Automated Epileptic Seizure Detection Method Based on the Multi-attribute EEG Feature Pool and mRMR Feature Selection Method

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Abstract. Electroencephalogram (EEG) signals reveal many crucial hidden attributes of the human brain. Classification based on EEG-related features can be used to detect brain-related diseases, especially epilepsy. The quality of EEG-related features is directly related to the performance of automated epileptic seizure detection. Therefore, finding prominent features bears importance in the study of automated epileptic seizure detection. In this paper, a novel method is proposed to automatically detect epileptic seizure. This work proposes a novel time-frequency-domain feature named global volatility index (GVIX) to measure holistic signal fluctuation in wavelet coefficients and original time-series signals. Afterwards, the multi-attribute EEG feature pool is constructed by combining time-frequency-domain features, time-domain features, nonlinear features, and entropy-based features. Minimum redundancy maximum relevance (mRMR) is then introduced to select the most prominent features. Results in this study indicate that this method performs better than others for epileptic seizure detection using an identical dataset, and that our proposed GVIX is a prominent feature in automated epileptic seizure detection.

Keywords: Medical signal processing · Epileptic seizure detection · Minimum redundancy maximum relevance · Global volatility index

1 Introduction

Epilepsy is a common chronic brain disorder characterized by convulsions from epileptic seizures [1]. More than 50 million people suffer from epilepsy all over the world, with the vast majority living in developing countries. The clinical manifestations of epileptic people are mainly sudden loss of consciousness, general convulsions, and abnormality of mind [2]. As a disease with complex and diverse causes, epilepsy severely affects patients' physical and psychological

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health. At the physical level, the violent convulsion of the body during epileptic seizures can result in a fracture. At the psychological level, the uncertainty of epileptic seizures can be very disturbing. Moreover, epileptic people are often stigmatized at school or at work and are thus mentally traumatized [3]. Therefore, finding prominent features and correctly detecting epileptic seizure bears importance in diagnosing and curing epilepsy.

Electroencephalography is a method of recording brain activity through electrophysiological indicators without inflicting trauma to the subject. Electroencephalogram (EEG) signals can be detected when many neurons in the same brain region are activated simultaneously. EEGs are widely used to detect brain-related disorders due to its noninvasiveness, low cost and high temporal resolution. However, artificially interpreting EEG recording is costly and subjective. Machine learning methods can be used for classification and detection and have shown good performance [4]. Therefore, machine learning combined with EEG signals are used to detect brain-related disorders [5]. Selecting effective features is crucial to epileptic seizure detection and pathological discovery. This means that more comprehensive features need to be used and more discriminating feature subsets need to be selected. To describe the information contained in EEG signals more comprehensively, many time-domain, frequency-domain and entropy-based features are used to automatically identify epilepsy [6–8]. However, a dearth of studies currently investigate effective features to measure holistic signal fluctuation in EEG signals. This work attempts to fill this gap.

This study primarily aims to improve the accuracy of automated epileptic seizure detection by establishing a novel method for the automated detection of epileptic seizure. First, a novel time-frequency-domain feature named global volatility index (GVIX) is proposed to measure holistic signal fluctuation in wavelet coefficients and original time-series signals. Second, to generalize information in a signal more comprehensively, time-frequency-domain features, time-domain features, nonlinear features, and entropy-based features are used to construct the multi-attribute EEG feature pool. Third, minimum redundancy maximum relevance (mRMR) feature selection algorithm is introduced to identify the most prominent features based on the multi-attribute EEG feature pool. Finally, 10-fold cross validation is achieved using a support vector machine (SVM) classifier. The key contributions and novelties of this work are as follows.

- Developing a novel time-frequency-domain feature GVIX to measure holistic signal fluctuation in the wavelet coefficients and original time-series signals.
- Constructing the multi-attribute EEG feature pool based on time-frequency-domain features, time-domain features, nonlinear features, and entropy-based features.
- Detecting epileptic seizure using a novel framework that applying the multi-attribute EEG feature pool combined with mRMR feature selection method and SVM.

The remainder of this paper is summarized as follows. Section 2 presents the different features and methods used in the prior studies, which has focused on

EEG classification. The details of the data used in this work and its processing framework are presented in Sect. 3. Section 4 presents our experimental results and compares them with previous work. Finally, this work is concluded in Sect. 5.

2 Related Work

Many previous studies have used machine learning methods to classify EEG signals. Many features are also used to display information in EEG signals.

Song et al. [9] utilized sample entropy (SampEn) as a feature extraction method to extract the features of EEG signals. Based on these features, back-propagation neural networks and extreme learning machines are used to achieve epilepsy detection. Results of their study show that SampEn is an outstanding feature in the automated epilepsy detection.

Acharya et al. [10] utilized nonlinear higher order spectra (HOS) and wavelet packet decomposition to construct a feature set. Finally, epileptic EEG signals are detected using SVM. Their results show that the automated epilepsy detection using HOS-based features is a promising approach.

Some nonlinear features such as fractal dimension (FD) and Hurst exponent are also used in the automated epilepsy detection. Acharya et al. [7] achieved the automated identification of epileptic EEG signals using some nonlinear features such as FD and Hurst exponent. Six classifiers have been used in their study, and the fuzzy classifier achieves the highest classification accuracy.

Wavelet transform (WT) is considered as a powerful tool for time-frequency analysis. EEG signals can reflect spontaneous and rhythmic neural activity of the brain, so WT has been introduced to obtain neural activity in different bands in some previous studies. Ibrahim et al. [11] obtained features using discrete wavelet transform (DWT) and cross-correlation. Afterwards, epilepsy and autism spectrum disorder diagnosis are achieved using four classifiers, whereas the k-nearest neighbor algorithm obtains the highest classification accuracy. Guo et al. [12] used multiwavelet transform and approximate entropy (ApEn) to constructed features, and epileptic seizure detection is achieved using these features and artificial neural network.

Principal component analysis (PCA) is a classical method for feature dimension reduction, which can effectively deal with the curse of dimensionality. Zarei et al. [13] combined PCA and cross-covariance to extract features. They subsequently used multilayer perceptron neural networks, least-square SVM, and logistic regression to achieve the classification of EEG signals.

The above-mentioned methods have realized the classification of EEG signals based on different methods. In the present study, we utilize a novel method for automated epileptic seizure detection. The method used in this paper is described in detail in the next section.

3 Data and Methods

In this study, a novel framework is proposed for the automated epileptic seizure detection. Figure 1 illustrates the steps of this work. First, wavelet coefficients of

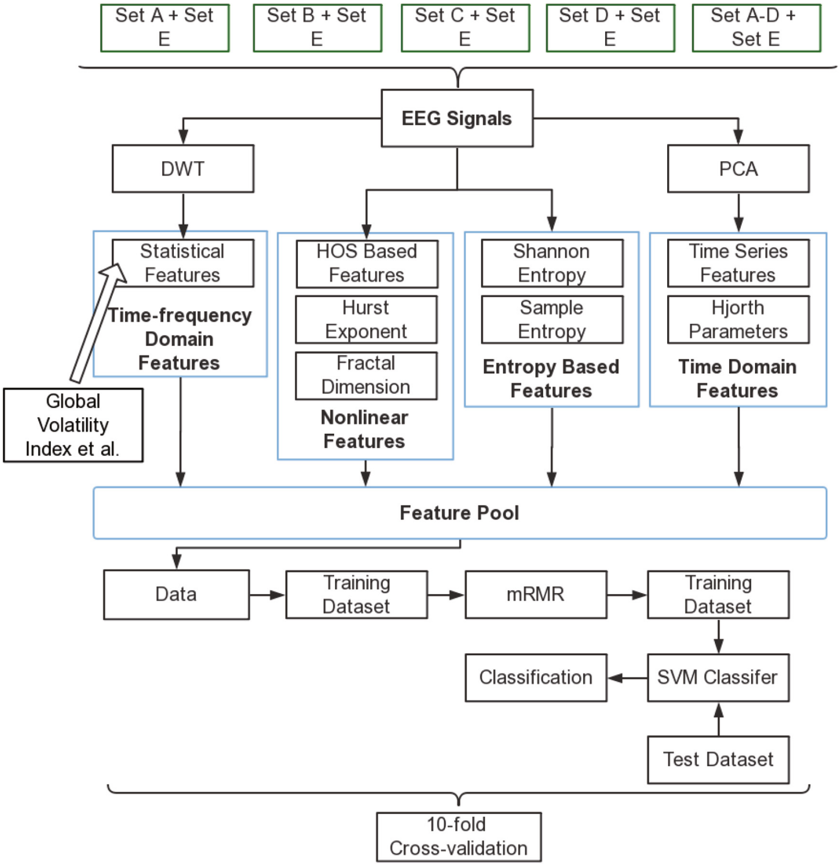

Fig. 1. Framework for the automated epileptic seizure detection.

different EEG frequency bands are analyzed using DWT, and related statistical features like GVIX are used to obtain features from both wavelet coefficients and EEG signals. Afterwards, PCA is used to extract time-series features, and many other features such as entropy-based features and nonlinear features are calculated. The multi-attribute EEG feature pool is then constructed based on these features and used for mRMR. Finally, 10-fold cross validation is achieved based on SVM.

3.1 Dataset

The EEG database (Set A–E) we used is obtained from a publicly available EEG database developed by University of Bonn [14]. The entire EEG database includes five sets each containing 100 segments with a duration of 23.6 s (4097 time points per segment). All these EEG signals are recorded using a 128-channel amplifier system, digitized with a sampling rate of 173.61 Hz and 12-bit A/D

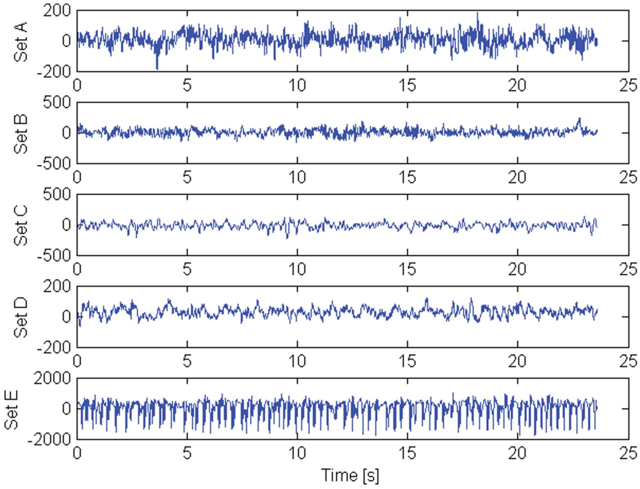

Fig. 2. Examples of EEG signals in the five different sets.

resolution and filtered using a 0.53–40 Hz (12 dB/octave) band pass filter. Manual and eye movement disturbances are removed from all EEG signals. The specific information of EEG data is summarized in Table 1. Figure 2 also shows some examples of Set A to E.

Table 1. Description of EEG data in five sets

	Set A	Set B	Set C	Set D	Set E
Subjects	Healthy	Healthy	Epileptic	Epileptic	Epileptic
State	Eyes opened	Eyes closed	Interictal	Interictal	Ictal
Electrode type	External	External	Intracranial	Intracranial	Intracranial

3.2 Feature Extraction

To establish a better classification model, the multi-attribute EEG feature pool is used. These features can be subdivided into four categories: (1) time-frequency-domain features, (2) time-domain features, (3) nonlinear features, and (4) entropy-based features.

Time-Frequency-Domain Features. The time-frequency-domain features used in this work include wavelet coefficients and related statistical features which can describe wavelet coefficients in sub-bands and original time-series signals.

WT is an important tool for numerical analysis and time-frequency analysis, and it can capture the frequency and location information compared with FT. The basic idea of WT is to represent the signal in a certain time period as a linear combination of a series of wavelet functions. The wavelet coefficient reflects the similarity between the signal and wavelet function in the time period. A multi-resolution analysis of signal X_J is shown as follows:

$$
\begin{aligned}
X_J &= L_{J-1} \bigoplus H_{J-1} \\
&= L_{J-2} \bigoplus H_{J-2} \bigoplus H_{J-1} \\
&= ... \bigoplus H_{J-3} \bigoplus H_{J-2} \bigoplus H_{J-1}
\end{aligned}
\tag{1}
$$

where H represents high frequency, L represents low frequency, and $\bigoplus$ represents the intersection.

Picking different numbers of decomposition levels for EEG signals should be based on the purpose of the study. An EEG signal usually shows different rhythms in different frequency ranges. Most useful frequency components contained in EEG signals are found to be below 30 Hz [15,16]. Therefore, the decomposition levels used in this study are set to 5, and the signals are decomposed into details D1-D5 and final approximation A5. Some previous studies have compared the effects of several wavelets and found that the Daubechies wavelet of order 4 is the most suitable one for automated epileptic seizure detection [17], so the wavelet coefficients are computed using the db4 in this work. DWT is used for each data set, approximation and details are thus obtained and are shown in Fig. 3. Table 2 shows the frequency range of different decomposition levels for db4 with a sampling frequency of 173.6 Hz. These wavelet coefficients, calculated for A5 and D3-D5 are used for automated epileptic seizure detection.

Table 2. Frequency range of different decomposition levels

Decomposed signal	Frequency range (Hz)
D1	43.4–86.8
D2	21.7–43.4
D3	10.8–21.7
D4	5.4–10.8
D5	2.7–5.4
A5	0–2.7

To represent the information in the wavelet coefficients and original EEG signals from multiple perspectives, statistical features are used to achieve this goal. In this paper, a novel feature GVIX is proposed to measure the holistic signal fluctuation in wavelet coefficients and original time-series signals, since it considers the signal fluctuation at any time interval. GVIX is calculated based on

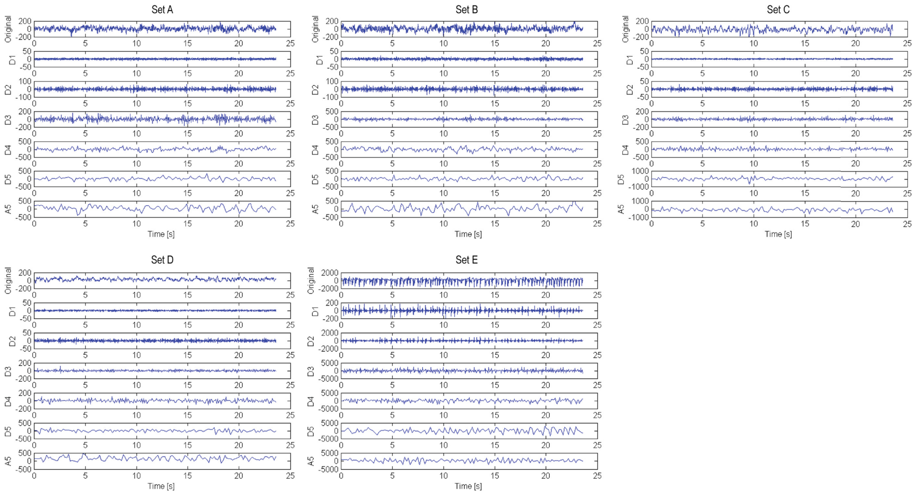

Fig. 3. DWT coefficients of EEG signals taken from the subject of each set.

Manhattan Distance. Calculation of the GVIX of a sequence data $X(1)$, $X(2)$,..., $X(n)$ can be obtained as follows:

$$GVIX(X) = \frac{2}{n^2 - n} \sum_{i=2}^{n} \sum_{j=1}^{i-1} |X(i) - X(j)| \tag{2}$$

where n is the number of points in the sequence data. The other statistical features used to describe wavelet coefficients in sub-bands and original time-series signals in this study are mean (M), mean square (MS), standard deviation (SD), skewness (Ske), kurtosis (Kur), interquartile range (IQR) and volatility index (VIX).

Time-Domain Features. The time-domain features used in this work include principal components and Hjorth parameters (HP).

PCA transforms the original data into a set of linearly independent representations between dimensions through linear transformation, and the linearly independent variables are named principal components [18]. In this paper, PCA is used to reduce the dimension of time-series data, and the standard of dimension reduction is to save 99% of the original information. HP are measurements used to study epileptic lateralization [19]. Mobility (Mobi) and Complexity (Comp) are used in this work.

Non-linear Features. The nonlinear features used in this work include FD, Hurst exponent and HOS parameters.

FD is a statistic that measures the dimensional complexity of signals [7]. The FD calculation algorithm proposed by Higuchi is used in this study. Hurst exponent is a feature that can measure the long-term memory of a time series [20]. HOS can provide more information than the two order statistics [10]. Bispectrum is the most in-depth and widely used method in HOS and it can be calculated as follows:

$$B(f_1, f_2) = E[X(f_1)X(f_2)X(f_1 + f_2)] \tag{3}$$

where $X(f)$ is the FT of the signal $X(nT)$. The used HOS parameters can be calculated based on bispectrum: (1) normalized bispectral entropy (P_1), (2) normalized bispectral squared entropy (P_2), and (3) mean bispectrum magnitude (M_{ave}). In addition, these parameters can be calculated as follows:

$$\begin{aligned} p_n &= \frac{|B(f_1, f_2)|}{\sum_{\Omega} |B(f_1, f_2)|} \\ P_1 &= \sum_n p_n \log p_n \end{aligned} \tag{4}$$

$$\begin{aligned} q_n &= \frac{|B(f_1, f_2)|^2}{\sum_{\Omega} |B(f_1, f_2)|^2} \\ P_2 &= \sum_n q_n \log q_n \end{aligned} \tag{5}$$

$$M_{ave} = \frac{1}{L} \sum_{\Omega} |B(f_1, f_2)| \tag{6}$$

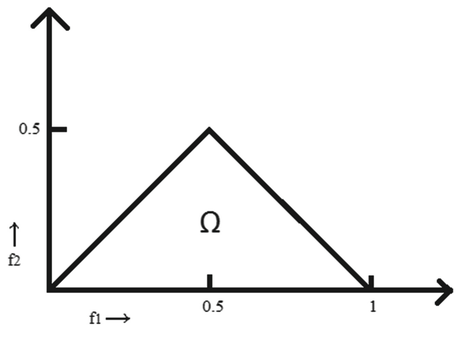

Fig. 4. Region of points that can avoid redundant computation.

where Ω is the region that avoids redundant computation, and its range is shown in Fig. 4. L is the number of points in Ω.

Entropy-Based Features. The entropy-based features used in this work include Shannon entropy (ShEn) and SampEn.

Shannon entropy (ShEn) can be used to measure the uncertainty of EEG signals [21]. As an improved version of ApEn, SampEn is a measure of time-series complexity [22]. SampEn is proportional to time series complexity, while it is inversely proportional to self-similarity. The SampEn of a given time series $X(1)$, $X(2)$,..., $X(n)$ is calculated as follows:

(1) Constructing an m dimensional vector based on the embedding dimension;
(2) Defining the distance function $d[X_m(i), X_m(j)]$ based on Chebyshev Distance;
(3) Calculating SampEn based on the similar tolerance r:

$$SampEn(X) = -\log \frac{A}{B} \tag{7}$$

where A is the number of template vector pairs having $d[X_{m+1}(i), X_{m+1}(j)] < r$, and B is the number of template vector pairs having $d[X_m(i), X_m(j)] < r$. In this paper, embedding dimension m is set to 2, and similar tolerance r is set to 0.2 based on a previous study [23].

Minimum Redundancy Maximum Relevance. mRMR algorithm is an effective feature selection algorithm, and widely used in the study of bioinformatics [24]. mRMR algorithm uses incremental search to select features and rates them based on mutual information. The selected features are added to the selected feature set in an incremental manner until the number of selected features achieves the termination condition. The average mutual information between a feature and its category is considered relevance (R), and the average mutual information between unselected features is considered redundancy (D). Each feature will get a score when using mRMR algorithm, and the evaluation criterion for each feature is calculated as follows:

$$\begin{aligned} maxR(F,C), Relevance &= \frac{1}{|F|}\sum_{f_r \in F} I(f_r, c) \\ minD(F,C), Redundancy &= \frac{1}{|F|^2}\sum_{f_r, f_o \in F} I(f_r, f_o) \end{aligned} \tag{8}$$

$$max\Phi(R,D), \Phi = R - D \tag{9}$$

where F represents the feature set, and C represents the target category.

Performance Evaluation Methods. To evaluate the performance of SVM, a 10-fold cross validation method is used. The data are divided into 10 parts. In each cross-validation process, one piece of data is used as the test set and nine pieces of data are used as the training set. In this paper, many criteria such as classification accuracy, sensitivity, specificity and F1 score are used to measure the performance of our method.

Table 3. Five cases for automated epileptic seizure detection

Case	Class 1	Class 2
1	A	E
2	B	E
3	C	E
4	D	E
5	ABCD	E

4 Results and Discussion

4.1 Results

Effective feature is one of the most important factors determining classification performance. In this paper, multi-attribute EEG feature pool is constructed for automated epileptic seizure detection. In this work, a total of five cases are considered for automated epileptic seizure detection, as shown in Table 3.

mRMR algorithm is used to select features for each case, and the classification performance of each case is shown in Table 4. Wilcoxon rank sum test is used to detect whether there were significant difference in GVIX of wavelet coefficients and original time-series signals between set E and control groups (all $P < 0.001$). Moreover, Fig. 5 shows average performance comparison between the multi-attribute EEG feature pool with and without GVIX in each case. It can be found that adding GVIX into the multi-attribute EEG feature pool can achieve better performance in automated epileptic seizure detection.

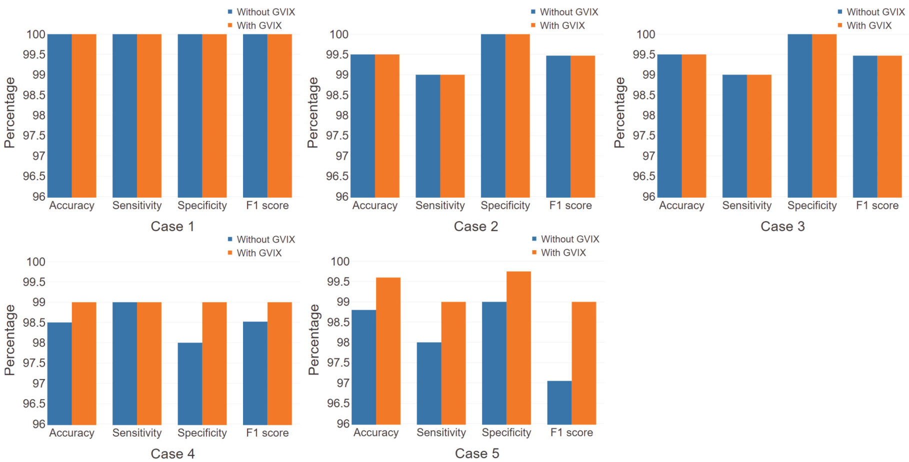

Fig. 5. Average performance comparison with and without adding GVIX into the multi-attribute EEG feature pool.

Table 4. Classification performance for each case

Case	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 score (%)
1	100	100	100	100
2	99.5	99.0	100	99.47
3	99.5	99.0	100	99.47
4	99.0	99.0	99.0	99.0
5	99.6	99.0	99.75	99.0

Results of Fig. 5 also show that case 1 has the best classification performance, whereas case 4 has the worst classification performance among all the cases. This finding is due to the data in case 1 being either healthy or epileptic; conversely, the data in case 4 is either interictal or ictal. Results of our study indicate that our method performs well in automated epileptic seizure detection. Moreover, a comparison of weight of each feature in different cases is shown in Fig. 6. It can be found that there were more significant differences in GVIX, ShEn, SampEn, SD, IQR and VIX between the two groups due to the calculation of the weight is based on mutual information. Results of our study obviously show that our proposed GVIX is a prominent time-frequency-domain feature in automated epileptic seizure detection. In addition, the accuracy comparison with other previous methods is discussed in the next subsection.

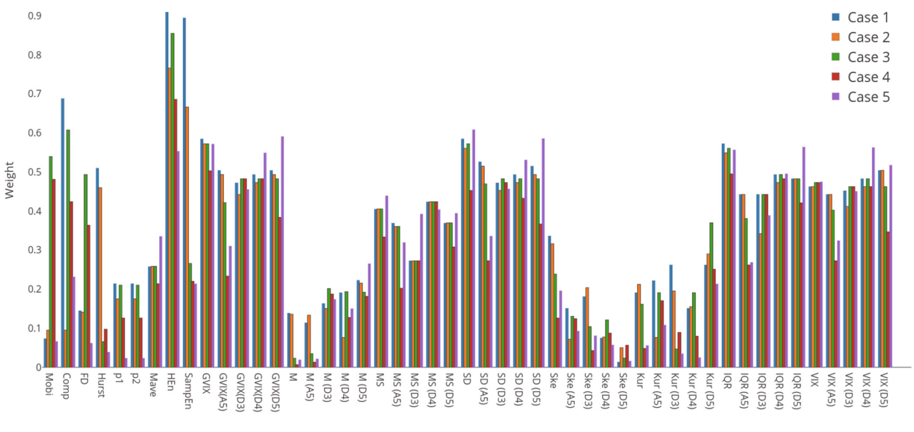

Fig. 6. Comparison of weight of each feature in different cases.

4.2 Comparison with Other State-of-the-Art Results

Table 5 shows a summary of studies that other current methods to epileptic seizure detection using the same data used in this work. It can be clearly seen

Table 5. Comparison between our method and other current methods

Authors	Cases	Accuracy (%)
Nicolaou [26]	A-E	93.55
	B-E	82.88
	C-E	88
	D-E	79.94
Tawfik [27]	A-E	98.5
	B-E	85
	C-E	93.5
	D-E	96.5
Fu [28]	A-E	99.85
	ABCD-E	98.8
Swami [25]	A-E	100
	B-E	98.89
	C-E	98.72
	D-E	93.33
	ABCD-E	95.24
Jaiswal [29]	A-E	99.3
	B-E	95.65
	C-E	97.79
	D-E	94.77
	ABCD-E	96.57
Mursalin [5]	A-E	100
	B-E	98
	C-E	99
	D-E	98.5
	ABCD-E	97.4
Our proposed method	A-E	100
	B-E	99.5
	C-E	99.5
	D-E	99
	ABCD-E	99.6

from Table 5 that it is the most difficult to identify epileptic seizure in case 4 and case 5. Moreover, results show that our method is comparable.

In case 1, this method shows the best performance and completely separates the normal EEG from the ictal EEG. The same results were also obtained in the works of [5] and [25]. Mursalin et al. [5] achieved automated epileptic seizure detection using improved correlation feature selection (ICFS) algorithm and random forest. Swami et al. [25] achieved epileptic seizure detection using dual-tree complex wavelet transform (DTCWT), entropy-based features and a general regression neural network (GRNN).

In case 2, this method achieves a classification accuracy of 99.5%, and it is the best compared with other studies. In case 3, classification accuracy of 99.5% is obtained in this work. In case 4, this method achieves 99% classification accuracy, which is the best compared with other current methods. Classification has also been achieved in the works of [26] and [27]. Nicolaou et al. [26] achieved epileptic seizure detection using Permutation Entropy (PeEn) and SVM. Tawfik et al. [27] achieved epileptic seizure detection using weighted PeEn and SVM.

In case 5, the classification accuracy obtained in this study is 99.6% which is higher than those obtained with other state-of-art methods. The best performance of these previous studies has been obtained in the work of [28], in which 98.8% classification accuracy is achieved using Hilbert marginal spectrum (HMS) and SVM. Similar works have been done in [29]. In [29], local neighbor descriptive pattern (LNDP) and SVM are used for epileptic seizure detection.

5 Conclusion

Finding prominent features and correctly detecting epileptic seizure is crucial in diagnosing and curing epilepsy. The main contribution of this work is automated epileptic seizure detection using a novel method. In this paper, a novel time-frequency-domain feature GVIX that can measure the holistic signal fluctuation in wavelet coefficients and original time-series signals is proposed. Time-frequency-domain features, time-domain features, nonlinear features, and entropy-based features are used to construct the multi-attribute EEG feature pool and feed them to mRMR algorithm. Results of this study show that GVIX is a prominent feature in automated epileptic seizure detection. We further compare our findings to other studies, and comparison results show that our proposed method is comparable. It can be concluded that using this proposed method would help clinicians make more efficient and reasonable decisions in the automatic detection of epileptic seizure.

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