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Research paper

Prediction of sudden cardiac death based on fundamental changes in nonlinear characteristics of cardiac signals

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Abstract

To quickly detect sudden cardiac death (SCD), it is decisive to gather suitable information and enhance the accuracy of the diagnosis algorithms. Consequently, in the present study, the heart rate variability (HRV) signal of subjects who experience sudden cardiac death (SCD) is studied. We looked at people's heart signals for one hour before something happens to see if there are any noticeable changes. The patients' HRV signals are segregated into 5-minute parts in the suggested approach. Each section is divided into four shorter signals. Thereupon, the energy and instant amplitude of each sub-signal are examined. The information flows between signal strengths and measuring the complexity of energy sub-signals are checked. A significant change from its former section is identified. A support vector machine classifier benefits from detecting individuals exposed to SCD by considering significant changes as indicators of the SCD process. It can anticipate SCD 15 minutes before it happens. Not restricted to any special subclass of cardiac diseases, this technique has priority. To evaluate the specificity of the algorithm, it has been used not only with patients having SCD but also with individuals who are healthy, as well as those with coronary artery disease (CAD) and congestive heart failure (CHF), analyzing their HRV signals. The specificity values for normal, CHF, and CAD patients are 100%, 93.3%, and 95.6%, respectively, in the results.

1. Introduction

Sudden cardiac death (SCD) is an emergency condition that can lead to death within minutes. If someone experiences sudden changes like arrhythmia, low blood pressure, chest pain, breathlessness, or dizziness and gets involved with cardiac arrest in an hour, those deaths are treated as SCD [1-6]. Even healthy, junior, and athletic people can die from SCD, but it is more common in the middle-aged and elderly [7-8]. SCD is responsible for over four million deaths globally [9], with a minimum of 300,000 cases reported in the United States [10]. The incidence of diagnosed SCD ranges from approximately 37 to 39 cases per 100,000 individuals in the four

European Union registries [11]. This syndrome includes a muddled electrical activity in the heart, hence, its ability to effectively pump blood to vital organs can be disrupted. The patient's death might be ineluctable if well-timed and proper clinical proceedings are not done. Cardiac arrhythmias are often detected as a prevalent cause of such deaths. In 75 to 80% of cases, ventricular fibrillation (VF) can be considered as the first cause of this cardiac incident. On the other hand, Brady Arrhythmia takes precedence in 10 to 15% of patients [10, 5]. Survival in a non-clinical environment is observable in only about 1-2% of patients who suffer from this syndrome [12]. The number of institutions that have studied the prediction of SCD is very few. American Heart Association is one of those whose researchers have published many papers in this field [13, 15]. The 2022 Heart and Stroke Statistics Update has been recently released by the American Heart Association [15]. According to this report, cardiac arrest is still one of the threats to public health. Recognizing subjects at risk of SCD quickly and accurately, therefore, is important for moderating their chances of dying. Recently, researchers have studied the SCD syndrome through the analysis of electrocardiogram (ECG) or Heart rate variability (HRV) signals. For example, Acharya *et al.* [16] used a developed support vector machine (SVM) algorithm to predict SCD four-minutes prior to the event with 86.8% accuracy. They used the wavelet method and then extracted several features based on fractal and sample entropy (SaE) analysis. Fujita *et al.* [17] studied the non-linear aspects of the HRV signal in twenty patients and eighteen normal individuals. They precisely predicted a death incident 94.7% of the time by taking advantage of the SVM algorithm, four minutes before it happened. Houshyarifar *et al.* [18] accomplished a 92% accuracy in anticipating the VF, accurately predicting it five minutes before its occurrence. Their study requires the use of four features from recurrence plots and three features from Poincaré plots. Ebrahimzadeh *et al.* [19] foresaw the event thirteen minutes before its occurrence by looking at nine classical, 11 time-frequency, and four nonlinear features. The multi-layer perceptron (MLP) network achieved an accuracy of 84.21%. Recurrence quantification was used by Khazaei *et al.* [20] to forecast SCD in less than a six-minute duration prior to its occurrence. Their recommended algorithm gained an accuracy, sensitivity, and specificity rate of 95%. Vargas-Lopez [21] used an ECG signal to forecast the syndrome. They made an MLP algorithm that can anticipate SCD with 94% accuracy by using a special analysis just 25 minutes before it happens. They look at different aspects of the heart signal (extracting components of the signal through EMD and then using Permutation Entropy and Higuchi Fractal values as features) to make this anticipation. Shi [22] used a technique named EEMD-based entropy to analyze HRV signals. They discovered that this approach could detect SCD 14 minutes earlier with a high accuracy of 96.1%, a specificity of 94.4%, and a sensitivity of 97.5%.

Despite all the previous studies, the methods predicting SCD are not used in medical examinations. The main reason is that the signals in this syndrome are similar to those in other heart diseases. It is well-known that SCD can happen for many different reasons. Many SCD patients also have a background of angina [23]. For example, about 50% of patients suffer from SCD following a myocardial infarction [24]. Also, a great number of SCD patients have CAD or CHF [25]. CAD refers to a disease in which, due to the narrowed coronary arteries, the blood supplied to the heart muscles becomes restricted [26]. In general, CAD results from the cholesterol plaques formed within coronary arteries due to environmental pollution, unhealthy lifestyles, smoking, or other unknown factors [27]. If CAD is not treated on time, it may finally decrease the capability of the heart to pump oxygenated blood to the other body organs. Such a syndrome of the heart is referred to as CHF. This syndrome is a28, in which, due to the lack of enough energy, the heart is not capable of pumping blood under normal heart pressure [29]. It is estimated that 26 million individuals are diagnosed with this disease around the world [30]. To enhance anticipation accuracy, Devi *et al.* [31] suggested a technique to discern signals of patients with SCD from healthy individuals and those identified with

CHF illness. The neural network reached an accuracy of 83.33% for predicting VF occurrences in less than ten-minute intervals. Rohila *et al.* [32] have come up with a new method to discriminate between patients diagnosed with SCD, those who are healthy, and patients with CAD and CHF. They use the HRV signal for this purpose. Their new method is usually accurate about 85% of the time when looking at one-hour chunks of heart signals.

Every algorithm mentioned poses noticeable restrictions. For example, a restricted number of patients in each patient group has been studied. Also, the features used in these sources might be similar to those found in other heart diseases. Therefore, if the cardiac signals of other cardiac patients are applied to these algorithms, these patients will be wrongly diagnosed by these algorithms as patients at risk of sudden death.

To diagnose SCD, the algorithm should focus on the unique features in the heart signals of patients with this syndrome. The present study suggests a novel algorithm designed to recognize individuals diagnosed with SCD syndrome in comparison to other heart disease patients and those who are normal. We record important changes in the heart signals of people who experience SCD before it happens. Therefore, the suggested approach is not restricted to any specific group, resulting in greater specificity compared to the current methods.

2. Methods and materials

2.1. Extracting features

This research analyzed the heart signal patterns of patients in danger of SCD during the hour before it happened. To achieve accurate HRV measures, it is an obligation to choose the right frequency for sampling ECG data which in turn causes a reliable and valid calculation. Recent developments affirm the need for ECG sampling rates of at least 125 Hz [33].

Following the de-noising of the ECGs, the subsequent signals are split into five-minute intervals. Then, the HRV signal is realized in patients with SCD. Later, the signals experience resampling at a frequency of 2 Hz. Eventually, every newly generated signal goes through decomposition to four sub-signals. Researchers often use the EMD method for this process. Nonetheless, in the last few years, a technique named local characteristic decomposition (LCD) has been used to study the vibrations in gearbox bearings. This technique has fewer problems with mixing modes than the EMD method [34-36]. Hence, this study has considered the potential of this method for decomposing the signals of HRV. In turn, it is expected that the amplitude of the sub-signals coming from the LCD algorithm is not stable and keeps changing. Sub-signals change in size and frequency along with the main signal. Hence, we used the Teager-Kaiser method to find the amplitude of every part of the signals produced by the LCD method. Afterward, we determine the SaE of the energy signal and the transfer entropy (TE) among every pair of instantaneous amplitude signals. Finally, an SVM neural network has been made to anticipate SCD by considering the abovementioned features and their variances from their reciprocal values within the preceding interval. Fig. 1 shows the block diagram of the proposed method.

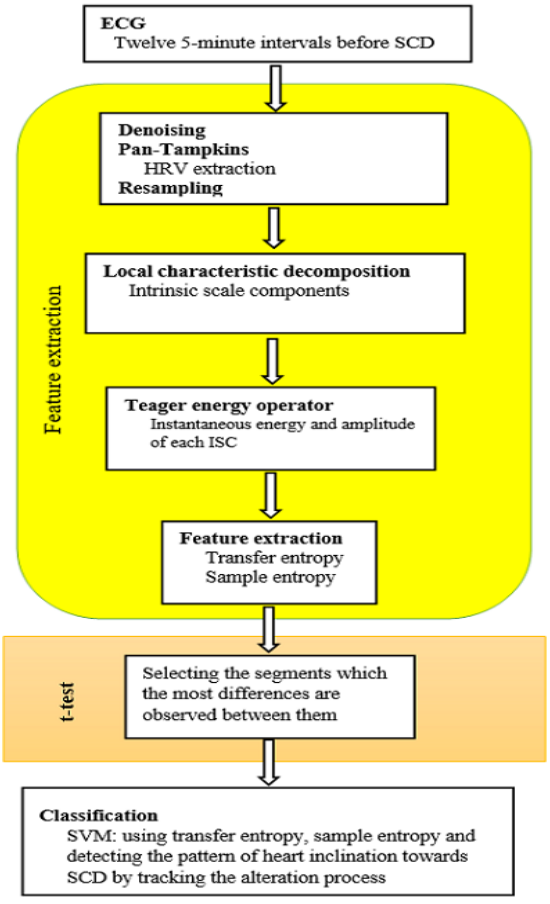

Fig. 1. Block diagram of the proposed method.

2.2. Database

We used the new algorithm on the signals from the MIT-BIT database [37]. This database includes heart signals from 23 patients who passed away suddenly (sampling frequency=256 Hz). The intervening variables of this research are the ECG signals of patients and normal subjects. Unlike the cardiac signals of SCD patients, which were studied in the last hour, the cardiac signals of other patients and healthy people were randomly selected.
The ECG signals were acquired from PhysioNet databases. Physionet is an Open-Source database for analyzing physiological signals which has strict standards regarding compliance with codes of ethics. The SCD syndrome subject database provides accurate timing information for the occurrence of VF. In 20 of the 23 patients for whom the data are accessible in the specified database, VF has been confirmed in 20, while the timing of VF occurrence in the signals of the remaining three subjects is uncertain. Hence, the study excluded these three signals.
We tested how well our method works by comparing it to other studies that used signals from databases related to Normal Sinus Rhythm, Coronary Artery Disease, and Congestive Heart Failure.

2.3. Signals preprocessing

Since there is extra noise with the received signals, it is an obligation to get rid of them before further analysis. Hence, we used a Butterworth filter to get rid of unwanted power line effects and disturbances caused by the person's breathing. Then, we focused on five-minute segments in less than an hour before VF happened in the cleaned-up signals. Therefore, a total of 240 intervals, comprising 12 five-minute parts for each patient have been collected. Ir should be kept in mind that during the processing stage, segments including severe noise lasting longer than 30 seconds have been excluded. Hence, sometimes we used a smaller number of subjects instead of 20.
Once the de-noising process is done, the Pan-Tompkins algorithm is used to create the HRV signal [38]. Finally, due to variations in the periods of the acquired signal data, The HRV signals were resampled using interpolation at a frequency of 2 Hz.

2.3.1. Local characteristic decomposition

LCD refers to a pioneer signal processing method operated in the decomposition of non-stationary time series [39]. It breaks down the provided signal *x(t)* into intrinsic scale components *(ISCs)*. Eq. (1) is used to find and show a leftover term *(r(t))* and K modes *($d_k(t)$)*.

$$x(t) = \sum_{k=1}^{n} d_k(t) + r(t) \qquad (1)$$

More information regarding the LCD method can be referred to references [34, 39].
Fig. 2 presents an HRV signal and its corresponding ISCs that were achieved through the LCD method as discussed earlier. As you can be seen, the initial ISCs exhibit a higher frequency range, and later ISCs bring a lower frequency range.

2.3.2. Extraction of signal amplitude and frequency

The LCD method produces several ISCs that exhibit fluctuation and inconsistency over time. The sub-signals vary in size and frequency during the signal. Therefore, signal characteristics can be understood from variations in size. The Hilbert transform (HT) [40] and the Teager-Kaiser energy operator (TKEO) techniques are two commonly used methods for determining the frequency band and spatial extent of the signals. The HT method works excellently for signals with specific and bounded frequency ranges, but it does not do as well with signals that have sudden changes or shocks. Negative frequencies can also be generated using this method. TKEO method is superior to the HT method for analyzing signals with sudden changes. It is also easier on computer resources compared to the Hilbert conversion method [41]. Based on the determined functionalities, the TKEO methodology is used to evaluate the frequency and dimensions of the achieved sub-signals. Eq. (2) characterizes this operator for discrete signals:

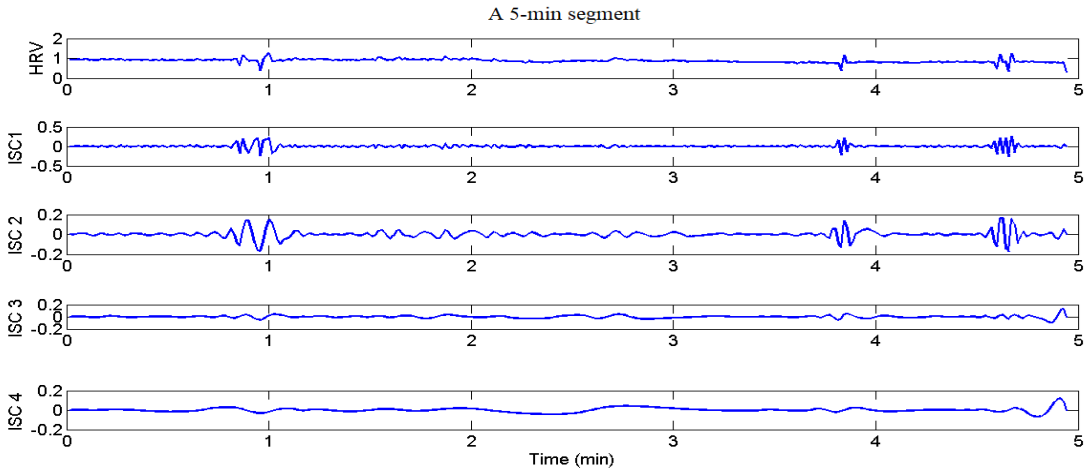

Fig. 2. The LCD analysis's results on a five-minute HRV section.

$$\varsigma[x(n)] = x^2(n) - x(n-1) \times x(n+1) \quad (2)$$

As can be seen, determining the value of the operator value necessitates solely *x(n)*, *x(n+1)*, and *x(n-1)*. Hence, it has a very high-quality image, and its sensitivity to change is noticeable. The instantaneous frequency and amplitude of the signal are determined using Eqs. (3 and 4):

$$F(n) = \frac{1}{4\pi f} \operatorname{acos}\left(1 - \frac{\varsigma[x(n+1) - x(n-1)]}{2\varsigma[x(n)]}\right) \quad (3)$$

$$|A(n)| = \frac{2\varsigma[x(n)]}{\sqrt{\varsigma[x(n+1) - x(n-1)]}} \quad (4)$$

The sampling frequency is denoted by *f*.

2.3.3. Sample entropy

The energy of the sub-signals attained in the preceding step experiences variations throughout the signal duration. Sample entropy (SaE) can be used to measure the energy complexity of the signal. SaE is engaged in the system complexity evaluation of biomedical signals, which are sensitive to noise interference. This method helps to discover how often a specific length of time *m* with a certain tolerance *r* is repeated. The SaE is calculated by these steps when the signal includes N data points:

Step 1. Consider *m* as a vector dimension Eq. (5):

$$X_m(i) = [x_i \; x_{i+1} \; \ldots \; x_{i+m-1}] \quad 1 < i < N + m - 1 \quad (5)$$

Step 2. Using Eq. (6), the area amid the vectors $X_m(i)$ and $X_m(j)$ is calculated:

$$d[X_m(i) - X_m(j)] = \max(x_{i+k} - x_{j+k}) \quad (6)$$

In which $0 \leq k \leq m-1$ and $j \leq N - m + 1$

Step 3. The amount of $d[X_m(i) - X_m(j)] < r$ is calculated. Here, the threshold is denoted with the letter 'r'. The calculation of the ratio is according to Eq. (7) and includes the previously tallied number divided by N-m + 1.

$$\varphi_i^m(r) = \frac{1}{N-m+1}\{the\ number\ of\ d[X_m(i) - X_m(j)] < r\} \quad (7)$$

Step 4. At this step it is averaged over i. Therefore:

$$\varphi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m} \varphi_i^m(r) \quad (8)$$

Step 5. Substituting m +1 instead of m, in this case, steps one to four are iterated, and it can be written as Eqs. (9 and 10).

$$\varphi_i^{m+1}(r) = \frac{1}{N-m}\{the\ number\ of\ d[X_{m+1}(i) - X_{m+1}(j)] < r\} \quad (9)$$

$$\varphi^{m+1}(r) = \frac{1}{N-m}\sum_{i=1}^{N-m-1}\varphi_i^{m+1}(r) \quad (10)$$

Step 6. Finally, the SaE can be computed by using Eq. (11):

$$SampEn = log\frac{\varphi^m(r)}{\varphi^{m+1}(r)} \quad (11)$$

It is noteworthy to mention that regular time series have lower SaE.

2.3.4. Transfer entropy

TE is a principle to measure the cause-and-effect connection between two sets of time series data. Suppose *Y(t)* and *X(t)* represent two time series for the respective Stochastic variables *Y* and *X*. $TE_{X\to Y}$ shows further information regarding the future of variable Y. This can be done by knowing the past and present of Y and the future and past of X [42].
Consider that X^m and Y^k are as follows in Eq. (12):

$$\begin{cases} X^m = (X_n\ X_{n-m}\ \dots\ X_{n-(m-1)\tau}) \\ Y^k = (Y_n\ Y_{n-k}\ \dots\ Y_{n-(k-1)\tau}) \end{cases} \quad (12)$$

If such is the case, TE can be calculated as Eq. (13):

$$TE_{X\to Y} = \sum P(Y_{i+1}\ Y_i^g\ X_{i-\tau-1}^l)log2\frac{P(Y_{i+1}|Y_i^g\ X_{i-\tau-1}^l)}{P(Y_{i+1}|Y_i^k)} \quad (13)$$

where, g and l suggest the embedding dimensions, meaning that the upcoming probabilities of Y and X can be calculated using the previous *k* and *m* values.
Additionally, τ exemplifies the embedding delay. $P(Y_{i+1}\ Y_i^g\ X_{i-\tau-1}^l)$ manifests the joint probability. $P(Y_{i+1}|Y_i^g\ X_{i-\tau-1}^l)$, and $P(Y_{i+1}|Y_i^g)$ are the possibilities of the functions of density.

3. Results and discussion

As it has been said, we compare the characteristics of every five-minute part of the signal with the next one. Since the cardiac signals are dynamic, the method of time segmentation of the signals affects the final results. Segments shorter than five minutes are not appropriate for the analysis. At shorter distances, the resolution improves, but the extracted features lose their effectiveness. Also, the accuracy of the calculation decreases when the time interval exceeds five minutes.
Undoubtedly, modifications in the signal take place as the event gets closer. Therefore, observing and analyzing these changes help to predict the probability of the occurring event. There are some slight variations in the way everyone's cardiac signals behave. Nevertheless, an immediate and extreme adjustment in the studied features suggests the probability of the occurrence of an event. The t-test method has been used to analyze the level of changes in various time interval features. This particular test can be used to determine if the presence or absence of a variable actually has any significant effect on the two sets of data. In a t-test, when the feature p-value goes down, it means that the feature is more impressive [43].
If we study various time intervals, we notice significant changes in the HRV signals. Specifically, there were potential changes in the TE between sub-signal amplitudes and the SaE of signal energy 25 to 10 minutes before the event happened (Table 1). According to the table, there is no big difference in the t-test results until 10 minutes before the event.
Table 2 shows the results of using the TE method for the 3rd, 4th, and 5th segments. Additionally, we calculated the p-value to compare these consecutive intervals. As you can see, there is an abrupt change in the TE between the momentary amplitudes of the 4ths and the 1st sub-signals 10 to 20 minutes prior to the VF. Simultaneously, there are no identical changes in the remaining sub-signals.
In Fig. 3 you can see how much information was flowing between the ISCs in the hour prior to VF occurrence. An observable change is evident in the 4th segment. The TE reaches its possible

minimum right after the third interval (p= 0.0016). The energy pattern in the 4th part suddenly changes when we compare the 4th and 5th time segments. This change is statistically significant (p= 0.0451), but there are no noticeable changes in the five minutes before this, as indicated in Table 3. This table provides the results of analyzing the patient's data in the 4th and 5th intervals using SaE of instant energy. As is shown, the value of SaE in the fourth sub-signal before the event changes greatly from the 5th to the 4th segments.

The average SaE of the energy in the ISC4 is observed to change in the hour leading up to SCD as shown in Fig. 4. A significant decrease in entropy size is observed in the 4th segment, compared to the preceding interval. In Fig. 5 and Fig. 6, you can see the p-values for the listed features in different periods. As it is evident, most of the changes we studied happened during the 4th and 5th periods. This means that the acute time before the event is around 15 to 25 minutes. These big changes suggest that the event might start soon. The way things are changing indicates that the beginning of SCD is getting closer. We do not know exactly why, but shocks during this time might make the heart more likely to go into a dangerous state named VF.

Table 1. Comparison results of successive segments using t-test: TE for 5-minute segments, SaE of energy signal, and P-value categorization (** for p-value < 0.05, # for p-value > 0.05).

Segment	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11	11-12
TE	#	#	**	**	#	#	#	#	#	#	#
SaE	#	#	#	**	#	#	#	#	#	#	#

Table 2. TE analysis results for 3ths, 4ths, and 5ths segments in patients with SCD, ** appears for p<0.01.

TE-O	(mean±std)			P value	
	3rd segment	4th segment	5th segment	3rd and 4th	4th and 5th
$TE_{1\to2}$	0.136 ± 0.128	0.2167 ± 0.155	0.1299± 0.112	0.667	0.052
$TE_{1\to3}$	0.1592 ± 0.068	0.1795 ± 0.076	0.1486±0.06	0.391	0.1708
$TE_{1\to4}$	0.1498 ± 0.06	0.1775± 0.054	0.1543±0.053	0.053	0.1849
$TE_{2\to1}$	0.1153 ± 0.135	0.1869 ± 0.145	0.1407±0.128	0.116	0.3003
$TE_{3\to1}$	0.0887 ± 0.110	0.1297 ± 0.093	0.1020±0.106	0.142	0.3906
$\mathbf{TE_{4\to1}}$	**0.0691 ± 0.088**	**0.1565 ± 0.0906**	**0.0812±0.0779**	$\mathbf{0.0016}^{**}$	$\mathbf{0.0086}^{**}$
$TE_{2\to3}$	0.1607 ± 0.078	0.1765 ± 0.062	0.1718±0.652	0.449	0.819
$TE_{3\to2}$	0.0963 ± 0.105	0.1318 ± 0.083	0.1149±0.087	0.150	0.537
$TE_{3\to4}$	0.1959 ± 0.073	0.1962 ± 0.053	0.1711±0.064	0.989	0.19
$TE_{4\to3}$	0.1712 ± 0.08	0.1999 ± 0.066	0.1610±0.068	0.148	0.080
$TE_{2\to4}$	0.1518 ± 0.051	0.1572 ± 0.056	0.1510±0.036	0.733	0.688
$TE_{4\to2}$	0.0921± 0.074	0.1112± 0.080	0.0831±0.0694	0.45	0.252

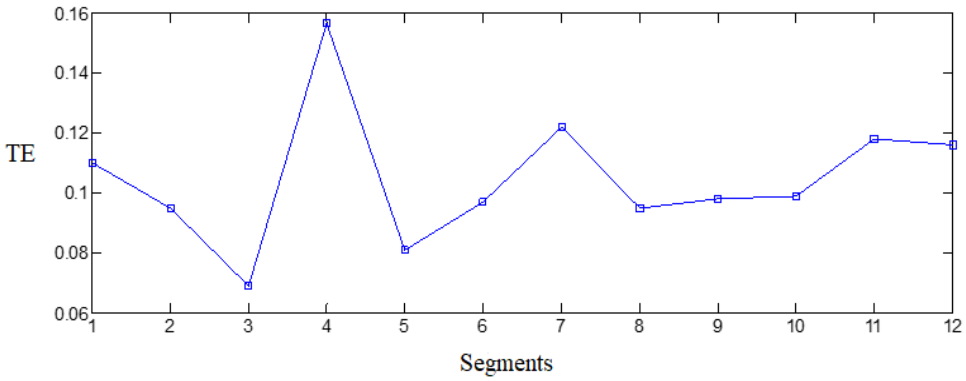

Fig. 3. Information transfer from 4ths sub-signal to first across various time intervals in the instantaneous domain.

Table. 3. SaE results for instant energy in 4ths and 5ths intervals of patients. * appears for p < 0.05.

SaE of energy	4th portion (mean±std)	5th portion (mean±std)	P-value
ISC4	**0.0223 ± 0.0205**	**0.0454 ± 0.0424**	**0, 0451***
ISC3	0.0519 ± 0.0453	0.0884 ± 0.0752	0.0858
ISC2	0.1244 ± 0.1427	0.1478 ± 0.133	0.6149
ISC1	0.219 ± 0.2375	0.2387 ± 0.2563	0.8121

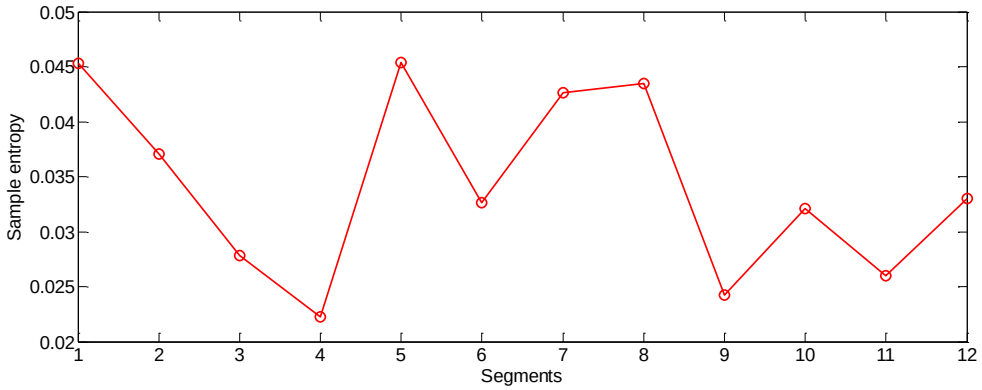

Fig. 4. The SaE results of instant energy across various intervals in the 4ths sub-signal.

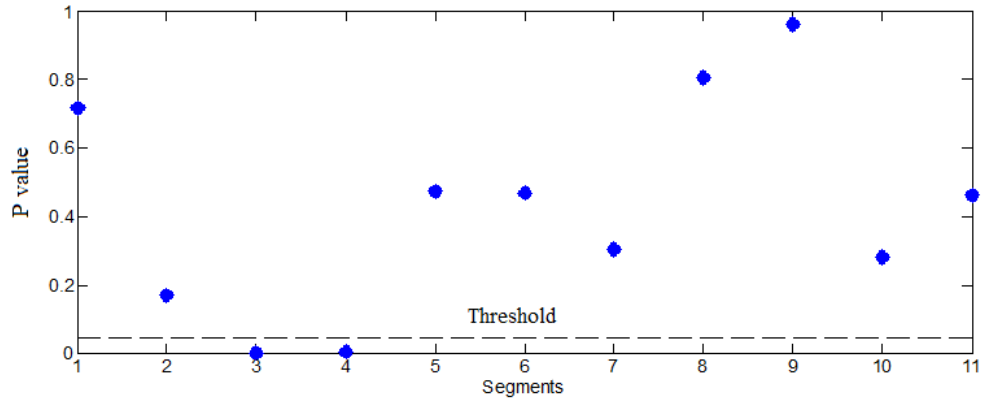

Fig. 5. P-value results for TE comparison of 4ths ISC across sequential intervals.

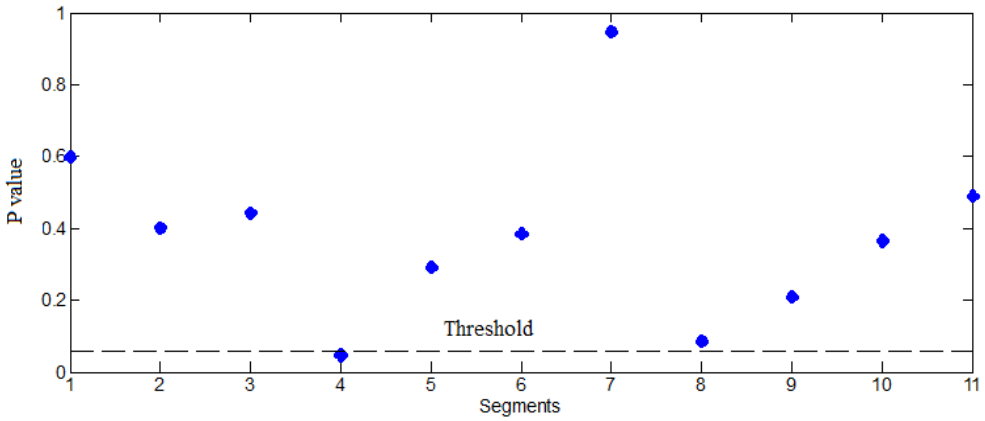

Fig. 6. P-value results for comparative analysis of SaE in successive intervals of 4ths ISC instant energy.

3.1. Classification results

Since cardiac shock makes VF 15 to 25 minutes before the event, we can group patient signals into two categories. If the signal shows characteristics from the first group (the 5th interval), the patient is safe from SCD. However, if it has features from the second group (the 4th interval), the patient is at risk of SCD. Therefore, according to what has been said, we have come up with a classification algorithm. This algorithm uses some particular features in the 5th and 4th intervals to separate signals from patients with SCD and signals from other patients. To do so, certain characteristics like the entropy of energy signals and the information flow between different parts of the signal's immediate magnitude at specific times have been analyzed. We also studied how these measures change from one time interval to the next. Here, we use a support vector machine to tell apart the HRV signals of the 4th from the 5th portions.

We used some criteria (Eqs. (14-16)) to evaluate the SCD prediction: specificity, accuracy, and sensitivity:

$$SN = \frac{TP}{FN + TP} \tag{14}$$

$$SP = \frac{TN}{TN + FP} \tag{15}$$

$$ACC = \frac{TP + TN}{TN + TP + FN + FP} \tag{16}$$

TP: The detection of the SCD victim is accurate.
TN: A non-SCD victim is accurately detected as no SCD.
FP: A non-SCD victim has been misdiagnosed as a person with SCD.
FN: The SCD victim has been misdiagnosed as a non-SCD subject.

Table 4 shows the results for the periods preceding the event, particularly the 4th and 5th intervals. Details such as levels of accuracy, specificity, and sensitivity are presented in this table. It is monitored that the cardiac ECG signal of one patient was omitted because of significant noise and the inability to extract the RR signal. In this regard, the classifier is trained by leave-one-out cross-validation. Hence, we use one data point to test the algorithm's performance and the other thirty-seven for training. It was found in the results that the Kernel's radial basis function performs the best when σ=0.4. The classification accuracy is calculated as 86.84%, which can be considered satisfactory. The outcomes prove that the proposed approach can precisely identify SCD fifteen minutes prior to its beginning.

We used signals from the 6th to 11th intervals to study the SVM-RBF classifier performance. The results are presented in Table 5.

Most errors occur during the 6th interval. This issue mostly happens since there are alterations in the HRVs in a few number of cardiovascular patients' signals during this period. Alternatively stated, most patients show important signal changes 25 to 15 minutes before the event. However, a few experience these changes a bit earlier.

We used HRV signals from different heart databases such as Normal Sinus Rhythm, Long-Term ST, and BIDMC Congestive Heart Failure to test our neural network and see how well it performs compared to previous studies (Table 6).

Using this method, we correctly identified signals from healthy people every time (100% specificity). For those with heart conditions like CHF and CAD, we were right 93.3% and 95.6% of the time, respectively. We did this process 50 times and averaged the results. The high specificities come from the fact that the features being studied do not change much among consecutive time intervals. These details prove that the method is efficient in telling apart signals from someone with SCD compared to other patients.

This study derives from the premise that sudden changes in the signal of subjects with SCD occur in the last hour leading to the event. Therefore, in this study, one hour leading to the incident has been investigated. This assumption could be extended to hours before the event. There is also a possibility that, apart from the features examined in this study, there may be changes in other hidden features in the cardiac signal of the subjects with SCD.

3.2. Discussion

Eq. (3) is utilized to determine the mean and standard deviation for each ISC.

Table 4. Results of classification using SVM.

Classifiers	TP	TN	FP	FN	Acc	Sen	Spec
SVM-RBF ($\sigma = 0{,}4$)	16	17	2	3	86.84%	84.21%	89.47%
SVM-RBF ($\sigma = 0{,}8$)	15	16	3	4	81.58%	78.95%	84.21%
SVM-poly (d=2)	15	16	3	4	81.58%	78.95%	84.21%
SVM-poly (d=4)	15	15	4	4	78.95%	78.95%	78.95%

Table 5. The outcomes of analyzing signals in consecutive intervals (6 to 11) in the SVM-RBF classifier.

Segments number	Time prior to SCD (minutes)	No of signals	Error (false positive)
6	30-25	19	5
7	35-30	18	1
8	40-35	19	0
9	45-40	20	2
10	50-45	20	2
11	55-50	20	1

Table 6. The outcomes of giving the signals of various patients in SVM-RBF classifier.

Subjects	Number of subjects	Error number	Specificity
NSR	18	0	100%
CAD	23	1	95.6%
CHF	15	1	93.3%

Table 7 shows the results of Eq. (3). As can be seen, ISC1 corresponds to the VHF component (0.4 - 1 HZ), ISC2 is the HF component (0.15 - 0.4 HZ), ISC3 is the LF component (0.04 - 0.15 Hz), and ISC4 is the VLF component (0.003-0.04 Hz). The origin of high and low frequencies is parasympathetic and sympathetic nerve activity, respectively. In healthy people, these frequency bands are in balance with each other, as a result, a change in the balance of these bands can indicate the event of SCD. The concept of TE can be used to identify the influence of these sub-signals on each other. As observed, there is a significant change in the $TE_{4\to1}$ in the 10-25 minutes before the event. This rapid rise denotes the strong impact of the low-frequency VLF agents of the cardiac signals on VHF fluctuations. In addition, it should be emphasized that in the period from 25-15 minutes prior to the VF, the instantaneous power signal's SaE in the 4ths sub-signal drops drastically, implying a reduction in the adaptability of the heart in this segment. In accordance with what was stated, it is determined that the changes in the 4ths sub-signal, which is distinguished by a VLF band, are the driving factor that leads to the SCD event. Although the physiological reason for the VLF band is not yet understood, it has been stated that this frequency band is likely influenced by the body temperature regulation mechanisms and renin-angiotensin-aldosterone [44]. This information may contribute to a superior comprehension of SCD in future research.

According to Table 5, 116 signals obtained from segments six to 11 have been used for testing, among which the algorithm has only 11 errors. This number of errors results in a specificity of 90.5%, which is quite satisfactory. Furthermore, the generated classifier correctly identifies all subjects as normal when exposed to the healthy individuals' signal. As far as we know, among similar studies, this function is truly satisfactory and unique.

Because the existing studies use data from different subjects and different signal durations, it is difficult to analogize the results of our research with the reported ones. Considering this issue, Table 8. compares the proposed method of this study with other similar studies. From the table, it can be observed that the signals of SCD victims were typically distinct from those of normal subjects in other studies, excluded from two recent studies conducted by Rohila and Devi.

Table 7. Average frequency content of each ISC.

ISCs	Mean IF±SD	Band
ISC4	0.0219 ± 0.019	VLF
ISC3	0.0821 ± 0.0312	LF
ISC2	0.182 ± 0.0532	HF
ISC1	0.44 ± 0.0387	VHF

Table 8. Comparison of the proposed method and some older classification method.

Author	Technique for extracting features	Separation validity	Prediction time frame (accuracy)	Prediction time frame (specificity)
Acharya (2015)	SaE, approximate entropy, fractal dimensions, correlation dimensions	SCD- Normal	Four minutes before: 86.8%	4 minutes before: 88.89%
Fujita (2016)	fuzzy entropy, tsallis entropy, Renyi entropy, and energy	SCD- Normal	Four minutes before: 94.7%	4 minutes before: 94.4%
Khazaei (2018)	increment entropy and recurrence quantification analysis-based features	SCD- Normal	Six minutes before: 95%	6 min before: 95%
Ebrahimzadeh (2019)	Poincaré plot, DFA, Frequency-time analysis, standard deviation and mean of all RR intervals, etc,	SCD- Normal	For thirteen minutes averagely: 90.18%	For 13 minutes averagely: 85.71%
Devi (2019)	Three features of the Poincare plots, SaE, 4 features extracted from DFA	Normal- CHF-CAD	ten minutes before: 83.33%	Non mentiond
Shi (2020)	Measuring the entropies of Fuzzy, Rényi, Dispersion, improved multiscale permutation, and Renyi distribution	Normal- SCD	fourteen minutes before: 96.1%	14 minutes before: 94.4%
Rohila (2020)	DFA, Poincaré plot, s-transform based features	Normal- SCD-CHF -CAD	Dividing 1 h signal of HRV before SCD into 12 segments of 5 minutes duration: 91.67%	Dividing one-hour signal of HRV prior to SCD into twelve segments of 5 minutes duration: 94.64%
Proposed method	An approach that incorporates LCD-TEO, SaE, TE, and the fluctuations in these features over different time frames.	Normal-SCD-CHF- CAD-other cardiac patients	15 minutes before 86.84%	15 minutes before: 89.47% for patients. for normal, CAD and CHF patients respectively: 100%, 95.6%, 93.3%.

When comparing the results, it is evident that our method outperforms other methodologies in discriminating normal subjects from SCDs, achieving a 100% success rate.

Devi and Rohila attempted to differentiate SCD patients from normal subjects and other cardiac patients in the cited studies. The most extensive investigation in this regard was carried out by Rohila. In his research, patients with CAD and CHF were included alongside healthy subjects.

As mentioned, various factors are effective in the occurrence of SCD and its mechanism is unknown. Consequently, since only a few subclasses leading to SCD were examined in their study, the performance of their algorithm is limited to these subclasses only. Moreover, according to their results, there are no changes in the cardiac signals of people with SCD in the one hour before death. This is in contrast to the definition of SCD, which means death within less than one hour from the beginning of symptoms.

Increasing the duration of SCD prediction prior to the occurrence is evidently one of the objectives of the research undertakings in this domain. Of course, this increase in time should be accompanied by an increase in the ability to distinguish the signals of subjects with SCD from other patients. It must be acknowledged that all the prediction algorithms do contain a substantial margin of error when confronted with signals resembling those exhibited by individuals with SCD.

As previously stated, in all previous studies, the cardiac signals of one or more groups of patients have been compared with the signals of people with SCD. To alleviate the limitation on methodology performance, the SCD signals were uniquely compared at various segments in the current investigation. Our algorithm is based on examining the changes in the signal of SCD individuals (after decomposing HRV signals, features such as TE and SaE) across various segments. This approach enables the proposed

method to distinguish the signal of patients with SCD from that of additional patient populations. Here, instances of no significant changes over time, are regarded as solely unhealthy signals. To put it another way, the proposed algorithm identifies the pattern of heart predisposition to SCD through the monitoring of the alteration procedure. Consequently, our analysis is not confined to any subclass of cardiac disease, which is a substantial benefit of the suggested method.

Furthermore, the suggested approach may not achieve optimal performance in terms of specificity and accuracy 15 minutes prior to the occurrence when compared to certain studies listed in Table 8. Except for normal subjects, we contend that the presented methodology offers a considerably greater degree of specificity than the current approaches when it comes to managing a wide variety of patients. The cause for this is that the problem becomes more difficult as the number of groups incorporated in the classification increases. Neglecting this issue may result in the misinterpretation of the performance of classification.

However, the provided algorithm predicts the VF 15 minutes before the event, which is completely consistent with the definition of sudden cardiac death, which refers to death in less than 1 hour from the onset of clinical symptoms. This interval affords the treatment staff sufficient time to execute suitable clinical procedures. Hence, the methodology is useful for clinical examinations.

Finally, it should be mentioned that all previous studies, as well as the present study, are based on determining the time of ventricular fibrillation, which is only one of the causes of SCD. To continue working in this field, it is suggested that other causes of SCD, such as bradyarrhythmia and pulseless electrical activity, should be studied separately.

3.3. Limitations

There are certain limitations regarding this study that are worth mentioning. First of all, the algorithm scans fluctuations in the HRV signal, typically occurring in a time frame of 15 to 25 minutes prior to the event. Hence, if we use signals from SCD patients just 5 minutes before it happens, the neural network cannot tell the difference. Therefore, the detection of SCD will go undiscovered. Then, we only lookat 20 patients with SCD. If we had more patients, the results would be different.

4. Conclusions

This study proves that significant alterations in the SCD subjects' 4th sub-signal take place approximately 15 to 25 minutes prior to the occurrence of the event. These changes involve a quick increase in information from the 4th to the 1st sub-signal during the 4th and 5th time periods. Moreover, there is a significant decrease in the SaE of the signal's instant energy of the 4ths ISC in this period. The suggested method uses how features change over time as a new aspect as well as evaluating properties based on LCD-TEO-Entropy. Compared to other methods, it shows greater reliability when faced with new signals.

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