IETE Journal of Research

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

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To cite this article: Gaurav G, Rahul Shukla, Gagandeep Singh & Ashish Kumar Sahani (2022): A Machine Learning Approach to the Smartwatch-based Epileptic Seizure Detection System, IETE Journal of Research, DOI: 10.1080/03772063.2022.2108918

To link to this article: https://doi.org/10.1080/03772063.2022.2108918

Published online: 18 Sep 2022.

IETE JOURNAL OF RESEARCH
https://doi.org/10.1080/03772063.2022.2108918

RESEARCH ARTICLE

A Machine Learning Approach to the Smartwatch-based Epileptic Seizure Detection System

Gaurav G[1,2], Rahul Shukla[1,3], Gagandeep Singh[4] and Ashish Kumar Sahani [1,3]

[1]Epilepto Systems, Rupnagar, Punjab, India; [2]Department of Biomedical Engineering, Faculty of Engineering and Technology, Datta Meghe Institute of Medical Science (Deemed University), Wardha, Maharashtra, India; [3]Department of Biomedical Engineering, IIT Ropar, Rupnagar, Punjab 140001, India; [4]Department of Neurology, Dayanand Medical College and Hospital, Ludhiana, Punjab 141001, India

ABSTRACT

Worldwide around 70 million people have epilepsy, and every year, more than 1 out of 1000 cases of epilepsy result in Sudden Unexpected Death in Epilepsy (SUDEP). Video – EEG is the standard clinical method for monitoring epilepsy and seizures. However, wearable systems are required to monitor epileptic activity in daily living due to the complexity of using EEG outside the laboratory. Also, to prevent SUDEP, early prediction of seizure onset is required. In this work, we propose a machine learning model to detect ictal and preictal conditions using an Empatica E4 smartwatch. The Empatica E4 records real-time photoplethysmography, electrodermal activity, accelerometry, and temperature. Clinical data were recorded from 11 patients with epilepsy (PWE) for 19 seizure onsets. Features from all the modalities were extracted by taking segments of the signal during the seizure (ictal), pre-seizure, and inter-ictal (non-seizure) conditions. These features were used on support vector machine (SVM-RBF), decision tree (DTC), and logistic regression (LRC)-based supervised training for ictal vs. non-ictal and pre-ictal vs. inter-ictal conditions. The highest accuracy of 99.40% was recorded for DTC-based seizure detection classifier during 10-fold cross-validation. Also, the highest accuracy of 95.42% was recorded for DTC-based pre-seizure onset detection classifier during 10-fold cross-validation.

KEYWORDS

Detection; Epileptic seizure; Machine learning; SUDEP; System; Wearable device

ABBREVIATIONS

PWE	People with epilepsy
SUDEP	Sudden unexpected death in epilepsy
SVM-RBF	Support vector machine radial basis function
DTC	Decision tree
LRC	Logistic regression
EMU	Epilepsy Monitoring Unit
V-EEG	Video-electroencephalography
KNN	K-nearest neighbor
SVD	Singular value decomposition
ELM	Extreme learning machine
GTCS	Generalized tonic-clonic seizures
FBTCS	Focal to bilateral tonic-clonic seizures
PGES	Post-ictal generalized EEG suppression
EDA	Electrodermal activity
ACM	Accelerometer
CEEMDAN	Complete ensemble empirical mode decomposition with adaptive noise
NIG	Normal inverse Gaussian
EMG	Electromyography
ECG	Electrocardiography
PPG	Photoplethysmography
Temp	Temperature
ANS	Autonomic nervous system
SVM	Support vector machine
LRC	Logistic regression classifier
BVP	Blood volume pulse
t_p	Peak-to-peak time interval (t_p)
ICU	Intensive care unit
HR	Heart rate
HF	High frequency
LF	Low frequency
VLF	Very low frequency
ROC	Receiver operating characteristic
AUC	Area under curve

1. INTRODUCTION

Epilepsy is a neurological disorder characterized by recurrent seizures. Around 70 million people worldwide have epilepsy, with about 12 million residing in India and approximately 3.4 million living in the U.S [1]. Roughly 20–40% of these patients have refractory epilepsy, meaning typical epilepsy medications do not control their seizures [2]. In a study done by Hoppe *et al.*, 55.5% of all seizures were unreported in the EMU [3]. There is a high possibility of the person losing consciousness and being unable to recall the seizure events [4]. The

situation can sometimes become alarming leading to SUDEP. Therefore, systems with high accuracy and sensitivity are required for epilepsy monitoring. Continuous monitoring of PWE with seizure detection and alarming is vital. The standard method to monitor and detect seizures is V-EEG. Many EEG-based seizure detection algorithms have been developed over the last few decades with very good performance. Salim *et al*. developed an automated seizure detection algorithm using generalized Hurst exponent features of EEG, by taking multi-scaling properties over a large spectrum, with K-nearest neighbor as a classifier [5]. The model achieved 100% classification accuracy. Gopal *et al*. have developed a multi-view SVM classification model that classifies seizure and non-seizure events based on single channel EEG and achieved accuracy greater than 99% [6]. A study by R. Harikumar *et al*. used SVD along with ELM as a classifier the model average epilepsy detection was recorded as 98.94% [7]. A wireless embedded EEG-based system with entropy and spectral features was able to detect seizures with 95% accuracy and 0.6 s latency in a real-time environment [8]. But EEG-based systems are much suited for a clinical lab environment. For outdoor monitoring, a seizure diary is a current standard, but this method is unreliable in cases causing loss of consciousness during GTCS and FBTCS [9]. Wearable and automated seizure detection systems can improve continuous monitoring, detection, and accurate counts [10]. To reduce the cases of SUDEP especially due to GTCS, a wearable system that can detect seizures, with high sensitivity and reduced false alarm rate is recommended [11,12].

In non-EEG signals for seizure detection, multiple sensors used together are found to increase sensitivity and decrease false alarm rates. These may help in supporting SUDEP risk assessment [13]. The duration of PGES has been found correlated with prominent amplitude changes in EDA during GTCS [14]. Accelerometers are fixed on or below mattresses to detect seizures during sleep [14]. Also, few other researchers have used audio-video monitoring to detect seizures during sleep reported in a few research studies [15,16]. But these studies have mixed results and they are confined to monitoring only convulsive seizures in a bounded setup.

In recent studies, the development of wearable devices to detect convulsive as well as non-convulsive seizures has been achieved. Convulsive seizures are associated with involuntary and repeated jerking motions, which are different from day-to-day motion activity. These recurrent jerking motions can be identified using accelerometry and EMG. Whereas non-convulsive seizures cannot be easily observed superficially but can be reflected through the ANS response of the patient. ANS responses could be fetched through HRV and electrodermal response.

There are distinct movement differences between myoclonic, tonic-clonic, clonic seizures, and general or normal movements, which could be identified through accelerometer signals. A myoclonic seizure is encountered with sudden jerks in muscles occurring in a group [17]. Myoclonic seizures may end with a person falling, which generates large impulses in the accelerometer signal. In a tonic seizure, a person's body gets rigid [18]. A tonic-clonic seizure is an observed event of the tonic event followed by clonic events, showing shaking and repeated jerking of the body [19]. Such distinct movement patterns can be identified through accelerometer signals.

Non-convulsive seizures can be monitored through activation in autonomic nervous system response. This could be achieved by various biosignals, such as heart rate variability and electrodermal activity response. Tachycardia is seen in more than 82% of seizure event cases [20]. During ictal events, an increase in heart rate, by at least more than 30% in comparison to, inter-ictal events is observed [21,22]. Also, HRV usually drops showing sympathetic activity triggering [23].

EDA sensor measures the amount of sweating. Since activation of the sympathetic nervous system increases sweating, and seizures trigger sympathetic activity, EDA can be used to detect seizure activities [24]. EDA can be combined with other modalities for seizure detection.

For the pre-ictal indicators of seizure, no convulsive behavior happens, hence, any functional changes may not be observed in the accelerometer signal. Whereas, heart rate variability, respiratory rhythm, blood oxygen level, and electrodermal responses could be observed as non-convulsive changes in pre-ictal conditions [25,26]. Tachypnoea, apnea, and hypoxia were seen in many cases of pre-ictal focal and generalized seizures [25].

Since a single sensor is not capable enough to detect all kinds of seizures, thereby many studies have proposed to use of multi-modal sensor systems [26–29]. The Empatica E4 wristband is a unique multimodal wearable system that provides the multi-resolution signal of PPG, three-axis accelerometer, EDA, and temperature (infrared thermopile) [30]. At MIT and Boston Children's hospital, an early machine learning method for seizure detection and alert system was developed using an Empatica E4 wristband with an accelerometer signal

and electrodermal activity signal [29]. It is a multiresolution sensor system with design consideration taken for long-term patient vitals monitoring in clinical as well as non-clinical environment and flexibility to monitor, process, or analyze the raw signals.

Multimodal sensor data with machine learning frameworks have achieved significant improvement in wearable epileptic detection systems. Accelerometry and EMG were used by Milosevic *et al.* on a least-squares SVM framework to achieve 91% accuracy [31]

Developments in EEG-based seizure detection using signal processing approaches have been in focus since the last decade. A lot of interesting work has been done by Hassan *et al.* for accurate prediction of seizure vs. non-seizure conditions based on EEG data using the tunable Q-factor wavelet transform with an accuracy of 99.60% [32], CEEMDAN ensembles with NIG with an accuracy of 99.20% [33–35]. But such signal processing techniques are more suited to EEG, while there is not much development in machine learning models to classify seizures from the non-seizure conditions using non-EEG wearable physiological sensors [36]. Such models are also limited only to GTCS. A wrist-worn accelerometer-based seizure detection system in phase 3, achieved a sensitivity of 91%, with a false alarm rate of 0.2 per day and an average delay in the detection of 55 s by Beniczky *et al.* [37]. An ECG-based seizure detection system with a sensitivity of 59% and a high false alarm rate of 7.15 per hour was developed [38]. A heart-rate variability recorded from ECG-based ictal autonomic changes achieved a sensitivity of 90% for non-convulsive seizures and a false alarm rate of 1.0 per day in phase 2 of algorithm validation by Jeppesen *et al.* [39].

Identifying the early onset of a focal or general tonic-clonic seizure is very essential, which can lead to SUDEP [40]. There are developments in non-EEG-based seizure detection systems, such as on-bed sensors, video or audio monitoring, ECG-based and accelerometry-based systems [41]. But most of the systems have limitations such as they are mostly non-wearable and can be used only in a confined space. Also, depending on the factor measured (body motion or autonomic nervous system response), the systems are confined to detect only convulsive seizures or non-convulsive with limitations. Hence, there is a requirement to develop a system that can continuously monitor the vitals of PWE during everyday activity to detect seizure activity. There is also a requirement to develop a system to predict the future onset of the seizure (pre-seizure onsets). Such systems will help caretakers to be alerted about the possible occurrence of future seizures so that adequate measures could be taken.

In this work, we have collected data from Empatica E4 smartwatch from admitted PWE to the video EEG lab of DMCH, Ludhiana, for detecting seizure and non-seizure samples. A machine learning model was developed to identify the ictal signal from the non-ictal signal and then similarly pre-ictal signal from the non-ictal signal. The seizure data were collected using an Empatica E4 smartwatch on a cloud repository software. Signal segments were taken in various ictal and inter-ictal durations and features were extracted from the three-axis accelerometer, EDA, PPG, and temperature signals of the smartwatch. The features were used in training and testing of SVM, DTC, and LRC, for seizure vs. non-seizure signal classification in both inter-ictal and pre-ictal periods.

We are in the process of developing a specialized smartwatch for the detection of seizures. This watch will have all the above four sensors and will run an ML Model directly within the watch. We aim to detect and predict both focal and tonic-clonic seizures with it. As a precursor to it, we have developed a smart band that can collect the above four sensor data [42].

The remaining paper is organized as follows: In Section 2, we define the data acquisition from the E4 smartwatch and preprocessing of acquired signals and feature extraction from these signals. In Section 3, we explained different machine learning seizure, classification models the classifier was developed for seizure vs. non-seizure and pre-seizure vs. non-seizure. In Section 4, we presented the evaluation of different machine learning models SVM-RBF, decision tree, and logistic regression on seizure vs. non-seizure and pre-seizure vs. non-pre seizure events. In Section 5, we presented our conclusion and future work.

2. MATERIAL, DATASET, AND METHOD

For recording epileptic seizure data, an Empatica E4 wearable device was used. The Empatica E4 device comprises BVP derived from PPG, three-axis accelerometer signals (ACM-x, ACM-y, and ACM-z), EDA, and Temp signals. Figure 1(a) shows the configuration of the Empatica E4 wrist band system along with various sensor modules embedded in the system. The data from this device can be collected on a cloud repository using Empatica connect web application and data could be processed to view in real-time or in the repository on the E4 manager application [43].

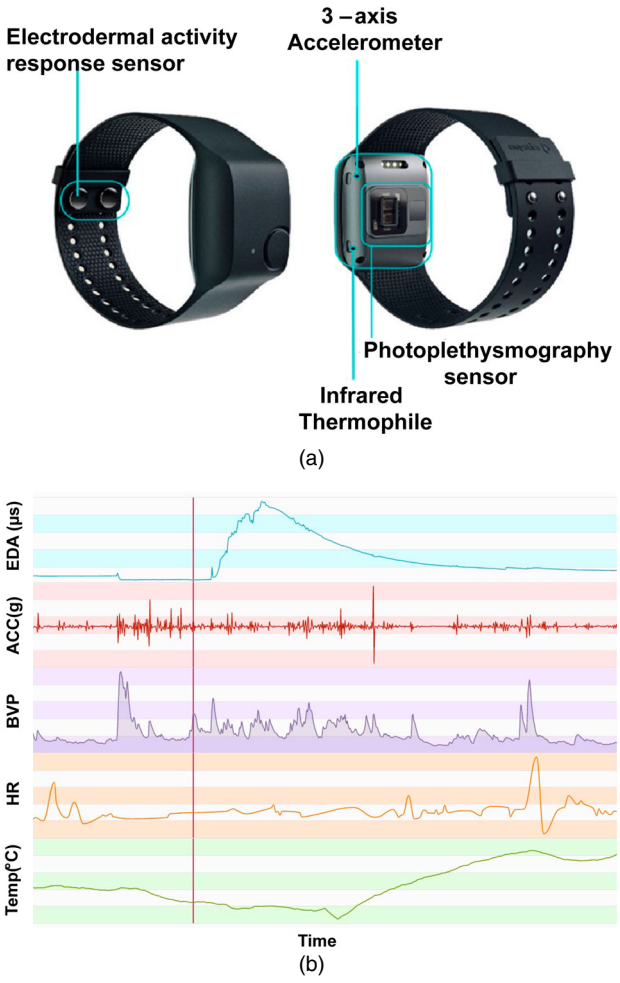

Figure 1: (a) Empatica E4 wrist band showing sensor modalities [27]. (b) E4 connect, a web application for viewing and downloading data in a repository

Figure 1(b) shows the plot of a subject's signal segment stored in a cloud repository. Keeping optimal data rate and information through each modality intact, the sampling rates of each modality are PPG at 64 samples/s, three-axis accelerometer signal at 32 samples/s, and EDA at 4 samples/s.

Data were recorded in a hospital ICU environment, and 11 PWE (five female and six male) were selected who had seizure events. Prior consent of each PWE was taken for the data recording. A total of 19 seizure (1 GTCS and 18 focal seizure) events were recorded. All other PWE who didn't encounter any seizure event during the recording were not taken into the study. Seizures ranged between 10 s and 40 s for seven PWE and between 70 s and 90 s for three PWE, with the average seizure duration being 46 s. For one PWE the seizure duration lasted more than an hour. The clinical setup of a PWE wearing

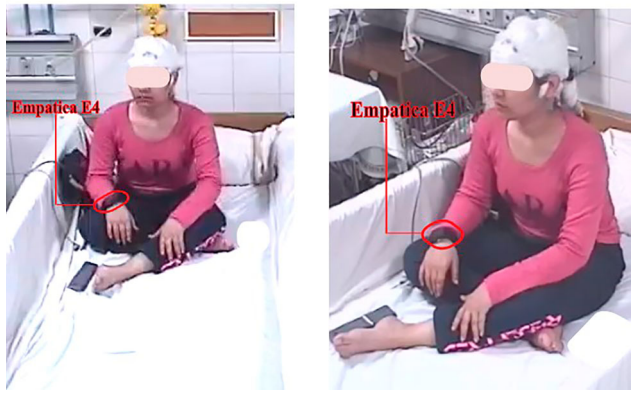

Figure 2: A subject wearing Empatica E4, during seizure monitoring

an Empatica E4 wrist band in a video EEG laboratory is shown in Figure 2. The study was approved by the ethical committee of DMCH, Ludhiana.

2.1 Preprocessing of Smart Watch Sensor Signals

Only those signals that are free from motion artifacts and other distortions are taken for the study by streaming and checking manually. Segments of data with GTCS or focal seizure, identified from EEG signal, along with neighboring 30 min data were taken for analysis. A portion of two minutes of seizure data was taken as seizure data and a portion beyond 15 min before a seizure was taken as non-seizure data. For feature extraction window segments of these portions of seizure and non-seizure data were taken. The data were collected in a clinical setup with the prior consent of the subject. A total of 11 subjects with the recent record of GTCS condition were selected. A total of 19 seizure events were captured. From these seizure events and 15 min before these events, features were extracted from PPG, EDA, ACM, and Temp signal.

In Figure 3, a segment of 45 min data is shown, along with a bounded portion in the red color of around 10 min. In the bounded portion, seizure events occur for a small interval of generally less than the 30 s. For each subject, the seizure events data were selected from the whole signal. Various artifacts or any other distortion were manually evaluated and if any data with such distortions were found then they were removed. Data were first segmented and windowed to do further processing and feature extraction.

2.2 Feature Extraction

A 5 s window segment of the PPG signal, with a 40% overlap of preceding and 40% overlap of succeeding signal

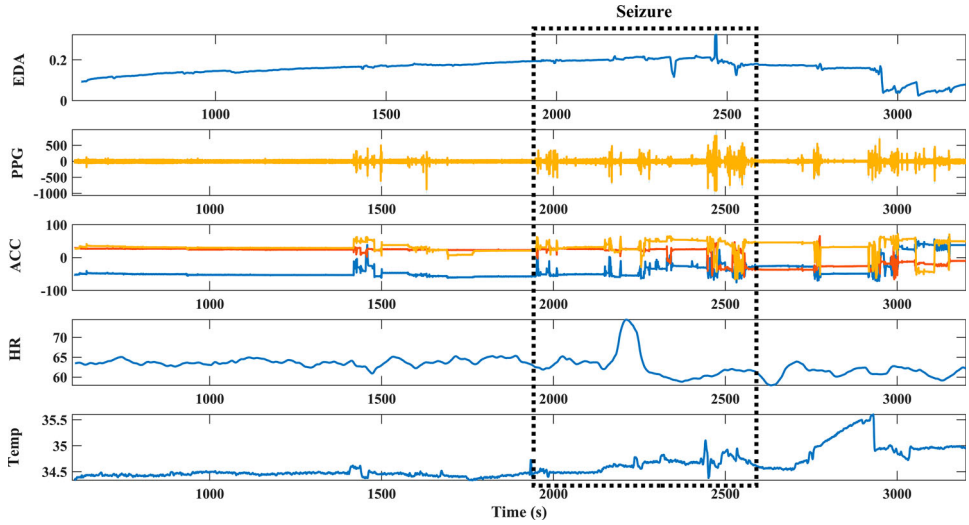

Figure 3: Empatica E4 signal showing the dotted boxed region with seizure event

is taken at each interval for feature extraction. A band power in the low-frequency region of 0.1–0.6 Hz is computed as an indicator of respiratory intensity as "Br". By taking peak points of PPG pulse and time-interval between two consecutive systolic peaks, the peak-to-peak t_p is computed and HR in beats per minute is computed using the moving average of t_p. Other features taken are average, median, standard deviation, maximum, minimum, skewness, and kurtosis of heart rate. Further from the window segment of PPG the approximate entropy of PPG is computed.

Using 7.5 min heart rate sample from both sides of the seizure point (total 15 min sample), and similarly, for the non-seizure point, frequency domain components of heart rate variability are computed. HF: 0.15 Hz–0.4 Hz, LF: 0.04 Hz–0.15 Hz, and VLF: 0.004 Hz–0.04 Hz is evaluated from HR using a periodogram [44]. For extracting features from the three-axis accelerometer sensor, a window segment of 2 s with an overlap of 1 s signals is taken at each interval.

A band power in the low-frequency region of 0.1–3 Hz is computed as an indicator of low-frequency shaking of limbs. Other features taken are approximate entropy, average, median, standard deviation, maximum, minimum, skewness, and kurtosis of the three-axis accelerometer signals (X, Y, and Z).

A window segment of 2 s with an overlap of 1 s temperature signal is taken at each interval. A band power in the low-frequency region of 0.1–0.4 Hz is computed. Other features taken are approximate entropy, average, median, standard deviation, maximum, minimum, skewness, and kurtosis of Temp signal.

In Figure 4(b–d), the feature comparison for each sensor is shown. The left side shows the features for non-seizure events and the right side shows the features for seizure events.

Figure 4(a) shows a segment of the non-seizure signal and a segment of the seizure signal. The features for PPG, EDA, and ACM-based features for windowed segments in time-series format are further plotted for these segments.

Figure 4(b) is the time-series subplots for various features of PPG and heart rate, Figure 4(c) is the time-series subplots for different features of EDA, and Figure 4(d) is the time-series subplots for different features of ACM.

3. SEIZURE AND PRE-SEIZURE DETECTION SYSTEM

3.1 Seizure vs. Non-seizure

A framework for detecting seizure signals is developed using supervised learning. The features extracted from each sensor modalities are sent to the machine learning framework. The sensor modalities generate 58 features (13 from PPG, 9 from EDA, 27 from ACM, and 9 from Temp). The first class is formed as seizure events positive and the second class as non-seizure events. Non-seizure events are specifically selected for signals at least five minutes away from seizure events. Seizure classes are selected considering if 90 s of the window segment of signal encompasses seizure events.

Figure 5 shows the machine learning framework for seizure detection. The input feature matrix is generated

from each of the sensor modalities, namely, PPG, three-axis accelerometer, EDA, and temperature. A total of 336 data samples are gathered out of which 168 seizure data samples are collected from 19 seizure events. Other 168 samples are from non-seizure events. This dataset is further randomly divided into training and testing sets by considering *k*-fold cross-validation. An exhaustive cross-validation method using leave-p-out cross-validation is

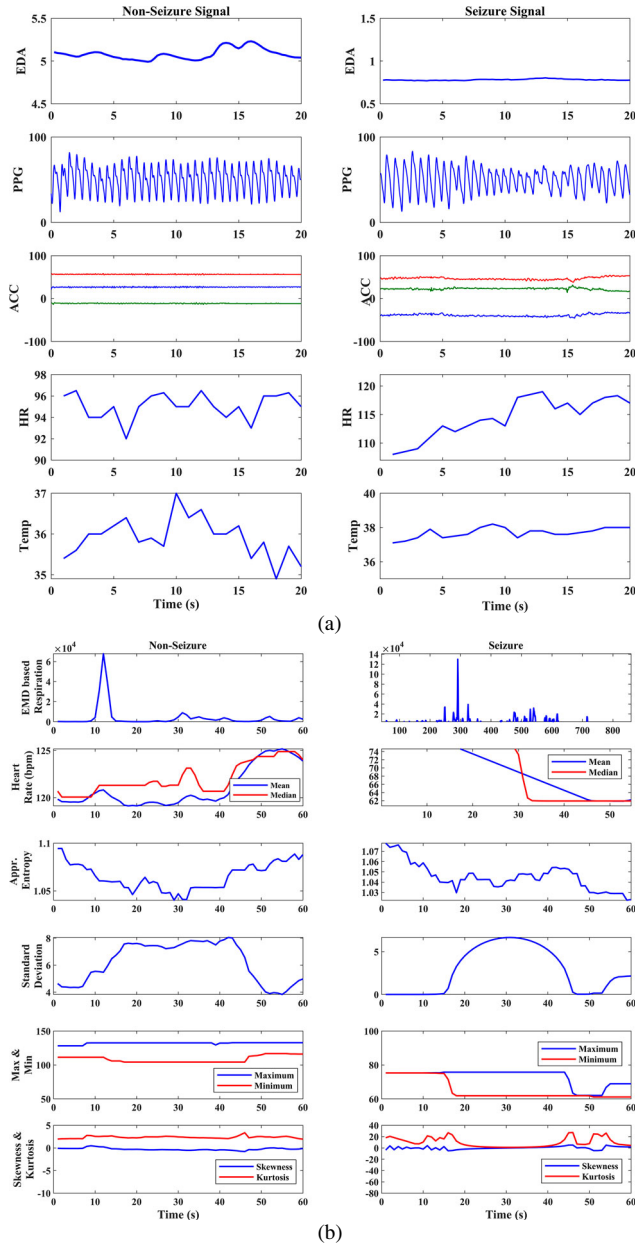

Figure 4: (a) Plot of various signals (EDA, PPG, ACC, HR, and Temp), through Empatica E4 wrist device in non-seizure and seizure conditions. (b) A plot of PPG-based features in non-seizure and seizure conditions. (c) A plot of EDA-based features in non-seizure and seizure conditions. (d) A plot of ACM-based features in non-seizure and seizure conditions

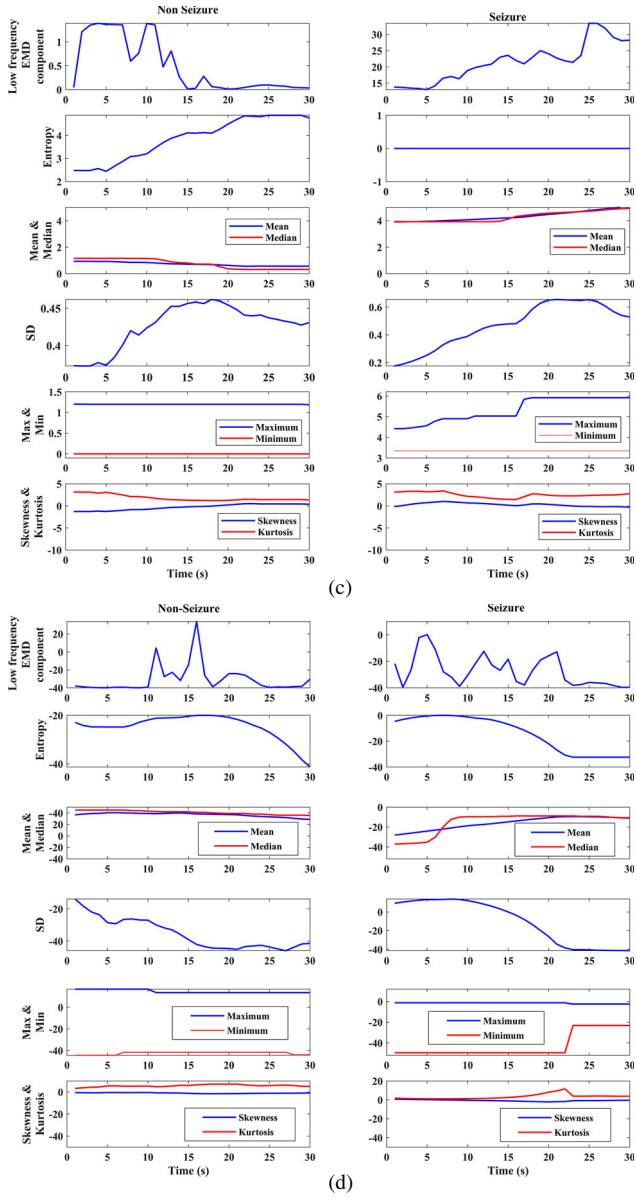

Figure 4: Continued.

used to analyze the performance of the supervised learning model. Various k-fold testings for k as integer values from 2 to 12 are tried and tested, and the value of "p" in leave-p-out is decided according to the k-fold. For 6-fold leave-p-out cross validation, from 336, 280 datasets are taken as training sets and 56 datasets are taken as testing sets, randomly. The training and testing process of each model can be done for ${}^{336}C_{56}$ times, but it increases processing time and becomes redundant after a few hundred iterations, thereby 1000 iterations of training and testing of the model were done.

Three machine learning models, support vector machine (radial basis function), decision tree, and logistic regression, are used to train the supervised learning model. For

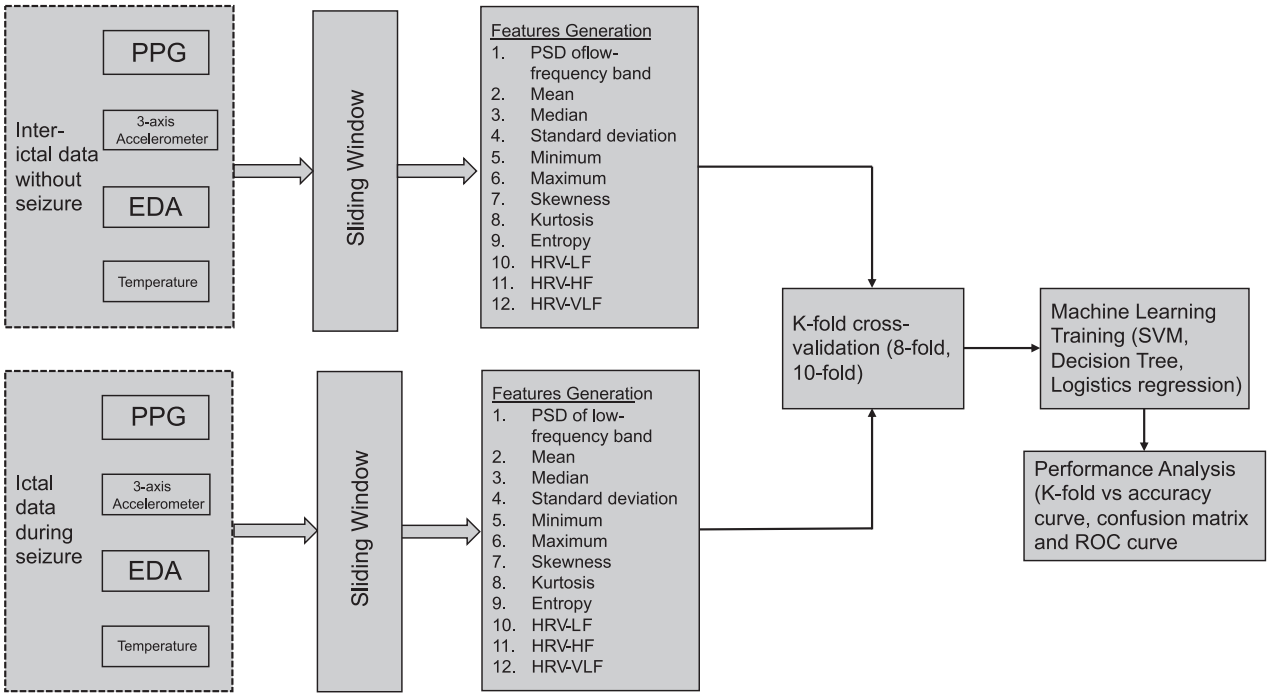

Figure 5: Flowchart of machine learning model framework for seizure detection and pre-seizure events detection

the performance analysis of the model, an averaged accuracy for 1000 iterations of *k*-fold cross-validation is plotted. Also, a classifier confusion matrix for 10-fold leave-p-out cross-validation is generated to check the amount of "true" and "false" predictions. An ROC curve with AOC is plotted to show the performance of a positive prediction rate for 10-fold leave-p-out cross-validation.

3.2 Pre-seizure vs. Non-Seizure

A similar machine learning framework for pre-seizure event prediction from a supervised learning model is developed. The same set of features from four sensor modalities generate 58 features (13 from PPG, 9 from EDA, 27 from ACM, and 9 from Temp). The first class is formed as pre-seizure occurrence event positive and the second class as non-seizure events. Pre-seizure event classes are selected considering that the window segment of a signal is at most 15 min before the seizure event. And non-pre-seizure events are window segments beyond 15 min from seizure events. A total of 210 data samples are gathered out of which 105 pre-seizure condition-based data samples are collected from 19 seizure events. Other 105 samples are generated from window segments adequately away from seizure events.

In a similar way, this dataset is randomly divided into training and testing sets by considering *k*-fold leave-p-out cross-validation, taking *k* as integer values from 2 to 12. For six-fold leave-p-out cross-validation, from 210 data 175 data are taken as the training set and 35 data are taken as the testing set, randomly.

The training and testing process of each model can be done for ${}^{210}C_{35}$ times, but it increases processing time a lot and becomes redundant after a few hundred iterations, thereby 1000 iterations of training and testing of the model were done.

Two machine learning models, a support vector machine (radial basis function) and a decision tree, are used to train the model and an averaged accuracy for 1000 iterations of *k*-fold cross-validation is plotted.

Also, a classifier confusion matrix supervised the learning model. For the performance analysis of for 10-fold leave-p-out cross-validation is generated to check the amount of "true" and "false" predictions. A ROC curve with AOC is plotted to show the performance of positive rate prediction for 10-fold leave-p-out cross-validation.

4. RESULTS AND DISCUSSION

4.1 Seizure vs. Non-seizure Signal Classifier

The performance of the proposed machine learning framework for seizure detection is evaluated. For the seizure and non-seizure event classification an input matrix is generated of 336 × 58 dimensions, 58 being the

number of features and 336 being the number of samples. This matrix is divided into training and testing sets based on selected "k" in *k*-fold cross-validation.

The efficacy of the features to detect positive seizure events is checked using three supervised learning techniques, namely, SVM (RBF), decision tree, and logistic regression.

For the evaluation of the performance of the ML framework, the average accuracy of the classifier for different *k*-fold leave-p-out cross-validation (where $k \in 2, 3, \ldots, 12$) is computed. Along with that, a confusion matrix and ROC curve for the classifier testing for 10-fold cross-validation are plotted. A tabular representation of performance parameters, such as accuracy, specificity, sensitivity, and AUC of ROC curve of classifiers for 10-fold cross-validation by taking features of only single sensor modules (PPG, EDA, and ACM), a pair combination of modalities (PPG + EDA, PPG + ACM, and EDA + ACM) and using all sensors together (PPG, EDA, ACM, and Temperature) is presented in Figure 6. Figure 6(a–c) is bar-plot of performance parameter for the SVM (redial basis function) model, decision tree classifier, and logistic regression model. Figure 7(a–c) depicts the average accuracy with respect to various k-fold cross-validations, $k \in 2, 3, \ldots, 12$, of each classifier model, along with confusion matrix and ROC curve for 10-fold cross-validation (leave-p-out).

The highest accuracy observed is 84.22% for SVM, 99.40% for decision tree, and 71.23% for logistic regression. The highest sensitivity observed is 89.41% for SVM, 100% for decision tree, and 84.45% for logistic regression. The specificity observed for the full feature is 78.97% for SVM, 98.79% and decision tree, and 57.84% for logistic regression. The AUC for ROC observed for the full feature is 0.9966 for SVM, 1.00 for decision tree, and 0.8323 for logistic regression. This suggests that decision tree-based classifiers are more accurate and even more sensitive.

For the performance of the individual sensor, a DTC with PPG features has the highest accuracy of 99.36% and highest sensitivity of 100%, and highest specificity of 98.72%. Figure 7(f–h) shows the confusion matrix for SVM, DTC, and LRC, respectively.

In the case of DTC the prediction of true positive is higher. In Figure 7(l) the AUC of ROC of DCT is higher than SVM or LR in Figure 7(k) and Figure 7(m), which shows a higher probability of predicting true positive and true negative cases.

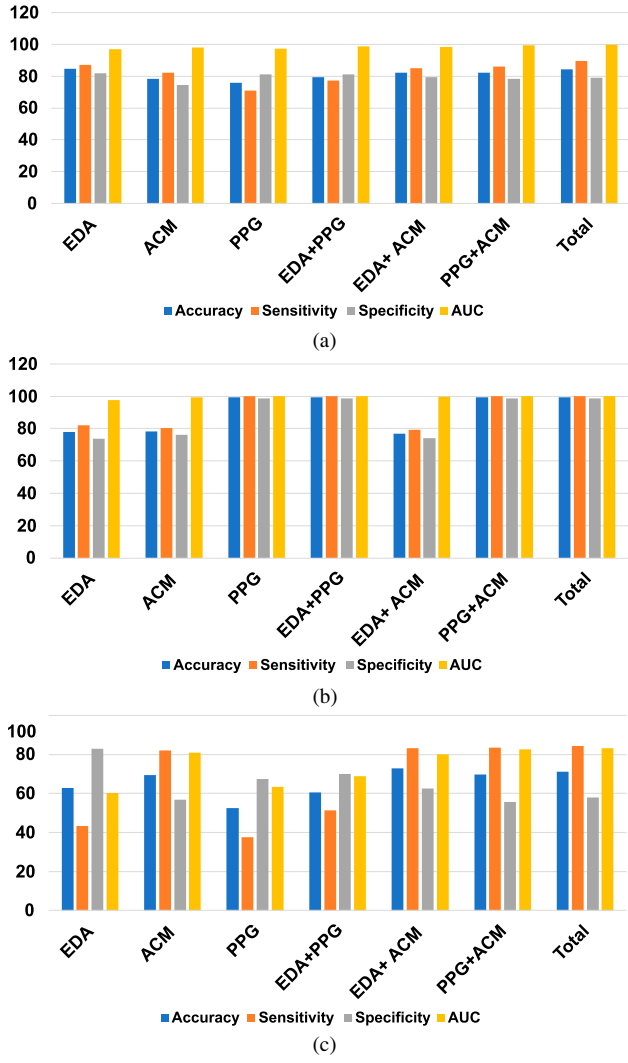

Figure 6: Bar plot of a performance parameter of seizure vs. non-seizure event detection using (a) SVM-RBF, (b) Decision tree, and (c) logistic regression

4.2 Pre-seizure vs. Non-pre-seizure Signal Classifier

For the pre-seizure event and non-pre-seizure or seizure event classification an input matrix is generated of 190×58 dimensions, 58 being the number of features and 190 being the number of samples. The classifier followed the same machine learning framework as in the case of seizure and non-seizure events classification. The efficacy of the features to detect positive pre-seizure events is checked using two supervised learning techniques: SVM (RBF) and decision tree.

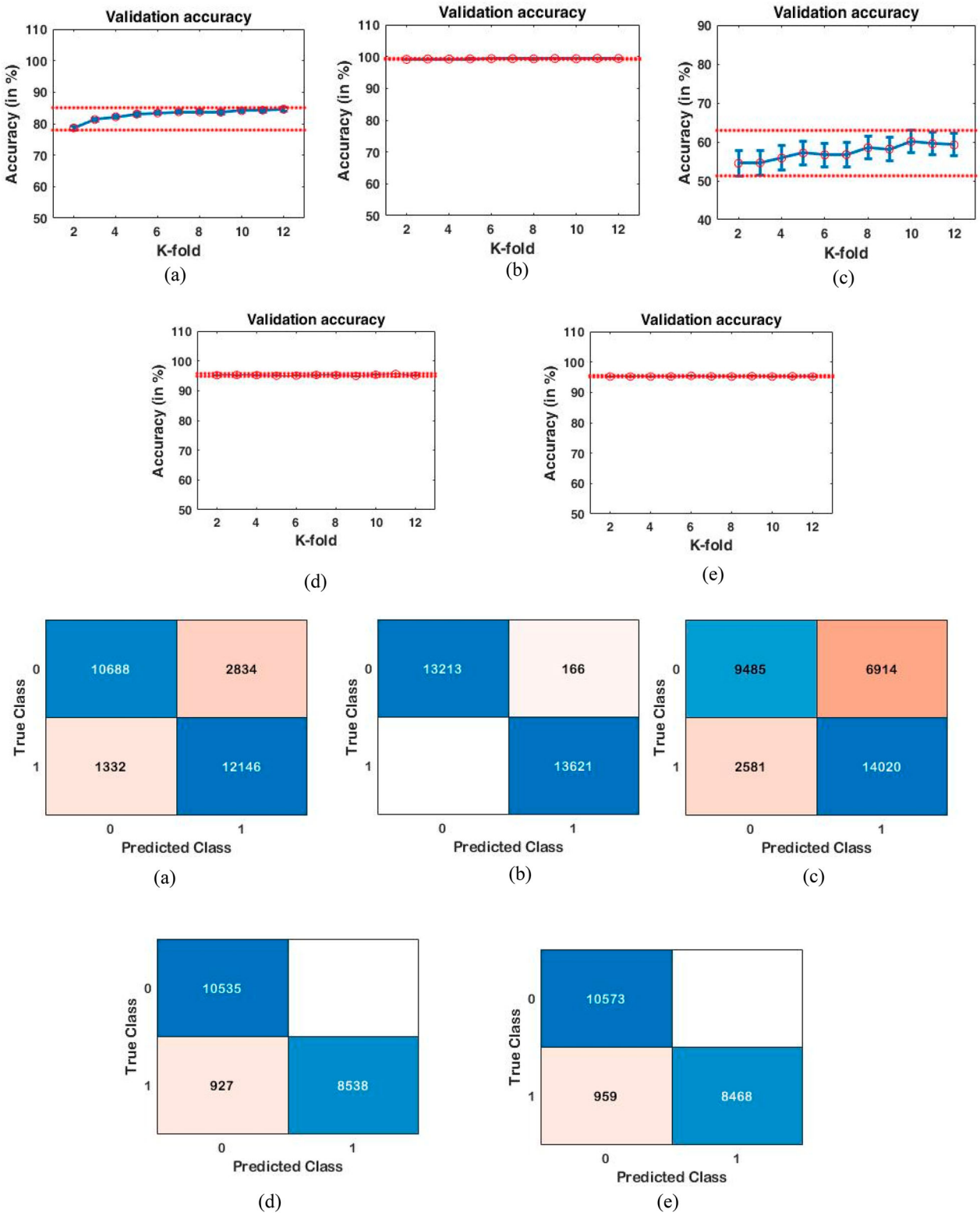

Figure 7: Performance of the classifier model; for detecting ictal-seizure vs. interictal-non-seizure condition; accuracy of classifier for (a) SVM-RBF, (b) Decision tree, (c) logistic regression; and ictal pre-seizure vs. interictal non-seizure condition; accuracy of classifier for (d) SVM-RBF, (e) Decision tree; Confusion matrix for 10-fold cross-validation; for detecting ictal-seizure vs. interictal-non-seizure condition; (f) SVM-RBF, (g) Decision tree, (h) logistic regression; and ictal pre-seizure vs. interictal non-seizure condition; (i) SVM-RBF, (j) Decision tree; AUC of ROC; for detecting ictal-seizure vs. interictal-non-seizure condition; for (k) SVM-RBF, (l) Decision tree, (m) logistic regression, and for detecting ictal pre-seizure vs. interictal non-seizure condition; (n) SVM-RBF, (o) Decision tree

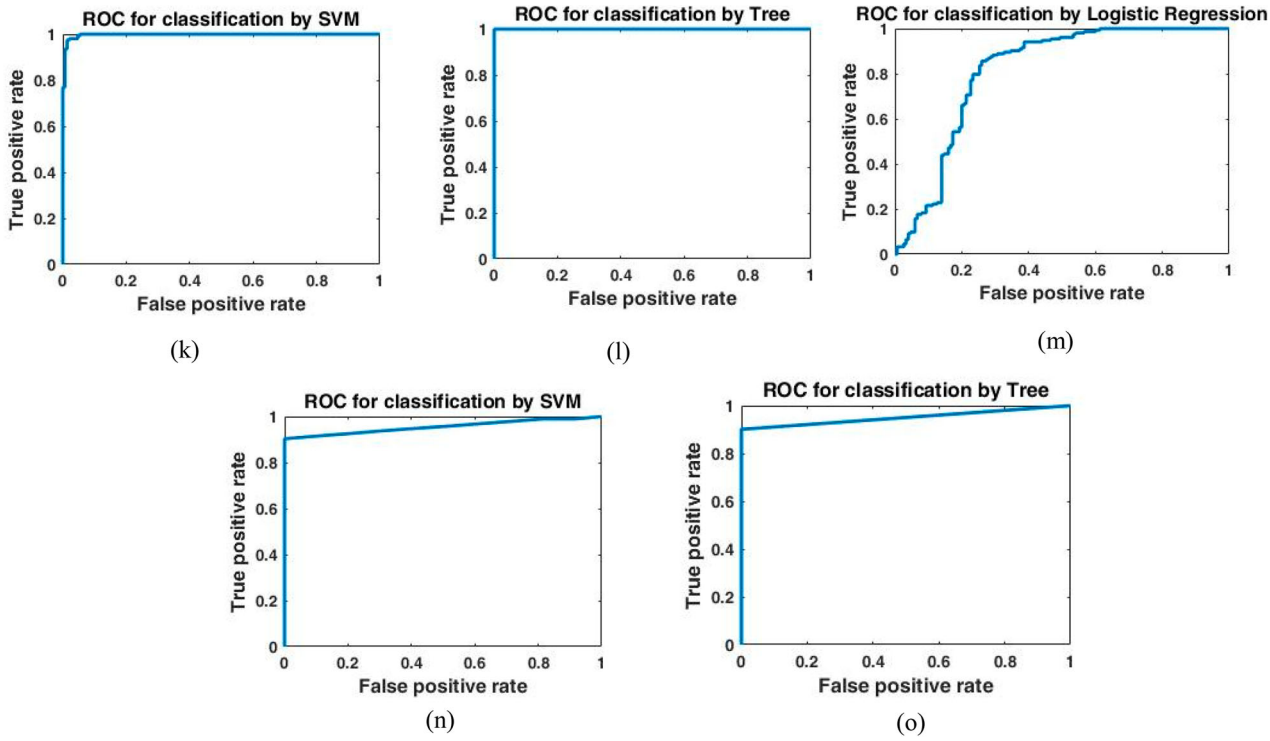

Figure 7: Continued.

Figure 8(a,b) is bar-plot of performance parameter for the SVM (redial basis function) model and decision tree classifier model.

Figure 7(d,e) depicts the average accuracy of SVM-RBF and DCT with respect to various *k*-fold cross-validations, $k \in 2, 3, \ldots, 12$, of each classifier model, along with the confusion matrix and ROC curve for 10-fold cross-validation (leave-p-out). For the performance of the individual sensor, a DTC has an accuracy of 94.86% for EDA, 95.24% for ACM, and 92.08% for PPG and sensitivity of 89.21% for EDA, 90.06% for ACM, and 83.20% for PPG. Figure 7(i,j) shows the confusion matrix for SVM and DTC, respectively. In the case of DTC the prediction of true positive is higher. In Figure 7(n) the AUC of ROC of DCT is higher than SVM in Figure 7(o), which shows a higher probability of predicting true positive with respect to false positive rate.

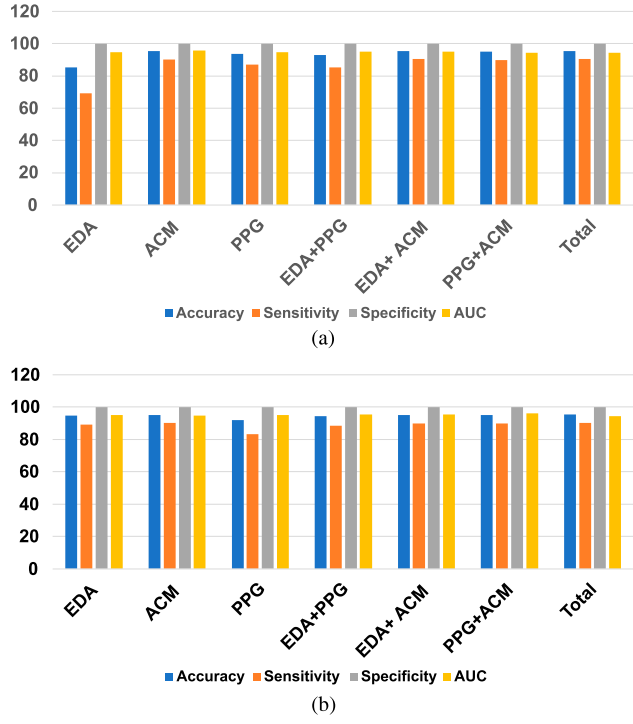

Figure 8: Bar plot of the performance parameter of pre-seizure vs. non-pre-seizure event detection using (a) SVM-RBF, (b) Decision tree

4.3 Advantages

The following are the key features of this study over other such reported in the literature:

a. While most earlier algorithms are designed for GTCS, our algorithm is more suited for focal seizures. Which are the more difficult types of seizures to detect due to their subtle nature.

b. The data have been collected in a clinical environment in a Video EEG Lab by experts in Neurology.

c. The model has been designed based on four different sensors singularly as well as in combination and thus can be implemented on consumer smartwatches with a fewer sensors.
d. Relatively simple ML models have been used to keep them compatible for future implementation on low computational power smartwatch hardware.
e. Models were built both for detection and prediction of seizures.

4.4 Limitations

The data used to train the model are relatively small and imbalanced. As the data are collected throughout the patient's admission period seizures occur only for a few minutes sporadically, the seizure data are much smaller than non-seizure data. Methods to balance the data and to rectify the biasing effect have been tried. To keep the data balanced, the number of non-seizure windows has been kept the same as the number of seizure windows during training. As the number of seizure events is small the accuracy reported in this paper may not be completely reliable. We have only explored relatively simpler ML models in this paper. More complex time-series models, such as LSTM, have not been explored. This has been deliberately done to keep the models deployable over low-computational-power hardware available on a smartwatch.

5. CONCLUSION

A seizure detection and pre-seizure condition detection system was developed for a wrist wearable system Empatica E4 with embedded PPG, Electrodermal activity sensor, accelerometry, and temperature sensors. The seizure detection system is developed using a machine learning framework. The present clinical method of epileptic events monitoring is EEG, which is not compatible with daily life use. These wearable continuous monitoring systems with seizure detection systems will be clinically useful in daily life monitoring of PWE and will help in providing seizure and pre-seizure alarms. Seizure alarms will help caregivers to take precautionary measures beforehand. This system will help to decrease SUDEP situations.

The system will be useful for clinicians and researchers to study the physiological markers of the PWE in normal and seizure conditions and provide feedback, support, and prescription accordingly. Since the data present in the study are dominantly for focal seizure events, the system is tuned for focal seizure events but with enough clinical data, and training, the system could be generalized for GTCS event detection, which could be very much helpful for caregivers of such PWE. The proposed machine learning model should be generalized to be used on other wearable systems with a similar set of sensor modalities.

ACKNOWLEDGEMENTS

We would like to thank the Department of Biomedical Engineering, Indian Institute of Technology Ropar, Dayanand Medical College & Hospital Ludhiana and Epilepto Systems Pvt Ltd for providing us with all the necessary infrastructure for carrying out this research.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

CONTRIBUTION

Gaurav G and Rahul Shukla contributed equally to this work as first authors.

FUNDING

This work was supported by Biotechnology Industry Research Assistance Council under the BIG-15 scheme [reference number BIRAC/SIIC0169/BIG-15/19].

ORCID

Ashish Kumar Sahani http://orcid.org/0000-0001-9173-3856

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AUTHORS

Gaurav G received his BTech degree in instrumentation and control engineering from Haldia Institute of Technology, Haldia, India, in 2010, MS in electrical engineering from Indian Institute of Technology Madras, India in 2014, and PhD in electrical engineering from the Indian Institute of Technology, Roorkee, India in 2021. He has been currently working as assistant professor in the Department of Biomedical Engineering, Faculty of Engineering and Technology, Datta Mege Institute of Medical Science, Wardha, Maharashtra, India, since 2021. His research areas are biomedical instrumentation, signal processing, and cognitive neuroscience.

Email: gauravg.feat@dmimsu.edu.in

Rahul Shukla received his integrated MTech in biomedical engineering from the Indian Institute of Information Technology, Allahabad, India in 2018. He is currently pursuing PhD at the Department of Biomedical Engineering, Indian Institute of Technology, Ropar, India. His research areas are the development of novel seizure detection devices, apps for seizure patients, the brain-computer interface, and machine learning for biological applications.

Corresponding author. Email: 2018bmz0006@gmail.com; 2018bmz0006@iitrpr.ac.in

Ashish Kumar Sahani received his BTech in electrical and electronics engineering from Kalinga Institute of Industrial Technology, Bhubaneswar, India in 2010 and a PhD from the Indian Institute of Technology, Madras, India in 2015. He is currently working as an assistant professor at the Department of Biomedical Engineering, Indian Institute of Technology, Ropar where he is heading the medical devices lab. His research interest spans multiple fronts of medical device development, including hardware, software, and simulations. He is equally active in deep-tech AI, web, app, and cloud-based research.

Email: ashish.sahani@iitrpr.ac.in

Gagandeep Singh received his MBBS and MD from Christian medical college Ludhiana India, in 1987 and 1991, respectively, and Dm from the Postgraduate Institute of Medical Education and Research, Chandigarh, India in 1994. He is currently professor and head at the Department of Neurology of Dayanand Medical College & Hospital Ludhiana, India. He specializes in the diagnosis and treatment of medical problems related to the brain. Gagandeep Singh's areas of specialization are seizure, muscle weakness, headaches, dizziness, and stroke.

Email: g.singh@ucl.ac.uk