Using Electrocardiogram Signal Features And Heart Rate Variability To Predict Epileptic Attacks

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Since the increase in neuronal activity during an epileptic attack affects the voluntary nervous system, and the voluntary nervous system also affects the heart rate variability, it can be concluded that seizures can be predicted by monitoring heart rate variability. In this study, a new method for predicting epilepsy through the analysis of heart rate variability is proposed. In the proposed method, 12 features are extracted from the heart rate variability signal in time, frequency, time-frequency, and nonlinear domains to predict epileptic seizures. We used a multivariate statistical process control algorithm for abnormality detection. The presented algorithm was evaluated on a dataset consisting of 17 patients, where the obtained results show that the proposed method can predict epileptic attacks with an accuracy of 88.2%. From a practical point of view, due to the ease of obtaining the heart rate variability signal, the proposed algorithm is more promising than the algorithms that use brain signal processing to predict epilepsy.

Keywords: Disease diagnosis; Epilepsy; Heart rate; Signal processing; Multivariate statistical process

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1. Introduction

Epilepsy is a neurological abnormality that causes serious discomfort and suffering in the patient due to its unknown and sudden nature. The onset of epileptic seizures can be predicted using Preictal signals. So far, various methods have been proposed to predict epilepsy, but studies to propose an efficient method are still the focus of many researchers [1–3]. Epilepsy, a chronic neurological disorder characterized by recurrent seizures, demands accurate prediction methods to enhance the quality of life for those affected. Traditional approaches like electroencephalogram (EEG) monitoring are often invasive and inconvenient, prompting interest in non-invasive techniques using electrocardiogram (ECG) signal features and heart rate variability (HRV) for early seizure prediction [4]. ECG measures electrical heart activity, with features such as heart rate, RR interval, and QT interval providing insights into autonomic nervous system activity, often altered before seizures. Heart rate variability, a marker of autonomic function, includes time-domain measures (SDNN, RMSSD), frequency-domain measures (LF, HF), and non-linear metrics, all of which can signal impending seizures. Integrating these ECG and HRV metrics into machine learning models, such as support vector machines, artificial neural networks, and random forests, has shown promise in identifying preictal states [5]. These models involve feature extraction, selection, training, and evaluation using metrics like sensitivity and specificity. Despite promising results, challenges such as data quality, individual variability, and real-time implementation remain. Future research should address these issues and explore combining ECG and HRV analysis with other modalities to improve prediction accuracy and reliability. Thus, leveraging changes in cardiac autonomic function through ECG and HRV offers a promising, non-invasive method for predicting epileptic attacks, potentially

enabling timely interventions and better management of epilepsy [6].

1.1. Literature review

Zandi et al. [7] using the histogram of EEG signal zero crossing intervals and based on the Gaussian mixture model (GMM), achieved 88% sensitivity for predicting epileptic attacks being able to predict attacks on average 22.5 minutes before them. Nabil et al. [8] presented an algorithm based on autoregressive analysis (AR) and support vector machine (SVM) classification for separating Preictal and Interictal episodes (time interval between 2 consecutive attacks), that was able to reach 98% sensitivity for the Freiburg database. Zhang et al. [9] predicted epileptic attacks by using the changes in general and local features of the EEG signal, which provided a sensitivity of 95.4% on the Freiburg database. In another algorithm, using Walsh-Hadamard transform and high-order spectral analysis, Preictal episodes were detected, and 91.95% accuracy was obtained. Also, in the algorithm presented by Anter et al. [10], using the adaptive learning approach, 73% sensitivity and 67% specificity have been obtained in predicting epileptic attacks. In such prediction systems, an automatic and real-time classifier should distinguish the Preictal episodes of the EEG signal from each other.

Since long-term recordings of the patient are needed to predict epilepsy, which is difficult to do and causes discomfort to the patient, the need to predict epileptic attacks using signals that are less disturbing for the patient is very important. Among vital signals, an electrocardiogram (ECG) signal is easier to record compared to an EEG signal. Epileptic attacks usually cause changes in the voluntary functions of the heartbeat. An increase in heart rate can occur before or after a seizure, and a decrease in heart rate is much less common in seizures with different origins [6]. In recent years, the analysis of HRV has gained great importance as a technique for investigating the voluntary nervous system. Santos et al. [11] highlighted that epilepsy affects over 50 million people worldwide, with around 20% experiencing psychogenic nonepileptic seizures (PNES), which require psychological rather than medical treatment. Misdiagnosis can lead to inappropriate epilepsy treatments. Their study proposed a method to differentiate PNES from epilepsy using EEG signals, employing Discrete Wavelet Transform (DWT) and a Support-Vector Machine (SVM) classifier. This approach achieved 100% accuracy, sensitivity, and specificity with specific configurations (Coiflet 1 wavelet and sigmoid or RBF SVM kernels). The method is practical for hospital use, requiring no prior EEG recordings and eliminating the need for accelerometer or electromyographic signals, thus offering a versatile, patient-independent, and superior diagnostic tool. Behbahani et al. [12] emphasized the significance of Heart Rate Variability (HRV) analysis for exploring autonomic nervous system (ANS) activity and identifying pathological conditions. They found that epilepsy progressively impacted cardiac autonomic activity, and HRV measures in time-domain, frequency-domain, and nonlinear metrics provided valuable insights into autonomic dysfunction caused by seizures. Their investigation into HRV features for detecting and anticipating epileptic seizures demonstrated HRV analysis's potential as an early marker for seizure prediction. Valenza et al. [13] explored autonomic dysregulation in temporal lobe epilepsy (TLE) and its link to sudden unexpected death in epilepsy (SUDEP). They analyzed heart rate variability (HRV) in 12 TLE patients during inter-ictal (INT) and pre-ictal (PRE) periods using standard HRV indices and nonlinear measures of instantaneous HRV complexity and higher-order statistics. Their results indicated that the best classification performance between INT and PRE periods (balanced accuracy: 73.91%) was achieved by considering the time-varying, nonlinear, and non-stationary structure of heartbeat dynamics. This approach demonstrated the potential for predicting ictal events using cardiovascular signals exclusively. Zambrana-Vinaroz et al. [14] investigated the impact of epileptic seizures on quality of life and the potential for a monitoring device to enhance patient independence. They developed a seizure predictive model using Ear EEG, ECG, and PPG signals collected by a device suitable for both static and outpatient settings. This device, tested in a clinical environment, processed the signals with supervised machine learning techniques to classify patient states into normal, pre-seizure, and seizure phases. A reduced model based on Boosted Trees achieved a prediction accuracy of 91.5% and a sensitivity of 85.4%. This model demonstrated potential as a tool for predicting and preventing seizures, thus improving quality of life for epilepsy patients. Pernice et al. [15] investigated epilepsy's impact on CNS and ANS interactions using Granger Causality (GC) and partial information decomposition (PID) to analyze EEG brain wave amplitude and heart rate variability (HRV) in 18 children with temporal lobe epilepsy during pre-ictal, ictal, and post-ictal periods. They found that CNS activities primarily drove ANS modulation of heart rhythm. However, PID analysis revealed that seizures reorganized brain-heart interactions, with HRV predictability originating from ipsilateral EEG δ waves and contralateral EEG α waves in the pre-ictal phase, which reversed after seizures. These findings underscore the importance of higher-order interactions for understanding neuro-autonomic effects in

epilepsy and have significant clinical implication. Mahmoudi et al. [16] recorded ECG signals for 8 patients under supervision and aged 30–48 years old, both female and male. They presented a new approach based on the geometric feature from extracted heart rate variation analysis and achieved a sensitivity of 100%, an accuracy of 90%, and a specificity of 88.33%.

The goal of the present research is to propose a method for predicting epilepsy through HRV analysis, which includes 2 steps. In the first step, different features of HRV signal are extracted from patients with epilepsy [17]. These features include time, frequency, time-frequency, and nonlinear features. In the second step, epilepsy is predicted by showing abnormalities by using the extracted HRV features. At this stage, the multivariate statistical process control (MSPC) method is used to predict epilepsy. Next, HRV analysis is introduced in 4 domains including time, frequency, time-frequency, and nonlinear domains. Then the method of multivariable control and epilepsy prediction is introduced. After that, the proposed algorithm is discussed, and the results are checked. Finally, the conclusion is presented.

2. Heart rate variation (hrv) analysis

As seen in Fig. 1, an ECG cycle includes P and R waves, and the distance between the 2 R peaks is called the RR interval. Fluctuations of RR intervals in ECG are called heart rate variability (HRV) and the features of this signal indicate the activity of the voluntary nervous system. The features of the HRV signal used in this research to predict epilepsy are extracted from different domains of time, frequency, time-frequency, and nonlinearity, which are described below.

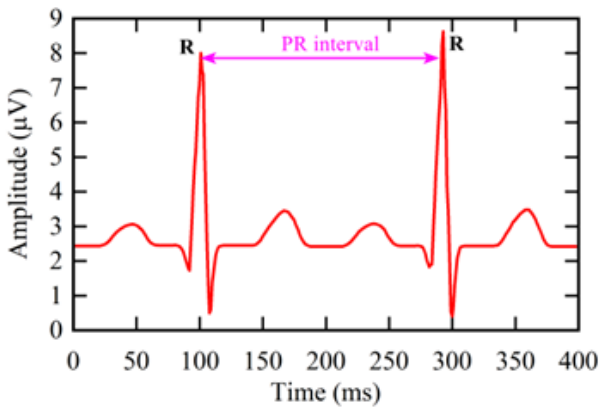


Fig. 1. Analysis of PR Interval Variability Using Electrocardiogram (ECG) Data.

2.1. Features of the time domain

The simplest methods of heart rate analysis and evaluation are associated with the time domain. In the proposed algorithm, the following time domain parameters are calculated:

1. Average RR intervals in each part of the signal (Mean): The average RR interval represents the mean time between successive R-wave peaks over a specific period. This measure provides a general overview of heart rate over time.

2. The standard deviation of RR intervals (SDNN) that is defined as: DNN is defined as the standard deviation of all normal-to-normal intervals within the recording period. It is calculated using the formula:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - \overline{RR}\right)^2} \quad (1)$$

where RRj is the value of the j^{th} RR interval, N indicates the total number of RR intervals, and $\overline{RR}$ is the average of the RR intervals.

3. The root mean square of successive RR intervals differences (RMSSD), which is expressed as:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}\left(RR_{j+1} - \overline{RR}\right)^2} \quad (2)$$

4. Variance of RR Intervals: The variance of RR intervals represents the total power of the signal, indicating the overall variability in the RR intervals. Higher variance suggests greater variability in heart rate.

5. NN50: This parameter counts the number of pairs of successive RR intervals that differ by more than 50 milliseconds. It is a measure of the frequency of significant changes in heart rate over short periods.

These time-domain features are crucial for developing a robust predictive model that detects abnormalities associated with the preictal state, thereby enhancing the accuracy of epileptic seizure prediction. By incorporating these features, the algorithm can effectively capture the variability and distribution of heart rate over time, providing valuable insights into the autonomic nervous system's response to impending seizures.

2.2. Features of the frequency domain

In the algorithm proposed in this study, the following frequency domain features are obtained from the power spectrum density (PSD) of the HRV signal:

1. Low-frequency power (LF): This feature represents the power of the HRV signal in the low-frequency range, typically between 0.04 and 0.15 Hz. The LF component is associated with both sympathetic and parasympathetic activity but is generally considered to reflect sympathetic activity in the context of heart rate variability.

2. High-frequency power (HF): This feature represents the power of the HRV signal in the high-frequency range, typically between 0.15 and 0.4 Hz. The HF component is primarily associated with parasympathetic activity (vagal tone), reflecting respiratory sinus arrhythmia.

3. The ratio of LF to HF (LF/HF): This ratio is a measure of the balance between sympathetic and parasympathetic activity. A higher LF/HF ratio indicates a dominance of sympathetic activity, while a lower ratio indicates a dominance of parasympathetic activity.

Since HRV varies greatly between different patients, to account for this variability in the frequency domain, normalized values of LF and HF are used instead of their absolute values. The normalization process involves the following calculations:

1. **Normalized Low-Frequency Power (LFnu)**: This is calculated by dividing the low-frequency power by the total power (TP) of the HRV signal within the desired interval:

$$LFnu = LF/TP \tag{3}$$

   Normalizing LF in this way helps to standardize the measurement across different patients, making the comparison of sympathetic activity more consistent.

2. **Normalized High-Frequency Power (HFnu)**: This is calculated by dividing the high-frequency power by the total power (TP) of the HRV signal within the desired interval:

$$HFnu = HF/TP \tag{4}$$

   Where TP represents the total power of the signal in the desired interval. Similarly, normalizing HF ensures that the measure of parasympathetic activity is standardized, allowing for better comparison across individuals. In these formulas, TP represents the total power of the HRV signal within the specified frequency range. By using normalized values, the algorithm can more accurately compare HRV features across different patients, accounting for individual variability in heart rate dynamics. This normalization is crucial for developing a reliable and generalizable predictive model for epileptic seizures, ensuring that the frequency domain features are robust and consistent across the study population.

2.3. Features of time-frequency domain

To calculate the low and high-frequency coefficients, the wavelet transform is applied and continued up to level 11. This involves decomposing the HRV signal into different frequency bands using wavelets, which are mathematical functions that divide the signal into various frequency components and then study each component with a resolution matched to its scale. This approach allows for the analysis of non-stationary signals like HRV, where frequency characteristics change over time. The wavelet transform provides a time-frequency representation of the signal, making it possible to capture both frequency and temporal information.

The coefficients are calculated as follows:

1. Wave flow: These are the wavelet coefficients corresponding to the low-frequency band, specifically in the interval of 0.04-0.15 Hz. This range is associated with both sympathetic and parasympathetic activities but predominantly reflects sympathetic modulation. By extracting these coefficients, the algorithm captures the energy and variability in this low-frequency range.

2. Wave of High: These are the wavelet coefficients corresponding to the high-frequency band, specifically in the interval of 0.15-0.4 Hz. This range is primarily linked to parasympathetic (vagal) activity, especially respiratory sinus arrhythmia. The high-frequency coefficients provide insights into the parasympathetic regulation of heart rate.

3. WaveCoeflow / WaveCoefHigh: This ratio represents the balance between low-frequency and high-frequency wavelet coefficients. It is calculated by dividing the total power of the low-frequency coefficients (WaveofLow) by the total power of the high-frequency coefficients (Wave of High). This ratio is an important measure as it indicates the relative dominance of sympathetic versus parasympathetic activity, similar to the LF/HF ratio in the frequency domain analysis.

By continuing the wavelet transform up to level 11, the algorithm ensures a detailed and fine-grained analysis of the HRV signal across different frequency bands. This level of decomposition captures the subtle changes in heart rate dynamics that occur before an epileptic seizure, providing

a robust set of features for the predictive model. The use of wavelet coefficients allows for a comprehensive time-frequency analysis, which is crucial for accurately identifying the pre-ictal state and predicting seizures.

2.4. Detrended fluctuation analysis (DFA)

Since the cardiovascular system is much more complex than a linear system and exhibits non-static behavior, in addition to the time-frequency features, a nonlinear analysis that reveals the chaotic dynamic characteristics in the HRV signal is also considered. DFA is used to quantify the fractal characteristics of short-term RR interval signals, capturing the inherent irregularities and long-range correlations within the data [18–21]. To perform DFA, the following steps are taken:

1. Summation of RR Intervals: The first step involves creating a cumulative sum of the deviations of RR intervals from their mean value. This is represented mathematically as:

$$y(k) = \sum_{i=1}^{k} (RR(k) - \text{ RRave }) \tag{5}$$

where $y(k)$ is the cumulative sum at the k^{th} interval, $RR(i)$ is the i^{th} RR interval, and RR_{avg} is the average of all RR intervals in the series. This step transforms the original RR interval time series into a new series that highlights deviations from the mean.

2. Division into Intervals: The cumulative sum series y(k) is then divided into non-overlapping segments of equal length n. This segmentation helps in analyzing the data at different scales, capturing both short-term and long-term variations.

3. Fitting Least Squares Lines: Within each segment of length n, a least squares line is fitted to the data points. This line represents the trend within each segment, and the purpose is to identify and remove these trends to isolate the inherent fluctuations in the data. Let yn(k) denote the fitted line in each segment.

4. Detrending the Series: The next step involves detrending the series by subtracting the fitted line yn(k) from the cumulative sum y(k) within each segment. This process removes the local trend from the data, allowing for the analysis of fluctuations around the trend. The detrended time series is calculated as:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]} \tag{6}$$

where F(n) is the fluctuation function for the segment length n, and N is the total number of data points.

5. Feature Extraction: The fluctuation function F(n) obtained through DFA serves as a feature representing the fractal characteristics of the HRV signal. In this study, the value of n is set to 50 to capture the short-term fractal properties of the RR interval series.

Detrended Fluctuation Analysis (DFA) analysis is crucial for understanding the nonlinear and chaotic dynamics of the cardiovascular system, which cannot be captured through linear methods alone. By quantifying the fractal nature of the HRV signal, DFA provides valuable insights into the complexity and irregularity of heart rate dynamics, which are essential for predicting epileptic seizures.

3. Multivariable statistical process control (mspc)

MSPC is a statistical technique used to monitor and control processes that involve multiple correlated variables. In the context of our study, MSPC was employed to analyze heart rate variability (HRV) signals, which consist of multiple features extracted from different domains (time, frequency, time-frequency, and nonlinear). The primary objective of using MSPC was to detect deviations in the HRV signal that could indicate the onset of an epileptic seizure. Steps involved in MSPC:

1. **Feature Extraction**: We began by extracting 12 features from the HRV signals. These features were selected to capture relevant information in the time domain (e.g., mean RR interval), frequency domain (e.g., power spectral density), time-frequency domain (e.g., wavelet coefficients), and nonlinear domain (e.g., sample entropy). These features collectively represent the dynamic behavior of the heart rate signal.

2. **Data Preprocessing**: The extracted features were standardized to ensure that each feature had a mean of zero and a standard deviation of one. This step was essential to eliminate any bias due to differing units or scales of the features.

3. **Principal Component Analysis (PCA)**: PCA was applied to reduce the dimensionality of the feature set and to capture the most significant patterns in the data. The principal components derived from PCA represent the directions of maximum variance in the data, which are crucial for identifying any abnormal changes.

4. **Monitoring Statistics**: Two key statistics were used in the MSPC framework:

- T^2 Statistic: This statistic monitors the overall variation in the principal components and is used to detect broad changes in the HRV signal. It provides an indication of whether the current HRV signal is within the expected range of normal variation.
- Q Statistic (Residuals): The Q statistic measures the residual variation that is not captured by the principal components. It is particularly sensitive to subtle, localized anomalies in the HRV signal, which might not significantly affect the T^2 statistic but could still be indicative of an impending seizure.

5. **Control Limits**: Control limits were established for both the T^2 and Q statistics based on the distribution of the HRV data during non-seizure periods. Any point that exceeded these control limits was flagged as an anomaly, suggesting a potential epileptic event.
6. **Anomaly Detection**: The MSPC method continuously monitored the HRV features using the T^2 and Q statistics. Anomalies detected by these statistics were then analyzed to determine whether they corresponded to the onset of an epileptic seizure. The effectiveness of the method was evaluated based on its ability to predict seizures with high accuracy.

The MSPC method, with its combination of T^2 and Q statistics, provided a robust framework for detecting anomalies in the HRV signal that could predict epileptic seizures. The method's strength lies in its ability to capture both broad and subtle variations in the signal, making it well-suited for this application. After the features of different domains are extracted from the HRV signal, to analyze and monitor these features and extract abnormal states before the occurrence of epileptic attacks, multivariable process control is used. As mentioned earlier, when a seizure occurs, the HRV signal and the extracted features show an abnormal and out-of-control state. These abnormalities before the seizure or the Preictal state are identified by controlling the multivariate process. The MSPC algorithm is a suitable technique for monitoring multivariate processes in which changes in the correlation between extracted features are modeled using principal component analysis (PCA). The MSPC algorithm can detect the abnormalities, and to find such changes two statistical indices T^2 and Q are monitored simultaneously [22, 23]. In the following section, the MSPC algorithm used to check the changes in the HRV signal before the attack is briefly described:

Let $x_n = \{x_{n,1}, x_{n,2}, \ldots, x_{n,M}\}^T$ be the feature vector extracted from the HRV signal, where $x_{n,m}$ is the n^{th} sample of the m^{th} HRV feature. Also, $X \in R^{N\times M}$ is a matrix whose n^{th} row is equal to X_n^T. The matrix $X \in R^{N\times M}$ is a normal data matrix in which the i^{th} row is equal to the it^{th} sample $X_i \in R^N$.

To obtain the 2 control factors Q and T^2, the X matrix is decomposed into U, Σ, and V vectors by the singular value decomposition (SVD) method, where the U and V matrices are orthogonal matrices. The columns of the U matrix are the orthogonal eigenvectors of the matrix xx^T, and the columns of the matrix V are the orthogonal eigenvectors of the matrix $x^T x$.Σ is a diagonal matrix whose diagonal elements are nonzero singular values of the matrix xx^T.

Matrix X is defined as:

$$X = U\Sigma V^T = \begin{bmatrix} U_R & U_0 \end{bmatrix} \begin{bmatrix} \Sigma_R & 0 \\ 0 & \Sigma 0 \end{bmatrix} \begin{bmatrix} V_R & V_0 \end{bmatrix} \tag{7}$$

where U is a left singular, and V is a right singular matrix. By using PCA or by considering the zero singular values of the X matrix, the components of the data set that have the greatest influence on the variance are retained. In PCA, the loading matrix $V_R \in R^{M\times R}$ is obtained as the right singular matrix. The V_R column space is a subspace that gives the selected principal components and the correlation between the values. Here, N and M represent the number of samples and the number of features, respectively, and R represents the number of principal components in the PCA model.

The T_R matrix is the image of the X matrix on these subspaces, which is obtained as:

$$T_R = XV_R \tag{8}$$

The matrix X can be reconstructed or estimated as follows:

$$\hat{X} = T_R V_T^R = XV_R V_R^T \tag{9}$$

By compressing, some information is lost, and the error is obtained as follows:

$$E = X - X = X\left(I - V_R V_R^T\right) \tag{10}$$

Using the error, the statistical Q (one of the control factors) is defined as follows [14]:

$$Q = \sum_{m=1}^{M} (x_m - \hat{x}_m)^2 = x^T \left(I - V_R V_R^T\right) x \tag{11}$$

Q shows the squared distance between the sample and the subspace formed by the principal components.

In addition to Q, Hotelings is used to show the abnormalities under the space created by the principal components of T^2, which is defined as [22]:

$$T^2 = \sum_{r-1}^{R} \frac{t_r^2}{\sigma_{t_r}^2} = x^T V_R \sum_{R}^{-2} V_R^T x \tag{12}$$

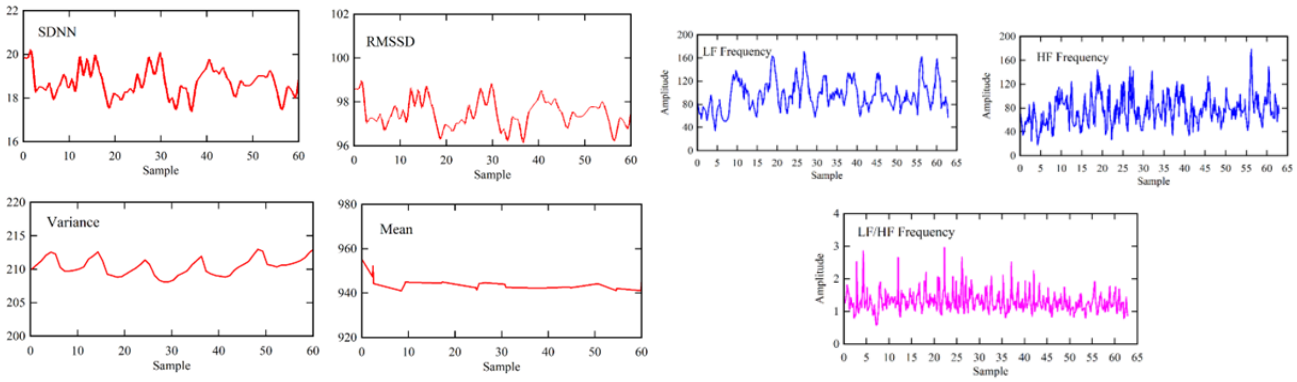


Fig. 2. (a) Time-Domain Analysis of Heart Rate Variability Metrics in the Preictal period of patient 12, and (b) Frequency-Domain Analysis of Heart Rate Variability Metrics in the Preictal period of patient 12.

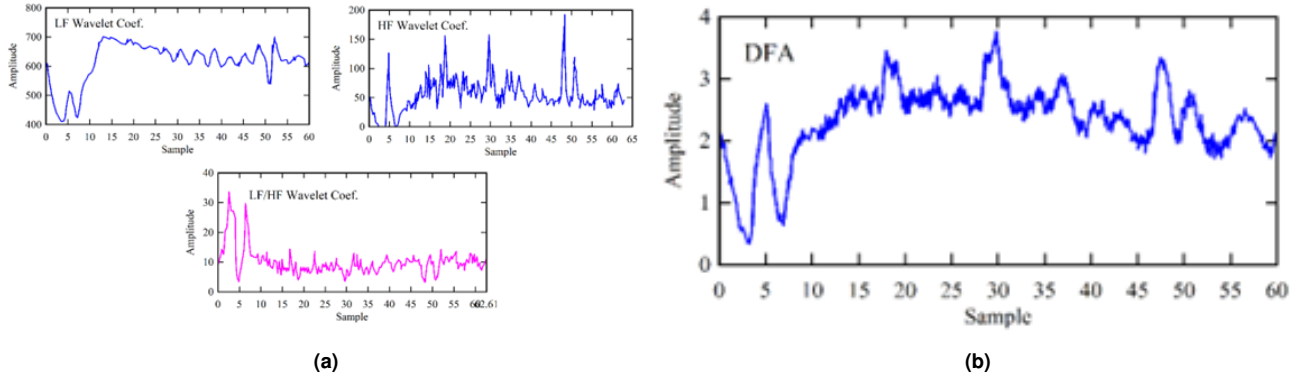


Fig. 3. (a) The Wavelet Transform Analysis of Heart Rate Variability Metrics in the Preictal period of patient 12, and (b) The DFA feature extracted from HRV in the Preictal period of patient 12.

where σ_{t_r} shows the standard deviation of the r^{th} t_r, and T^2 shows the distance from the origin. The MPC algorithm detects an abnormality when any of the statistical components T^2 and Q becomes higher than the predetermined control value.

In the proposed method for predicting epileptic attacks, 15 minutes before the seizure is considered prenatal, and HRV features are extracted in 2 Preictal and Interictal states. By applying the mentioned algorithm, the abnormality is detected.

4. The proposed method

4.1. The used database

The data used in this research includes a 2-hour 64-channel recording of patients' vital signals, and one of its channels is related to lead 2 of the ECG signal. In this collected database, epilepsy and its occurrence time are specified by the medical team. Table 1 shows the patients and their type of epilepsy. This database contains 51 Interictal episodes lasting 14.65 hours and 26 Preictal episodes.

In the proposed method for predicting epileptic attacks, 15 minutes before the seizure is considered Preictal, and HRV features are obtained in 2 Preictal and Interictal states.

4.2. Epilepsy prediction algorithm and the obtained results

To predict epileptic attacks, first, the R wave is extracted using the Pan_Tompkin algorithm, and the HRV signal is extracted by putting the RR intervals together. Then, 12 different time, frequency, time-frequency, and nonlinear features are extracted, and these features are normalized so that their average is zero, and their standard deviation is one. Finally, the abnormalities related to seizures are revealed by the MSPC algorithm.

Figs. 2 and 3 show the HRV features extracted from the Preictal period of patient number 12, and Figs. 4 and 5 show the features extracted from the same patient during the In-

Table 1. The patients' specifications of the collected database.

Patient	Epilepsy Type	Recording duration of Interical (min)	Age	Gender
1	minor	135	35	Male
2	minor	35	27	Male
3	minor	30	20	Male
4	major	86	27	Male
5	minor	43	25	Female
6	minor	95	23	Male
7	minor	45	22	Male
8	minor	30	9	Male
9	minor	43	47	Male
10	major	102	30	Female
11	minor	86	35	Male
12	minor	32	16	Male
13	major	27	19	Female
14	minor	28	41	Male
15	minor	23	14	Male
16	major	47	15	Female
17	minor	92	23	Female

terictal period. The horizontal axis is based on the sample, which represents the HRV number extracted from the ECG signal. As observed in these figures, the changes in features extracted from the HRV signal in the Preictal state are different from each other compared to the Interictal state. The important point here is that it is not possible to predict epileptic attacks only by monitoring one of the extracted features and to have an acceptable result, the relationship between the extracted features should be monitored before the attack occurs.

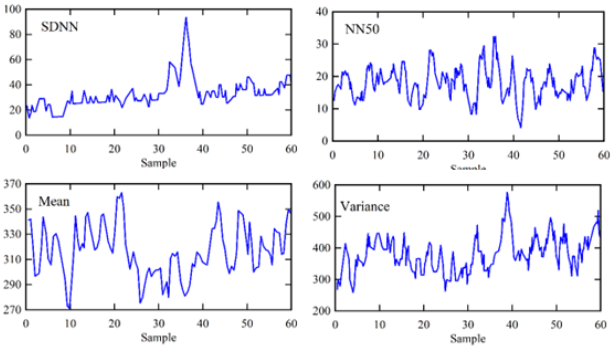
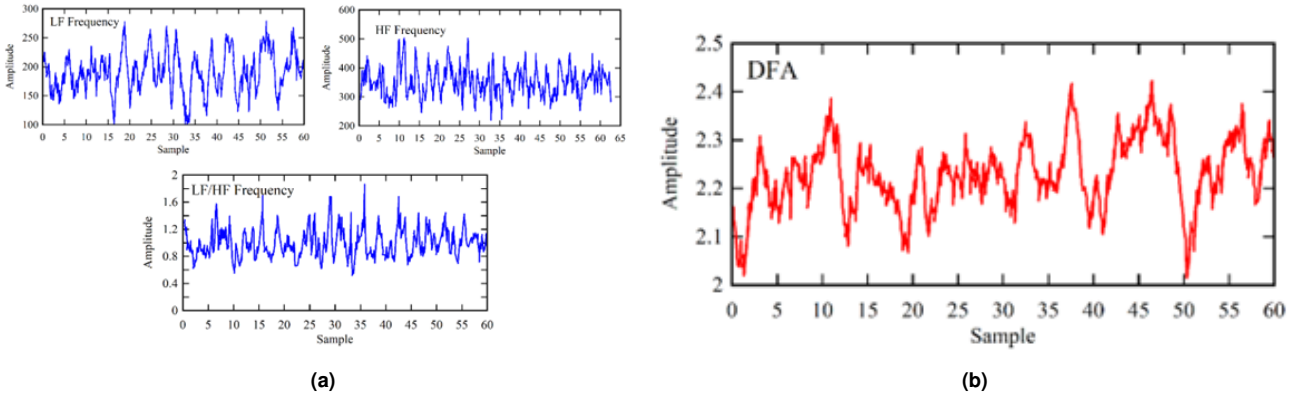


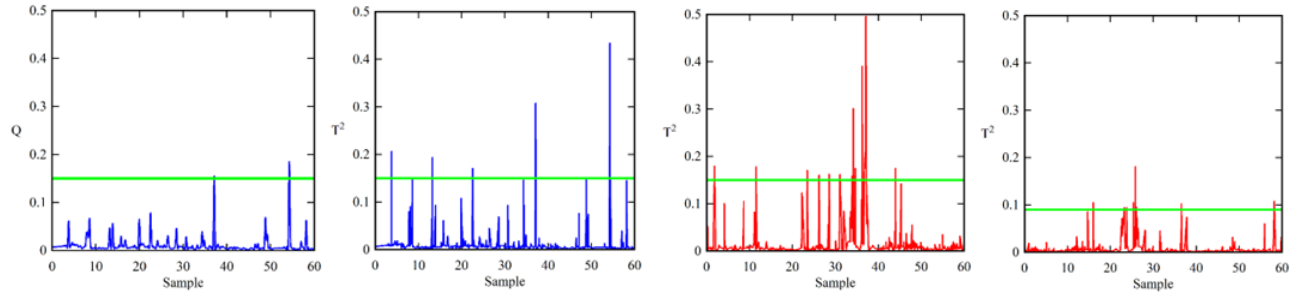
Fig. 4. Comprehensive Time-Domain Analysis of Heart Rate Variability Metrics for Cardiac Function Assessment in the Interictal period of patient 12.

To detect abnormalities in the Preictal period, as mentioned, 2 control factors were used, and the results can be seen in Fig. 6a. In this figure, the values of T and Q of the prevalent period are compared with the average T and Q thresholds obtained from the Interictal period, respectively. If their value exceeds the threshold for 15 consecutive seconds, it is considered an alarm to predict a seizure. In Fig. 6a, colored areas show the period of 15 seconds before the alarm. With the help of abnormality detection in the Preictal period, it will be possible to predict epileptic seizures. Examining the 2 control factors T^2 and Q in different Preictal episodes shows that the control factor T^2 is not able to detect abnormalities in some episodes, and the control factor Q is a stronger factor compared to it. It can be observed that the control factor T^2 could not detect the abnormality in one of the Preictal episodes. Fig. 6b shows these 2 control factors for the Interictal period, and as expected, no abnormalities were detected in this period. The distinction between these two factors is rooted in how they capture different aspects of variability in the heart rate signal. The T^2 factor is primarily a measure of the overall variability in the signal across multiple features, often capturing the combined effects of changes in the mean and variance of the heart rate variability (HRV) features. This makes T^2 particularly effective in detecting broad changes in the HRV signal that might indicate an impending seizure. On the other hand, the Q factor (or residuals) measures the deviations from the model or the unexplained variance after accounting for the primary variations captured by T^2. This means that Q is more sensitive to subtle, localized anomalies or patterns in the HRV signal that T^2 might miss. In some cases, these localized deviations are better indicators of the early stages of an epileptic attack, making the Q factor more effective in those instances. For certain patients or specific seizure patterns, the Q factor may capture critical anomalies that precede an epileptic event, while T^2 might overlook these details due to its focus on broader signal variations. This is why, in some cases, the Q factor outperforms the T^2 factor in predicting seizures. In summary, the



(a) (b)

Fig. 5. (a) Analysis of Low Frequency (LF), High Frequency (HF), and LF/HF Ratio in Time Series Data in the Interictal period of patient 12, and (b) DFA feature extracted from HRV in the Interictal period of patient 12.



(a) (b)

Fig. 6. (a) The Wavelet Transform Analysis of Heart Rate Variability Metrics in the Preictal period of patient 12, and (b) The DFA feature extracted from HRV in the Preictal period of patient 12.

Q factor's effectiveness in some cases is due to its ability to detect subtle, localized variations in the heart rate variability signal that are not captured by the T² factor. This makes it a valuable complement to T² in a multivariate statistical process control framework for predicting epileptic seizures.

The proposed algorithm for epilepsy diagnosis was evaluated on a database of 17 patients, which includes a total of 879 minutes of Interictal episodes and 255 minutes of prectal episodes. According to these results, the presented algorithm can able to correctly detect the abnormalities in the prerectal period for 15 patients, and these abnormalities in the signal indicated the occurrence of seizures at later times. The obtained results show that the proposed method was able to correctly diagnose the abnormality for 15 patients. By detecting these abnormalities in the Preictal period, epileptic seizures can be predicted before they occur. The Q control factor with 88.2% accuracy and the T^2 control factor with 64.7% accuracy was able to detect abnormalities. On average, this algorithm can predict epilepsy 7 minutes before the onset of seizures, and it can be seen that the Q control factor is more accurate compared to the T^2 factor.

Table 2 shows the results of this algorithm for each patient, as well as the time when the algorithm can predict an epileptic seizure before its occurrence in minutes. As can be seen, for some patients, the control factor Q has performed better compared to the T^2, while in some cases none of the 2 factors have been able to detect the abnormality in the Preictal period.

5. Conclusions

The present research proposes a new method for predicting epileptic seizures through Heart Rate Variability (HRV) analysis, in which abnormalities in HRV features are identified before the onset of epilepsy by a multivariate process control algorithm. Since the heart rate can be easily measured by medical sensors, this proposed method can be used in daily life, improve the patient's living conditions, and reduce the complications caused by epilepsy.

In the proposed algorithm, various time, frequency, time-frequency, and nonlinear features were extracted from the HRV signal. It is observed that these features are more

Table 2. Results obtained from the proposed algorithm for the patients.

Patient	Q	T2	Time before seizures occur (min)
1	Yes	No	15.3
2	No	No	8.8
3	Yes	Yes	6.1
4	Yes	Yes	14
5	Yes	Yes	16.4
6	Yes	Yes	13.2
7	No	No	–
8	No	Yes	5.6
9	Yes	Yes	16.3
10	Yes	Yes	14.6
11	Yes	Yes	10.6
12	Yes	Yes	9.6
13	No	Yes	4.6
14	Yes	Yes	7.6
15	Yes	Yes	10.3
16	No	No	–
17	Yes	No	14.6

fluctuating in the Preictal state compared to the Interictal state. By applying the MSPC algorithm to the obtained features, abnormalities can be detected in the Preictal period, and epileptic seizures can be predicted. The results of applying this algorithm in Interictal show that no abnormality was detected. This indicates that the signal has more abnormality in the Preictal state compared to the Interictal state.

By applying the MSPC algorithm to the obtained features, abnormalities in the Preictal period were diagnosed, and epileptic seizures were predicted. The results of applying this algorithm in the Interictal state show that no abnormality was detected and it indicates that the signal in the Preictal state has more abnormality compared to the Interictal state. Table 2 shows the results of this algorithm for each patient and also when the algorithm can predict seizures. Epilepsy before its occurrence was shown in minutes. As observed, for some patients, the Q control factor is stronger than the T^2 factor, and in some cases, none of the 2 factors could diagnose the abnormality in the Preictal period. In the existing database, more than one record is available for some patients, and the results of the algorithm are presented separately for each one.

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