Automated diagnosis of Epilepsy from EEG signals using Ensemble Learning approach

Abstract

Epilepsy is generally considered as a group of neurological disorders characterized by epileptic seizures. It is often confirmed with an electroencephalogram (EEG). EEG signals are non stationary, nonlinear and non Gaussian. In order to tackle this problem in this paper, we have used three different approaches for feature extraction namely wavelet based entropy (Approximation entropy, sample entropy, permutation entropy), Nonlinear features (Hurst exponent, Higuchi Fractal Dimension) and Higher Order Spectra (Mean, Normalized entropy1 and Normalized entropy2). Further multiclass classification using indirect approach with One vs One method is employed using heterogenous ensemble learning approach. Entropy features are used for classifying normal and interictal class using K-Nearest Neighbor . Higher Order Spectra features are used for classifying normal and ictal class using Support Vector Machine with Radial basis function as kernel and Non linear features are used for classifying interictal and ictal class using NaiveBayes. Final verdict is taken by meta classifier with meta learning algorithm Stacking Correspondence Analysis and Nearest Neighbor **(SCANN).** The proposed method outperforms the existing methods in literature interms of sensitivity and specificity.

Keywords: Ensemble learning, Higher Order Spectra, Entropy, Nonlinear, Stacked learning

1.0 : INTRODUCTION

Epilepsy is a medical condition where a person experiences seizures due to some disorder in the brain. Involuntary movements of body, unconsciousness are the general symptoms observed during the occurrence of a seizure [1]. These seizures generally recur and last for a period of time. Two thirds of patients achieve sufficient seizure control from anti-convulsive medication [2]. Almost 30 % of epileptic patients suffer from pharmacoresistance which is associated with dependent behavior, social isolation, psychological problems and low quality life [3]. Head injuries, brain tumors, strokes may cause epilepsy. Epileptic seizures can occur for long periods of vigorous shaking and also they tend to recur [4]. ILAE Commission for classification of Epilepsies divided epilepsies into three categories as genetic, structural/metabolic and unknown cause [5].

Epilepsy can be detected and diagnosed using neuroimaging and electroencephalogram [6]. The electroencephalogram is generally a non-stationary and nonlinear signal.

EEG signal characteristics such as amplitude, frequency etc. gets deviated from normal signal during the occurrence of seizure[7].The detection of such abnormalities generally requires skilled doctors and is also a time consuming process[8].Predetermination of epilepsy can help in controlling this disorder and thus automatic detection of seizure is required[9].For this wavelet coefficients (approximation and detail coefficients) have to be computed and novel features which can help for automatic detection must be extracted and some of the classifiers like support vector machine classifier ,k –nearest neighbor classifier ,random forest classifier ,maven classifier ,idpa classifier ,forest tree classifier can be employed. Majority is considered from all classifiers output and these are fed as input to meta classifier which does the task of final classification and detection of seizure .Features such as entropy measures, nonlinear features and higher order spectra were extracted. Power spectrum cannot give any information about the phase spectrum. In order to know about the phase spectrum higher order spectra characteristics have been employed.

1.1 : LITERATURE SURVEY

U.RajendraAcharya et al (2012) proposed a Computer Aided Diagnostic technique (CAD) which can be easily developed into an automatic seizure monitoring software application. Nonlinear features (Hurst exponent, Fractal Dimension), Entropies (Approximation entropy, Sample Entropy), Higher order spectra are extracted as features and Anova Test is used for selecting significant features .Six classifiers (Decision Tree, Fuzzy Sugeno classifier, Gaussian mixture model, K-Nearest neighbor, Support Vector machine, Radial Basis Probabilistic Neural Network), are used for classification purpose and in case of Fuzzy classifier a classification accuracy of 99.7% is obtained.

Gang Wang*(2015) proposed a method which is based on Partial Directed Coherence (PDC) for feature extraction which are used as a part of automatic seizure detection whose application reflects the physiological changes of brain activity before and after the occurrence of seizure .In this method, multivariate autoregressive (MVAR) model was first established for a moving window and then the direction and intensity of information flow based on PDC analysis was thus calculated. Finally, according to features of epileptic seizures, the outflow information is taken as input to a support vector machine (SVM) classifier for classifying into healthy and ictal EEG signals.

N. Kannathal, U.R. Acharya, C.M. Lim, P.K. Sadasivan(2005),employed various set of entropy features namely Approximation Entropy, Renyi'sEntropy,Shannon's entropy and Kolmogorov-Sinai Entropy .Out of all these features Kolmogorov entropy differentiated the healthy and epilepsy signals (p-value < 0.05) accurately .Using Adaptive Neuro Fuzzy Inference System (ANFIS) classifier a classification accuracy of around 90% is obtained .

ChastineFatichah et al (2014) proposed a method for automatic detection of epileptic seizures in multichannel EEG in which healthy, ictal and inter ictal signals are studied with the help of Higher Order Spectra (HOS).The measures obtained were able to distinguish epileptic signals from normal and interictal EEG with high confident level.

K. Polat, S. Gunes (2007) developed an epilepsy detection algorithm by combining Decision Tree (DT) classifier and Fast Fourier Transform technique (FFT) .FFT Based Welch method is used for extracting power spectral density features from EEG recordings. DT classifier reported a classification accuracy of 98.72% in this method.

A new method was proposed by WaqasRasheed(2013), states that MEG (magneto encephalography) offers greater accuracy in epilepsy detection leading to higher spectral resolution when compared with EEG (electroencephalography) and to visualize epilepsy an automated framework using open source solutions has been proposed and capability of the proposed framework is demonstrated with a case of epilepsy surgery.

A methodology is proposed by D. PuthankattilSubha (2010) for automatic detection of healthy, inter ictal and ictal conditions from recorded EEG signals. The wavelet transform is used for the feature extraction and from the decomposed wavelet coefficients statistical parameters are obtained .The Generalized Feed Forward Neural Network (GFFNN), Multilayer Perception (MLP), Elman Neural Network (ENN) and Support Vector Machine (SVM) are used for the calculation and performance of the proposed system in terms of classification accuracy, sensitivity, specificity and overall accuracy was evaluated. The effect of different events on EEG signal and different signal processing techniques used for extracting the hidden information from the signal are discussed in [17]and Linear ,Frequency domain ,time-frequency and nonlinear techniques like correlation dimension (CD),largest Lyapunov exponent (LLE),Hurst exponent (H),different entropies ,fractal dimension (FD),Higher Order Spectra (HOS),recurrence and phase space plots are discussed in detail with the help of a typical normal EEG signal.

U.R. Acharya, R. Yanti, J.W. Zheng, M.M. Krishnan, J.H. Tan, R.J. Martis, C.M.Lim(2013) proposed a technique in which Continuous Wavelet Transform(CWT) is applied to EEG dataset. From CWT plot, Higher Order Spectra (HOS) and texture features are extracted and then significant features are fed to four different classifiers namely k-nearest neighbor classifier (KNN), DT, SVM, PNN.SVM along with RBF yielded highest classification accuracy of 96%, specificity of 97% and sensitivity of 96.9%.

An automatic system that detects seizure onsets and thus allow patients or people around them to take necessary precautions is proposed by Chua K. C (2008). and this uses nonlinear features motivated by the higher order spectra (HOS) which differentiate between normal, inter ictal and epileptic EEG signals is proposed. The features are extracted from the power spectrum (provides only magnitude spectrum but not phase spectrum) and bispectrum. By feeding them to a Gaussian mixture model (GMM) classifier the performance is studied.

VairavanSrinivasan(2007) proposed an automated epileptic EEG detection system which is based on neural networks that uses approximate entropy (ApEn) as input feature. .ApEn is a statistical parameter which measures the predictability of current amplitude values of physiological signal based on its previous amplitude values .The fact used in the paper is value of ApEn drops sharply during an epileptic seizure and two types of neural networks namely Elman and probabilistic neural networks are used .The overall accuracy values as high as 100% was achieved by the proposed system.

Discrete Wavelet Transform (DWT) is adopted to separate normal and epileptic EEG signals by H. Ocak (2009).Approximation entropy obtained classification accuracy of 96% when applied on wavelet coefficients.

MATERIALS AND METHODS

2.0 : EEG Dataset:

The EEG signals used in this work are taken from University of Bonn database. The entire database is divided into five sets Z, O, N, F, and S. Each set comprises of 100 EEG signals each with total time period of 23.6 sec. The sampling rate of data is about 173.61 Hz. Sets Zand O consists of recordings which are obtained through external surface electrodes under normal eyes in open and closed conditions .While the sets N,F,S are recorded with the help of intracranial electrodes which are exhibiting interictal and ictal epileptic activities. While the set N in particular readings are obtained from within epileptic zone during seizure free intervals which indicates focal interictal activity and set F recordings are obtained from hippocampal formation of opposite hemisphere portion of brain which indicates non focal interictal activity All EEG signals are recorded with the same 128 channel amplifier system with an average common reference, with 12 A/D conversion bit rate of 12.

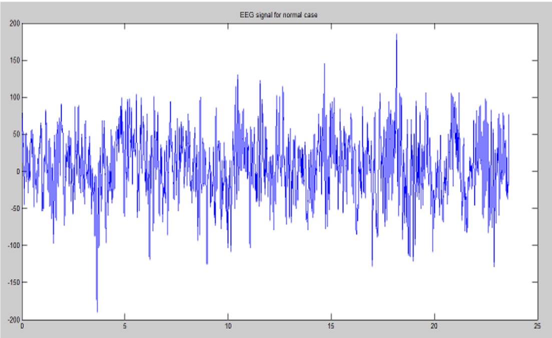

Figure (1) Plot of normal EEG signal

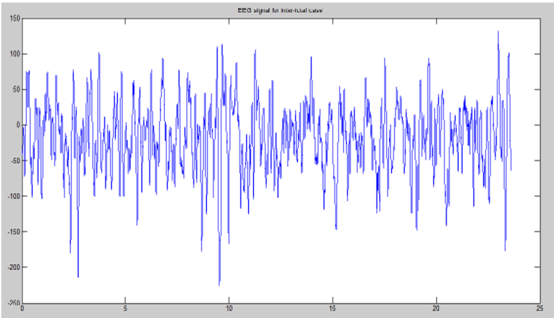
Figure (2) plot of EEG signals interictal case

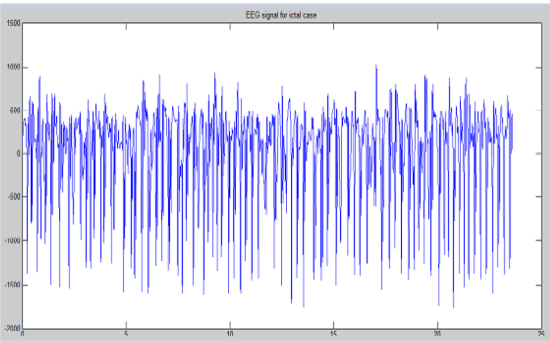

Figure (3) plot of EEG signals Ictal case

Methodology:

Figure (1) depict the block diagram of the proposed method. Three base classifiers prediction fed in to Meta learning algorithm and based on stacked learning principle final label for the test input is predicted by the Meta classifier.

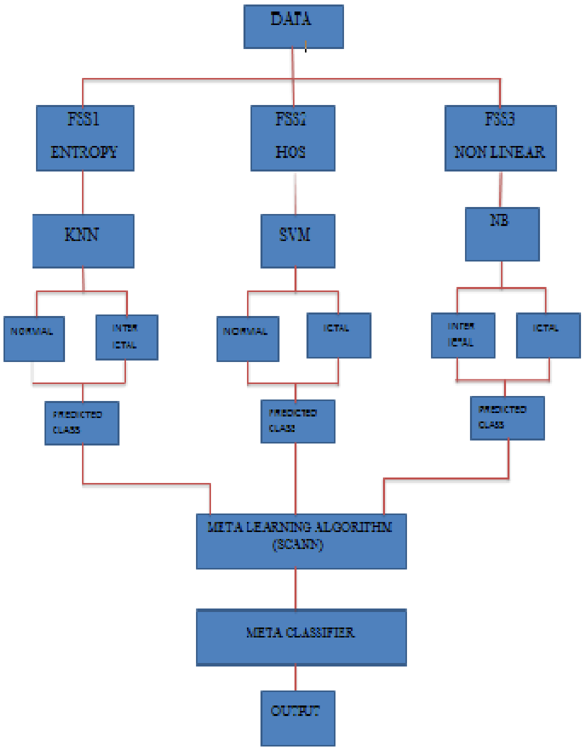

Figure (4) Block diagram of the proposed method

2.1 Discrete Wavelet Transform (DWT): Wavelet Transform is a powerful signal processing technique used to overcome the drawbacks of Fourier transform by providing efficient time and frequency localization. The DWT is performed by passing the discrete time signal through a series of low pass and high pass filters followed by decimation by factor two which gives out approximation and detail coefficients respectively. This is called as Mallat algorithm and it is important to note that the two filters used are related to each other and they are known as Quadrature Mirror Filters. Let ψ(x) is basis function or mother wavelet .All functions which are used in transformation derived by performing scaling and translation operations on mother wavelet and Φ(x) denotes a scaling function.

Wavelet series expansion of a function f(x) is given by

$$f(x) = \sum_k c_{j_0}(k)\phi_{j_0,k}(x) + \sum_k \sum_{j=j_0}^{\infty} d_j(k)\varphi_{j,k}(x) \qquad (1)$$

Where

j_0 = arbitrary starting scale

$c_{j_0}(k)$ =approximation coefficient

$d_j(k)$ =detail coefficient

DWT transform pair is given by following equations

$$W_\emptyset(j_0,k) = \frac{1}{\sqrt{M}}\sum_x f(x)\emptyset_{j_0,k}(x) \qquad (2)$$

$$W_\varphi(j,k) = \frac{1}{\sqrt{M}}\sum_x f(x)\varphi_{j,k}(x) \qquad (3)$$

The wavelet used for obtaining wavelet coefficients in this paper is Daubechies 10. The obtained wavelet coefficients (approximation) are further analyzed by entropy method to extract features.

2.2: Entropies:

Approximation Entropy: This was first proposed by Pincus et al.[25, 26] It is used to measure the regularity of data. ApEn value increases with increase in complexity or irregularity of data .A regular and a predictive time series will result in lower ApEn value while an irregular time series will result in higher non-negative value. For calculating ApEn,consider a time series x(n),n=1,2,3……..N.A series of patterns of lengths 'e'(embedding dimension which is the smallest integer for which the patterns do not intersect with each other)is derived from x(n).ApEn is defined by

$$Apen(e,r,N) = \frac{1}{N-e+1}\sum_{i=1}^{N-e+1} logC_i^e(r) - \frac{1}{N-e}\sum_{i=1}^{N-e} logC_i^{e+1}(r) \qquad (4)$$

where index r is a fixed parameter which sets the tolerance of the comparison and C_i^e(r) is the correlation integral defined by

$$C_i^e(r) = \frac{1}{N-e+1}\sum_{j=1}^{N-e+1} \quad (r\|x_i - x_j\|) \qquad (5)$$

where _ is the Heavyside step function .We choose r as 0.2 times that of standard deviation of the time series and e as 1.

Sample Entropy:

This was proposed by Richman et al., [27]. It is also used to measure the complexity and regularity of the time series data .It also measures self-similarity. Lower SampEn values accounts for high self similarity and higher values are registered for more irregular data.SampleEn is the better measure compared to the ApEn. Epilepsy will cause a reduction in both these entropy parameters. For calculating the sample entropy, runs of points matching are stored in counters A (k) and B (k) for all lengths k up to e. Sample Entropy is defined by the formula

SampEn (k, r, N) $=ln(\frac{A(k)}{B(k-1)})$ ……………. (6)

where k=0, 1, 2.........e-1 and B (0) =N, the length of the input series.

Permutation Entropy:

It is a measure of chaotic and non-stationary time series signal in the presence of dynamical noise. It is used to estimate the complexity of the time series. The dynamics associated with the EEG signal can be derived by assessing the presence and absence of permutation patterns of varying elements in the given time series signal. At high frequencies, Permutation entropy elevates with asymmetry of the time series while at low frequencies, the permutations corresponding to peaks and troughs observed are seldom.

Permutation Entropy (PE) is defined by

$PE = -\sum_{j=1}^{n} p_j log p_j$ ……………… (7)

where$p_j$represents relative frequencies of the possible sequence patterns, n indicates permutation order of n≥2.The main advantage of this method is robust, efficient and produces fast results irrespective of noisy data. It is suitable for non-linear processes.

Non-Linear Parameters:

Non-linear models are used to understand complex physiological phenomena such as abrupt transitions and chaotic behaviour. Sleep stages and sustained fluctuations of automatic functions like temperature, bloodpressure, electroencephalogram (EEG), etc., can be described as chaotic process. The EEG signals are highly subjective and the information about the various states may appear at random in the time-scale. It is far more superior to the traditional linear methods such as Fourier transforms and Power spectral analysis.

Hurst exponent: It is a measure of self- similarity, predictability and the degree of long range dependence in a time-series. It also measures smoothness of a fractal time-series based on asymptotic behaviour of rescaled range of the process. According to Hurst's generalized equation of time series, Hurst exponent is given by

$H = \frac{\log(\frac{R}{S})}{\log(T)}$………… (8) where T is the duration of the data sample and R/S is the corresponding value of rescaled range. R is the difference between the maximum and minimum deviation from the mean while S is the standard deviation .Hurst exponent is estimated by plotting (R/S) versus T in log-log axes. The slope of the regression line approximates the Hurst Exponent.

Higuchi's fractal dimension: Fractal Dimension (FD) is a powerful tool for transient detection. It is used to measure the dimensional complexity of biological signals. It gives an indication of how completely the fractal appears to fill space. This algorithm was proposed by Higuchi for finding FD of EEG signals. EEG segment was assumed as a time sequence x(1),x(2),.........x(n).

Time series x (k, m) may be defined by

x(k,m)={x(m),x(m+k),x(m+2k)......,x(m+int[(N-m)/k]k)} where m=1, 2, 3........k and int [] is an integer function. Here m implies the initial time value and k is the discrete time interval between the points.

The length $L_m(k)$ for each of the k time series or curves x_m^k is defined by

$$L_m(k) = \frac{\sum_{i=1}^{\lfloor a \rfloor} |x(m+ik) - x(m+(i-1)k|(N-1)}{\lfloor a \rfloor k} \text{ ---- (9)}$$

where n is the total length of the data sequence x. The mean value of the curve length $L_m(k)$ is calculated for each k by averaging $L_m(k)$ is obtained.A plot of log(L(k)) versus log(1/k) was made and FD was estimated from the slope of least squares linear best fit from the plot.Thus FD can be defined as

FD=log (L (k))/log (1/k) ----- (10)

HIGHER ORDER SPECTRA:

HOS is efficient in the analysis of non-linear and non-stationary processes. Third and higher order moments and cumulants come under the category of HOS. The spectrum of the third order cumulant is called the bispectrum

$$B(f1, f2) = E[X(f1)X(f2)X^*(f1+f2)]$$

Where X(f) is the Fourier transform of the signal and E[.] is the expectation operator. It has two frequency components unlike the power spectrum which has a single frequency component. The parameters are calculated in the principal region Ω as the bispectrum exhibits symmetry property.

Mean magnitude of the bispectrum is given by

$$M_{avg} = \frac{1}{L} \sum_{\Omega} |B(f1, f2| \text{ ----- (11)}$$

Normalized Bispectral entropy $P_i = -\sum_i p_i \log p_i$ where

$$p_i = \frac{|B(f1, f2)|}{\sum_{\Omega} B(f1, f2)} \text{ ---- (12)}$$

Normalized Bispectral squared entropy

$$p_n = -p_n \sum_n \log p_n \quad \text{where} \quad p_n = \frac{|B(f1, f2|^2}{\sum_{\Omega} |B(f1, f2|^2} \text{ ---- (13)}$$

Classification:

K – Nearest Neighbor Classifier -Base Classifier 1:

It is a non parametric method used for classification and regression in pattern recognition [25].Input samples in both the cases consists of k closest training examples in the feature space. In K-NN classification, object is classified by a majority vote of its neighbors, output is assigned to the class which is most common among its k nearest neighbors. The training data is a vector in a multidimensional feature space, each with a class label .It consists of two phases namely training phase and classification phase. Training phase of algorithm consists only of storing feature vectors and class labels of training samples. In classification phase, k is a user defined constant and a query is classified by assigning the label which is most frequent among the k training samples nearest to that query point. Distance metrics such as Euclidean distance (continuous variables) and Hamming distance (discrete variables) is generally used. If the distance metric is learned with specialized algorithms such as Neighborhood components analysis k-NN can be improved significantly. An extended k-NN method termed ENN [24] makes use of two way communication for classification.

Base Classifier 2 -Support Vector Machine Classifier: SVM [22] classifies the data by finding the best hyper plane class and is used when binary class classification has to be adopted. The one with the largest margin between two classes is the best hyper plane for an SVM where margin refers to the maximal width of slab parallel to the hyper plane which has no interior data points.

Training data is considered as standard reference to classify test data which is taken as input into one of the output classes. Group is a vector which consists of labels of binary classes.

The data for training is a vector x_i along with their features or categories y_i.The equation of hyper plane for some dimension d, xi ϵR^d and y=±1.

<W, x>+b=0,

Where wϵR^d, <w, x>is dot or inner product of w and x, b is real.

For best separating hyper plane find w and b that minimize ||w|| (norm) for all data points (x_i, yi),

y_i (<w, x>+b) ≥1.

The support vectors are the x_i on the boundary, those for which yi (<w, x>+b) =1.

Base Classifier 3 Naive Bayes Classifier:

Naïve Bayes method is a supervised learning method which is based on application of Bayes theorem. The features are assumed to have strong independency among them.

Naïve Bayes model is a conditional probability model. Consider ‘n’ features x1, x2, x3…xn then the probability that a sample vector belongs to one of the ‘k’ classes is

Class	NORMAL Mean±SD	INTER ICTAL Mean±SD	ICTAL Mean±SD
Hurst Exponent	0.6221±0.0673	0.5715±0.0780	0.3467±0.1171
Higuchi Fractal Dimension	1.5903±0.1038	1.3247 ±0.0807	1.4417±0.1675

Table 2:

$$p\left(\frac{c_k}{x}\right) = p(c_k) * \frac{p(\frac{x}{c_k})}{p(x)}$$

Posterior = (prior * likelihood) / (evidence);

Ensemble learning:

Result Discussion: Table (1) (2) and (3) depicts the feature vector values for the 3 labels namely normal, interictal and

Class	NORMAL Mean±SD	INTER ICTAL Mean±SD	ICTAL Mean±SD
Sample Entropy	1.6704 ±0.1699	1.1274 ±0.1549	1.1361±0.3045
Approximation Entropy	1.7881±0.1645	1.2557±0.1513	1.4816±0.2681
Permutation Entropy	1.6577±0.0414	1.5229±0.1074	1.4507±0.0907

ictal. Figure (2), (3) and (4) depicts the scatter

Table 3: Results of various HOS feature vector values for normal, interictal and ictal EEG signals

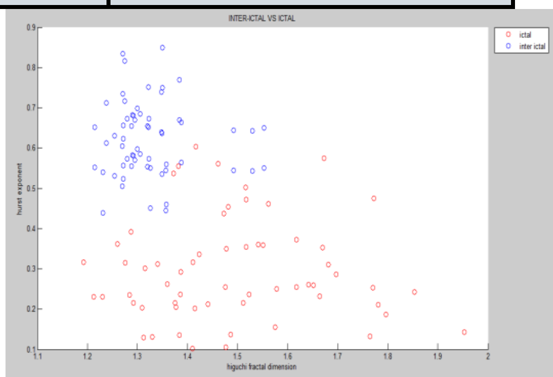

Figure 5 : Scatter plot of nonlinear features

Table 1:Result of various entropy feature vector values

Table 3: Results of various Higher Order Spectra feature vector values for normal, interictal and ictal EEG signals

FEATURE	NORMAL Mean±SD	INTER ICTAL Mean±SD	ICTAL CLASS Mean±SD
Normalised Entropy	0.5696±0.517	0.5629±0.0406	0.5771±0.0183
Normalised square Entropy	0.3526±0.0585	0.3370±0.0676	0.4162±0.0477
Mean Average	$2.3304*10^{10}$±$1.036*10^{11}$	$6.0248*10^{8}$±$8.3187*10^{8}$	$3.299*10^{11}$±$3.4867*10^{11}$

Kannathal et al. [28]	Entropy Measures – ANFIS	92.2	The Bonn University – Germany
Chua et al. [29]	S1,S2 and bispectrum magnitude – Gaussian mixture model	93.1	The Bonn University – Germany

Chua et al. [30]	Magnitude+PhEn, S1, and S2-GMM Power spectrum+GMM	93.1	The Bonn University – Germany
Acharya et al. [31]	Non-linear parameters – ApEn, Gaussian mixture model	95	The Bonn University – Germany
Acharya et al. [32]	ApEn, SampEn, PhEn, S1, and S2 – Fuzzy	98.1	The Bonn University – Germany
Acharya et al. [33]	Entropies+HOS+Higuchi FD+Hurst-Fuzzy	99.7	The Bonn University – Germany
Acharya et al. [19]	CWT+S1+S2+PhEn+Texture-SVM	96	The Bonn University – Germany
Acharya et al. [34]	RE+RQA-SVM	95.6	The Bonn University – Germany
Martis et al. [35]	SEN-EMD-C4.5	95.3	The Bonn University – Germany
Martis et al. [36]	SampEn-DT	95.7	The Bonn University – Germany
Song and Lio [37]	SampEn-ELM	95.7	The Bonn University – Germany
PROPOSED METHOD		98	The Bonn University – Germany

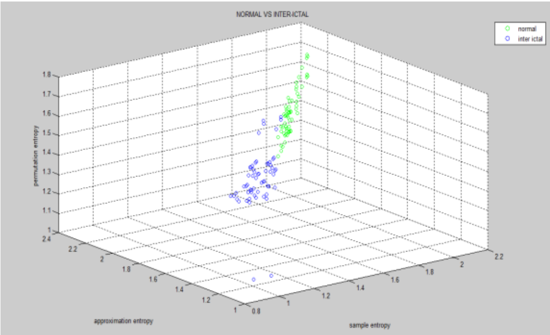

Figure 6: Scatter plot of entropy features

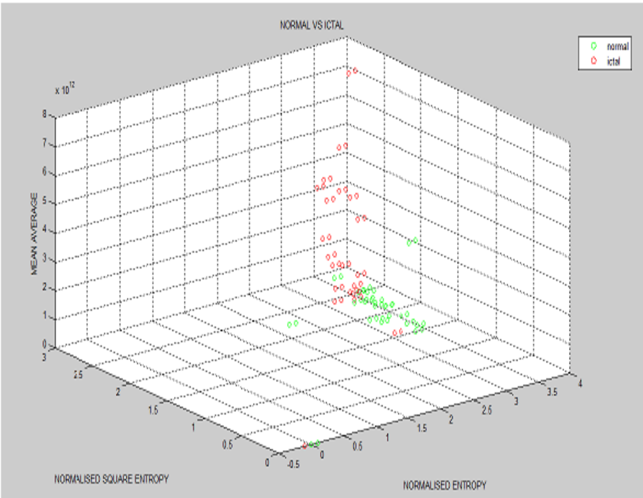

Figure 7: Scatter plot of HOS features

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