An efficient approach for early prediction of Sudden Cardiac Death using two-stage feature selection and Gradient Boosting classification

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Abstract. Sudden cardiac death (SCD) is one of the leading causes of death worldwide, resulting in unpredicted loss of heart function. This complex problem occurs in people with or without a history of cardiac illness. The symptoms of SCD start 1 hour prior to its onset. The early detection of SCD may save many lives around the world. Hence it is vital to develop an accurate and precise method for identifying individuals at risk of developing SCD. This paper presents an efficient methodology for the early prediction of SCD using heart rate variability (HRV) and wavelet transform analysis by comparing diseased and non-diseased subjects. To accomplish this, the ECG signals of Normal sinus rhythm (NSR), Sudden cardiac death (SCD), and coronary artery disease (CAD) subjects were collected and pre-processed. HRV signals were derived from the ECG signal to extract various time domain, frequency domain, and non-linear method-based features. These features along with wavelet features and statistical features were considered for the selection of significant features. In this work, a two-stage feature selection method is proposed based on mutual information (MI) and recursive feature elimination (RFE) along with gradient boosting (GB) classification for accurately detecting SCD. Using the proposed MI-RFE-GB scheme, we achieved SCD detection 1 hour before its onset with accuracy, sensitivity, specificity, and precision at 97.60 %, 97.54%, 98.80%, and 97.59 % respectively. The experimental results of the proposed scheme demonstrate the superiority over state-of-the-art methods. However, the current study can be extended using various cardiac disease datasets that cause for the development of SCD.

Keywords: Artifact correction, heart Rate Variability, wavelet transform, gradient boosting classifier, feature selection.

1. Introduction

According to World health organization (WHO) statistics, cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, taking 17.9 million lives annually

[1]. Electrocardiogram (ECG) is a non-invasive golden standard to identify the heart's electrical activity. Sudden cardiac death (SCD) is a severe cardiac disorder caused for unconsciousness and death within a few minutes due to the development of irregularities in the electrical conduction system of the heart. SCD is responsible for 25% of deaths among CVDs [2]. SCD is associated with patients with or without a history of cardiac diseases. The common symptoms of SCD start one hour prior to its onset [3]. The survival rate after the incidence of SCD is about 10% due to a lack of early prediction techniques. The main cardiac abnormalities which are responsible for the onset of SCD are coronary artery disease (CAD), ventricular fibrillation (VF), ventricular flutter (VFL), ventricular tachycardia (VT) and bradyarrhythmia etc [4]. Individuals with a history of CAD are more susceptible to developing SCD due to the thinning of the coronary arteries caused by the obstruction of blood flow to the heart muscle due to the build-up of plaque in the arteries. Delaying the CAD diagnosis leads to the body receiving inadequate oxygen, which can result in cardiac arrest and heart failure [5]. Many authors proposed different strategies for the early prediction of SCD using ECG and HRV signals.

Heart rate variability (HRV) provides the most significant electrophysiological marker used to identify cardiovascular problems. HRV refers to the fluctuation in the time interval between successive heartbeats. The autonomic nervous system (ANS) is significantly influenced by the transitory signal known as HRV, which is acquired from the electrocardiogram's RR intervals [6]. A healthy heart requires higher HRV to react to environmental changes and balance the two ANS branches.

The wavelet transform is a strong time–frequency analysis and signal coding method for complicated nonstationary data. Wavelets record both short-term, high-frequency, and longer-term, low-frequency information. The approach is excellent for analyzing transients, aperiodicity, and other non-stationary signal properties because tiny variations in signal shape may be emphasized over the scales of interest [7]. The multiplicity of wavelet functions allows the most suited one to be picked for the signal under study.

The main contributions of this study are (i) the development of an accurate strategy for early prediction of SCD by classifying NSR SCD and CAD subjects. (ii) Multistage feature selection algorithm is proposed to identify the best subset of features using mutual information- recursive feature elimination along with gradient boosting classification algorithm. (iv) The proposed method includes the fusion of HRV, wavelet, and statistical features that provides enhanced classification results which could be helpful in the field of early prediction of SCD.

2. Methods and Materials

2.1 Data

In this study, three datasets were examined for classification, a total of 58 ECG signals acquired from the physioBank database. To maintain the balance among the dataset sampling rate of the NSR dataset is up-sampled to 250 Hz. The symptoms of SCD start 1 hour before its onset, so a 1-hour signal is acquired for each subject randomly chosen from the 24-hour data for NSR and CAD [8]. For SCD, data is collected one hour prior to the commencement of VF. The collected 1-hour ECG signal is further segmented into 12 non-overlapping segments for short-term analysis of HRV. The complete description of the dataset is mentioned in Table 1.

Table 1. The complete description of the dataset used in the study of SCD prediction.

Dataset	No. of subjects	Sampling frequency	No. of segments	Gender and Age (range)
NSR	18	128 Hz (Up-sampled to 250 Hz)	216	5 males (26-45) 13 females (20-50)
SCD	20	250 Hz	240	10 males (34-80) 8 females (30-89) 2unknown
CAD	20	250 Hz	240	16 males (44-73), 4 females (62-67)

2.2 Pre-processing

In this stage, the ECG signal of a 5-minute duration is denoised using the sym6 discrete wavelet transform (DWT) [9]. The denoised signal is used to identify the QRS peak detection using wavelet transform [10]. The HRV signal is derived from the ECG signal with the help of Wavelet-based R peak detection algorithm. Further, it is processed for artifact correction to remove ectopic beats, extra beats, and missing beats. The artifact correction algorithm is developed using median filtering and the threshold value. The steps involved in the correction algorithm followed as (i) The average RR interval value is calculated from the median filtered HRV signal. The 20 % of the average value is set as the threshold limit. (ii) Any RR interval greater than the average RR interval + threshold value is considered an artifact. (iii) Any RR interval less than the average RR interval - threshold value is considered an artifact. The identified artifact is corrected by using cubic spline interpolation. The effectiveness of artifact correction of a 5-minute HRV signal is represented in Fig 1.

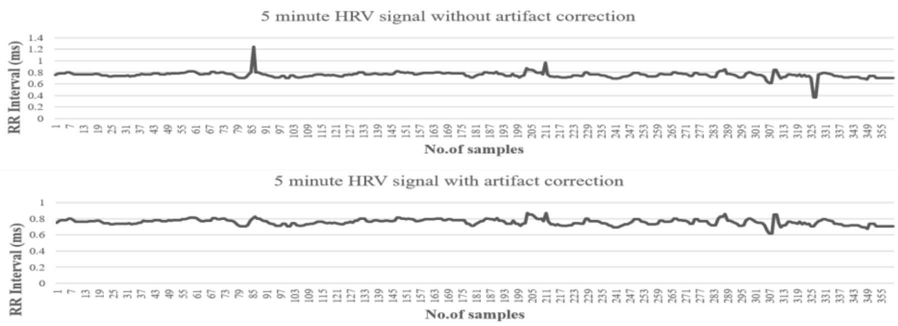

Fig 1. Comparison of 5-minute HRV signal with and without artifact correction.

Block diagram representation of the proposed method for early prediction of sudden cardiac using two-stage feature selection algorithm is mentioned in Fig 2

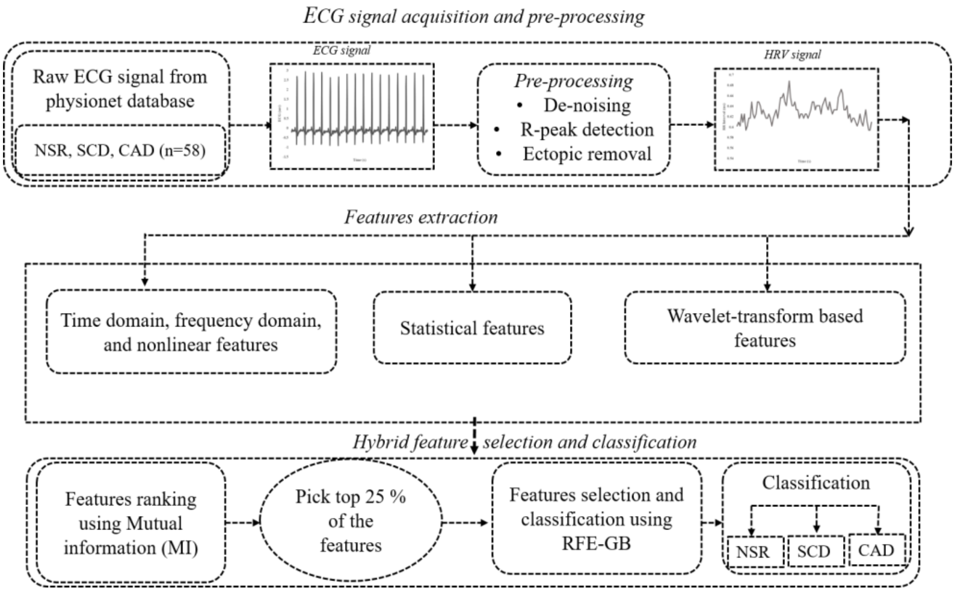

Fig 2. Block diagram representation of proposed scheme for early prediction of SCD using HRV features and MI-RFE-GB based feature selection.

2.3 Features extraction

Heart rate variability features:

In this study, 35 features extracted from the HRV signal can be divided into three methods: time domain, frequency domain, and nonlinear methods. The statistical and geometric methods applied in time domain analysis to retrieve the features and the list is Mean RR (ms), SDNN (ms), Mean HR (beats/min), SD HR (beats/min), Min HR (beats/min), Max HR (beats/min), RMSSD (ms), NN50 (beats), pNN50 (%), RR triangular index, Stress index, TINN (ms) Max RR (s), Min RR(s), and Mean absolute deviation. Fourier transform techniques are used to retrieve the frequency-domain features, and these measurements assist in determining the relative or absolute power distribution in the four frequency bands. The list of frequency domain features given as VLF (Hz), LF (Hz), HF (Hz), VLF (ms^2), LF (ms^2), HF (ms^2), VLF (log), LF (log), HF (log), VLF (%), LF (%), HF (%), LF (n.u.), HF (n.u.), Total power (ms^2), Max power spectrum, Maximum frequency (Hz) and LF/HF ratio. In nonlinear methods, Poincare plots, entropy-based, and fractal-based measures are used to retrieve features. The list of nonlinear features is SD1 (ms), SD2 (ms), SD2/SD1 ratio, Approximate entropy (ApEn), Sample entropy (SampEn), short-term fluctuation alpha 1, and short-term fluctuation alpha 2 [11].

Discrete wavelet- transform based features:
DWT decomposition level 8 was set using the daubechies wavelet of order 4 (db4) as illustrated in Fig. 4. The wavelet features extracted from the DWT decomposition level 8 are absolute mean, Energy, standard deviation and variance. The approximation and detail coefficients shown in Fig 3.

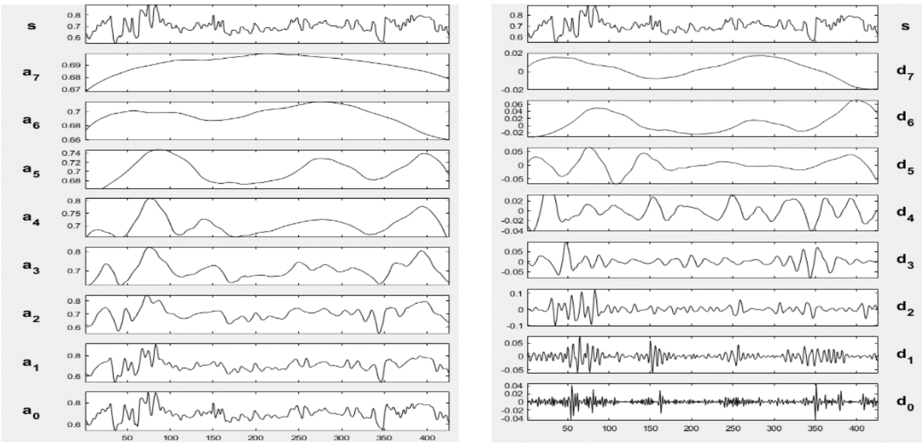

Fig 3. DWT applied on HRV signal up to level 8 using daubechies4 for 3 classes.

Other Statistical features:
The derived HRV signals are used to extract the extra statistical features such as Skewness, Kurtosis, Interquartile range, and Histogram.

2.4 Feature selection

This study proposes a two-stage feature selection scheme for selecting best significant features using Mutual information (MI) and Recursive feature elimination (RFE) methods.

a. Mutual Information based FS

The concept of feature selection is extensively used in statistics and machine learning, Previous to developing a model, it includes identifying a subset of pertinent features. Since the 1970s, the selection of features has been a growing and developing area of research. It has successfully removed redundant and irrelevant features, increased the performance of learning tasks, and improved abilities to understand learning methods' outcomes. According to information theory, the degree of uncertainty in X caused by knowing anything about Y is called mutual information [12].

$$I(X; Y) = \sum_{X,y} P(x,y)\, log \frac{P(x,y)}{P(x)P(y)} \quad (1)$$

where the marginal probability distribution functions for X and Y are p(x) and p(y), respectively, and P (x, y) is the joint probability distribution function of X and Y.

b. Recursive Feature Elimination (RFE)

A recently created feature selection technique for problems with limited sample classification is called recursive feature elimination (RFE). It is a successful method for choosing features for limited samples. By eliminating the least significant features whose removal would have the least impact on the training mistakes, RFE tries to increase the generalization performance. Random forest algorithm, which has been shown to generalize well even for small sample classification, is also closely related to RFE. RFE is a kind of backward feature elimination that works by iteratively removing features based on decision- and discrimination-related criteria. The features with the highest rankings are retained, while those with the lowest rankings are eliminated. The process is continued until the required features are achieved, or the performance can no longer be enhanced [13][14]. The MI-RFE-GB scheme used in this research is a two-stage scheme, combining the mutual information as a filter with Recursive Feature Elimination as wrapper technique for selecting features before attempting to run a classification model. The block diagram representation for the experimental development of the two-stage feature selection method is mentioned in Fig 2.

2.5 Classification

Gradient boosting is a type of machine learning that can be used for tasks like regression and classification. It gives a prediction model in the form of a group of weak prediction models, usually decision trees. Gradient-boosted trees are the name of the algorithm that is made when a decision tree is a weak learner [15]. It usually does better than a random forest. A gradient-boosted trees model is built in stages, like other boosting methods. However, it is more general than the other methods because it can be used to optimize any loss function that can be differentiated. In this study, Gradient boosting and a group of classifiers used for classification.

3. Results

This study developed a novel methodology for implementation for early prediction of SCD by classifying NSR, SCD, and CAD subjects. 35 HRV features were extracted from 696 HRV signals of 3 classes with a duration of 5 minutes for each signal. The feature selection analysis has been implanted on these 87 features for SCD detection analysis. The mean and standard deviation values of each feature are mentioned in Table 2.

Table 2. Mean and SD values of the time domain, frequency domain, and nonlinear methods of three classes.

Time domain features			
HRV feature	NSR	SCD	CAD
Mean RR (ms)	744.14 ± 127.80	849.77 ± 222.31	856.21 ± 136.50
SDNN (ms)	35.17 ± 18.65	85.60 ± 57.34	31.79 ± 14.97

Mean HR (beats/min)	82.99 ± 14.31	75.42 ± 19.39	71.89 ± 11.711
Min HR (beats/min)	69.77 ± 12.31	63.58 ± 16.41	64.35 ± 8.94
Max HR (beats/min)	99.55 ± 16.14	104.36 ± 41.98	82.65 ± 16.13
RMSSD (ms)	**32.59 ± 21.38**	**114.77 ± 78.24**	**23.86 ±14.11**
NN50 (beats)	**39.27 ± 36.78**	**133.96 ± 107.89**	**8.10 ± 9.27**
pNN50 (%)	10.60 ± 11.57	39.55 ± 29.41	5.01 ± 5.77
SD HR (beats/min)	3.79 ± 1.49	9.84 ± 8.05	2.89 ± 1.90
RR triangular index	8.54 ± 3.44	12.57 ± 9.80	6.81 ± 2.42
TINN (ms)	182.66 ± 85.21	451.25 ± 234.66	151.32 ± 84.19
Stress Index	14.32 ± 6.08	8.15 ± 5.42	15.59 ± 6.083
Max RR (s)	0.981 ± 0.14	0.97 ± 0.14	0.97 ± 0.13
Min RR(s)	0.72 ± 0.14	0.72 ± 0.14	0.71 ± 0.14
Mean absolute deviation	0.04 ± 0.02	0.04 ± 0.02	0.04 ± 0.02
Frequency domain features			
VLF (Hz)	0.035 ± 0.00	0.03 ± 0.00	0.03 ± 0.00
LF (Hz)	0.09 ± 0.02	0.08 ± 0.03	0.07 ± 0.02
HF (Hz)	0.21 ± 0.07	0.25 ± 0.03	0.17 ± 0.03
VLF (ms^2)	88.02 ± 129.81	330.42 ± 677.83	112.00 ±150.31
LF (ms^2)	831.75 ± 910.35	3093.9 ± 5716.17	754.73 ± 938.77
HF (ms^2)	619.5 ±1754	4561.61±7705.95	249.97 ± 416.29
VLF (log)	2.76 ± 2.31	4.36 ± 1.91	4.15±1.12
LF (log)	6.20 ± 1.11	6.69 ± 1.82	6.12 ± 1.04
HF (log)	5.50 ± 1.22	7.12 ± 1.83	4.79 ± 1.17
VLF (%)	5.61 ± 6.41	5.18 ± 4.82	12.05 ± 7.65
LF (%)	60.91 ± 15.22	37.73 ± 13.50	67.51 ± 12.16
HF (%)	33.41 ± 17.18	56.84 ± 15.94	20.40 ±11.71
LF (n.u.)	**64.97 ± 16.94**	**40.21 ± 15.31**	**76.91 ± 12.61**
HF (n.u.)	34.96 ± 16.93	59.54 ± 15.21	23.06 ± 12.611
Total power (ms^2)	1539.94 ± 2395.62	7995.35± 13585	1116.94 ± 1387.53
LF/HF ratio	2.75 ± 2.34	0.83 ± 0.71	4.80 ± 3.66

Max power spectrum	0.38 ± 0.24	0.39 ± 0.25	0.39 ± 0.25
Maximum frequency	**16.34 ± 6.74**	**16.06 ± 7.15**	**16.64 ± 8.01**
Nonlinear methods features			
SD1 (ms)	**23.07 ± 15.14**	**81.29 ± 55.44**	**16.92 ± 10.01**
SD2 (ms)	43.63 ± 22.44	87.99 ± 61.74	41.28 ± 19.27
SD2/SD1	1.97 ± 0.58	1.12 ± 0.36	2.60 ± 0.67
Approximate entropy (ApEn)	**1.17 ± 0.08**	**0.98 ± 0.21**	**0.80 ± 0.07**
Sample entropy (SampEn)	1.64 ± 0.26	1.30 ± 0.58	1.20 ± 0.26
Short-term fluctuations, alpha 1	**1.13 ± 0.24**	**0.69 ± 0.22**	**1.32 ± 0.22**
Long-term fluctuations, alpha 2	0.33 ± 0.2	0.34 ± 0.16	0.42 ± 0.16

From the Table 2, it was clear that 7 out of 40 features were selected using MI-RFE-GB feature selection scheme. The selected features RMSSD (ms), NN50(beats), SD1 (ms) have highest mean and SD values in case of SCD compared to NSR and SCD. The features LF (n. u), Short-term fluctuations alpha1and Maximum frequency have highest values of mean and SD in case of CAD compared to NSR and SCD.The remaining selected feature approximate entropy has highest values of mean and SD in case of NSR compared to SCD and CAD.

Table 3. Mean and SD values of other statistical features.

Statistical features	NSR	SCD	CAD
Skewness	-0.26 ± 0.86	-0.20 ± 0.84	
Kurtosis	0.93 ± 3.53	0.85 ± 3.36	0.93 ± 3.42
Interquartile range	**0.07 ± 0.04**	**0.07 ± 0.04**	**0.06 ± 0.04**
Histogram_7	4.03 ± 14.07	4.96 ± 17.94	9.11 ± 34.91
Histogram_8	67.26 ± 81.85	69.86 ± 82.56	69.40 ± 82.23
Histogram_9	80.33 ± 62.22	81.26 ± 63.56	79.65 ± 64.21

From the Table 3, it was clear that 1 out of 6 other statistical features was selected using MI-RFE-GB feature selection scheme. The selected feature Interquartile range has highest mean and SD values in case of NSR and SCD compared to CAD.

Table4. Mean and SD values of absolute mean, energy, standard deviation and variance of detail coefficients d0-d7.

Class	Feature	D0	D1	D2	D3	D4	D5	D6	D7
NSR	Absolute mean	**0.0031 ± 0.001**	0.009 ± 0.003	0.017 ± 0.006	0.026 ± 0.009	0.03 ± 0.01	0.04 ± 0.01	**0.06 ± 0.02**	0.07 ± 0.02
	Energy	0.04 ± 0.01	0.07 ± 0.02	0.115 ± 0.03	0.14 ±0.03	0.17 ± 0.04	0.20 ± 0.05	0.24 ± 0.06	0.27 ± 0.07
	Standard deviation	0.04 ± 0.01	0.07 ± 0.02	0.113 ± 0.03	0.14 ±0.03	0.17 ± 0.04	0.20 ± 0.05	0.23 ± 0.06	0.26 ± 0.07
	Variance	0.001 ± 0.001	0.006 ± 0.004	0.013 ± 0.007	0.022 ± 0.01	0.032 ± 0.01	0.04 ± 0.02	0.05 ± 0.03	0.07 ± 0.04
SCD	Absolute mean	**0.003 ± 0.002**	0.001 ± 0.008	0.026 ± 0.015	0.04 ± 0.02	0.05 ± 0.03	0.07 ± 0.04	**0.09 ± 0.05**	0.11 ± 0.06
	Energy	0.07 ± 0.05	0.12 ± 0.08	0.16 ± 0.09	0.20 ± 0.10	0.24 ± 0.12	0.28 ± 0.14	0.32 ± 0.15	0.36 ± 0.17
	Standard deviation	0.07 ± 0.05	0.12 ± 0.07	0.16 ± 0.09	0.20 ± 0.10	0.23 ± 0.11	0.27 ± 0.13	0.31 ± 0.14	0.34 ± 0.16
	Variance	0.008± 0.01	0.02 ± 0.03	0.03 ± 0.04	0.05 ± 0.05	0.07 ± 0.07	0.09 ± 0.09	0.11 ± 0.11	0.14 ± 0.14
CAD	Absolute mean	**0.008 ± 0.002**	0.02 ± 0.007	0.04 ± 0.01	0.06 ± 0.02	0.09 ± 0.03	0.12 ± 0.04	**0.16 ± 0.05**	0.19 ± 0.06
	Energy	0.06 ± 0.01	0.11 ± 0.02	0.17 ± 0.04	0.22 ± 0.05	0.27 ± 0.06	0.33 ± 0.07	0.38 ± 0.09	0.43 ± 0.10
	Standard deviation	0.06 ± 0.01	0.11 ± 0.02	0.16 ± 0.03	0.21 ± 0.04	0.26 ± 0.05	0.30 ± 0.06	0.35 ± 0.07	0.39 ± 0.08
	Variance	0.004± 0.002	0.01± 0.007	0.02 ± 0.01	0.04 ± 0.02	0.07 ± 0.03	0.09 ± 0.04	0.12 ± 0.05	0.16 ± 0.07

From the Table 4, it was clear that 2 out of 36 features were selected using MI-RFE-GB two-stage feature selection. The selected features Wavelet absolute mean_0 and Wavelet absolute mean_6 have highest mean and SD values in case of CAD compared to NSR and SCD. Box plot representation of all selected features using the MI-RFE-

GB method is shown in Fig 5. The selected features using the proposed two-stage FS algorithm are highlighted in table 2, 3 and, 4 respectively.

The current study proposes MI-RFE-GB procedures to evaluate significant features for accurate SCD prediction results. The steps involved in the development of two-stage feature selection are followed as, Step 1: Initially, a mutual information-based technique is used to rank all 86 features. Fig 3 indicates the descending ranking order of the features. Step 2: Pick the top 25% of the features for further feature selection and classification using the RFE-GB technique. Step 4: The MI-RFE-GB method was used to choose find the best combination of features along with a classification accuracy of 97.60%. Step 5: The list of selected features are Short-term fluctuations, alpha 1, Approximate entropy (ApEn), SD1 (ms), NN50 (beats), RMSSD (ms), Interquartile range, Wavelet absolute mean_0, Maximum frequency, LF (n.u.) and Wavelet absolute mean_6.

The performance of MI-RFE-GB is compared with various feature selection schemes such as RFE-RF, RFE-GB, MI-RFE-GB and MI-RFE-RF based feature selection is mentioned in Fig 3.

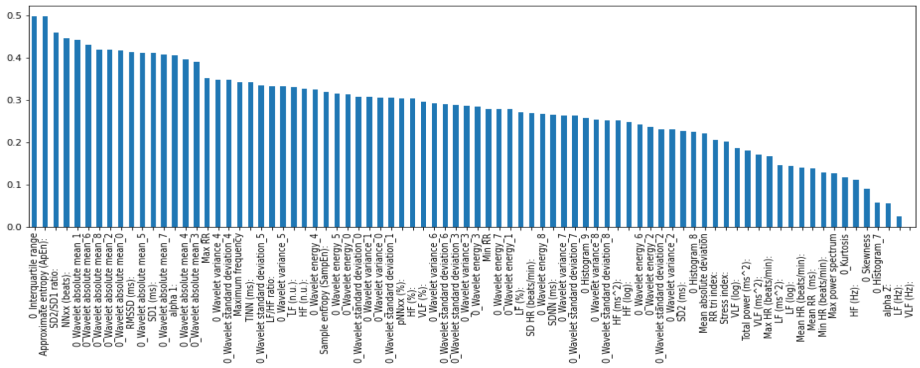

Fig 3. Features ranking in descending using Mutual information (MI).

The comparison of performance analysis RFE-GB and RFE-RF with and without MI is mentioned in figure 4.

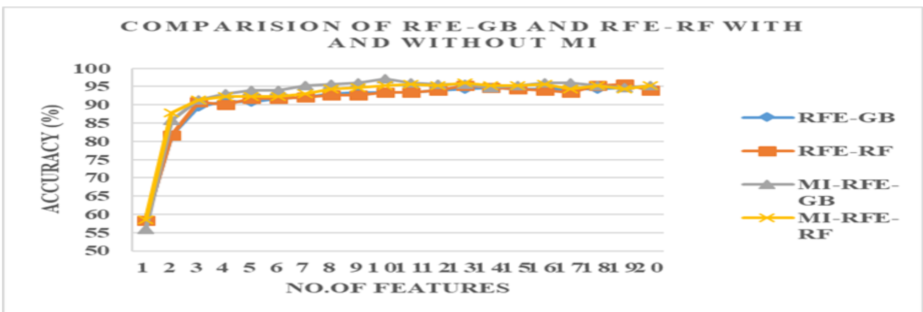

Fig 4. Comparison of RFE-GB and RFE-RF with and without Mutual information stage.

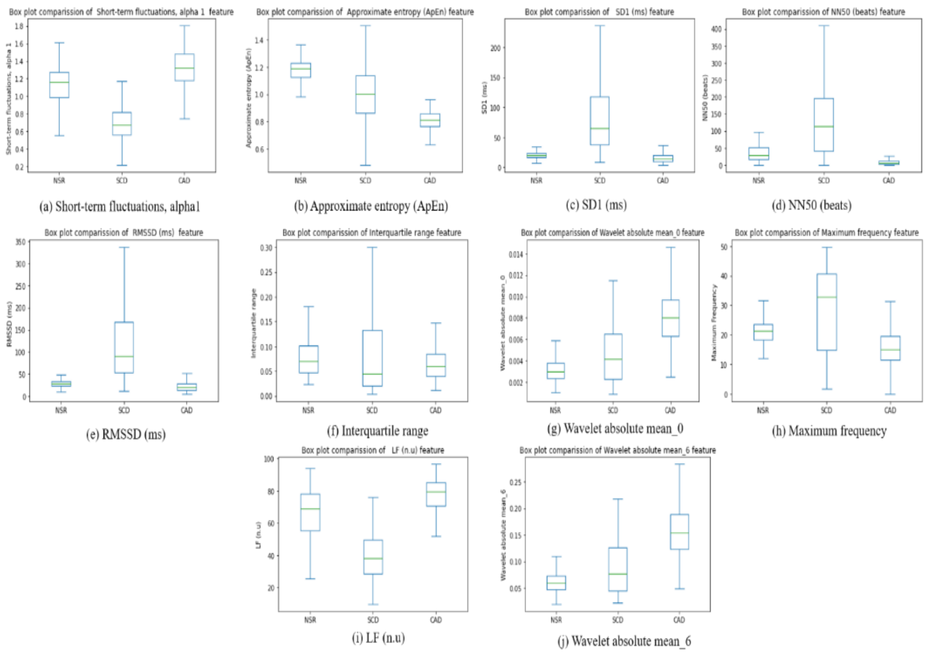

Fig 5. Box plot representation of MI-RE-GB based selected features (a) Short-term fluctuations, alpha 1, (b) Approximate entropy (ApEn), (c) SD1 (ms), (d) NN50 (beats), (e) RMSSD (ms), (f) Interquartile range, (g) Wavelet absolute mean_0, (h) Maximum frequency, (i) LF (n.u.) and (j) Wavelet absolute mean_6.

Table 5. Comparison of feature selection models in terms of number of features vs accuracy.

Feature selection method	Number of features	Accuracy (%)
HRV features	40	94.74
Wavelet transform features	36	85.86
RFE-RF	28	95.65
RFE-GB	20	95.25
MI-RFE-GB	10	97.13
MI-RFE-RF	13	96.1

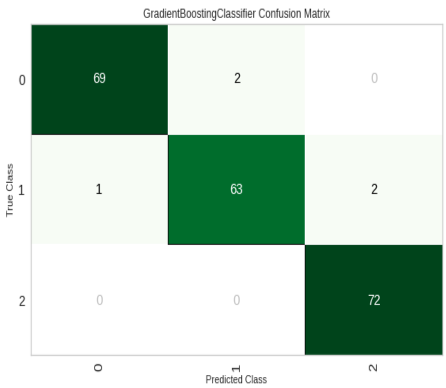

Fig 6. Confusion matrix for the classification using selected features (MI-RFE-GB).

4. Discussion

This research proposes a new methodology for the early detection of SCD using HRV features. Initially, ECG signals of classes were taken from the physioBank database. Wavelet transform is used to denoise the ECG signal, i.e., to remove the baseline wandering and powerline interface, etc. Wavelet based R peak detection using Hilbert transform algorithm is used to derive QRS peak from the given signal. Heart rate variability (HRV) signal is derived from a denoised ECG signal may contain different artifacts such as extra beat, missing beat, ectopic peak, etc., which were corrected using a artifact correction algorithm. The artifact correction algorithm has two steps for determination of the artifact i.e., (i) Median filtering is implemented on the HRV signal (ii) Take the average of the HRV signal after median filtering (iii) Setting a threshold value for RR interval gives artifact confirmation whether the signal is having or not. The complete explanation of the artifact correction algorithm is mentioned in section 2. The pre-processed HRV signal is used to extract the features using the time domain in which 15 features were extracted using statistical and geometric methods, the frequency domain in which 18 features were derived using a Fourier transform-based tool, and nonlinear methods in which 7 features were extracted from HRV signal using Poincare plot analysis, entropy and detrended based fluctuations. Wavelet transform based features such as absolute mean, energy, standard deviation and variance of 8 level decomposition signals were calculated. The extracted features were further used for the classification, and the performance evaluation of different classification models was tested using all features without feature selection, which caused more computational time and deduction in accuracy. Feature selection is an important task used to find the optimal set of features that produces good classification accuracy with less computational time. In this study, the proposed two-step feature selection technique using mutual information recursive feature elimination with Gradient boosting classifier (MI-RFE-GB), which produced a classification accuracy of 97.60% with ten selected features.

This study uses two popular machine learning algorithms i.e. Random forest (RF) and Gradient boosting classifiers. Table 5 indicates the comparison of performance analysis of ensemble of features and various combinations of subset of features. The individual performance of HRV features, Wavelet decomposition features and statistical features has produced a classification accuracy of 94.74%, and 85.86% and 96.17% with 40, 36 and 82 features respectively. The proposed method of ensemble of features along with feature selection has produced superior results than individual performance of different feature combinations.

Most of the previous studies for early detection of SCD have taken two classes such as NSR and SCD. The detailed description of comparison of proposed method with state-of the art as followed as Acharya et al have developed a SCD detection methodology by extracting nonlinear features from the ECG signal. Using decision tree (DT) and Support vector machine (SVM), authours have predicted SCD 4 minute before its onset with an accuracy of 86.8% [16]. Fujitha et al have developed a SCD detection methodology by extracting nonlinear features from the HRV signal. Using Support vector machine (SVM, authours have predicted SCD 4 minute before its onset with an accuracy of 94.7% [17]. M khazaei et al have predicted SCD 6 minutes before with an accuracy of 95% using HRV signal and RQA analysis [4]. Compared to prior studies, the current study has gained importance by increasing the SCD prediction time, no, of classes (three), and new feature selection algorithm. The present study of early detection of SCD is compared with state-of-the-art techniques.

Table 6. Comparison of proposed method with state of the art.

Author (year)	Type of signal	Prediction time	No. of classes	Accuracy (%)
Acharya et al [16]	ECG	4 minutes before SCD	NSR SCD	92.11
Fujita et al [17]	HRV	4 minutes before SCD	NSR SCD	94.7
M Khazaei (2018) [4]	HRV	6 min Before	NSR SCD	95
Ebrahimzadeh et al [18]	HRV	13 min before	NSR, SCD	84.24[18]
Devi et al [19]	HRV	10 min before	NSR, SCD, CHF	83.33
Manhong et al [20]	HRV	14 minutes before SCD	NSR SCD	94.7
Present study	HRV	**1 hour before**	**NSR, SCD, CAD**	**97.60**

5. Conclusion

The present study suggests a unique method for assessing SCD risk by analyzing HRV and wavelet transform in healthy and unhealthy cardiac conditions. According to available data, the experiment's findings showed a significant difference in extracted features between the SCD and non-SCD groups. This illustrates that even though other cardiac abnormalities including CAD may be ruled out, SCD risk can be identified. Linear (time and frequency domain) and nonlinear features were retrieved from HRV signals, and wavelet coefficient features (D0-D7) and statistical features. The most effective set of features for classification was found using the developed MI-RFE-GB hybrid feature selection method. The accuracy, sensitivity, specificity, and precision of the proposed technique are 97.60%, 97.54%, 98.80 %, and 97.59% respectively for classifying normal and abnormal states. The suggested technique may be included in automated diagnostic tools and continuous monitoring systems to increase survival rates by accurately predicting SCD at an early stage. The present study has limitations on number of classes considered for the early detection of SCD. The present study can be extended in future by adding more number of classes, prediction time and various methods such as time frequency analysis, deep learning etc.

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