IETE Journal of Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tijr20

A Multi-View SVM Approach for Seizure Detection from Single Channel EEG Signals

Gopal Chandra Jana, Mogullapally Sai Praneeth & Anupam Agrawal

IETE JOURNAL OF RESEARCH
https://doi.org/10.1080/03772063.2021.1913074

Check for updates

A Multi-View SVM Approach for Seizure Detection from Single Channel EEG Signals

Gopal Chandra Jana [1], Mogullapally Sai Praneeth [2] and Anupam Agrawal [1]

[1] Department of Information Technology, Indian Institute of Information Technology Allahabad (IIITA), Interactive Technologies & Multimedia Research Lab, Prayagraj, UP 211015, India; [2] Indian Institute of Technology (IIT), Bhubaneswar 752050, Odisha, India

ABSTRACT
Seizures are the part of the epilepsy that occurs in central nervous system which leads abnormal brain activity. Electroencephalogram (EEG) signal recordings are mostly used in epileptic seizure detection process. Detection of seizures is a crucial part for further treatment of patients. This paper proposes a multi-view SVM model for seizure detection using the single channel EEG signals. In this experiment, two views of the EEG data have been extracted, (1) the time domain features using Independent Component Analysis (ICA) and (2) power spectral densities are obtained in the frequency domain. Extracted features have been fed to multi-view SVM classification model. In this study, a single channel EEG dataset is used for seizure detection. Performance estimation parameters namely Accuracy, Sensitivity, Specificity, F1-score, and AUC value have been estimated for evaluating the proposed model. The model classified seizure and non-seizure over the sets A vs E and B vs E with an accuracy greater than 99% using k-fold cross validation. The classification accuracy obtained by multi-view SVM is better by 1–4% than single view SVM using the same features. Furthermore, the proposed model is also compared with existing single view SVM models. It is observed that the multi view SVM model performed significantly better, compare to a single view SVM model over the same features.

KEYWORDS
Electroencephalogram; EEG signals; Epilepsy; Independent Component Analysis (ICA); Power Spectral Density (PSD); Seizure; Support vector machine (SVM)

INTRODUCTION

Over fifty million people worldwide are suffering from epilepsy, and close to 80% reside in low and middle income nations [1]. Electroencephalogram (EEG) has been extensively used for detection of epilepsy. Epilepsy can be detected by experts, who can observe the entire EEG length and detect epileptic seizures. However, this task can be time consuming, tedious and can be prone to mistakes. Timely detection of epileptic seizures can be helpful for diagnosis of the patient. In recent times the advances in machine learning (ML) and availability of computational power has led us to create automatic seizure detection systems.

Detection of seizures using machine learning involves mainly three steps: (1) Signal/data preprocessing, (2) Feature extraction from signal/data, (3) Classification of processed data in which machine learning techniques are required. In this process, feature extraction and selection are crucial steps as machine learning techniques are highly dependent on the chosen features. Generally, EEG signals are time domain signals and can be converted into frequency domain as well. These two domains make available two separate views of the same dataset, the time domain describes the change in amplitude of signals with respect to time, whereas the frequency domain conveys the energy distribution of the signal over a frequency range. Over the years various feature extraction methods and classification methods were proposed for seizure detection. Yuan et al. [2] proposed a multi-view deep learning based on short-time Fourier transform for seizure detection. Nicoletta Nicolaou et al. [3] proposed epileptic detection using Permutation entropy and SVM. Fu et al. [4] proposed a Hilbert marginal spectral analysis for Hilbert huang transformed data and the obtained features were classified using SVM. For epilepsy detection, Polak et al. [5] used Decision Tree Classifier over the preprocessed data using Fast Fourier Transform. A discrete wavelet transforms based feature extraction method has been used by Subashi et al. [6] to propose seizure detection approach. The processed features were classified using an artificial neural network. Atemangoh et al. [7] used Laguerre wavelet based feature extraction and SVM for seizure detection. de la O Serna et al. [8] used Taylor-Fourier EEG-band energy (TFEBE) features and least square SVM for seizure detection. In the similar fashion, Gupta et al. [9] used least square SVM and other classifiers over Fourier–Bessel series expansion and weighted multiscale Renyi permutation entropy for seizure detection. Also, we have studied several works (Sharma et al. [10], Nishad et al. [11] and Sharma, et al. [12]) where only time domain or frequency domain features were considered for seizure detection. So, in this study we focus on using time and frequency domain features simultaneously through a Multi-view classification model (Multi-view SVM) and compared the same with Single-view classification model (Single-view SVM).

Motivation: From literature, we have observed various approaches which have utilized a single view of the dataset for seizure detection either using time or frequency domain features. But valuable information present in other views is not utilized simultaneously. So, we are motivated to do this study to show the usability of the both views of the dataset simultaneously in seizure detection.

Our Contributions: In this study, we propose a multi view SVM model to utilize information from two views of the dataset for seizure detection. In multi view learning, a ML model is able to learn features from multiple views of the same dataset. Multi view learning algorithms can be categorized based on: (1) Co-training, (2) Co-regularization, (3) Margin Consistency techniques [13]. Co-training is a type of semi-supervised learning algorithm in which two classifiers are trained separately on two views of the dataset. It uses features of labeled and unlabeled data, later incrementally builds the two classifiers over the two views. Co-regularization technique is adding an additional regularization term to the main cost function in order to make sure that data from different views are consistent as well make sure that the predictions from different views are close to each other. In margin consistency techniques, margin variables from different views of model to be consistent based on the product of output variables to be greater than every margin variable. In this paper, we have used a modified co-regularization technique to build SVM-2K [14]. Two views of the dataset were created in time and frequency domain using independent component analysis (ICA) and power spectral densities (PSD) respectively. Finally, extracted time and frequency domain features have been feed into proposed Multi-view SVM. Performance of the proposed model has been compared with single view SVMs (time and frequency domain feature individually) as well as with other relevant existing SVM based state of the art seizure detection models.

The rest of the paper is prepared and is organized as follows: section II describes few related works on multi-view learning, Section III describes the experimental dataset. In section IV, data preprocessing steps are mentioned. In section V, we have described the modified multi-view SVM model. Section VI describes the proposed seizure detection approach based on multi-view SVM model. The results are described in section VII. Section VIII contains a comparison with existing schemes and finally, section IX concludes the study with possible future scope.

RELATED WORK ON MULTI-VIEW LEARNING

The experimental approach presented in this study is interrelated to multi-view learning. Multi-view learning approach has progressive and substantial application in signal processing to learn features from the various perspectives to enhance classification performance [15].

Over the past few years, various research works have been published using multi-view learning approaches and suggested several multi-view learning concepts, and some are discussed in this section. In [15], authors have proposed an approach based on multi-view deep learning for detecting seizure from EEG signal. EEG-based motor imagery intention detection has been proposed by the authors of [16] using deep multi-view feature learning. A clustering approach has been proposed in [17], where authors have used multi-view techniques and extreme learning machine. In [18], a deep multi-view embedding model (DMVEM) based on multi-view representation learning has been proposed for learning social images, where authors have used three view of social image. Other than learning images, in [19] a multi-view approach has been applied for image annotation. A clustering and feature selection approach based on weight multi-view technique has been suggested in [20]. Similarly, another multi-view clustering approach based on self-paced learning has been proposed by the authors of [21]. Also, a subspace co-training scheme has been suggested in [22] for multi-view clustering. Similarly, in [23] authors have suggested maximum entropy discrimination approach for multi-view learning, where authors have used consensus and complementarity property. A subspace clustering method based on multi-view approach has been suggested in [24] for image clustering. Another multi-view clustering technique has been proposed by the authors of [25] where low-rank and matrix-induced regularization have been used. In [26], for enhancing classification performance over highly imbalanced classes, a multi-view learning-based approach has been applied for data proliferator. In this section, we have mentioned few multi-view learning-related works and understood the background of the multi-view learning approach. Also, we have studied article [13] to understand recent progress and new challenges in multi-view learning.

Our present study based on multi-view learning with SVM for seizure detection. The details of our proposed approach have been described in section IV, V and VI accordingly.

EXPERIMENTAL DATA

In this Experiment, EEG dataset [27] and [28] given by the University of Bonn, Germany has been used. The dataset comprises five folders labeled with A to E. Each folder contains 100 text files and each text file has 4097 data points and is of 23.6 s duration sampled at 173.61 Hz. The dataset contains frequency components in the range of 0–85 Hz. EEG signals are mainly distributed in the frequency range 0–40 Hz. The frequency components 0–40 Hz are useful for seizure detection. The excluded components mainly contain artifacts which possess no useful information. We have used a Butterworth low pass filter with cut-off frequency of 40 Hz to attenuate frequency components above 40 Hz.

The data set was further divided into sub-groups as follows, each text file containing 4097 data points which make a period of 23.6 s were segmented into 23 parts with each 1 s and containing 178 data points. The last 0.6 s was not included in the experiment. The description of the dataset is given in Table 1 and sample signal plots from each sets have been shown in Figure 1.

Table 1: Experimental Dataset specifications

Data Folders	A	B	C	D	E
Data Type	Non - Epileptic		Epileptic		
Special State	Eyes closed	Eyes open	Interictal		Ictal

EXPERIMENTAL DATA PREPROCESSING

In this data preprocessing step, we have preprocessed the filtered data in two feature domains. Later these two pre-processed data are given as an input to the proposed multi view SVM model. ICA has been applied for the time domain feature extraction. This method helps in improving independency among features as well as in dimension reduction of the data. In frequency domain, PSD is obtained using Welch method [29]. PSD is the measure of signal power versus frequency components. For better understanding we have represented ICA and PSD mathematically as follows.

Independent Component Analysis (ICA): ICA technique has enormous usability in EEG signal analysis. In EEG signal analysis, ICA technique has been used in different aspects like for EEG Channel selection [30–32], EEG artifact elimination [33–35], EEG signal Feature reduction [36], and EEG channel source separation [37–39]. More significances of ICA are described in [40] for seizure detection using EEG signal.

Let random EEG data vector $E = [E_1, E_2, \ldots, E_r]^T$ where r component are mixtures of r independent components of random vector $S = [S_1, S_2, \ldots, S_r]^T$. Now vector E can be expressed as $E = AS$, where A is a $r \times r$ mixing matrix. The objective of ICA is to find an inverse matrix of A (assumed the inverse matrix is W). Now, independent components I can be calculated using $I = WE \cong S$ [39,41]. We have estimated the outputs after

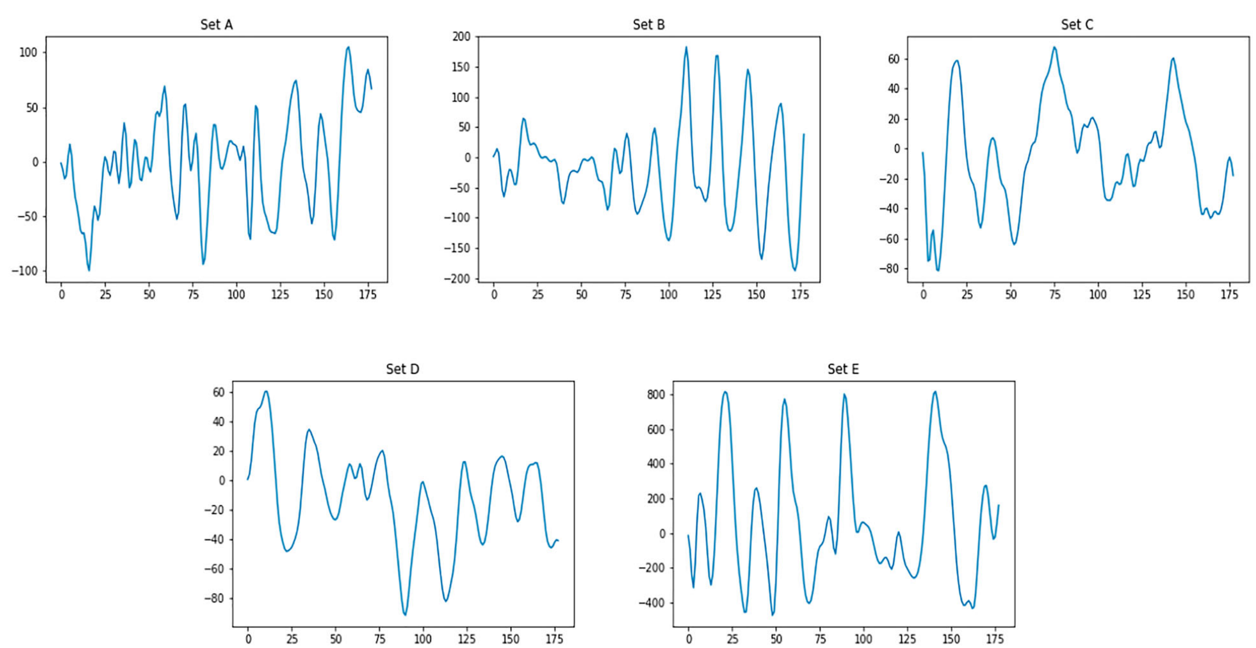

Figure 1: Shows the data segments of original input EEG datasets (Set-A, B, C, D, E)

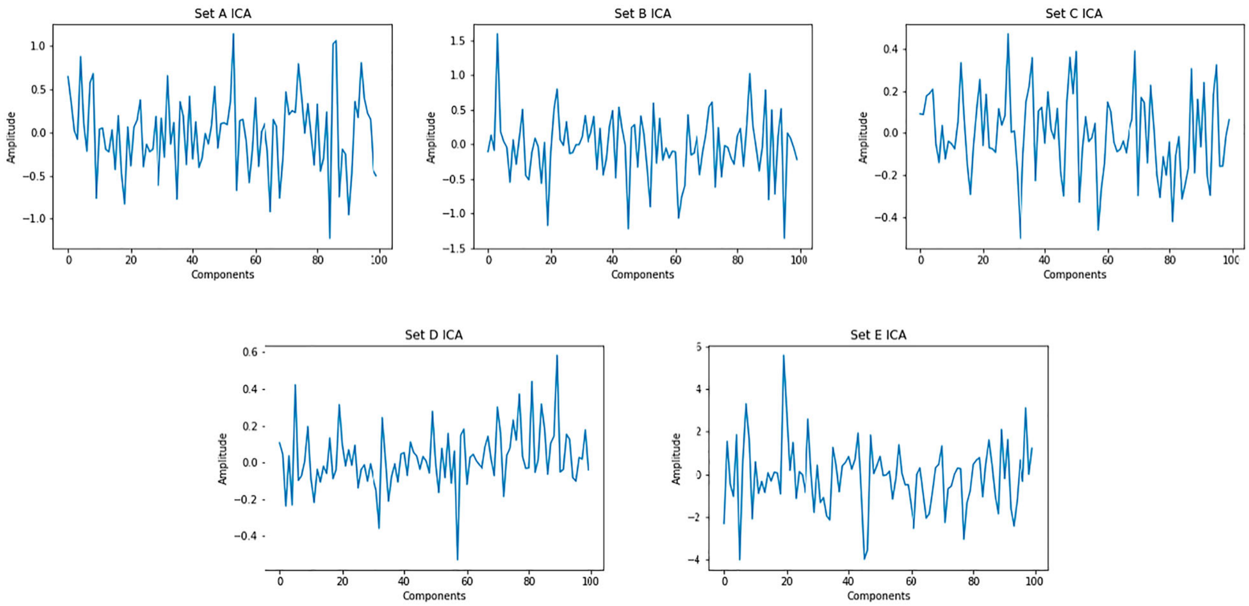

Figure 2: Shows five data segments after applying ICA over the five EEG datasets (Set-A, B, C, D, E)

applying ICA over each data sets and have shown the corresponding sample outputs in Figure 2.

Power Spectrum Density (PSD): Power Spectrum Density feature has considered in several research [42–44] related to seizure detection using EEG signals. In this experiment, we have used welch's [29,45,46] method for extraction PSD features from EEG signals. In this part, we have described the PSD mathematically.

Let we have EEG time series data sequence $s[0], s[1], \ldots,$ $s[N-1]$, now divided this data sequence into K segments (or batches). So, we will get segments can be represented as

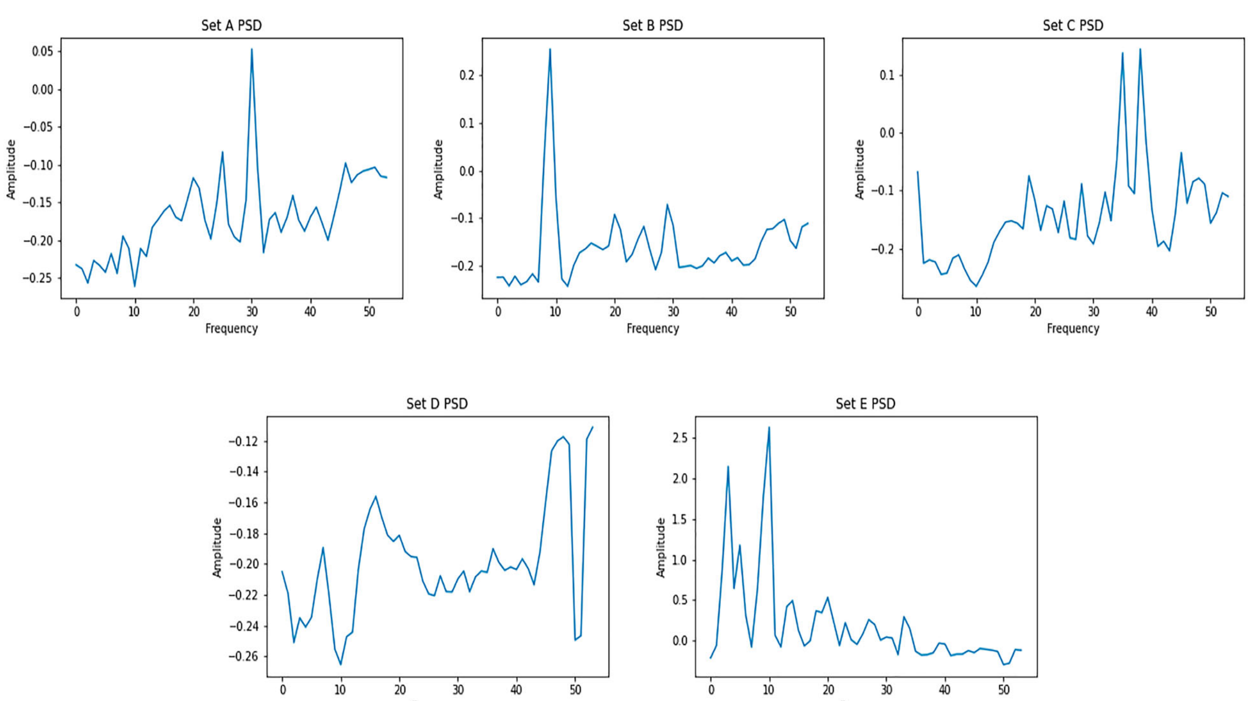

Figure 3: Shows the data segments of PSD. In this figure we have plotted five segments of extracted PSD features from five EEG datasets (Set-A, B, C, D, E)

segment 1 : $s[0], s[1], \ldots, s[M-1]$, *segment* 2 : $s[P], s[P+1], \ldots, s[M+P-1], \ldots$,*segment* $k : s[N-M], s[N-M+1], \ldots, s[N-1]$, where M is the number of data points from each data segments, P is the number of data points to shift between in data segments and K is the number of data segments.

Now, calculate a windowed discrete Fourier transform (DFT) for each data segments ($k = 1$ to K) at some frequency $\gamma = \xi/M$ with $-(M/2-1) \leq \xi \leq M/2$ So, DFT can expressed as

$$X_k(\gamma) = \sum_r s[r]w[r]exp(-j2\pi\gamma r),$$

where $r = (k-1)P, \ldots, M+(k-1)P-1$ and $w[r] =$ the window function. Next generate modified periodogram value $Q_k(\gamma)$ for each segment ($k = 1$ to K) from the DFT. We can express $Q_k(\gamma)$ as $Q_k(\gamma) = \frac{1}{W}|X_k(\gamma)|^2$ where $W = \sum_{r=0}^{M} w^2[r]$. Finally, average the modified periodogram values to generate Welch's estimate of PSD using $P_s(\gamma) = \frac{1}{K}\sum_{k=1}^{K} Q_k(\gamma)$ [29,43]. We have calculated the PSD outputs for each data sets and have shown the corresponding sample outputs in Figure 3.

MULTI-VIEW SVM MODEL

Support Vector Machines (SVMs) are a set of supervised learning approach which can be used for outliers detection, regression and classification. The SVM does classification by finding hyperplanes which can well differentiate the classes. This idea can be extended to classify multiview data as well, by making changes in the algorithmic steps.

SVM-2K is one such algorithm proposed in [14] which is a co-regularization algorithm used for classification. In this experiment we have used a modified SVM-2K algorithm, which is as follows. Consider two views of data as (X_A, Y), (X_B, Y) such that $Y \in \{-1, 1\}$ and $X_A \in R^n$, $X_B \in R^m$ where n, m is number of features in the respective view. The loss function for this experiment is given by: $L = \frac{1}{2} * ||W_A|| + \frac{1}{2} * ||W_B|| + C_A \sum_{i=1}^{l} \xi_A^i + C_B \sum_{i=1}^{l} \xi_B^i + D \sum_{i=1}^{l} \eta_i$ (Equation (1)) with constraints: $|(W_A.X_A + b_A) - (W_B.X_B + b_B)| \leq \eta_i + \varepsilon$ (Equation (2)). $Y^i.(W_A.X_A^i + b_A) \geq 1 - \xi_A^i$ (Equation (3)) and $Y^i.(W_B.X_B^i + b_B) \geq 1 - \xi_B^i$ (Equation (4)). where $\xi_A^1 \geq 0$, $\xi_B^i \geq 0$ and $\eta_i \geq 0$ for all $1 \leq i \leq L$. Here ξ_A^i, ξ_B^i and η_i are the slack variables. W_A, W_B are the weights of view-1 and view-2 respectively. L is the total samples.

Equation (2) is the additional cost that we add, which can be modeled as cost for not meeting similarity. The output of these two views is combined in a weighted manner. Mathematically, $\hat{Y} = W_1 Y_1 + W_2 Y_2$ such that $W_1 + W_2 = 1$, $W_1 \geq 0$ and $W_2 \geq 0$ where Y_1, Y_2 are outputs of SVM1 and SVM2 respectively, $\hat{Y}$ being the predicted output and $Y_1 = W_A.X_A + b_A$, $Y_2 = W_B.X_B + b_B$. The final output of the model is given by the following.

$$Y_f = -1 \; if \; \hat{Y} \leq \text{threshold}$$

$$Y_f = +1 if \; \hat{Y} \geq \text{threshold}$$

The weights W_1, W_2 and the threshold value can be tuned after completion of training.

PROPOSED MULTI-VIEW SVM BASED SEIZURE DETECTION APPROACH

The experiment has several phases as shown in Figure 4. The first phase involves in data preprocessing. In the process, we have filtered the EEG data using a 5th order Butterworth filter to remove frequency components above 40 Hz, as components above 40 Hz can lead to poor performance of the model.

In the second phase, filtered data were segmented. Segmentation process has been mentioned in Section III.

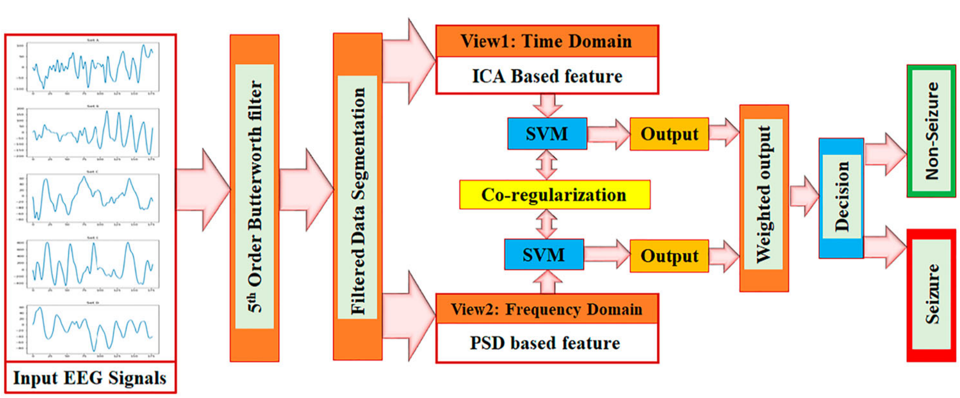

Figure 4: Illustration of the experimental phases involved in this study

In total 11,500 samples of the dataset were created, each sample having 178 data-points. In the third phase, two views of the dataset are created, in time domain and frequency domain as mentioned in Section IV. Later these two views act as input to the multi view SVM model.

The fourth phase involves in training the model. We have created two SVM models for two views of the processed dataset, these SVMs will be optimized together according to the loss function mentioned in Equation (1). In training session, we have fitted both SVMs over the training data. In training we have used a stratified K-fold (here $K = 10$) cross validation method, this method ensures that equal amounts of positive and negative class data are present in each fold, the data set was divided into 70% for training and 30% testing. After minimizing the loss function, the third phase of the model is implemented.

The fifth phase involves in tuning the model parameters W_1, W_2 and the threshold value. We have obtained the values of W_1, W_2, threshold by running a loop for values W_1, W_2, threshold with the constraints $W_1 + W_2 = 1$ and $W_1 \geq 0$, $W_2 \geq 0$. We have considered the values of W_1, W_2, and threshold which result in best training accuracy.

RESULTS AND DISCUSSION

The performance of the proposed model has been evaluated based on the statistical measures mentioned in Table 2, where sensitivity (Recall) indicates the percentage of actual seizures that were detected and specificity tells us the percentage of actual non-seizures that were detected. In addition to this we have evaluated AUC values, ROC curves and Precision (positive predictive value (PPV)) vs. Recall curves for each considered cases. Where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

As the experiment is on multi-view SVMs, we have experimented with single view SVMs for the both views separately and also performed concatenation of both the features and gave input to SVM. The estimated results are listed in Table 3. In single view SVMs, we have observed that frequency domain features *i.e.* power spectral densities as features performed better than the time domain features by ICA.

These results imply that frequency domain features provide better information than the time domain features. Furthermore, we observed that when simple concatenation of frequency domain and time domain features were given as input to the SVM, performance was less than that of the frequency domain experiment. Finally, it observed that the proposed multi-view SVM model out-performed the single view SVMs in all scenarios. Results obtained by proposed multi view SVM are shown in Table 4. Including accuracy, sensitivity, specificity, and f1 score, also we have plotted Precision vs Recall curve and Receiver operating characteristics (ROC) curve to under the effectiveness proposed seizure detection model. Also, we have calculated area under curve (AUC), which showed a closer value to “1”, implies a better classifier. Time complexity of our proposed approach for training is of order O(min(n ∗ d1, n ∗d2)) This is can be seen from (Equation (1)). We have $\mathrm{W_A} * \mathrm{X_A}$ which has d1 multiplications over n samples and similarly, for $\mathrm{W_B} * \mathrm{X_B}$ which has d2 multiplications over n samples. On the other hand, Classification time complexity is O(min(d1, d2)).

Precision vs Recall curves (Figures 5–11) describes the tradeoff in Precision and Recall of the proposed model over different cases upon different threshold values. On the other hand, Receiver operating characteristics (ROC)

Table 2: Statistical measures for evaluating proposed model

Statistical measures	Definition
Accuracy	(TP + TN)/(TP + TN + FP + FN)
Sensitivity	TP/(TP + FN)
Specificity	TN/ (TN + FP)
Precision	TP/(TP + FP)
f1 score	(Precision Recall)/(Precision + Recall)

Table 3: Estimated results (detection accuracy) based on different views of SVM

Cases	Single view SVM	Single view SVM	SVM	Multi-View SVM
	Features by ICA	PSD Features	Concatenation of ICA and PSD features	ICA and PSD features
A vs E	94.06%	96.88%	95.51%	99.54%
B vs E	90.43%	95.57%	94.41%	99.43%
C vs E	92.40%	95.07%	94.27%	98.16%
D vs E	90.80%	92.10%	91.45%	96.17%
AB vs E	94.34%	97.77%	96.81%	99.45%
CD vs E	93.09%	95.44%	93.57%	97.05%
ABCD vs E	95.56%	96.43%	96.02%	97.63%

Table 4: Results obtained by proposed multi view SVM

Cases	Accuracy (%)	Sensitivity (%)	Specificity (%)	f1 score ($<=1$)	AUC ($<=1$)
A vs E	99.54	99.53	99.55	0.99	0.9990
B vs E	99.43	99.45	99.42	0.99	0.9994
C vs E	98.16	97.53	98.81	0.98	0.9974
D vs E	96.17	96.32	96.04	0.96	0.9874
AB vs E	99.45	99.63	99.09	0.99	0.9989
CD vs E	97.05	97.90	95.38	0.96	0.9792
ABCD vs E	97.63	98.38	94.67	0.95	0.9764

curves (Figures 12–18) describes the change in True positive and False Positive rate over the different cases upon the different threshold values.

Figures 5–11 contains precision vs recall graphs of different cases of the dataset, where the Y-axis indicates distribution of precision and X-axis indicates distribution of recall. Figures 12–18 contains the ROC graphs of different cases of the dataset, in where the Y-axis indicates True positive rate and X-axis indicate False Positive rate.

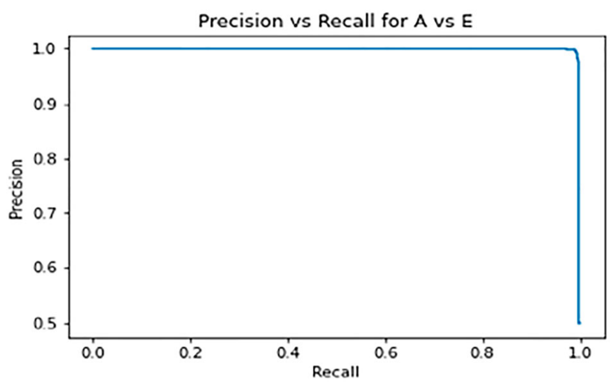

Figure 5: Precision vs Recall curve over the A vs E

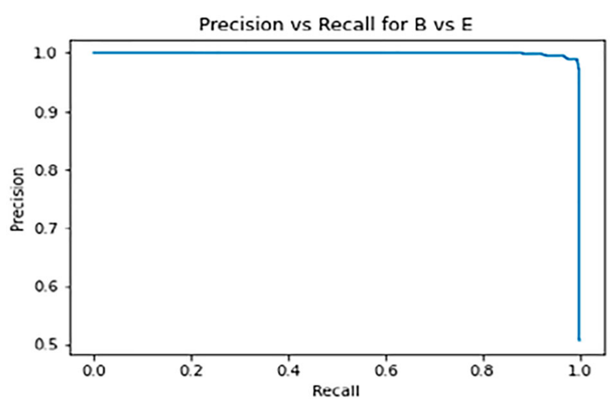

Figure 6: Precision vs Recall curve over the B vs E

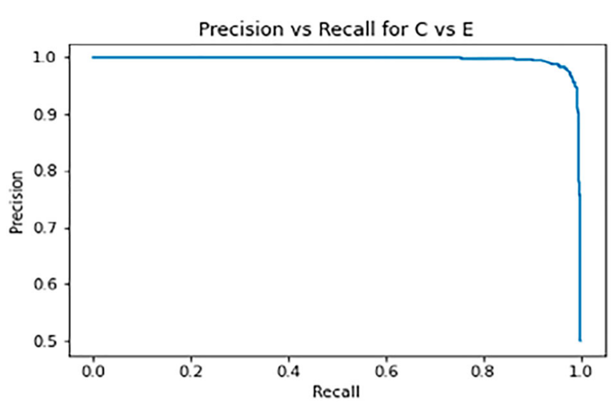

Figure 7: Precision vs Recall curve over the C vs E

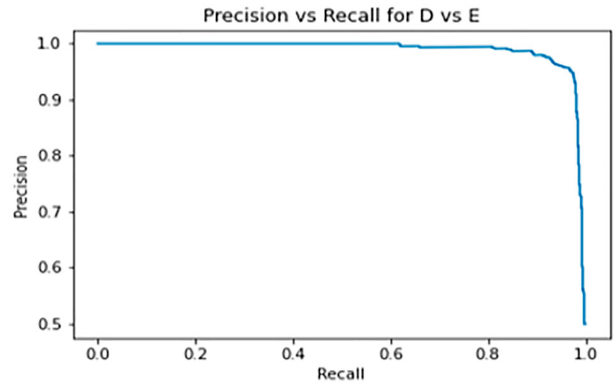

Figure 8: Precision vs Recall curve over the D vs E

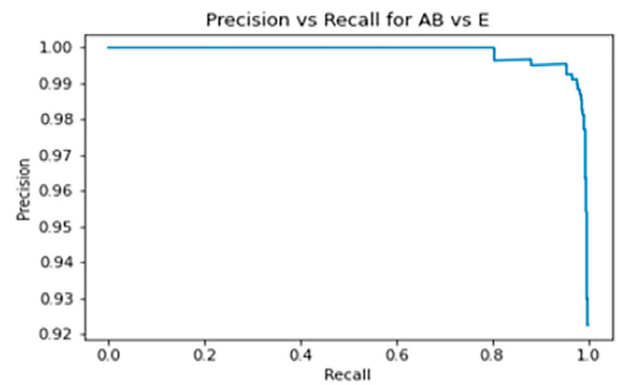

Figure 9: Precision vs Recall curve over the AB vs E

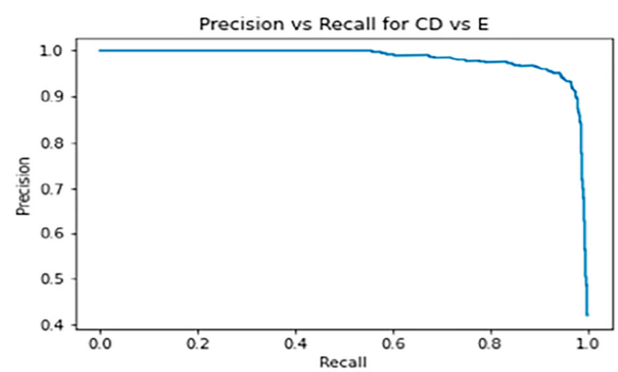

Figure 10: Precision vs Recall curve over the CD vs E

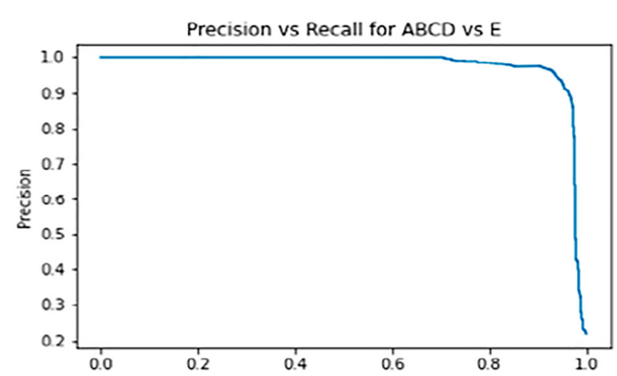

Figure 11: Precision vs Recall curve over the ABCD vs E

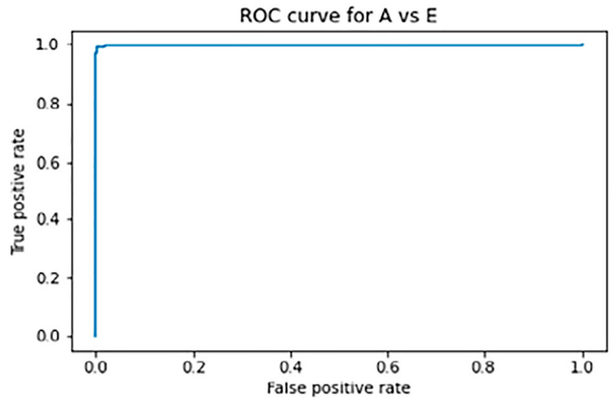

Figure 12: Proposed model performance ROC curve over the A vs E

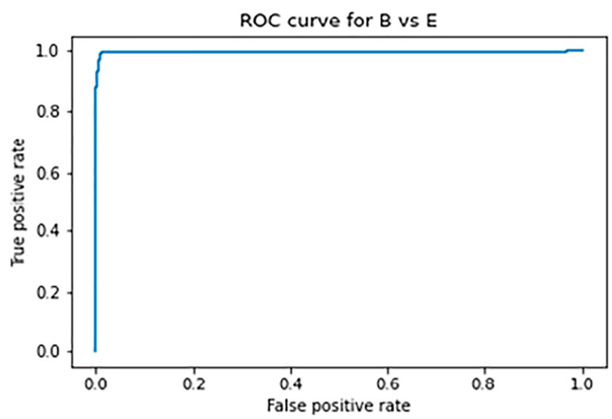

Figure 13: Proposed model performance ROC curve over the B vs E

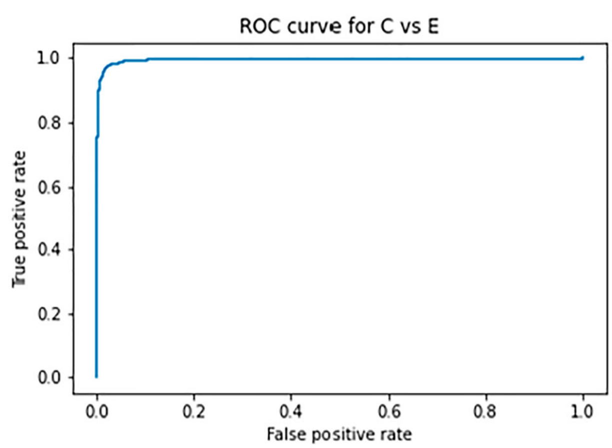

Figure 14: Proposed model performance ROC curve over the C vs E

COMPARISON WITH OTHER SVM BASED SEIZURE DETCTION MODELS

To understand and emphasize the usability of the proposed multi view SVM w.r.t the single view SVMs, the

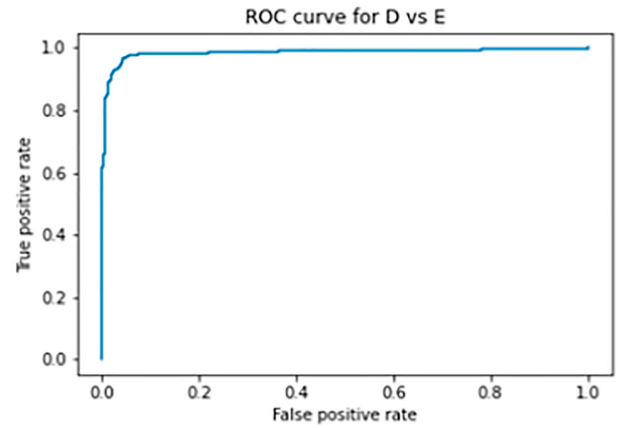

Figure 15: Proposed model performance ROC curve over the D vs E

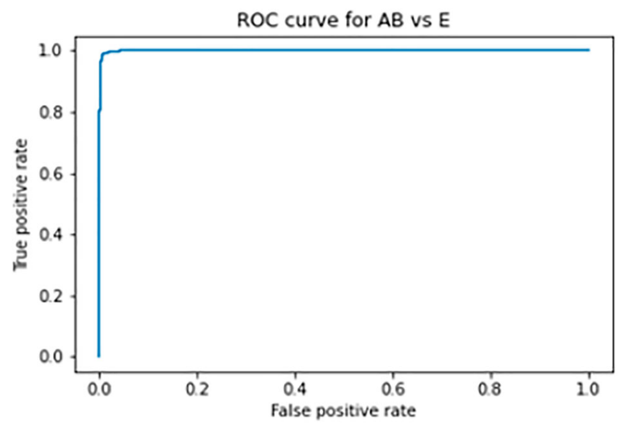

Figure 16: Proposed model performance ROC curve over the AB vs E

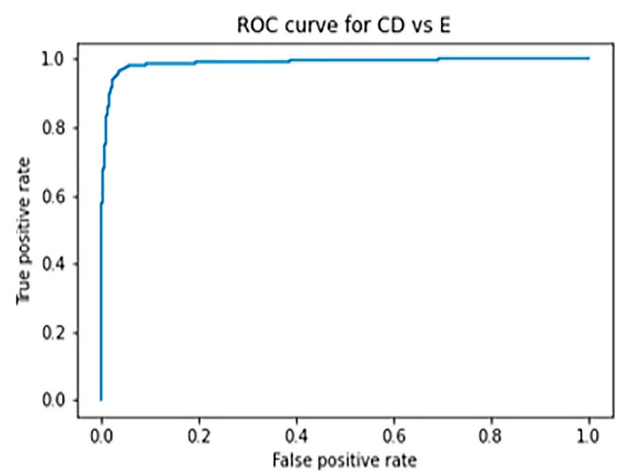

Figure 17: Proposed model performance ROC curve over the CD vs E

performance of the proposed seizure detection model has been compared with existing models that uses SVM for seizure detection. Performance of all compared models

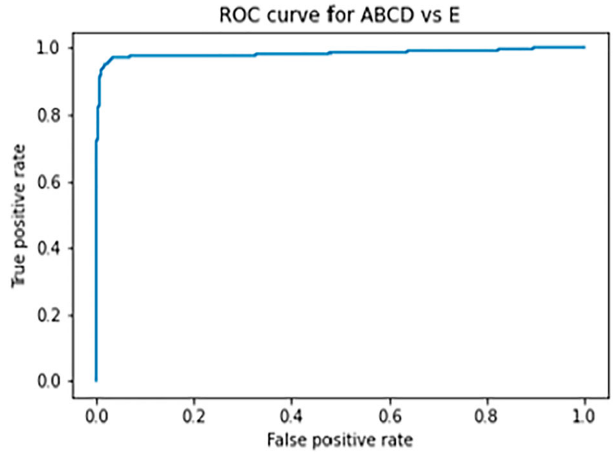

Figure 18: Proposed model performance ROC curve over the ABCD vs E

is estimated on University of Bonn Epilepsy EEG dataset [23,24]. The detailed comparisons are given in Table 5 and it has been observed that the proposed multi view model has achieved better performance than other mentioned approaches.

CONCLUSIONS WITH FUTURE SCOPE

This work proposes a multi-view support vector machine-based approach for epileptic seizure detection from single channel EEG signals. Multi views of the dataset are created in time domain and frequency domain. The proposed model produced a classification accuracy maximum of 99.54% and minimum of 96.17%. In this experiment, we observed that the proposed multi view SVM approach performed significantly better in compared to a single view SVM approach over the same features. So, the proposed approach can be applied in seizure detection. Moreover, the proposed Multi-view approach will be useful for developing a real-time clinical seizure detection system by considering both time and frequency domain features. In future, different feature extraction techniques need to be tested to improve the model performance. The model needs to be tested over the other epileptic EEG datasets. On the other hand,

Table 5: Comparison with existing SVM based seizure detection models

Cases	Author	Method	Accuracy (%)
A vs E	Fu et al. [47]	SVM, Time Frequency images,	99.125
	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet	98
	Nicolaou et al. [3]	SVM, Permutation entropy	93.55
	Anubha Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent,	96.15
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	99.54
B vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet	98.3
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent	99.00
	Nicolaou et al. [3]	SVM, Permutation entropy	82.88
	Sharmila et al. [49]	SVM, DWT and approximate entropy	96
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM ICA, PSD	99.43
C vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet	95.5
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent	97.50
	Nicolaou et al. [3]	SVM, Permutation entropy	88.33
	Sharmila et al. [49]	SVM, DWT and approximate entropy	98
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	98.16
D vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet,	93.3
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent,	96.35
	Nicolaou et al. [3]	SVM, Permutation entropy	79.94
	Sharmila et al. [49]	SVM, DWT, approximate entropy	93.1 (rbf) and 95.85 (linear)
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	96.17
AB vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet,	98.1
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent,	97.27
	Sharmila et al. [49]	SVM, DWT, approximate entropy	92
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	99.45
CD vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet,	95.2
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent,	96.92
	Sharmila et al. [49]	SVM, DWT, approximate entropy	78
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	97.05
ABCD vs E	Peachap et al. [7]	SVM, temporal and spectral features based on Laguerre wavelet,	96.4
	Gupta et al. [48]	SVM, ARMA parameters, DCT based filter bank, Hurst Exponent,	97.79
	Sharmila et al. [49]	SVM, DWT, approximate entropy	97.38
	de la O Serna et al. [8]	Least square SVM, Taylor-Fourier filter-bank	94.88
	This work	Multi view SVM, ICA, PSD	97.63

the proposed approach needs to be tested over the multi-channel EEG datasets. Also, this proposed Multi-view SVM approach can be used for Motor Imagery, Autisms, Alzheimer's, and Schizophrenia detection using EEG signals. Source code of this study is available at https://doi.org/10.5281/zenodo.4660295

ACKNOWLEDGMENT

This work was carried out at Interactive Technologies & Multimedia Research Lab (ITMR Lab) supported by the Department of Information Technology, Indian Institute of Information Technology Allahabad (https://www.iiita.ac.in/), UP, India. The authors are grateful for this support.

ORCID

Gopal Chandra Jana http://orcid.org/0000-0003-2793-1721

REFERENCES

1. World Health Organisation. https://www.who.int/health-topics/epilepsy.
2. Y. Yuan, G. Xun, K. Jia, and A. Zhang, "A multi-view Deep learning method for Epileptic seizure detection using short-time Fourier transform," *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics (ACM-BCB '17)*, 213–222, Aug. 2017. https://doi.org/10.1145/3107411.3107419.
3. N. Nicolaou, and J. Georgiou, "Detection of epileptic electroencephalogram based on permutation entropy and support vector machines," *Expert. Syst. Appl.*, Vol. 39, no. no. 1, pp. 202–209, Jan. 2012.
4. K. Fu, J. Qu, Y. Chai, and T. Zou, "Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals," *Biomed. Signal Process. and Contr.*, Vol. 18, pp. 179–185, Apr. 2015.
5. K. Polat, and S. Gunes, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform," *Appl. Math. Comput.*, Vol. 187, no. 2, pp. 1017–1026, Apr. 2007.
6. A. Subasi, "Epileptic seizure detection using dynamic wavelet network," *Expert. Syst. Appl*, Vol. 29, no. 2, pp. 343–355, Aug. 2005.
7. A. B. Peachap, and D. Tchiotsop, "Epileptic seizures detection based on some new Laguerre polynomial wavelets, artificial neural networks and support vector machines," *Inform. in Medic. Unlocked*, Vol. 16, pp. 100209, Jul. 2019.
8. J. A. de la O Serna, M. R. A. Paternina, A. Zamora-Méndez, R. K. Tripathy, and R. B. Pachori, "EEG-Rhythm Specific taylor–Fourier filter bank implemented with O-splines for the detection of epilepsy using EEG signals," *IEEE Sensors J.*, Vol. 20, no. 12, pp. 6542–6551, June 2020.
9. V. Gupta, and R. B. Pachori, "Epileptic seizure identification using entropy of FBSE based EEG rhythms," *Biomed. Signal. Process. Control.*, Vol. 53, pp. 101569, Aug. 2019.
10. R. Sharma, R. B. Pachori, and P. Sircar, "Seizures classification based on higher order statistics and deep neural network," *Biomed. Signal. Process. Control.*, Vol. 59, pp. 101921, May 2020.
11. A. Nishad, and R. B. Pachori, "Classification of epileptic electroencephalogram signals using tunable-Q wavelet transform based filter-bank," *J. Ambient. Intell. Humaniz. Comput.* (Jan. 2020). https://doi.org/10.1007/s12652-020-01722-8.
12. R. R. Sharma, P. Varshney, R. B. Pachor, and S. K. Vishvakarma, "Automated system for epileptic EEG detection using iterative filtering," *IEEE Sensors Lett.*, Vol. 2, no. 4, pp. 1–4, Dec. 2018.
13. J. Zhao, X. Xie, X. Xu, and S. Sun, "Multi-view learning overview: recent progress and new challenges," *Inform. Fusion*, Vol. 38, pp. 43–54, Nov. 2017.
14. J. D. R. Farquhar, H. Meng, S. Szedmak, D. R. Hardoon, and J. Shawe-taylor, "Two view learning: Svm-2k, theory and practice," *In NIPS. MIT Press*, pp. 355–362, 2006.
15. Y. Yuan, G. Xun, K. Jia, and A. Zhang, "A multi-view deep learning framework for EEG seizure detection," *IEEE J. Biomed. Health Inform.*, Vol. 23, no. 1, pp. 83–94, Jan. 2019.
16. J. Xu, H. Zheng, J. Wang, D. Li, and X. Fang, "Recognition of EEG signal motor imagery intention based on deep multi-view feature learning," *Sensors (Basel)*, Vol. 20, no. 12, pp. 3496, Jun. 2020.
17. Q. Wang, Y. Dou, X. Liu, Q. Lv, and S. Li, "Multi-view clustering with extreme learning machine," *Neurocomput*, Vol. 214, pp. 483–494, Nov. 2016.
18. F. Huang, X. Zhang, Z. Zhao, Z. Li, and Y. He, "Deep multi-view representation learning for social images," *Appl. Soft Comput.*, Vol. 73, pp. 106–118, Dec. 2018.
19. W. Liu, D. Tao, J. Cheng, and Y. Tang, "Multiview Hessian discriminative sparse coding for image annotation," *Comput. Vision and Image Underst.*, Vol. 118, pp. 50–60, Jan. 2014.
20. Y. M. Xu, C. D. Wang, and J. H. Lai, "Weighted multi-view clustering with feature selection," *Pattern Recogn.*, Vol. 53, pp. 25–35, May. 2016.
21. Y. Ren, S. Huang, P. Zhao, M. Han, and Z. Xu, "Self-paced and auto-weighted multi-view clustering," *Neurocomputing*, Vol. 383, pp. 248–256, Mar. 2020.
22. X. Zhao, N. Evans, and J. L. Dugelay, "A subspace co-training framework for multi-view clustering," *Pattern Recogn. Lett.*, Vol. 41, pp. 73–82, May. 2014.

23. G. Chao, and S. Sun, “Consensus and complementarity based maximum entropy discrimination for multi-view classification,” *Inform. Sci.*, Vol. 367–368, pp. 296–310, Nov. 2016.

24. W. Zhu, J. Lu, and J. Zhou, “Structured general and specific multi-view subspace clustering,” *Pattern Recogn.*, Vol. 93, pp. 392–403, Sep. 2019.

25. Y. Zhao, Y. Dou, X. Liu, and T. Li, “A novel multi-view clustering method via low-rank and matrix-induced regularization,” *Neurocomputing*, Vol. 216, pp. 342–350, Dec. 2016.

26. O. Graa, and I. Rekik, “Multi-view learning-based data proliferator for boosting classification using highly imbalanced classes,” *J. Neurosci. Meth.*, Vol. 327, pp. 108344, Nov. 2019.

27. Department of Epileptology. University of Bonn. http://epileptologie-bonn.de/cms/.

28. R. G. Andrzejak, K. Lehnertz, C. Rieke, F. Mormann, P. David, and C. E. Elger, “Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state,” *Phys. Rev. E.*, Vol. 64, pp. 061907, Dec. 2001.

29. P. D. Welch, “The use of fast Fourier transforms for the estimation of power spectra: A method based on time averaging over short modified periodograms,” *IEEE Trans. Audio Electroacous.*, Vol. 15, no. 2, pp. 70–73, Jun. 1967.

30. R. Chai, G. R. Naik, S. H. Ling, Y. Tran, A. Craig, and H. T. Nguyen, “Channels selection using independent component analysis and scalp map projection for EEG-based driver fatigue classification,” in 2017 *39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Sep. 2017, pp. 1808–1811.

31. J. Ruan, X. Wu, B. Zhou, and X. Guo, “Automatic electroencephalogram channel selection of independent component analysis based motor imagery brain-computer interface,” *10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 1–6, 2017.

32. J. Ruan, X. Wu, B. Zhou, X. Guo, and Z. Lv, “An Automatic channel selection approach for ICA-based Motor Imagery brain computer interface,” *J. Med. Syst.*, Vol. 42, no. 253, pp. 1–13, Nov. 2018.

33. T. Radüntz, J. Scouten, O. Hochmuth, and B. Meffert, “EEG artifact elimination by extraction of ICA-component features using image processing algorithms,” *J. Neurosci. Meth.*, Vol. 243, pp. 84–93, Mar. 2015.

34. I. Winkler, S. Haufe, and M. Tangermann, “Automatic classification of artifactual ICA-components for artifact removal in EEG signals,” *Behav. Brain Funct.: BBF*, Vol. 7, no. 30, Aug. 2011. https://doi.org/10.1186/1744-9081-7-30.

35. N. Mammone, F. La Foresta, and F. C. Morabito, “Automatic artifact rejection from multichannel scalp EEG by wavelet ICA,” *IEEE Sens. J.*, Vol. 12, no. 3, pp. 533–542, Mar. 2012.

36. M. Naeem, C. Brunner, and G. Pfurtscheller, “Dimensionality reduction and channel selection of motor imagery electroencephalographic data,” *Computat. Intell. Neurosci.*, Vol. 2009, pp. 537504, Jan. 2009.

37. S. Hsu, T. R. Mullen, T. Jung, and G. Cauwenberghs, “Real-Time adaptive EEG Source separation using online recursive independent component analysis,” *IEEE Trans. Neural Sys. Rehabil. Eng.*, Vol. 24, no. 3, pp. 309–319, Mar. 2016.

38. Y. Chen, Q. Zhang, and Y. Kinouchi. “Blind Source Separation by ICA for EEG Multiple Sources Localization”. In: Magjarevic R., Nagel J.H. (ed.) *World Congress on Medical Physics and Biomedical Engineering. IFMBE Proceedings*, vol 14. Berlin, Heidelberg: Springer, 2006.

39. I. Rejer, and P. Górski, “MAICA: an ICA-based method for source separation in a low-channel EEG recording,” *J. Neural Eng.*, Vol. 16, no. 5, pp. 056025, Sep. 2019.

40. V. K. Harpale, and V. K. Bairagi. “Significance of Independent Component Analysis (ICA) for Epileptic Seizure Detection Using EEG Signals,” In: Satapathy S., Bhateja V., Joshi A. (ed.) *Proceedings of the International Conference on Data Engineering and Communication Technology. Advances in Intelligent Systems and Computing*, vol 469. Singapore: Springer, 2017.

41. D. Langlois, S. Chartier, and D. Gosselin, “An Introduction to Independent Component Analysis: InfoMax and FastICA algorithms,” *Tut. Quantitative Meth. Psychol.*, Vol. 6, no. 1, pp. 31–38, Mar. 2010.

42. A. T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, “Epileptic seizure detection in EEGs using time–frequency analysis,” *IEEE Trans. Inform. Tech. Biomed.*, Vol. 13, no. 5, pp. 703–710, Sep. 2009.

43. A. Ameera, A. Saidatul, and Z. Ibrahim, “Analysis of EEG Spectrum bands using power spectral density for pleasure and displeasure state,” *IOP Conf. Series: Mater. Sci. Eng.*, Vol. 557, pp. 012030, Jun. 2019.

44. M. H. Myers, E. Jolly, Y. Li, A. D. J. Curry, and H. Parfenova, “Power spectral density analysis of electrocorticogram recordings during cerebral hypothermia in neonatal seizures,” *Annals Neurosci.*, Vol. 24, no. 1, pp. 12–19, May. 2017.

45. K. K. Parhi, and M. Ayinala, “Low-complexity welch power spectral density computation,” *IEEE Trans. Circu. Sys. I: Regular Papers*, Vol. 61, no. 1, pp. 172–182, Jan. 2014.

46. J. R. Solomon, and M. Otis. “PSD computations using Welch’s method. Power Spectral Density (PSD),” No. SAND-91-1533. Sandia National Labs., Albuquerque, NM (United States), 1991.

47. K. Fu, J. F. Qu, and Y. Chai, "Classification of seizure based on the time-frequency image of EEG signals using HHT and SVM," *Biomed. Signal Process. Control*, Vol. 13, pp. 15–22, Sep. 2014.

48. A. Gupta, P. Singh, and M. Karlekar, "A novel signal modeling approach for classification of seizure and seizure-free EEG signals," *IEEE Trans. Neural Sys. Rehab. Eng.*, Vol. 26, no. 5, pp. 925–935, May. 2018.

49. A. Sharmila, A. R. Suman, S. Pandey, and P. Mahalakshmi, "Epileptic seizure detection using DWT-based approximate entropy, shannon entropy and support vector machine: a case study," *J. Med. Eng. Technol.*, Vol. 42, no. 1, pp. 1–8, Jan. 2018.

AUTHORS

Gopal Chandra Jana currently pursuing PhD degree in the Department of Information Technology, IIIT Allahabad. He is associated with Interactive Technologies & Multimedia Research (ITMR) Lab, IIIT Allahabad. He received his BE degree in Information Technology from University Institute of Information Technology, Burdwan University, West Bengal, India and M.Tech. degree in computer science and engineering from KIIT Deemed to University, Bhubaneswar, Odisha, India. His research interest includes EEG signal analysis, Machine Learning application in Non-invasive Neuro-imaging Modalities.

Corresponding author. E-mail: go.gopal.ch.jana@gmail.com, rsi2018508@iiita.ac.in

Mogullapally Sai Praneeth was Summer Research Intern at Interactive Technologies & Multimedia Research Lab (ITMR Lab), IIIT Allahabad. He was born in Hyderabad, India, in 2000. He is currently pursuing B.Tech degree in Electronics and Communication Engineering from Indian Institute of Technology, Bhubaneswar. His research interests are in the area of Artificial Intelligence, Self-Supervised Learning, Computer Vision, and Machine Learning.

E-mail: msp10@iitbbs.ac.in

Anupam Agrawal is working as a Professor of Computer Science and Information Technology at Indian Institute of Information Technology Allahabad (IIIT-A) since the year 2012. Before joining IIIT-A in the year 2000, he was working as scientist "D" at DEAL, DRDO, Govt. of India, Dehradun where he had contributed significantly in various national level projects. He is head of the "Interactive Technologies and Multimedia Research" (ITMR) Lab. which he had setup at IIIT-A with funding from a MHRD-sponsored R&D project (2003) as principal investigator. He received his M.Sc. degree in Computer Science from JK Institute of Applied Physics & Technology, University of Allahabad, Allahabad, M.Tech. degree in Computer Science and Engineering from Indian Institute of Technology (IIT) Madras, Chennai and Ph.D. degree in Information Technology from Indian Institute of Information Technology Allahabad (in association with Indian Institute of Technology, Roorkee). He was a postdoctoral researcher at the Department of Computer Science & Technology, University of Bedfordshire (UK) during which he had contributed significantly in two major European Commission projects which were rated 'excellent' by the commission. He is a senior member of IEEE (USA), member of ACM (USA), and a fellow of IETE (India). His research interests include Computer Vision, Signal and Image Processing, Visual Computing, Machine Learning, Remote Sensing, Soft Computing and Human-Computer Interaction. He is the recipient of Er. Hari Mohan Memorial Award for the best research paper by the Institution of Engineers (India), Lucknow in November, 2005 and other similar awards subsequently.

E-mail: anupam@iiita.ac.in