS-SVM generates a hyperplane in the input feature space which can be used for accurate and efficient classification of the signals.

The maximum classification accuracy of 90%, sensitivity and specificity of 88 and 92%, respectively is achieved using 50 pairs of focal and non-focal EEG signals and the same method has achieved maximum classification accuracy, sensitivity and specificity of 82.53, 81.60 and 83.46% respectively with 750 pairs of signals.

2.9 Title: Detection of Focal EEG Signals using Higher Order Moments in EMD-TKEO Domain.

In this method a combined approach of Empirical Mode Decomposition (EMD) and Teager-Kaiser energy operator (TKEO) is used for the classification of Focal and Non-Focal EEG signal. At first all the signals belonging to focal and non-focal group were decomposed into Intrinsic Mode Function (IMF) using EMD. Further TKEO is applied was applied on each of the IMF in order to obtain two higher order statistical moments which are Skewness and Kurtosis and are extracted as features from the TKEO of each IMF.

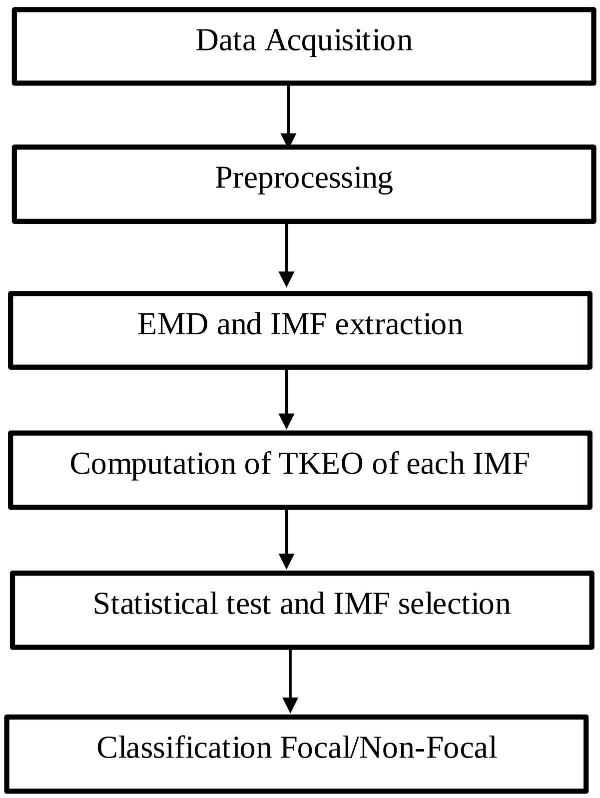

Fig. 2.9.1 Methodology

Based on statistical test, the statistical significance of the features which were selected are evaluated, the feature from the IMFs which showed very high discriminative capability between Focal and Non Focal EEG signal. These Features are selected to feed as input to the Support Vector Machine (SVM) classifier for the detection of Focal and Non Focal EEG signal. In the same way a set of feature were selected to get a reasonably high degree of accuracy. After extracting the higher order moments from the TKEO of each IMF, some selective features have gone under the student's t-test. A t-test can be considered as Analysis of Variance (ANOVA) test. The output of the t-test act as an indicator for the ability of discrimination between the Focal and Non Focal EEG signal. The low output value 'p' of the t-test is an indicator of high discriminative capability and the statistical significance of the selected feature. After the analysis of the outputs of t-test it was found that the features which were extracted from the TKEO of first three IMF of the Focal and Non Focal EEG signal have more statistical significance and satisfying the Null Hypothesis testing compared to the other IMFs.

At first at each level of the decomposition the perfformance of the SVM classifier is evaluated by using the features extracted from the TKEO of first three IMFs. Total number of signal used is 100 with 50 Focal signals and 50 Non Focal signals of EEG, the two higher order moments are selected from TKEO at each IMFs. In the performance analysis of the first three IMFs, the performance of the IMF 2 is best with CAC , CSE, CSP and '$\boldsymbol{\sigma}$' as 88.75%, 87.25%, 89.50% and 1.4 respectively.

The classification accuracy of 92.65% is found when Radial basis Kernel function is used while with polynomial Kernel Function having 88.13% classification accuracy and Linear Kernel Function having 89.63% of classification accuracy.

2.10 Title: Automated Focal EEG Signal Detection based on Third Order Cumulant Function

In this paper, the use of non-linear third order cumulant function has been proposed for the classification of the non-focal and focal intracranial EEG signals. The logarithm of the diagonal slice of third-order cumulant enables the measurement of the attributes which provide information about the non-linearity. For data reduction, a technique called locality sensitive discriminant analysis (LSDA) is introduced to map the measured features at higher dimensional space. SVM is used for classification of the signal.

The database used here is the Bern-Barcelona database which is available online for the discrimination of the focal and non-focal signals. It has 3750 pairs of focal and non-focal signals each. These signals are simultaneously recorded from five patients and are sampled at 512Hz or 1024Hz.

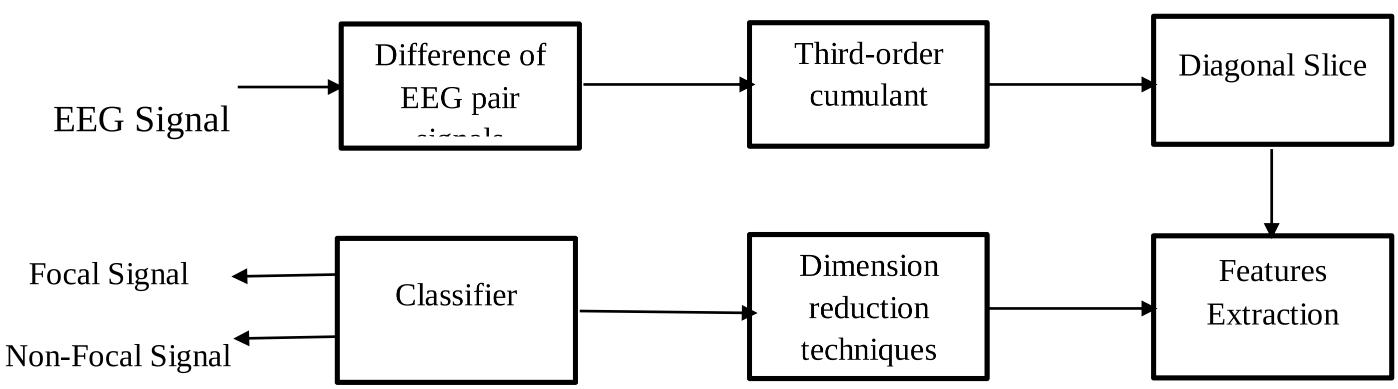

Fig. 2.10.1 Methodology

In this article, a non-linear higher order statistics (HOS) based method is proposed to identify focal epileptic seizures. The HOS is commonly used to analyze the non-stationary and non-linear signals. The HOS function used here is the third order cumulant function in this case is applied onto the signal and a contour plot is obtained .Any variation in the EEG signals reflects analogous change in its third order cumulant (ToC) plot.

After obtaining contour plot diagonal slicing of the obtained 3-D graph is done to critically analyze the signals. The diagonal slice of the ToC is very sensitive to its nonlinear variations and contains relatively high variance and captures the subtle information about the non-linear dynamics of the EEG signals.

There is no standardized set of attributes that can perfectly reflect the signal dynamics. Here, the local features are selected, which capture the maximum information about the dynamic nature of the center slice. The measured features of this study are local in nature, very simple, and immune to noise that reveals the nonlinear variations of the EEG signals

The various local statistical attributes are measured from the logarithm of the diagonal slice which are then used as an input to the locality sensitive discriminant analysis (LSDA). These selected attributes are sequentially subjected to the SVM classifier.

The various features monitored are maximum, minimum, summation, mean of absolute difference, skewness, root mean square value and spectral flatness.

$$\text{Maximum value} = \text{Max}\,(z_i)$$

$$\text{Minimum value} = \text{Min}\,(z_i)$$

$$\text{Summation} = \text{Sum}(z_i)$$

$$\text{Mean of absolute difference} = \frac{1}{k}\sum_{i=1}^{k}(|z_i - \text{mean}(z_i)|)$$

$$\text{Skewness} = \sum_{i=1}^{k}(z_i - \text{mean}(z_i))^3\, p(z_i)$$

$$\text{RMS value} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(z_i - \text{mean}(z_i))^2}$$

$$\text{Spectral flatness} = \frac{GM(z_i)}{AM(z_i)}$$

The maximum classification accuracy observed by this method is obtained using SVM classifier which gives an accuracy of 99% on Bern-Barcelona EEG database.

Chapter 3

PROPOSED SYSTEM

3.1 DATASET USED:

The data set used in this is Bern-Barcelona intracranial EEG signals database, available on internet for the detection of Focal Epileptic seizures. This dataset includes 3750 pairs of EEG signal X and Y which are associated to each Focal and Non-Focal classes. This data-set consists of the EEG signals recorded from 5 patients simultaneously who are suffering from Epilepsy. These signals are selected from a pool of multichannel EEG signal. These intracranial signals are taken with the help of deep penetrating electrode through the scalp of the patient in "The Department of Neurology, Bern University". For the extracranial EEG signal recording is 10/20 international electrode placement system. Each pair of signal includes one patients EEG channel (signals X) and other signal for this channels neighboring channel (signal Y). The sampling rate at which these non-stationary bivariate brain signal were recorded is 512Hz or 1024Hz.

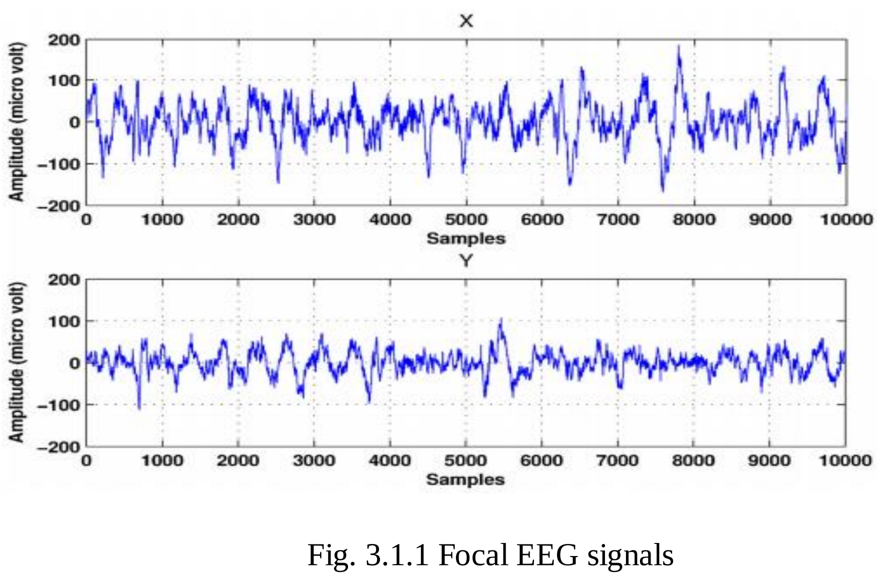

Fig. 3.1.1 Focal EEG signals

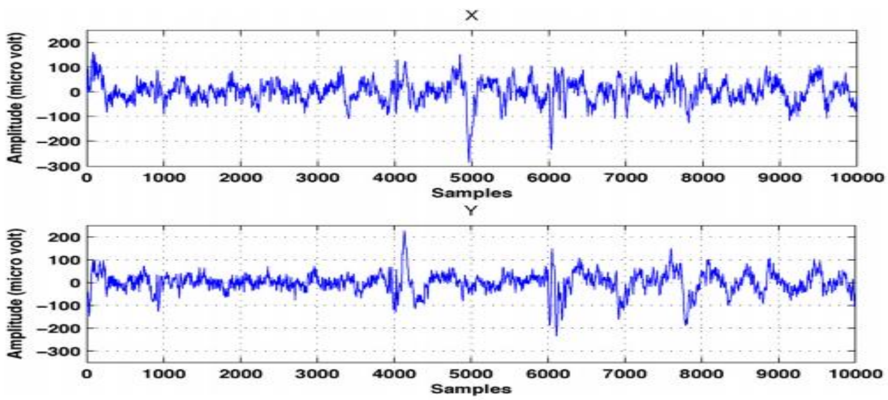

Fig. 3.1.2 Non-Focal EEG Signals

3.2 PROCEDURE

According to our approach we have followed the process given below and got the optimum result with this process. First, we took a web-available database which was the Bern-Barcelona database. The signals here are used to train the neural network. The signals from this database were decomposed into several frequency bands using Fourier Decomposition Method (FDM).

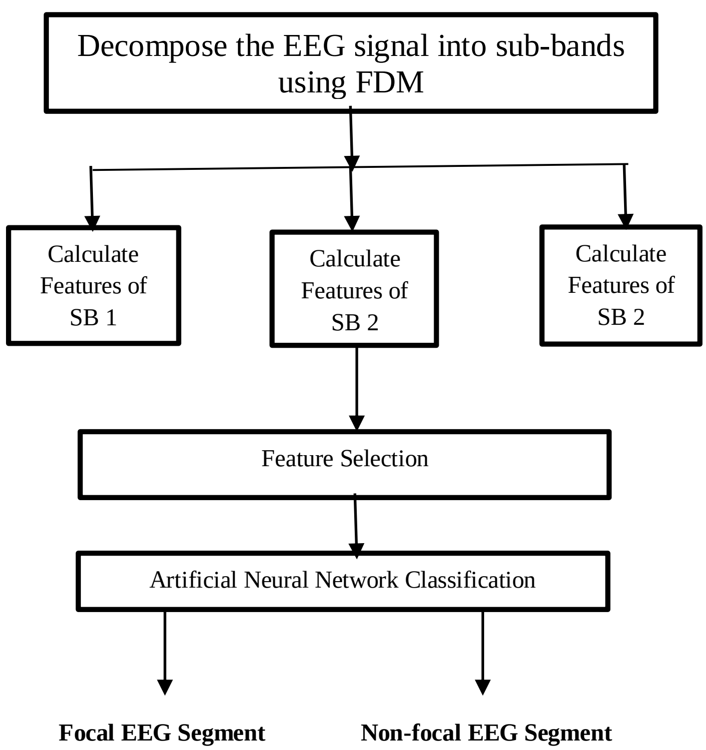

Fig. 3.2.1 Proposed System

In FDM, we decompose the input signal (1*1000 matrix) and after decomposing the signals are divided into various sub-bands of different frequencies. The signals were divided into 30 sub bands and we get a 30*1000 matrix total signals

After decomposing, features are calculated and extracted from each of these sub-bands. The features which provided the best results were then selected accordingly. From these 30*1000 matrix we have selected 205 features (approximately 7 features per sub-band) which provided the best results statistically and then these features are fed into the Neural network for classification into focal and non-focal signals.

A. Decomposition by Fourier Decomposition Method (FDM)

The goal of signal decomposition is extraction and separation of signal components from composite signals, which should preferably be related to semantic units. In general we define decomposition method as, a common term for solutions of various problems and design of algorithms in which the basic idea is to decompose the problem into sub-problems. Signal decomposition methods are closely related to classification of underlying features, which characterize the component to be separated. A function is proposed termed as FIBFs, belonging to $C\infty[a,b]$, here with the following formal definition.

According to definition, let us consider x(t)is an arbitrary signal, which is defined in the interval [a, b], follows the Dirichlet condition.

A set of functions, $\{yi(t) : yi(t) \in C\infty[a, b], 1 \leq i \leq M$ Called a FIBF set of x(t), if the follows conditions below:

1. $x(t)= \sum_{i=1}^{M} yi(t) + a0$

   where a0 is mean value of x(t)

2. FIBFs are zero mean function

$\int_a^b yi(\mathrm{t})\mathrm{dt} = 0$ for all values of I

3. FIBFs are orthogonal functions

$\int^b yi(t)yl(t)dt = 0$ for i≠l

4. Analytic FIBFs (AFIBFs) representation:

$$yi(t) + jy\hat{}i(t) = = ai(t)\ \exp(\ j\varphi i(t))$$

With IF $\omega i(t) = (d/dt)\varphi i(t) \geq 0, \forall t$, amplitude $ai(t) \geq 0, \forall t$.

y^i(t) is obtained by the complex exponential Fourier representation and it is equivalent to the HT of FIBF yi(t).

The AFIBFs are mono-component signals. Mono-component signals consisting of a narrow range of single-frequency components known as IF or frequencies which varies as a function of time, the FIBF is sum of zero mean sinusoidal functions of consecutive frequency bands.

The main purpose of this is to develop a novel and adaptive decomposition method, completely on the basis of fourier theory, to obtain a unique representation of multi-component signal as a sum of the mean-value and non-stationary mono-component signals, which satisfies the Properties explained above.

The equation 3 is the necessary condition for a set of basis vectors to represent a nonlinear and non-stationary time series are completeness, orthogonality, locality and adaptiveness. The FIBFs, intrinsically, follow all the necessary conditions by virtue of the proposed decomposition.

	FDM	**Wavelet**
Basis	A priori	A priori
Uncertainty	yes	yes
Presentation	frequency–energy	frequency–time-energy
Nonlinear	no	no
Non-stationary	no	yes
Harmonics	yes	yes
Theoretical base	complete	complete
Frequency	Convolution: global	Convolution: regional

Table I.

From the above table we can explain the differences between FDM and other methods like wavelet etc. For high efficiency and accuracy we use FDM method.

B. Feature extraction and selection

After the decomposition of the EEG signals using Fourier Decomposition Method (FDM), various features are calculated for each of the sub-band that the original EEG signal has been divided into. The features are calculated first and then extracted for further calculation in the system.

After calculation and extraction, the features are selected with the help of test known as Kruskal-Wallis Test. The Kruskal-Wallis Test (sometimes also called the "one-way ANOVA on ranks") is a rank-based non-parametric test that can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. This test works on two hypotheses namely Null hypothesis and Alternative Hypothesis.

If the null hypothesis is true there is no significant difference between the two entities and if the alternate hypothesis is true, there is a significant difference. The Kruskal-Wallis Test ranks the calculated features according to the p-value calculated from all the features. If the p-value obtained has a higher value then it supports the null hypothesis and vice-versa. So, lesser the p-value, more the difference between the features calculated for focal and non-focal signals which means it becomes easier to differentiate or classify these two signals.

After obtaining the p-value, the features are ranked according to their particular values. The features having less p-value are ranked higher and according to these ranks the process of feature selection is done. The features selected here will help the system to achieve the highest overall accuracy. The features selected are Variance, Kurtosis, Renyi entropy, Shannon Entropy, Spectral Flatness, Energy, Mean Absolute Deviation. The dataset is then fed to the Artificial Neural Network for the final classification into focal and non-focal signals

Variance: $\mathrm{Var}(X) = E((X - \mu)^2)$

Kurtosis: $\mathrm{Kurt}[X] = E\left[\frac{(x-\mu)^4}{\sigma^4}\right]$

Renyi Entropy: $H_\alpha(X) = \frac{1}{1-\alpha}\log_2\left(\sum_{i=1}^{n} p_i^\alpha\right)$

Shannon Entropy $H_s(X) = \sum_{i=1}^{M} p(x)\log p(x_i)$

Spectral Flatness : $\frac{\sqrt[n]{\prod_{n=0}^{N-1} x(n)}}{\frac{1}{N}\sum_{n=0}^{N} x(n)}$

Energy: $E = \sum_{n=-\infty}^{\infty} |x(n)|^2$

Mean Absolute Deviation: $\frac{1}{N}\sum_{i=1}^{N} |x_i - \bar{x}|$

C. Artificial Neural Network

In our proposed system, we have used a pattern recognition toolbox known as the neural network toolbox for classification between focal and non-focal signals. Apart from classification, this toolbox is also used for regression (including time-series regression), and clustering as well. A neural network has to be trained first with a known dataset before it can actually start with the classification of the signals. This is known as supervised learning. This is done to make the network more reliable, accurate and efficient when an unknown dataset is entered into it. Whenever a dataset is given to the neural network, 70% of the signals in the dataset is used for training, 15% of the signals is used for validation and another 15% of the signals is used for testing. In a neural network, an algorithm called Levenburg-Marquardt Backpropagation algorithm is used but as it requires more memory we have used another algorithm known as Scaled Conjugate backpropagation algorithm is used which actually requires less space and thus makes the system faster and more efficient.

D. Training Epoch

Training Epoch is an important parameter when it comes to the accuracy of Artificial Neural Network (ANN). It helps in improving the classification accuracy between focal and non-focal signals. Basically Epoch is the number of cycles that is repeated by the Artificial Neural Network to understand the entire data sample. In each cycle the ANN tries to differentiate and identify the samples of the data set.

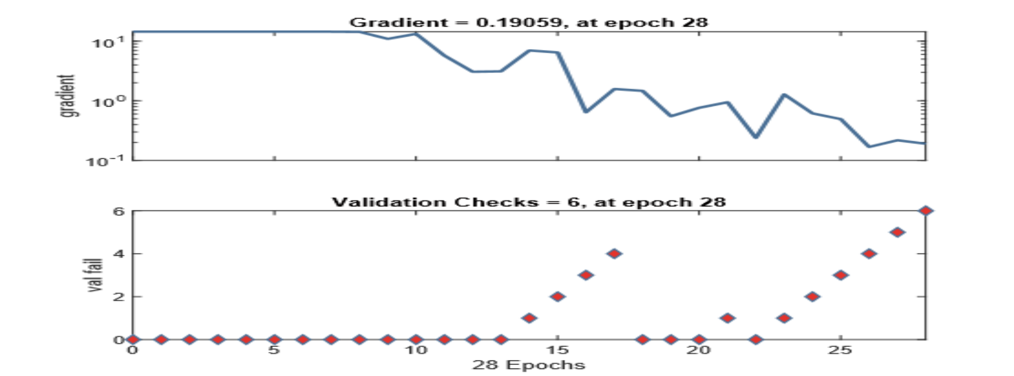

Fig. 3.2.2 Training Epoch

Chapter 4

EXPERIMENTAL EVALUATIONS

The results are shown with the help of Confusion Matrix. In the Machine Learning field, a confusion matrix also called as error matrix is used. It is a specific table layout which helps in visualization of efficiency of the algorithm used, especially in supervised learning one.

Each row of the confusion matrix represents the instances in predicted class, and the instances in actual class are shown in each column.

Output Class \ Target Class	1	2
1	**47**	**5**
2	**3**	**45**

Fig. 4.1 All Confusion Matrix for 5 Sub bands

Here the class 1 stands for focal EEG signal and class 2 stands for Non Focal EEG signal. Out of total 50 signals in class 1, 47 signals are successfully detected as class 1 signal but 3 signals are detected as class 2 signals. An equivalent matrix to the above matrix is shown in fig 4.2.

		Actual class	
		P	N
Predicted class	P	TP	FP
	N	FN	TN

Fig. 4.2 Confusion Matrix format

As confusion matrix is a technique for binary classification on of the class is treated as positive and other one as negative. The signal of class 1 which are actually detected in class 1 is called as True Positive and the signal of class 2 which is detected in the positive class 1 is called as false positive. Similarly signals from class 2 which are actually detected in class 2 are called as true negative and those are detected in class 1 are called as false negative. A specific table of the overall accuracy of the focal and non-focal classification is shown in Table II and Accuracy for each stage from training, validation, testing is shown in the table III for 5 sub bands.

EEG signal	**Focal (1)**	**Non-Focal (2)**	**Accuracy**
Focal (1)	47	5	90.4%
Non-Focal (2)	3	45	93.8%
Average Accuracy			92.0%

Table II. Class-wise classification Accuracy for 5 sub bands

	No. Of Bands	Accuracy	Sensitivity (TPR)	Specificity (TNR)
Training	5	91.4%	90.9%	91.9%
Validation	5	93.3%	90.9%	100%
Testing	5	93.3%	83.3%	100%
All	5	92.0%	90.0%	94.0%

Table III. Result for 5 sub-band and 500 neurons

Similarly for the decomposition of signal in 10 bands, the overall confusion matrix is shown in figure 4.3 and its overall class wise classification accuracy is shown in Table IV followed by classification accuracy of each stage.

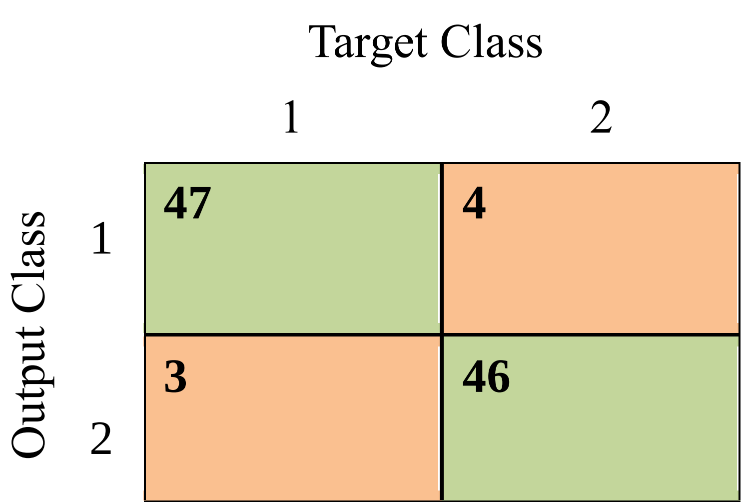

Fig. 4.3 All confusion Matrix for 10 sub bands

EEG signal	Focal (1)	Non-Focal (2)	Accuracy
Focal (1)	47	4	92.2%
Non-Focal (2)	3	46	93.9%
Average Accuracy			93.0%

Table IV. Class wise classification Accuracy for 10 sub bands

	No. Of Bands	Accuracy	Sensitivity (TPR)	Specificity (TNR)
Training	10	95.7%	94.3%	97.1%
Validation	10	86.7%	100%	75.0%
Testing	10	86.7%	75.0%	100%
All	10	93.0%	92.0%	94.0%

Table V. Result for 10 sub-band and 500 neurons

And for the decomposition of signal in 20 bands, the overall confusion matrix is shown in figure 4.4 and its overall class wise classification accuracy is shown in Table VI followed by classification accuracy of each stage in Table VII.

Fig. 4.4 All confusion Matrix for 20 sub bands

EEG signal	**Focal (1)**	**Non-Focal (2)**	**Accuracy**
Focal (1)	45	5	90.0%
Non-Focal (2)	5	45	90.0%
Average Accuracy			90.0%

Table VI. Class-wise classification accuracy for 20 sub-bands

	No. Of Bands	**Accuracy**	**Sensitivity (TPR)**	**Specificity(TNR)**
Training	20	97.1%	97.5%	96.7%
Validation	20	73.3%	60.0%	80.0%
Testing	20	73.3%	60.0%	80.0%
All	20	90.0%	90.0%	90.0%

Table VII. Result for 20 sub-band and 500 neurons

From the above table overall classification accuracy of each stage for each number of sub band division can be seen.

(i) Condition Positive (P):

The number of real positive cases in the data (Here Focal EEG Signal)

(ii) Condition Negative (N)

The number of real negative cases in the data (Non- Focal EEG signal)

(iii) True Positive (TP)

No. Of positive cases detected as positive

(iv) True Negative (TN)

No. Of negative cases detected as negative

(v) False Positive (FP)

No. Of negative cases detected as positive

(vi) False Negative (FN)

No. Of positive cases detected as negative

Sensitivity or True Positive Rate:

TPR = (TP / P) = (TP / (TP + FN)) = 1 - FNR

Specificity or True Negative Rate:

TNR = (TN / N) = (TN / (TN + FP)) = 1- FPR

Accuracy:

ACC= (TP + TN)/(P+N) = (TP + TN) / (TP + TN + FP + FN)

Receiver Operating Characteristics:

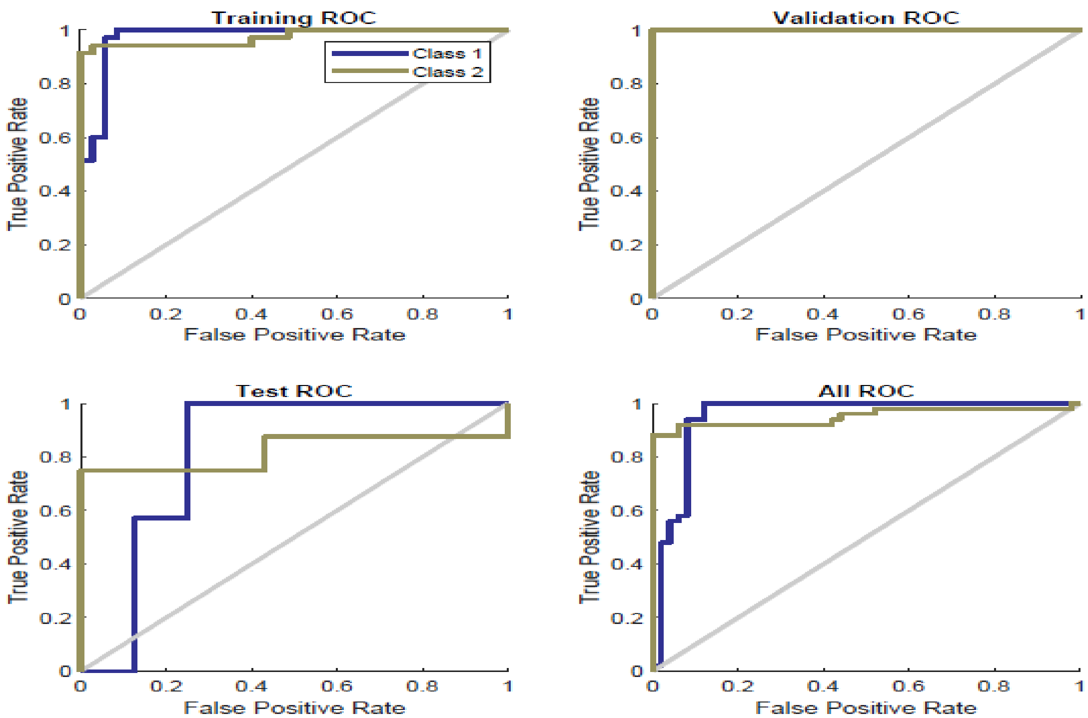

Fig. 4.5 Receiver Operating Characteristics

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

The above figure shows two curves showing results of training, validation, testing and all ROC which are of different classes, class 1 corresponds to the focal class of the signals and class 2 corresponds to the non-focal class. The straight line at the centre of the plot is the reference line.

The ROC curve is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity or probability of detection in machine learning. The false-positive rate is also known as probability of false alarm. The ROC curve can be generated by plotting the cumulative distribution function. The TPR should have a high value and FPR should have a low value.

Classification Accuracy of various literature papers referred

EEG Literature	Method and Classifier used	Accuracy (%)
S. Deivasigamani et al [2]	DT-CWT, ANFIS classifier	99
A. M. Taqi et al. [6]	DNN, soft-max classifier	94.375
M. M. Rahman et al. [7]	VMD-DWT, ensemble stacking classifier	95.2
Rahul Sharma et al. [13]	Third order cumulant, SVM	99
S. Raghu et al. [18]	NCA, K-NN, SVM	96.1
Soumya Chatterjee et al. [28]	EMD-TKEO,SVM	92.65
Proposed Work	Artificial Neural Network	93

Table VIII.

Chapter 5

DISCUSSION AND CONCLUSION

A method based on the use of FDM and Artificial Neural Network has been proposed for the discrimination of focal and non-focal types of EEG signals. The sub-bands obtained after FDM from EEG signal has been used for the feature extraction and selection for the classification of the EEG signals. The sub-bands carry the dynamic information of EEG signal, and the Neural Network gives us higher accuracy for the classification of EEG signals than most methods previously used.

As has been noted, the system has shown the maximum classification accuracy of 93.0% with minimum training and validation loss of 4.3% and 13.3% respectively for 10 sub bands and minimum accuracy of 90.0% with training and validation loss of 2.9% and 26.7% respectively for 20 sub bands also the minimum number of sub bands which we have taken is 5 and for that the classification accuracy is 92.0%. This shows taking too many sub bands or taking very few will decrease the classification accuracy of the neural network.

Initially we used Third Order Cumulant function for the detection and discrimination of the EEG signals but that model did not work well and provided us with an average classification accuracy of 87%.

Considering all the papers in the literature survey and the previous methodology used by us, we have found that the methodology incorporating the Artificial Neural Network gives us the highest accuracy of 93.0% when dividing the signal into 10 sub-bands and using 500 neurons.

CHAPTER 6

FUTURE WORK

In order to improve the performance and accuracy of the system, a multi-layer Deep Neural Network will be used instead of single layer neural network. Also an increased number of features will be calculated and extracted from the sub-bands of the signal by maintaining the optimum time cycle. Several other Machine Learning algorithms will also be attempted and will be checked for better performance and accuracy as compared to the existing algorithm used. Moreover Machine Learning with Python can also be used to get an increased accuracy for the classification of the EEG signal.

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