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ORIGINAL ARTICLE

Automated detection of epileptic seizures using successive decomposition index and support vector machine classifier in long-term EEG

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Abstract
Epilepsy is a commonly observed long-term neurological disorder that impairs nerve cell activity in the brain and has a severe impact on people's daily lives. Accurate seizure detection in the long-term electroencephalogram (EEG) signals has gained vital importance in the diagnosis of patients with epilepsy. Visual interpretation and detection of epileptic seizures in long-term EEG is a time-consuming and burdensome task for neurologists. Therefore, in this study, we propose a computationally efficient automated seizure detection model using a novel feature called successive decomposition index (SDI). We observed that the SDI feature was significantly higher during the epileptic seizure as compared to normal EEG. The performance of the proposed method was evaluated using three databases, namely the Ramaiah Medical College and Hospital (DB1), CHB-MIT (DB2) and the Temple University Hospital (DB3) consisting of 58 h, 884 h, and 408 h of EEG, respectively. Experimental results revealed the sensitivity–false detection rate–median detection delay of 97.53%–0.4/h–1.5 s, 97.28%–0.57/h–1.7 s, and 95.80%–0.49/h–1.5 s for DB1, DB2, and DB3, respectively, using the support vector machine classifier. The proposed method significantly outperformed previously presented methods (wavelets and other feature extraction methods) while being computationally more efficient. Further, to the best of the author's knowledge, present study is the first study that was tested on three different EEG databases and showed consistent results leading to the generalization and robustness of the algorithm. Hence, the proposed method is an efficient tool for neurologists to detect epileptic seizures in long-term EEG.

Keywords EEG · Epilepsy · Epileptic seizures · Real-time seizure detection · Successive decomposition index · SVM

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1 Introduction

Epilepsy is the fourth most common neurological disorder and affects 65 million people of all ages around the world [6, 22, 36]. It is a chronic disorder that causes unprovoked recurrent seizures and characterized by unpredictable seizures that leads to health problems [6, 22, 28]. Epilepsy is treated using medication, surgery, vagus nerve stimulation, deep brain stimulation of the anterior nucleus of the thalamus [50], responsive neurostimulation, and dietary therapy [19, 36]. In epilepsy patients, seizure traces can be identified using electroencephalogram (EEG), electrocorticography (ECoG), stereo-EEG, and noninvasive imaging techniques (e.g., PET, SPECT, and fMRI). Epilepsy patients undergo pre-surgical investigation prior to surgery that determines the area where the seizure begins. Long-term EEG is the potential brain parameter for the pre-surgery examination that concludes the need for surgery. In the EEG time series, the appearance of traces of spikes or sharp waves does indicate the reflection of seizure activities. The routine EEG shows the temporal and spatial information regarding brain activity, which is used to diagnose, monitor, and localize the epileptogenic focus. Interpreting long-term EEG for pre-surgical evaluation lasting several hours to days is a time-consuming and burdensome task since epileptic activities present in a small percentage of the entire data. However, robust seizure detection remains a challenging problem, due to the absence of adequate seizures EEG for training and testing. These challenges have motivated for development of automated seizure detection algorithm using three databases [3, 6, 22]. Thus, our study focuses on introducing an automated system using a novel feature and support vector machine (SVM) classifier that is competent in recognizing the seizure onset quickly with better sensitivity and less detection delay. We expect that such system support the neurologist to overcome visual inspection and avoid human errors.

EEG is the gold standard for the classification of seizures and the diagnosis of epilepsy in terms of cost and safety. [3, 12, 13, 22, 23, 55]. The morphological shape of seizure EEG are spikes (20–70 ms), sharp waves (70–200 ms), and spike-and-wave discharges (a spike followed by a slow wave) referred to as epileptic waves [36, 39, 53]. In other words, seizure onset is characterized by a sudden change in frequency and the appearance of a new rhythm. Spikes and sharp wave EEG in a specific area of the brain relates to focal seizure, whereas spike-and-wave discharges, which widely spread over both sides of the brain, are referred to as generalized seizures. Therefore, proposing a discriminating feature that is capable of separating normal and epileptic seizures is the most essential and challenging procedure.

1.1 Related work

Many studies have proposed different algorithms over the years using the University of Bonn EEG database [2, 41, 42, 45, 48, 54, 60, 61]. The recurrent Elman neural network (RENN) showed a classification accuracy of 100% using approximation entropy [61]. Time-domain, frequency domain, time-frequency domain, and entropy-based techniques have been reported in the literature [2, 41, 45, 61]. Shannon's and wavelet entropy [41], log-energy and norm entropies derived from wavelet packet decomposition [45], spectral entropy, [60], sigmoid entropy [48] and variations of entropies [2] have been applied for the seizure detection-related studies.

Several studies have been proposed using different databases for epileptic seizure detection [14, 33, 40, 47, 58, 65]. Gotman introduced a wavelet decomposition-based algorithm that showed the sensitivity of 76% with 1/h [22]. Zhou et al. proposed multichannel EEG signal classification using the fuzzy feature and tested with several sets of real EEG data [69]. Multichannel fusion-based seizure detection was introduced with two different schemes [8]. The first concatenated EEG feature vectors were independently obtained from the various EEG channels to form a single feature vector. The second approach was to combine independent decisions of different EEG channels to create an overall decision. Classification results showed that the feature fusion method performed better than the decision fusion approach. A hybrid model for epileptic seizure detection with genetic algorithm and particle swarm optimization showed a classification accuracy of 99.38 % using the SVM classifier [63]. Another hybrid method was proposed using fuzzy entropy-based features obtained from EEG signals in the fractional Fourier transform and wavelet packet decomposition domain [30]. A self-organizing map-based spatial clustering of entropy topography revealed that the critical electrodes shared the same cluster long time before the seizure onset [31]. A binary magnetic optimization algorithm using wavelet-based features was introduced in [38]. The algorithm proposed in [59] focused on reducing the epileptic seizure detection time while maintaining high accuracy, and locate the brain hemisphere, which is affected by seizure activity. Automated detection of focal EEG signals using empirical wavelet transform and least-squares support vector machine (LS-SVM) showed the maximum accuracy of 82.53% [10]. Different entropies were investigated in normal, pre-ictal and epileptic EEGs and fuzzy classifier showed the highest accuracy of 98.1% [2]. Further, Acharya et al. [5] provided an extensive review on the application of entropies for seizure detection. Weighted permutation entropy-based study showed an accuracy of 99.0% using the SVM classifier [64].

The physiology-based seizure detection system was proposed using sample entropy and statistical features on two datasets [55]. The results showed 86.69% of spike detection and 99.77% of seizure detection for dataset I and 91.18% of spike detection and 99.22% of seizure detection for dataset II using the SVM classifier. Short-term Fourier transforms (STFT)-based scheme was introduced using an adaptive threshold technique and tested on 159 patients [25]. Patient-specific seizure onset detection method was proposed using wavelet decomposition and SVM classifier [58]. In this study, 36 pediatric subjects were considered, and the quantitative algorithm detected 131 of 139 seizures within 8 ± 3.2 s of seizure onset. In [57], spatial and spectral features were used to train the SVM classifier and tested for

916 h of EEG from 24 patients. The algorithm detected 96% of seizures from 173 seizures with a median detection delay of 3 s and 2 false detections per 24-h duration. Improved classification results were obtained in psychogenic non-epileptic seizures and vasodepressor syncope generalized epileptic seizures from non-epileptic using time domain, frequency domain and then combining all features across channels [40]. Features were selected using a relief ranking algorithm that yielded the classification accuracy of 95% using a Bayesian network. A brief review was provided on the features such as time domain, frequency domain, nonlinear measures, time-frequency domain and application of entropies for seizure detection [4, 5].

The patient-independent neonatal seizure detection system was developed using the SVM classifier and validated for 267 h of EEG from 17 newborns [65]. This system achieved the average detection rate of 89%, 96%, and 100% with one, two, and four false detections per hour, respectively. In [56], prediction of epileptic seizures from intracranial EEG showed the sensitivity about 90–100% with the false positive rate of about 0–0.3 times per day using features derived from heart rate variability. Combined seizure index derived from wavelet coefficients revealed the sensitivity of 90.5%, the false detection rate of 0.5/h, and median detection delay of 7 s [68]. A patient-specific early seizure detection algorithm using spectral parameters, time domain parameters, and wavelet analysis detected 14 of the 25 seizures before seizure onset with a median pre-onset time of 51 s, and the false positive rate of 0.06/h using recurrent neural network [32]. A simple threshold-based scheme was introduced using the minimum variance modified fuzzy entropy (MVMFzEn) feature that obtained 100% classification accuracy [46].

Quantitative analysis of non-convulsive seizures in intensive care unit showed the mean sensitivity and mean false detection rate of 90.4% and 0.066/h, respectively [49]. Relative amplitude and relative fluctuation index features with improved wavelet neural network classifier showed the sensitivity, specificity, and false detection rate of 96.72%, 98.91 %, and 0.27/h, respectively [21]. Age-independent seizure detection algorithm using the SVM classifier was proposed using 78 patients with 592 seizures [14]. The area under the curve of 0.90 and 0.93 was obtained for neonatal and adults EEG with the application of feature baseline correction. Further, the assessment of epileptic seizures was performed using three significant features, namely pattern-match regulation static, maximum local frequency and amplitude variation [27]. Greene et al. made use of multi-features from different domains for neonatal seizure detection [23]. The fuzzy rule-based system was proposed for seizure detection in intracranial EEG [1]. Various features were used for the detection of temporal lobe epilepsy from scalp EEG [66]. The long-term audio and video EEG was used for detection of focal EEG seizures [37]. Mirowsaki et al. presented a study of prediction patterns for seizure prediction [33]. Further, wavelet transforms-based approaches gained much attention toward EEG analysis due to its temporal and spatial analysis of signal [1, 6, 29, 45, 67].

Table 1 reports the information about various EEG databases that were used in the state-of-the-art epileptic seizure detection algorithms. All the studies have recorded the EEG using the International 10–20 system electrode placement. The CHB-MIT [57, 58], and the University of Bonn [7] databases are available in the public domain. In all the studies reported in Table 1, a notch filter was applied to EEG signals to attenuate power line noise.

The thorough literature survey confirms that existing approaches found to have its limitations toward attaining good sensitivity, less false detection rate, low detection delay, and being less computational complexity. Further, the existing algorithms have validated their algorithm on a single database. In order to obtain the generalization of seizure detection, the algorithm must be tested on several databases with a good number of epileptic seizure events. Hence, the proposed study attempts to overcome the above limitations through the application of a novel feature and SVM classifier using three different databases.

1.2 Proposed methodology

The proposed technique includes EEG data acquisition followed by preprocessing, segmentation of each channel at a constant window length, estimation of successive decomposition index (SDI) and classification. Figure 1 shows the flow of the proposed automated seizure detection method. Initially, EEG recordings were preprocessed for noise and artifact removal. EEG was segmented into a constant non-overlapping window length of 1 s and SVM classifier was used to classify SDI feature. Furthermore, the proposed algorithm applied to three datasets that consist of a good number of epileptic seizure events to validate its performance.

The rest of our paper was organized as follows. In Sect. 2, materials and methods were discussed in detail. Experimental results were presented in Sect. 3, and the salient features of the proposed study were reported in Sect. 4. Finally, the concluding remarks were reported in Sect. 5.

2 Materials and methods

2.1 Clinical data

The experimental study was conducted on three EEG databases, namely the DB1-Ramaiah Medical College and

Table 1 Information on different EEG databases that were used in the state-of-the-art epileptic seizure detection studies in the past

References	EEG database center	No. of subjects	No. of electrodes	Length of EEG data	Sampling frequency (Hz)	EEG system	Band-pass filter (Hz)
[8]	Royal Brisbane and Women's Hospital, Brisbane, Australia	8	20	4.82	256	Medelec Profile System	0–70
[11]	Neonatal Intensive Care Unit, Dept. of Neonatology, SSKM, Kolkata, India	12	6	~ 11 h	125 & 2000	NicOne 5.3	0.5–35
[18, 57]	CHB-MIT, USA	23	21	969 h	256	–	0.5–30
[25]	Epilepsy Center Erlangen (University Hospital Erlangen, Germany)	159	64	25,278 h	256	NATUS Europe	0.08–86
[9]	National Institute of Neurology and Neurosurgery Rhode Island Hospital	12	21	62 h	200	Nihon Kohden EEG 1200	0–70
[2, 45] [60, 61]	University of Bonn, Germany	5	1	0.65 h	173.61	–	0.53–40
[51]	CHB-MIT, USA	21	21	884 h	256	–	0.5–30
[32]	Thomas Jefferson University, Dartmouth University	25	20–32	~ 500 h	200	Grass-Telefactor Beehive LTM	0.3–70
[21, 33]	Epilepsy Center of the University Hospital of Freiburg, Germany	21	6	286 h	256	Neurofile NT digital video EEG	4–30
[68]	Vancouver General Hospital, Canada	14	15	75.8 h	256	–	0.1–100
[14]	Maastricht University Hospital, Netherlands	78	19	~ 132 h	250	–	0.5–32
[40]	Department of Clinical Neurophysiology and Epilepsies in St. Thomas Hospital, London	11	21	–	250	–	–
[65]	Neonatal Intensive Care Unit of Cork University Maternity Hospital, Ireland	55	8	267.9	256	Viasys NicOne	0.5–13
[27]	Allegheny General Hospital, Pittsburgh, PA	55	–	~ 1208	–	–	–
[66]	Universitair Ziekenhuis Gasthuisberg, Leuven, Belgium	–	19	–	250	Brainlab digital EEG system	0.5–30

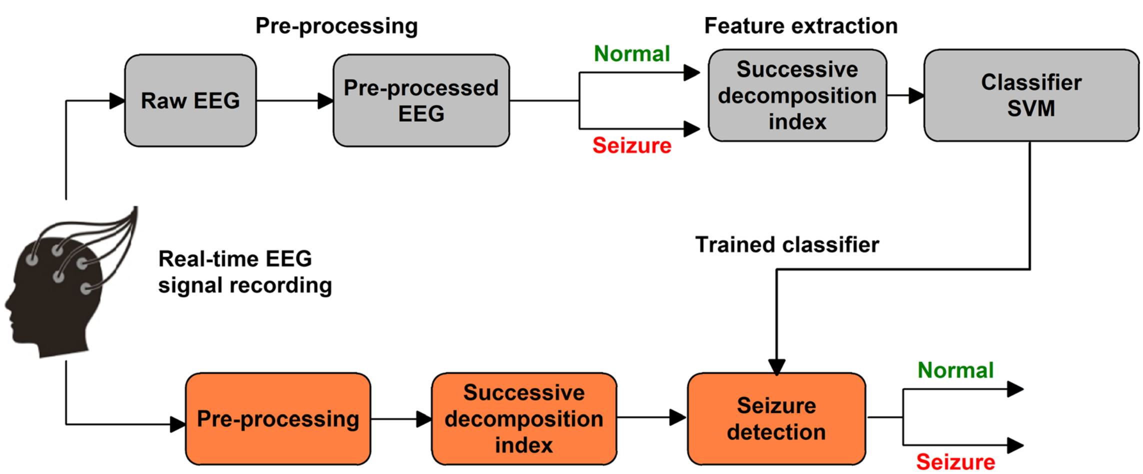


Fig. 1 The general framework of the proposed automated epileptic seizure detection algorithm

Hospital (RMCH), DB2-Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT), and DB3-Temple University Hospital which will be described briefly.

2.1.1 DB1

EEG recordings of DB1 were collected from the Institute of Neuroscience, RMCH, Bengaluru, India, after appropriate ethical clearance. It includes 58 h of 19 channel scalp

EEG from 115 subjects (male-67, female-48) ranging from 2.5 to 75 years old. Among 115 subjects, 38 were suffering from epilepsy and 77 were healthy subjects. EEG signals were recorded using the International 10–20 system electrode placement at a sampling rate of 128 Hz. These EEG recordings were made from the following electrode placements: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. Experts at the local hospital visually marked the epileptic and normal events of patient recordings. The subjects used for the study were suffering from either one of the following seizures: focal seizures, generalized seizures, absence seizures, clonic seizures, tonic seizures, and myoclonic seizures.

2.1.2 DB2

The second database used in this study was obtained from the CHB-MIT [58] EEG database from Physionet repository which is available in the public domain.[1] DB2 consists of 844 h of data from the 23 patients recorded at a sampling rate of 256 Hz. It was recorded with 23 channels using the International 10–20 system bipolar montage. It contains 23 channels, namely FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FZ-CZ, CZ-PZ, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8. This database includes 23 pediatric patients with the mean age of 9.9 ± 5.5 years.

2.1.3 DB3

The third and final database was obtained from the TUH EEG resource[2] [34, 35]. This dataset consists of focal non-specific, generalized non-specific, simple partial, complex partial, absence, tonic, tonic-clonic, and myoclonic seizure from 316 subjects. These EEGs were recorded with the same as electrode configuration of DB1 at a sampling rate of 250 Hz. In total, 222 seizures from 316 subjects were considered from massive EEG recordings.

Table 2 shows the detailed information on all three databases. DB2 and DB3 recordings were already annotated with seizure start and end time.

2.2 Preprocessing

EEG recordings of DB1 were filtered using a notch filter (50 Hz) followed by a Butterworth bandpass filter (0.5–40 Hz) to attenuate noise and artifacts (eye blink and muscular). The power spectral density analysis confirmed the attenuation of 50 Hz power line noise after notch filter implementation. In the next step, filtered EEG was passed through the independent component analysis (ICA) algorithm to separate the eye blinks and muscular artifacts [16]. Finally, experts annotated the preprocessed EEG as normal and epileptic seizures to develop a seizure detection algorithm.

2.3 Successive decomposition index

Wavelet-based studies have performed better in the past using different mother wavelets and the level of decomposition [2, 32, 45, 67]. However, the selection of the best wavelet and decomposition level for EEG analysis requires a thorough investigation in terms of classification results and computation time. In [6, 10, 15, 29, 30, 44, 45, 67], suitable wavelet, and decomposition levels were concluded by considering the results obtained from different mother wavelets and levels of decomposition.

The proposed SDI feature was derived by the motivation of the discrete wavelet transform (DWT). As we know, in the first level of DWT, the signal is passed to low-pass filter and high-pass filter. In the next levels, the output of low pass filter is simultaneously passed through a set of low-pass and high-pass filters. Finally, the coefficients are considered from different sub-bands to extract the features for classification. Whereas, in our proposed study, there is no restriction on levels of decomposition. The single coefficient from the last level is considered for further analysis.

The transition in the EEG from the normal to epileptic seizure activity is associated with the significant changes in the shape of the EEG signal. Therefore, capturing such an abrupt transition is essential to detect epileptic seizure activities.

Consider the EEG time series $x = \{x_1, x_2, x_3, x_4, \ldots\ldots, x_n\}$, where n is the total number of the EEG samples (in one window) in the time series x. Here, we define two terms X^+ (average of $|x|$) and X^- (difference average of x). The terms X^+ is given by:

$$X^+ = \frac{1}{n}\sum_{i=1}^{n} |x_i| \tag{1}$$

The coefficient X^+ is mean of the absolute of x.

In the next step, X^- is calculated by the iterative process. In the first level ($x^{(1)}$), EEG samples are arranged into $n/2$ non-overlapping pairs as shown below.

$$x^{(1)} = \left\{\frac{x_1 - x_2}{2}, \frac{x_3 - x_4}{2} \ldots, \frac{x_{n-3} - x_{n-2}}{2}, \frac{x_{n-1} - x_n}{2}\right\} \tag{2}$$

The new coefficients of level 1, i.e., $x^{(1)}$ of length $n/2$ (n is updated in each level) after decomposition is represented as:

[1] http://www.physionet.org/pn6/chbmit.

[2] https://www.isip.piconepress.com/projects/tuh_eeg/index.shtml.

Table 2 Database details considered for the proposed study

	DB1	DB2	DB3
Open source database	No	Yes	Yes
Sampling frequency (Hz)	128	256	250
Electrode position	10–20	10–20	10–20
No. of subjects			
Male	67	5	151
Female	48	18	165
Total	115	23	316
Age range			
Male	3–60	3–22	2–90
Female	2.5–75	1.5–19	1.5–100
Total duration (h)	58	884	408
No. of channels	19	23	19
No. of seizures	162	182	222
File format	ASCII	EDF	EDF

DB1: RMCH, DB2: CHB-MIT, DB3: TUH

$$x^{(1)} = \{x_1^{(1)}, x_2^{(1)}, \ldots\ldots, x_{n/2-1}^{(1)}, x_{n/2}^{(1)}\} \tag{3}$$

In general, the difference average can be written as follows:

$$X_i^L = \left(x_{2i-1}^L - x_{2i}^L\right)/2 \tag{4}$$

Here, i goes from 1 to n, L is the number of levels of decomposition required to estimate the X^- and it is calculated by $L = 3.33\log_{10}(n)$. The coefficient obtained in the last level of decomposition is taken as X^-. Number of coefficients in each level is given by $n/2^L$.

In the next step, defining two new terms X^{++}, and X^{--} using X^+ and X^- as follows:

$$X^{++} = \frac{X^+ + X^-}{2} \tag{5}$$

$$X^{--} = \frac{X^+ - X^-}{2} \tag{6}$$

The coefficients X^{++} and X^{--} gives the relation between X^+ and X^-. The square matrix A is formed using the four coefficients X^+, X^-, X^{++}, and X^{--} as follows:

$$A = \begin{bmatrix} X^+ & X^{--} \\ X^- & X^{++} \end{bmatrix} \tag{7}$$

In our previous study [47], matrix determinant showed a good classification results for detection of epileptic seizure. Therefore, in this study, SDI was estimated by finding determinant [24] of the square matrix A.

$$SDI = \log_{10}\left(\frac{n}{L}(X^+X^{++} - X^-X^{--})\right) \tag{8}$$

The term n / L is a scalar parameter. The coefficient X^+ is much greater than the other three coefficients. SDI was arrived at by successively decomposing the EEG signal into the final level. Hence, the proposed parameter was labeled as SDI. We speculate that the SDI better tracks the transitions in the EEG of the time series along with the amplitudes of the EEG samples. Since the proposed parameter follows linear relation in every step, SDI of epileptic EEG is expected to be higher as compared to normal EEG (refer to Sect. 3.1). The rationale behind using the determinant of all four coefficients has been explained in the discussion section.

2.4 Classifier

SVM is a supervised machine learning algorithm, and it classifies the data by finding the best hyperplane that differentiates the two classes very well [26]. It was selected based on the reliable performance reported in previous studies for seizure detection [2, 10, 14, 43, 55, 56, 62, 63, 65]. The radial basis kernel function was chosen based on preliminary results and hyperparameters were determined using the optimization technique [62]. SVM classifier was trained with the class labels of 0 and 1 for normal and epileptic seizures EEG, respectively. The training and testing were performed separately for each database using leave-one-subject-out cross-validation method. In this method, EEG data from one subject was used for testing and remaining were used for training. The procedure was repeated until all the subjects were used for training and testing.

2.5 Performance metrics

The performance of the epileptic seizure detection algorithm using SDI feature and SVM classifier was evaluated in terms of sensitivity, false detection rate, median detection delay, and F measure [3, 29, 58].

- *Sensitivity* the number of correctly identified epileptic seizure events.
- *False detection rate* percentage of false detection during normal EEG over a period of data.
- *Median detection delay* an average delay between expert marking and algorithm detection.
- *F measure* The F measure is the harmonic mean of precision and recall. The recall is the same as sensitivity and precision is positive predictive value.

3 Results

3.1 Analysis of SDI feature

According to the behavior of the SDI feature discussed earlier (refer to Sect. 2.3), a seizure onset can be captured by the significant increase in its values. A Wilcoxon rank sum test exhibit $p < 0.05$ and z-score of $-$ 70.51 between normal and epileptic EEG. Further, descriptive statistics such as mean±standard deviation, upper quartile, lower quartile, and inter-quartile range between normal and epileptic showed a significant difference. Figure 2 represents the boxplot of SDI derived from normal and epileptic seizures EEG for each channel. From the boxplot, the excellent discrimination between two activities was noticeable in each channel.

Figure 3a shows the epileptic EEG example from DB1, and Fig. 3b shows the image derived using SDI values for corresponding channels. As can be seen, a significant increase in the SDI during seizure activity that is between 1110 and 1171 s. The topographical map describes the distribution of electrical activity across the brain by considering electrodes potential [17]. In this study, the SDI value of each channel was mapped onto the topoplot using the International 10–20 system electrode placement. Figure 3c, d shows the topographical map derived from SDI for the EEG shown in Fig. 3a. It is clear from the topoplot that the seizure onset started at 1110 s and continued till 1171 s. Refer to "Appendix 1" for EEG and corresponding SDI values obtained for DB2 and DB3.

3.2 Seizures detection results

Figure 4 presents the EEG, SDI, and SVM classifier output corresponding to randomly selected channels F7, T3, T5, and P3. The seizure onset is at 1110 s and offset is at 1171 s according to the neurologist. As shown in the middle panel of Fig. 4, SDI was found to be significantly higher during epileptic activities that is well discriminated from normal EEG. Thus, the epileptic seizure activity was identified correctly shortly after the onset by the SVM algorithm as shown in the lower panel of Fig. 4 in red color. Applying the proposed algorithm to DB1, results showed the mean sensitivity of 97.53% with the mean false detection rate of 0.4/h, median detection delay of 1.5 s and an F measure of 97.22%.

The study was extended on DB2 and DB3 to validate the efficiency, generalization capability, and robustness of SDI for seizure detection. Table 3 shows epileptic seizure detection results using all the three databases. Experimental results revealed that the mean sensitivity of 97.28%, mean false detection rate of 0.57/h, median detection delay of 1.7 s, and an F measure of 96.29% for DB2. From DB3, 106 and 210 subjects with epilepsy and normal subjects were selected, respectively, from the huge EEG resource. The mean sensitivity of 95.80%, mean false detection rate of 0.49/h, median detection delay of 1.5 s, and an F measure of 94.70% were obtained. Figure 5 shows the receiver operating characteristic curve obtained for the seizure detection algorithm for all the three databases. The area under the curve of 0.9811, 0.9756, and 0.9623 was obtained for DB1, DB2, and DB3, respectively.

3.3 Automated detection using GUI

To provide an automated seizure detection, we have developed a graphical user interface (GUI) in MATLAB 2017b using *APP Designer*. The GUI tests the EEG by feeding its SDI feature into the trained model (refer Fig. 1). The screenshot of the automated seizure detection tool is displayed in Fig. 6. The detailed function of each component in the GUI is given in Table 8 (refer to "Appendix 2"). The GUI video is available at https://bit.ly/2O7xDxN. The sample EEG was shown in Fig. 6 includes an epileptic seizure event that was correctly detected using our algorithm. Finally, the results obtained using GUI were validated by experts.

4 Discussion

The foremost importance of our real-time automated seizure detection algorithm was to achieve better performances regarding sensitivity, false detection rate, and median detection delay. Hence, to meet the objective, we have proposed the seizure detection algorithm using SDI and SVM classifier. It was observed that SDI increases significantly during the epileptic activity that confirms the suitability of SDI for identifying brain activities. Experimental results showed the highest sensitivity of 97.53%, the false detection rate of 0.4/h, median detection delay of 1.5 s, and an F measure of 97.22% among the three databases, which provide evidence for clinical implementation in real-time.

The rationale behind using the determinant of all four coefficients has been explained here. During the initial simulation, it was observed that alone X^{+} was more susceptible to outliers. The coefficient X^{-} was obtained by successively decomposing the EEG time series where it retained the high-frequency component. This formed the basis for estimation of SDI where it calculates the determinant by taking all four coefficients. The net impact was that the SDI was not susceptible to more outliers that

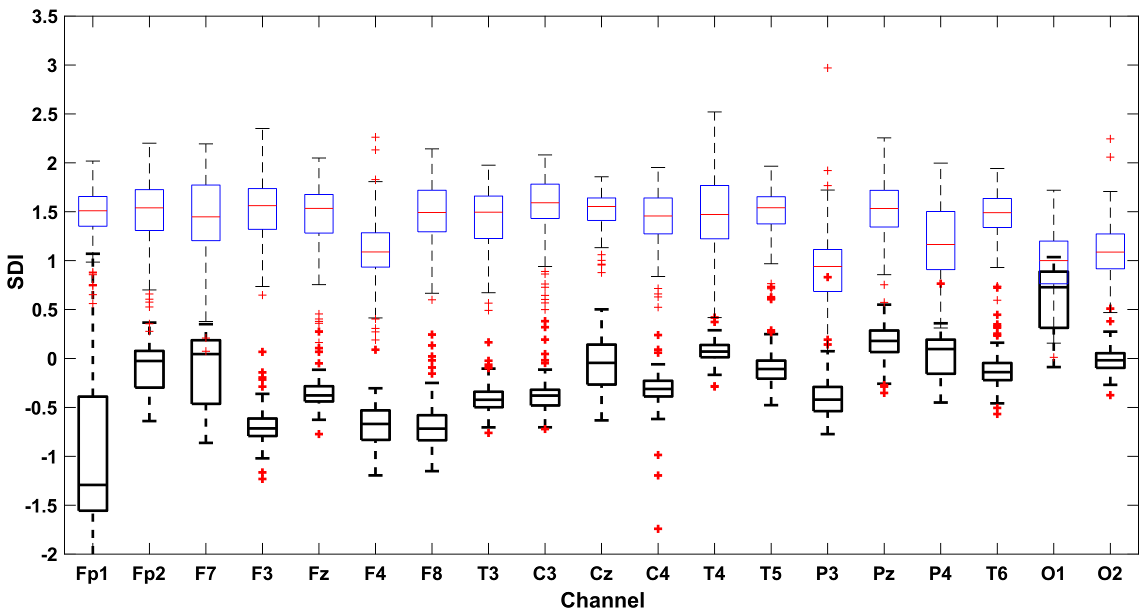


Fig. 2 Boxplot derived from SDI correspond to normal (black boxes) and epileptic seizures EEG (blue boxes). The red + indicates the outliers which are beyond the whiskers. A Wilcoxon rank sum test showed $p < 0.05$ between normal and epileptic seizures SDI in each channel (color figure online)

significantly improved the classification results. Thus SDI outperformed over other feature extraction methods.

4.1 Classification results using other classifiers

Table 4 shows the comparison results of the proposed study using three linear classifiers, namely linear regression, linear discrimination, and linear SVM classifiers. Among all the three databases, the results obtained using radial basis kernel function based SVM classifier (refer to Table 3) was superior as compared to the results of linear classifiers. Further, it was observed that the false detection rate was too high using linear classifiers.

4.2 Comparison with wavelet decomposition

Wavelet decomposition of EEG signals using different mother wavelets and decomposition levels have been widely used for seizure detection [1, 6, 29, 45, 67]. The majority of the studies have used different mother wavelets, namely Haar, Symlets, Coiflets, and Meyer and varied the decomposition levels until 8. In order to compare the computational time of different wavelets against SDI, above-mentioned wavelets were decomposed till 8th level followed by estimation of wavelet energy using DB1. Wavelet energy was considered as a feature due to the reason that it has shown superior performance. Figure 7 shows the computation time required for feature extraction using different mother wavelets. In total, the mean time was calculated from 10 trials. As the results demonstrated, the computation time taken from the SDI approach was 1.25 s that was less than all wavelet-based results. Besides, Coiflets and Meyer wavelets at the 6th level of decomposition showed the highest sensitivity of 96.2%. On the other hand, the lowest sensitivity of 89.6% was attained for Symlets wavelet at the 8th level of decomposition. The sensitivity of 96.2% achieved by Coiflets and Meyer wavelets at the 6th level was slightly less than the sensitivity of 97.53% shown by SDI. Interestingly, the highest sensitivity by Coiflets and Meyer wavelets at the 6th level was achieved at the highest computation time of 10.50 s among all. However, the computation time taken by SDI was only 1.25 s that was less in comparison with results obtained using wavelets. Hence, as compared to the SDI method, the wavelet-based approach required the selection of mother wavelet and decomposition level for better results at the cost of computational time.

4.3 Comparison with state-of-the-art approaches

Table 5 shows the comparison of the proposed method against existing methods that used different databases. As compared to the studies [20, 21, 25, 58], the highest sensitivity of 97.53% was achieved in our study. Similarly, the lowest median detection delay of 1.5 s was obtained in our method that was lower than other studies reported in Table 5. Further, the false detection rate of 0.40/h was better as compared to studies [20, 57, 65, 68]. Attention must be taken while comparing the performance between

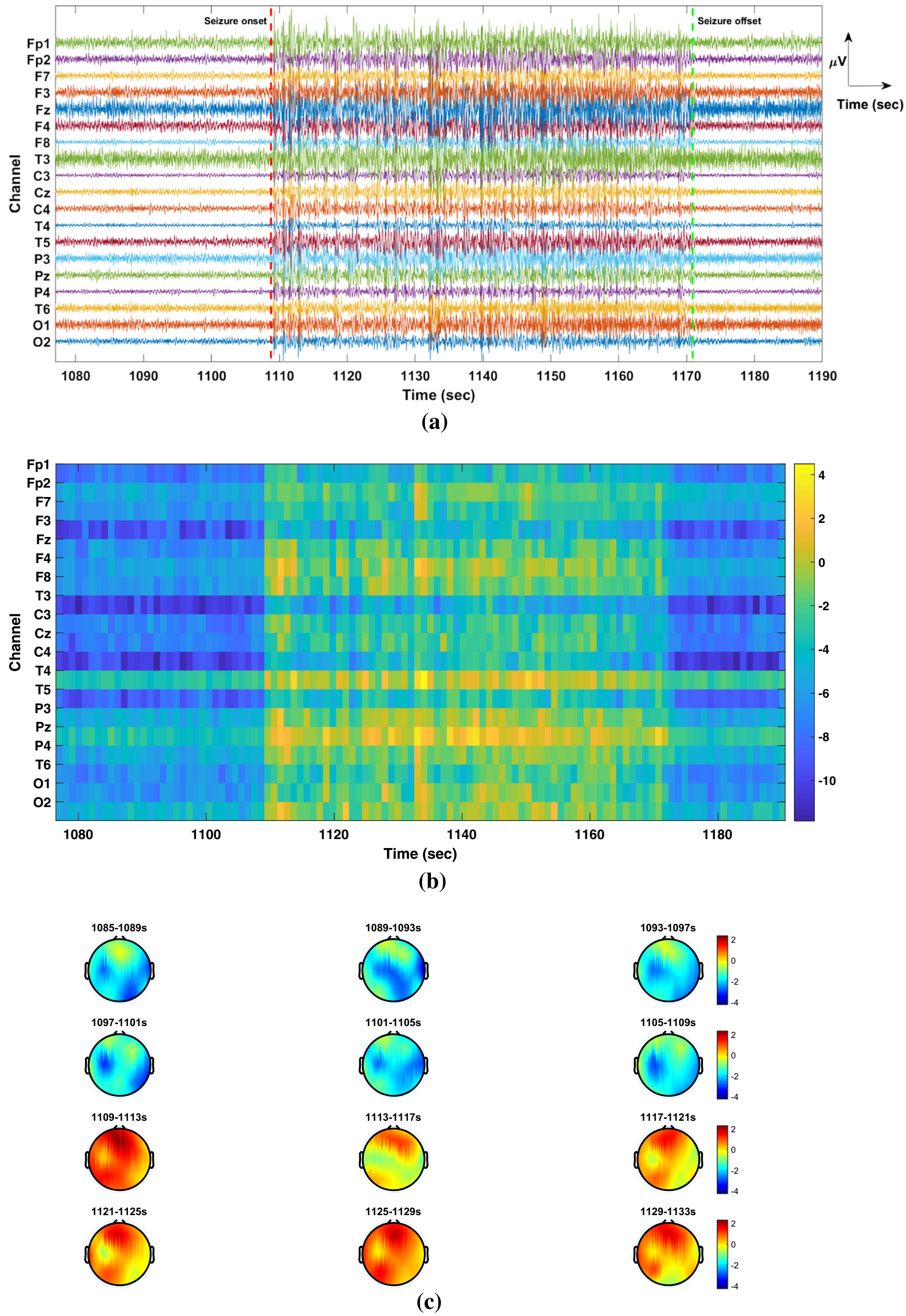
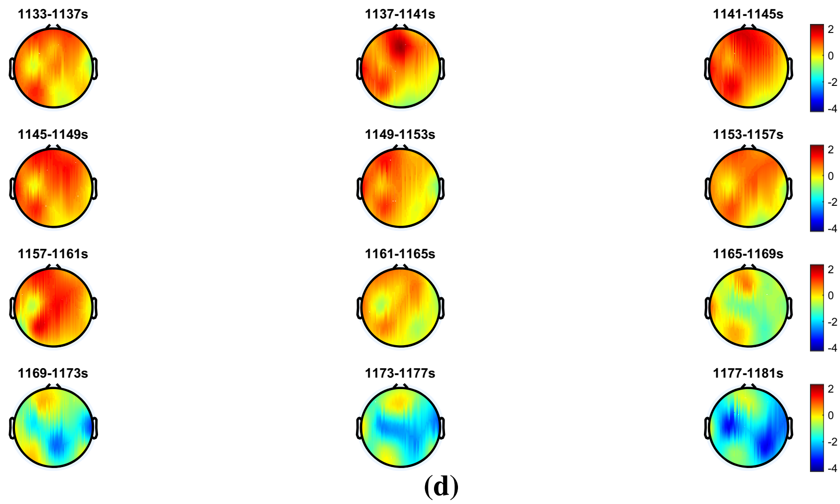


Fig. 3 **a** Epileptic seizure EEG example from DB1. The red marker indicates the beginning of the seizure onset and green marker its end. **b** Image derived from SDI for the EEG as shown in Fig. 3a. The *x*-axis and *y*-axis represent time and channel, respectively. The colormap represents the SDI values. **c, d** The topographical map for the same EEG between 1085 to 1181 s derived from SDI (color figure online)

Fig. 3 continued



various approaches since researchers have used different EEG databases.

In order to compare the performance and examine the efficiency of SDI feature, we perform a comparative study using other existing feature extraction methods. The features considered for the comparative study include: spectral entropy [60], approximate entropy [61], sample entropy and statistical features [55], log energy entropy derived from wavelet packet decomposition [45], and wavelet entropy [41] have been implemented on DB1 and classified using the SVM classifier. Table 6 shows the performance comparison in terms of computational time required for feature extraction and classification results. Even though the sensitivity of the other feature extraction methods was close to SDI, our method outperformed other methods in terms of computation time. It has almost 2.13% improvement in sensitivity as compared to [41] and 2.23% as compared to [60] and [45]. Further, approximate entropy [61] was found to be computationally expensive as reported in [45]. The false detection rate was superior in the proposed method as compared to the other features reported in Table 6. Overall, we observed the best performance

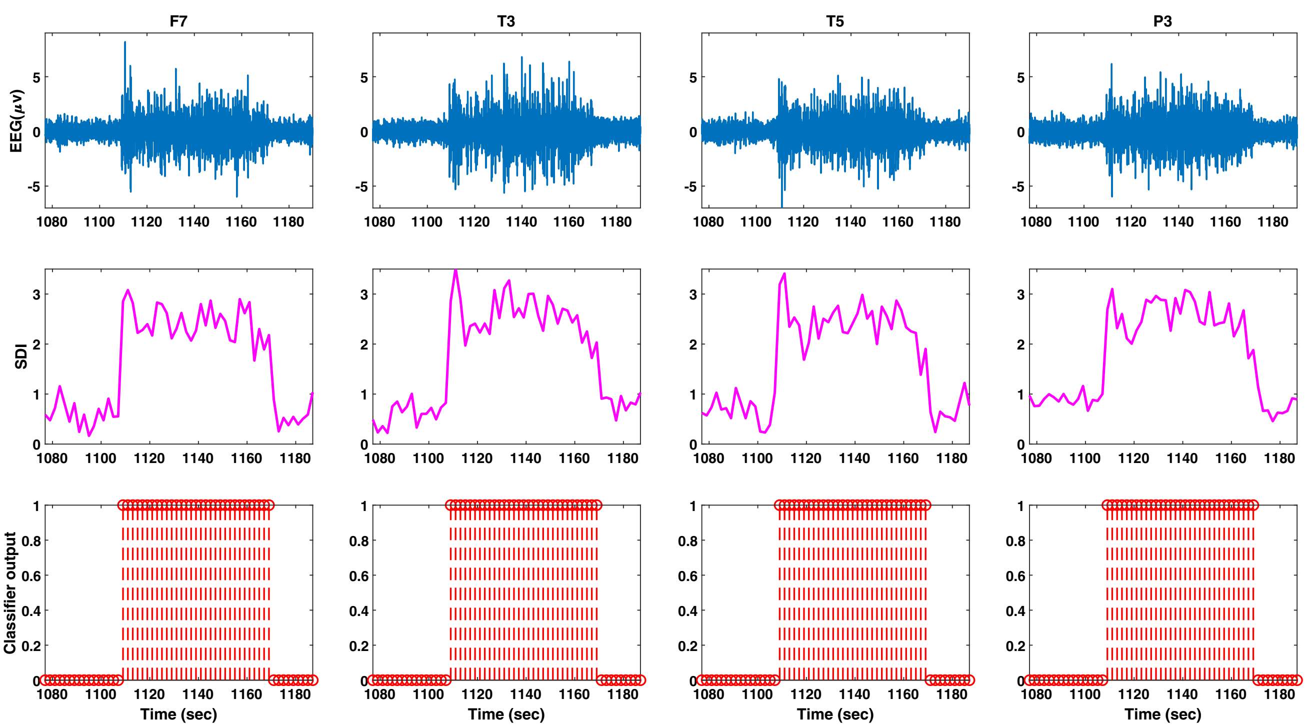


Fig. 4 EEG, SDI, and SVM classifier output corresponding to different channels. The seizure starts at 1110 s and ends at 1171 s. Classifier output 0 and 1 represent normal and seizure activity respectively. First row: EEG, Second row: SDI, and Third row: classifier output

Table 3 Results of epileptic seizure detection using the proposed method

Database	Sensitivity (%)	False detection rate (/h)	Median detection delay (s)	F measure (%)
DB1	97.53	0.40	1.5	97.22
DB2	97.28	0.57	1.7	96.29
DB3	95.50	0.49	1.5	94.70

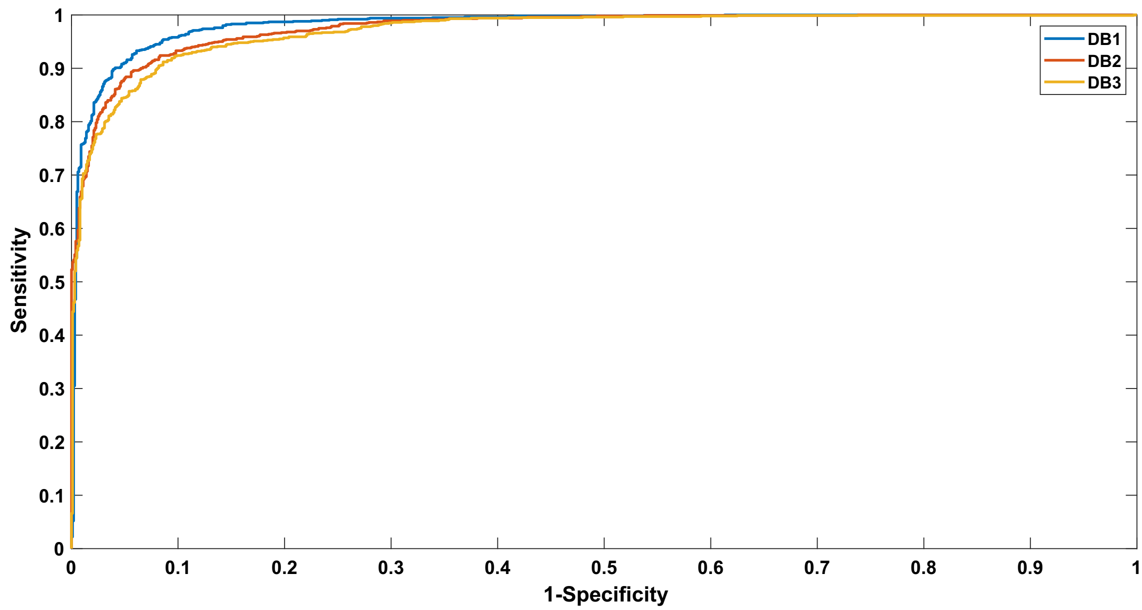


Fig. 5 Receiver operating characteristic curve obtained from all the three databases. The area under the curve of 0.9811, 0.9756, and 0.9623 was obtained for DB1, DB2, and DB3 respectively

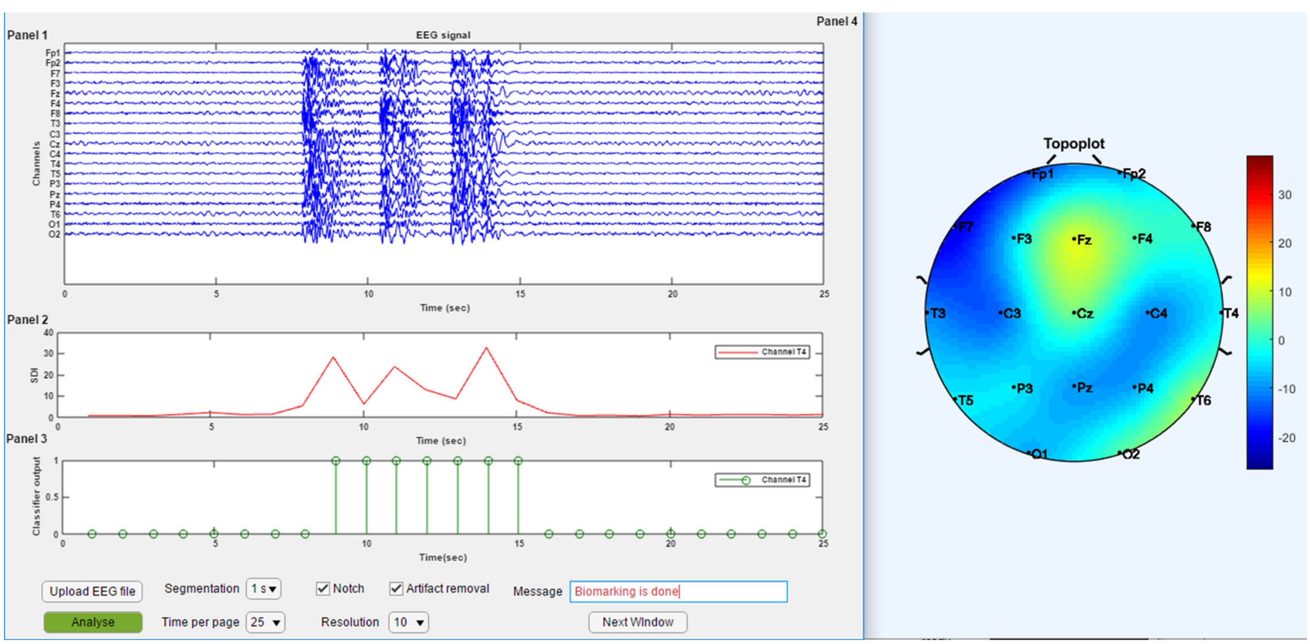


Fig. 6 Screenshot of automated seizure detection implemented in MATLAB. Panel 1: Axes show EEG of all 19 channels that include two seizure events. Panel 2: Figure shows the SDI of the selected channel T4. Panel 3: Figure shows the classifier output of the channel T4. Panel 4: The topoplot designed for every 1 s of EEG

Table 4 Sensitivity obtained using linear classifiers for all the three databases

Classifier	DB1 (%)	DB2 (%)	DB3 (%)
Linear regression	94.00	75.36	86.46
Linear discrimination	63.63	89.80	86.34
Linear SVM	95.12	88.36	88.35

by SDI against other existing feature proposed for seizure detection.

The spectral [60], approximate [61], sample [55], log energy [45], and wavelet [41] entropy methods have been implemented on all three databases and classified using the SVM classifier. Figure 8a shows an F measure obtained for different entropies and SDI. The highest F measure was obtained using the SDI feature for all the three databases. The least F measure of 93.20% (approximate entropy), 92.10% (sample entropy), and 91.00% (sample entropy) was observed for DB1, DB2, and DB3, respectively.

The algorithms proposed in [51, 52, 58, 70] have used the same EEG recordings from DB2, and the results are reported in Table 7. The highest sensitivity and less detection delay were achieved in our study as compared to the other methods reported in Table 7. An improvement of 1.28% in sensitivity and 12.3 s in mean detection delay was achieved in comparison with [70]. The false detection rate

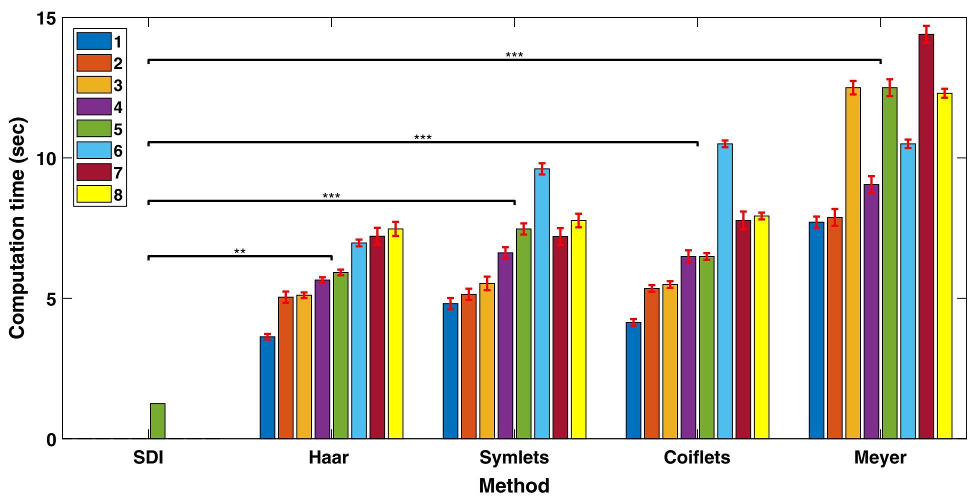


Fig. 7 Computation time (s) required for estimation of wavelet energy using wavelet decomposition and SDI on DB1. The legends in each color show the level of decomposition. The SDI results are presented for the last level of decomposition. $p < 0.05(*), p < 0.01(**), p < 0.001(***)$

Table 5 Performance comparison of state-of-the-art epileptic seizure detection algorithms

References	Method	Classifier	Sensitivity (%)	Median detection delay (s)	False detection rate (/h)
[58]	Wavelet decomposition, morphology and Spatial features,	SVM	94.24	8	15/60h
[57]	Spatial features	SVM	96	3	2/24h
[68]	Combined seizure index	Threshold	90.5	7	0.5/h
[32]	Spectral parameters, time domain, wavelet analysis parameters, and complexity measures	RENN	100	4	0.023/h
[49]	Signal amplitude variation and regularity statistics	Quantitative analysis	90.4	–	0.06/h
[65]	Multi-features	SVM	89	–	1/h
[25]	STFT and statistical features	Adaptive threshold	89.9	–	0.19/h
[21]	Relative amplitude and relative fluctuation index	Improved wavelet neural networks	96.72	–	0.27/h
[20]	HRV	Multivariate statistical process control	91	–	0.7/h
Proposed	SDI	SVM	**97.53**	**1.5**	**0.40/h**

The results of our method are highlighted in bold of 0.13/h in [52, 70] was better than ours, but the other two performances were better in our method. These comparisons underline that proposed method is a robust method for seizure detection.

In our previous study [46], classification of epileptic seizure was performed based on a threshold parameter derived using MVMFzEn. EEG recordings from 20 channels were taken into consideration to estimate the MVMFzEn followed by a threshold. However, in the proposed study, the decision was made based on the individual channel information. Our previous study [46] was implemented using only 38 subjects but, present study was extended the validation on 115 subjects.

Several nonlinear entropy measures developed from the concepts of chaos and nonlinear dynamics have been introduced for the recognition of epileptic EEG signals [1, 2, 29, 41, 60, 61]. Some of the entropy features, namely Shannon entropy, Renyi entropy, approximate entropy, sample entropy, permutation entropy, fuzzy entropy, and distribution entropy have been proposed and achieved promising results in the field of epilepsy detection. Further, resulting entropy of the EEG signal bounded in a range due to its nonlinear property. The detection of epileptic seizure would be possible using entropy measurements, whereas it would be difficult to identify the intensity of the seizure occurrence accurately due to the bounded entropy. However, the proposed SDI feature performs linear measurement showing the excellent reflection of variation in the EEG signal for the epileptic condition. Such a thing helps in identifying the intensity of epileptic activity in a specific EEG channel or the location of the brain.

4.4 Relative performance

We have compared the results of different entropies using the relative performance (RP) [45]. In this study, RP was measured using an F measure and computation time (s). The RP can be written as:

$$RP = \frac{(100 - F\text{measure})}{\text{Computation time}} \tag{9}$$

The higher the RP indicates better performance of the algorithm [45]. Best RP can be obtained with the higher F measure and less computation time. Figure 8b shows the RP obtained for different entropies using all three databases. As can be seen, the SDI algorithm showed the highest RP as compared to the other entropies of all three databases.

The complete study was conducted on MATLAB 2017b using 8GB RAM, CPU 2 GHz with an Intel i3 processor. The average/median computation time required to extract SDI for a 19 channels $\times$ 1 s EEG epoch was about 281 μ/262μs.

4.5 Limitations and future directions

The proposed method is yet to be implemented on a hardware platform. Although it performed well for seizure detection in MATLAB software, it must be implemented in hardware for real-time seizure detection. Further, parallel processing for feature extraction from multichannel EEG in real time would reduce the computation time that enhances the performance of the overall algorithm. The cross-database evaluation (using three or more databases) of the seizure detection will be implemented in future study.

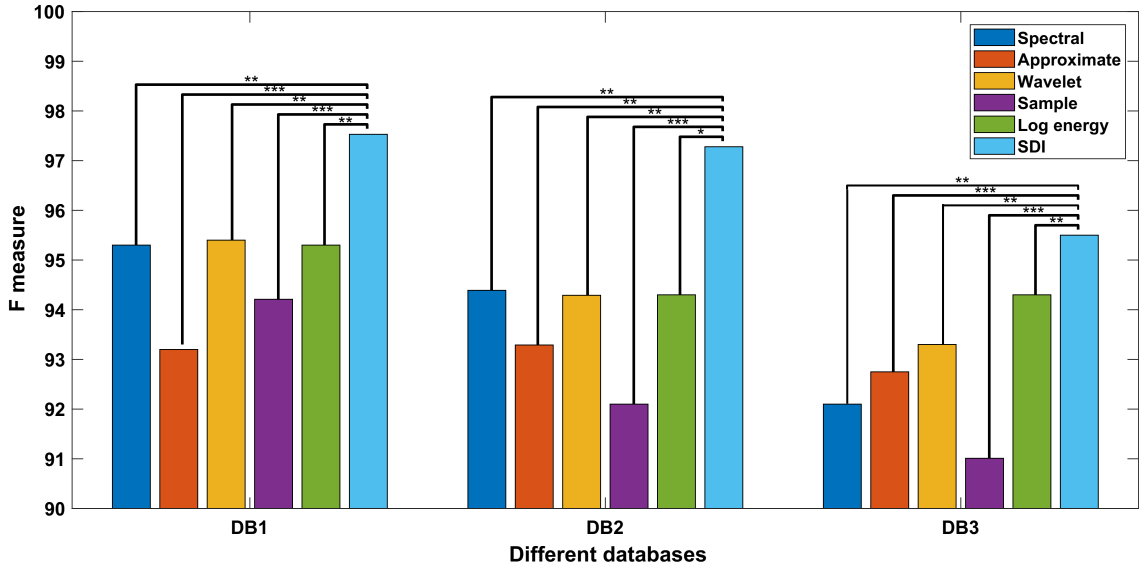
4.6 Summary of the study

In summary, we have evaluated the SDI feature using three databases for automatic seizure detection in long-term EEG. Experimental results confirm that seizure detection using SDI feature outperforms in terms of sensitivity, false detection rate, and median detection delay. Our conclusions are based on statistical analysis, classification results, and comparison results. Also, MATLAB GUI was developed for automated seizure detection. Therefore, the

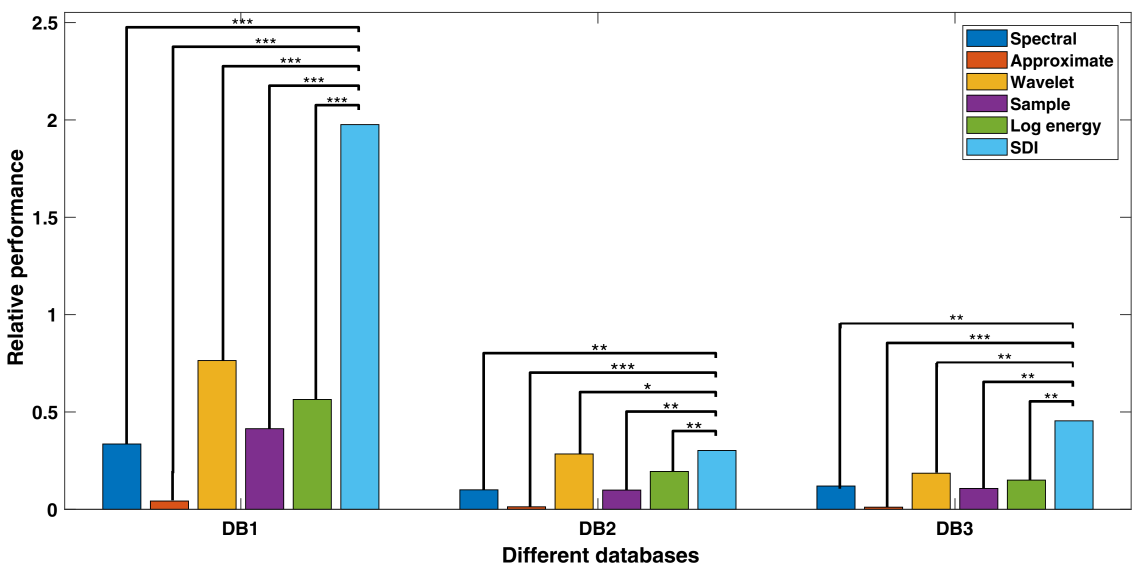
Table 6 Performance comparison of SDI with other feature extraction methods on DB1 using the SVM classifier

Method	Computation time (s)	Sensitivity (%)	Median detection delay (s)	False detection rate (/h)
Spectral entropy	14.01	95.30	1.5	0.70
Approximate entropy	159.76	93.20	1.6	0.95
Wavelet entropy	6.02	95.40	1.5	0.64
Sample entropy and statistical features	13.98	94.21	1.55	0.88
Wavelet packet decomposition and log energy entropy	8.33	95.30	1.5	0.64
SDI	**1.25**	**97.53**	**1.5**	**0.40**

The best performances are highlighted in bold



(a) F measure



(b) Relative performance

Fig. 8 Comparison results using different entropies on all three databases **a** F measure **b** relative performance. $p<0.05(*)$, $p<0.01(**)$, $p<0.001(***)$

proposed automated system for seizure detection can significantly reduce the neurologist burden that enhances the efficiency of medical diagnosis and the treatment of patients with epilepsy.

5 Conclusion

A novel feature called SDI was proposed and evaluated for real-time recognition of epileptic seizure in long-term EEG using three databases. It was observed that the SDI better tracks the transition in the EEG by reflecting the significant increase during seizure activity with less computation complexity. The significant difference ($p<0.05$) was observed between normal and epileptic seizures EEG. Classification results revealed the sensitivity—false detection rate—median detection delay of 97.53%-0.4/h-1.5 s, 97.28%-0.57/h-1.7 s, 95.80%-0.49/h-1.5 s using DB1, DB2, and DB3 respectively. The computation time analysis shows that SDI is faster among several feature extraction methods including wavelet-based features and other feature extraction methods. Experimental results obtained using SDI performed better than existing methods on all three databases proving the robustness, efficiency and general

Table 7 Performance comparison for different methods using DB2

References	Method	Sensitivity (%)	Median detection delay (s)	False detection rate (/h)
[58]	Wavelet decomposition, morphology,	94.24	8	15/60h
[57]	Spatial features and SVM	96	3	2/24h
[70]	Lacunarity and Bayesian linear discriminant analysis	96.25	13.8	**0.13/h**
[51]	Multivariate feature and SVM	70	–	–
[52]	Sparse rational decomposition, the local Gabor binary patterns and SVM	91.13	–	0.35
Proposed method	SDI and SVM	**97.53**	**1.5**	**0.40/h**

The best performances are highlighted in bold

applicability of the proposed seizure detection algorithm. Hence, the proposed algorithm is the optimal choice to assist neurologists as a valuable diagnostic tool providing better and timely care for epilepsy patients.

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Compliance with ethical standards

Conflict of Interest The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical approval The proper consent was taken from the ethics committee to use the RMCH database for research purpose. The proposed study makes use of two open source databases (DB2 and DB2), where appropriate ethical clearance has been already taken before database made available to public.

Appendix 1

Figure 9a illustrates the EEG from DB2 (subject no:chb01) and Fig. 9b shows its image representation derived from SDI feature. An epileptic seizure activity begins at 327 s and ends at 420 s; Fig. 9b shows a significant increase of SDI during seizure activity. Similarly, Fig. 10a shows the epileptic EEG from DB3 (subject no.:1217, session:s03, and file:a02) and Fig. 10b presents an image representation of the corresponding SDI feature.

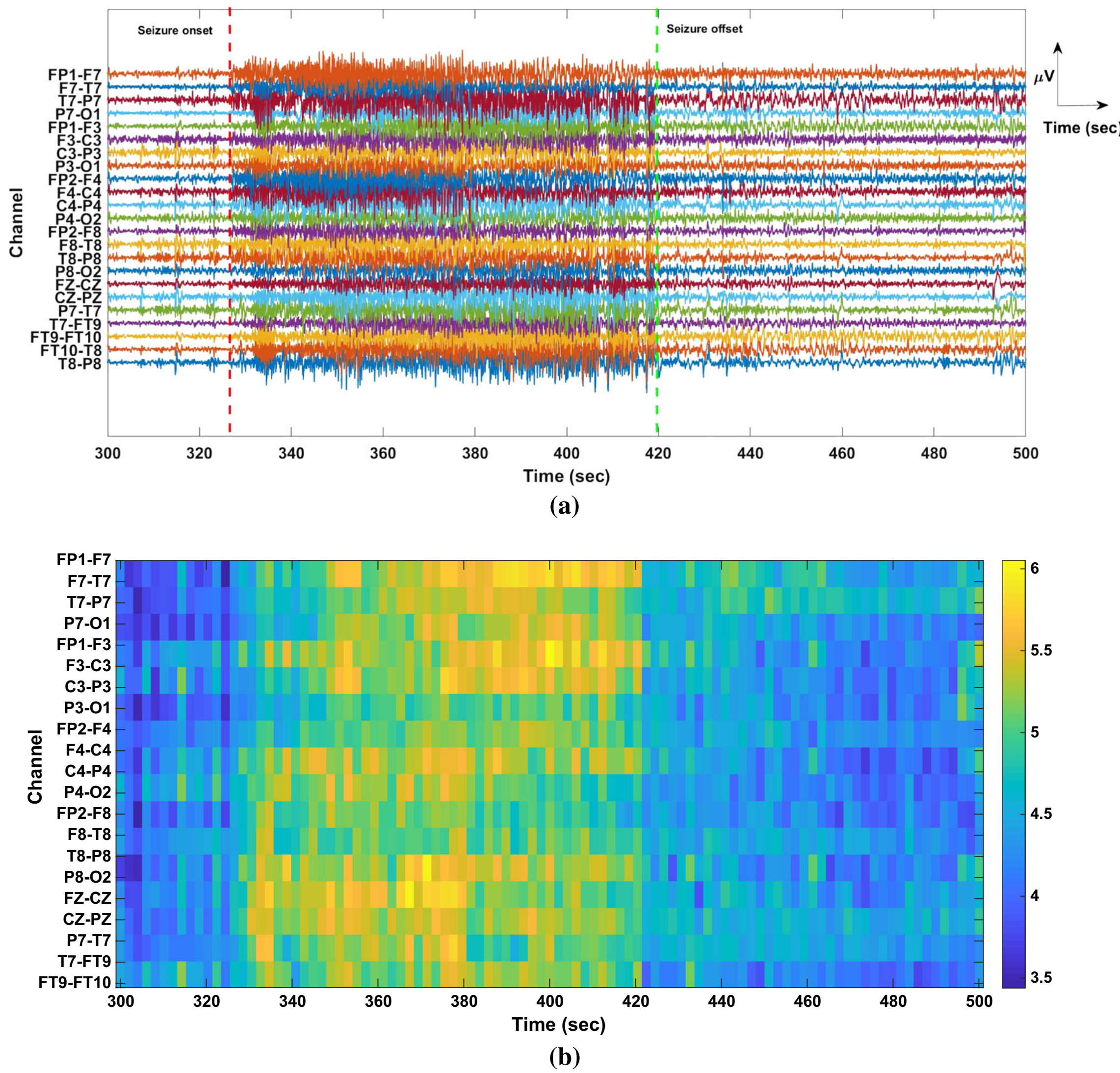

Fig. 9 **a** Epileptic EEG example collected from DB2 which consist of 23 bipolar channels and display shows the EEG between the time duration of 300–500 s. **b** Image derived from SDI for the EEG as shown in Fig. 9a. The x-axis and y-axis represent time and channel, respectively. The colormap represents the SDI values (color figure online)

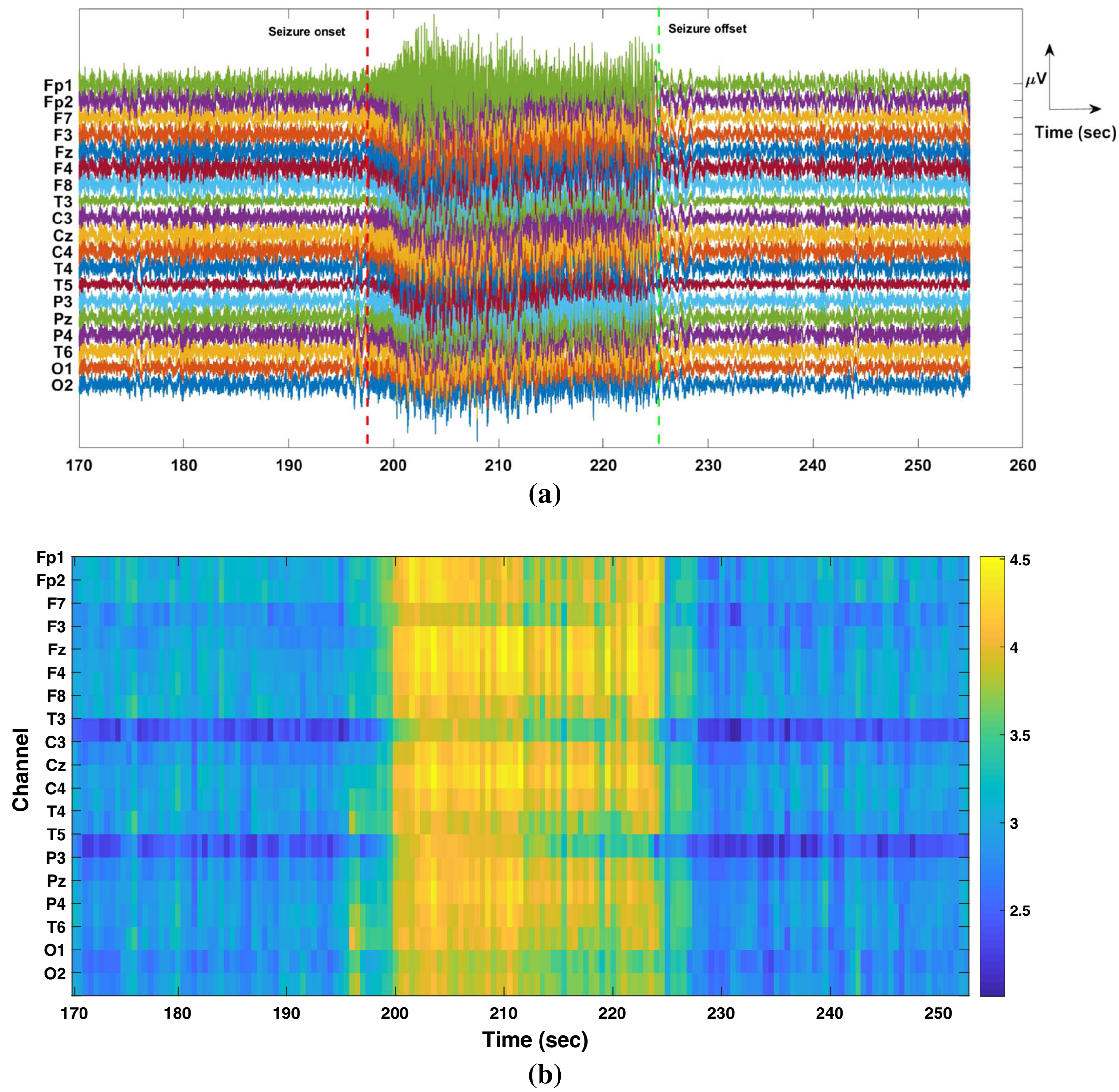

Fig. 10 **a** Epileptic EEG example collected from DB3 which consist of 19 channels and EEG displayed between the time duration of 170–255 s. **b** Image derived from SDI for the EEG as shown in **a**. The x-axis and y-axis represent time and channel respectively. The colormap represents the SDI values (color figure online)

Appendix B

Table 8 shows the functions of MATLAB GUI components.

Table 8 Functions of MATLAB GUI components

GUI Components	Function
Load EEG file	It loads the EEG file from the folder
Panel 1	Display EEG
Panel 2	Display SDI of selected channel
Panel 3	Display classifier output of the channel shown in Panel 2
Panel 4	Display topoplot for every 1 s of EEG
Segmentation	Window length for feature extraction (default: 1 s)
Time per page	Duration of EEG displayed in one page (default: 70 s)
Notch	Checked box shows EEG with 50 Hz line noise (default: Notch applied)
Artifact removal	Checked box shows EEG with artifacts (default: ICA applied)
Resolution	Sensitivity for EEG display (default: 10 µs)
Previous window	Display previous window EEG (previous 70 s)
Next window	Display next window EEG (next 70 s)

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