Circuits, Systems, and Signal Processing (2023) 42:2782–2803
https://doi.org/10.1007/s00034-022-02223-z

An Intelligent Method for Epilepsy Seizure Detection Based on Hybrid Nonlinear EEG Data Features Using Adaptive Signal Decomposition Methods

Sandeep Singh[1] · **Harjot Kaur**[2]

Received: 12 May 2022 / Revised: 21 October 2022 / Accepted: 21 October 2022 /
Published online: 27 November 2022

Abstract
Epilepsy is a neurological disorder directly linked with brain electrical activities, which causes sudden and recurrent seizures in the patient. Epilepsy seizures can be detected by using automatic detection systems by analyzing significant features extracted from EEG recordings. In this work, we aim to focus on adaptive mode decomposition methods, namely empirical mode decomposition (EMD), empirical wavelet transform (EWT) and variational mode decomposition (VMD) methods, that decompose EEG signals into different levels of resolution and enable extracting relevant nonlinear features for accurate detection of epilepsy seizures. We propose an intelligent epilepsy seizure detection system using a neural network (NN) classifier based on nonlinear features extracted from ECG signals using adaptive mode decomposition methods. In addition, we propose to use hybrid features selected using a wrapper-based feature selection method from nonlinear features extracted using different adaptive mode decomposition methods. The experimental results prove that the proposed system can detect epilepsy seizures up to an accuracy of 99%, the sensitivity of 98%, specificity of 99% and area under ROC (AUC) of 99% using NSC_ND dataset. We also conduct nonparametric statistical significance tests, Friedman test and Wilcoxon signed ranks post hoc test for demonstrating statistical differences between the obtained results and superior performance of the proposed system. This study enables researchers and practitioners to examine the proposed method and adaptive mode decomposition methods for detecting epilepsy seizures.

✉ Sandeep Singh
er.ss1989@gmail.com

Harjot Kaur
harjot.csegsp@gndu.ac.in

1 Department of Computer Science Engineering, Guru Nanak Dev University, Regional Campus, Gurdaspur, India

2 Chandigarh and Assistant Professor (CSE), CSIR-CSIO, GNDU Regional Campus, Gurdaspur, India

Keywords Electroencephalogram (EEG) · Epilepsy · Machine learning · Seizure detection · Empirical mode decomposition

1 Introduction

Epilepsy is a neurological disorder disease-causing sudden and recurrent seizures ranging from mild to severe effects on the behavior of the subject [23]. It has been observed that more than 50 million people are suffering from epilepsy disease [45]. Epilepsy disease is generally diagnosed and detected by using electroencephalogram (EEG) by neurological experts visually. EEG recordings represent nonlinear and non-stationary data collected from brain activities. However, manual inspection of nonlinear and non-stationary EEG data is time-consuming, cumbersome and error-prone in inspecting long EEG recordings spanning many days. An automatic and intelligent method for analyzing EEG recordings to detect epilepsy seizures is highly required to assist neurological experts.

Recently, many automatic epilepsy seizure detection methods have been developed based on EEG signal analysis. Most methods involve the decomposition of EEG signals in different modes, extracting features from decomposed modes and classifying signals using machine learning methods [2]. Important signal processing methods used in detecting epilepsy seizures from EEG recordings comprise of Fourier transform [41], empirical mode decomposition (EMD) [13], discrete wavelet transform (DWT) [39], tunable-q wavelet transform [5], flexible analytic wavelet transform (FAWT) [12] and variational mode decomposition (VMD) [35]. A critical challenge in most automatic epilepsy detection systems involves extracting and choosing appropriate features from EEG recordings. Many adaptive mode decomposition methods have recently been proposed, addressing the limitations of conventional Fourier-based methods when dealing with nonlinear and non-stationary data. Empirical mode decomposition (EMD), empirical wavelet transform (EWT) and variational mode decomposition (VMD) methods are the most commonly used adaptive mode decomposition methods.

This work proposes an intelligent method for epilepsy seizure detection based on hybrid nonlinear EEG data features using adaptive signal decomposition methods. We extract features from EEG recordings using adaptive mode decomposition methods, namely EMD, EWT and VMD, to generate a hybrid feature set by applying a wrapper-based feature selection method to combined features of adaptive mode decomposition methods. Firstly, EEG recordings are decomposed into four modes by respective adaptive mode decomposition method, followed by extracting time-domain and spectral features. Finally, the feature selection method selects the most relevant 30 features that are further used to train and test the performance of the proposed method based on benchmark real-time NSC_ND dataset. The proposed method's performance is analyzed for different adaptive mode decomposition methods and hybrid feature datasets with different 4-mode segmentation in terms of accuracy, sensitivity, specificity and area under the ROC curve (AUC).

Here, we performed two sets of experiments with (1) All features (Experiment set-I); and (2) Selected features (Experiment set-II). In each case, we conducted four sets of experiments using different epilepsy datasets containing time-domain and spectral features extracted by EMD method, EWT method, VMD method and using hybrid features-based dataset. The proposed method is used for classifying seizure and seizure-free EEG signals. Ten independent executions are performed for each dataset, and the mean performance of the proposed method is presented in this work. Performance of the proposed method for each adaptive mode decomposition method generated dataset and hybrid feature-based dataset is recorded in terms of accuracy, sensitivity, specificity and AUC using tenfold cross-validation strategy. We also conduct nonparametric statistical significance tests, Friedman test and Wilcoxon signed ranks post hoc test for demonstrating statistical differences of the obtained results and superior performance of the proposed method in comparison with the other ones.

Major contributions of this work are listed below.

1. Processing and decomposing EEG signals for extracting time-domain and spectral features using adaptive mode decomposition methods.
2. Extracting spectral and time-domain features from decomposed ECG signals.
3. Pre-processing extracted spectral and time-domain features for processing with the proposed method.
4. Proposal of generating a hybrid featured dataset using a wrapper feature selection method based upon features of EMD, EWT and VMD methods.
5. Proposal of an intelligent method for epilepsy seizure detection based on hybrid nonlinear EEG data features using adaptive signal decomposition methods using NN classifier.
6. Empirical validation of the proposed method for epilepsy seizure detection based on a benchmark real-time dataset collected by Neurology and Sleep Centre, New Delhi (NSC_ND).
7. Conduct of nonparametric statistical significance tests, Friedman test and Wilcoxon signed ranks post hoc test for demonstrating statistical differences of the obtained results and superior performance of the proposed method in comparison with the other ones.

Rest of the paper is organized as follows. Section 2 presents the earlier research efforts made in detecting epilepsy using different types of features extracted from EEG recordings. Section 3 provides the basics of adaptive mode decomposition methods and NN classifier used in this work. Section 4 presents the proposed intelligent method for epilepsy seizure detection based on hybrid nonlinear EEG data features using adaptive signal decomposition methods and its working. Section 5 presents the experimental setup, benchmark dataset and result analysis using nonparametric statistical significance test. Finally, the paper is concluded in Sect. 6.

2 Prior Research Efforts

In recent year, several research efforts have been made for accurate epilepsy seizure detection using different types of features extracted from EEG recordings. Most automated epilepsy detection systems extracted features from EEG recordings using different signal processing methods such as Fourier transform [41], empirical mode decomposition (EMD) [13], discrete wavelet transform (DWT) [39], tunable-q wavelet transform [5], flexible analytic wavelet transform (FAWT) [12] and variational mode decomposition (VMD) [35].

Several researchers used a single feature "line length" of EEG dataset for detecting epilepsy seizure [3, 15, 22, 40]. For example, Guo et al. [22] used the line length feature for training a NN classifier to classify EEG signals. They reported accuracy of 99.6%. Similarly, Koolen et al. [24] also used "line length" feature extracted from EEG recordings. They reported an accuracy, sensitivity and specificity of 84.27%, 84% and 85.7%, respectively. They reported reserves are inferior to the results of Guo et al. [22].

Several other researchers have also advocated and used "line length" to normalize and discriminate class values of EEG datasets recordings. In addition, they suggested using "line length" feature along with other features for promising epilepsy seizure detection results. Some researchers have also used a single feature like entropy and its subtype such as sample entropy and approximate entropy [1, 31, 42, 47]. The use of entropy enables finding the random behavior in EEG signals by measuring the impurity of signals [28]. Several researchers used entropy as a promising feature for detecting epilepsy seizures. For example, Acharya et al. [1] proposed the use of four types of entropy features of the EEG dataset, namely sample entropy, phase entropy (S1) and phase entropy (S2), and approximate entropy.

Similarly, Chen et al. [10] proposed using eight kinds of entropy-based features of EEG dataset, approximate, sample, spectral, fuzzy, permutation, Shannon, conditional and correction conditional. The authors reported an accuracy of 99.5% based upon entropy features of the EEG dataset.

Selvakumari et al. [37] developed a tool based upon four distinct features of the EEG dataset, namely entropy, root-mean-square (RMS), variance and energy. They applied SVM and naive Bayes classifiers for detecting epilepsy seizures. Their experimental results demonstrate 95.63% accurate results.

Song and Li [42] used two classifiers, neural network trained using backpropagation strategy and extreme learners machine for classifying epilepsy seizure detection dataset. They reported 95.6% accurate results.

Zhang et al. [47] used extreme learning machine and support vector machine classifiers based upon entropy features of the dataset, namely approximate entropy and sample entropy. They concluded that sample entropy features provide better results with ELM than the approximate entropy feature of the EEG dataset. Researchers have also focused on energy features for classifying epilepsy seizure dataset [32]. Energy-based features are promising features for detecting epilepsy seizures based upon segmentation of EEG signals [44]. Researchers have also used the explanation energy feature for recognizing irregularities in the amplitude of EEG signals [16].

Peng et al. [33] proposed a novel method for seizure detection using the Stein kernel-based sparse representation (SR) for EEG recordings. They constructed a stein kernel-based SR framework seizure detection in the space of the symmetric positive definite (SPD) matrices, which form a Riemannian manifold. They validated the proposed framework using three widely used EEG datasets in terms of classification accuracy on each dataset. They reported an accuracy of 97.%5, sensitivity of 97.65% and specificity of 98.48% for NSC_ND dataset.

It can be observed from the literature cited above that most studies used features derived from discrete or continuous wavelet transforms, which decompose a signal into different levels of resolution. They focused on statistical features single as well as multiple features for detecting epilepsy seizures in EEG recordings. However, there are no benchmark features of EEG recording for detecting epilepsy seizures. It is a challenge for an automated epilepsy detection system. Another issue that is worth mentioning is the use of irrelevant EEG features can unnecessarily increase dataset size and hence can cause long training/execution time and reduce the accuracy of the results [30, 34]. Application of feature selection method can help to remove irrelevant and redundant features, leading to reduce computational burden and improving epilepsy detection results [4, 42, 47].

3 Preliminaries

Artificial intelligence/machine learning classifiers may not accurately detect epilepsy seizures if applied to raw EEG dataset directly. But, selecting significant features from ECG recording can help to produce promising results. However, extracting appropriate features from raw EEG signals is very challenging due to the nonlinear, non-stationary, complex and temporal nature of EEG signals [9, 36]. Many researchers use different features extracted features derived from discrete or continuous wavelet transforms that decompose a signal into different levels of resolution.

Of particular interest in this work due to the potential benefits of adaptive mode decomposition methods compared to conventional ones, we used features derived from EMD, EWT and VMD methods for classifying epilepsy seizure dataset collected by Neurology and Sleep Centre Delhi (NSC_ND). These adaptive mode decomposition methods are practical for analyzing complicated and multi-channel signals such as the brain's EEGs. These methods are data-driven and posterior methods for decomposing the multi-channel EEG signals [17]. Furthermore, these methods do not require any prior knowledge about the signals and impose any condition on signal representation in different domains such as time and frequency. Consequently, these methods can extract oscillation modes of mono-component nature representing oscillation properties from an arbitrary signal. Furthermore, these methods can represent oscillation properties as a superposition of several mono components. The ability to decompose the signal into mono-component helps to estimate the instantaneous frequency and amplitude accurately. These parameters lead to frequency decomposition and time variability of the signal. Adaptive mode decomposition methods are very adaptive to complicated and morphological contents that enable their suitability for harmonic, impulsive and modulated components. In addition, these methods can extract dynamic features of the system by analyzing the amplitude and frequency of the resultant mono-component of the signal. Several adaptive mode decomposition methods have been proposed, such as EMD and its variants, EWT and VMD methods. This work focuses on EMD, EWT and VMD methods to decompose EEG signals for detecting epilepsy seizures. These methods are described briefly in the following subsections.

3.1 Empirical Mode Decomposition (EMD) Method

EMD is an adaptive and data-dependent method for decomposing signals without any stationary and linearity condition. It decomposes nonlinear and non-stationary EEG signals into a sum of intrinsic mode functions (IMFs) satisfying conditions of same or with one difference between the number of extrema and zero crossings and defines the mean value envelope using local maxima and envelope of local minima of zero. EMD method is very effective in mono-component decomposition. However, it suffers from the limitation of lack of mathematical foundation [17]. It suspects to mode mixing under singularity. It is unstable under noise interference and overfitting and underfitting problems because of cubic spline interpolation. The details of EMD of Method can be further explored in [17, 18].

3.2 Empirical Wavelet Transform (EWT) Method

Gilles et al. [21] developed an empirical wavelet transform method with a solid mathematical foundation. EWT is a signal processing method that addresses the limitations of conventional non-adaptive methods such as DWT. This method decomposes non-stationary EEG data signals in two different modes by employing an adaptive filter bank. This method involves building an adaptive wavelet that can extract amplitude modulated and frequency modulated components of a signal. This method is proposed by the motivation of the concept such that such constituent AM–FM components have a compact support Fourier spectrum. This method is similar to Fourier spectrum segmentation for separating different modes and apply filters according to the detected Fourier support. This method does not require following a specific method such as dyadic discretization for computing dilation factor [17]. Instead, it detects dilation factor as per characteristics of signal Fourier spectrum empirically. This method is similar to the wavelet transformation method in separating empirical mode in a frequency order from low to high. But bandwidth is not dyadic as the frequency band is segmented empirically.

EWT method addresses the problems with the EMD method by adopting wavelet transform and designing appropriate wavelet filter banks that enable decomposition of a signal into a predetermined number of modes [8]. This method has been successfully applied in different domains such as EEG signal analysis [27], decomposing seismic activities [29] and representing time-frequency representation of non-stationary signals [6].

3.3 Variational Mode Decomposition (VMD) Method

VMD is a non-recursive decomposition method that decomposes a multi-component signal into constituent amplitude modulated and frequency modulated components in the presence of noise [14, 17]. Extract constituent amplitude modulated and frequency modulated components of a multi-component signal dynamically and simultaneously. This method involves defining IMFs as explicit amplitude modulated and frequency modulated models and associating these models' parameters to the bandwidth of IMFs.

This parameter is determined by minimizing bandwidth as per the narrow-band property of IMFs.

This method involves the conversion of real value multi-component signals into the discrete number of sub-signals initially [26]. These sub-signals have specific sparsity traits of bandwidth in the spectral domain. Gaussian smoothness function is applied to each mode of bandwidth. This method has several advantages over other mode decomposition methods. The primary advantages include rationale and noise robustness theoretically.

3.4 Neural Network (NN)

NN is a computational model that mimics the biological neural network concerning its structure and functioning. It provides a nonlinear statistical data modeling that involves the multipart association of money input data and output data [38]. Multilayer perception (MLP) is the most popular neural network architecture [7]. It is a feed-forward neural network consisting of different layers of interconnected neurons. It contains three layers: the input layer, hidden layer and output layer containing different neurons in each layer. Each neuron performs a partial weighted sum of its inputs and applies an activation function to transfer its output to the next layer. MLP can model any arbitrary complexity with many layers and the number of units in each layer. During the training process, weights are optimized to obtain minimum error at the output layer [7].

4 The Proposed Method

This study proposes an intelligent method for epilepsy seizure detection based on hybrid nonlinear EEG data features using adaptive signal decomposition methods. This section describes the proposed method. It explains different phases of the proposed method, including extracting the time-domain features and spectral features from EEG recordings, feature selection and classification of epilepsy seizure detection data using a NN classifier.

Figure 1 presents the proposed method for epilepsy detection, which includes six modules, namely data collection, feature extraction, pre-processing, feature selection, classification and performance analysis for detecting epilepsy seizures from benchmark EEG NSC_ND dataset. The details are described below.

4.1 Data Collection Module

The experimental data are collected using an EEG cap and other equipment in the form of EEGs. The details of the real-time dataset used in this work are provided in Sect. 5.2. The collected data are further processed to extract the relevant features.

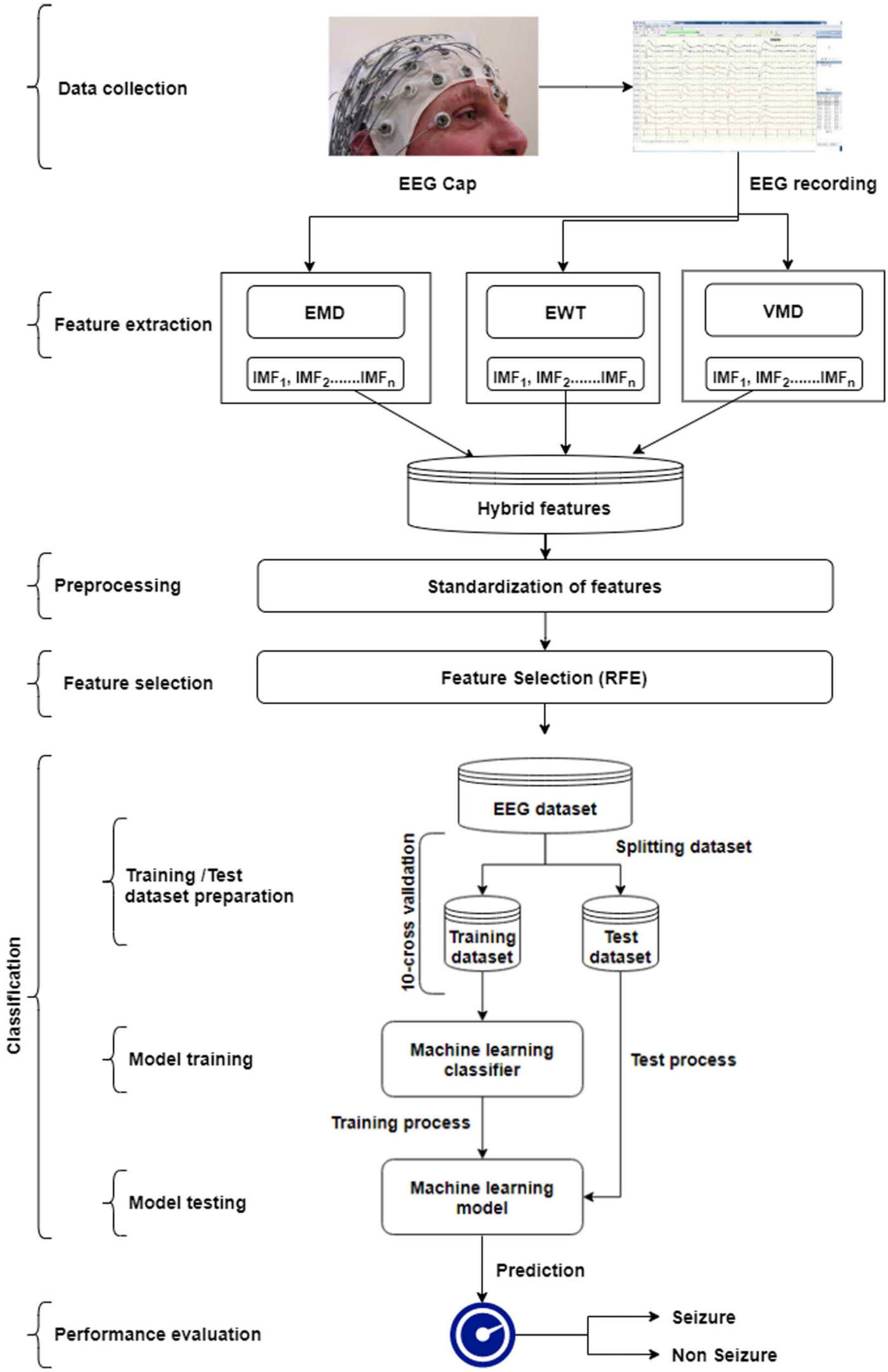

Fig. 1 The proposed method

Table 1 Features extracted from EEG signals

Sr No	Feature	Description
1	Spectral power	The power spectral density (power spectrum) reflects the frequency content of the signal or the distribution of signal power over the frequency
2	Spectral entropy	Spectral entropy (SE) is a measure of signal irregularity, which sums the normalized signal spectral power
3	Spectral peak	EEG power is typically split up into bands that correspond to different spectral peaks related to behavior or cognitive state.
4	Frequency	Frequency associated with spectral peak
5	Spectral centroid	Spectral centroid (SC) measures the shape of the spectrum of EEG signals. It is defined as the average frequency weighted by amplitudes, divided by the sum of the amplitudes.
6	AM bandwidth	Bandwidth parameters
7	FM bandwidth	Bandwidth parameters
8	Hjorth mobility	Mean frequency of the signal and proportional to the variance of its spectrum
9	Hjorth complexity	estimate of the signals' bandwidth
10	Skewness	Signal distribution's asymmetry
11	Kurtosis	Tails of the distribution yielded by the signal

4.2 Feature Extraction Module

In this module, data signals from EEGs are processed to extract relevant features and arranged in rows and columns. It applies EMD, EWT and VMD as adaptive mode decomposition methods for analyzing EEG signals in 4-modes. The decomposed signals are further analyzed by Hilbert transform to obtain different features.

This module extracts time-domain and spectral features for each adaptive mode decomposition method in 4-modes. In addition, it extracts features using 4-mode decomposition of EEG signals that are considered frequency modulated and amplitude modulated signals as features. The extracted features represent the properties of the spectrum of different signal modes [8]. This module extracts nine spectral features and two time-domain features in the set of experiments as described in Table 1.

The proposed method involves combining features extracted using EMD, EWT and VMD by decomposing EEG signal data into four modes to generate a hybrid featured dataset as depicted in Fig. 1.

4.3 Pre-processing Module

It has been observed that most machine learning methods report better performance when input values are preprocessed to a uniform scale. Normalization and standardization are the most commonly used methods for scaling numeric data to a standard range by the preprocessing module. The normalization process scales numeric values to a range of 0 to 1. In contrast, the standardization process scales each numeric value separately by subtracting the mean and dividing by the standard deviation to shift the distribution with a mean of 0 and a standard deviation of 1.

Pre-processing module performs a standardization process to convert hybrid features to a uniform scale using the following equations.

$$X_{\text{standardized}} = \frac{X - \text{mean}}{\text{standard\_deviation}} \tag{1}$$

4.4 Feature Selection Module

The hybrid feature dataset contains features extracted using 4-mode decomposition of EEG signals using EMD, EWT and VMD methods. This has increased the size of the dataset containing a large number of features. Some features of the hybrid feature dataset may contain some irrelevant and redundant features for predicting the target class of EEG signal as seizure or seizure-free. The feature selection module applies a wrapper-based feature selection method called "Recursive Feature Elimination" because of its effectiveness in selecting the most relevant features from the training dataset. RFE method involves two configuration options, the number of features to select and the choice of the algorithm used to help choose features. We configured the RFE method with the top 30 relevant features using the SVM algorithm in this work. This module selects the top 30 relevant features from the hybrid feature dataset. The selected 30 features are further used for developing an epilepsy detection system. Feature selection module is an optional step in machine learning projects. In this work, we performed two sets of experiments with and without feature selection modules with datasets generated by EMD, EWT, VMD adaptive mode decomposition methods in 4-modes and hybrid feature dataset as described in Sect. 5.

4.5 Classification Module

This module is the brain of the proposed epilepsy detection system. It trains a NN classifier using the top 30 features selected from the hybrid feature dataset produced by the feature selection module as described in Sect. 4.4. The preprocessed data of the selected hybrid features are divided into training dataset and test dataset. We used a tenfold cross-validation strategy to train and test the NN classifier in this work. In the tenfold cross-validation process, the dataset is divided into ten parts. Nine parts are used as training dataset, and one part of the dataset is used to evaluate the performance of machine learning classifiers.

We evaluated the proposed method using datasets generated using EMD, EWT, VMD adaptive mode decomposition methods in 4 modes and hybrid feature datasets with and without using feature selection module separately. Each experiment is repeated ten times, and mean values of results are recorded in terms of identified performance metrics as described in Sect. 5.

Table 2 Hyperparameters of neural network classifiers

Classifier	Hyper parameter values
MLP	alpha=1 max_iter=200 hidden_layer_sizes=100 activation=relu solver=adam learning_rate=constant

4.6 Performance Evaluation Module

This module evaluates the performance of the proposed method for conducting a comprehensive comparison. It measures the proposed method's performance in terms of four metrics, accuracy, sensitivity, specificity and area under the ROC curve (AUC).

These values are computed from the confusion matrix representing the values of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) defined as below [25].

– True positives (TP): Cases predicted as seizures that are seizures.
– True negatives (TN): Cases predicted as non-seizure that are non-seizure.
– False positives (FP): Cases predicted as seizures that are non-seizures.
– False negatives (FN): Cases predicted as non-seizures that are seizures.

These performance metrics can be computed as per the following equations.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{2}$$

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{3}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{4}$$

5 Experiment and Results

This section presents a description of the experimental setup, benchmark datasets and results obtained to demonstrate the proposed method's validity.

5.1 Experimental Setup

The proposed method used in this work is implemented in Python language using Scikit library for machine learning methods along with adaptive methods described in [8]. We conducted experiments on a machine Intel(R) Core(TM) i5-6400 CPU @ 2.70 GHz, 8GB RAM and 1TB HDD under 64-bit Windows 10 operating system. We performed classification of the NSC_ND dataset into three classes, ictal, interictal and preictal. Hyperparameters of NN classifier in this work are presented in Table 2.

5.2 Dataset

In this work, we use the EEG dataset provided by Neurology and Sleep Centre, New Delhi (NSC_ND), for evaluating the proposed method with dataset generated using adaptive mode decomposition methods and hybrid feature dataset. This dataset contains segmented EEG recordings of 10 epilepsy patients collected at Neurology and Sleep Centre, New Delhi (NSC_ND) [8, 43]. This dataset is collected using the Grass Telefactor Comet AS40 amplification system at 200 Hz and the gold-plated scalp EEG electrodes placed following the international 10–20 electrode placement system. Further, the signals have been processed by a band-pass filter with cutoff frequencies of 0.5 Hz and 70 Hz.

These signals are classified into three categories, namely preictal, interictal and ictal by expert physicians. There are 50 single-channel recordings in each class of dataset. Each recording consists of 1024 samples with a duration of 5.12 s. In this work, we classify the dataset samples into three classes, namely preictal, interictal and ictal and presented the recorded results.

5.3 Experiment Results

In this work, we performed two sets of experiments with (1) All features (Experiment set-I); and (2) Selected features (Experiment set-II). In each case, we conducted four experiments using different epilepsy datasets containing time-domain and spectral features extracted by EMD, EWT, VMD methods and hybrid features-based dataset. NN classifier is used for classifying seizure and seizure-free EEG signals in the proposed method. Ten independent executions are performed for each dataset, and the mean performance of the proposed method is presented in this work. In this work, we extracted time-domain and spectral features using different adaptive mode decomposition methods by decomposing benchmark real-time NSC_ND EEG signals into four modes. Performance of the proposed method for each adaptive mode decomposition method generated dataset and hybrid feature-based dataset is recorded in terms of accuracy, sensitivity, specificity and AUC using a tenfold cross-validation strategy.

5.3.1 Experiment Set-I

In this experiment, we used all features extracted using adaptive mode decomposition methods for classifying NSC_ND real-time EEG dataset for epilepsy seizure detection. The classification performance of the proposed method is recorded by repeating each experiment ten times and computed its mean performance.

Figure 2a–d presents box plots of experimental results in terms of accuracy, sensitivity, specificity, and area under the ROC curve for ten independent experiments using a tenfold cross-validation strategy using EMD, EWT, VMD mode decomposition methods and hybrid features.

It can be observed from Fig. 2a–d that the proposed method produced stable results for dataset generated using the EMD method in comparison with EWT and VMD

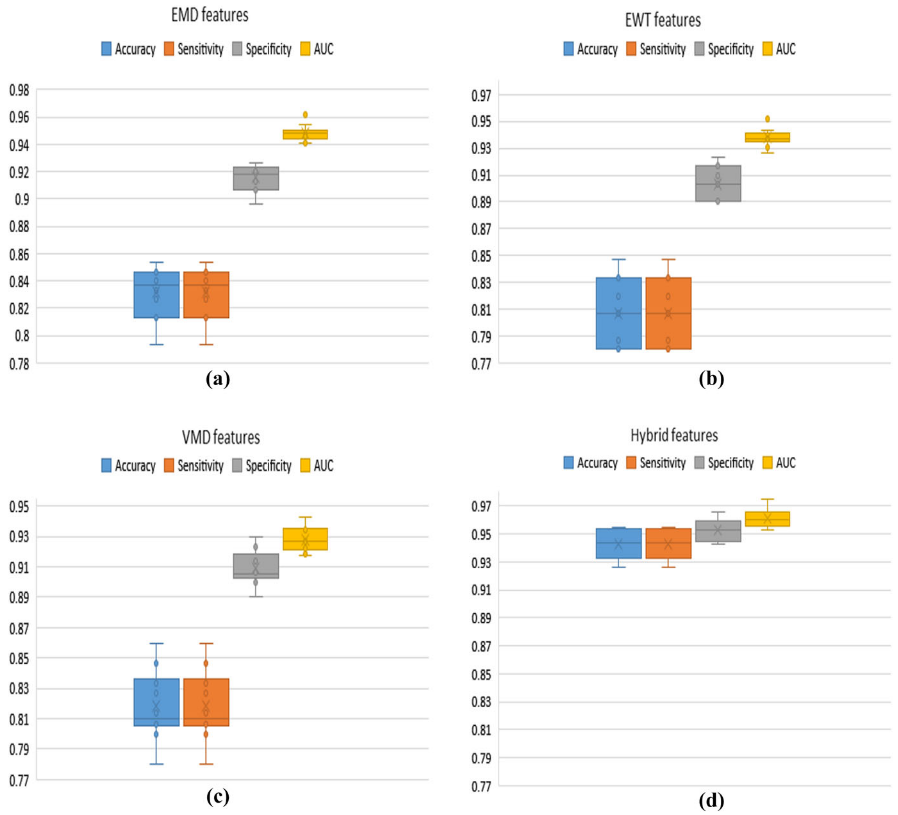

Fig. 2 Box plots of the proposed method performance for various feature sets (all features)

Table 3 Mean performance comparison (± standard deviation) (all features)

Method/Metric	Accuracy	Sensitivity	Specificity	AUC
EMD	0.8313 ± 0.0184	0.8313 ± 0.0184	0.9157 ± 0.0092	0.9481 ± 0.0057
EWT	0.8073 ± 0.0239	0.8073 ± 0.0239	0.9037 ± 0.012	0.9378 ± 0.0065
VMD	0.818 ± 0.0225	0.818 ± 0.0225	0.909 ± 0.0113	0.9278 ± 0.0075
The proposed method	0.9428 ± 0.01	0.9428 ± 0.01	0.9526 ± 0.005	0.9607 ± 0.0062

methods in terms of accuracy, sensitivity and specificity. Thus, the proposed method's performance is observed as more stable than other methods.

Table 3 presents a comprehensive comparison of mean values for accuracy, sensitivity, specificity and AUC with standard deviation provided by the proposed method in ten independent sets of experiments based upon different features extracted from NSC_ND EEG signals using EMD, EWT, VMD mode decomposition methods and hybrid features.

Figure 3 provides a comparative analysis of accuracy, sensitivity, specificity and AUC of the proposed method for different datasets generated using adaptive mode

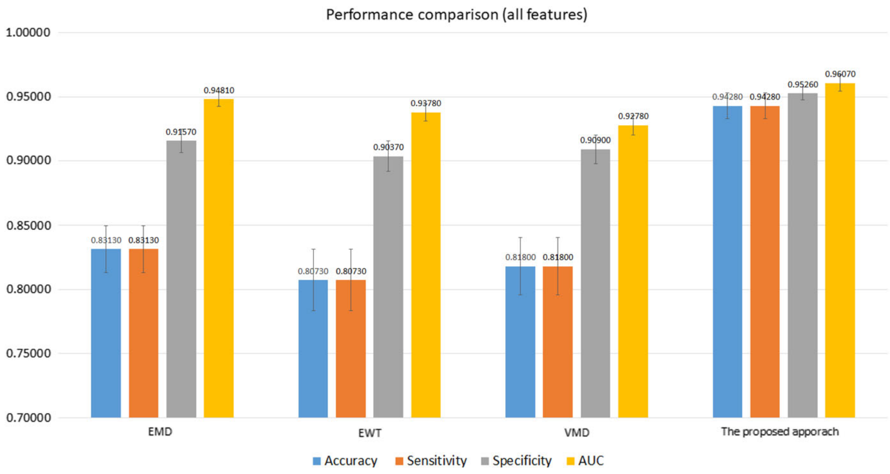

Fig. 3 Mean performance comparison($\pm$ standard deviation) (all features)

decomposition methods and hybrid feature dataset. Here, error bars indicate the standard deviation of the proposed method performance in ten repetitions of experiments. It can be concluded from Fig. 3 that performance of the proposed method outperforms using hybrid features in comparison with other features. EMD method can provide an accuracy of the proposed method up to 83.13%, followed by the VMD method to 81.8% approximately for 4-mode decomposition of EEG signals. A set of hybrid features of EMD, EWT and VMD methods can result in 94.28% accuracy of the proposed method. Similarly, a hybrid set of features can produce sensitivity, specificity and AUC up to 94.28%, 95.26% and 96.07%, respectively. The performance metric values obtained using a hybrid set of features outperform the respective values using features extracted using EMD, EWT and VMD methods separately. EMD method leads to the performance of the proposed method in terms of sensitivity, specificity and AUC up to 83.13%, 91.57% and 94.81%, respectively.

It can be concluded from Table 3 and Fig. 3 that hybrid set of features is suitable for detecting epilepsy seizure from EEG signals in benchmark real-time NSC_ND dataset without using any feature selection method.

Reporting results reflect that the overall extraction of features using the adaptive decomposition methods from EEG signals in benchmark real-time NSC_ND dataset is promising for detecting epilepsy seizures. Furthermore, the high value of accuracy, sensitivity, specificity and AUC demonstrate better class separability of the extracted time-domain and spectral features using adaptive mode decomposition methods. However, hybrid features from EMD, EWT and VMD methods produce the best results with 4-mode signal decomposition, demonstrating the potential of using combined features to accurately exploit different aspects of signal decomposition for detecting epilepsy seizures.

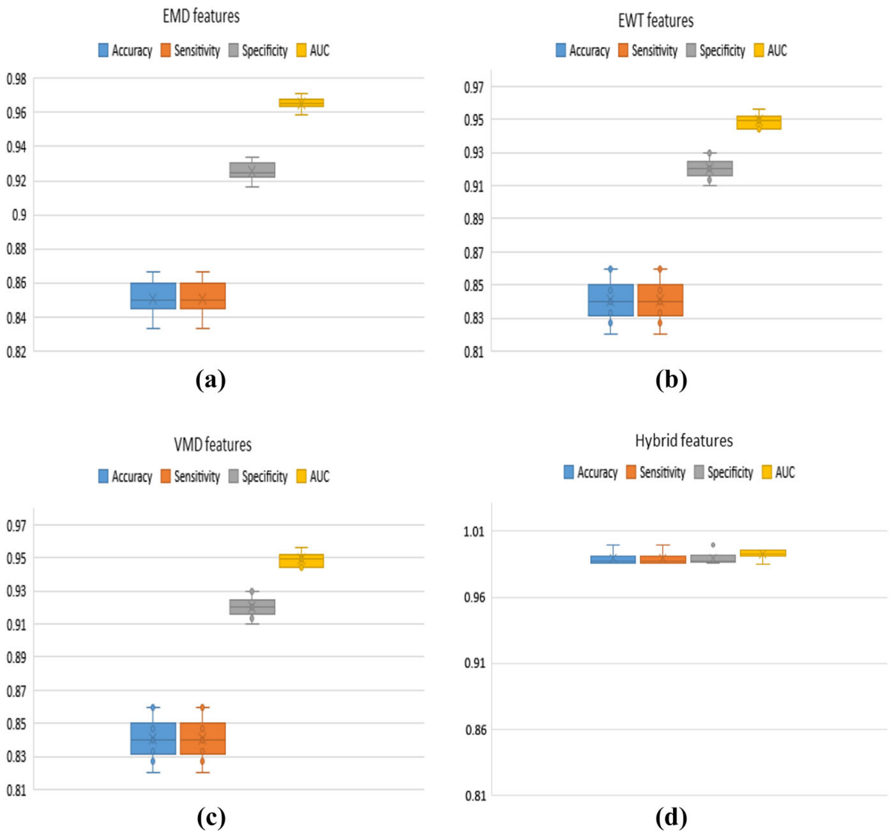

Fig. 4 Box plots of the proposed method performance for various feature sets (top 30 features)

5.3.2 Experiment Set-II

In this set of experiments, we employed "Recursive Feature Elimination (RFE)" [11], a wrapper-type feature selection algorithm, to hybrid features and features extracted using adaptive mode decomposition methods, EMD, EWT and VMD methods. RFE method is an efficient and popular method for selecting those features in a training dataset that is more relevant in predicting the target variable. We used SVM with the linear kernel as a base classifier in RFE for ranking features extracted by adaptive mode decomposition methods from benchmark real-time NSC_ND dataset. In this set of experiments, we used the top 30 features for training and testing the proposed method. Ten independent sets of experiments are performed for each dataset generated with adaptive mode decomposition methods and hybrid feature dataset. Classification performance of the proposed method is recorded by computing the mean performance of the proposed method over ten repetitive experiments for each dataset.

Figure 4a–d presents box plots of experimental results in terms of accuracy, sensitivity, specificity, and area under the ROC curve for ten independent experiments

Table 4 Mean performance comparison (± standard deviation) (top 30 features)

Method/Metric	Accuracy	Sensitivity	Specificity	AUC
EMD	0.8507 ± 0.0095	0.8507 ± 0.0095	0.9253 ± 0.0048	0.9653 ± 0.0035
EWT	0.8407 ± 0.0125	0.8407 ± 0.0125	0.9203 ± 0.0062	0.9493 ± 0.004
VMD	0.7893 ± 0.0187	0.7893 ± 0.0187	0.8947 ± 0.0093	0.9289 ± 0.0093
The proposed method	0.9894 ± 0.0076	0.9894 ± 0.0076	0.9897 ± 0.0038	0.9927 ± 0.0062
Peng et al. [33]	0.975	0.9765	0.9848	NA

using a tenfold cross-validation strategy using dataset generated using EMD, EWT, VMD mode decomposition methods and hybrid feature dataset.

It can be observed from Fig. 4a–d that the proposed method produced stable results for dataset generated using the EMD method in comparison with EWT and VMD methods in terms of accuracy, sensitivity, specificity and AUC with top 30 most relevant features decided by RFE method. Thus, the proposed method's performance is more stable than other methods in this set of experiments.

Table 4 presents a comprehensive comparison of mean values for accuracy, sensitivity, specificity and AUC with standard deviation provided by the proposed method (using top 30 relevant features) in ten independent sets of experiments based upon different features extracted from NSC_ND EEG signals using EMD, EWT, VMD mode decomposition methods and hybrid feature dataset. We compared the performance of results obtained in this work with the results reported in Study [33]. It can be noticed from Table 4 that the proposed method demonstrated better performance than Study [33].

Figure 5 provides a comparative analysis of accuracy, sensitivity, specificity and AUC of the proposed method for different datasets generated using adaptive mode decomposition methods and hybrid feature dataset (using top 30 relevant features). Here, error bars indicate the standard deviation of the proposed method performance in ten repetitions of experiments. It can be concluded from Fig. 5 that performance of the proposed method outperforms using hybrid features in comparison with other features. EMD method can provide an accuracy of the proposed method up to 85.07%, followed by the EWT method to approximately 84.07% approximately for four-mode decomposition of EEG signals. A set of hybrid features of EMD, EWT and VMD can result in up to 98.94% accuracy of NN classifier (using top 30 relevant features). Similarly, a hybrid set of features can produce sensitivity, specificity and AUC up to 98.94%, 98.97% and 99.27%, respectively. The performance metric values obtained using a hybrid set of features outperform the respective values using features extracted using EMD, EWT and VMD methods separately. EMD method led to the performance of the proposed method in terms of sensitivity, specificity and AUC up to 85.07%, 92.53% and 96.53%, respectively.

We also compared performance of the proposed method to that of Peng et al. [33]. It can be observed that our proposed approach achieves better performance in comparison with the study [33].

It can be concluded from Table 4 and Fig. 5 that hybrid set of features (using top 30 relevant features) is suitable for detecting epilepsy seizure from EEG signals

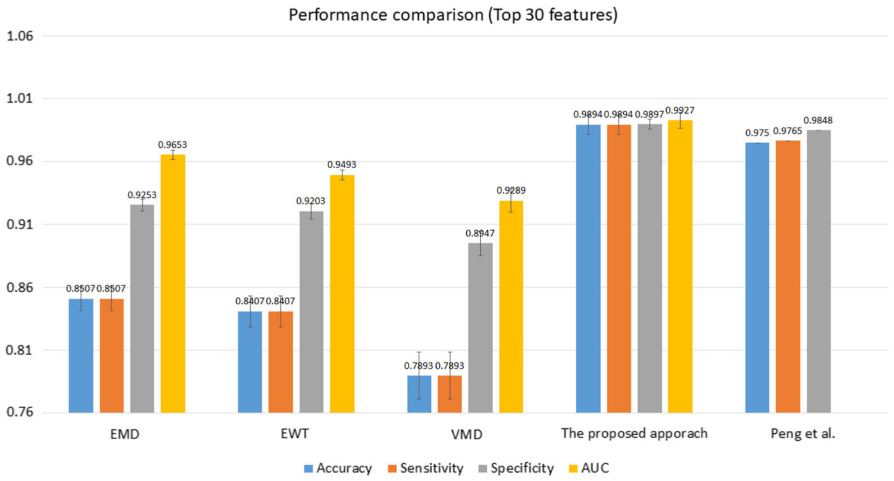

Fig. 5 Mean performance comparison(± standard deviation) (top 30 features)

in benchmark real-time NSC_ND dataset with more accuracy by processing similar amount of data. This demonstrates that hybrid sets of features extracted from EMD, EWT and VMD adaptive mode decomposition methods can be used to detect epilepsy seizure detection quickly and accurately.

Reporting results reflect that the overall extraction of features using the adaptive decomposition methods from EEG signals in benchmark real-time NSC_ND dataset, followed by selecting the most relevant features, is promising for detecting epilepsy seizures. Furthermore, the high value of accuracy, sensitivity, specificity and AUC demonstrate better class separability of the extracted spectral and time-domain features using adaptive mode decomposition methods. Hybrid features (top 30 relevant features) from EMD, EWT and VMD methods produce the best results with 4-mode signal decomposition, demonstrating the potential of using combined features to exploit different aspects of signal decomposition for detecting epilepsy seizures accurately and quickly.

5.4 Nonparametric Statistical Significance Test

We conducted a statistical significance test for evaluating the statistical difference among the obtained results. We used Friedman [19], a nonparametric test for ranking the approaches to detect epilepsy seizures from EEG signals using a benchmark dataset. The Friedman statistical test is conducted based upon two hypotheses, null hypothesis (H0) and alternative hypothesis (H1). The null hypothesis (H0) defines no significant difference between the performance of different methods, EWT, EMD, VMS and the proposed method. The alternative hypothesis is a statistical difference between the performances of different methods used in this work. The value of the Friedman metric is distributed over 3 degrees of freedom as we are using four methods in this comparison. The value of the Friedman metric is obtained and compared

Table 5 Friedman test-based mean ranking

Method	Rank
The proposed method	4.00
EWT	2.20
EMD	2.80
VMD	1.00

Table 6 Friedman test statistics

N	10
Chi-square	28.653
df	3
Asymp. Sig.	0.000

at a specific significance level (alpha = 0.05). The null hypothesis is rejected if the Friedman value < alpha (= 0.05), indicating a statistical difference between the results obtained for different methods. Otherwise, the null hypothesis is accepted.

We also performed post hoc analysis using the Wilcoxon signed ranks test [46]. Wilcoxon signed ranks test is the nonparametric statistical test for performing a pair-wise comparison of differences in performance of different methods. We assume a significance level of 0.05 for both Friedman and Wilcoxon signed ranks test using IBM-SPSS software [20].

We performed nonparametric tests based on the accuracy results obtained in ten independent experiments in this study. Friedman test- based mean rank of different methods using accuracy performance is presented in Table 5. It can be seen from Table 5 that there is an overall statistically significant difference between the mean ranks of the obtained results using different methods.

Friedman test statistics are presented in Table 6. Friedman test indicated that the results obtained using different methods are statistically different having, Chi-Square = 28.653, p-value (significance level) = 0.000 (< 0.05). Therefore, we reject the null hypothesis (H0).

Furthermore, we also conducted a post hoc test using the Wilcoxon signed ranks test on the different combinations of the methods used in this study. In this work, we performed a comparison of the following combinations of methods.

– The proposed method vs EWT method
– The proposed method vs EMD method
– The proposed method vs VMD method

Wilcoxon signed ranks test results are presented in Table 7. It can be observed from Table 7 that the proposed method has a better mean rank than EWT, EMD and VMD methods.

Table 8 shows Wilcoxon signed rank test statistics for comparing different methods.

It can be observed from Table 8 that the exact p value (Exact Sig. (2-tailed)) is less than 0.05 significance level. A Wilcoxon signed ranks test indicated that the proposed method (mean rank = 55) was rated more favorably than the other methods (mean rank = 0), $Z = -2.803$, $p = 0.002$.

Table 7 Wilcoxon signed ranks test results

	N	Mean rank	Sum of ranks
The proposed method—EWT			
Negative ranks	0[a]	0.00	0.00
Positive ranks	10[b]	5.50	55.00
Ties	0[c]		
Total	10		
The proposed method—EMD			
Negative ranks	0[d]	0.00	0.00
Positive ranks	1[e]	5.50	55.00
Ties	0[f]		
Total	10		
The proposed method—VMD			
Negative ranks	0[g]	0.00	0.00
Positive ranks	1[h]	5.50	55.00
Ties	0[i]		
Total	10		

[a]The proposed method < EWT
[b]The proposed method > EWT
[c]The proposed method = EWT
[d]The proposed method < EMD
[e]The proposed method > EMD
[f]The proposed method = EMD
[g]The proposed method < VMD
[h]The proposed method > VMD
[i]The proposed method = VMD

Table 8 Wilcoxon signed rank test statistics

	The proposed method—EWT	The proposed method—EMD	The proposed method—VMD
Z	− 2.803[a]	− 2.803[a]	− 2.803[a]
Asymp. Sig. (2-tailed)	0.005	0.005	0.005
Exact Sig. (2-tailed)	0.002	0.002	0.002
Exact Sig. (1-tailed)	0.001	0.001	0.001
Point Probability	0.001	0.001	0.001

[a]Based on negative ranks

6 Conclusion

This work aims to develop an intelligent method for epilepsy seizure detection based on hybrid nonlinear EEG data features using adaptive signal decomposition methods, namely EMD, EWT and VMD methods, due to their potential advantages over conventional Fourier transform-based methods. The adaptive signal decomposition methods decompose EEG signals into different levels of resolution and enable extracting relevant nonlinear features for the accurate detection of epilepsy seizures. The proposed method uses hybrid features selected using a wrapper-based feature selection method from nonlinear features extracted using different adaptive mode decomposition methods.

Comparative experiments have been conducted using the proposed method to demonstrate its effectiveness for detecting epilepsy seizures based on a real-time benchmark epilepsy dataset collected by Neurology and Sleep Centre-New Delhi (NSC_ND). The experimental results prove that the proposed method can detect epilepsy seizures up to an accuracy of 99%, the sensitivity of 98%, specificity of 99% and area under ROC (AUC) of 99% using NSC_ND dataset. We conducted nonparametric statistical significance tests, Friedman test and Wilcoxon signed ranks post hoc test for demonstrating statistical differences of the obtained results and superior performance of the proposed method in comparison with the other ones. The reporting results indicate that the proposed method based upon nonlinear hybrid features extracted using adaptive mode decomposition method is well suited for detecting epilepsy seizures from ECG recordings. This study enables researchers and practitioners to examine the proposed method and adaptive mode decomposition methods for detecting epilepsy seizures. Furthermore, the proposed method is validated using NSC_ND dataset by decomposing EEG signals into 4-modes. We plan to validate the proposed method for considering high mode EEG signal decomposition and a realistic large dataset for epilepsy detection in future work.

Funding No funds, grants, or other support were received during the preparation of this manuscript

Data Availability Data available publically for academics and research purpose.

Declarations

Competing interests The authors have no relevant financial or nonfinancial interests to disclose.

Ethical Approval This is an observational study, and the Neurology and Sleep Centre-New Delhi has confirmed that no ethical approval is required.

Consent to Participate Not applicable

Consent to Publish Not applicable

References

1. U.R. Acharya, F. Molinari, S.V. Sree, S. Chattopadhyay, K.H. Ng, J.S. Suri, Automated diagnosis of epileptic EEG using entropies. Biomed. Signal Process. Control **7**(4), 401–408 (2012)
2. H. Akbari, M.T. Sadiq, Detection of focal and non-focal EEG signals using non-linear features derived from empirical wavelet transform rhythms. Phys. Eng. Sci. Med. **44**(1), 157–171 (2021)
3. M. Alolaiwy, M. Tanik, L. Jololian, From CNNs to adaptive filter design for digital image denoising using reinforcement q-learning. in *SoutheastCon 2021* (IEEE, 2021), pp. 1–8
4. H.U. Amin, A.S. Malik, R.F. Ahmad, N. Badruddin, N. Kamel, M. Hussain, W.T. Chooi, Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques. Australas. Phys. Eng. Sci. Med. **38**(1), 139–149 (2015)

5. A. Bhattacharyya, R.B. Pachori, A. Upadhyay, U.R. Acharya, Tunable-q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals. Appl. Sci. **7**(4), 385 (2017)
6. A. Bhattacharyya, L. Singh, R.B. Pachori, Fourier–Bessel series expansion based empirical wavelet transform for analysis of non-stationary signals. Digit. Signal Process. **78**, 185–196 (2018)
7. C.M. Bishop et al., *Neural Networks for Pattern Recognition* (Oxford University Press, Oxford, 1995)
8. V.R. Carvalho, M.F. Moraes, A.P. Braga, E.M. Mendes, Evaluating five different adaptive decomposition methods for EEG signal seizure detection and classification. Biomed. Signal Process. Control **62**, 102073 (2020)
9. W.A. Chaovalitwongse, O.A. Prokopyev, P.M. Pardalos, Electroencephalogram (EEG) time series classification: applications in epilepsy. Ann. Oper. Res. **148**(1), 227–250 (2006)
10. S. Chen, X. Zhang, L. Chen, Z. Yang, Automatic diagnosis of epileptic seizure in electroencephalography signals using nonlinear dynamics features. IEEE Access **7**, 61046–61056 (2019)
11. X. Chen, J.C. Jeong, Enhanced recursive feature elimination, in *Sixth International Conference on Machine Learning and Applications (ICMLA 2007)* (IEEE, 2007), pp. 429–435
12. M. Dalal, M. Tanveer, R.B. Pachori, Automated identification system for focal EEG signals using fractal dimension of FAWT-based sub-bands signals, in *Machine Intelligence and Signal Analysis* (Springer, 2019), pp. 583–596
13. A.B. Das, M.I.H. Bhuiyan, Discrimination and classification of focal and non-focal EEG signals using entropy-based features in the EMD-DWT domain. Biomed. Signal Process. Control **29**, 11–21 (2016)
14. K. Dragomiretskiy, D. Zosso, Variational mode decomposition. IEEE Trans. Signal Process. **62**(3), 531–544 (2013)
15. R. Esteller, J. Echauz, T. Tcheng, B. Litt, B. Pless Line length: an efficient feature for seizure onset detection, in *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, vol 2 (IEEE, 2001), pp. 1707–1710
16. O. Fasil, R. Rajesh, Time-domain exponential energy for epileptic EEG signal classification. Neurosci. Lett. **694**, 1–8 (2019)
17. Z. Feng, D. Zhang, M.J. Zuo, Adaptive mode decomposition methods and their applications in signal analysis for machinery fault diagnosis: a review with examples. IEEE Access **5**, 24301–24331 (2017)
18. P. Flandrin, G. Rilling, P. Goncalves, Empirical mode decomposition as a filter bank. IEEE Signal Process. Lett. **11**(2), 112–114 (2004)
19. M. Friedman, A comparison of alternative tests of significance for the problem of m rankings. Ann. Math. Stat. **11**(1), 86–92 (1940)
20. D. George, P. Mallery, *IBM SPSS Statistics 26 Step by Step: A Simple Guide and Reference* (Routledge, London, 2019)
21. J. Gilles, G. Tran, S. Osher, 2D empirical transforms. Wavelets, ridgelets, and curvelets revisited. SIAM J. Imaging Sci. **7**(1), 157–186 (2014)
22. L. Guo, D. Rivero, J. Dorado, J.R. Rabunal, A. Pazos, Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. J. Neurosci. Methods **191**(1), 101–109 (2010)
23. S.A. Hosseini, A hybrid approach based on higher order spectra for clinical recognition of seizure and epilepsy using brain activity. Basic Clin. Neurosci. **8**(6), 479 (2017)
24. N. Koolen, K. Jansen, J. Vervisch, V. Matic, M. De Vos, G. Naulaers, S. Van Huffel, Line length as a robust method to detect high-activity events: automated burst detection in premature EEG recordings. Clin. Neurophysiol. **125**(10), 1985–1994 (2014)
25. G. Kumar, Evaluation metrics for intrusion detection systems—a study. Evaluation **2**(11), 11–7 (2014)
26. M.R. Kumar, Y.S. Rao, Epileptic seizures classification in EEG signal based on semantic features and variational mode decomposition. Clust. Comput. **22**(6), 13521–13531 (2019)
27. R. Kumar, I. Saini, Empirical wavelet transform based ECG signal compression. IETE J. Res. **60**(6), 423–431 (2014)
28. Y. Kumar, M. Dewal, Complexity measures for normal and epileptic EEG signals using ApEn, SampEn and SEN. IJCCT **2**(7), 6–12 (2011)
29. W. Liu, S. Cao, Y. Chen, Seismic time–frequency analysis via empirical wavelet transform. IEEE Geosci. Remote Sens. Lett. **13**(1), 28–32 (2015)
30. F. Manzouri, S. Heller, M. Dümpelmann, P. Woias, A. Schulze-Bonhage, A comparison of machine learning classifiers for energy-efficient implementation of seizure detection. Front. Syst. Neurosci. **12**, 43 (2018)

31. H. Ocak, Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. Expert Syst. Appl. **36**(2), 2027–2036 (2009)
32. P.R. Pal, R. Panda, Classification of EEG signals for epileptic seizure evaluation, in *2010 IEEE Students Technology Symposium (TechSym)* (IEEE, 2010), pp. 72–76
33. H. Peng, C. Lei, S. Zheng, C. Zhao, C. Wu, J. Sun, B. Hu, Automatic epileptic seizure detection via stein kernel-based sparse representation. Comput. Biol. Med. **132**, 104338 (2021)
34. S. Raghu, N. Sriraam, Classification of focal and non-focal EEG signals using neighborhood component analysis and machine learning algorithms. Expert Syst. Appl. **113**, 18–32 (2018)
35. M.M. Rahman, M.I.H. Bhuiyan, A.B. Das, Classification of focal and non-focal EEG signals in VMD-DWT domain using ensemble stacking. Biomed. Signal Process. Control **50**, 72–82 (2019)
36. S. Sanei, J.A. Chambers, *EEG Signal Processing* (John Wiley & Sons, Hoboken, NJ, 2013)
37. R.S. Selvakumari, M. Mahalakshmi, P. Prashalee, Patient-specific seizure detection method using hybrid classifier with optimized electrodes. J. Med. Syst. **43**(5), 1–7 (2019)
38. P.O. Shafer, J.I. Sirven, *Epilepsy Statistics* (Epilepsy Foundation, Bowie, 2014)
39. M. Sharma, A. Dhere, R.B. Pachori, U.R. Acharya, An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks. Knowl.-Based Syst. **118**, 217–227 (2017)
40. M.K. Siddiqui, R. Morales-Menendez, X. Huang, N. Hussain, A review of epileptic seizure detection using machine learning classifiers. Brain Inform. **7**, 1–18 (2020)
41. P. Singh, R.B. Pachori, Classification of focal and nonfocal EEG signals using features derived from Fourier-based rhythms. J. Mech. Med. Biol. **17**(07), 1740002 (2017)
42. Y. Song, P. Liò et al., A new approach for epileptic seizure detection: sample entropy based feature extraction and extreme learning machine. J. Biomed. Sci. Eng. **3**(06), 556 (2010)
43. P. Swami, T.K. Gandhi, B.K. Panigrahi, M. Tripathi, S. Anand, A novel robust diagnostic model to detect seizures in electroencephalography. Expert Syst. Appl. **56**, 116–130 (2016)
44. X. Wang, G. Gong, N. Li, S. Qiu, Detection analysis of epileptic EEG using a novel random forest model combined with grid search optimization. Front. Hum. Neurosci. **13**, 52 (2019)
45. WHO Epilepsy. https://www.who.int/news-room/fact-sheets/detail/epilepsy(2021)
46. F. Wilcoxon, Individual comparisons by ranking methods. Biometrics **1**, 80–83 (1945)
47. Y. Zhang, Y. Zhang, J. Wang, X. Zheng, Comparison of classification methods on EEG signals based on wavelet packet decomposition. Neural Comput. Appl. **26**(5), 1217–1225 (2015)