

A Review on Automatic Epilepsy Detection from EEG Signals



Satyender, Sanjeev Kumar Dhull, and Krishna Kant Singh

Abstract Epilepsy is a well-known neurological disorder which affects moreover 2% of the World's population. Irregular excessive neuronal activities to the human brain cause epileptic seizures onset. Electroencephalograph (EEG) signals are mostly examined for the detection of epileptic seizure onsets. But an EEG signal consists of a huge amount of complicated information and it is very difficult to analyze it manually. Over the decades, a lot of research has been focused on the development of automated epilepsy diagnosis systems. These systems are dependent on sophisticated feature captureization and classification techniques. The paper aims to present a generalized review and performance comparison of the work reported over a decade in the area of automated epilepsy diagnosis systems that will help future researchers lead a better direction.

Keywords Electroencephalogram (EEG) · Epilepsy · Feature extraction · Classifier

1 Introduction

Epilepsy is among the commonly existing neurological infirmity and is described as an unexpected change in the usual electrical activities in some parts of the brain or in the entire brain. These abnormal responses in the brain are called epileptic seizures [1]. A normal brain produces low amplitude electrical pulses but if a person is suffering from epilepsy then these pulses are produced in excessive amounts and

Satyender (✉) · S. K. Dhull
Guru Jambheshwar University of Science and Technology, Hisar, India
e-mail: jaglan86@gmail.com

S. K. Dhull
e-mail: sanjeevdhull2011@yahoo.co.in

K. K. Singh
GL Bajaj Institute of Technology and Management, Greater Noida, India
e-mail: krishnaiitr2011@gmail.com

are not easily controllable. The diagnosis of seizures is not easily predictable and if it is ignored, then it may lead to the death of the patient. According to a recent study, epilepsy affects around 6–10 million people in India, and less than half are treated [2].

Electroencephalogram (EEG) is a method of recording the electrical signals of the brain developed by cortical neurons. As per international standards, 10–20 electrodes are located around the scalp of the person to record the brain signals which are produced by the cerebral cortex nerve cells [3]. Neurologists generally use EEG signals for detection and diagnoses of epileptic seizures. Analyzing the EEG signals visually or manually requires a lot of time and neurological knowledge, making the epilepsy detection process tedious, difficult and may sometimes result in incorrect diagnoses. So, a lot of research has been done to propose computer-based automatic EEG epilepsy detection systems. Such a system must be able to classify the epileptic seizure signal from non-epileptic signals with more accuracy and in less time.

To automatize the seizure detection from an EEG signal, various machine learning approaches have been proposed by various researchers. Machine learning methods are more fast, accurate, and consistent in performance compared to manual labelling [4–9]. The machine learning approach is basically based on training a classifier with a repository of existing data consisting of both, epilepsy seizure signals and normal signals. A typical automated diagnosis system for epilepsy detection generally consists of following modules: EEG signal pre-processing, feature extraction and feature selection and finally classification of extracted features as normal, seizure or non-seizure. The performance efficiency of a typical automated epilepsy seizure detection technique is dependent on the type of classifier used, as well as on the features that are inputted to that classifier. Figure 1 presents a typical approach of detecting epileptic seizures for single-channel dataset, for example, the University of Bonn dataset. Similarly, Fig. 2 provides a general framework of epilepsy seizure detection for a multichannel dataset, for example, CHB-MIT dataset. These datasets are discussed in detail in the next section.

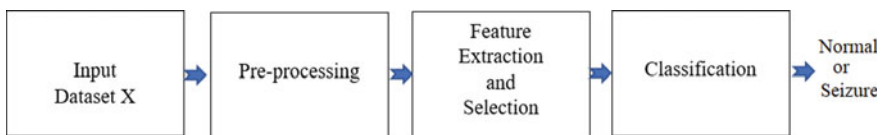


Fig. 1 Common approach to detect epilepsy seizure for single-channel dataset

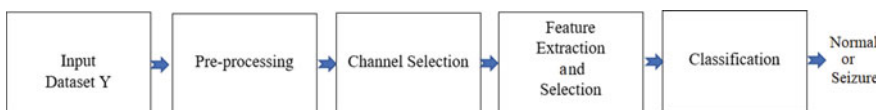


Fig. 2 Schematic illustration of the general approach to detect epilepsy seizure for multichannel dataset

The objective of this literature is to present an advanced review of the methods and techniques used for designing these modules. The remaining part of this paper is organized as follows: Sect. 2 focused on the various freely available standard seizure and non-seizure EEG signal datasets. Section 3 briefly summarizes various pre-processing and feature extraction techniques available in the literature. Section 4 studies various classification techniques used in the literature. Finally, the conclusion is given in Sect. 5.

2 EEG Dataset

In literature, many standard datasets for epileptic EEG signals and non-epileptic EEG signals have been utilized by authors for their research work. Online access is available for all such datasets; some are freely accessible and some have paid access. Two well-known datasets are being discussed, in this paper, that have free access online, and these are the University of Bonn dataset and CHB-MIT dataset. The details of these datasets are given below:

(i) University of Bonn dataset

The above-mentioned EEG dataset was recorded at the University of Bonn, Germany acquired by Andrzejak et al. [10]. This dataset comprises five sets A, B, C, D and E of EEG signal, where every set encompasses 100 single-channel EEG fragments of 23.6 s, which are sampled at a rate of 173.61 Hz, thus giving a total of 4097 samples per set. The spectral bandwidth for all sets ranges between 0.5 and 85 Hz. All the recordings were made using the same 128 channel amplifier system. Set A and B comprises of information gathered from five healthy volunteers with eyes open and closed, separately, utilizing the standardized surface EEG recordings. Sets C, D and E were obtained from five epileptic patients experiencing pre-surgical epilepsy diagnosis. Set C and set D were recorded during epilepsy free interval and set E was recorded during the occurrence of epileptic seizures. More information about this dataset can be gathered from [10]. The authors in papers [4, 6, 12, 13, 16–20] have utilized the University of Bonn dataset for their research work. Table 1 depicts a summary for the University of Bonn dataset and Fig. 3 presents waveforms of typical signals from set A to set E. As can be observed from Fig. 3 the amplitude of set E (ictal with seizure) is much greater than the amplitude of other sets.

(ii) CHB-MIT Dataset

It is also one of the commonly used datasets. This dataset is also referred to as the EEG PhysioNet dataset. It was acquired at Boston Children's Hospital [11], consisting of multichannel EEG signals that were recorded from 23 paediatric patients (5 males and 18 females) suffering from intractable epilepsy. The paediatric patients were reported to be between age 1.5 and 22 years.

The data was recorded for 23 channels using the international Federation of clinical neurophysiology standard of 10–20 electrode placement. Each channel data was

Table 1 Detail of University of Bonn dataset

	Set A	Set B	Set C	Set D	Set E
Patient's condition	Conscious and eyes open (normal)	Conscious and eyes closed (normal)	Seizure-free (inter-ictal)	Seizure-free (inter-ictal)	Seizure activity(ictal)
Type of electrode	Surface	Surface	Intra-cranial	Intra-cranial	Intra-cranial
Placement of electrode	International 10–20 system	International 10–20 system	Opposite to epileptogenic zone	Within epileptogenic zone	Within epileptogenic zone

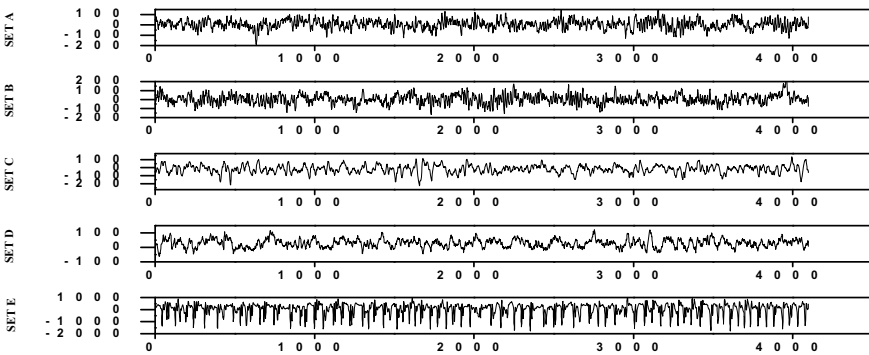


Fig. 3 Single channel Bonn dataset typical EEG signal from set A, B, C, D and E

digitized at a sampling rate of 256 Hz with 16-bit resolution. While recording clinical experts manually annotated the beginning and end of each seizure, and classified the EEG signals as epileptic seizures and non-seizures. The acquired dataset was 916 h long and consisted of a total of 198 identified seizures. The shortest duration seizure lasts for 6 s and the longest duration seizure lasts for 752 s with an average seizure duration of 72 s. The authors in papers [7, 8, 27–31] have utilized CHB-MIT dataset for their research work. Table 2 further gives detailed insight into the CHB-MIT dataset. Figure 4 plots a typical multichannel CHB-MIT dataset signal.

3 Pre-processing Techniques and Feature Extraction Methods

Pre-processing is a process of removing unwanted artifacts and noise from raw EEG signal that is collected directly from the scalp. These artifacts/noise may be present either because of blinking eyes, muscle movements, head motion during the record

Table 2 CHB-MIT dataset detailed description

Identification No.	Patient gender	Patient age	Seizure events ($T_{\min} - T_{\max}$) in seconds	Total seizure time in seconds	Total seizure-free time in seconds
1	F	11	7 (28–102)	449	23,475
2	M	11	3 (10–83)	175	7983
3	F	14	7 (48–70)	409	24,791
4	M	22	4 (50–117)	382	37,976
5	F	7	5 (97–121)	563	17,437
6	F	1.5	9 (13–21)	147	93,051
7	F	14.5	3 (87–144)	328	32,208
8	M	3.5	5 (135–265)	924	17,076
9	F	10	4 (63–80)	280	34,218
10	M	3	7 (36–90)	454	50,008
11	F	12	3 (23–753)	809	9249
13	F	3	12 (18–71)	547	28,253
14	F	9	8 (15–42)	117	25,023
15	M	16	20 (31–205)	2012	48,420
16	F	7	10 (7–15)	94	21,506
17	F	12	3 (89–116)	296	10,528
18	F	18	6 (31–69)	323	19,951
19	F	19	3 (78–82)	239	10,307
20	F	6	8 (30–50)	302	19,732
21	F	13	4 (13–82)	203	13,587
22	F	9	3 (59–75)	207	10,593
23	F	6	7 (21–114)	431	31,823
24			16 (17–71)	527	42,673

of the data, any problem in the channel/electrode, or any connectivity issue. Pre-processing thus may be utilized not just for artifacts removal but also for improving the Signal to Noise ratio and spatial resolution. Digital filters have been used by most of the authors in the pre-processing step.

In [12] EEG sample data is filtered through a 50 Hz IIR notch filter to eliminate AC power supply noise. In [13] the raw EEG signal is made to pass from a band-pass filter having a lower cut-off frequency of 0.53 Hz and higher cut-off frequency of 40 Hz for the removal of artifacts and noise. In [14] seventh order Chebyshev IIR filter is utilized. In [15] the EEG signal is de-noised by passing it through an FIR low-pass filter designed using Hamming with cut-off frequency at 60 Hz.

For an EEG prediction model to accurately classify between epileptic and non-epileptic signals, feature extraction is a very crucial step. Feature extraction is required because of the non-linear, stochastic and non-stationary behaviour of the

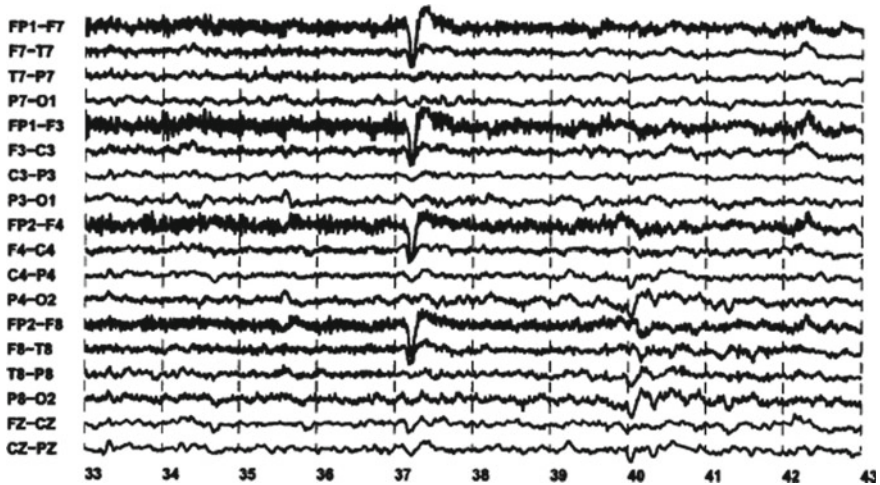


Fig. 4 Multichannel CHB-MIT dataset typical signal

EEG signal [6]. A good feature extraction technique must minimize the resources required for accurate classification of the signal as well as the loss of valuable information. The feature extraction process basically converts the raw signal information into a set of mathematical descriptors so that a better understanding of the complex data can be gained. Feature extraction is followed by a feature selection that aims to select the most relevant features and removes redundant features. Although there exist a number of feature selection algorithms in the literature, however Independent Component Analysis (ICA) [14] and Principal Component Analysis (PCA) [18] being the most popular.

The feature extraction techniques used in EEG signals analysis model are either time-based [2–14, 23], frequency-based [5, 12, 14, 23] or time-frequency based [4, 5, 16–18, 20, 21, 23–25, 27]. The most popular being the time-frequency analysis since it is able to provide both time and frequency information of the signal simultaneously. Time-domain features are obtained by analyzing the EEG signal as a function of time. Examples of typical features of time-domain include mean, median, standard deviation, kurtosis, amplitude, etc. Likely frequency-domain features are extracted by analyzing EEG data as a function of frequency. Various techniques like Fourier Transform are used for frequency-domain feature extraction. These features are related to spectral information of EEG signals. Examples of such features include spectral flux, power spectrum, spectral centroid, spectral entropy, etc. In the time-frequency domain both time-domain as well as frequency-domain features are extracted simultaneously. Discrete Wavelet Transform (DWT) is the most popular time-frequency domain based feature extraction technique.

In [4] authors have proposed a unique feature extraction technique based on Stockwell-transform (ST). It is a joint time-frequency analysis technique that is applicable to non-stationary signals. Such technique is more noise-robust, able to

retain the absolute phase of the individual frequency component and provide more information with less features. After performing S-transform, two features namely, energy and standard deviation are extracted for both seizure and seizure-free EEG signals. In [12] the cross-bispectrum values for three EEG channels are computed to determine various linear (average, maximum and minimum) and non-linear features in EEG data. In [13], for feature extraction EEG signals are sampled twice and plotted as vertical bars. Then a feature called visibility height is computed for the three adjoining neighbours from the top of the referenced bar. Then four various types of entropy are computed to reduce the dimension of data. In [14] after pre-processing the EEG signal, Wavelet Analysis also known as DWT is used for feature extraction. DWT is a time-frequency analysis method used for analyses of non-stationary signals. In this technique the signal is passed through a set of consecutive low-pass and high-pass filters to decompose the signal into set of five sub-bands. Thus, decomposing the initial signal into a set of coefficients that describe the frequency content. But to lower the spectrum usage and time complexities authors in this paper have used only the lowest frequency sub-band for feature extraction. The feature extracted from these identified sub-bands helps in further classification of data. In [15] authors have extracted thirteen features like min amplitude, max amplitude, Entropy, Mean, Median, Standard Deviation, etc. belonging to time, frequency as well as both domains. In [16] also authors have utilized DWT for feature extraction. After DWT decomposition, the sub-bands of EEG signals are discretized using Equal Frequency Discretization (EFD) technique. EFD technique helps to compute the probability density for all sub-band of each EEG segment. Thus, providing the probability densities of both healthy EEG dataset and epilepsy patient EEG dataset. In [17] Local Mean Decomposition (LMD) is utilized that iteratively transforms raw EEG data into a set of product functions (PFs) where a PF is generated by multiplying envelope signal with a frequency modulated signal. This technique has got the advantage of high processing speed along with low computational complexity. From each PF three time-domain features namely maximum amplitude, minimum amplitude, average absolute value, and three frequency-domain features namely maximum power spectral density, skewness, kurtosis are extracted. The authors have further computed the Fractal Dimension (FD), Renyi Entropy (RE) and Hurst exponent for EEG dataset to form a nine-dimensional feature vector. In [18] for feature extraction authors have utilized Daubechies Wavelet order 4 (DB4). Then for the dimensionality reduction, PCA is applied to the extracted data. PCA reduces the data to lower dimensional space by modifying the signal into the new Principal Components (PCs). This is done to reduce the complexity in both space and time. In [19] authors have proposed a Discrete Cosine Transform (DCT) based 3-level multi-rate filter bank that extracts alpha, beta, gamma, delta and theta brain rhythms. Delta brain rhythms are modelled using fractional Brownian motion (fBm) process and the other four brain rhythms namely alpha, beta, gamma and theta are modelled using fractional Gaussian noise (fGn) process. Autoregressive Moving Average (ARMA) model and Hurst exponent (H value) together constitute the extracted feature vector. In [20] Daubechies 4 (DB4) wavelet transform (WT) of the EEG signal is computed to produce wavelet coefficients. Then, phase-space reconstruction (PSR) is computed

for the wavelet coefficients of both normal and epileptic EEG signals. Then, in the third step Euclidean Distance (ED), the distance between the origin and the wavelet coefficients plotted in PSR, is calculated. These EDs form the initial feature vector.

4 Classification

An automated epilepsy diagnosis system must be able to accurately classify the EEG signals as epileptic and non-epileptic signal. In this regard many machine learning-based classification algorithms have been proposed in the literature. These algorithms usually train the system using either supervised, unsupervised or semi-supervised learning bypassing the selected features of the relevant class of the training data; and then the trained system performance is evaluated using different parameters for predicting the class of testing data. Although in literature there exists so many machine learning-based classification algorithms that classify the EEG signal as an epileptic class and non-epileptic class but the most popular being Support Vector Machine (SVM) [12, 13, 17, 21, 25, 26], K-nearest neighbour (KNN) [17, 18, 27, 30, 31], Linear Discriminant Analysis (LDA) [17] and Random forest (RF) [8, 13].

SVM is a very commonly used supervised learning-based classifier. It works by a creating hyperplane or set of hyperplanes in a multi-dimensional space that will separate data into various classes linearly. For a two-dimensional space, the hyperplane reduces to a line. The vectors that define the hyperplane are termed as support vector. This algorithm has got good generalization properties but the poor speed of execution. LDA is also one of the most commonly used supervised learning-based pattern reduction and dimensionality reduction algorithms. Like SVM this technique also separates the data into different classes using hyperplanes. In this algorithm, the first separability between different classes is computed which is termed as a between-class variance. Then it calculates within-class variance, i.e. the distance between the mean of the class and the individual samples of the class. Then creates a low-dimensional space that will maximize the between-class variance and minimize the within-class variance. KNN is also a very simple, popular and supervised based learning algorithm. The basic idea behind this is to first make the system learn through training data and as the new instance comes, it is assigned the class that is closest among the k -neighbours. The performance of the algorithm is very much dependent on k value. Greater k value reduces the effect of noise and increases the processing time. Random forest (RF) is a simple, flexible and easy to use machine learning algorithm. RF is also a supervised learning algorithm that works by creating an ensemble of decision trees. As a new instance comes, the class of this instance is decided by travelling from the root node of the tree to its leaf. At each node end, the successor may be chosen if there is a need to split the input space data. For the design of more efficient classifiers, future work can be done in the direction of using various optimization algorithms that have been explored in other applications [32–35].

The performance of a classifier is very much dependent on the characteristics/features of the data that is being inputted. Thus, if the extracted features are

not relevant then the classification algorithm may not be able to accurately identify the class of the data. Also, the performance of a classifier is evaluated by using a number of performance measures/parameters that include classification accuracy, false alarm rate, specificity, sensitivity, latency and Receiving Operating Characteristic (ROC). The performance measures that are being accessed also depends on the dataset that is being used. Authors that have used the University of Bonn dataset have evaluated the accuracy, sensitivity, specificity, confusion matrix, and ROC as the performance parameters, with accuracy and confusion matrix being the most common and widely used performance measure. Table 3 presents the comparison of accuracy level achieved through different classifiers inputting different extracted features. In literature, as briefed in Table 4, it is also found that some researchers have computed the classification accuracy by considering different cases that constitute a different combination of sets (from A to D) with set E from the University of Bonn dataset. For the CHB-MIT dataset apart from performance parameters evaluated for the University of Bonn dataset, two more parameters namely latency and false alarm rate are also evaluated. Table 5 briefs the literature work of different performance parameters evaluated and their experimental values for the CHB-MIT database.

5 Conclusion

This paper presents a review of the automatic epilepsy detection system that is able to classify EEG signals as epileptic or non-epileptic. A brief literature survey of the automated epilepsy detection system with a focus on its modules such as pre-processing, feature extraction and selection, and finally classification is been given. Two most commonly used and freely available datasets, i.e. University of Bonn dataset and CHB-MIT dataset are also discussed. The findings of different authors in terms of different performance parameters have also been summarized and compared. This review will give a clear birds-eye view of the recent advancements and techniques to the upcoming researchers in this field.

Table 3 Comparison of accuracy level of different classifiers designed for University of Bonn dataset

Researchers	Year	Feature Extraction Technique	Classifier	Accuracy
Orhan et al. [16]	2011	DWT + Equal Frequency Discretization (EFD) + Probability density	Mean square error (MSE)	82.5%
Leeet al. [20]	2014	Wavelet transform (WT) + Phase-space reconstruction (PSR) + Euclidean distance (ED)	Neural network with weighted fuzzy membership functions (NEWFM)	98.17%
Lasefr et al. [14]	2017	DWT	SVM	96%
			ANN	98%
Zhang et al. [17]	2017	Local mean decomposition (LMD)	BPNN	98.10%
			KNN	98.87%
			LDA	98.47%
			SVM	98.40%
			GA-SVM	100%
Jiang et al. [5]	2017	Wavelet packet decomposition (WPD) Short time-frequency transform (STFT) Kernel principal component analysis (KPCA)	S-TL-SSL-TSK A-TL-SSL-TSK	Above 95% in all cases
Rahmawati et al. [18]	2017	DWT + PCA	KNN	99.83%
Tiwari et al. [21]	2017	Key points detection + Local binary patterns (LBPs) computation	SVM	99.89%
Saini et al. [15]	2018	Standard mathematical formulas	ANN	99%
			PSO-ANN	99.3%
Mahmoodian et al. [12]	2019	Cross-bispectrum Analysis	SVM	96.84%

Table 4 Accuracy comparison of classifier used for University of Bonn dataset with different dataset combinations

Researchers/Year	Methodology	Dataset	Accuracy	No. of features
Kaleem et al. [22]	Empirical mode decomposition modified peak selection (EMD-MPS) + 1-NN classifier + 10-fold cross validation	A and E AB and CD ABCD and E	100% 99% 98.2%	4
Peker et al. [23]	Dual-tree complex wavelet transformation + Complex-valued neural network			5
	DTCWT + CVANN-1 + 10-fold cross validation	A-E	100	
	DTCWT + CVANN-2 + 10-fold cross validation		99.5	
	DTCWT + CVANN-3 + 10-fold cross validation		100	
	DTCWT + CVANN-3 + 10-fold cross validation	A, D, E	99.3	
	DTCWT + CVANN-3 + 10-fold cross validation	AB-CD-E	98.23	
Alsharabi et al. [24]	DWT-based shannon entropy feed-forward neural network (FFNN)	A-E	100	1
Zhang et al. (2017) [17]	Local mean decomposition (LMD) + GA-SVM	A-E	100	9
		D-E	98.10	
		ABCD-E	98.87	
		A-D-E	98.47	
		AB-CD-E	98.40	
Sharma et. al. [26]	Analytic time-frequency flexible wavelet transform (ATF-FWT) + Fractal dimension (FD) least squares SVM classifier	A-E	100	7
		B-E	100	16
		C-E	99	17
		D-E	98.50	17
		AB-E	100	17
		CD-E	98.67	16
		AB-CD	92.50	17
		ABCD-E	99.20	16
Zeng et al. [13]	Entropy of visibility heights of hierarchical neighbours (EVHHN) + 4 different classifiers (i) SVM (ii) Least squares SVM (iii) KNN (iv) RF	A-E	100	4
			100	
			100	
			100	
			100	

(continued)

Table 4 (continued)

Researchers/Year	Methodology	Dataset	Accuracy	No. of features
	(i) SVM (ii) Least squares SVM (iii) KNN (iv) RF	AB-E	99.67 99.67 99.67 99.67	
	(i) SVM (ii) Least squares SVM (iii) KNN (iv) RF	C-E	98 98.50 97.3 97.25	
	(i) SVM (ii) Least squares SVM (iii) KNN (iv) RF	CD-E	97.67 98.37 97.63 97.20	

Table 5 Performance comparison of different techniques used for CHB-MIT dataset

Researchers/Year	Technology/Method/Algorithm used	Dataset/Parameters used	Experimental values
Samiee et al. [29]	Sparse rational decomposition and the local gabor binary patterns (LGBP)	Average sensitivity Rate of false alarms per hour	91.13% 0.35
Abhijit et al. [27]	Empirical wavelet transform (EWT) + Random forest classifier	Average sensitivity Specificity Accuracy	97.91% 99.57% 99.41%
Shanir et al. [30]	Morphological attribute extraction method based on the local binary pattern (LBP) operator + K-nearest neighbour classifier	Mean accuracy Mean specificity Average false detection Sensitivity	99.7% 99.8% 0.47/h 99.2%
Solaija et al. [7]	Dynamic mode decomposition (DMD) + RUS boost classifier + Post processing step	Sensitivity Specificity	0.87 0.99
Wu et al. [8]	Mixed seizure finding algorithm by combining cEEG-based and aEEG-based seizure finding algorithm + Random forest classifier	Accuracy (AC) Specificity (SP) Sensitivity based on the event (SE) False positive ratio based on the event (FPRE)	99.36% 82.98% 99.41% 0.57 times/h
Bashivan et al. [31]	Spectral features (using STFT), spatial features (using Multi-scale 3D-CNN), temporal features (using bidirectional GRU) + Deep neural network (DNN) classifier	Sensitivity False positive rate	89.4% 0.5/h
Fan et al. [28]	Recurrence network (RN) based multivariate seizure detection	Sensitivity Latency	98% 6 s

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