A Novel approach for Epilepsy Classification using Fuzzy C-means and ANN

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Article History: *Do not touch during review process (xxxx)*

Abstract: Detection from the EEG recorded signals to epileptic seizure activity is critical and challenging to locate and classify epileptic seizures. It is evident from the study that seizure development is essentially a dynamic, non-static process consisting of multiple frequencies. The traditional methods for extracting useful data out of EEG signals have limited applications. Hence, in this paper, we present a time frequency analysis (t-f) along with deep learning technique to classify epilepsy. There are four stages to the analysis: 1) Initially the t-f analysis and calculation of power spectrum density (PSD) of each EEG segment is performed. 2) Relevant features will be extracted from the specific t-f window. 3) The obtained dataset is then clustered using the Fuzzy-C Means technique before being fed to a neural network model for better results.4) And finally, the recorded EEG segment will be classified into different epilepsy classifications using ANN. The study's findings show that the proposed clustering approach is highly effective in epilepsy classification, with an accuracy of 99% which is significantly higher than many existing methods.
Keywords: Power Spectrum Density, Artificial Neural Networks, EEG, Fuzzy-C Means, Epilepsy

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1. Introduction

The word Epilepsy comes from the Greek word "epilambanein," which means "to seize". If a person has frequent seizures then the person is in epileptic state. It may begin at any stage of life and its occurrence may be intermittent in nature or systemic. It is symptomatic epilepsy if the cause is known such as suffocation, head injury etc. Epilepsy is idiopathic if the cause is unknown [1]. These seizures are the result of a dysfunction associated with the brain that results in electrical secretions in the brain that affect any part of the body. These secretions occur in different sites of the brain and have a varied effect on patients such as twisting and trembling of the tongue and limbs, feeling strange, loss of consciousness, behavioral disturbances, etc., causing serious physical damage and psychological trauma. Therefore, its location, the nature of its spread, the extent to which the brain is affected, and its longevity all have profound implications for patients. Monitoring electrical activity in the brain and detecting advanced epileptic conditions and the likelihood of seizures can thus be beneficial in reducing the negative effects of seizures [2].

The electroencephalogram (EEG) is a widely used method for examining and analyzing brain activity in epilepsy patients. Hans Berger, a German psychiatrist, discovered EEG in 1929.It is a simple non-invasive and reasonably economical test that gives valuable information when used in a wise manner and correlated with the clinical description of epilepsy. In epilepsy patients, EEG signals for the brain can be classified as interictal, preictal, and seizure states. When a seizure occurs, the EEG signal displays some unusual patterns. [3]. These patterns in EEG signals can be used to differentiate epileptic states, identify advances and the possible onset of an attack, and mitigate harmful effects on patients. Manual detection of epileptic seizure activities takes a long time, especially for long recordings, so neurophysiologists are needed to interpret the detected seizure activity and make an accurate diagnosis, which is difficult in most developing countries.

The solution for this impeccable problem is to design efficient computer-aided systems that can track onset of seizures with high precision within required time constraint. These systems can aid the medical staff, especially the neurophysiologists, for the automated detection and for classifying the EEG seizure activities. The detection of seizures has been investigated using EEG signals for quite a long time. For instance, long ago in 1982 Gotman [4] used EEG waveform to extract time domain features for detecting seizure. A method for extracting features from EEG signals using DWT was devised by Khalid et.al. They used the following four classifiers namely ANN, Naive Bayes, k-NN, and SVM for epilepsy classification [5]. Similarly another researcher Satapathy et.al. too used DWT method for extracting features from EEG signals but for classification purpose they used Radial basis function neural network (RBFNN) method which was later optimized by using Particle swarm optimization (PSO) algorithm for epilepsy classification [6].

A classification method was devised by R.P. Costa et al. to extract 14 relevant features that were derived from EEG signals and fed to neural networks to classify the epileptic behaviour. For single patients and multiple patients, a classification accuracy of 99% and 98% percent was achieved respectively [7]. Approximate entropy and sample entropy have been used as EEG features and combined with the extreme learning machine (ELM), which detects epileptic seizures automatically [8]. A wavelet based transform method was used for extracting important features from EEG signals and the reduction of the features space dimension was carried out by using the scatter matrices technique to improve the overall result and finally using quadratic classifiers classification was accomplished. A 99% classification accuracy was achieved [9].Artificial neural networks (ANNs) dominate in the area of pattern recognition particularly in disease diagnosis. They work in two different modes of learning that are supervised and unsupervised. A known diagnostic outcome is presented in the supervised method and not in the other method. In this study, we use an ANN methodology to try to overcome the difficulties that arise in handling large amounts of EEG data generated within weeks of patient observation. Our study on the use of ANN is clear and is one of the best methods in classifying epilepsy.

Many vital contributions can be seen in this particular field where the researchers have widely used ANN in epilepsy classification, here in one work ANN methods and wavelet transform was used to identify epilepsy [10], to effectively distinguish between normal and epileptic case, a DWT based method for extracting features from EEG signals and minimizing the measured coefficients using Shannon entropy was fed to neural network classifier that provided an accuracy of 100% [11]. Laguerre polynomials method for wavelet construction was proposed in this work. These constructed wavelets were applied to ANN and support vector machines (SVM) classifiers for epileptic seizure classification [12] ANN provided good accuracy. Using a multistage nonlinear pre-processing filter in combination with ANN was proposed for the automated detection of epileptic seizures. A 97% overall accuracy was obtained in this method [13]. Therefore it was motivating to use ANN in performing epilepsy classification. In following sections we discuss few notable works in this regard, section 3 discusses about the epileptic dataset being used for the proposed work, the proposed work is discussed in detail in section 4, section 5 contains the experimentation and the outcome of the proposed work and finally we conclude.

2. Related Work

In this work [14], a framework for automatic detection of epileptic seizures was proposed. To accomplish this automatic sparse stack encoder, used for data pre-processing and for training and classification, a softmax classifier was used. The proposed method was better than most inefficient methods in dealing with complex and unstable EEG signals. The proposed framework obtained an average accuracy of 96%. Manual monitoring of EEG signals to interpret an epileptic seizure causes a lot of unexplained problems, one being the heavy time consumption required in analyzing the signals and the other being the availability of an expert to diagnose the condition.Here, in this study [15] a system was introduced that would help replace the existing manual system. The proposed system consisted of four phases. First, the signal was pre-processed to remove noise and other distortions generally present in the signals that, if ignored, would affect the performance of the system being designed. The following features were extracted and only salient features were identified by a multi-target evolutionary algorithm, and finally, the SVM classifier was used for classification. SVM was compared with Linear Discriminant Analysis (LDA) and Quadratic Linear Analysis (QLDA) methods and the accuracy obtained by the SVM was 97% much better than the other classifiers. Three phases of absentia, pre-seizure, seizure, and seizure-free were classified using real clinical data in this work. Therefore, different supervised learning algorithms (SVM and ANN) and unsupervised techniques were used to classify the different stages of epileptic seizures. Computationally intelligent techniques were better at recognizing and categorizing complex and intricate patterns in input data, and demonstrated with better recognition accuracy. However, when fed with a noisy dataset, the ANN system outperforms the SVM [16].

A way to classify the epilepsy risk level from EEG signals was proposed in this work [17]. Features were extracted from EEG signals and fuzzy techniques were used to obtain the level of risk from each epoch for EEG channel. An important consideration in this work was to achieve a low false alarm rate which is extremely vital for classification. Two certain limitations were observed in this particular work, the first is that if one of the channels has a high risk level then the whole group will be maximized to this risk level which will eventually affect the non-epileptic area in the groups and the other is the of number cases must be increased from the current number of six for better system analysis. Entropy approximation was used as a feature extraction technique and for subsequent classifiers, the following distance measurement methods such as Euclidean Distance Scale (EDM), City Mass Distance Measurement (CBDM) and Correlation Distance Scale (CDM) were used to classify the level of risk of epilepsy. We can conclude from the results that when approximate Entropy is used with the correlation distance measurement classifier, the level of risk of epilepsy is high and appropriate [18].The precise description of various epileptic states is one of the most difficult tasks of epilepsy diagnosis. This paper proposes a new deep learning-based classification approach [19].

The epileptic EEG signals are first converted to power spectrum density energy diagrams (PSDEDs), after which deep convolutional neural networks (DCNNs) are used to automatically extract features from the PSDED and divide four epileptic states into four groups. According to the results, the proposed system outperforms other benchmark models in classifying various epileptic states.Since EEG signals are considered to be a sect of bio-signals, they are extremely arbitrary and the symptoms too appear randomly on a time scale. Computer-assisted extraction and analysis of these signal parameters can greatly aid in diagnosis. The authors compared and interpreted the results of various classifiers as applied to EEG data in this study [20]. To distinguish regular and epileptic EEG signals, they suggested an adaptive neural fuzzy network (ANFN) classifier. Other classifiers such as SVM, ANFIS, and FBNN (Feed forward Back-propagation Neural Network) were used to compare the performance. From the results it is observed that a classification accuracy of about 86% was achieved using ANFN and it is competent enough to handle large scope of features extracted from diverse datasets.

Generally in medical diagnosis systems there is an urgent necessity that the medical data is to be inspected in lesser time with good accuracy. Therefore, in this study [21] for epileptic seizure diagnosis, the authors suggested a system in which only three statistical features obtained from EEG signals using the DWT method are necessary. The NB and k-NN classifiers are used as post classifiers to identify epileptic seizures, and the outcome is that the application of the NB classifier and the DWT resulted in a 100% precision. In this paper [22], a low-cost SVM mechanism for classifying patients' epilepsy risk levels has been suggested. For this they applied fuzzy techniques as a level I classifier based on parameters extracted from EEG signals. The optimized risk level that characterizes the patient's epilepsy risk level was obtained using a SVM as a post classifier on the classified results. We may infer from the results that the SVM Method outperforms Fuzzy Techniques in terms of optimizing epilepsy risk levels.Hassan and Subasi [23] decomposed single-channel EEG signal with adaptive noise using total ensemble analytical mode decomposition, and then used ensemble learning (linear programming boosting) to perform accurate epileptic seizure classification. Jaiswal et al. subpattern dependent PCA and cross-subpattern correlation-based PCA, along with SVM for automatic seizure detection, were proposed as two useful approaches for EEG feature extraction. It was clear from the results that both methods were 100 percent accurate in classifying normal and epileptic EEG signals [24].

3.Epileptic EEG Signal Data

To verify the efficacy of the proposed methodology in the case study, we have taken the EEG signals that were recorded at Bharati University, Sangli, Maharashtra, India. The dataset includes subsets recorded with a 32-channel amplifier system and a 12-bit analog to digital converter taken at a frequency of 512 Hz. EEG samples in datasets number 24 is acquired from healthy participants. Samples are collected with external surface electrodes for both closed and open eye conditions. Other datasets are collected from epileptic patients before and during seizures, as well as during seizure-free periods. The EEG signals can be divided into interictal, preictal, and seizure states. Moreover, classifying epileptic seizures early will definitely help prevent and mitigate the harmful effects of potential seizures. However, predicting the precise diagnosis time before the seizure occurs is difficult. For the experimentation purpose we keep 70% of the data as the training set and use the remaining 30% as the trial set for the classification algorithm.

4.Proposed Method

The proposed method uses the TFD that belong to Cohen's class of distributions for extracting features from the EEG signals. The nonlinear time series dataset is initially clustered into the following categories ictal, preictal and normal by means of Fuzzy-C means clustering. This clustered dataset is used to train the neural network. Finally the ANN classifier is used for classifying epilepsy risk level. The below block diagram shows flow of proposed methodology. A brief explanation of each phase of the proposed model is given in the following sections.

Fig1. Block Diagram of Proposed System Architecture

4.1 Feature Extraction

Feature extraction aims to minimize the original data by calculating specific features that separate one input pattern from another. When the input data to an algorithm is too big to process and is suspected to be inherently redundant (lots of data and not much information), the input data is transformed into a reduced representation set of features (also named feature vector). Feature extraction refers to the process of transforming input data into a set of features. If the derived features are deliberately selected, it is assumed that the features collection would extract the necessary information from the input data to execute the desired task using this reduced representation rather than the full-size input.The TFD used in our study belong to the Cohen's class of distributions. The Cohen's class of time-frequency (t-f) representations is quadratic.

$$\rho\ (t, f) = \int\int\int e^{i2\pi\upsilon(u-t)} g(\upsilon,\boldsymbol{\tau})\ x^{*}(u\text{-}1/2\ \boldsymbol{\tau})\ x(u + 1/2\boldsymbol{\tau})\ e^{-i2\pi f\tau} d\upsilon\ du\ d\boldsymbol{\tau} \ldots\ldots (1)$$

where 't' is the time, 'f' is the frequency, x(t) is the signal, x∗(t) is its complex conjugate, and g (υ, τ) is an arbitrary function called kernel, which is different for each TFD. Table-1depicts the TFDs, which are used in our study along with the corresponding kernels. The most common TFDs that belong to the Cohen's class have been employed.

Distribution		***Kernel (g(υ, t))***
1.	Margenau Hill (MH)	$\cos(\pi\upsilon\boldsymbol{\tau})$
2.	Wigner-Ville (WV)	1
3.	Rihaczek (RIH)	$e^{-i\pi\upsilon\tau}$
4.	Pseudo Margenau Hill (PMH)	h($\boldsymbol{\tau}$)$e^{-i\pi\upsilon\tau}$(h($\boldsymbol{\tau}$): window function)
5.	Pseudo Wigner-Ville (PWV)	h($\boldsymbol{\tau}$) (h($\boldsymbol{\tau}$): window function)
6.	Born-Jordan(BJ)	$\sin(\pi\upsilon\tau)/(\pi\upsilon\tau)$
7.	Butterworth(BUT)	$1/\left[1 + (\frac{\upsilon}{\upsilon_1})^{2N} (\frac{\tau}{\tau_1})^{2M}\right]$ (N, M , υ_1, τ_1 > 0)
8.	Choi-Williams(CW)	$e^{(-\pi\upsilon\tau)^2/2\sigma^2}$
9.	Generalized rectangular (GRECT)	$\sin\left(\frac{2\pi\sigma\upsilon}{\lvert\tau^{\alpha}\rvert}\right)/(\pi\upsilon) \begin{pmatrix} \sigma\text{: scaling factor} \\ \alpha\text{: dissemmetry ratio} \end{pmatrix}$
10.	Reduced Interference (RI)	$\int_{-\infty}^{+\infty} h(t)e^{-j2\pi\upsilon\tau t}\, dt$ (h($\boldsymbol{\tau}$): window function)
11.	Smooth Pseudo Wigner-Ville (SPWV)	G(υ) h($\boldsymbol{\tau}$) (h($\boldsymbol{\tau}$): window function)
12.	Zhao-Atlas-Marks(ZAM)	h($\boldsymbol{\tau}$) $\sin(\pi\upsilon\tau)/(\pi\upsilon\tau)$ (h($\boldsymbol{\tau}$): window function)

Table1: Cohen's Distribution Class

Using t-f analysis, the Power Spectrum Density (PSD) of the signal is calculated, which represents the distribution of the energy of the signal over the t-f plane. The PSD is used to extract several features. A grid is used based on a partition both in the time and the frequency axis. In the time domain, three equal-sized windows were selected while in the frequency domain it was divided into five subbands defined based on medical knowledge on EEG, they are 0–2.5 Hz, 2.5–5.5, 5.5–10.5, 10.5–21.5, and 21.5–43.5 Hz, in these subbands specific features are expected to be found. Each feature f (i, j) is calculated as:

$$f\ (i\ ,j) = \int\int PSD_x\ (t, w) dw\ dt \ldots\ldots\ldots\ldots (2)$$

where PSDx is the PSD of the signal x calculated using one of the aforementioned methods, ti is the ith time window, and ωj is the jth frequency band. Each feature represents the fractional energy of the signal in a specific frequency band and time window; thus, the feature set depicts the distribution of the signal's energy over the t-f plane. It is expected that the feature set carries sufficient information related to the nonstationary properties of the signal which will be forwarded to next phase of the model.

4 .2 Fuzzy C-Means

Clustering is an unsupervised machine learning technique that divides a given data into separate clusters based on their distances from one another. FCM is a clustering approach that requires a single piece of data to belong to several clusters. In this case, we use FCM to find the centroid of the data points and then measure the distance between each data point and the given centroids until the clusters formed becomes constant. Basically it is based on minimization of the following objective function:

$$J_m=\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\|X_i - C_j\right\|^2 \text{ .... (3)}$$

where 'm' is any real number greater than 1, uij is the degree of membership of xi in the cluster j, xi is the ith of d-dimensional measured data, Cj is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership uij and the cluster centers Cj:

$$u_{ij}=\frac{1}{\sum_{k=1}^{C}\left[\frac{\left\|X_i-C_j\right\|}{\left\|X_i-C_k\right\|}\right]^{2/m-1}} \text{......(4)} \qquad C_j=\frac{\sum_{i=1}^{N}u_{ij}^{m}X_i}{\sum_{i=1}^{N}u_{ij}^{m}} \text{...... (5)}$$

This iteration will stop when$\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where ε is a termination criterion between 0 and 1 and 'k' is number of iteration steps. This procedure converges to a local minimum or a saddle point of Jm.

4.3 Artificial Neural Network

Deep learning based on artificial neural networks (ANN) has seen significant progress in the medical field, especially in disease complications linked to neurological disorders. In this study, a feed-forward neural network (FFNN) is used to classify epilepsy. FFNN is composed of three layers: the input layer, the hidden layer, and the output layer. The input features derived from the EEG signals are IF1, IF2,…..and IF12 which make up the neural network's input layers. Typically there will be 'n' hidden layers, and are labeled as HL1, HL2,…..HLn the processing occurs in these hidden layers. The output layer of the neural network is used to determine the classification of epilepsy.

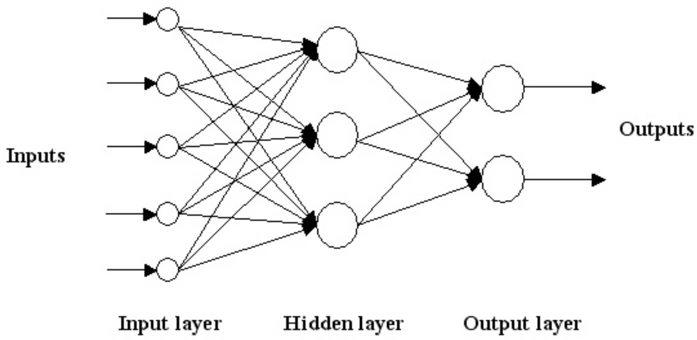


Fig 2. A multi-layer feed-forward neural network

Figure-2 shows the neural network training structure. There are three layers: an input layer, a hidden layer, and an output layer. W1 denotes the weight between the input and hidden layers, while W2 denotes the weight between the hidden and output layers. The bias is set to one in this case. The sigmoid function is used as an activation function to prevent any slight difference in the input that may cause the output to flip. And lastly, the weight shift is determined by the output requirement. When the training process is over, the network is saved for testing. In the testing phase, an input EEG signal is applied to the trained network, which will classify the given input signal into one of the following states i.e. whether it is of interictal state or preictal state and or seizure state.

5. RESULTS and DISCUSSION

Given the importance and significance of epilepsy classification, we attempted to build an ANN-based model in this paper by optimizing data collection and pre-processing feature selection and improved machine learning-based classification. Our primary concern, in this case, was determining the most appropriate computing environment for epilepsy classification, which could result in higher precision, reliability, and computational performance, both of which are mandatory for a competent computer-aided diagnosis (CAD) solution. The MATLAB 2018 software was used to implement the proposed method for epilepsy classification. We carried the classification process using an Artificial Neural Network classifier and dataset from Bharati University, Sangli, and Maharashtra, India.

As discussed earlier in the experimental dataset section, the dataset included three distinct sets of EEG signals from healthy and unhealthy people. The Artificial Neural Network training began with 12 neurons at the input layer and 3 neurons at the output layer.

Notably, with any machine learning classifier, choosing a suitable set of features that can sustain higher precision with the least amount of computing overhead is vital. Choosing a performance-sensitive optimum feature selection process, on the other hand, may be critical. In light of this motivation, we used Cohen's class of distributions to derive features from EEG signals in this paper. The primary objective of using Cohen's feature selection approach was to keep the most desirable features for high accuracy with minimal computation. In the following steps, Fuzzy-C means clustering is used to divide the dataset into three categories: ictal, preictal, and regular. Finally, an ANN classifier which classified the subject into either of the three categories. The simulation-based performance comparison in terms of accuracy, precision, F-measure, and recall confirmed the proposed system's supremacy over major existing methodologies. To accomplish this, we obtained True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. Using the matrix values listed above, we calculated the output parameters accuracy, precision, recall, and F-Measure, as shown in Table-2.

Parameter	**Mathematical Expression**	**Definition**
Accuracy	$\frac{(TN + TP)}{(TN + FN + FP + TP)}$	A metric that sums up how well the model performs in all classes.
Precision	$\frac{TP}{(TP + FP)}$	The degree to which repeated measurements under the same conditions yield the same results.
Recall	$TP/((TP + FN))$	It specifies the number of relevant items that must be identified.
F-measure	$2.(Recall.Precision)/(Recall + Precision)$	It creates a single score by combining the precision and recall numeric values.

Table 2: Performance Parameters

Figure-3 illustrates the generation of an epileptic patient's EEG signals using the international standard 10-20 model. As seen in the diagram below, each electrode represents a general location (F- frontal, C-central, P-parietal, T- temporal, O- occipital, A- earlobes), with odd electrodes in the left hemisphere and even electrodes in the right hemisphere. The percentage of the distance between adjacent electrodes in proportion to the distance between the beginning and end of a row is denoted by 10-20 system.

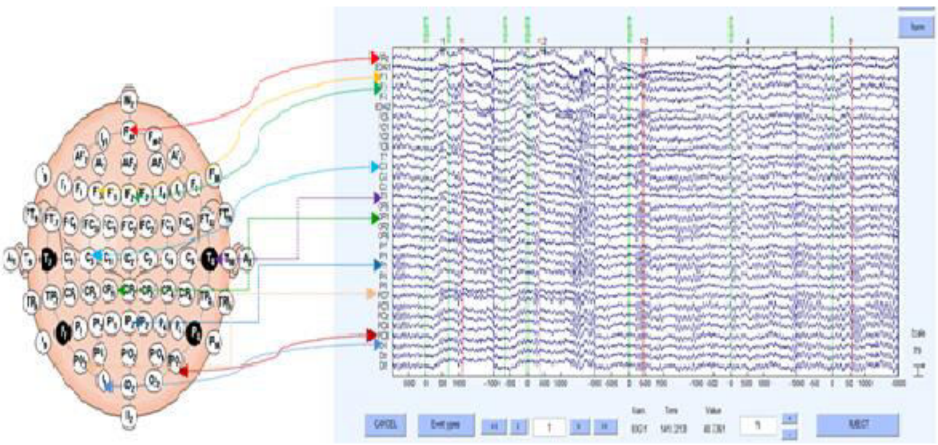


Fig 3: Generation of an EEG Signal with its mapping according to the standard 10 – 20 International System

The figure below shows a raw EEG signal that is generated from single electrode. The signals have amplitudes of the range 100 volts and frequency parameters ranging from 100 to 300 Hz. Signals must be filtered to minimize noise to make them ideal for encoding and simulation in order to preserve the effective information. The filters are constructed in such a manner that they do not alter or distort the signals. The key artefacts are categorized into patient-related physiological artefacts such as body movement, eyelid movement, and so on, and system-related artefacts such as impedance fluctuation, cable glitches, electrical noise, and so on. These artefacts are greatly reduced during the pre-processing period, and the informative material is restored.

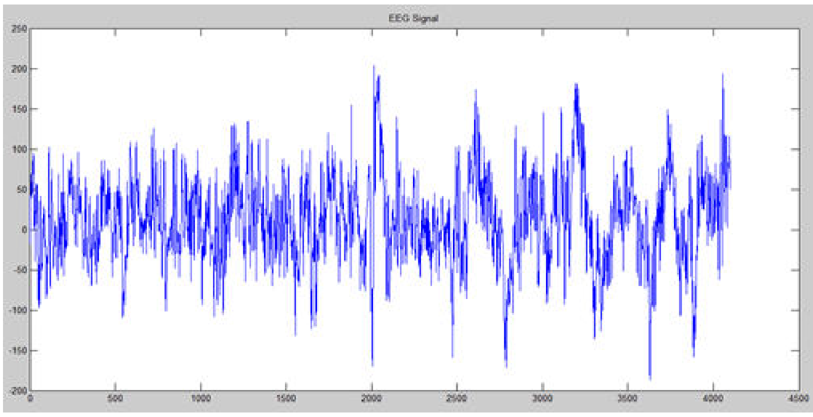
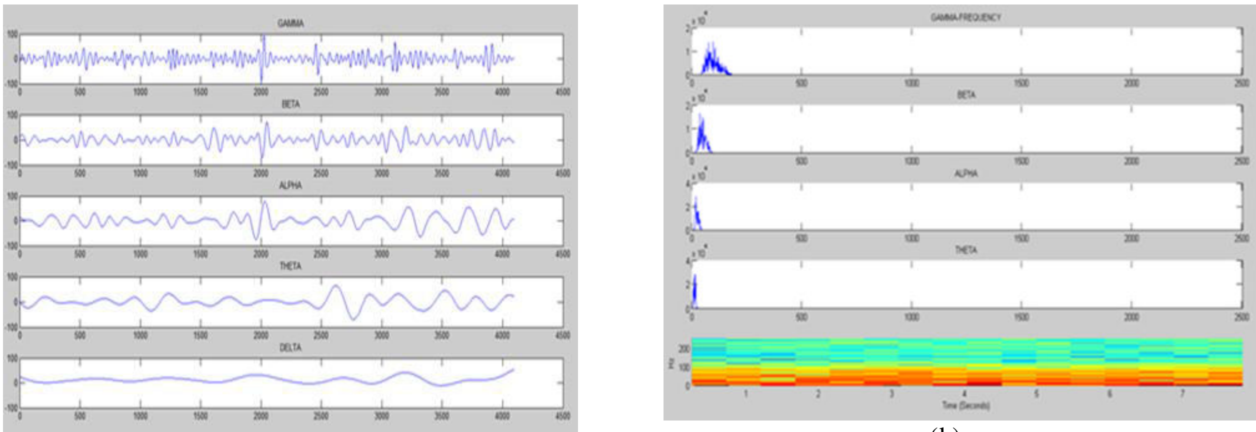


Fig 4: Generation of Raw EEG Signal from single Electrode

The raw recording of an EEG signal, as shown in Figure-4, is too complex to interpret. Frequency domain analysis, like many other signals, is widely used. Decades of EEG research have identified five major frequency bands for EEG signals and established a link between behaviour and neural activity in a specific part of the brain. Delta (0.54 Hz), Theta (48 Hz), Alpha (814 Hz), Beta (1430 Hz), and Gamma (3063 Hz are the most commonly used frequency bands. Figure-5 depicts a raw EEG signal from a channel as well as corresponding signals in different bands. It can be seen that low frequency Delta activity is the dominant wave in raw EEG, whereas high-frequency Gamma is almost noise-like with a small amplitude.



(a) (b)

Fig 5 (a) & (b): Separation of EEG bands & spectrogram of the same EEG signal

The spectrogram analysis also ensures the presence of line noise as shown in Figure-6. The spectrogram shows the time–frequency components of the EEG signal. By visual inspection, a qualitative discrimination of healthy and epileptic seizure can be seen in the figure below.The details of the computation of power of EEG Signals in various EEG Sub bands is as shown in the table-3 and the values obtained by performing the computation of different complexity measures from the EEG signals is as shown in the below table-4.The following Table-5 depicts the comparison of results obtained from this study with the few existing methods from the literature. All the methods are listed with their feature extraction methods, the classifier's used along with the performance metrics in the proposed and existing study. It is evident that the proposed method outperforms all the other existing methods listed in

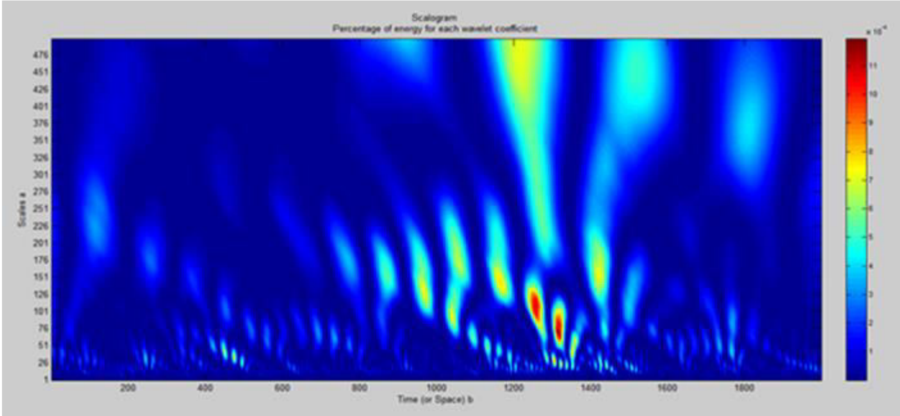


Fig 6: Spectrogram of an Epileptic EEG

Fig 6: Spectrogram of an Epileptic EEG

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

Table 3: Computation of Power of EEG Signals in various EEG Sub bands

EEG Band/ Feature	Central (C3)				Frontal (F4)				Parietal (P4)				Frontal (F3)			
	ZCR	SC	SR	SE	ZCR	SC	SR	SE	ZCR	SC	SR	SE	ZCR	SC	SR	SE
Sample 1	0.622	0.088	1.992	5.3981	0.0584	0.0863	1.9754	5.2619	0.0553	0.0744	1.9342	5.0385	0.0420	0.074	0.9807	5.0385
Sample 2	0.0012	0.0628	1.9321	5.95343	0.0018	0.0952	1.5423	2.8722	0.0343	0.0021	0.2311	2.0432	0.0143	0.055	0.9876	2.980
Sample 3	0.0916	0.1212	0.987	5.6044	0.0709	0.1102	1.9987	5.5409	0.0229	0.0458	1.9928	4.1449	0.0756	0.1104	0.801	3.9801
Sample 4	0.0100	0.0373	0.1322	3.6440	0.0033	0.0437	0.9921	3.7955	0.0167	0.0363	0.9786	3.6440	0.0032	0.032	0.8878	3.089
Sample 5	0.0033	0.0489	0.0343	3.9189	0.033	0.0443	1.0932	3.9773	0.0200	0.1921	1.0932	6.4532	0.143	0.564	2.323	5.5567
Sample 6	0.0900	0.1249	1.0323	5.7615	0.0967	0.1252	0.9812	5.0921	0.0967	0.1946	1.565	6.4519	0.0367	0.0979	1.3433	5.3064
Sample 7	0.0021	0.0032	0.0054	2.907	0.0034	0.087	0.878	3.0545	0.0212	0.0343	1.0989	3.098	0.034	0.0023	0.879	3.9704
Sample 8	0.0900	0.1178	0.0324	4.897	0.0433	0.1245	0.2432	5.3429	0.0900	0.1245	1.9878	5.4637	0.1100	0.1595	1.9956	5.5765
Sample 9	0.0167	0.1197	0.3432	3.5532	0.0167	0.0175	0.9980	2.8790	0.0367	0.0848	0.8790	4.0177	0.0233	0.0824	1.3432	4.9456
Sample 10	0.0987	0.1526	1.980	6.0060	0.0167	0.0956	1.9878	4.9978	0.1100	0.1900	1.980	6.2752	0.0377	0.1100	1.9801	5.5574
Sample 11	0.0833	0.1417	1.9801	5.980	0.0433	0.1465	NaN	5.9099	0.0833	0.1417	0.6743	5.8690	0.0767	0.917	2.3214	5.0768
Sample 12	0.067	0.1362	0.9802	4.4121	0.043	0.1321	0.8890	4.1765	0.0033	0.0554	1.231	3.8331	0.0033	0.0943	0.9565	4.4555
Sample 13	0.0433	0.0981	1.9322	5.2557	0.033	0.0297	0.9121	3.4978	0.0633	0.0987	1.0213	5.3167	0.0300	0.0637	1.3221	4.6784
Sample 14	0.0900	0.1724	1.0932	6.2905	0.0833	0.1456	0.9912	5.9235	0.1100	0.1808	0.9912	6.2519	0.0833	0.1207	1.923	5.6688
Sample 15	0.0367	0.0756	0.9912	4.9820	0.0500	0.1379	0.9012	3.77812	0.0700	0.0732	1.0912	4.7801	0.0500	0.0671	1.0921	4.7075

Table 4: Computation of Different complexity measures

The following Table-5 depicts the comparison of results obtained from this study with the few existing methods from the literature. All the methods are listed with their feature extraction methods, the classifier's used along with the performance metrics in the proposed and existing study. It is evident that the proposed method outperforms all the other existing methods listed in the table below. The accuracy of the proposed method is 99% which is better than the other existing methodologies listed below. Ocak [46] used approximated entropy for feature extraction combining with DWT. ANN classifier was used for classification. 96% accuracy was achieved with DWT they also experimented the performance of their model without DWT and the obtained accuracy was reduced as low as 73%. Their accuracy was best among the list of existing methods. Subasi [48] proposed the approach where they used DWT method to extract the features from EEG signals and Mixture of experts (ME) classifier which is a modular neural network architecture for supervised learning was used for classification and they obtained an accuracy of 94% was achieved. Rajaguru et.al. [49] and Rajendran et.al. [50] obtained accuracy of 93% and 94% using ELM and FMSVM methods respectively. From the table it can be concluded that our model exhibits better performance in all of the parameters considered for evaluating the model. But it should be noted that the gained results from each work are not directly comparable as the datasets used for experimentation differ.

Author	Feature	Classifier	Acc (%)	Sensi (%)	Speci (%)	Recall (%)
Ocak[46]	Apen+ DWT	ANN	96	N/A	N/A	N/A
Chu et.al. [47]	Phase Locking Value	SVM	N/A	82	83	N/A
Subasi[48]	DWT	Mixture of expert (ME)	94	94	95	N/A
Rajaguru et.al. [49]	---	ELM	93	98	94	N/A
Rajendran et.al. [50]	AR-Burg	FMSVM	94	92	93	N/A
Proposed Method	Cohens Distribution	Fuzzy C-Means +ANN	99	99	98	99

Table 5: Comparison of the proposed method's performance with previous work

The performance metrics values that are presented in the above table is shown graphical in the following section. Basically we are taking into consideration the accuracy, sensitivity and specificity values of all the methodologies discussed in the previous section. The figure-7 below depicts the accuracy values of all models, and it can be observed from the graph that our approach provides better accuracy in comparison with other models. The figure-8 (a) and (b) shows the sensitivity and specificity values of all the models considered.

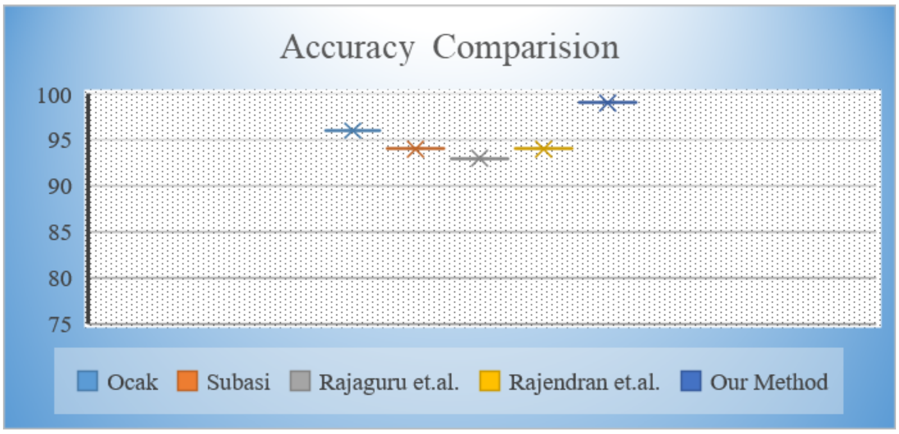
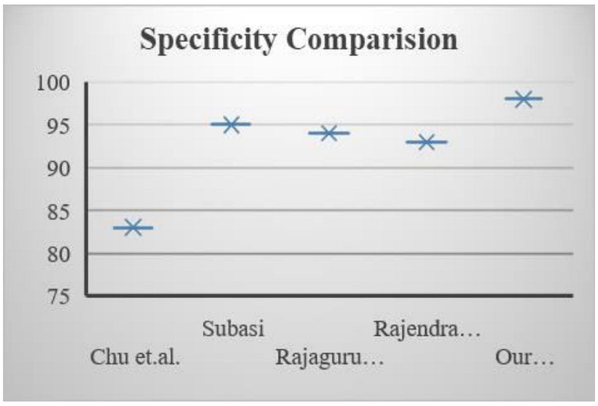
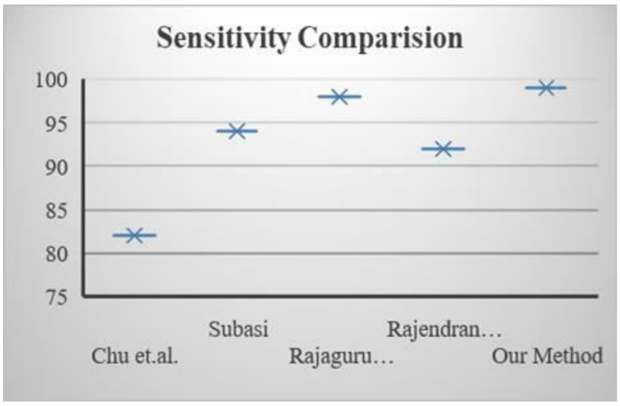


Figure 7: Accuracy Comparison of different Studies



(a)



(b)

Figure 8 (a) and (b): Specificity and Sensitivity Comparison of different Studies

6.Conclusion

In this paper, we demonstrated how to use the most typical TFDs from Cohen's class to determine the nonstationary properties of an EEG signal in order to classify epilepsy. Relevant features are extracted based on the t-f plane's signal energy distribution. Fuzzy-C means clustering was applied to the collected dataset to improve the result, which was then labelled using an ANN classifier. The proposed model outperformed many conventional methods with a 99% accuracy rate. The developed system has the capability of being used in clinical practice. It will be useful in diagnosing and classification of the disease, which is epilepsy. Soon, our focus will be on using other classifiers and creating a practical application that will benefit epileptic patients because access to a neurologist is almost impossible in developing countries. The system will also be useful in determining the stage of diseases such as mild cognitive impairment (MCI), epilepsy, dementia, and Alzheimer's disease so that early disease diagnosis will help effectively treat the patients and reduce casualties.

Acknowledgment

We are grateful for the support given to this research by Visvesvaraya Technological University, Jnana Sangama, Belagavi. We also like to thank PA College of Engineering, Mangalore for providing all of the resources necessary to finish this project, as well as Bharati University in Sangli, Maharashtra, India, for providing the EEG dataset.

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