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Characterizing Functional Connectivity Network Based on Multi-Domain Analysis for Epilepsy Classification

S. Anupallavi, G. Mohan Babu, S. R. Ashokkumar

Abstract: *Epileptic is a neural disease exemplified through untypical concurrent signal discharge from the neurons present in the brain region. This abnormal brain functionality could be captured through electroencephalography (EEG) system. Generally the observed EEG signals are examined by the experienced neurologist, which may be time consuming when observing hours of EEG signal. Therefore, this proposed work provides a fully automatic epileptic seizure detection system by means of the multi-domain features along with various machine learning algorithms. Initially, the obtained EEG signals are processed to clear noise and artefacts. Subsequently, the pre-processed signals are segregated as 5 seconds epochs and for each epoch various features are extracted from frequency domain, time domain. Additionally entropy, correlation and graph theory approaches has been used for analysis the connectivity of the brain network. Subsequently, distinguishable features are chosen carefully in this regard from the immense feature set by virtue of multi-objective evolutionary method and convincingly, classification has been performed using support vector machine(SVM).A Bayesian optimization (BaO) algorithm was utilized to optimize the SVM's hyper-plane parameters. In addition, Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA),Random Forest Ensemble (RFE) and k-Nearest Neighbor Ensemble (k- NNE) was also used for comparing the proposed results. These obtained results validates by considering the performance of this work is competing along with state-of the-arts approaches. The proposed work is implemented on a CHB-MIT database .The obtained performance measure of the classifiers are 99.09%, 81.49%,80.90%,76.85% and 84.14 % in SVM , LDA, QDA, k- NNE and RFE respectively. Finally SVM with Bayesian Optimization (BaO) algorithm outperforms than other classifiers with accuracy, AUC, sensitivity and specificity, as 99.09%, 99.67%, 98.06% and 98.12%, respectively.*

Keywords: *About four key words or phrases in alphabetical order, separated by commas.*

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I. INTRODUCTION

Epilepsy is a nervous disease and it's often caused within functionality variation occur in the brain neuronal activities. It may trouble all age group peoples [1]. It is amongst the most known brain disorder that ends in around 1% among the whole populace worldwide and around 0.2% of affected peoples are expire due to this epileptic seizure. Clinically, many diagnostic tools namely, computed tomography scan, magnetic resonance imaging and ultrasound are used for epilepsy diagnosis but these are considered to be expensive and cannot be utilized for evaluation for long time. Rather, EEG is a non-surgical and inexpensive tool perhaps employed for long-lasting evaluation [2]. Thus, it is considered as the greatest practical mechanism for the epilepsy diagnosis.EEG signals are acquired from the scalp of the head. Neurologist observes EEG patterns and decisions are made based up on his observation.

In recent days, many researcher's extracted features from standard deviation, wavelet features [4], entropy , line length , absolute mean value, average power and proportion of absolute mean values[3] and fractal dimension [5] from epileptic signals. Then, the obtained features can be fed into various classifiers such a SVM [7], fuzzy logic model [8], artificial neural network [6] and Markov modelling to classify the seizure occurrences. The most familiar uni-variant features obtained from EEG signal is spectral power estimation. Wavelet [9] and Fourier Transforms [10] are utilized for transforming the EEG signal from time domain into frequency domain. Over the beyond, establishing the overall power of EEG signal of each channel, the energy of the signals is also obtained from the frequency bands: delta (< 3 Hertz), theta (4-7 Hertz), alpha (8-13 Hertz), beta (14-30 Hertz) and gamma (>30 Hertz).

The negative and positive zero level crossing of the signals are also considered for prediction of seizures [11].The known bi-variant feature for estimating the dependence among a pair of EEG channel is obtained from cross-correlation. Secondary cross-correlation features could be extracted as spatiotemporal Eigen values estimated between channels covariance and correlation matrices [12]. In previous work, Connectivity measures for analyzing the synchronization among the signal phase have been calculated from phase coherence, phase locking value and weighted phase locking value [13].

Similarly, the graph theoretic feature has been originated towards observing the functional and analytical connectivity of the brain network [14]. Preceding the constructed graphs, secondary features such as degree, global efficiency, diameter, and eccentricity, characteristic path length and centrality [15] can be obtained.

From the previous studies of epilepsy seizure, it is noticeable that it is very predominant to identify distinguishable features from large set of features. Based upon this reason, we have chosen different features from variety of domains. In this approach, a distinctive feature extraction approach is implemented to extract multi-domain feature from EEG signals for detection of seizure. On account of these analyses, a group of intervals is combined with each other using temporal constraints. These set of intervals is utilized for multi- domain feature extraction and that are fed as input to different machine learning algorithms. The extracted features are provided into SVM along Bayesian optimization approach. The proposed work includes LDA,QDA,k- NNE, and RFE for the comparison of the proposed performance results.

II. METHODOLOGY

PROPOSED ALGORITHM:

Details of dataset:

To substantiate the conception of the designed methodology, herein the research paper the CHB-MIT EEG database [16] is utilized and it is publicly accessible. The description of the dataset comprising of EEG signal records of 24 patients with intractable seizures. Among 24 patients, five males from age of three to twenty two years old and eigteen females from age one to nineteen years old are included. The Duration of EEG signal recording of each patient ranges from 1 hours to 4 hours .All the recorded signals are sampled at a sampling rate of 256 hertz and thus 256 samples per second is obtained with a 16-bit resolution. The 10-20 International electrode positioning system has been followed for recording signals from the scalp. The EEG record which consists of seizure signals and normal signals are called as seizure and seizure free signals respectively. Table.1 presents database description utilized for latency study. The pre-processing of the EEG signal is preformed to remove the artefacts and noise .This is done by utilizing the band-pass filtering value from 0.5Hertz to 30 Hertz. The records of the patients are saved as European data format (.edf) and each subject (Chb_01, Chb_02, etc...)comprises of nine to forty two .edf files from a unitary case. The time duration of the .edf files varies from 1 hour to 4 hours, for example Chb_10 contains 2 hours long duration, Chb_04, Chb_06, Chb_07, Chb_09, and Chb_23 are 4 hours long. Almost other .edf files are about 1 hour duration EEG signals. Particularly files with seizure record contain short duration.

It is important to separate the set of subjects from the dataset for training and testing the classifier. In this paper, subjects Chb_01 to Chb_17 (CTR) are considered for training and tuning the model. Likewise subjects Chb_18 to Chb_24 (CTE) are considered for testing the proposed model. Since, the placement of FP1 and FP2 electrodes are placed closed to the eye region, they are extraneous responsive to the eye movement. It should be considerable that for seizure detection the ocular artefacts should be eliminated, therefore channels linked with FP1 and FP2 are removed in this work.

The channels, 'FP1-F3', 'FP1-F7', 'FP2-F8' and 'FP2-F4' are not considered in this work. Additionally channels 'FT9-FT10', 'P7-T7', 'FT10-T8' and 'T7- FT9' are eliminated following the 10-20 system nomenclature. Finally ,14 channels are considered in this proposed paper such as 'F4-C4', 'F8-T4', 'F3-C3' ,'F7-T3', 'C3-P3', 'O1-P3', 'C4-P4', 'O2-P4', 'T3-T5', 'O1-T5', 'T4-T6', 'CZ-PZ', 'O2-T6', and 'CZ-FZ'. Subsequently, a new 6 channels combination are calculated such as, 'T3-C3', 'P3-T5', 'C4-T4', 'F8-F4', 'F7-F3' and 'P4-T6' for obtaining more relevant information from EEG signals.

The fore mention channel combinations are calculated from Eq (1) to Eq (6).

TABLE 1: SUMMARY OF THE PATIENT DATA OBTAINED FROM THE CHB-MIT DATASET

Patient id	Age (years)	Gender	No. of seizures	No. of. sessions
Chb_01	11	F	7	7
Chb_02	11	M	3	3
Chb_03	14	F	7	7
Chb_04	22	M	4	3
Chb_05	7	F	5	5
Chb_06	1.5	F	10	7
Chb_07	14.5	F	3	3
Chb_08	3.5	M	5	5
Chb_09	10	F	4	3
Chb_10	3	M	7	7
Chb_11	12	F	3	3
Chb_12	2	F	40	13
Chb_13	3	F	12	8
Chb_14	9	F	8	7
Chb_15	16	M	20	14
Chb_16	7	F	10	6
Chb_17	12	F	3	3
Chb_18	18	F	6	6
Chb_19	19	F	3	3
Chb_20	6	F	8	6
Chb_21	13	F	4	4
Chb_22	9	F	3	3
Chb_23	6	F	7	3
Chb_24	-	-	16	5

$$F7-F3=(FP1-F3)-(FP1-FP7) \qquad -(1)$$

$$P4-T6=(P4-O2)-(T6-O2) \qquad -(2)$$

$$F4-F8=(FP2-F8)-(FP2-F4) \qquad -(3)$$

$$T5-P3=(T5-O1)-(P3-O1) \qquad -(4)$$

$$C4-T4=((F4-F8)-(F4-C4))+(F8-T4) \qquad -(5)$$

$$T3-C3=(F7-F3)+((F3-C3)-(F7-T3)) \qquad -(6)$$

Obviously, the final dataset comprises of total 20 channels of EEG signals. This paper computes the seizure onset that continues longer more than 10s.

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Therefore 5s long epochs with 4s overlap is chosen in this paper for epileptic seizure detection for one second. But despite that segmenting the EEG signals could lead to an imbalance between epochs of seizure and seizure-free signals. This problem has been sorted out by performing statistical analysis and finally the duration of seizure is considered within a short duration with a range of 6s-752s.

Feature Extraction:

Following channel selection, from the EEG signals the multi-domain features are extracted using their corresponding formulae's and algorithms. The multi-domain feature includes spectral features, average feature, connectivity features and entropy features. The performance of the EEG signals for seizure detection could be improved by extracting features from time domain and frequency domain, and its network analysis are done with correlation ,connectivity and graph analysis. All the features that are extracted from EEG signals are profiled in Table 2.

i) Time domain

The time domain feature extraction incorporates Statistical features and correlation features. The statistical moment features measures the Min, max, kurtosis, skewness, and Mean [17].Since, these features are computed for each segment of every channel, total 100 statistical features are obtained for 20 channels.The correlation coefficients among two channels are computed; particularly all the correlation coefficients don't have influence over seizure detection when the channels are far apart to one other. Therefore, in this proposed work correlation matrix has been implemented, provided the values 0 and 1. The value '1' represents the adjacency between two channels in spatial position and vice versa for value '0'.In order to obtain a non-repetitive features, the elements present in the lower triangle region of correlation matrix is set '0'.The final correlation matrix with non-zero correlation values could be computed by multiplying regional correlation matrix with correlation matrix .The total features obtained from this features is about 108 features. In additional to these features 20 Eigen values are computed for the correlation matrix.

It should be noted that the seizure onset generally commence from certain regions of both the right and the left cerebral hemisphere, the posterior and frontal lobe. Henceforth, four regions are divided as shown in Fig.1 to calculate the maximum, minimum, and mean correlation coefficients of the above mentioned regions.

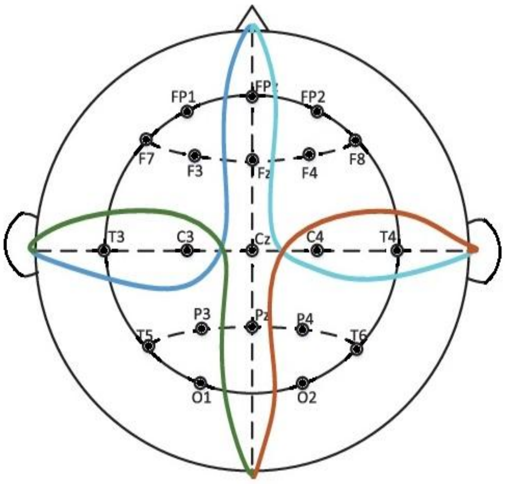

Fig 1.Representative diagram of multi-channel partition

Fig. 2 provides the pair-wise correlation coefficients of each subject computed among pair of features obtained from the graph features characterizing Functional connectivity network (FCN). Correlation coefficient is computed and it is color coded with columns as graph measures and rows as study subject. It can be understood that higher dependences amongst features may cause dimensionality issue. Thus multi-objective evolutionary (MOE) are used for feature selection.

Table 2: Tabulation of the obtained features for each 5-s long EEG segment

Feature types	Feature measures	Feature parameters
Time	Statistical moments	Max,Min,Mean,Kurtosis,Skewness
	Correlation coefficient	Non-zero crossing of correlation, Eigen value of correlation matrix, Max, Min and mean in the front and rear of left region,Max, Min and mean in the front and rear of right region
Frequency	Total frequency area	Absolute mean area under signal
	FFT–Power spectral Density	Energy value at: • delta (≤3 Hz) • theta (4–7 Hz) • alpha (8–13 Hz) • beta (14–30 Hz) • gamma (30–55 Hz)
Connectivity	Cross-correlation	Autocorrelation, Maximum absolute coefficient
Graph theory	Local measures	Eccentricity(ECC) ,Local efficiency (LOCEF), Clustering coefficient (CC), Betweenness (BW), Centrality(CEN), Pearson Degree Correlation (PC),Rich Club Metric (RCM)
	Global measures	Global efficiency(GLOEF) ,Diameter(DIA), Radius(RAD) , Characteristic path(CP), Algebraic Connectivity of a graph(AC)

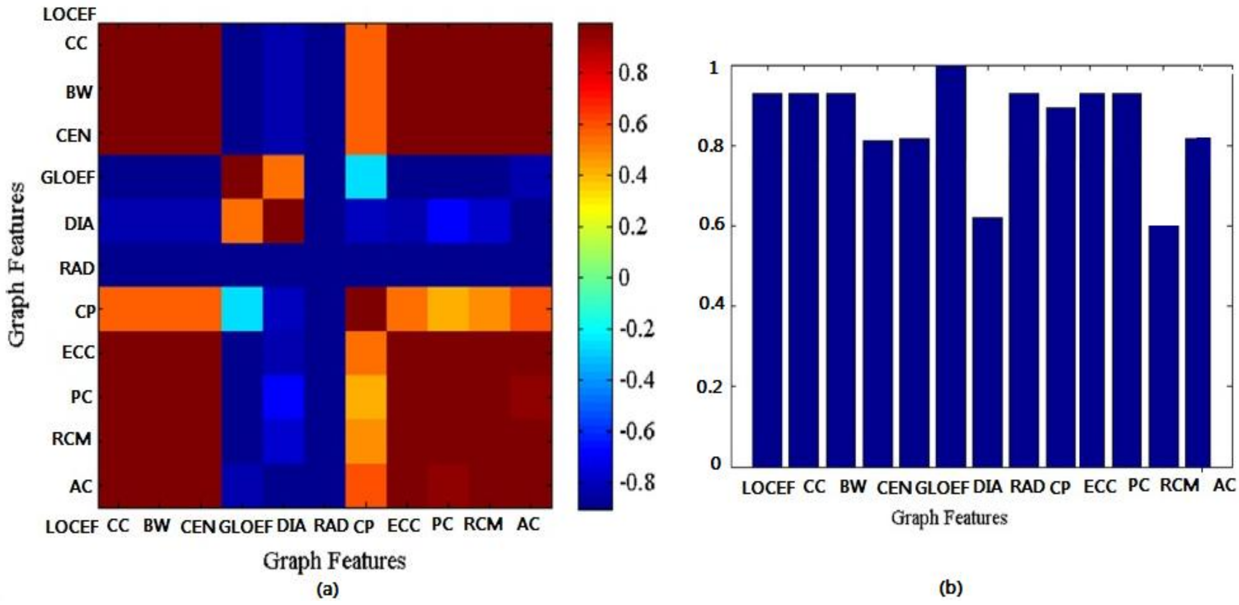

Fig 2 (a) Color-coded pair wise matrix for correlation coefficient among FCN graph features (b) Average correlation coefficient for one –on-one graph features.

ii)Frequency domain

It is important to extract the spectral information to understand the synchronization effect present in EEG signals. In this paper, the band pass filter is utilized for filtering the EEG signal within a range of 1 Hz to 48 Hz. The Fast Fourier Transform is applied as signal transformation and the amplitude is obtained for all frequency components. The power spectral density and its energy percentage are calculated for all five fundamental frequency sub-bands.

iii)Brain connectivity

The similarity between two different EEG signals can be computed using maximum absolute cross correlation to provide the functional connectivity of the brain region. Potential time variations are phased among two different spatially distant signals. Thus the maximum absolute cross correlation among the signals can be calculated as:

$$C_{ab} = \max_{\tau}\left(\left| \frac{C_{ab}(\tau)}{\sqrt{C_a(0) * C_b(0)}} \right| \right) \qquad -(7)$$

Where the time delays are represented as, $\tau, \tau \in [-5,5]$

iv) Graph connectivity measures

In this research work, the graph analysis is implemented as an acceptable methodology for explaining the connectivity of the brain network in functional aspect. From the weighted graph, set of nodes (channels) and its corresponding weights are calculated. The adjacency symmetric matrix is utilized to represent each graph as Wij where provides the nodes. It is also important to measure the local and global measures for the extracted graph.

For each node the local measures are computed such that :(a) local efficiency which calculates the mean of the adjacent node's as average inverse shortest path length. (b) Clustering coefficient which provides the density of the nearby nodes connections corresponding to a particular node [18] (c) eccentricity is the measure of longest path from one node to any different node within the network. (d) betweenness centrality provides the least path between any two different nodes .

Similarly for each node the global measures are extracted from the global efficiency, the characteristic path, radius and diameter of the graph. Global efficiency provides the complete network efficiency. The characteristic path length is measured as the proportion of the shortest network path length, which provides better functional integration [18]. The radius is measure of the minimum value of the eccentricity. The diameter is the measure of the highest value of the eccentricity of the nodes.

Feature Selection:

Feature selection maintains the less data usage by reducing the complexness of the classification system. It also boosts the computation efficiency of the machine learning models. In this work, for the purpose of feature selection multi-objective evolutionary (MOE) algorithm has been used [19]. The MOE algorithm concurrently optimizes two main objectives: (i) provides minimum classification error and (ii) selects least number of features.

III. MACHINE LEARNING MODELS

The input provided to several machine learning models are obtained using several multi-domain features. In this proposed work, we have two obtainable classes, i.e non-seizure and seizure. The best machine learning models are chosen in accordance with our experimentation to model a joint approach to prove the performance of the individual models.

Then these frameworks are evaluated with two familiar ensemble approaches to confirm their performance rate.

Classification Models:

As mentioned above, three classification models were considered for the EEG Seizure detection task: Quadratic Linear Discriminant Analysis, Linear Discriminant Analysis and Support Vector Machine.

Linear Discriminant Analysis (LDA)

LDA is extracted in relating the difference of the test data with the pre-estimated database of LDA. After performing a comparison, every attempt might have a decision associated with discriminant ratings and it is concluded from the methodology. It also handles dimensionality reduction. The shape of the discriminant rating to compute the performance of the discriminant performs is provided as:

$$LDA = \omega_1 Y_1 + \omega_2 Y_2 + \omega_3 Y_3 \dots\dots\dots \omega_p Y_p \qquad -(8)$$

Quadratic Discriminant Analysis (QDA)

QDA is an alternative of LDA in which separate covariance matrix is constructed for every class of observation. The covariance matrix Σ_l is disassociated for every individual class, l= 1,2, … … L. Quadratic discriminant function is computed as:

$$\alpha_1 = -\frac{1}{2}\log\left|\sum_1\right| - \frac{1}{2}(a-\mu_1)^T \sum_1^{-1}(a-\mu_1) + \log \pi l \qquad -(9)$$

Support Vector Machine (SVM):

SVM tries to find an optimal hyper plane from the provided data features to allocate the data point's uniquely.SVM supports the classification among recent models. Provided a training data with label pairs (a_i, b_i) , =1, 2,…….., where $a_i \in R^n$ and $b \in (1,-1)^l$ the support vector machines (SVM) [20] provides the resultant of the optimization challenge using Bayesian Optimization (BaO) algorithm :

$$\min_{\omega, y} \in \frac{1}{2} W^T W + c \sum_{i=1}^{l} \varepsilon_i \qquad -(10)$$

The training vectors a_i are delineated into a best dimensional space with the function $\emptyset$. C>0 is the error parameter. In addition, $K(a_i,a_j) \equiv \emptyset(a_i)^T \emptyset(a_j)$ is known the kernel function[21]. It is evident from Table.5 that values of LDA and QDA are generally lower than SVM attributable to the fact that no linear separation is found between feature vector and data points.

The function of kernel is to convert the consistent features into inconsistent feature space in order to improve the accuracy rate. In this research work, most known kernels with Radial Basis Function (RBF) kernels are utilized and it can be expressed as:

$$b_i(W^T \varphi(a_i) + y) \geq 1 - \varepsilon_i, \quad \varepsilon_i \geq 0$$

$$K(a_i, a_j) = E\left(\frac{-\|a_i - a_j\|^2}{2\sigma^2}\right), \sigma > 0 \qquad -(11)$$

The $\|a_i - a_j\|^2$ is the square of Euclidian distance among different features and might be portrayed as similarity calculation and σ is the control parameter. To conclude, optimized parameters of RBF-SVM are used to enhance classification performance.

Ensemble Methods:

An ensemble methods is also called as ensemble of classifiers is a machine learning algorithm that integrate several base classification approach to generate one optimal predictive model. These combined approaches generally outperform the classifier which is individually used as model. The proposed work utilized Random Forest (RF) and k-Nearest Neighbor Ensemble (k-NNE) for boosting overall performance of the classifier and to improve the predictions.

IV. RESULTS AND DISCUSSION

This research work provides the performance of various machines learning algorithm to detect the epileptic seizure from EEG signal. So as to validate the generality of the proposed methodology the classification performance measures like specificity (SPEC), sensitivity(SEN), accuracy(ACC) and area under curve (AUC) are calculated. The considered work is implemented on CHB-MIT dataset. The EEG data are pre-processed and it was filtered by band-pass filter to get frequency range of about 0.5Hertz to 30Hertz.Various features like frequency domain, time domain, connectivity and graph theory based features are derived. About 146 features were obtained. Since the number of seizure data is fewer than non-seizure dataset imbalanced was eventuate. Therefore this was resolved by using adaptive synthetic sampling algorithm for imbalanced learning [21].The Multi-objective evolutionary feature selection was used for selecting the features.

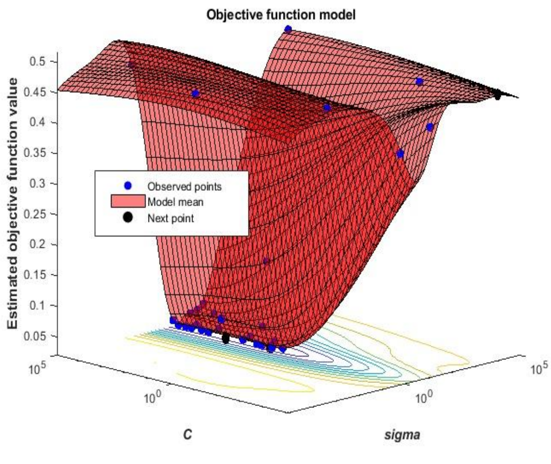

Fig. 3: SVM parameter optimization using BaO algorithm.

Fig.3 provides an objective function of the classifier; it provides a minimum classification error by optimizing C and σ. Various combinations of C and σ provide various minimization values, but the Bayesian optimization (BaO) algorithm are utilized to obtain the minimum one among them. From the figure it could be realized that the lowest point provides lowest classifier error value. Highest accuracy value is obtained from the lowest minimized error value.

Table 3: Patient-by-patient classification results for CHB-MIT dataset using SVM with BaO approach.

Patient id	Classification performance measures (%)			No. of actual seizure event	No. of detected seizure event
	SEN	SPEC	ACC		
Chb_18	97.67	93.72	95.69	6	4
Chb_19	100	100	100	3	3
Chb_20	97.5	99.83	98.66	8	7
Chb_21	95.01	94.58	94.79	4	1
Chb_22	100	100	100	3	3
Chb_23	98.5	99.48	98.99	7	6
Chb_24	97.75	99.26	98.5	16	15
Overall	98.06	98.12	99.09	47	39

Table 4: Comparison of SVM operation with different feature domain

SVM Operation	Classification performance measures (%)			
	SEN	SPEC	ACC	AUC
Time domain	79.19	76.71	77.95	81.37
Frequency domain	83.43	78.41	80.92	81.63
Connectivity	94.42	93.9	98.16	97.54
Graph theory	95.24	92.91	98.75	89.64
Without Feature selection	92.17	89.33	90.75	93.12
SVM with MOE feature selection (**Proposed**)	98.06	98.12	99.09	99.67

Table 5: Results of classification performance obtained from the individual machine learning approach

Classifiers name	Classification performance measures (%)			
	SEN	SPEC	ACC	AUC
LDA	76.25	86.74	81.49	83.05
QDA	73.41	88.40	80.90	89.98
RFE	84.40	83.89	84.14	84.20
k-NNE	90.80	62.91	76.85	76.80
SVM with BaO	98.06	98.12	99.09	99.67

For analysing the accuracy of the detected seizure, in this paper patient-by-patient outcomes are provided in Table 3 .In the Table 3, the patient id of chb_21 has actually 4 seizures, but only one seizure is detected. In addition to get the point of importance of the different window epochs of the proposed work, Fig. 4 provides the overall performance of the proposed work .

It could be noticed that accuracy and sensitivity increases with the increase in size of window and maintain constant with 5s window size. Similarly, optimum value is achieved at 5s window size for sensitivity also.

Some configurations were made for the classification models so as to prove the performance rate of the proposed work. The classification models used in this work are SVM,LDA, QDA,RF and k-NNE.for SVM , an Radial basic functional kernel [22] was opted since it plots the samples into a larger dimensional space ,therefore it could able to match the nonlinearity between class labels and its values.

For RF classifier, bootstrap re-sampling technique was chosen to generate new training sample values by selecting its samples randomly from the original training samples. The Spearman's Distance [23] was chosen for k-NNE for estimating the distance amongst two feature values. The 10 -fold cross validation approach was adapted for all models to achieve lowest classification error.

With the aim to evaluate the considered optimized SVM method. We obtained accuracy of the proposed methods in frequency domain, time domain, connectivity based and graph theory features.

This comparison are provided in Table.4 with accuracy of 80.92%,77.95%,98.16%,98.75% and 99.09 % for frequency domain, time domain, connectivity based, graph theory based and SVM with MOE feature selection. In Table 5, the classifier performance rates of various classifiers are provided.

The accuracy of the LDA, QDA, RF, k-NNE and SVM are 81.49%, 80.90%, 84.1%, 76.85% and 99.09% respectively. Similarly, the obtained sensitivity are 76.25%,73.41%,84.40%,90.80%and 98.06% and AUC are 83.05%,89.98%,84.20%,76.80% and 99.67% for LDA , QDA, RF, k-NNE and SVM respectively.

Besides, to determine the implication of feature selection, we related the proposed work with feature selection and without feature selection methods utilizing optimized SVM method. It has been observed that 8.34% improved in the accuracy result after feature selection. The optimized SVM outclasses other classifiers..

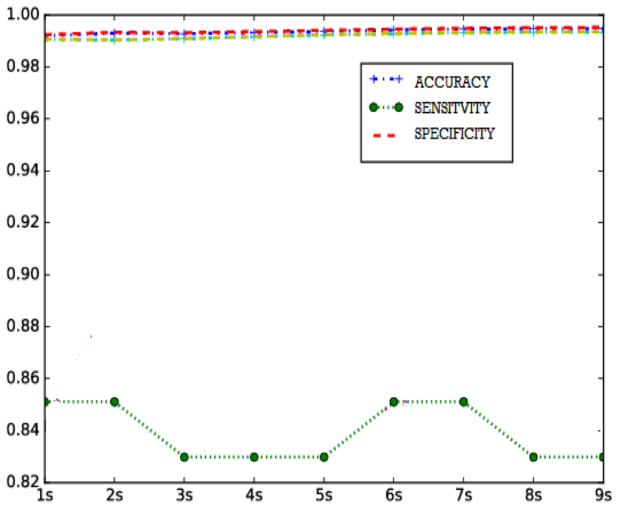

Fig 4.Performance metrics of proposed methodology with various window sizes

V. CONCLUSION

The automatic seizure detection method is proposed in this paper using four processes so called pre-processing, feature extraction, selection of salient features and classification. In order to clear noise and artefacts EEG data's are pre-processed and it has been followed by feature extraction. In addition, the features are obtained from multi domains namely frequency domain, time domain, connectivity based and graph theory based features .Among the extracted features, best features are chosen using MOE algorithm and it has been passed to the classifier. The SVM with Bayesian optimized method has been utilized for obtaining best results. The SVM results are compared with LDA, QDA, RFE and k-NNE. The overall performance metrics of the proposed work has achieved accuracy, AUC, sensitivity and specificity, as 99.09%, 99.67%, 98.06% and 98.12%, respectively. In future, more analysis can be implemented to classify EEG data into non-seizure, pre-seizure and post -seizure states. Localization of the seizure can be addressed along with other features and classifiers.

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