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A Machine Learning Framework for Epileptic Seizure Detection by Analyzing EEG Signals

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Abstract: Electroencephalography (EEG) signals are non-stationary and mixed with artefacts. A clinical finding through observation is relatively difficult and may lead to misinterpretations. In particular, epilepsy is the brain neural disorder which is hard to be diagnosed by visual observation of EEG signals. In an attempt to avoid such key issues, automated detection of epilepsy is proposed by analyzing EEG signals in a systematic way to support the clinical decision making process. Initially the EEG signal data is preprocessed by removing signal noise and artefacts by adopting selective threshold denoising method of Discrete Wavelet Transform (DWT). Distinct statistical features are mined from each signal sub bands through multiscale approximation. The dimensionality of the signal features are reduced by using kernel based robustified Principal Component Analysis (PCA). A two-class Support Vector Machine (SVM) nonlinear classifier is used for classifying the ictal and interictal EEG signals with its two variants namely Polynomial Kernel and Radial Basis Function kernel. The performance of the various classification experiments are determined by computing of sensitivity (SEN) and specificity (SPE) and accuracy (ACC). The 5-fold cross validation is exercised to assess the performance of the classifier. Classification accuracy of 99.6% is obtained with the proposed model and outperforms similar benchmarking classification works reported recently.

Keywords: EEG, Discrete Wavelet Transform, SVM, Principal Component Analysis

1. Introduction

Analysis of non-stationary biomedical signal data is the prime talk in signal processing domain today. On employing biomedical equipments huge volume of physiological data is acquired for analysis and diagnostic purposes. Inferring certain decisions from these signals by manual observation is quite tedious due to artefacts and its time series nature. As large volume of data involved in biomedical signal processing, adopting suitable computational methods is important for analysis [1].

Epilepsy is one of the chronic brain disorders and around one percentage of global population is affected by this disorder according to World Health Organization. Though many researchers from medical and computer science fields have contributed their knowledge for developing automated diagnosis systems by using scientific techniques and authenticated EEG data bases, the efficiency of these systems are still questionable due to several reasons. For the last one decade many researchers have been bringing automated systems for epileptic seizure detection using machine learning methods. As a continuous effort to enhance the accuracy in epileptic seizure detection, this machine learning framework is brought.

2. Research Problem

In general, two types of abnormalities found with patient with epilepsy: i) interictal, abnormal signals recorded between two epileptic seizure episodes; and ii) ictal, the abnormal brain signals obtained during an epileptic seizure episode of a patient. The EEG signal segments of interictal activity are intermittent transient waves such as spikes or sharp waves, spike trains and random spikes. EEG signal segments during the epileptic seizure period termed “ictal” is in the form of continuous discharge of polymorphic waveforms of changing frequency and amplitude, sharp and spike wave complexes, rhythmic hypersynchrony, or electrocerebral inactivity noticed over time more than the average duration of aforesaid abnormalities throughout the

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interictal periods according to McGrogan [2]. As ictal readings are significantly rare, the EEG analysis of epileptic patients solely depends on interictal recordings. In some situation seizure activity will be observed by provocation methods such as photo stimulation, hyperventilation and other methods. So the long-term EEG recording is suggested to record and analyze ictal events for automated systems.

Clinical evaluation of epileptic seizure is generally done by experienced neurophysiologists through visual scanning of EEG recordings for epileptic and non-epileptic activities. There are serious issues in manual review of long-term EEG recordings such as possibility of human errors and time consuming. Furthermore, the epileptic seizure EEG patterns are more or less similar to signals that are part of the external noise and to artefacts like physical body movements. Therefore, it is essential to develop an automated mechanism for detecting epileptic seizures in a computationally efficient manner. A novel machine learning framework is developed for epileptic seizure detection by analyzing long-term recordings of EEG.

Clinical EEG Data

The EEG database by the University Hospital Bonn, Germany [3] is popular for EEG analysis for various biomedical signals processing applications. In Bonn EEG database provided with five datasets (designated A to E). Each datasets presented with 100 single channel EEG signal segments of 23.6 seconds duration obtained by using 128-channel amplifier system. The signal data were written into system with a sampling frequency of 173.61 Hz (corresponding Nyquist frequency bandwidth of 86.8 Hz). These segments were obtained by windowing and cutting out continuous multi channel EEG recordings on diverse scenarios. The Bonn EEG database cheat sheet is given in Table.I.

TABLE I. SUMMARY OF CLINICAL DATA

	Dataset A (Z)	Dataset B (O)	Dataset C (N)	Dataset D (F)	Dataset E (S)
Every Dataset containing 100 segments in 23.6 Seconds duration					
Patient state	Awake and eyes open (normal)	Awake and eyes closed (normal)	Seizure-free (interictal)	Seizure-free (interictal)	Seizure activity (ictal)
Electrode types & Placement	Surface	Surface	Intracranial, Opposite to epileptogenic zone	Intracranial, Within epileptogenic zone	Intracranial, Within epileptogenic zone

3. Related Works

Feature engineering has two important phases namely data preprocessing and, feature extraction and feature selection. For data preprocessing diversified approaches are adopted by the researchers including wavelet denoising. For extracting features by processing EEG signal data, three domain methods are widely used such as frequency domain, time domain and wavelet or time-frequency domain.

In time domain, EEG signals are viewed as time-series signals and based on that statistical features are extracted for classification. Since the frequency component is missing in time domain, some have included frequency domain too in their problems like the one reported by Chunchu et al. [4]. Many researchers have employed spectral analysis by considering that the signals are stationary. EEG waveforms are usually non-stationary signals of time-series nature and will provide only time and frequency information. Later researches added that the frequency component may vary over time in EEG. Therefore, time-frequency method (wavelet method) for feature extraction is recommended to retain time and frequency information for processing the signal data.

Many EEG classification problems for epileptic seizure detection were used wavelet domain feature extraction methods. Umut Orhan et al. [5] and Reza et al. [6] were taking up DWT method to obtain different frequency sub bands and then statistical features were derived for their EEG classification works. DWT based wavelet coefficients such as mean, variance, energy and different entropies were used after four to eight level signal decompositions for detecting epileptic seizures as reported in various literatures [7] [8]. Other works such as Benzy et al. [9] for finding the depth of anaesthesia also used DWT based features for EEG classification. Few works reported in the recent years used different variants of DWT such as Lifting Based Discrete Wavelet Transform (LBDWT) [10], Dual Tree Complex Wavelet Transform (DTCWT) [11], and Maximal Overlap Discrete Wavelet Transform (MODWT) for extracting features and claimed their superiority in classification accuracy. Elif Derya Ubeyli [12] used DWT based feature engineering for comparing various neural network based EEG classification models. Mrigank Sharad et al. [13] proposed another variant of DWT called simplified Low-Pass Filter (LPF)-only-DWT for epileptic seizure detection problem.

In a recent work proposed by Tzimourta et al. [14] and claimed that DWT is contributing well for their classification methodology with SVM. The two similar literatures put forth by Sharmila et al. [15] and Kavita Mahajan et al. [16] have also used DWT based feature extraction through MRA by obtaining various signal sub-bands. According to Sang-Hong Lee et al. [17], DWT based signal processing in combination with phase-space reconstruction (PSR) worked well for classification of EEG signals. Several observations are noticeable upon carefully looking at the research methodologies adopted in the literatures.

- Many EEG classification problems have been taken up for epileptic seizure detection in the past decade.

- In the epileptic seizure detection problems, time-frequency domain (wavelet) feature engineering approach is widely used for classification. It was noticed in the literatures that the time-frequency approach is enhancing the classification accuracy than time and frequency domain approaches.
- For wavelet analysis, DWT and its variants [42] are commonly adopted for the classification problems of EEG.
- The latest researches witnessed that the wavelet based statistical are extracted for classification.
- PCA is widely adopted for feature dimension reduction in the EEG classification problems.

Automated diagnosis of epileptic seizure by analyzing EEG recordings started in 1970's and improved sharply from 1990s. In the recent past many review studies [18][19][20][21] brought up for analyzing the diversified signal processing approaches for EEG especially for automatic epileptic seizure detection applications. From the review studies it is evident that the epileptic seizure detection problem is more appropriate in the present scenario and need to be addressed with more and more strengthened and state-of-the-art technologies in computational sciences.

Most of the EEG classification frameworks reviewed shows that SVM is an effective machine learning algorithm for EEG signal classification. Another important fact revealed from this literature study is that the wavelet domain feature analysis is well appropriate for EEG feature engineering in order to preserve time and frequency components in the signals.

4. Methods

A. Proposed Framework

On reviewing related literatures, it is evident that diversified methods and algorithms are proposed for epileptic seizure detection using classical and few modern signal processing techniques. All signal processing techniques aimed at identifying distinctive patterns that are used to describe the epileptic seizure activity. In this experimental model, binary classification is exercised by analyzing interictal (C and D subjects) and ictal (E subject) signal segments for detecting epileptic seizure activity. The proposed classification framework for this epileptic seizure detection is depicted in Fig.1. Following are the novel approached adopted in this framework:

- EEG signal preprocessing using selective threshold denoising method of Multiresolution analysis.
- Wavelet domain feature extraction to retain time and frequency components of the signals.
- Robustified PCA for feature dimension reduction to reduce the outliers.

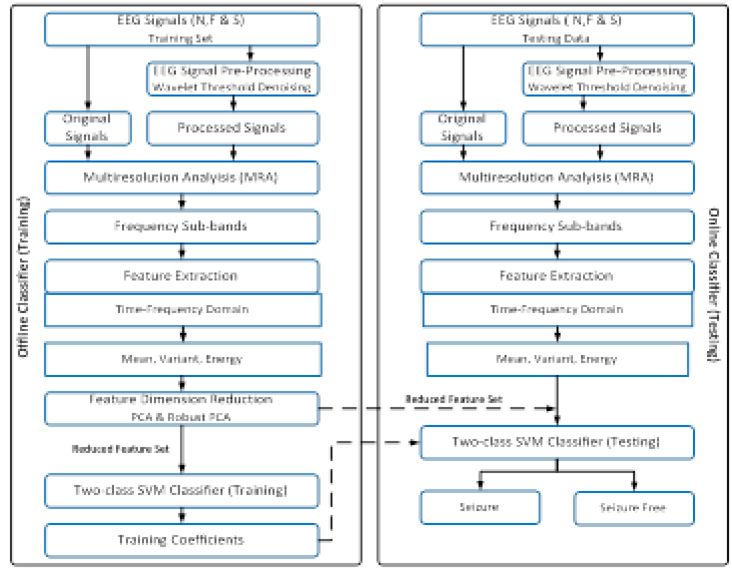

Figure.1 Epileptic Seizure Detection Framework

B. Signal Preprocessing

Acquired signals from EEG are not always ready for analysis to obtain distinguishable features. Weak and low amplitude EEG signals may cause low frequency noise due to unsolicited interferences. Hence the signal preprocessing for noise removal is significant before analysis for the classification of EEG signals [22][23]. Though many noise reduction approaches in place for signal processing, a wavelet threshold denoising by DWT is considered as it has showcased best performance compared to other methods [24]. Due to better localization in non-stationary EEG signals, Daubechies (Db4) wavelet is used for analysis in this framework.

Consider the equation:

$$\mathbf{f} = \mathbf{s} + \mathbf{n} \tag{1}$$

where **f** is the polluted signal, **s** is the original signal and **n** is noise:

In order to eliminate random noise, the wavelet threshold denoising method is taken up at specific decomposition level. Trade off between different amplitude values are used at the desired decomposition level for the threshold value. The transform values which are greater than the threshold Ts >0 are retained for analysis. Likewise, all the transform values whose magnitudes coming below a noise threshold Tn (Tn < Ts) will be discarded. The efficacy of signal denoising is calculated with the Root Mean Square Error (RMSE):

$$RMSE(\sigma) = \sqrt{\frac{\sum_{i=1}^{N}(f_i - S_i)^2}{N}}$$

$$= \sqrt{\frac{\sum_{i=1}^{N}(n_i)^2}{N}}$$
$$= \frac{\sqrt{\varepsilon_n}}{\sqrt{N}} \qquad (2)$$

Better denoising result is showcased with less RMSE which is equivalent to the least square method for finding error in a data set. The wavelet threshold function as stated in [39] is:

$$\lambda = \sigma\sqrt{2logN} \qquad (3)$$

where λ is the wavelet threshold, σ is the standard deviation of the noise and N is the length of the sample signals, respectively. Inducting wavelet threshold method of noise reduction produces better results as the noise hidden with the original EEG is in the form of sharp waves [25].

Through DWT, larger coefficients are obtained by amplifying signal magnitudes by limiting the noise. Noise coefficients will be smaller than the desired signals to be analysed. Fig.2 illustrates the wavelet decomposition and reconstruction framework using DWT.

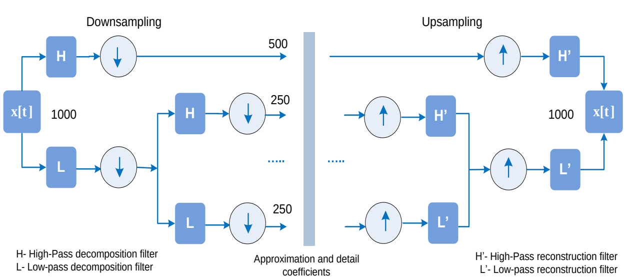

Figure 2. Wavelet Decomposition and Reconstruction

After decomposition, each sub band will be analysed and the low frequency and low magnitude signals which are not significant for analysis will be filtered out by using wavelet threshold function stated in (3). The outcome of EEG signal denoising experiment is shown in Fig.3 and Fig.4.

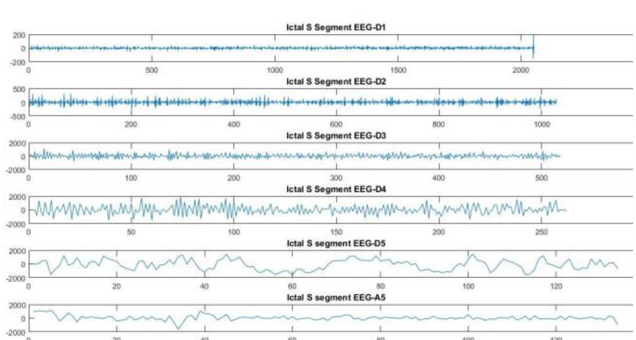

Figure 3. Frequency sub bands of ictal S segment before denoising

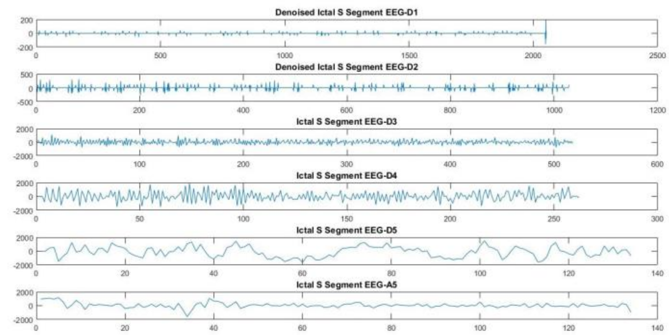

Figure 4. Frequency sub bands of ictal S segment after denoising

C. *Feature Engineering*

As the first step in feature engineering DWT based multiresolution analysis is adopted to extract the features using wavelet decomposition [26]. Six frequency sub-bands are obtained from five levels of decomposition. Time-frequency domain based statistical features with better localization characteristic are obtained from each signal sub-band.

The wavelet basis function φ in the wavelet domain [27] with limited duration and zero mean is given as:

$$\sum_{N=-\infty}^{\infty} |\varphi[N]|^2 < \infty \,, \sum_{N=-\infty}^{\infty} \varphi[N] = 0 \qquad (4)$$

where **N** is the length of the input signal. The non-stationary property of the wavelet is represented by using eq.(5) as the wavelet shall move over time by the parameter **b** and scaled by the dilation parameter **a.**

$$\varphi_{a,b}[N] = \frac{1}{\sqrt{a}}\varphi\left[\frac{N-b}{a}\right] \qquad (5)$$

It must be observed that the wavelets with higher dilation parameter **a** are more appropriate for obtaining steady changes, whereas the wavelets having small dilation parameter **a** are helping to extract fast changes. Wavelet based statistical features are obtained by processing EEG signals using the wavelet basis function, which preserves both the time and frequency information.

By changing the dilation parameters **a** and scaling parameter **b,** wavelet transform coefficients will be derived by using the following eq.(6):

$$WT_{a,b}[n] = \sum_{\tau=1}^{N} x[\tau]\varphi_{a,b}[n-\tau], \;\; 1 \le n \le N \qquad (6)$$

where x[τ] is the sample signal of N samples. Deciding the wavelet function type and level of decomposition is significant step before the application of *Discrete Wavelet Transform* (DWT) [28]. The wavelet decomposition equation of DWT can be formulated as:

$$DWT_{a,b}[m,k] = \frac{1}{a}\sum_{\tau=0}^{N-1} x[\tau]\varphi\left[\frac{\mathrm{N-b}}{\mathrm{a}}\right] \quad (7)$$

where, φ(.) - the wavelet function, **m** - the decomposition level and **k** – the type of wavelet. In the proposed method, the daubechies4 wavelet is used for its localization property in the time-frequency domain [29]. Several recent EEG classification works for seizure detection adopted db4 because of its shape, smoothening property and the superior performance at various non-stationary signal processing scenarios.

The principal concept of Multiresolution Analysis (MRA) is to characterize a wavelet function as a limit of successive approximations, each of which is a smoother version of the wavelet function [26][30]. There will be more resolution levels in the successive approximations. MRA is a formal method of constructing orthogonal wavelets with well defined procedures [29].

Mostly, the level of decomposition relies on the dominant frequency components of the signal and is problem dependent. In this proposed EEG classification problem, the levels are chosen in a way to correlate the signal sub bands with the required frequencies for the EEG signal analysis in clinical background [14]. As there are no valuable frequency components beyond 30 Hz in EEG signal, the level of decomposition is considered five.

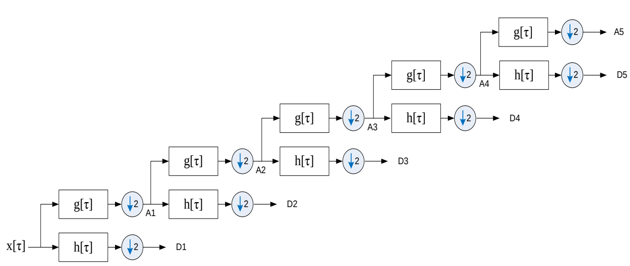

Figure 3. Five-level wavelet decomposition

The wavelet decomposition is shown in Fig.3. In this decomposition, D1, D2, D3, D4, D5 are detail coefficients and A5 is the approximation coefficient. The coefficients represent the frequency components of the EEG signal with sub bands fs/4 – fs/2, fs/8 – fs/4, fs/16 – fs/8, fs/32 – fs/16 fs/64 – fs/32 and 0 – fs/64, where fs is the sampling frequency of the signal input x[τ].

The signal sub bands and with their related frequencies are tabulated in Table II. Signal feature vectors are obtained from EEG signal sub bands and the coefficients are retained for further analysis.

Table II. Signal Decomposition and elated frequency bands

Decomposed Segment	Frequency in Hz
D1	43.4 to 86.8
D2	21.7 to 43.4
D3	10.8 to 21.7
D4	5.4 to 10.8
D5	2.7 to 5.4
A5	0 to 2.7

D. *Feature Dimentionality Reduction*

In the second phase of feature engineering, extracted features are then subjected to reduction of feature dimension with Principal Component Analysis (PCA) and Robust PCA algorithms to remove spurious features which are not significant for classification. By applying PCA, the linear combinations of the given features are obtained as principal components.

The feature matrix X (figure 5.1) is in dimension 300 x 54 (100 samples each from F, N & S segments and each with 54 features). The input feature space is normalized by de-mean the feature matrix. As the first step the covariance matrix of the feature matrix is obtained. The eigenvalues and eigenvectors are then calculated by using covariance matrix. This has been achieved by using the following Matlab code:

```
[coeff, score, latent,~, explained] = pca(X);
```

where,

a) "coeff" represents the eigenvectors of the covariance matrix and are called principal component vectors.

b) "latent" are the variances of feature vectors represented by using eigenvalues of the covariance matrix.

c) "score" is the output projection on the original data in principal component vector space.

The features now in principal component space with variations specified in a vector “explained”. The traditional PCA is further improved by adopting the techniques to find principal components which are nonlinearly related to the input space. Guassian kernel is applied to robustify the PCA. After implementation of robustified PCA using guassian kernel function, the features of the input data is mapped into the principal components space.

By observing the concentrated principal components in PC1, PC2 and PC3 obtained from robustified PCA, it is very much clear that the above said three principal components can together identify 99.13% of the variations in the input data. This is 1.03% ahead of the traditional PCA. The scree plot in Fig.4 illustrates the concentrations in the principal components of robustified PCA.

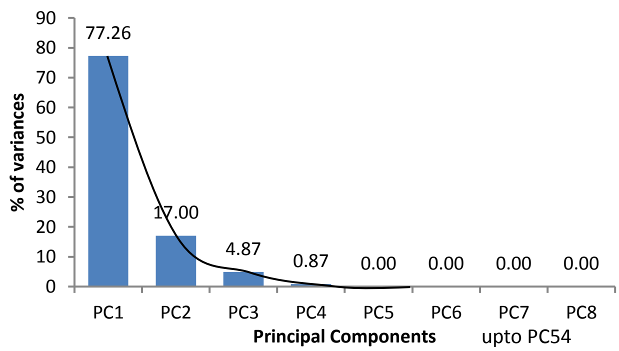

Figure 4. Scree plot showing percentage of variances among PCs in robustified PCA

The reduced features in the principal component space are visualized by using 3D scatter plot shown in Fig.5.

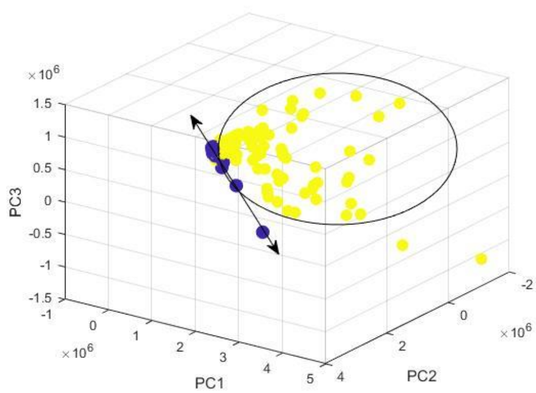

Figure 5. 3D Scatter plot – Reduced feature sets (interictal vs ictal)

E. Binary Classification

Two-class SVM classifier is employed for classifying seizure (ictal) and seizure-free (interictal) EEG signals with distinctive features obtained after PCA and Robustified PCA. Three experiments (as stated in Table II) are designed to carry out in the proposed machine learning framework and compared with the existing research outcomes. The experiments are designed to study the performances of the classification framework and its progress while adopting innovative approaches in feature engineering, dimensionality reduction and the kernel functions of the classifier.

To validate the classification, 5-fold cross validation is adopted by making training and test sets as shown in Fig.6. Classification performance is evaluated using the statistical measurements Accuracy (ACC), Sensitivity (SEN) and Specificity (SPE).

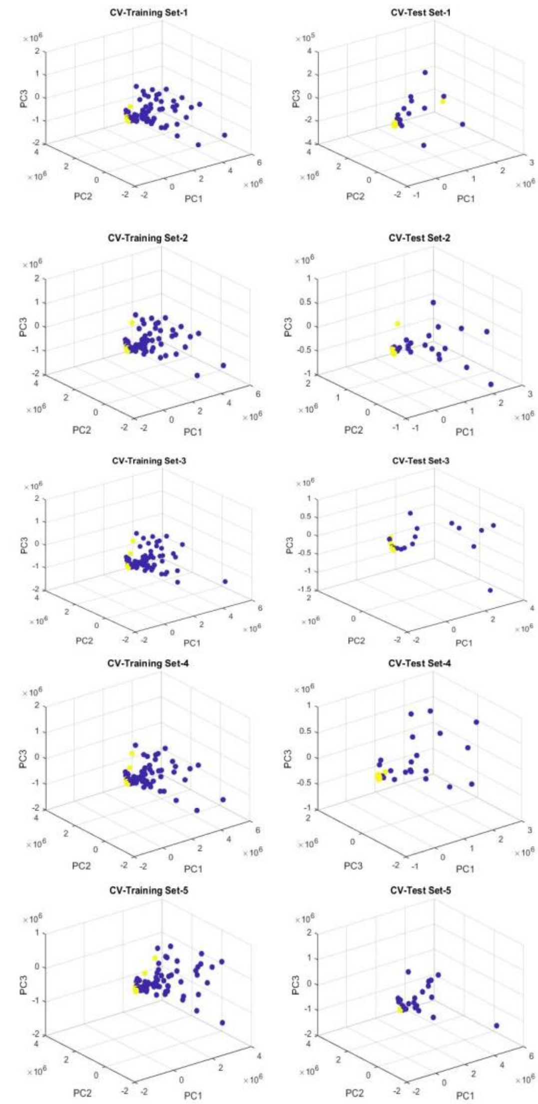

Figure 6. Scatter plots of Training and Test samples for 5-fold Cross Validation (CV)

5. Results

A. Experiment-1

The objective of this experiment is to assess the performance of the classification model with unprocessed (with noise) EEG signals and compare its classification performance with processed (denoised) EEG which is to be carried out in experiment-2. During the experiment with polynomial kernel, trade-off with different values between 2 and 11 are carried out and the optimum performance reached at polynomial degree d=5.

The performance of the classifier with experiment-1 is shown in Table III. It is noted that the 5-fold cross validation with fixed division is emerged as efficient method than random k-fold selection method of cross validation.

TABLE III. CLASSIFICATION PERFORMANCE OF EXPERIMENT-1 USING TRADITIONAL PCA WITH UNPROCESSED SIGNAL INPUT

Classifier	Kernel Parameters	5-fold CV Random sub-sampling			5-fold CV Fixed division		
		SEN	SPE	ACC	SEN	SPE	ACC
SVM-Polynomial Kernel	d=2	0.845	0.749	0.817	0.901	0.831	0.880
	d=5	0.907	0.904	0.909	0.926	0.920	0.924

B. *Experiment-2*

The primary objective of this experiment is to evaluate the performance of classification framework with processed EEG signal inputs and compare its performance with unprocessed input; i.e., experiment-1. In this experiment, two different kernel functions are applied with SVM nonlinear classifier to choose the best classifier for our innovative framework which will be carried out through experiment-3. Also, this experiment enables us to analyze the effectiveness of the robustness applied in PCA for dimensionality reduction later in experiment-3 by comparing with traditional PCA.

On training with RBF kernel, trade-off between different values of sigma (σ) has been set and finally two values are considered as appropriate (i.e. σ = 0.5 & σ =0.05) for providing optimum classification performance within this framework. Similar to experiment-1, trade-off with different values between 2 and 11 are carried out and the optimum performance reached at polynomial degree d=5. The outcome of experiment-2 is shown in Table IV. Among the two kernel functions of the SVM classifier, polynomial kernel is exhibiting better performance than RBF kernel.

TABLE IV. CLASSIFICATION PERFORMANCE OF EXPERIMENT-2 USING TRADITIONAL PCA WITH PROCESSED SIGNAL INPUT

Classifier	Kernel Parameters	5-fold Cross Validation(Fixed division)		
		SEN	SPE	ACC
SVM-RBF Kernel	σ = 0.5	0.867	0.935	0.903
	σ = 0.05	0.913	0.952	0.930
SVM-Polynomial	d=2	0.937	0.967	0.938

C. *Experiment-3*

The motive of this experiment is to analyze the enhancement of the classifier performance after employing robustified PCA for dimensionality reduction. This is a novel classification framework for identifying epileptic seizures through its binary SVM nonlinear classifier using polynomial kernel. The polynomial kernel function is applied in this experiment along with robustified PCA as it has showcased elevated classification performance over RBF kernel function in experment-2 with traditional PCA.

This experiment is aimed at enhancing the epileptic seizure detection by adopting robustness in dimensionality reduction so as to elevate the classifier performance. The features obtained from DWT based MRA analysis is subjected to dimensionality reduction using robustified PCA. The reduced features obtained are then used with the SVM nonlinear classifier (polynomial kernel) as carried out in experiment-2. Table V shows the classification performance of experiment-3.

TABLE V. CLASSIFIER PERFORMANCE AFTER EXPERIMENT-3 USING ROBUSTIFIED PCA WITH PROCESSED SIGNAL INPUT

Classifier	Kernel Parameters	5-fold Cross Validation(Fixed division)		
		SEN	SPE	ACC
SVM-Polynomial Kernel	d=2	0.927	0.989	0.975
	d=5	0.989	0.994	0.996

Among the chosen values of d (d=2 & d=5) in the experiments, degree 5 exhibited optimum performance.

6. Discussions

The classification experiments carried out using this framework provide significant interpretations. 5-fold cross validation is exercised in this classification framework. Two different versions namely fixed-division and random sub-sampling are tested with experiment-1. On performing 5-fold cross validation, fixed-division method achieved higher accuracy with 92.4 % and is found ideal than random sub-sampling with 90.9%.

The power of wavelet denoising method in the epileptic seizure classification task using time-frequency domain feature engineering is evident on comparing the experimental results shown in Tables 6.3 and 6.4. Even if the classification of ictal & interictal EEG signals without denoising provides considerably good results (accuracy of 92.4%), from table 6.4 it is noticeable that, with denoising the classifier enhanced its performance by providing accuracy of 98.9%. So it is obvious that the EEG signals must be processed before classification to reduce the noise signals and artefacts, so as to improve the classification accuracy.

Among the two kernel functions that are employed in experiment-2, the polynomial kernel outperforms (with the accuracy of 98.9%) RBF kernel (with the accuracy of 93.0%).

Experiment-3 exhibits the outcome of the enhanced classification model using processed EEG, wavelet based feature engineering, robustified PCA and nonlinear SVM polynomial kernel. It shows that the usage of reduced features using robustified PCA does better classification of seizure & seizure-free EEG with an elevated accuracy of 99.6%.

This novel classification system provides superior performance on comparing with bench marking classification works (given in Table VI) reported recently. It is noted that most of the works use Bonn database as data input, wavelet based feature engineering, and SVM as classifier. All works tabled here for comparison were reported the binomial classification of ictal (seizure) and interictal (non-seizure) EEG signals.

TABLE VI. COMPARISSION OF THE PROPOSED MODEL WITH STATE-OF ART BENCH MARKING WORKS REPORTED

Binary Case	Author [Ref]	Year	Methods	Accuracy
Ictal-interictal	Tzimourta et al. [13]	2017	DWT, SVM	93.00
FN-S	Swami et al. [31]	2016	DT-CWT, GRNN	95.15
FN-S	Jaiswal et al. [32]	2017	LNDP, 1D-LGP, k-NN, SVM, DT, ANN	95.00
FN-S	Md Mursalin et al. [33]	2017	Statistical, DWT, ICFS, Random Forest	98.67
FZ-S	Mingyang Li et al. [34]	2017	DT-CWT, SVM	98.87
FNOZ-S	Lina Wang et al. [35]	2017	DWT, PCA, k-NN, LDA, NB, LR, SVM	99.25
FN-S	Tiwari et al. [36]	2017	LBP, SVM	99.45
Focal-Non-focal	Bhattachary a et al. [37]	2018	Empirical WT, LS-SVM	90.00
Ictal-interictal	Wang *et al.*, [29]	2018	Wavelet based DTF, SVM	99.55
Ictal-interictal	Qi Yuan et al., [38]	2018	LBP based WT, SVM	98.88
Ictal-interictal	A. Subasi et al. [40]	2019	GA, PSO, SVM	99.38
Ictal-Interictal	Mandhouj, B el al. [41[	2021	STFT, CNN	98.22
FN-S	**This work**	**2020**	**DWT, Robustified PCA & SVM**	**99.60**

7. CONCLUSION

The machine learning model brought in this research does attain elevated accuracy of 99.60% and outperforms the state-of-art research works listed here and shall thus be applied to detect epileptic seizures. The enhanced classification performance is attributed to the highly discriminative features. Due to its superior classification performance, this model is highly recommended for the automated epileptic seizure detection systems for clinical purposes as diagnostic decision support system.

8. ACKNOWLEDGMENT

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