Development of an intelligent Neurologist Support System (iNSS) for diagnosing epilepsy

By

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Approval

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Certificate of Originality

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Contents

Abbreviations

ANN	Artificial Neural Network
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
iNSS	Intelligent Neurologist Support System
PCA	Principal Component Analysis
QDA	Quadratic Discriminant Analysis
SVM	Support Vector Machine
CAAS	Computer Aided Analysis System

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Abstract

Epilepsy is a chronic neurological disease which is suffered by every one out of 100 people in the world. Neurologists are those types of clinicians which specializes in treatment if epilepsy. Even though this disease is very common but Neurologist in general is a rare commodity in the world. Hence in developing Countries like Pakistan their rarity is obvious. This work is an effort to supplement the clinicians during the diagnosis of Epilepsy.

Electroencephalography is a very abstract way of analysing human's brain activity. Voltage fluctuations are caused by the flow of ionic current in neurons. During electroencephalography these voltages are recorded using a voltmeter. Representation of these voltages is called as Electroencephalogram (EEG). Epileptic patient's EEG exhibits some unique patterns which are called as Epileptic Patterns. Clinicians analyse these unique patterns to diagnose Epilepsy. The origin and location of these patterns also helps the clinician in diagnosing the type and intensity of the Epileptic disorder. In our work we have tried to supplement a clinician during the diagnostic analysis of an EEG of epilepsy suspected patient.

Computer Assisted Analysis (CAA) tools are those software programs which helps the user in analysing, managing or organizing certain information in the form of a data. CAA has an immense amount of potential in assisting clinicians during EEG analysis. CAA tools highlights the epileptic patterns among whole of an EEG, which lessen up the fatigue for the clinician to analyse whole of the EEG hence saving his precious time. CAA is not built to replace the clinician rather they are there to assist them. Neurologists are the one who provide the ground truth to train these CAA tools so that they may classify the EEG as epileptic or benign. So, there is a need to develop a mechanism in the existing systems using which its incorrect markings can be mentioned and the system should improve its classification rate by learning from its mistakes.

In this work we have developed a simple mechanism for clinicians to improve classification of the system while encountering any wrong markings by the system. The working of this system is based on application of discrete wavelet transform (DWT) on EEG epochs. The statistical features from the detailed coefficients representing the desired frequency ranges are then reduced using Principal Component Analysis which is then fed into a classifier. In this write up, first we have discussed our approach then we have shown the results. We have shown the performance of three types of classifiers i.e. Support Vector Machine (SVM), Quadratic Discriminant Analysis and Artificial Neural Network. We have found SVM to be the best working classification technique. Our work is an exhibition of importance and feasibility of a self-improving and user adapting computer assisted EEG analysis system for Epileptic diagnosis.

Abstract

Chapter#1: Introduction

1.1 Epilepsy

Epilepsy is a collection of chronic neurological disorders. This disease is recognized by recurring epileptic seizures. These seizures can last for variable amount of time with variable intensity. They could be very brief and undetectable and they could be very vigorous and long. In most of the cases the cause of epileptic disorder is unknown.

It has been cited that 1% of human population is suffering from this disorder [**1**]. Almost 8 out of every 10 epileptic patients belong to a developing country [**2**]. Epileptic disorders become more severe with age if not treated properly and in time. This disease can seriously affect a man's normal life so much so that at some places epileptic patients are even not permitted to drive. Epilepsy is often diagnosed by a test called Electroencephalogram.

Figure 1 : Epilepsy

1.2 EEG

Electroencephalography is a widely used technique for Epileptic diagnosis. EEG signal represents the voltage fluctuations caused by the neuron's ionic current flow. Brain's electric charge is maintained by billions of neurons. Transport proteins pump ions across the membranes. These membranes electrically charge the neurons. Volume conduction is the process because of which wave of ions reaches the electrodes placed on the scalp. These electrons are pushed and pulled by the metal of the electrode. The voltage difference caused by the pulling and pushing of the electrons is measured by voltmeter whose readings are displayed as the EEG readings. Very small amount of charge is generated by individual neurons which cannot be measured by EEG. It is the sum of synchronous activity of lots of neurons whose similar spatial orientation is measured by an EEG signal. Epileptic seizure causes the generation of unique patterns in the EEG recording. These unique Epileptic patterns help the diagnostician during the diagnostic analysis and treatment of Epileptic disorder. EEG is a widely used technique to detect the epileptic seizure and epileptic zone. Localization of epileptic activity in the brain is very significant for epileptic diagnosis. EEG alongside some imaging methods helps the clinician in answering few important quires during the diagnostic workup of the epilepsy suspected patients, the questions like “Is the patient suffering from epilepsy or not?”, “where is the location of the epileptic zone?” and “how is therapy’s performance?” [**3**].

Typically EEG recording duration is about few hours. In case of a prolonged EEG the recording may last up to 72 hours which produces a huge amount of data to be analysed which is a very fatiguing task.

The usage of EEG is not restricted to epilepsy it is also used during the diagnostic analysis of coma and brain death. EEG is also analysed for an initial diagnosis of tumours, stoke and other focal brain disorders. Other than diagnosis EEG is also used for studies of sleep and disorders related to sleep.

1.3 Computer Aided Analysis

Computer Aided Analysis tools uses computer’s assistance for the efficient analysis of massive and complex data. These analysis tools facilitate the efficient and effective work process. With the help of advancements in the field of signal processing, machine learning, statistical learning and pattern recognition analysis of massive and complex data is becoming easier using computers.

These Computer Aided Analysis tools are used in multiple disciplines for science and engineering like construction design in Civil Engineering, Non-Destructive Testing in Mechanical and Material Engineering, IC design in Electronics and Electrical Engineering and Diagnostic analysis in Medical Sciences.

Even in Medical Computer Aided Analysis has grown a lot. It is used in pre surgical planning, Medical Image Analysis like analysis the Functional Magnetic Resonant Imaging, Computed Tomography Analysis, Pose estimation for Physical therapy for physiotherapist and lot else.

1.4 Computer Aided Analysis of EEG for Epileptic Diagnosis

EEG is an Electrical Signal and involvement of computer aided analysis using the application of signal processing is evident. Now a day the EEG analysis using computer aided analysis tools is very common among the clinicians.

Application of multiple advance signal processing and machine learning techniques is making it possible to analyse EEG data. In this automatic analysis computer detect epochs with epileptic patterns. These systems aid neurologists by highlighting the epileptic parts of the EEG. Diagnosis is left on the neurologist himself. However, neurologist’s job become less tiring because of these tools as they reduces the amount of EEG data to be monitored. These analysis tools also provide simultaneous visualization of multiple channels. This simultaneous visualization helps the clinician in relating different channels’ behaviour with each other.

1.4.1 Epileptic Patterns

EEG signal’s spectral contents has a great importance in CAA of Epilepsy for diagnostic purposes. In the field of neurology, epilepsy is the primary diagnostic application of the EEG [**4**]. The EEG of a human brain shows some unique signal shapes and frequency during a seizure caused by epilepsy. These unique events can be identified as some unique patterns. If recognized properly, these patterns can give valuable information which can be extremely helpful in diagnosing and curing the disease.

Noachtar et al. [5] suggested ten types of generally accepted epileptic patterns which are Spikes, Sharp wave, Benign epileptic discharges of childhood, Spike & wave complexes, Slow spike & wave complexes, 3-Hz spike & wave complexes, Polyspikes, Hypsarrhythmia, Seizure pattern, Status pattern[5] [6].

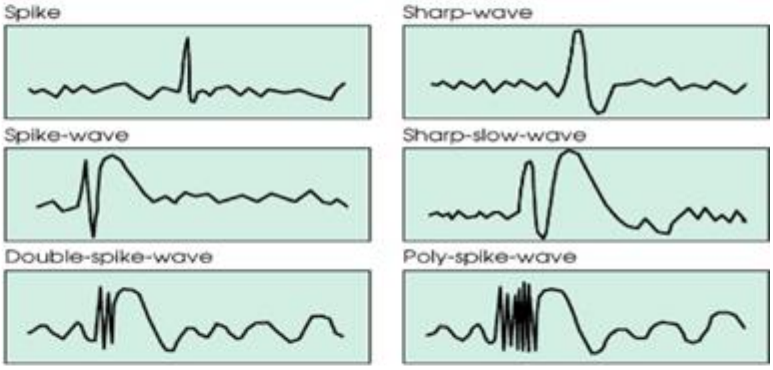

Figure 2: Multiple types of epileptic Pattern [7]

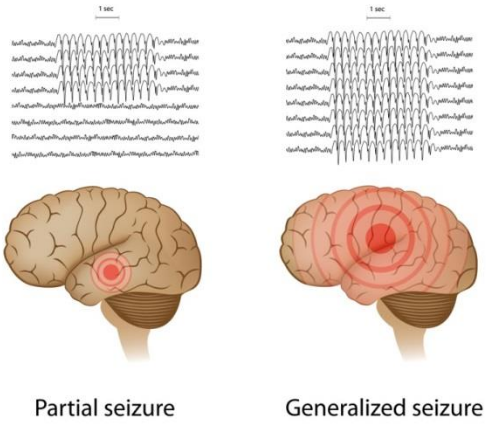

Figure 3: Partial and Generalized 3Hz Spike & Wave [8]

1.4.2 Frequency Band of Interests

Spectral contents of an EEG have a great importance in the field of computer aided EEG analysis. It has been shown in the latest studies that there are four major frequency ranges which get significantly affected during an epileptic seizure. These four regions are 0.4 to 4 Hz), 4 – 8 Hz, 8 - 12 Hz and 12 – 30 Hz [9].

Table 1: Frequency Bands of Interest

Name	Symbol	Frequency Range (Hz)
Beta	β	12 – 30
Alpha	α	8 – 12
Theta	θ	4 – 8
Delta	δ	0.4 – 4

1.4.2.1 Beta Waves

EEG patterns which lies in between 12 to 30 Hz frequency range is known as Beta wave. In a normal person's EEG, Beta states are associated with normal waking consciousness state.

1.4.2.2 Alpha Waves

EEG patterns which lies in between 8 to 12 Hz frequency range is known as Alpha wave. Alpha waves predominantly originate from the occipital lobe region when the person is awake and relax with his eyes closed. These waves get lessen up when the person opens his eyes, in sleep or in drowsiness. In past Alpha waves were associated with the visual cortex activity during an idle state but latest research has different stance on this. According to the latest research Alpha waves inhibit areas of the cortex which are not in use and they have an important part in coordination and communication of the network. Alpha waves generated from occipital region during closed eyes are considered to be the strongest brain signals recorded on EEG. Alpha waves do not appear in neonatal.

1.4.2.3 Theta Waves

EEG patterns which lies in between 4 to 8 Hz frequency range is known as Theta waves. Theta waves are frequently observed in young children. It usually appears during meditative, drowsy, or sleeping states. Theta waves do not appear during the deep sleep stage. Multiple brain pathology can cause strong or iterant theta waves in cortical region.

1.4.2.4 Delta Waves

EEG patterns which lies in between 0.4 to 4 Hz frequency range is known as Delta waves. These are usually associated with the deep stage 3 of Non Rapid Eye Movement sleep. The slow-wave pattern in delta region aids in characterizing the depth of sleep. 3Hz spike and wave pattern also exist in this region. The 3Hz spike & wave pattern represents the absence seizure epileptic pattern.

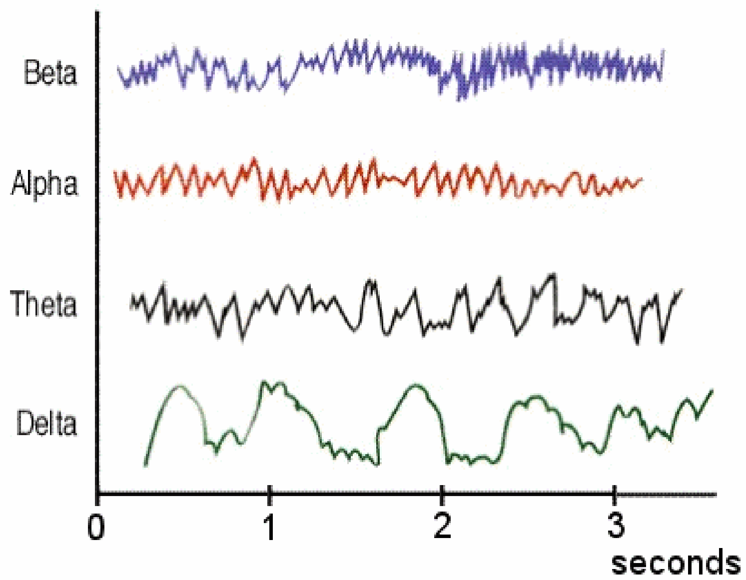

Figure 4: Beta, Alpha, Theta & Delta are the spectral range distributions by clinicians for diagnostic purposes [10]

1.5 Our Contribution

Our work resulted in four major contributions.

1.5.1 Alive System

Computer assisted electroencephalograph analysis tools are trained to classify the data based upon the “ground truth” provided by the clinicians. After development and delivery of these systems there is no simple mechanism for these clinicians to improve the system’s classification while encountering any false classification by the system. So the improvement process of the system’s classification after initial training (during development) can be termed as ‘dead’. We consider neurologist as the best available benchmark for system’s learning. In this article, we propose an ‘alive’ system, capable of improving its performance by taking clinician’s feedback into consideration.

1.5.2 Versatile data set

In order to ensure the robustness of our system, we tested our data on a versatile set of data set. We tested our system on the online available data sets collected from Children Hospital Boston by Massachusetts Institute of Technology (CHB-MIT) [**11**] [**12**] and the dataset collected by us from Punjab Institute of Mental Health (PIMH). This data set included

1.5.3 Exclusive Processing

In the existing work all channels were processed as a big data in series. Our analysis reveals that these channels are not dependent on each other and processing them exclusively to each other will generate better results. Even during generalized 3Hz Spike and Wave all channels do not exhibits in the same manner. So for the first time we made a study on how good a classifier will perform in general if we have separate classifier of same type for each channel and we figured out that there is a significant improvement.

1.5.4 Graphical User Interface

In this project we have built a new user interface for our system. During the development we emphasised that the User Interface should be user friendly and easy to use.

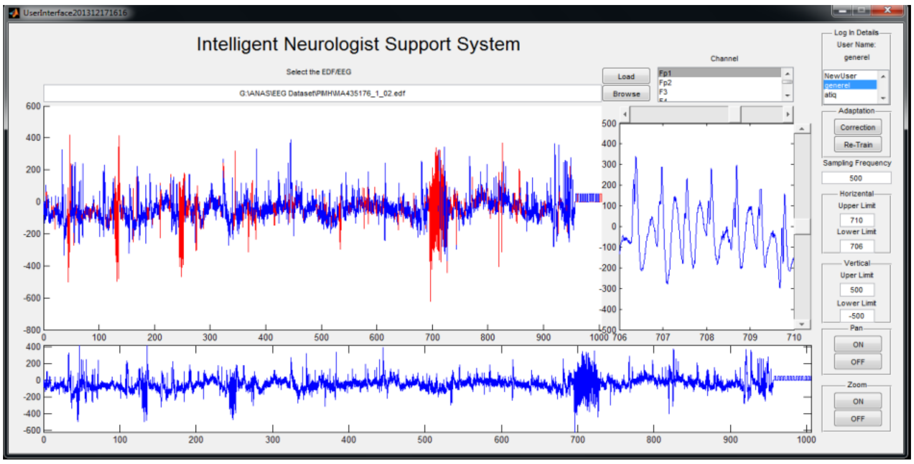

Figure 5: Graphical User Interface if iNSS [63]

Chapter#2: Literature Review

The diagnosis of the epilepsy is clinical but it is supported by EEG. Prolonged EEG techniques significantly increase the sensitivity [**13**]. Computer based analysis plays an important role in long-term epilepsy monitoring. Computer assisted seizure detection algorithms using EEG have been intensively investigated over the past few years. There are lots of techniques to analyse an epileptic activity for diagnoses purposes like EEG, Video and functional MRI. Here we will discuss only discuss the oldest and the most common analysis techniques that is EEG.

As indicated earlier, the EEG recorded from epileptic patient exhibits distinctive signal patterns. Epileptic seizures give rise to changes in certain frequency bands. Recent studies have focused on the analysis of δ (.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz) bands, and their association with epilepsy [**9**]. Some latest work is also analysing High Frequency Oscillations (HFOs) which lies in the range of 80-500Hz band. Scientists think that important biomarkers of epileptogenic brain areas could be learnt through analysis at this high frequency which could prove to be a central role in the process of epileptogensis and seizure genesis. Due to high computational power demands and hardware limitations, the research into high frequency bands of the EEG greater than 80 Hz is restricted. The advent of new technology and the increase in computational power will certainly facilitate the research into higher frequency bands of EEG signals [**14**].

Now a day's computer-based analysis addresses two major problems: 1) IEDs (spike detection) 2) epileptic seizure analysis, with emphasis on the epileptic seizure analysis [**15**]. If the hallmark electrical features of IEDs are not observed by the physicians, the evaluation is marked as uncertain. Probably this explains the fact that an average time to diagnose non-epileptic seizures is 7.2 years [**16**]**.**

Automated seizure detection algorithms currently help physicians identify transient events [**17**] but they do not detect the stable pathology underlying each patient's chronic disease. There is a great potential to impact patient care by better understanding of the chronic state of epilepsy. In this regard automatic computer methods have the potential to identify this stable abnormality which will lead to the improvement in the diagnostic accuracy [**18**].

Several well-defined epilepsy syndromes are reconsidered by associated characteristic EEG patterns. This patter recognition helps in selection of the therapy and assesment of diseases' reason. That characterestic makes the highlighting of interesting patterns more clinically importanant. These distinctions are quite arbitary. For instanse a continum between interictal and ictal states for both focal and generalized epilepsies are more likely then a clear-cut borderline [**19**]. Tests like klicker test help better asses the responsiveness during epileptiform discharges [**20**]. Tests like that help in evaluating the patient's ability to drive a car.

Reviewing 24-h continuous EEG recordings, particularly if the number of EEG channels increases is a time concuming and tedious task. The introduction of automatic seizure detection significantly reduce the work load and is a valuable application. This can also lead to new approaches for seizure prevention.

Because of their huge success in the past for predicting the seizures, most of these automatic computer methods used wavelet based analysis and time frequency decompositions of short time windows signal [**17**] [**21**]. In general, temporal lobe is studied in CAD literature or any specific diagnostic subclass is not specified. Usually there are three major steps of in most of the automatic computer method for detecting a seizure made to help the doctors [**15**] 1) Feature selection, 2) Dimensionality reduction and 3) Classification. The performance of any automatic computer based analysis is usually measured by six parameters 1) Sensitivity, 2) Specificity, 3) Accuracy, 4) Positive Predictive Value (PPV), 5) False detection rate6) Delay time of onset. We have made the use of first three in our analysis.

CAAS proposed in [**18**]used Fast-Fourier-Transform for feature selection and minimum redundancy feature selection for dimensionality reduction. Later these were used in Multi-Layer Perceptron Neural Network (MLPNN) algorithm for classification. The performance of this method is fairly low then the rest with an accuracy of approximately 71%, sensitivity of 91% and positive predictive value of 67%. The specificity was very modest as it was 44%.

One way to implement automatic computer method like [**14**] is to make an interactive Graphical user interface where user is been given option to select the feature selection method as per his desire. Chaibi et al. [**14**] offered the user to select one of the three given options, which were FIR filter based detection, complex Morelet wavelet based detection or Matching pursuit based detection. This type of GUI allows us to reject false detected events, in addition to classifying and estimating the durations, frequencies and positions of relevant events. This work can be further enhanced to make this type of detection method, intelligently learn from its own mistake those who are marked by expert neurologist.

In [**15**] novel methods were proposed for feature extraction and classification. Wavelet based Combined Seizure Index (CSI) method for feature extraction and Adaptive Multi Class Support Vector Machine (MCSVM) for classification is used. In this proposed method according the reason behind the usage of wavelet packets instead of simple discrete wavelet transform was its allowance to handle more details of the EEG signal then a simple DWT.

In biomedical signal processing, wavelets have played an important role for its ability to capture localized spatial-frequency signal information of the EEG signal. Usually the seizures occur in between 3 and 29 Hz of EEG signal. If the sampling frequency of an EEG is 256Hz the 5 level Discrete Wavelet Transform (DWT) gives the approximation coefficients representing 0-4 Hz and details coefficients representing 64-128 Hz for level one, 32-64 Hz for level two, 16-32 Hz for level three, 8-16 Hz for level four and 4-8 Hz for level five. So the detail coefficients starting from detail coefficient level 3 to detailed coefficient level 5 are of subsequent importance [**22**].

Mostly non-linear based feature extraction techniques use correlation dimension, Lyapunov Exponent and standard deviation for extracting the features of EEG signal. Approximate Entropy is used by entropy based techniques as the input features. Max, Min, Mean and Standard deviation are used by wavelet based techniques [**23**]. Local variance is the base of the Time frequency based technique [**15**].

In [**24**] the author proposed a method for detection seizures and epilepsy using higher order statistical moments of EEG signals, calculated in the empirical mode decomposition (EMD). Later the Artificial Neural Network (ANN) using the signal’s moments as a feature was employed as a classifier. The author claim to achieve 100% accuracy, sensitivity and specificity, in the case of discriminating seizure activities from the non-seizure one while being much faster as compared to the time frequency analysis based techniques.

In the detailed analysis presented in [**25**] DWT was used for feature selection, Principal Compoenet Analysis (PCA) was used for dimenstionality reduction and different ANN techniques were employed to analyze their performance. Techniques like Multilayer Perceptron (MLP), Generelized Reduction Neural Network (GRNN), ELMAN neural Network(ELMAN), Probalistic Neural Networ (PNN) and Radial Basis Function neural network (RBF) were applied and out of them GRNN was found to be the best performing neural network technique with 100% specificity, sensitivity, selectivity and accuracy while RBF proved out to be second best with 99% specificity, 100% sensitivity, 99% selectivity and 99.5 % accuracy.

In Sezer et. al.'s [**25**] work is a good guide for shortlisting the classifier but not many variants of feature reduction or dimentionalty reduction were analyzed in it. In [**26**] multiple dimentionality reduction techniques' performance were analyzed, including PCA, Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA). The reduced features were further used in Support Vector Machine (SVM) with two discrete groups epileptic or not. LDA proved out to be the best performing on with 100% accuracy, sensitivity and specificity.

In [**27**] author proposed a method in which they used PCA and ICA for feature reduction and Neural network as a classifier. they found ICA along with ANN to be more accurate(96.75%) and sensitive(96.75%) then PCA with ANN which yielded better specificity with 98.83%.

Lacunarity is a measure of heterogenity for a fractal. The basic idea of lacunarity is to quantify the gaps presenting in a given surface. The ictal EEG commonly displays larger fluctuations than the interictal. [**28**] used lacunarity as a novel EEG feature for seizure detection. In his work he proposed an algorithms to detect seizure using lacunarity and Baysian Linear Discriminant Analysis (BLDA) in long term invasive EEG. In this algorithm wavelet decomposed coefficients up to 5 levels were examined for features like lacunarity and fluctuation index which were further fed into BLDA to classify the epoch of the EEG signal. To enhance sensitivity post processing like smoothing, threshold judgment, multi channels integration, and collar techniques were applied. This algorithm yielded a sensitivity of 96.25% with false detection rate of 0.13 per hour and mean delay time of 13.8 seconds.

Epilepetic patients' one of the most important cause of stress, morbidness and anxiety is the inability of predictiong seizure onset. Various automated intervention systems and measures could be implemented like applying electrical brain stimulations or delivering short-acting anticonvulsant drugs using implanted devices. To study the prediction of a seizure we can classify the brain states into four classes i.e. inter-ictal, pre-ictal, ictal and post ictal [**22**].

Prediction is done in preictal state which can be defined as the transition from interictal state to the ictal. [**29**] proposed a novel patient specific seziure prediction method which is based on recognizing preictal changes. The proposed method is based on the analysis of the variational Gaussian Mixture Model(GMM) of the zero-crossing intervals in scalp EEG. One of the reason of using zero-crossing approach is its robustness against amplitude noise. In his work an alarm sequence for each channel was developed. This method was evaluated using 561 hours of non invasive EEG which included 86 seizures in 20 patients. The proposed method resulted with 88.34% sensitivity with a false prediction rate of 0.15 per hour and an average pridiction time of 22.5 minutes.

Succesfully detecting the preictal stage (stage just before the seizure) is the step toward predicting a seizure. In an effort to predic the preictal stage [**22**] took the DWT of the signal, where its sub-bands statistical features were calculated and fed as inputs to MLP and RBF classifier using ten fold cross validation. Multiscale PCA (MSPCA) denoising method were applied to enhance the classifier's performance by applying dimentionalty reduction. The proposed method achieve a classification accuracy of 95.09%.

For forcasting an epileptic seizure, [**22**] used MLPNN as a classifier and DWT as a feature extractractor to forcast a seizure. They achieved an accuracy of 86.67% with the sensitivity of 85.7% and specificity of 87.5%.

Singular Value Decomposition (SVD) and SVM techniques' performance were compared in optimization of fuzzy outputs toward the classification of epilepsy risk levels from EEG. The extracted parametrs used were energy, covariance, variance, peaks, sharp, duration, events and spike wave. The performance index as high as 98.2% was obtained for SVD. SVD is a very robust and numerically reliable technique [**30**].

Usually all of the Classification techniques are divided in the following three major categories. 1) Conventional classifier, 2) Neural Network, 3) Combinational classifier. Conventional classifiers are like LDA, SVM, and Naive Bayes Classifier. MLPNN, PNN and RBFNN come under the hood of Neural Network Analysis. Combinational classifiers are such as Boosting, Voting and stacking.

The above told techniques are applied on very small data set which gives no certainty for its accuracy for diagnostic purposes in real life scenario. This is a big reason that these CAD are not available in the market even after yielding such an amazing accuracy. The establishment of the certainty of the accuracy of these techniques can be seriously enhanced if applied on a larger and more versatile data set. Determination of an epileptic pattern its self is matter of debate as neurologist has dis-senses over the importance of some the epileptic patterns, especially when EEG is used for therapy evaluation. The inclusion of Neurologist adaptive system will surely prove to be a great assistance and this way there will be platform for the entire neurologist to compare their analysis for a bigger data set of the patient and it will also make the CAD learn more versatile cases.

One another problem is majority of the work done till now is on the detection of the 3Hz spike and wave pattern which is often associated with the absence seizure. For other 9 types of the patterns which are the indication of the more than 40 types of the epileptic disorder these CAD tools' assistance don't remain as much effective.

Several stages are involved are involved in a working of a Computer Assisted EEG classification which includes feature extraction, feature reduction and feature classification.

One of the most popular feature extraction techniques is Wavelet transform of an EEG data. Wavelet Transform has the capability to capture transient features, as well as time-frequency information dynamics of the signal [**34**]. Other previously used feature extraction approaches for epilepsy diagnosis include Empirical Mode Decomposition (EMD), multilevel Fourier Transform (FT) and orthogonal matching pursuit [**35**] [**36**] [**37**] [**38**] [**39**].

Feature extraction is followed by feature reduction to reduce computational complexity and avoid curse of dimensionality. Most commonly, the reduced feature vector consists of statistical summary measures (such as mean, energy, standard deviation, kurtosis, entropy) of different sets of original (un-reduced) features, although other methods such as principal component analysis, discriminant analysis and independent component analysis have also been used for feature reduction [**34**] [**12**] [**15**] [**37**].

Feature extraction/reduction is followed by classification using a machine learning algorithm, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Hidden Markov Models, Quadratic Discriminant Analysis [**38**] [**40**] [**15**] [**26**] [**25**].

Chapter#3: Method

Because of their huge success in the past for predicting the seizures, most of these automatic computer methods used wavelet based analysis and time frequency decompositions of short time windows signal [**17**] [**21**]. In general, temporal lobe is studied in CAD literature or any specific diagnostic subclass is not specified.

Computer aided EEG analysis system uses the neurologists marking and labelling of the EEG data as a benchmark to train themselves during initial training phase. But after initial training phase these systems have no simple mechanism for these neurologists to improve system's classification after encountering any false classification. So we have proposed a method by which system's classification can be improved by the user in a relatively simpler way. This analysis system only tries to detect the epileptic spikes as mentioned by Noachtar et al. Later it adapts its detection of epileptic spikes exclusively for every user according to that user.

In this proposed system we are processing each channel for each epileptic pattern exclusive to each other. This exclusive processing of each channel not only helps the user in diagnosing localized epilepsy but it also eases up the classifier's job. We have considered that different epileptic pattern are independent to each other and there separate handling will help us in avoiding error propagation from one epileptic pattern type's detection to other.

Our system's working has two major phases A) Initial Training Phase and B) Adaptation Phase. These two major phases have further three parts which are 1) feature extraction 2) feature reduction 3) classification. Next we will briefly explain all of these steps.

3.1 Initial Training

In this part we will briefly explain the initial training phase of our system. Like the existing systems, at first our system also goes through typical supervised learning routine. We provided our systems with some training examples to get trained on.

The summary of the initial training phase is that we extract features from the signal using some signal processing techniques then we applied feature reduction to remove the redundant and noisy data and used these reduced features to classify the epoch to be epileptic or not. Following are the details of each step.

3.1.1 Feature Extraction

To decide which parts of the signal are epileptic and which not we first divided whole of the signal in small chunks known as epochs. Then DWT was applied on those epochs so that visibility of epileptic activity can be enhanced which is distinguished by some spectral characteristics. These features are then processed to make them more suitable for the classification technique.

3.1.1.1 Epoch size

The first important part of the feature extraction is epoch selection. Epoch is a small chunk of the signal which is processed at a time. The size of the epoch is very important. The larger it is the less accurate it will be. The smaller it is the higher the processing time will be. After testing different epoch sizes we found epoch size of non-overlapping 1 sec window to be best yielding in terms of accuracy. It also re-established the work of Seng et. al [**41**].

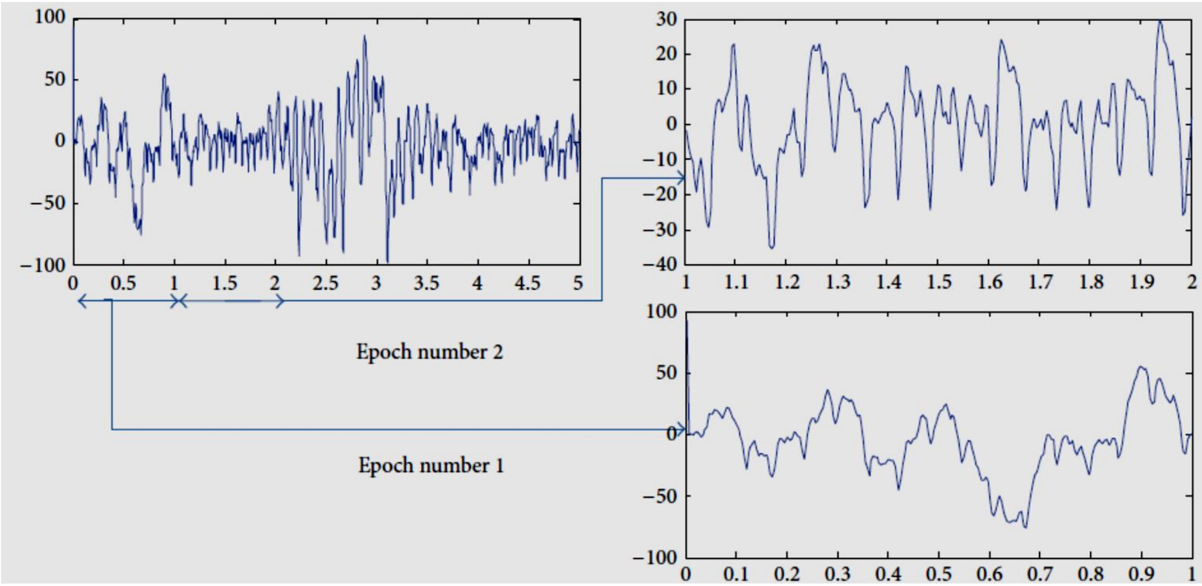

Figure 6: Size of an Epoch is 1 second

3.1.1.2 DWT

As discussed in introduction spectral analysis is very informative while examining the epilepsy suspected patient's EEG. There are profound advantages of wavelet decomposition which is a multi-resolution analysis technique. A multi resolution analysis technique allows us to analyse a signal for multiple frequency resolutions while maintain time resolution unlike a normal frequency transform. Wavelet decomposition allows us to increase frequency resolution in the spectral band of our interest while maintaining the time resolution, in short we can decimate simultaneously in time and frequency domain.

During wavelet transform the original epoch is split in different sub-bands, the lower frequency information is called as approximate coefficients and the higher frequency information is called as detail coefficients. The frequency subdivision in these sub-bands helps us in analysing different frequency ranges of an EEG epoch while maintaining its time resolution. [**38**] [**34**] [**26**]

The choice of coefficients' level is very important as the epileptic activity only resides in the range of 0-30 Hz. Coefficients' levels of the DWT are determined with respect to sampling frequency. So, the detailed levels of interest are adjusted on the run according to the sampling frequency such that we may get if not exact than at least the closest separate δ (0.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz) component of the signal. We discarded all the detail coefficient levels which were beyond the 0-30Hz range.

Then DWT was applied on each epoch with Daubechies-4 (db4) as mother wavelet. The detailed coefficient levels of the DWT were determined with respect to sampling frequency.

3.1.1.3 Statistical Features

After the selection of detail coefficients which represents the frequency band of our interest, we calculated the statistical features by calculating the mean, standard deviation and power of these selected wavelet coefficients. These statistical features are inspired from Subasi et al. work [26].

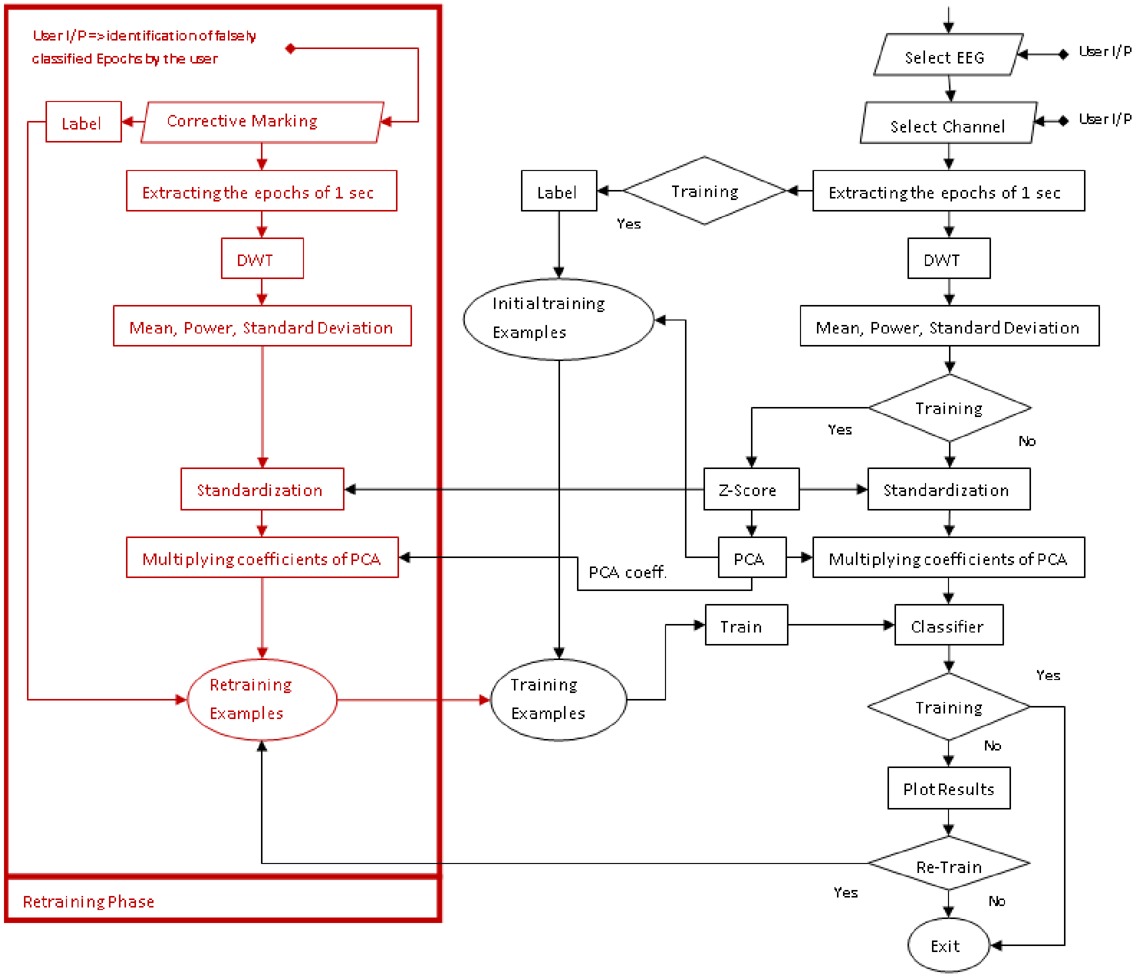

Figure 7: Workflow of a single channel

3.1.1.4 Standardization

These statistical features were then standardized. During training stage z-score standardization was applied on these features [42].

This standardization is just like usual z-score normalization, but as we do not know the exact mean and standard deviation of the data (to be classified) during classification/test stage so we used the mean and standard deviation of the training examples during training stage for standardizing (normalizing) the features during classification stage. We normalized the features by subtracting and dividing them by training examples' mean and standard deviation respectively.

3.1.2 Feature Reduction

In order to avoid over-interpretation by redundant data and misinterpretation by noisy data we applied feature reduction method. Inclusion of this part increases the processing time thus exacerbating the latency.

Dimensionality reduction using Principal Component Analysis (PCA) is based on a very important trait that is variance of the data. PCA develops the nonlinear mapping in such a way that it maximizes the variance of the data, which helps us in discarding that part of the data which is marked by lesser variances. This reshaping and omission not only removes the redundant data but it also lessens up the noise.

During training stage PCA was applied on these features in order to reduce the redundant and/or noisy data. We kept the components which projected the approximate 95% of the total variance. We were able to reduce the 21 features into 9. Then we fed these reduced features to a classifier's trainer.

Here as per our observation we again assumed that the EEG data is stationary for a small length. So, during the testing stage, we took the PCA coefficients matrix from training stage and multiplied it with the standardized statistical features of the blind test data and then fed the top 9 features to classifier.

3.1.3 Classification

Classification is a machine learning technique in which a new observation's belonging to a category is identified. This identification is based on the training set which contains the observations with known labelling of their category. These observations are also termed as features. We tried three types of classification methods 1) SVM, 2) QDA, and 3) ANN.

The reduced features were fed to these classifiers. Here the reduced features mean those statistical features of the selected wavelet coefficients are reduced using PCA as described in previous section. All of the three processing parts were exclusive for each channel and each epileptic pattern. So like previous parts the classifiers were also trained and tested exclusively for each channel.

Our system requires individual labelling of channels. There is a separate classifier for each channel and for each epileptic pattern type. So it makes total of number of classifier as the product of number of channels by ten where ten is the number of epileptic patterns described by Noachtar et al. [7].

3.1.3.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning models machine learning technique. SVM tries to represent the examples as points in space which are mapped in a way that points of different categories can be divided by a clear gap that is as wide as possible. After wards that division is used to categories the new test examples based on which side they fall on.

3.1.3.2 Quadratic Discriminant Analysis

Quadratic Discriminant Analysis (QDA) is a widely used machine learning method among statistics, pattern recognition and signal processing to find a quadratic combination of features which are responsible for characterizing an example into two or more categories. QDA's combination of discriminating quadratic multiplication factors are used for both classification and dimensionality reduction.

3.1.3.3 Artificial Neural Network

Artificial Neural Network (ANN) is a computational model which is inspired from animal's central nervous system. That's why ANN is represented by a system of interconnected neurons which are capable of computing values as per their inputs. In ANN training, the weights associated to the neurons are iteratively adjusted according to the inputs and the difference between the outputs with expected outputs. The iteration gets stopped when either the combination of neurons start generating the expected results within an error of a tolerable error range or the iteration limit finishes up.

3.2 Adaption Phase (Retraining/User adaptation mechanism)

In order to keep the classifier improving its performance with the encounter of more and more examples, we have introduced a user adaptive mechanism in our system. Our system allows the user to interactively select epochs of his choice by simply clicking the "correction" button.

While using our system, when a user thinks that a certain epoch is falsely labelled/categorised, our system allows him to interactively mark them as a mistake. These details will be saved in a log in the background and they will be used to retrain the classifier to improve its classification rate and adapt itself according to the user with the passage of time. When the user is going to select the retraining option in our system then classifiers will re-train themselves on the previous and the newly logged training examples. As every user has to log in with his personal ID so every corrective marking details will only be saved in that user's folder and only classifier will update itself for that user. Hence the system's classifier tries to adapt itself according to that user without damaging anyone else' classification.

The concept behind the inclusion of the retraining is that, if there is more than one example with same attributes but different labels, the classifier is going to get trained to the one with most population. The user's corrective marking will increase the examples of his choice thus making that classifier adapt itself to the user's choice in a trivial way. Every user will have exclusive classifiers trained for him and his marking will not affect other user's classifier.

As we know that the users some time don't agree on the choice of the epileptic pattern or its type.

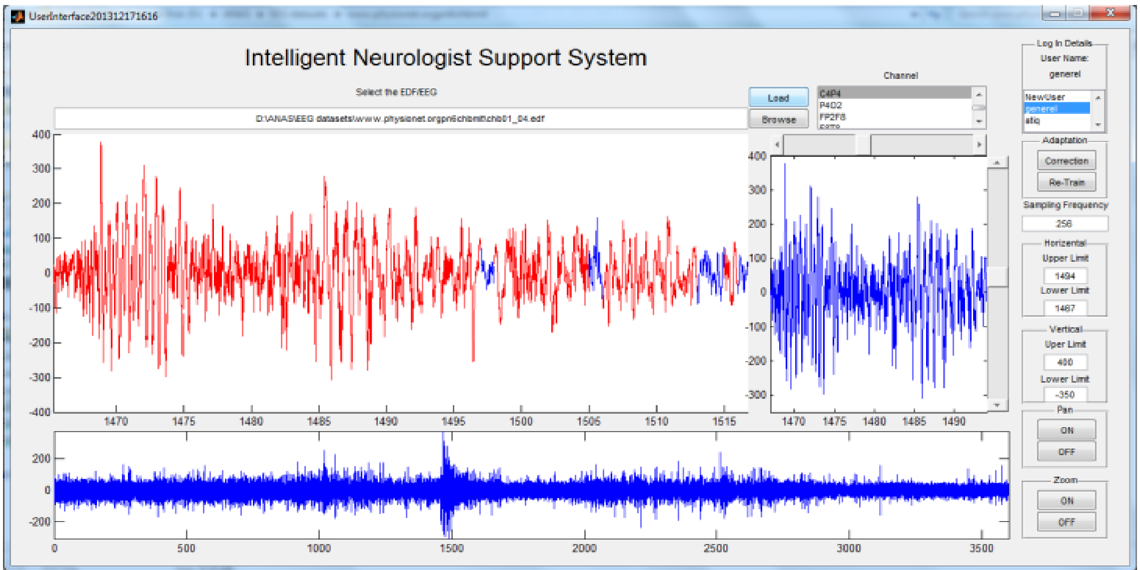

Figure 8: iNSS interface

The exclusive processing for each user will help the same software keep the system trained for every user and it will also let different user compare their marking with each other.

We don't have any standard right now to measure which Neurologist is the most righteous among a disagreeing group of neurologist users. So we kept the corrective markings of each user to their account so that it may not interfere with the one who may not agree on his choice. Whereas this system is developed to assist the neurologist as per his choice and after initial training on every re train it tries to adapt the user more and more. This system does not want to dictate the neurologist rather learn from him to adapt him for saving his time.

We want the classifier to think like the user and supplement him by highlighting the epochs of his choice, so the gold standard after few retraining will be the user himself. Already tested examples with new labels' inclusion in the training examples for the retraining will bias the classifier's choice in favour of user.

3.3 User Adaption Mechanism

A very important and the novel phase of our system is user adaptation mechanism or retraining mechanism, there are multiple reasons according to which introduction of this phase have lots of advantages. During this phase, system will try to adapt its classification as per user's desire. It has been cited that some time even the expert neurologist have some disagreement over a certain observation of an EEG data. There is also a threat of over fitting by the classifier. In order to keep the classifier improving its performance with the encounter of more and more examples, we have introduced this user adaptive mechanism in our system. We consider the existing systems as 'dead' because they cannot improve their classification rate after initial training. They don't have any mechanism of learning or improvement from neurologist's corrective marking [**43**] [**44**] [**45**]. The agreement between different EEG readers is low to moderate, Our Adaption Mechanism also help the user in catering this issue as our system tries to adapt the detection according to the users' corrective marking. The new corrective markings generates new examples with improved labels hence it populates the training examples with newly labelled ones. So after retraining machine learning algorithms in the system adapt users' set of choices.

Method

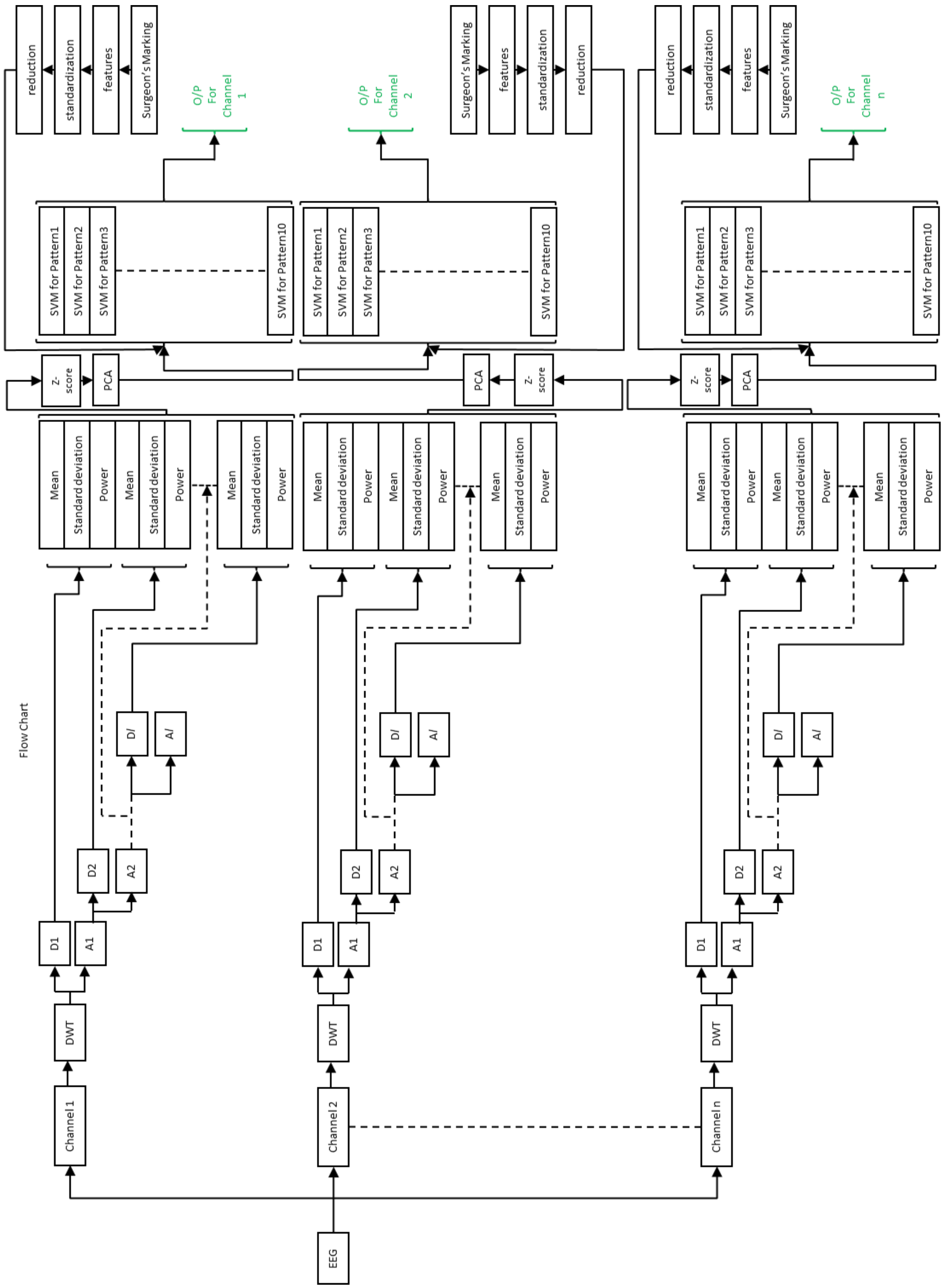

Figure 9: Flow Chart

Chapter#4: Results

In this section we will discuss the results in detail. At first we will describe the datasets which we used to train, test and validate our method. Then we will discuss their versatility.

4.1 Data set

Two labelled datasets of epilepsy suspected surface EEG data was available to us. Both of these data sets have lots of versatility in between them in terms of ethnicity, age, gender and equipment. The datasets available to us were only about generalised absence seizure which is characterized by the 3Hz spike and wave epileptic pattern in almost each channel. But as mentioned in section 3.2.1, Table 1 and Table 2 we are considering all four epileptic frequency ranges in our method so that we can also test this system on a non 3Hz spike and wave epileptic EEG data when available.

4.1.1 CHBMIT

This database is the online available surface EEG dataset [**11**] which is provided by Children Hospital Boston and Massachusetts Institute of Technology and it is available at physionet website [**12**]. It contains 916 hours of 23 channels' scalp EEG recording from 24 epilepsy suspected patients. These EEG are sampled at 256 Hz with 16 bit resolution. The 23rd channel is same as 15th channel.

4.1.2 PIMH

The second database of EEG datasets is provided by our collaborator at Punjab Institute of Mental Health (PIMH), Lahore. Its sampling frequency is 500 Hz and it was recorded on 43 channels (among whom 33 channels are for EEG). This dataset consists of 21 patient's EEG recording.

4.2 Features

4.2.1 Feature extraction

Data which interests us lies in between the frequency range of 0.3Hz to 30Hz. So after applying DWT with db4 mother wavelet we have to select detailed coefficients with this frequency range.

So in case of 256 Hz sampled CHBMIT dataset we have to go to at least 3 levels of decomposition and discard the earlier two as it is demonstrated in Fig. 2. In order to get the discriminating information between different types of epileptic patterns and identifying them correctly without mistaking it with each other, decomposition of this detailed coefficient further in Beta, Alpha, Theta and Delta is hugely help full. So we further decomposed them until the 7th level. Hence we used the DWT's detailed coefficients of level 3,4,5,6 and 7 for 256 Hz sampled CHB-MIT dataset.

Table 2: This table describes the affiliation of detailed coefficients with epileptic frequency band of interest for 256Hz sampled CHB-MIT dataset

Epileptic Frequency Range	Detailed Coefficients' level
Beta **(β)**	CD3 (32Hz to 16Hz)
Alpha **(α)**	CD4 (16Hz to 8Hz)
Theta **(θ)**	CD5 (8Hz to 4Hz)
Delta **(δ)**	CD6 (4Hz to 2Hz)
Delta **(δ)**	CD7 (2Hz to 1Hz)

In case of 512 Hz sampled PIMH dataset we used the DWT's detailed coefficients of level 4,5,6,7 and 8.

Table 3: This table describes the affiliation of detailed coefficients with epileptic frequency band of interest for 512Hz sampled PIMH dataset

Epileptic Frequency Range	Detailed Coefficients' level
Beta **(β)**	CD4 (31.2Hz to 15.6Hz)
Alpha **(α)**	CD5 (15.6Hz to 7.8Hz)
Theta **(θ)**	CD6 (7.8Hz to 3.9Hz)
Delta **(δ)**	CD7 (3.9Hz to 2Hz)
Delta **(δ)**	CD8 (2Hz to 1Hz)

After the selection of the wavelet coefficients we calculated the statistical feature out of them. The statistical features were the mean, power and standard deviation of all of the selected coefficients.

4.2.2 Standardization

During training stage we first used simple z-score normalization to standardize the features [**42**] before applying feature reduction. But the real issue arose when we tried to normalize them during testing stage. One way of doing this is that we keep all of the examples and apply z-score on them along with the new test data. Instead of this time taking process we made an assumption on our observation that mean and standard deviation dose not deviate a lot. It is analysed in this study that the EEG time series are assumed to be stationary over a small length of the segments. So we used the mean and standard deviation of the training examples from the training stage to normalize the test examples. Fig. 9 and Fig. 10 illustrate our observation. In which you can see that there is not much deviation in train and train + test examples' mean and standard deviation.

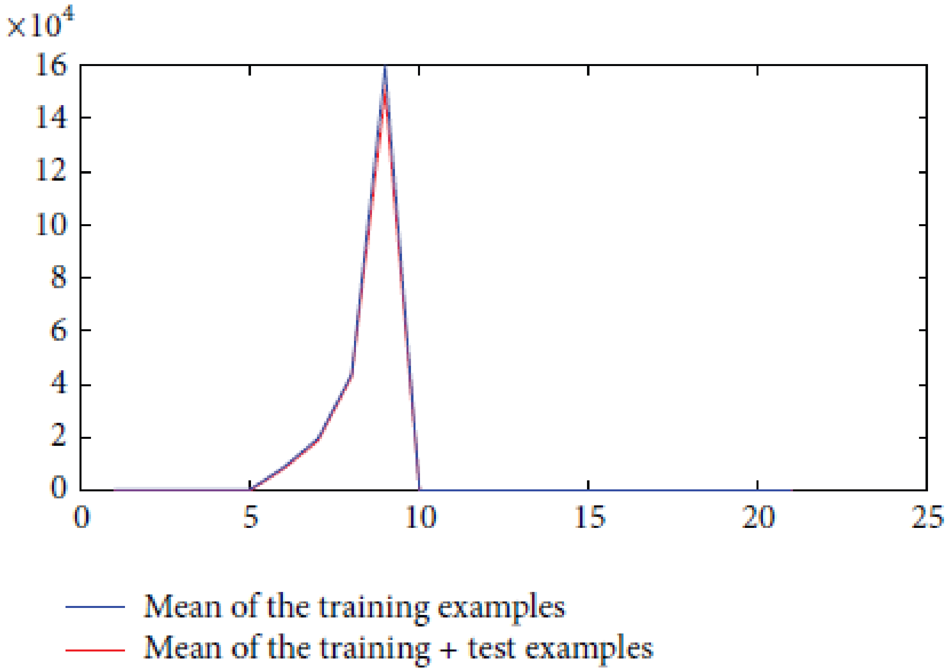

Figure 10: Horizontal axis represents the channel's number and vertical axis represents the mean value of the statistical features of wavelet coefficient. Here the blue line shows the mean of the training examples' features whereas the red line shows the mean of the training + test examples.

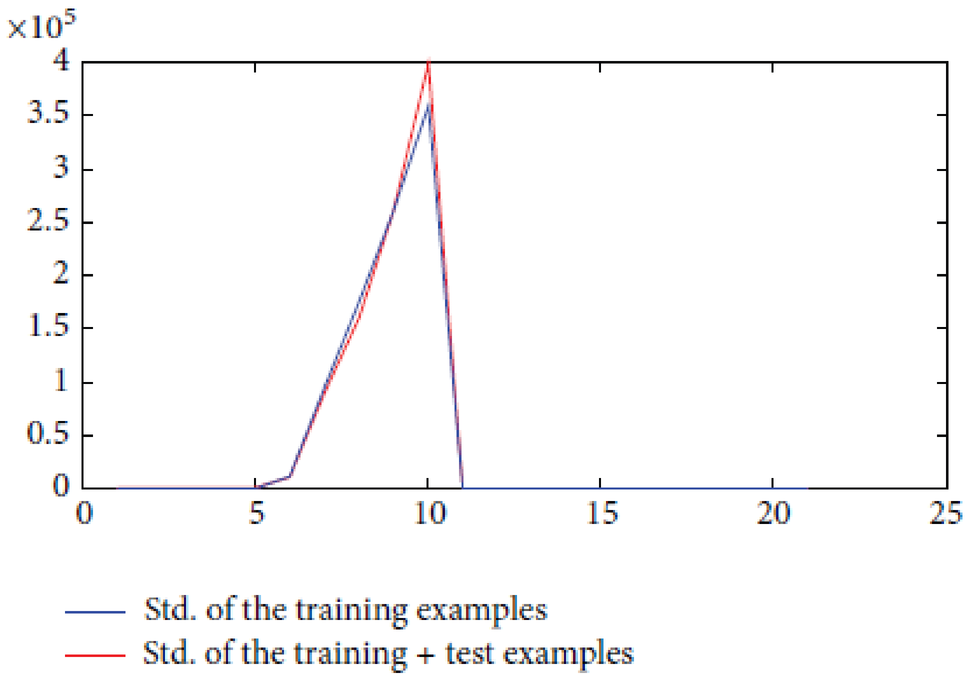

Figure 11: Horizontal axis represents the channel's number and vertical axis represents the standard deviation value of the statistical features of wavelet coefficient. Here the blue line shows the standard deviation of the training examples' features whereas the red line shows the standard deviation of the training + test examples.

4.3 Classifier

Classification is used in machine learning to refer to the problem of identifying a discrete category to which a new observation belongs. Observations with known labels are used to train a classification algorithm or classifier using features associated with the observation. For CHBMIT database we had to train 220 classifiers in initial training stage. The calculation behind 220 is the 22 channels multiplied by 10 types of epileptic pattern. The 23rd channel was same as 15th. For PIMH dataset 330 classifiers were trained where 33 channels of EEG were utilized. We tried three different classifiers and found SVM to be the most accurate.

We have used blind validation mechanism for the ten different feature data distributions to estimate the classification performance. These 10 different and separate blind data distributions were taken from a huge set of EEG data set. These 10 data distributions we randomly divided in two groups. We trained our classifier on one half of the distribution and tested them on the other. We repeated that on all ten distributions. Then we calculated the average of the classification rate for the all ten distributions.

3229 out of 3297600 epochs were randomly taken for ten times from CHBMIT data set. Each time half of them were used to train and half of them were used to test the initial classification. The average of the sensitivity, specificity and accuracy for these ten distributions is considered as the initial training phase performance.

Same approach was applied on PIMH data sets where 3229 out of 24097 epochs were randomly taken from PIMH data set for the six times instead of ten times.

Due to unavailability of the non 3Hz spike and wave epileptic EEG data currently we have only classification rates for generalized absence seizure.

4.3.1 Exclusive processing

In this study we have analysed that even in the case of absence seizure, epileptic pattern do not appear in an exact same way in each channel. Handling of each channel exclusive to each other was also another very important decision. We tested the classification in both ways i.e. one classifier for all of the channels at once vs one separate classifier for each channel.

This processing of each channel exclusive to each other improved over average accuracy from approximately 91 % to approximately 95% in case of SVM. So for SVM there is a significant improvement of 4% by this change. In case of QDA accuracy arose from 91% to 94% with an improvement of 3% and in case of ANN it rose from 91.8% to 92.9 with an improvement of 1.1%.

Results shows that SVM suites our method in the most efficient way. ANN has a lesser classification time and LDA has a lesser training time as compare to SVM but considering the sensitivity and classification improvement through corrective marking, we think that SVM is the better choice than LDA and ANN. In upcoming sections we have shown the results for all three types of classifier.

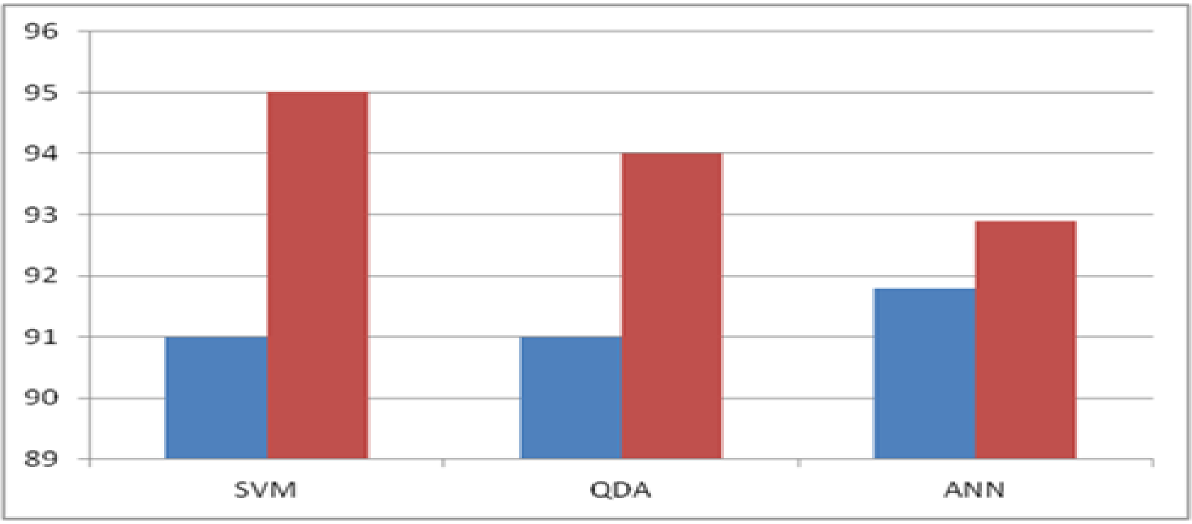

Figure 12: Horizontal axis represents the classifier's name and vertical axis represents the classification rate. Here the blue bar shows the average accuracy after initial training of all channels for both datasets while processing all channels in series. The red bar shows the average accuracy after initial training of all channels for both dataset while processing all channels exclusive o each other

4.3.2 Adaption Mechanism

To test the adaption Mechanism 807 corrective epochs were marked by the user for a CHBMIT data set file, he marked the same amount of epochs for each channel. These corrective markings were saved in his log as training examples. These corrective markings as the new examples along with the 32290 epochs of initial training stage were used to retrain the classifier. The number 32290 has come from the 3229 randomly selected epochs from whole of the CHBMIT dataset for the ten separate times during initial training phase. Then later the performance of the classifier after retraining was judged again on another random 3000 epochs.

In case of PIMH dataset 57 corrective epochs were selected for PIMH dataset. This time 19374 epochs of the PIMH data set was used along with the 57 corrective markings as for the PIMH we randomly selected the 3229 numbers of epochs for the six times. The retrained classifier was tested on the 2361 remaining epochs.

Table 4 : Average Improvement in different data sets due to Adaption Stage

Data Set	Corrective Markings	Classifier	Initial Stage	Adaption Stage
CHB-MIT	807	SVM	**95.5**	**96.3**
	807	QDA	**94**	**95**
	807	ANN	**92.88**	**93.96**
PIMH	57	SVM	**89**	**90**
	57	QDA	**89**	**90**
	57	ANN	**84**	**85.43**

4.3.2.1 Support Vector Machine

We used the support vector machine classifier package available in Matlab's Bioinformatics toolbox. We found "linear" to be the most accurate SVM kernel with 50 as the box constraint.

4.3.2.1.1 CHBMIT

For CHBMIT dataset, initial training of the classifier resulted with 96.3% average accuracy, 97.4% average specificity and 93.5% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure. After initial training our specificity is better than the Shoeb et al. and Nasehi et al. [**12**] [**46**] who used the same dataset to validate their technique with different features and application technique. This shows that our technique is resulting better even at the initial training phase.

Below in TABLE 5 we have shown the average initial classification and retrained classification results of our system for each channel. In this system we have shown that after correction of few epochs there is a visible improvement in the system's classification. The average accuracy of the system rose from 95.5% to 96.3%.

Table 5: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy.

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
'FP1F7'	96.3805	807	97.2696
'F7T7'	96.9302	807	97.2645
'T7P7'	96.4295	807	97.1892
'P7O1'	97.6660	807	97.9844
'FP1F3'	96.5932	807	97.1636
'F3C3'	95.2557	807	95.8268
'C3P3'	94.3129	807	95.4354
'P3O1'	96.1653	807	96.7156
'FP2F4'	96.5520	807	97.1408
'F4C4'	94.0773	807	95.1094
'C4P4'	97.2442	807	97.9201
'P4O2'	92.3547	807	93.8824
'FP2F8'	94.5957	807	95.1480
'F8T8'	96.2118	807	96.8850
'T8P8'	96.8148	807	97.3952
'P8O2'	95.1268	807	95.4580
'FZCZ'	89.5010	807	91.4936
'CZPZ'	93.1258	807	94.6167
'P7T7'	96.3280	807	97.0216
'T7FT9'	95.0556	807	96.1656
'FT9FT10'	97.4703	807	97.8714
'FT10T8'	97.7348	807	98.1905

Figure 13 : Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining.

4.3.2.1.2 PIMH

For PIMH dataset, initial training of the classifier resulted with 90% average accuracy, 94% average specificity and 80% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure.

Below in TABLE 6 we have shown the average initial classification and retrained classification results of our system for each channel. TABLE 6 shows that our technique is robust and it works also on a different dataset. The average accuracy of the system rose from approximately 89% to 90%.

Table 6: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy.

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
‘Fp1’	90.3692	57	90.9779
‘Fp2’	90.7681	57	91.9478
‘F3’	95.0380	57	95.6088
‘F4’	91.3297	57	91.3627
‘C3’	93.3561	57	93.3813
‘C4’	93.6448	57	93.8244
‘P3’	88.7797	57	89.0716
‘P4’	90.1133	57	89.3159

‘O1’	86.5848	57	87.8883
‘O2’	90.8300	57	92.5787
‘F7’	93.7438	57	94.3815
‘F8’	94.4563	57	94.8470
‘T3’	93.9221	57	94.3731
‘T4’	93.8322	57	94.1035
‘T5’	93.5670	57	93.1092
‘T6’	94.1287	57	95.3485
‘Fz’	88.9061	57	88.6571
‘Cz’	88.6708	57	89.2548
‘Pz’	91.2450	57	91.8549
‘E’	91.8499	57	93.2420
‘PG1’	82.7552	57	83.0715
‘PG2’	86.7638	57	87.3141
‘A1’	90.7149	57	91.0081
‘A2’	87.3506	57	87.7646
‘T1’	84.1250	57	85.0581
‘T2’	89.7853	57	90.4835
‘X1’	90.9339	57	94.5756
‘X2’	92.9365	57	93.3816
‘X3’	86.3529	57	85.7929
‘X4’	86.2634	57	85.8934
‘X5’	69.7540	57	71.9493
‘X6’	81.2648	57	81.9323
‘X7’	82.0801	57	81.3344

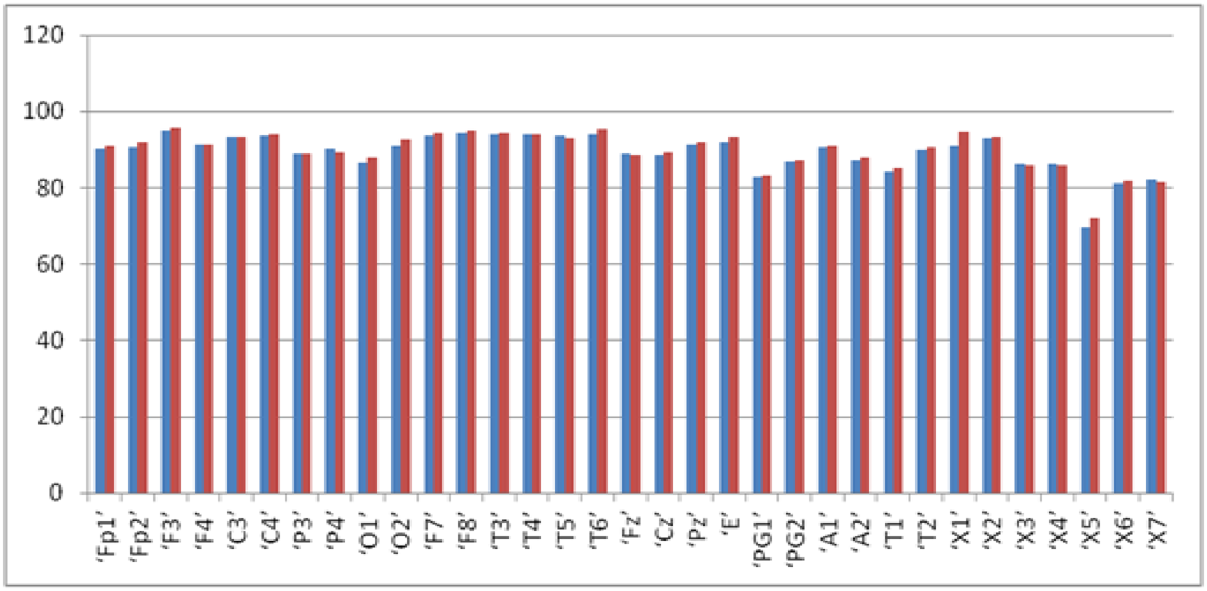

Figure 14: Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining

4.3.2.2 Discriminate Analysis

We used the discriminant analysis package available in Matlab's Statistics toolbox. We found "pseudoQuadratic" to be the best performing discriminate type with uniform probability.

4.3.2.2.1 CHBMIT

For CHBMIT dataset, initial training of the classifier resulted with 94% average accuracy, 96% average specificity and 90% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure. After initial training our specificity is better than the Shoeb et al. and Nasehi et al. [**12**] [**46**].

Below in TABLE 7 we have shown the average initial classification and retrained classification results of our system for each channel. In this system we have shown that after correction of few epochs there is visible improvement in the system's classification. The average accuracy of the system rose from 94% to 95%.

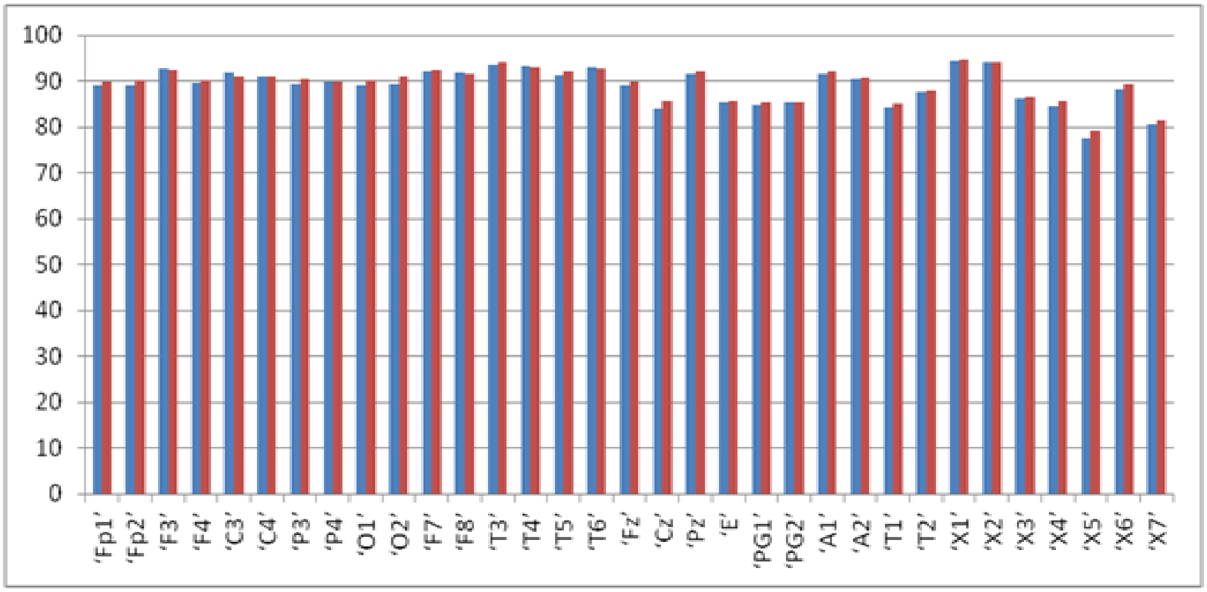

Figure 15: Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining.

Table 7: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
'FP1F7'	96.1757	807	96.6399
'F7T7'	95.7686	807	96.1467
'T7P7'	94.5025	807	95.5098
'P7O1'	96.2598	807	96.9693
'FP1F3'	95.8724	807	96.1773
'F3C3'	93.9484	807	94.4194
'C3P3'	92.8110	807	93.9872
'P3O1'	94.1724	807	94.7690
'FP2F4'	95.3442	807	95.9999
'F4C4'	92.7255	807	93.8686
'C4P4'	96.2509	807	96.8740
'P4O2'	91.0961	807	92.1808
'FP2F8'	93.4976	807	93.9840
'F8T8'	94.8939	807	95.5075
'T8P8'	95.2540	807	96.2940
'P8O2'	93.4941	807	94.3612
'FZCZ'	87.1507	807	88.3645
'CZPZ'	91.4283	807	92.4912
'P7T7'	94.5118	807	95.3794
'T7FT9'	94.8031	807	95.5306
'FT9FT10'	96.8328	807	97.0555
'FT10T8'	96.4514	807	96.9534

4.3.2.2.2 PIMH

For PIMH dataset, initial training of the classifier resulted with 90% average accuracy, 95% average specificity and 73% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure.

Below in TABLE 8 we have shown the average initial classification and retrained classification results of our system for each channel. TABLE 8 shows that our technique is robust and it works also on a different dataset. The average accuracy of the system rose from approximately 89% to 90%.

Table 8: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy.

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
'Fp1'	89.0861	57	89.7390
'Fp2'	89.0432	57	90.0443
'F3'	92.5991	57	92.3307
'F4'	89.6807	57	90.1430
'C3'	91.9454	57	90.8942
'C4'	91.1039	57	90.9973
'P3'	89.3490	57	90.3629
'P4'	89.7354	57	89.7726
'O1'	89.1013	57	90.2593
'O2'	89.2719	57	91.0779
'F7'	91.9906	57	92.4641
'F8'	91.7540	57	91.6937
'T3'	93.4416	57	93.9856
'T4'	93.2478	57	92.9901
'T5'	91.3400	57	92.1312
'T6'	92.8583	57	92.6363
'Fz'	88.8938	57	89.7298
'Cz'	84.0064	57	85.7228
'Pz'	91.6708	57	92.0561

'E'	85.2267	57	85.5279
'PG1'	84.6921	57	85.2892
'PG2'	85.3189	57	85.3886
'A1'	91.6580	57	92.0482
'A2'	90.4476	57	90.6291
'T1'	84.2211	57	85.0355
'T2'	87.7382	57	87.7849
'X1'	94.3820	57	94.7490
'X2'	94.0092	57	94.1500
'X3'	86.2930	57	86.6199
'X4'	84.5908	57	85.6526
'X5'	77.4855	57	79.1122
'X6'	88.1346	57	89.2410
'X7'	80.6365	57	81.5108

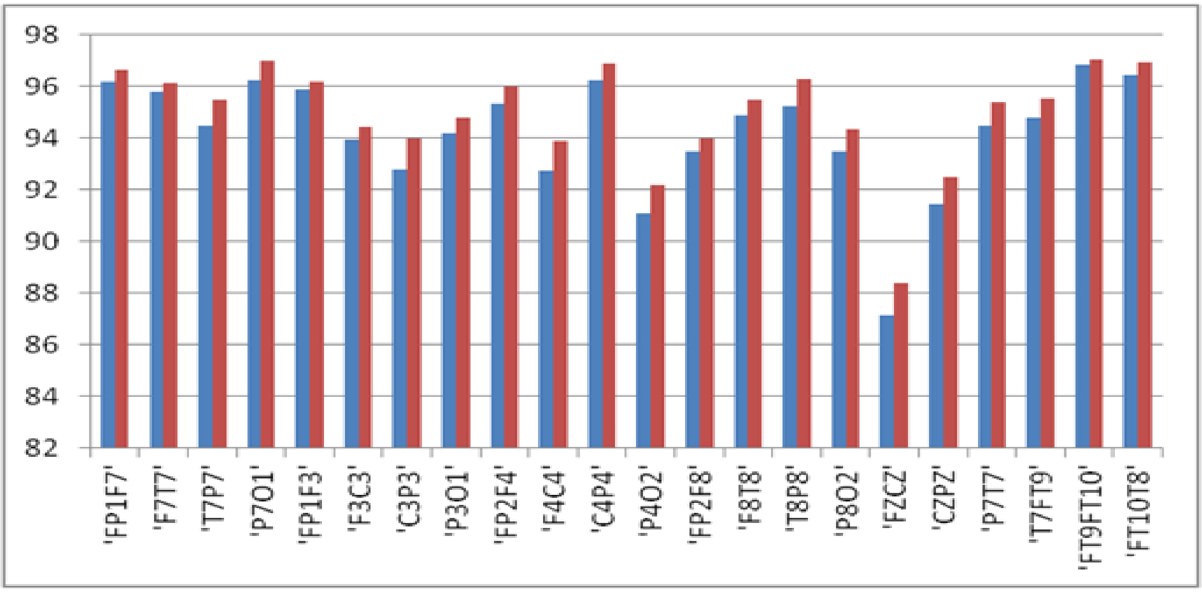

Figure 16: Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining.

4.3.2.3 Artificial Neural Network

We used feed forward back propagation package available in Matlab's Neural Network toolbox and found "Levenberg-Marquartd" to be the best method, with 0.05 learning rate.

4.3.2.3.1 CHBMIT

For CHBMIT dataset, initial training of the classifier resulted with 92.88% average accuracy, 98.66% average specificity and 75.75% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure.

Below in TABLE 9 we have shown the average initial classification and retrained classification results of our system for each channel. In this system we have shown that after correction of few epochs there is visible improvement in the system's classification. The average accuracy of the system rose from 92.88% to 93.96%.

Table 9: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy.

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
'FP1F7'	94.0520	807	94.7708
'F7T7'	94.7174	807	95.8794
'T7P7'	93.2686	807	94.7645
'P7O1'	95.6134	807	96.6610
'FP1F3'	93.6408	807	95.0283
'F3C3'	91.8523	807	93.3858
'C3P3'	91.9485	807	92.6572
'P3O1'	93.4837	807	94.4496
'FP2F4'	93.2756	807	94.1740
'F4C4'	91.0014	807	92.1137
'C4P4'	96.1309	807	96.4253
'P4O2'	88.8798	807	90.5184
'FP2F8'	91.0906	807	92.0630
'F8T8'	92.3974	807	93.8587
'T8P8'	94.3950	807	95.4360
'P8O2'	93.6889	807	93.7203

'FZCZ'	86.2812	807	87.6928
'CZPZ'	90.0607	807	91.9421
'P7T7'	93.7488	807	95.0216
'T7FT9'	93.1506	807	94.5268
'FT9FT10'	95.8059	807	96.3352
'FT10T8'	95.0270	807	95.8781

Figure 17: Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining.

4.3.2.3.2 PIMH

For PIMH dataset, initial training of the classifier resulted with 84% average accuracy, 94.8% average specificity and 56.5% average sensitivity for 3Hz spike and wave which is a characteristic of absence seizure.

Below in TABLE 10 we have shown the average initial classification and retrained classification results of our system for each channel. TABLE 10 shows that our technique is robust and it works also on a different dataset. The average accuracy of the system rose from approximately 84% to 85.43%.

Table 10: First column shows the channel label, the second column shows the initial training accuracy, and third one shows the marked correction by a neurologist and the last one shows the final accuracy.

Channel	Accuracy after initial training (%)	No of epochs marked by the user	Accuracy after retraining (%)
‘Fp1’	84.1736	57	84.6666
‘Fp2’	85.9321	57	86.2142

'F3'	89.3863	57	90.1669
'F4'	82.5886	57	84.0065
'C3'	84.6526	57	85.6825
'C4'	84.0094	57	87.0688
'P3'	82.8481	57	84.6240
'P4'	83.0264	57	85.0625
'O1'	84.6445	57	84.1711
'O2'	83.3906	57	84.7017
'F7'	85.0919	57	88.3044
'F8'	84.8240	57	86.7992
'T3'	87.8007	57	88.8983
'T4'	92.0082	57	92.0256
'T5'	83.5051	57	86.4678
'T6'	85.5538	57	87.3744
'Fz'	83.2279	57	83.9403
'Cz'	80.0350	57	82.1546
'Pz'	90.5629	57	91.4475
'E'	87.3452	57	86.5264
'PG1'	88.4426	57	88.3773
'PG2'	83.0150	57	83.3391
'A1'	84.1149	57	85.5487
'A2'	84.0726	57	85.0169
'T1'	81.1019	57	83.0590
'T2'	83.5085	57	86.0844
'X1'	85.4925	57	87.7204
'X2'	85.2431	57	86.6259

'X3'	78.6937	57	80.5123
'X4'	81.2826	57	81.3851
'X5'	73.0822	57	77.2667
'X6'	83.9101	57	84.7386
'X7'	76.2795	57	79.2632

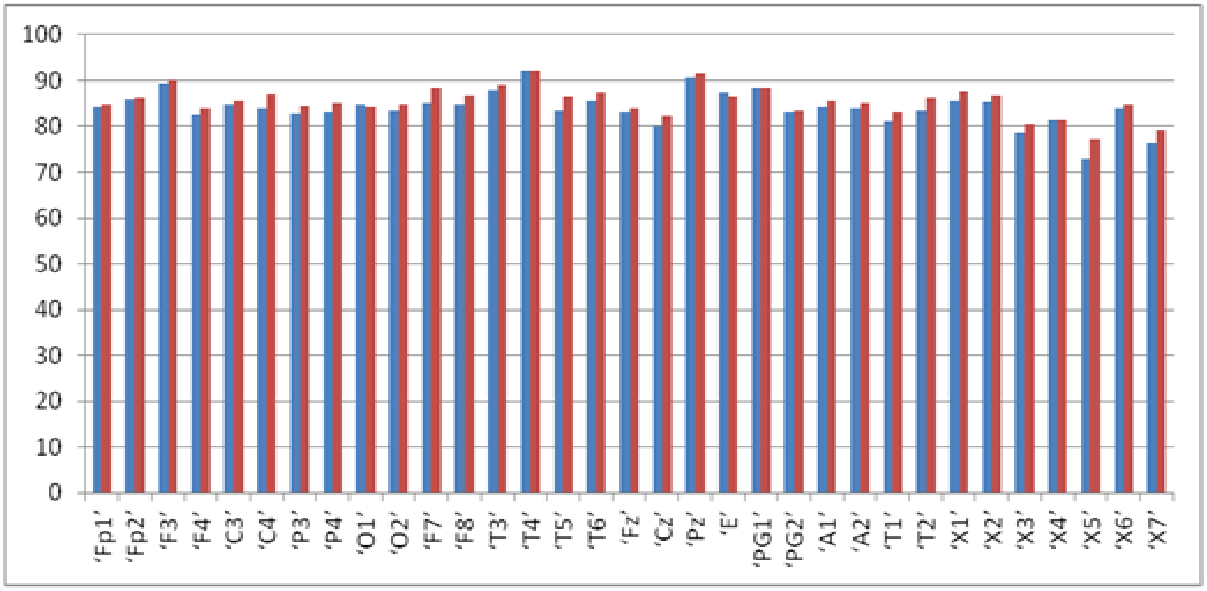

Figure 18: Blue bars represent the average classification rate of the channels after initial training whereas the red bars shows the average accuracy of the channels after retraining.

Chapter#5: Discussion & Future Work

Computer assisted analysis of EEG has tremendous potential for assisting the clinicians in diagnosing. A very important and the novel phase of our system is user adaptation mechanism or retraining mechanism. Introduction of this phase has importance in multiple aspects. In this phase, system tries to adapt its classification as per user's desire. This technique personalizes the classifier's classification. It has been cited that some time even the expert neurologist have some disagreement over a certain observation of an EEG data. This system will be useful for both disagreeing users and it will also help them in comparing their results with each other.

There is also a threat of over fitting by the classifier. In order to keep the classifier improving its performance with the encounter of more and more examples, we have introduced this user adaptive mechanism in our system. We consider the existing systems as 'dead' because they cannot improve their classification rate after initial training (during software development). The self-improving mechanism after deployment makes this tool an 'alive' tool.

This system can be made the part of the whole epileptic diagnoses process. It will highlight the epileptic spikes among the whole EEG thus reduce the fatigue and time consumption of a user.

We obtained high classification accuracy on datasets obtained from two different sites, which indicates reproducibility of our results and robustness of our approach.

In future we are planning to make this a web based application in which a neurologist can login and consult each other's reviews about a particular subject. This will make our system experience a whole versatile of examples and learn from all of them. Integration of the video and its automatic analysis (video EEG) can help a neurologist in diagnosing epilepsy in better way whereas this can also help him in distinguishing between psychogenic and epileptic seizures.

We would also be investigating how much over fitting is an issue in the reported performances which are now even touching 100% based on some claims. There is a need of method/criteria which could limit these algorithms improving their detection on a limited number of available examples.

This system is made keeping in mind that we have to facilitate the neurologist by supplementing him in the analysis of the EEG. We do not want to enforce the classification of the EEG data on a user.

In future we will also include a slider in the system which will allow the user to adjust the sensitivity and specificity before retraining.

This assisting system is more like a detection tool which is continuously learning with encounter of better examples. More and better examples will certainly improve its performance. The agreement between different neurologists over the EEG readings is low to moderate. If we could find the agreement on at least few of the epileptic patterns' correspondence with epileptic disease then we can take this tool further ahead and use it for diagnosis instead of just assistance.

One of the biggest limitations to this study is the unavailability of non 3Hz spike and wave data. Even though we have included the data features of the entire epileptic frequency ranges exclusive to each other but proof testing on the data will certainly prove worthy for the progress of the these assisting tools toward a diagnostic tool.

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