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Parameter-Selective Based CAD System For Epileptic Seizure Classification

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Abstract

Features are the crucial basis for detection, classification and regression tasks in biomedical signal processing and are one of the key elements in the data analysis process. The objective of this work is to conduct a preliminary evaluation identify appropriate specific features from a large set of candidate features for predicting seizures. The main implication of this work is to design a Parameter Selective based CAD system, so the authors have laid emphasis on selection of relevant features which are less related, balanced and converge to best solution. These promising, prominent, statistically analyzed features are used for classification of brain signals into ictal and normal conditions. Experimental results show that the resulting attributes when used for classification results in 100 % classification accuracy with CSFV, 99.5% with RSFVand 98.5% classification with SFV with MLPNN as classifier. The net increase in percentage classification accuracy is 1.5% with MLPNN, 2% with SVM and 1.8% with KNN with CSFV when compared to efficiency obtained with SFV.

Keywords: Electroencephalogram (EEG), Epilepsy, Computer Aided Diagnostic system, Hjorth Parameters, SVM, MLPNN, KNN.

Introduction

The electroencephalogram is defined as electrical activity picked up by metal electrodes and conductive media from the scalp surface. The amplitude of an EEG signal typically ranges from about 1 to 100 μV in a normal adult, and approximately 10 to 20 mV when measured with subdural electrodes [1]. The standard method for the scalp electrode localization is the international 10-20 electrode system. The “10” and “20” represent actual distances between neighboring electrodes and measured as 10% or 20% of the total font-back or right-left distance of the skull. [2].

EEG measures local current flowing inside the brain that flow during synaptic excitations of the dendrites in the cerebral cortex. The electrical dipoles are created between soma (body of neuron) and apical dendrites that are caused due to the differences of electrical potentials [3]. With abnormal synchronous increase in the neural activity, number of peaks occurs in normal EEG signal. Epilepsy is a crucial neurological disorder which results in epileptic seizure caused by abnormal electrical discharges from the brain. Around 1% of the world's population is affected by this disease. These seizures occur without any warning and mostly lead to uncontrollable movements, convulsions and loss of conscious and contend the patient to increased possibility of accidental injury and even death. So, monitoring the person with epilepsy from being exposed to the danger is among the basic death to life transformation solutions [4].

In clinical routines EEG is used as a diagnostic tool for practical methods. Its higher temporal resolution gives EEG an edge to be considered in applications such as epilepsy seizures detection, sleep disorders and BCI [5]. One of the challenges in the current biomedical research is to classify electroencephalographic signals as accurately and efficiently as possible. EEG data is voluminous and visual analysis of these signals is exhaustive, time consuming and is prone to subjectivity constraint (interpretation by different specialist may result into inconsistent and inappropriate diagnosis). As a result the requirement of developing an automated computer aided classification system for proper diagnosis and treatment is of utmost importance. Typical patterns of the EEG signals are used to identify and classify different neurological diseases and are extensively reported in [6-8]. An efficient way to analyze the signals (with volume and complexity) is feature selection [9-11], which results in dimensionality reduction by selecting a subset of features from the whole set of inputs.

Several methods are reported in the literature for extracting quantitative features from EEG signals. Iasemidis and Sackellares [12] applied nonlinear dynamical techniques methods based upon the principal Lyapunov exponent for predicting seizures. Lehnertz and Elger et al.[13] employed nonlinear dynamics to larger datasets, greater numbers of patients for seizure prediction. Lyapunov exponents were further expanded by Güler & Übeyli [14]. Features based on time frequency analysis are presented in Subasi [15] and Tzallas et al. [16]. In [17] Guerrero-Mosquera, used stochastic analysis approach for feature extraction and authors in [18] have used hybrid feature selection technique. Classification algorithms that have used features such as standard deviation, median arithmetic mean, zero crossing value [19-20], wavelet transform [21-22], rényi entropy spectral entropy [23-24], are reported in literature.

As the prima facie of this work is to design a Parameter Selective (PS) based CAD system, the authors have laid emphasis on selection of relevant features, after stringent statistical analysis which are less related, balanced and converge to best solution to classification problem. Feature set constitutes Signal Feature Vector (SFV) and set of prominent features after analysis is framed as Reduced Signal Feature Vector (RSFV).After analysing non linear features, combined signal feature vector(CSFV) is framed. The designed CAD system results from classification analysis for SFV, RSFV and CSFV as feature vectors and with three classification algorithms. The rest of the paper is organized as follows: In Section II the research methodology, data acquisition and data processing is explained. Section III elaborates the Parameter Selective (PS) module detailing the composition of SFV, RSFV, CSFV and classifiers used for classification. Section IV, illustrates the results and discussions while concluding remarks appear in Section V.

Methodology

Dataset

EEG data set used in this paper consists of EEG recordings taken from Epileptologie at the Universitat Bonn, German [25]. The data set of different classes contains 100 single-channel EEG segments, with segment duration of 23.6s and each segment has 4096 samples. The first set corresponds to the five healthy normal subjects relaxeing in an awaken state with eyes open. The second set comprises of epileptic EEG signal recorded from five different epileptic patients, during the occurrence of the epileptic seizures. The EEG signals are recorded with 128-channel amplifier system, with the spectral bandwidth of 0.5 to 85 Hz. The signals are digitized after passing through 12-bit analog-to-digital conversion, the data are sampled at the rate of 173.61Hz with band pass filter settings (12 dB / octave).

Proposed Technique

The development of PS based CAD system is a two stage classification system. The first stage is feature extraction and selection and second stage comprises of classification technique, employing MLPNN, KNN, and SVM classifier. The flow diagram of the proposed methodology is depicted in Figure 1.

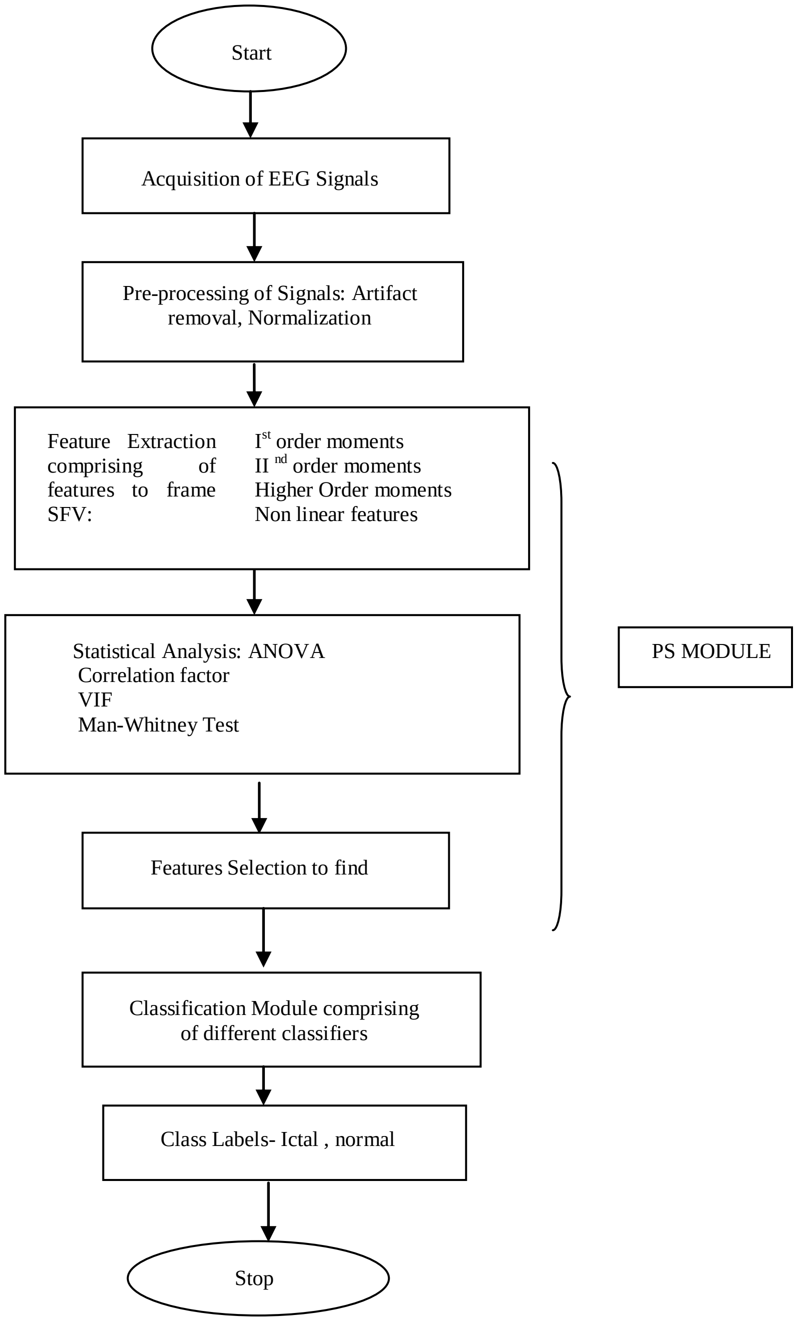


Figure 1: The structural flow diagram of the proposed methodology for the design of PS based CAD system

Preprocessing of the acquired signals is of prime importance and primarily is a two step formulation: Artifact Removal: EEG recording may be contaminated by biologically generated signals from human body and signals from power line, electrode movement etc.[26]. The presence of this kind of "artifacts" makes it difficult to discriminate between brain signals and noise. To differentiate these two kinds of signals, a preprocessing step is essential to obtain clean signals before the detection task. Normalization, All the extracted features were normalized in the range of [0, 1] by using min–max normalization procedure in order to avoid the bias caused by unbalanced feature values[27].

Processing

In this research work, authors have utilized five key steps in designing of PSS based CAD system. The first step involves the extraction of features to achieve linear separability for epileptic and non epileptic cases. Feature extraction approach comprises of first order cumulants, second and higher order features, and features representing non linear dynamics of the raw data. In parameter selective system, the features are extracted and selected based on expertise, observations, and our understanding of EEG signal characteristics framing SFV.

The second step involves the evaluation of these features on the basis of F ratio using ANOVA test with the significance value of less than 0.05 .The importance of resultant feature set is verified by calculating the Importance parameter in terms of VIF. A non-parameteric Man-Whitney test is also performed to strengthen the viability of RSFV. Classification is performed with three classifiers MLPNN, SVM and KNN with RSFV. The EEG signals are chaotic and non linear in nature, so the third step leads to extraction of non linear features (NLFV) to describe the non linearity exhibited by EEG signals. The fourth step evaluates the importance of these non linear features and framing of combined set of feature vector (CSFV). The final step results in evaluating the performance of the classifiers with SFV, RSFV, and CSFV in terms of Accuracy, Specificity and Sensitivity and is tabulated as Confusion Matrix. These five steps ensure the soundness and robustness of the design of PS based CAD system for seizure classification

PS Module

Feature Selection Module

Parameter Selective (PS) module includes feature extraction and features selection modules. Feature extraction involves finding a set of information that include the hidden information embedded in the signals and take into account the important properties such as dimensionality, noise, and time information, non-stationarity, set size and so on. These extracted features constitute a novel way of expressing the data, that can be continuous, binary, discrete and categorical and may represent attributes of signal. The cumulates can be computed as non-linear combinations of moments as

$$C_1^x = m_1^x \tag{5}$$

$$C_2^x = m_1^x(i) \tag{6}$$

$$C_3^x = m_1^x(i, j) \tag{7}$$

$$C_4^x = m_4^x(i, j, k) - m_2^x(i)m_2^x(j-k) - m_2^x(k-i) - m_2^x(k)m_2^x(i-j) \tag{8}$$

Where C_n^x are the first four order cumulants and $m_1^x, m_2^x, m_3^x, m_4^x$ are the first four order moments [28].The first and second order statistics such as mean, mode, median standard deviation have gained significant importance in the area of biomedical signal processing. For non linear signals, first two order statistics are not sufficient to represent the signal, so we have gone for higher order cumulates in this research work. To represent chaotic nature of EEG signals Hurst exponents and Hjorth parameters (Activity, Mobility and complexity) are taken into account. All the initial twenty features comprising of cumulates and non linear features are reported with a short explanation of all the attributes in the table 1.

Feature selection Module

We model all the features of a patient EEG signals into a single vector, (in total of 100 vectors of one class) forming a SFV, in order to understand the contribution of each feature for seizure recognition. Feature selection involves choosing the best feature amongst the entire initially chosen relevant features. The motivation behind this research work is dimensionality reduction of the SFV to achieve prominent set of features to frame RSFV. The main focus after feature extraction is on removing irrelevant and redundant features, increasing learning accuracy and enhancing learning comprehensibility. In this research work, Fisher ratio, ANOVA test, non parametric test are proffered to choose the best suited subset of the features. The chosen SFV comprising of 20 features are statistically analyzed for dimensionality reduction to achieve conclusive RSFV comprising of hybrid parameter set.

Classifier

The intent of the classification is to assign class category to the features extracted from the observations of a set of data in a specific problem [29]. Three classifiers MLPNN, kNN and SVM are preferred amongst the various available classifiers to compare and analyze the achieved performance for the efficient design of PS based CAD system.

KNN

K nearest neighbors is an algorithm that uses a similarity measure (e.g., distance functions) to classify new cases based on all available stored cases. This classifier makes a decision on comparing a sample testing data with the baseline training data and assign unseen data to the class to which the majority of its K nearest neighbors belongs[30]. “For a given time series, the KNN rule finds the K “closest” neighborhood labeled time series in the training data set and assigns X to the class that lie close to neighborhood of K time series”. In this work, Euclidean metric is used to calculate the distance between neighboring classes as given by Eqn 9. The optimum values for parameter ‘k’ for this work is determined empirically by repeated experimentation for values of ‘k’ € {1,2,...,9}.

$$dist(x_t, y) = \sqrt{\sum_{i=1}^{n} (y_i - x_t)^2} \qquad (9)$$

Support Vector Machine (SVM)

SVM tries to map the input vector into high dimensional feature space, either linearly or by methods depending on kernel type chosen; such that error is minimized over the training dataset. SVM performs classification tasks by handling multiple continuous and categorical variables and constructing hyper planes in a multidimensional space to separate cases of different class labels [31]. The kernel functions available are linear, polynomial, radial basis and sigmoid. A crucial step for obtaining good generalization performance with SVM classifier is the correct choice of the regularization parameter C and kernel parameter γ. The regularization parameter C attempts to maximize the margin while keeping low value for training error given by eqn (10)

Minimizing

$$\|w\|^2 + C\sum_{i=1}^{m} \xi_i$$

Subject to (10)

$$y_i(w_i.x + b) \geq 1 - \xi_i, \xi_i \geq 0$$

MLPNN

Neural networks are trained and are capable of solving complex and different problems. One or more layers of hidden neurons enhance network's learning of difficult problems by extracting more significant features from the input vectors [32]. The overall classification system used in this work consist of three layers of artificial NN with tan-hyperbolic and softmax function as the activation function for hidden and output layers with Cross Entropy as error function and BFGS (Broyden-Fletcher-Goldfarb-Shanno) as the technique used for training neural network. We have used 70 % data set for training, 30% data set for testing using bootstrapping method with 1000 seed points. The bootstrap data set is representative of a generic training set extracted from input space.

Results and Discussion

SFV comprises of twenty features of one patient, comprising of precisely F1:Mean, F2:Median, F3: Mode, F4:Coefficient of variation(COV), F5: Minima, F6: Skew, F7: Kurtosis, F8: SNR, F9: Energy, F10:Non linear energy(NE), F11:Maxima F12:Entropy F13: Standard deviation, F14: Activity, F15: Mobility, F16:Complexity, F17-F20 coefficients of Hurst exponents.

Table 1: Attribute table representing all the attributes with their mathematical descriptors and relevance.

F ID	*Feature*	*Formulae*	*Relevance*
F1	Mean	$Mean(n)=\frac{1}{N}\sum_{n=1}^{N}x_i(n)$	A measure of central tendency to describe the data by identifying the central position of data.
F2	Median	$Median(n)=l+\frac{h}{f}\left(\frac{n}{2}-c\right)$	It is measure of central tendency that is NOT affected by the extreme scores in a distribution when the data is skewed.
F3	Mode	$Mode=L+\left(\frac{f_1-f_0}{2f_1-f_0-f_2}\right)\text{X}h$	It is the only measure of centre appropriate for nominal data
F4	Coefficient of variation	$c_v=\frac{\sigma^2}{\mu^2}$	The ratio of samples's variance to the quare of the sample's mean
F5	Min Amplitude	$MinAmp(n)=\min[x_n]$	The maxima and minima of the signals are given by the amplitude of the sampled signals
F6	Skew	$SK=E\left[\frac{(x-\mu)^3}{\sigma^3}\right]$	Skew characterizes the degree of asymmetry of a distribution around its mean.
F7	Kurtosis	$K(s)=E(s^4)-3E(s^2)^2$	It characterizes the relative peakedness of a distribution as compared with the normal distribution.
F8	Signal to Noise Ratio	$SNR=\frac{\mu}{\sigma}$	This is ratio of mean to standard deviation of a signal
F9	Energy	$EG(n)=\frac{1}{N}\sum_{n=1}^{N}x_i(n)^2$	It signifies the strength of the EEG signal.
F10	Non linear energy	$NE(x_j)=\sum_{i=2}^{n-1}x_j(i)^2-x_j(i-1)x_j(i+1)$	This operator is useful for providing an indication as to the spectral content of the signal since it is sensitive to spectral changes
F11	Max Amplitude	$MaxAmp(n)=\max[x_n]$	
F12	Entropy	$E_n(n)=-\sum_{k=n}^{n+N}x(k)\log_2 x(k)$	It measures the signal complexity and quantify regularity and order in the signal.
F13	Standard Deviation	$STD=\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x[n]-\frac{1}{N}\sum_{n=1}^{N}X[n])^2}$	It is a statistical feature which indicates the distribution of the data with respective to the mean.

F14	Activity	$\sigma_j^2 = \frac{1}{n}\sum_{i=1}^{n}(x_j(i) - \mu_j(x_j))^2$	This parameter indicates the surface of power spectrum in frequency domain.
F15	Mobility	$mob(x_j) = \sigma_{\Delta j} / \sigma_j$	This parameter is defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal.
F16	Complexity	$compx(x_j) = \frac{\sigma_{\Delta 2j} / \sigma_{\Delta j}}{\sigma_{\Delta j} / \sigma_j}$	This parameter indicates how the shape of a signal is similar to a pure sine wave
F17 - F20	Hurst Exponent	$E\left[\frac{R(n)}{S(n)}\right] = Cn^H$	It is the relative tendency of an event in time series to either regress to a longer term mean value or 'cluster' in a given direction.

Note: FID: Feature ID, F1-F20 : Features

Statistical Analysis of SFV

To begin with, the analsysis is performed for the linear features. The "fitness" of each individual feature is measured using Fisher's discriminant ratio (FDR) when classes to be classified are uncorrelated [34]. Table 2 illustrates the output of the ANOVA analysis depicting F value along with a vital parameter p (significance level) to provide statistically significant difference between components.

Table 2: Summary of ANOVA analysis for linear features in terms of F value for every extracted attribute

Feature	*F value*	*P value*
F1	41.986	0.000
F3	58.09	0.000
F2	2.296	0.105
F11	99.33	0.000
F5	49.299	0.000
F6	31.473	0.000
F9	49.96	0.000
F12	41.575	0.000
F7	35.285	0.000
F13	51.145	0.000
F8	0.4543	0.637
F4	1.05	0.356
F10	1.28	0.279

Note: F value = Fisher's Discrimination ratio, p= significant value<0.05

On inspecting, the Table 2, some features, in particular, standard deviation, mean, minima of the signal have relatively higher value of F. Consequently, they are more significant compared to remaining features. The features having significance value > 0.05 (median, SNR, non linear energy and cov) have less significance for our problem at hand. To verify whether the extracted features are distinct and uncorrelated to each other or not, prediction importance of each feature, in terms of rank and importance parameter is extracted. The inter correlation between these features was calculated based on variance inflation factor (VIF) signifying multi-collinear analysis. The VIF value for each feature was calculated using

$$VIF = \frac{1}{1 - R_j^{\,2}}, \; Tolerance = 1 - Rj^2 \qquad (11)$$

where R_j^2 is the multiple correlation coefficient of one feature's effect regressed onto the remaining features. Tolerance value obtained is less than 1 for these features indicating that the variable under consideration is almost a perfect linear combination of the independent variables[35].

Statistical Analysis For Non Linear Feature Set

For this work authors have compared estimates of variance for non linear features by dint of F test, that tests whether the estimate of ratio of the two variance is significantly greater than 1. In this work, this test along with ANOVA is highly significant and authors have used it as a basis to select the prominent features, which are significantly different from each other.

Table 3: ANOVA analysis for non linear feature set in terms of F ratio and p value

		SS	***df***	***MS***	***F***	***p***
Activity	Between Groups	2.082	2	1.041	29.827	0.000
	Within Groups	10.26	294	0.035		
	Total	12.342	296			
Mobility	Between Groups	1.223	2	0.612	109.298	0.000
	Within Groups	1.645	294	0.006		
	Total	2.869	296			
Complexity	Between Groups	4.748	2	2.374	151.893	0.000
	Within Groups	4.595	294	0.016		
	Total	9.343	296			
Hurst1	Between Groups	0.975	2	0.487	259.753	0.000
	Within Groups	0.551	294	0.002		
	Total	1.526	296			
Hurst2	Between Groups	0.677	2	0.338	200.614	0.000
	Within Groups	0.496	294	0.002		
	Total	1.172	296			

Hurst3	Between Groups	1.223	2	0.612	362.365	0.000
	Within Groups	0.496	294	0.002		
	Total	1.719	296			
Hurst4	Between Groups	0.941	2	0.471	274.85	0.000
	Within Groups	0.504	294	0.002		
	Total	1.445	296			

Note: F value = Fisher's Discrination ratio, p= significant value<0.05, SS =Sum of Squares, MS=Mean Square

If the FDR of the extracted feature is high, two classes are distinguishable. It is evident from the table that F ratio of all the non linear extracted features is prominent enough to distinguish the classes. [36]. After statistical analysis the resultant CSFV comprises of 13 features which are tabulated in Table 4 with the respective mean values.

Table 4: Mean value of normalized RSFV with variation of variance for normal, interictal and ictal signals

Feature ID	***Mean±var (ictal)***	***Mean±var (normal)***	***Mean±var (inter-ictal)***
F1	0.50007±0.0475	0.46151±0.0348	0.519806±0.0392
F3	0.13562±0.0138	0.48437±0.0255	0.08538±0.0087
F5	0.57462±0.0939	0.54670±0.0332	0.82954±0.0212
F6	0.39269±0.0392	0.58710±0.0408	0.41979±0.0247
F7	0.18853±0.0232	0.30659±0.0300	0.1247±0.0475
F9	0.58902±0.0767	0.31251±0.0483	0.0397±0.0131
F11	0.36365±0.0594	0.47909±0.0271	0.1126±0.0195
F12	0.60609±0.2669	0.84852±0.0784	0.85712±0.0418
F13	0.40082±0.0184	0.27288±0.0242	0.11015±0.0188
F14	0.23625±0.0686	0.10008±0.0159	0.03536±0.0201
F15	0.32967±0.0061	0.33987±0.0081	0.198906±0.0026
F16	0.50741±0.0118	0.79078±0.0133	0.747027±0.0268
F18	0.63288±0.0037	0.72559±0.0054	0.9078±0.0133

F1 – Mean, F3- Mode, F5- Minima, F6- Skew, F7- Kurtosis, F9 – Energy, F11- Maxima, F12- Entropy F13- Standard deviation, F14- Activity, F15- Mobility, F16-Complexity, F18 Hurst exponent.

The various features extracted from the signals are informative and apt to analyze the EEG signals and few of them are reported. The energy signifies the strength of the signal, entropy quantifies how randomly the seizure signals are distributed as compared to non-seizure signals whereas variance indicates the distribution of the data with respect to mean. Third order cumulants highlight the nonlinear behaviour of

EEG signals. Fig 2 represents some of the features chosen for the study for three different classes of signals.

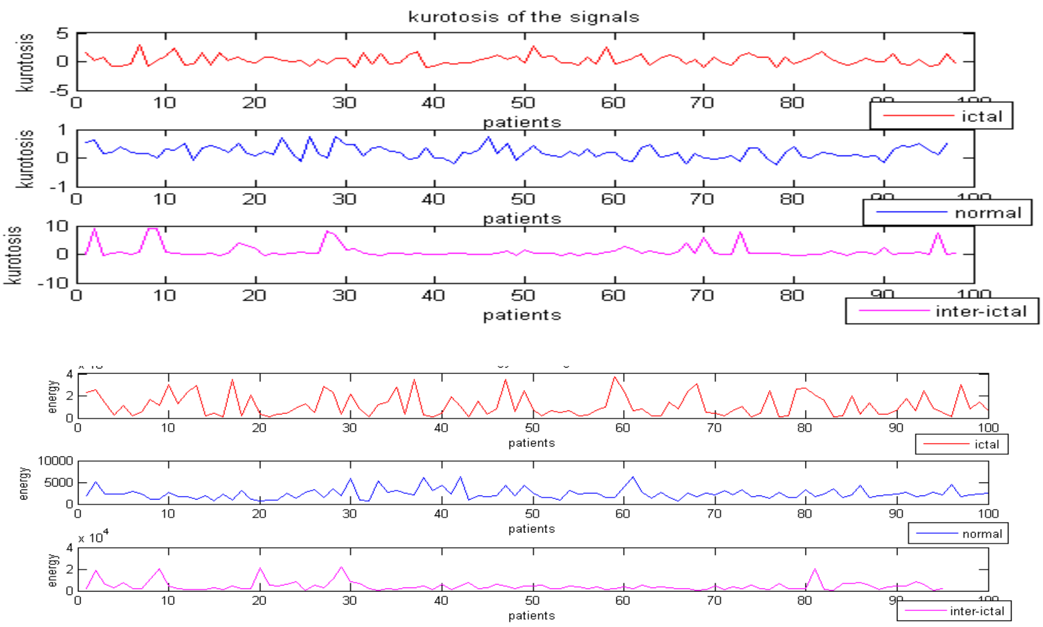
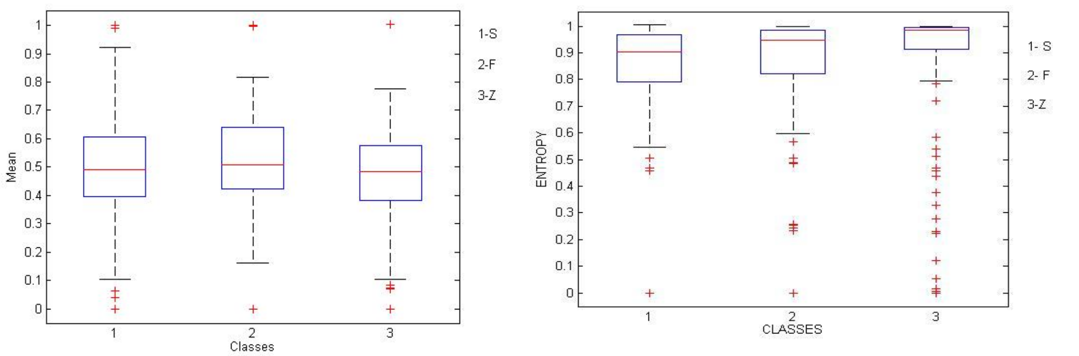


Figure 2: Extracted features (a) Kurotosis of the signals (b) Skew of the signals of patients in (i) ictal state (ii) normal state and (iii) inter-ictal state.

Box plots without making any assumptions of the underlying statistical distribution display the variation in samples of distribution. Box plots of some of the selected features are depicted in Fig 3. Quartiles are preferred over the mean and standard deviation when the dataset have extreme outliers and are ditributed asyymetrically, as they are “insensitive to outliers and preserve information about the centre and spread”[37].



a b

Figure 3: Box plots for the features for three different datasets for the attributes a) Mean b) Entropy

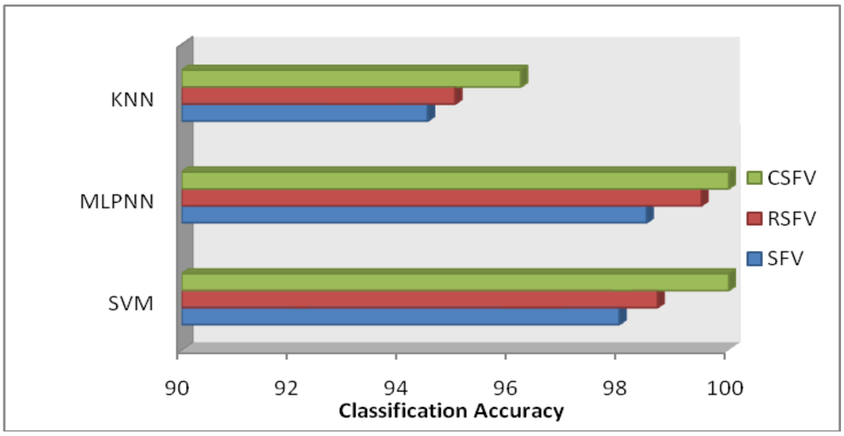


Figure 4: Comparative depiction of classification accuracy with SFV, RSFV and CSSFV for the design of PS based CAD system.

Classification Analysis

To evaluate the performance of the PS based CAD system; classifiers are designed utilizing three set of feature sets i) SFV ii) RSFV iii) CSFV. The dataset is divided into subsets for training, testing and validating the classification and classification accuracy is measured with three classification algorithms ANN, KNN and SVM. Firstly, SFV comprising of twenty features are used as input to the three classifiers and the performance measures: classification accuracy, sensitivity and specificity are tabulated in Table5 as confusion matrix. Secondly, after the statistical analysis of SFV, deduced RSFV comprises of thirteen attributes with dimensions of 13 * 100*2 and is used as input to the same group of classifiers and results are tabulated in table 6. Thirdly, classification with different classifiers is done with CSFV data set and all the three performance measure parameters are reported in table 7.

Table 5: Classification accuracy of normal and ictal signals using SFV with MLPNN, KNN and SVM classifiers

Feature vector	*Classifier*	*CM*			*Acc.*	*Sen.*	*Spc.*	*Miss rate*
			NOR	ICT				
SFV	SVM	NOR	97	3	98.0%	97.0%	99.0%	0.04
		ICT	1	99				
			NOR	ICT				
	KNN	NOR	96	4	94.5%	96.0%	93.0%	0.05
		ICT	7	93				
			NOR	ICT				
	MLPNN	NOR	98	2	98.5%	98.0%	99.0%	0.015
		ICT	1	99				

Note: CM: Confusion Matrix for classification, Acc.(Bin-Class): Accuracy for binary classification expressed in percentage, Sen: Sensitivity Sen:Sensitivity, Spc:Specificity expressed in percentage.

Table 6: Classification accuracy of normal and ictal signals using RSFV with MLPNN, KNN and SVM classifiers

Feature vector	*Classifier*		*CM*		*Acc.*	*Sen.*	*Spc.*	*Miss rate*
			NOR	ICT				
RSFV	SVM	NOR	40	0	98.7%	100%	97.5%	0.01
		ICT	1	39				
			NOR	ICT				
	KNN	NOR	39	1	95.0%	97.5%	92.5%	0.05
		ICT	3	37				
			NOR	ICT				
	MLPNN	NOR	99	1	99.5%	99%	99%	0.01
		ICT	1	99				

Note: CM: Confusion Matrix for classification, Acc.(Bin-Class): Accuracy for binary classification expressed in percentage, Sen: Sensitivity Sen:Sensitivity, Spc:Specificity expressed in percentage.

Table 7: Classification accuracy of normal and ictal signals using RSFV with MLPNN, KNN and SVM classifiers

FV	*Classifier*		*CM*		*Acc.*	*Sen.*	*Spc.*	*Miss rate*
			NOR	ICT				
CSFV	SVM	NOR	40	0	100%	100%	100%	0.00
		ICT	0	40				
			NOR	ICT				
	KNN	NOR	39	1	96.2%	97.5%	95%	0.03
		ICT	3	37				
			NOR	ICT				
	MLPNN	NOR	100	0	100%	100%	100%	0.00
		ICT	0	100				

Note: CM: Confusion Matrix for classification, Acc.(Bin-Class): Accuracy for binary classification expressed in percentage, Sen: Sensitivity Sen:Sensitivity, Spc:Specificity expressed in percentage.

It can be inferred from the results presented in tables 5,6,7, that the proposed PS based CAD system outperforms with PS based CSFV approach, with consistent improvement in classification accuracy. Comparing the performance of classifiers with all the three cases it can be observed that Acc obtained with SVM and MLPNN is 100 % with sensitivity and specificity also 100%, whereas accuracy obtained with KNN is 96.2% . As a result of statistical analysis of all the extracted features and appropriate choice of features, the proposed methodology is able to capture the variations more effectively. Experimental results presented in this paper also demonstrate the effect of parameter selection technique on overall perofrmance is found to be more positive nad encouraging and also that non linear parameters more effective in capturing variations of the signal and as a result provide improved classification accuracies

The proposed approach uses linear and non linear parameter selection and classification with the three classifiers. It may also be observed from tables 5 and 6, that there is improvement in the classification accuracy when RSFV is employed for classification, and it is evident from the table 7 that there is much influence on performance of the proposed approach when CSFV is utilized. More importantly, the proposed approach for classification of seizure and seizure-free EEG signals outperforms the existing methods, which is represented in table 8.

Table 8: Comparison Of The Results Obtained By Our Method And Others'methods For Normal And Ictal Classification Problem

Authors	***Method***	***Data selection***		***Results***	
			Acc.	***Sen.***	***Spc.***
Srinivasan et al. [6]	Time & frequency domain feature-Recurrent neural network	Hold out (%60 training-% 40 test)	99.60%	99.4%	99.8%
Subasi and Ercelebi [15]	WT+ANN	Hold out (%60 training-%40 test)	92 %	91.6%	91.4%
Kannathal et al. [23]	Chaotic measures-Surrogate data analysis	N/A	90.00%	N/A	N/A
Tzallas et al. [16]	Time frequency analysis- ANN	Hold out (%50 training-%50 test)	100%	100%	100%
Polat et al. [38]	Fast Fourier transform-Decision tree	10-fold cross-validation	98.72%	99.4%	99.31%
Acharya et al. [28]	Entropies + HOS + Higuchi FD+ Hurst exponent + FC	10-fold cross-validation	99.7%	100%	100%

Guo et al. [24]	WT–RWE-MLPNN	Hold out (%50 training-%50 test)	95.20%	98.17%	92.12%
Present study	CSFV+SVM	(%70 training-%30 test)	100%	100%	100%
Present study	CSFV+KNN	(%70 training-%30 test)	96.2%	97.5%	95%
Present study	CSFV+MLPNN	(%70 training-%30 test)	100%	100%	100%

Acc: Accuray, Sen:Sensitivity, Spc:Specificity

On visualizing the figure 4 we can summarize the performance analysis of design of CAD system for classification of seizures. It can be concluded that a hybrid system comprising of PS based CAD syatem provides an edge over the simple CAD system for classification purposes of EGG signals.

Conclusion

The objective of this work is to design, implement and validate a parameter selective automatic classification system of EEG signals. The proposed methodology addresses a seizure classification problem and focuses on what features delineates the EEG signals of a normal patient from an epileptic patient. As the prima facie of this work is to design a PS based CAD system, the authors have laid emphasis on selection of relevant features which are less related, balanced and converge to best solution to classification problem.The uniqueness of the propsed methodology is to select most appropriate feature vector that can be extracted and efficiently be used for classification. The results obtained are clear indicators of the great potential in classifying epileptic signals and normal signals. As features researched in this paper were chosen with an eye toward real-time implementation, this method has the potential to be applied in prototype implantable devices for treating epilepsy. In future, we wish to apply our approach for classification of other different type of signals and biomedical applications and larger database.

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