# EEG SIGNAL PROCESSING FOR ABNORMALITY DETECTION USING DWT, SE AND KNN TECHNIQUES

Madhavi Devi Lanka
Prasad V.Potluri Siddhartha Institute of Technology

**ABSTRACT:** The EEG signal is pre-processed to remove major artifacts before being decomposed into several EEG sub-bands using a discrete-wavelet-transform (DWT). The nonlinear method Shannon entropy, which measure complexity and chronicity in the EEG recording, is used to extract the features. The extracted features are then classified using several classification methods. Different EEG datasets are used to verify the proposed design technique: The University of Bonn dataset, the MIT dataset, the King Abdulaziz University dataset, and many more. The proposed method could potentially be used to assist epilepsy and ASD diagnosis. The combination of DWT, Shannon entropy and k-nearest neighbor (KNN) techniques produces the most promising classification result, with an overall accuracy of up to 94.6% for the three-class (multi-channel) classification problem.

**KEYWORDS:** EEG, epilepsy, chronicity, DWT, nearest neighbor

**1. INTRODUCTION:** Computer-based systems have many applications in the medical field, such as for electronic health records (EHR) systems, hospital information systems (HISs), and computer aided diagnosis (CAD) systems. Computer system can be used by medical doctors to diagnose certain disorders by automatically analyzing medical images or physiological signals recorded from patients, such electroencephalography (EEG) signals[1]. Medical diagnosis is often a challenging task that requires deliberate effort and expertise from medical experts.

With advances and developments in signal processing and machine learning methods, computer-based systems have become able to perform more sophisticated tasks, including EEG signal analysis. These automatic mechanisms would ultimately save time and improve global diagnosis accuracy. Analyzing abnormality in brain signals may provide a clue to brain conditions and pathologies[2]. EEG, which captures signals from the human brain, has great potential to be used for brain activity and condition analysis. EEG recordings have been used for a long time as a diagnostic tool for epilepsy. Recently researchers have utilized EEG for autism spectrum disorder (ASD) diagnosis purposes.

Alzheimer's and other neurological disorders are among targets of EEG-based analysis applications. Despite their low spatial resolution, EEG recordings have several advantages such as high temporal resolution, simplicity, lower costs, and wider availability.

## 1.1 LITERATURE

An electroencephalogram (EEG) is a test used to detect abnormalities related to electrical activity of the brain. Scientists first captured and recorded brain waves in dogs in 1912. German physiologist and psychiatrist Hans Berger (1873–1941) began his studies of the human EEG in 1920[3]. He gave the device its name and is sometimes credited with inventing the EEG, though others had performed similar experiments. His work was later expanded by Edgar Douglas Adrian.

In 1934, Fisher and Lowenback first demonstrated epileptic-form spikes. In 1935 Gibbs, Davis and Lennox described interictal spike waves and the 3 cycles/s pattern of clinical absence seizures, which began the field of clinical electroencephalography. Subsequently, in 1936 Gibbs and Jasper reported the interictal spike as the focal signature of epilepsy. The same year, the first EEG laboratory opened at Massachusetts General Hospital.

Franklin Offner (1911–1999), professor of biophysics at Northwestern University developed a prototype of the EEG that incorporated a piezoelectric ink-writer called a Crystograph (the whole device was typically known as the Offner Dynograph).
In 1947, The American EEG Society was founded and the first International EEG congress was held. In 1953 Aserinsky and Kleitman described REM sleep[4].

In the 1950s, William Grey Walter developed an adjunct to EEG called EEG topography, which allowed for the mapping of electrical activity across the surface of the brain. This enjoyed a brief period of popularity in the 1980s and seemed especially promising for psychiatry. It was never accepted by neurologists and remains primarily a research tool.

**1.2 APPLICATIONS OF EEG:** The main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study[5]. A secondary clinical use of EEG is in the diagnosis of coma, encephalopathies, and brain death. EEGs can also help to identify causes of other problems such as sleep disorders and changes in behaviour as well it can be used to evaluate brain activity after a severe head injury or before heart or liver transplantation. EEG used to be a first-line method for the diagnosis of tumours, stroke and other focal brain disorders, but this use has decreased with the advent of anatomical imaging techniques such as MRI and CT[6].

**1.3 LIMITATIONS OF EEG:** EEG has several limitations. Most important is its poor spatial resolution. EEG is most sensitive to a set of post-synaptic potentials: those generated in superficial layers of the cortex, on the crests of gyri directly abutting the skull and radial to the skull. Dendrites, which are deeper in the

cortex, inside sulci, in midline or deep structures (such as the cingulate gyrus or hippocampus), or producing currents that are tangential to the skull, have far less contribution to the EEG signal[7]. The meninges, cerebrospinal fluid and skull "smear" the EEG signal, obscuring its intracranial source. It is mathematically impossible to reconstruct a unique intracranial current source for a given EEG signal, as some currents produce potentials that cancel each other out. This is referred to as the inverse problem. However, much work has been done to produce remarkably good estimates of, at least, a localized electric dipole that represents the recorded currents.

**1.4 EEG ABNORMALITIES:** Abnormal results on an EEG test may be due to:

• An abnormal structure in the brain (such as a brain tumour)

• Attention problems

• Tissue death due to a blockage in blood flow (cerebral infarction)

• Drug or alcohol abuse

• Head injury

• Inflammation of the brain (encephalitis)

• Haemorrhage (abnormal bleeding caused by a ruptured blood vessel)

• Migraines (in some cases)

• Seizure disorder (such as epilepsy or convulsions)

• Sleep disorder (such as narcolepsy)

**An abnormal EEG may consist of:**

- Abnormal changes in normal rhythm: If asymmetrical, the side with lower amplitude is usually pathological
- Abnormal slow activity: A sensitive indicator of encephalopathy if diffuse; correlate with regional cerebral dysfunction if localized; may appear as intermittent rhythmic delta (FIRDA in adult or OIRDA in children)[8].
- Distinctive abnormal pattern: Regular repetition of spikes, sharp waves, slow waves or any of the combination

  e.g. PLED, burst suppression, tri-phasic waves, pseudo periodic generalized sharp waves in CJD, pseudo periodic slow complexes in HSV encephalitis
- Epileptic-form discharges: Spikes, poly spikes, sharp and slow waves

## 2. MODELS OF COMPUTATION AND ANALYSIS OF EEG's:

A hybrid principal component analysis (PCA) based neural network with fuzzy membership function (NEWFM) is proposed for epileptic seizure detection. By combining PCA and NEWFM, the proposed method improves the accuracy in epileptic seizure detection. The PCA is used for wavelet feature enhancement needed to eliminate the sensitivity of noise, electrode artifacts, or redundancy. NEWFM, a model of neural networks, is integrated to improve prediction results by updating weights of fuzzy membership functions[9].

### 2.1 Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis

Epileptic seizures, a crucial neurological disorder, reflect the excessive and hyper-synchronous activity of neurons in the brain. Human knowledge of functioning of the brain is still insufficient to understand the neurophysiology of suddenly occurring epileptic seizures[10]. But the detection of the disorder and recognition of the affected brain area is essential for the clinical diagnosis and treatment of epileptic patients. Epilepsy is not only a disorder, but rather acts as a syndrome with divergent symptoms involving episodic abnormal electrical activities in the brain.

EEG is the most economical and effective tool with high temporal resolution for understanding the complex dynamical behavior and studying physiological states of the brain. Statistical features depicting morphology of EEG signals are extracted, selected and utilized to classify the signals by Artificial Neural Network, Radial Basis Function, Naive Bayes Classifier, K means classifier, Support vector machine.

Efficiency of technique is evaluated on the basis of performance measures, sensitivity, specificity and accuracy. It has been observed that artificial neural network and support vector machine with radial basis function kernel are more successful as compared to other soft computing paradigms.

### 2.2. Preprocessing and Feature Selection

Many different features have been thought up to be extracted from EEG signals. The most frequent transformation used is Fourier analysis to be able to look at specific frequency bands. Firstly, we applied the Common Spatial Patterns (CSP) method (Muller-Gerking, Pfurtscheller and Flyvbjerg (1999)) to the raw EEG data. The standard CSP is applicable to two class problems; it transforms the original signal into a new space where the variance of one of the classes is maximized while the variance of the other is minimized.

Good feature selection is the key to the success of a classification algorithm. It is needed to reduce the number of features by selecting the most informative and discarding the irrelevant and redundant features. As EEG data is known to be highly correlated, a feature selection method which exploits this property seems appropriate. Good subsets of features contain features that are highly correlated with the

class and uncorrelated with each other. The search space is very big for employing a brute-force search algorithm.

## 2.3. CLASSIFIERS

### 2.3.1 Linear Discriminant Analysis (LDA)

In order to classify the extracted features, Linear Discriminant Analysis (LDA) is one of the most popular and efficient classifier for EEG-based BCI. Linear Discriminant Analysis, have a low complexity. They are said stable as small variations in the training set does not affect considerably their performance. The aim of LDA (also known as Fisher's LDA) is to use hyper-planes to separate the data representing the different classes. This technique has a very low computational requirement which makes it suitable for online BCI system. Moreover this classifier is simple to use and generally provides good results.

### 2.3.2 Quadratic Discriminant Analysis (QDA)

Quadratic classification aims at assigning to a feature vector the class it belongs to with the highest probability. The Bayes rule is used to compute the so called a posteriori probability that a feature vector has of belonging to a given class. Using the MAP (Maximum A Posteriori) rule and these probabilities, the class of this feature vector can be estimated. Bayes quadratic consists in assuming a different normal distribution of data. This leads to quadratic decision boundaries, which explains the name of the classifier.

### 2.3.3 Gaussian Mixture Model (GMM)

Gaussian classifier is used to separate the signal into different classes of mental task. Each class is represented by a number of Gaussian prototypes, typically fewer than four. Training of the classifier starts from an initial model that can be either a previously trained classifier or a new classifier created by estimating the prototype centers with a clustering algorithm. This initial estimate is then improved by stochastic gradient descent to minimize the mean square Error.

## 3. IMPEMENTATION

Discrete Wavelet Transform has been used to extract features from the EEG segment. KNN has been implemented for classification. DWT is able to capture small changes in the EEG signal by representing the signal in multi scale time-frequency domains in terms of approximate (Ax) and detail (Dx) coefficients. Six-level decomposition based on the Daubechies 8 (Db8) wavelet, which is commonly used for EEG analysis.

Only the D5, D6, D7, D8, and A8 coefficients are used for feature extraction to represent the EEG sub-bands in the 0- to 32-Hz spectrum range. These wavelet coefficients correspond to several EEG sub-bands, namely, delta (1–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz), and gamma (30-60Hz). EEG sub-bands with higher frequency, i.e., beta and gamma, have lower magnitude or power than lower frequency sub-bands, i.e., delta, theta and alpha.

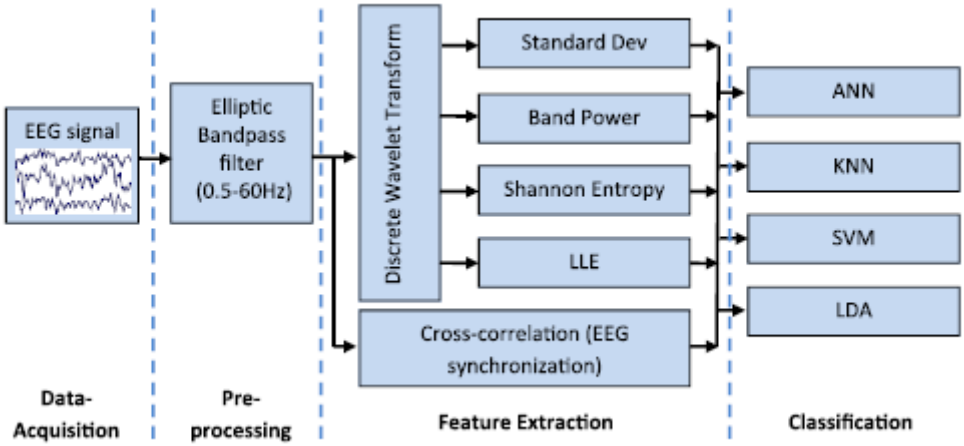


**Figure. 1 Generic block diagram of CAD system for medical pathology diagnosis**

Different EEG datasets can be used to verify the proposed method. The first dataset is provided by the University of Bonn, Germany. This dataset contains five sets, named A, B, C, D, and E, where each set includes exactly 100 single-channel EEG segments. Sets A and B were recorded using scalp EEGs from a normal person, whereas sets C, D, and E were recorded using intracranial EEGs from epileptic patients. The data were recorded with a sampling rate of 173.61 Hz. The total duration of each segment was approximately 23.6 sec.

The second dataset was provided by a research team from MIT, USA. The data contain 906 h of EEG data recorded from 23 epileptic patients. In this, only data for the first ten subjects was used. This data includes 23 EEG channels; the sampling rate is 256 Hz.

The third dataset was provided by King Abdulaziz University (KAU), Saudi Arabia. This dataset was recorded from ten normal subjects (males, aged 9–16 years) and nine autistic subjects (six male and three female, aged 10–16 years). The dataset was recorded in a relaxed state with 16-channel EEG at a sampling rate of 256 Hz.

### 3.1 FEATURE EXTRACTION

**Discrete Wavelet Transform:** In numerical analysis and functional analysis, a **discrete wavelet transform** (**DWT**) is any wavelet transform for which the wavelets are discretely sampled. As with other

wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

The most commonly used set of discrete wavelet transforms was formulated by the Belgian mathematician, Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale. Daubechies derived a family of wavelets, the first of which is the Haar wavelet.

### 3.2 FEATURE ANALYSIS

Before performing EEG classification, we first analyze the EEG signals and the extracted features. As noted above, the normal and autistic EEGs are taken from the KAU dataset, whereas the epileptic EEG is taken from the MIT dataset. The power spectral density is shown with a logarithmic scale to simplify the visualization. The electrode map is shown for the three different frequencies: 6 Hz (within the theta band), 10 Hz (alpha), and 22 Hz (beta).

In general, the low frequency spectrum has higher power density than the high frequency spectrum. Frequencies above 30 Hz, i.e., the gamma band and above, have negligible power. Usually, this high frequency range can be treated as noise in the EEG. Comparing the three subjects, we see different power spectral density patterns. The subject with ASD has higher theta powers than the normal subject.

To demonstrate the effectiveness of the extracted features for differentiating between the classes (or subjects), we visualize them in Cartesian coordinates. The feature vector size for each single-channel EEG segment is equal to 5, which represents the extracted values within the EEG sub-bands, namely, delta, theta, alpha, beta, and gamma. Shannon Entropy (SE) shows the best ability to differentiate between the three types of EEG data, followed by SD. LLE shows the worst ability to differentiate between the subjects. The epileptic EEG has higher SE values in almost all sub-bands, as compared with normal and autistic EEGs. Autistic EEGs also have higher SE values than normal EEGs. As mentioned above, SE measures the distribution of the data, in this case, representing the complexity of the EEG signals.

# 4. RESULTS

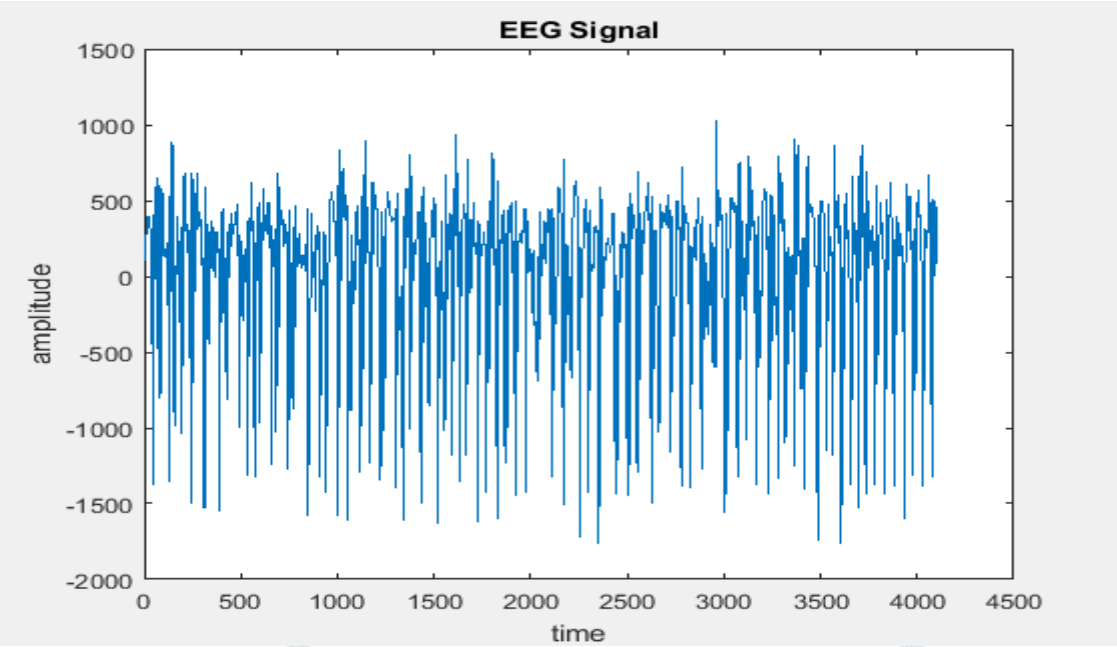


**Fig.2. EEG Data**

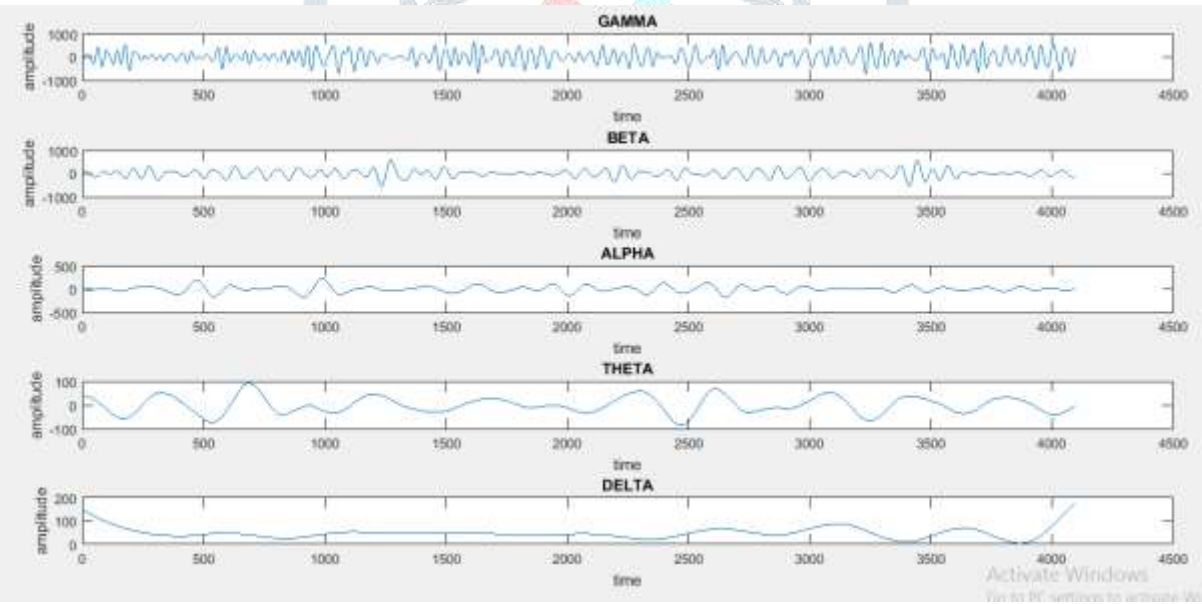


**Fig.3. EEG Sub bands**

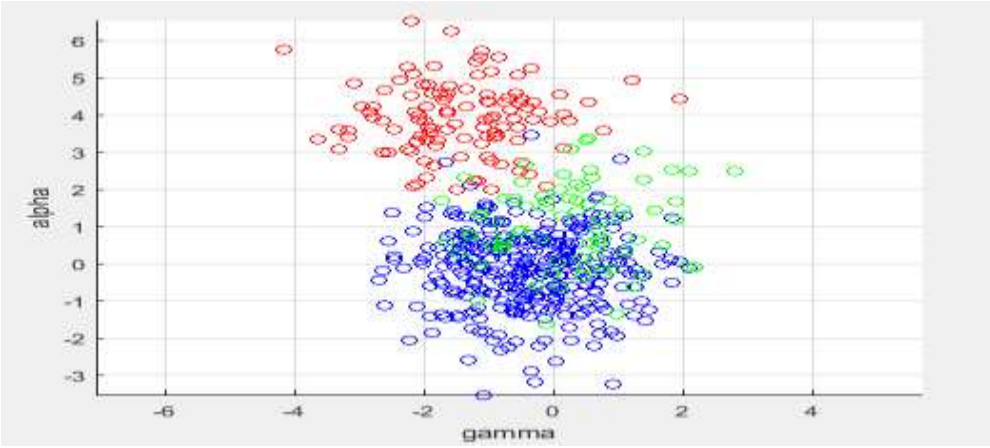


Fig.4.a

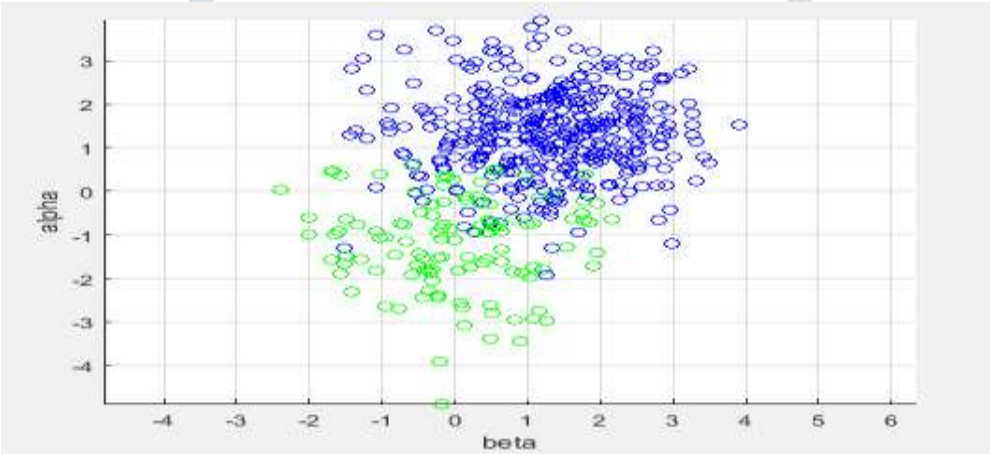


Fig.4.b

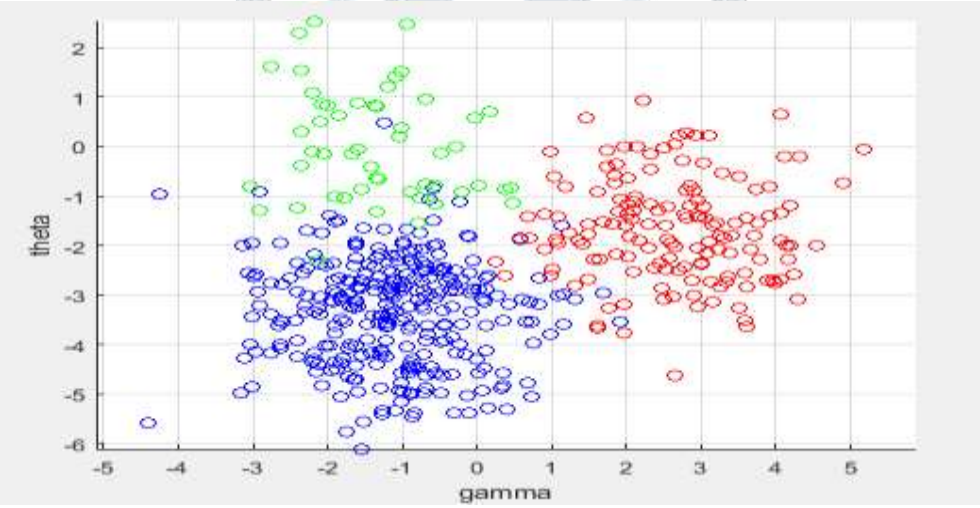


Figure 4.c

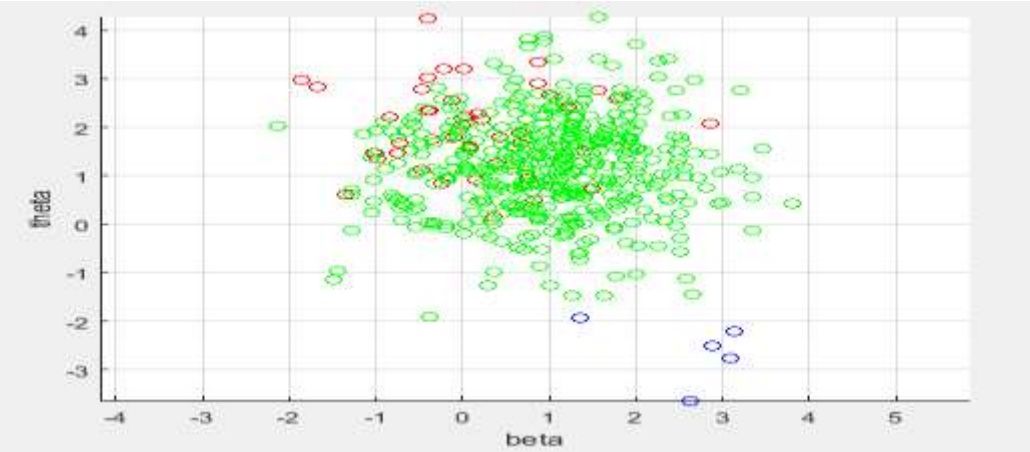


Figure 4.d

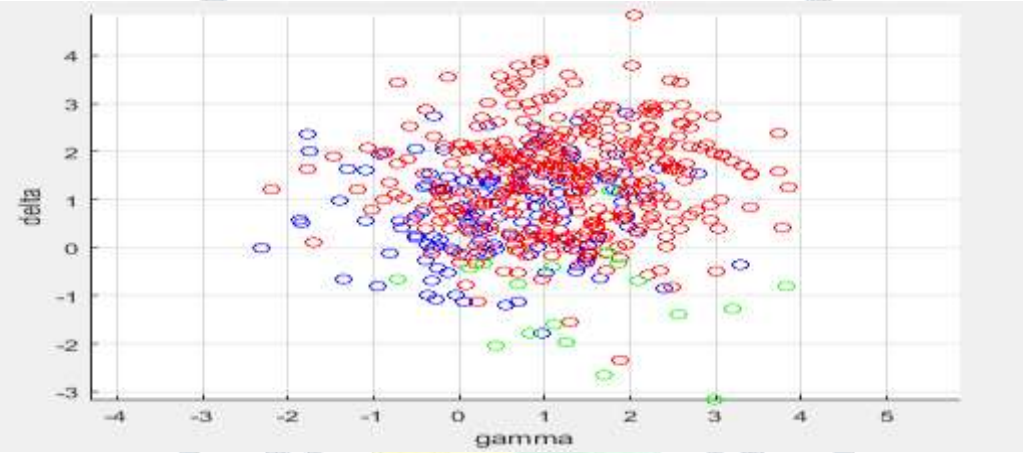


Figure 4.e

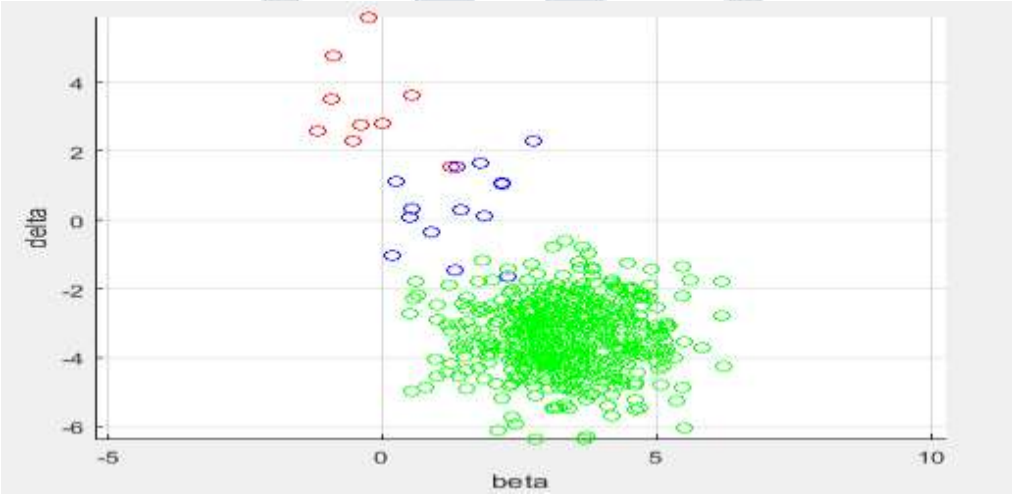


Figure 4.f

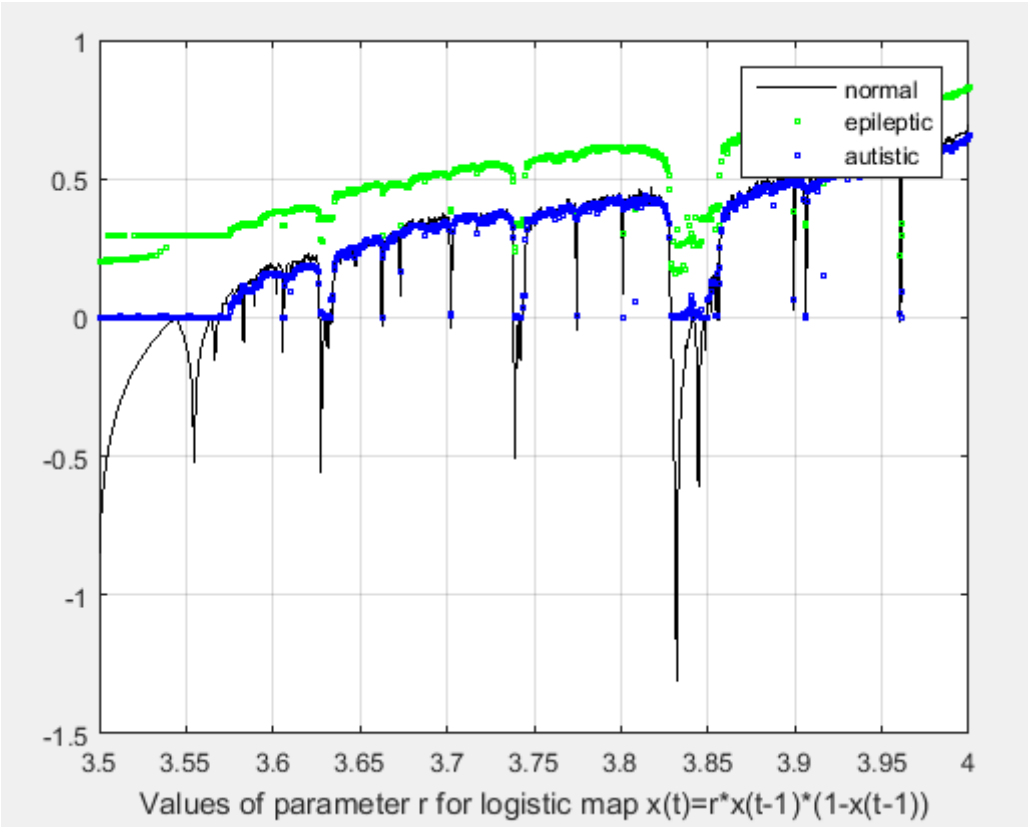


**Figure 5. Three class classification**

Figure 4. (a-f) SE values within EEG sub bands

## FUTURE SCOPE

The ability to automatically analyze EEG data would improve the speed and accuracy of diagnosis processes. Different datasets are used to evaluate the proposed method, with different numbers of EEG channels and electrode positions, which increases the problem complexity. The combination of DWT, SE, and KNN always achieved the best results, with an overall accuracy of 94.6% on the three-class classification problem (normal vs. epilepsy vs. autism).

Future research directions include testing the proposed method with even larger datasets, and possibly with different levels of severity. Another neurological disorder such as Alzheimer's disease will be incorporated into the classification problem. Adaptive learning to improve the system performance over time can also be investigated.

## REFERENCES:

[1] Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Comput Med Imaging Graph 2007;31(June–July (4–5)):198–211.

[2] Acharya UR, Tree SV, Swapna G, Martis RJ, Suri JS. Automated EEG analysis of epilepsy: a review. Knowl Based Syst 2013;45:147–65.

[3] Noachtar S, Rémi J. The role of EEG in epilepsy: a critical review. Epilepsy Behav 2009;15(1):22–33.

[4] Bhat S, Acharya UR, Adeli H, Bairy GM, Adeli A. Automated diagnosis of autism: in search of a mathematical marker. Rev Neurosci 2014;25(6):851–61.

[5] Faust O, Acharya UR, Adeli H, Adeli A. Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure 2015;26(March):56–64.

[6] Shannon CE. A mathematical theory of communication. Bell Syst Tech J 1948;27(July–October (3)):379–423.

[7] Weinberger KQ, Saul LK. Distance metric learning for large margin nearest neighbor classification. J Mach Learn Res 2009;10(February):207–44.

[8] Boser BE, Guyon IM, Vapnik VN. A training algorithm for optimal margin classifiers. Proceedings of the Fifth Annual Workshop on Computational Learning Theory – COLT'92; 1992. p. 144.

[9] Duda RO, Hart PE, Stork DG. Pattern classification; 2012.

[10] Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: dependence on recording region and brain state. Phys Rev E 2001;64:061907.