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Intelligent prediction of sudden cardiac death based on multi-domain feature fusion of heart rate variability signals

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Abstract

Background and objective: Sudden cardiac death (SCD) is one of the leading causes of death in cardiovascular diseases. Monitoring the state of the heart in real time and giving early warning of possible dangers by using ambulate electrocardiogram signals are the keys to prevent cardiovascular death. However, due to the diversity inducing factors of SCD and great individual differences, accurate prediction of SCD using electrocardiogram is a hard task, especially applied in portable electrocardiograph.

Methods: This paper proposed a multi-domain features fusion algorithm to predict SCD. Heart rate variability (HRV) signals was used to investigate the characters of SCD. A multiscale variation feature extracted from multiscale poincare plots was proposed to demonstrate the dynamic changes of HRV along different scales. A time-domain feature, Shannon entropy and this multiscale variation feature were combined by using SVM classifier to classify SCD. HRV signals from different time periods prior to SCD onset were used to test the effectiveness of the SCD prediction algorithm. And the dynamic variation characteristics of SCD prediction accuracy for each minute were also studied.

Results: In the prediction of SCD using the 70-min HRV signals before the onset of SCD, the average prediction accuracy only using the multiscale variation feature reached to 85.83%, which verified the effectiveness and high specificity of this multiscale variation feature. By combining time domain, Shannon entropy and the multiscale variation feature, the average prediction accuracy was improved to 91.22%. Through fusing multi-domain feature extracted in this paper, the advance prediction time was increased to 70 min before the onset of SCD.

Conclusions: A feature with high sensitivity and specificity is proposed to predict SCD. By fusing multi-domain features of HRV signals, a high prediction accuracy is achieved and the advance prediction ability is improved. The algorithm is low computational complexity and easy to integrate into cardiovascular intelligent monitoring equipment, making the intelligent monitoring and real-time early warning of SCD becomes possible.

Keywords: Sudden cardiac death, Heart rate variability, Multiscale analysis, Feature fusion

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1 Introduction

Sudden cardiac death (SCD) refers to the sudden death caused by acute cardiac symptoms. The whole process usually occurs within 1 h. It is a sudden, fatal, and irreversible disease. In North America and Europe, SCD affects 50–100 out of every 100,000 people [1]. Although the primary cause of SCD is unknown, ventricular fibrillation (VF) is thought to be the initiating factor in approximately 20% of SCD episodes [2, 3]. When SCD occurs outside the hospital, only 1–2% of patients survive [4]. Therefore, the accurate prediction and timely early warning of SCD become very important, which could provide more treatment time to patients and improve the survival rate.

In recent years, the prediction of SCD using electrocardiogram (ECG) signals has been studied extensively. Murugappan et al. [5] predicted an impending sudden cardiac arrest (SCA) by exploring the morphological characteristics of the R-peak to T-end of 5 min ECG before the onset of ventricular fibrillation. By extracting four nonlinear features, the Largest Lyapunov Exponent, Hurst exponent, sample entropy, and approximate entropy, and classifying with a support vector machine, subtractive fuzzy clustering, and a neuro-fuzzy classifier, the average classification accuracy can reach 100%. Amezquita-Sanchez et al. [6] used a wavelet packet transform, homogeneity index, and an enhanced probabilistic neural network classification algorithm for ECG signals to predict SCD. The approach can predict the risk of SCD events within 20 min before onset, with an accuracy of 95.8%. Lai et al. [7] proposed a more effective and practical method based on the SCD index (SCDI), which was able to predict SCD within 30 min before the occurrence of SCD by using five classifiers with an average accuracy of 98.91% (k-nearest neighbor-KNN), 98.70% (support vector machine-SVM), 98.99% (decision tree-DT), 97.46% (Naive Bayes-NB), and 99.49% (random forest-RF). Vargas-Lopez et al. [8] achieved the prediction 25 min before the onset of SCD with an accuracy of 94.00% by combining empirical mode decomposition (EMD), nonlinear index, and neural network. Ebrahimzadeh et al. [9] applied a novel local feature subset selection method to extract nonlinear, time–frequency, and classical features from ECG signals, which could predict SCD 12 min before its onset with 83.88% accuracy. Lopez-Caracheo et al. [10] proposed a method to automatically predict SCD using ECG signals, fractal dimension (FD), and artificial neural networks, which achieved an average accuracy of 91.4% at 14 min before the onset of SCD.

Heart rate variability (HRV) is another important electrophysiological indicator for detecting cardiac abnormalities and is highly recommended in both clinical and non-clinical applications. HRV analysis also provides a noninvasive method for assessing cardiac autonomic control and is considered a strong independent predictor of acute myocardial infarction [11]. More importantly, HRV reduction is strongly associated with the risk of severe ventricular arrhythmias and SCD [12]. In this filed, Khazaei et al. [13] proposed a nonlinear feature extraction algorithm based on recurrence quantification analysis and increment entropy. By using classifiers such as decision tree, K-nearest neighbor, naive Bayes, and support vector machine, it can detect SCD 6 min before occurrence with an accuracy of 95%. Heng et al. [14] used linear and nonlinear features to detect VF and realized the detection 4 min before the onset of SCD by applying a support vector machine to the two nonlinear features, obtaining an accuracy, sensitivity, and specificity of 94.7%, 100%, and 88.9% respectively.

Ebrahimzadeh et al. [15] proposed a novel local feature subset selection method to predict SCD by selecting the optimal features from nonlinear, time–frequency, and classical features at each minute interval of the HRV signal. The algorithm could predict SCD 13 min before onset with an accuracy, sensitivity, and specificity of 84.28%, 85.71%, and 82.85% respectively. Shi et al. [16] proposed an automatic prediction method which combines ensemble empirical mode decomposition (EEMD) based entropy and classical linear (time domain and frequency domain) features. The accuracy, sensitivity, and specificity of this method were 96.1%, 97.5%, and 94.4% respectively 14 min before SCD occurred. Devi et al. [17] took heart failure patients and normal people as the control group, and achieved prediction 10 min before the occurrence of SCD by extracting linear, time–frequency, and non-linear features, with an average accuracy of 83.33%.

With the development of deep learning, its advantages for automatic feature extraction have been verified. SCD prediction algorithms based on deep learning have developed rapidly. Kaspal et al. [18] used a combination of a convolutional neural network (CNN) with a Recurrence Complex Network (RCN) to improve the accuracy of SCD classification, and achieved a classification accuracy of 90.60%. Haleem et al. [19] used a convolutional bidirectional long short-term memory neural network with an attention mechanism and a time-adaptive CNN to achieve 4-min ECG signal automatic detection of SCD with 100% accuracy. Although deep learning methods show certain advantages and can avoid complex mathematical abstraction or manual intervention and improve the computational efficiency of early prediction [20], their models have high computational complexity and require a large number of SCD ECG data for training, which is not easily integrated into portable devices.

SCD prediction using ECG signals is easily affected by individual morphological differences and noise. To solve this problem, multi-lead ECG signals are usually used, which will increase the computational burden. However, SCD prediction using HRV signals is too dependent on feature selection, and effective feature extraction is a difficult task. Due to the limited amount of SCD data, the application of deep learning methods in SCD prediction is very limited.

In view of the problems above, this paper proposes an intelligent prediction algorithm for SCD based on HRV signals. A multiscale variation feature of the HRV signal, which has very high sensitivity and specificity for characterizing the heart rate variation of patients at risk of SCD, is innovatively extracted. By fusing this feature, a time-domain feature, and a nonlinear entropy feature, accurate prediction of SCD is achieved and the advance prediction time is increased to 70 min before the onset of SCD. In this study, the HRV signal is used for analysis and a single-lead ECG acquisition device can meet the signal analysis requirements. The proposed algorithm has a very low computational complexity and is easy to integrate into portable ECG devices, making intelligent monitoring and real-time early warning of SCD becomes possible.

2 Materials and methods

The flowchart of the method is shown in Fig. 1. It mainly contains three parts: preprocessing and HRV extraction, feature extraction, and classification.

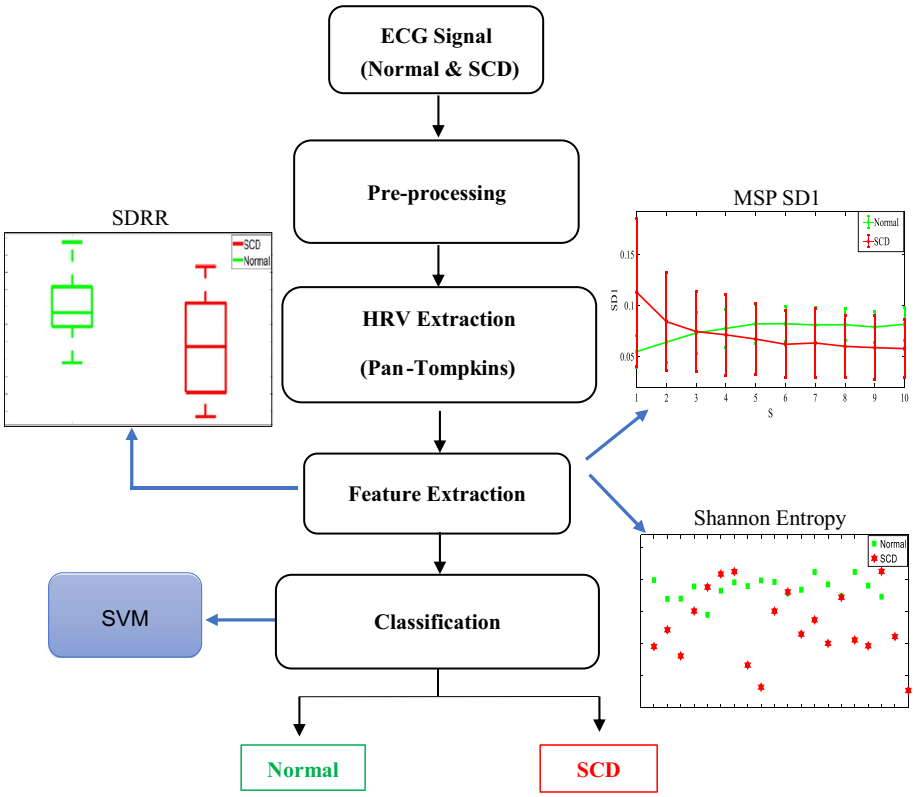


Fig. 1 The flowchart of proposed method

Table 1 Details of the data used in this work

Diagnosis	Total	Subjects features	Number of leads	Sampling rate (Hz)
Normal	18	13 females (age 20–50) 5 males (age 26–45)	1	128
SCD	23	8 females (age 30–89) 13 males (age 17–79) 2 sex unknown	1	250

2.1 Pre-processing and HRV signal extraction

This study uses ECG signals from the MIT-BIH SCD Holter database and the MIT-BIH Normal Sinus Rhythm database. Details of the data used in this work are shown in Table 1. The Normal Sinus Rhythm database includes 18 ECG signals without apparent arrhythmia at a sampling frequency of 128 Hz. The MIT-BIH SCD Holter database has ECG recordings of 23 SCD patients with a sampling frequency of 250 Hz. Only 20 SCD subjects are used in this study because the remaining three subjects did not experience VF episodes. In order to maintain the consistency of sampling frequency, the ECG signal of the SCD group is sampled at 128 Hz. In this study, 80-min ECG signals before the onset of sudden death are obtained from 24-h ECG recordings of SCD patients. Since the ECG signals of normal people are not affected by any pathology, 80-min ECG signals are randomly selected. The 80-min HRV signal

is obtained for analysis by using the Pan–Tompkins algorithm [21]. In this paper, the data interception method is shown in Fig. 2 and the data segment length is 10-min. In Fig. 2a, SCD10 represents 0–10 min before the occurrence of SCD, SCD20 represents 10–20 min before the occurrence of SCD, and so on. Figure 2b shows each minute before sudden death. Figure 3 depicts an example 10-min HRV extracted from these two databases. The heart rate is calculated as follow:

$$HR = \frac{60}{RR} \tag{1}$$

2.2 Multiscale variation feature S_v extraction

Henriques et al. [22] proposed a multiscale Poincare (MSP) plots and validated that the complexity of HRV data in patients with chronic (congestive) heart failure syndrome or atrial fibrillation is lower than that in healthy subjects. The same pattern was observed in patients with SCD. At the same time, the complexity loss may be different along scales. Inspired by this, we deeply study the variation differences of features on scale and propose a multiscale variation feature. The implementation steps of the MSP of the HRV signal are as follows: (1) Build a coarse-grained time series from the original time series; (2) Construct Poincare scatter plots for the original and each coarse-grained time series. (3) Colorize the Poincare plots based on the estimated normalized probability density function. Coarse-grained time series [23, 24] are obtained by using non-overlapping moving average low-pass filters, and the window length s determines the scale of the coarse-grained time series $\{Z_s(i)\}$. Each value in the time series of scale s is determined by the following formula:

$$Z_s(i) = \frac{1}{s} \sum_{n=(i-1)s+1}^{is} RR_n,\ 1 \le i \le \frac{N}{s} \tag{2}$$

where s is the scale factor, $\{RR_n\}$ is the original time series, $1 \le n \le N$.

Figure 4a, b are the MSP of normal and SCD patients at 10 scales, respectively. SD1 is used to characterize the features of a multiscale Poincare plot, and is defined as:

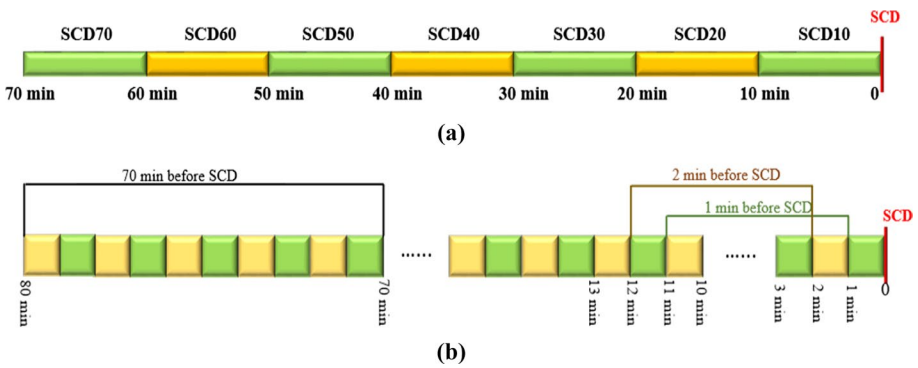


Fig. 2 The segmentation of HRV signal

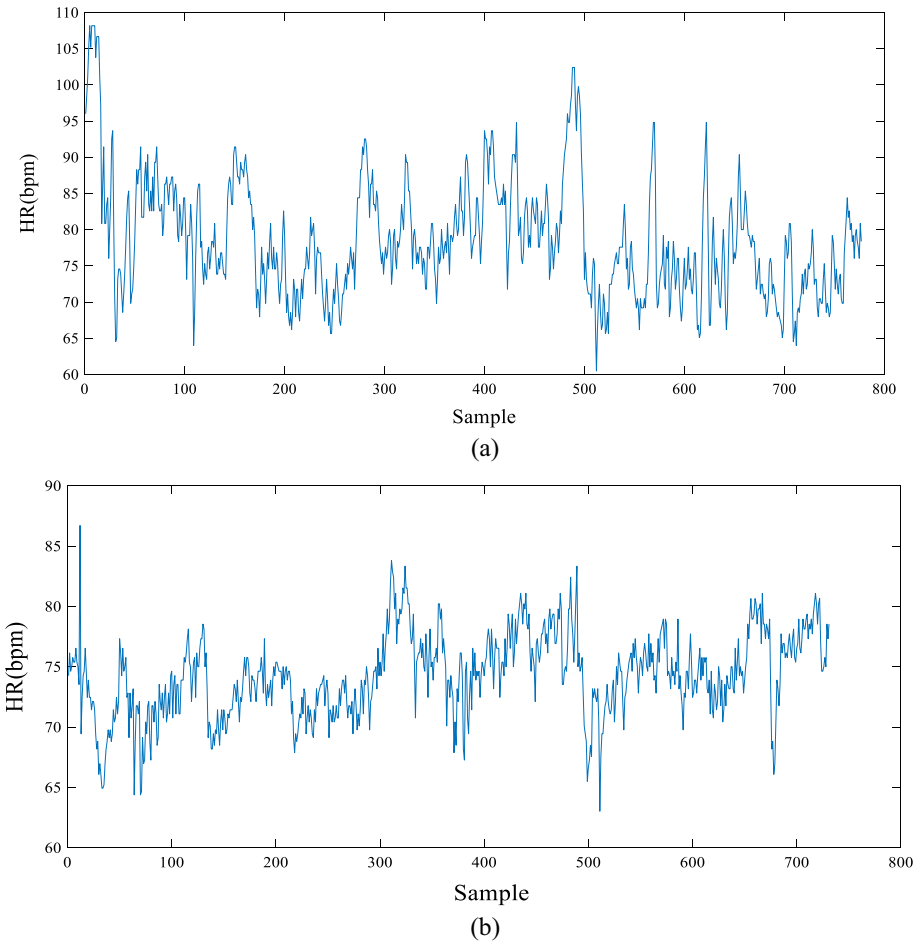


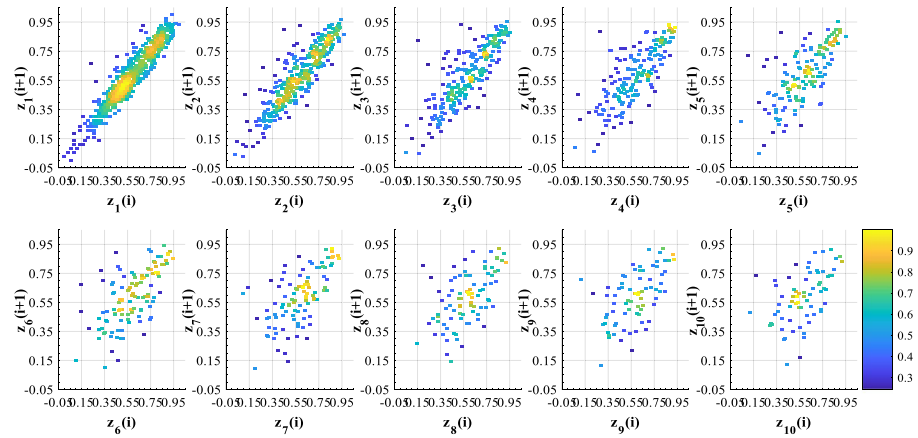
Fig. 3 **a** HRV signal extracted from normal signal and **b** HRV signal extracted from SCD signal

$$SD1_s = \sqrt{variance\left(\frac{Z_s(i) - Z_s(i-1)}{\sqrt{2}}\right)}, 2 \le i \le \frac{N}{s} \tag{3}$$

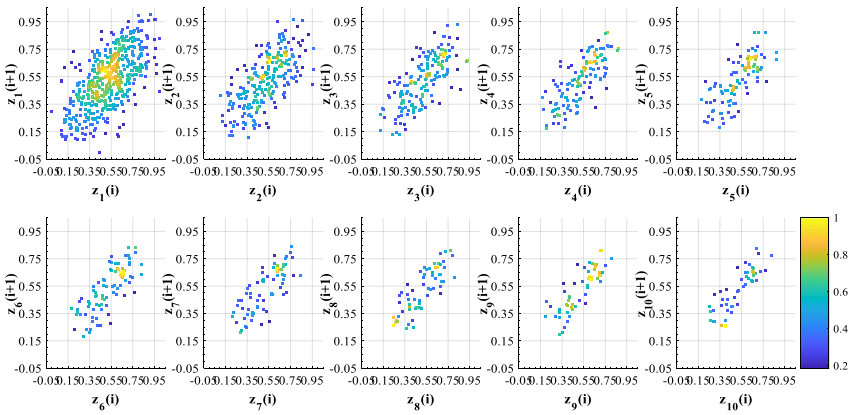
where $SD1_s$ is the SD1 value of the s-th scale.

From Fig. 4a, it can be seen that the points on the Poincare scatter diagram of normal people diverge outward around the line $y = x$ as the scale increases. It leads to an overall trend of increasing in the short axis SD1 (green line) of the Poincare scatter plot as the scale increases, as shown in Fig. 4c. In Fig. 4b, the points on the Poincare scatter plot of SCD patients gradually approach the straight line $y = x$ as the scale increases. It leads to the short axis of the Poincare scatter plot SD1 (red line) generally showing a decreasing trend with the increase of scale, as shown in Fig. 4c.

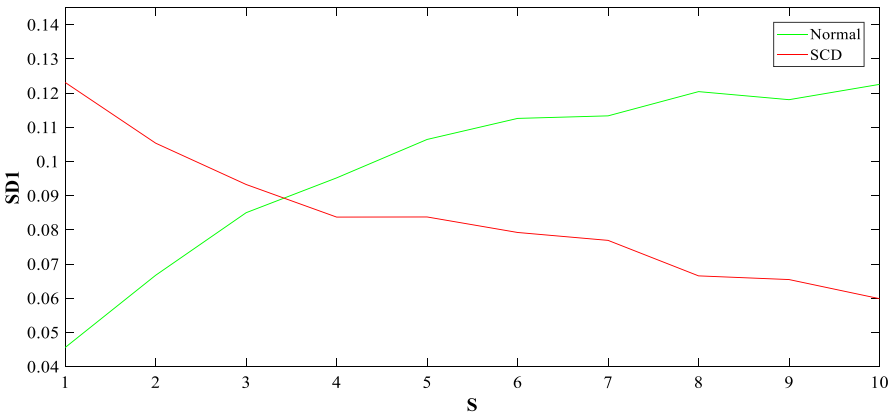
Studies have shown that HRV reduction is strongly associated with the risk of severe ventricular arrhythmias and SCD [12]. Therefore, we take the mean value of the slope and sum of SD1 between scales as a feature parameter to represent the overall trend of SD1 and this feature parameter is recorded as the multiscale variation feature S_v. This parameter is used as one of the predictive features of SCD. The specific formula is:



(a)



(b)



(c)

Fig. 4 **a** Multiscale Poincare plots of normal people (The data is from 16:13:49 to 16:23:49 of record No.19093 in Normal Sinus Rhythm database); **b** Multiscale Poincare plots of SCD patients (The data is from 12: 04: 56 to 12: 14: 56 of record No.35 in SCD database); **c** SD1 at each scale in (**a**) and (**b**)

$$S_v = \frac{1}{I}\sum_{s=1}^{I}(SD1_{s+1} - SD1_s) \tag{4}$$

where $I=9$, $SD1_s$ is the SD1 value under the s-th scale.

2.3 Time domain feature and entropy feature

2.3.1 Time domain feature

Van Hoogenhuyze et al. [25] showed that HRV is usually low in SCD patients, whereas HRV is high in young healthy subjects. Therefore, we choose the RR interval standard deviation in the time domain as one of the characteristics of SCD prediction.

The standard deviation of RR intervals (SDRR) is expressed as:

$$SDRR = \sqrt{\frac{1}{N}\sum\left(RR(n) - \overline{RR}\right)^2} \tag{5}$$

2.3.2 Shannon entropy (information entropy)

Studies have shown that the heart is a chaotic system and HRV signals are complex. The healthier the heart, the higher the complexity of the HRV signal. Shannon entropy is a measure of the complexity of a system. The more complex the system, the greater its Shannon entropy. The calculation process is as follows:

For a given time series $\{RR_n, n = 1, 2, 3, \ldots, N\}$, its amplitude range is $x \le RR_n \le y$. If the amplitude range of the time series is divided into m segments, the amplitude range of each segment is:

$$x + \frac{y-x}{m}(j-1) \le D_j \le x + \frac{y-x}{m}j, 1 \le j \le m \tag{6}$$

The number of time series $\{RR_n\}$ in D_j is respectively C_j, then:

$$N = \sum_{j=1}^{m} C_j, 1 \le j \le m \tag{7}$$

Then the ratio P_j of C_j to the length N of time series is:

$$P_j = \frac{C_j}{\sum_{j=1}^{m} C_j}, 1 \le j \le m \tag{8}$$

Then the Shannon entropy value H of the time series $\{RR_n\}$ is:

$$H = -\sum_{j=1}^{m} P_j log_2 P_j \tag{9}$$

2.4 Support vector machine classification and evaluation indicators

This paper uses a support vector machine classifier to distinguish normal subjects from SCD patients. The support vector machine achieves the maximum distinction between two classes by finding the optimal hyperplane. Since nonlinear signals are not easily

separable, a kernel function is used to map them to a high-dimensional space. In this study, a radial basis function (RBF) is chosen as the kernel function. To evaluate the performance of the classifier, a 5-fold cross-validation method is used. In the training phase, four parts are used to train the classifier and one part is used to test the classifier. To improve the generalization ability of the classifier, we perform 5-fold cross-validation ten times. In this study, we evaluate the ability of this method to predict SCD with accuracy (Acc), sensitivity (Sen), and specificity (Spe). In the formula below, TP refers to true positives (correctly predicted SCD), TN refers to true negatives (correctly predicted non-SCD), FN refers to false negatives (misclassified non-SCD), and FP refers to false positives (misclassified SCD).

$$Acc = \frac{TP + TN}{TP + TN + FN + FP} \tag{10}$$

$$Sen = \frac{TP}{TP + FN} \tag{11}$$

$$Spe = \frac{TN}{FP + TN} \tag{12}$$

3 Results and discussion

Figure 5 is a boxplot of the multiscale variation feature of normal subjects and SCD, in which NSR represents normal subjects and SCD10–SCD70 represent HRV signals 10–70 min before sudden death, respectively. It can be seen from the figure that the average value of the multiscale variation feature of normal subjects is greater than 0, while the average value of the multiscale variation feature of SCD is less than 0. The mean and standard deviation of the multiscale feature are shown in Table 2, and the p-value also demonstrates the effectiveness of this feature.

The SCD prediction results based on multiscale variation feature are shown in Table 3. From this table, it can be seen that the average prediction accuracy, specificity, and sensitivity based on a single feature are all above 80%, which demonstrates the effectiveness

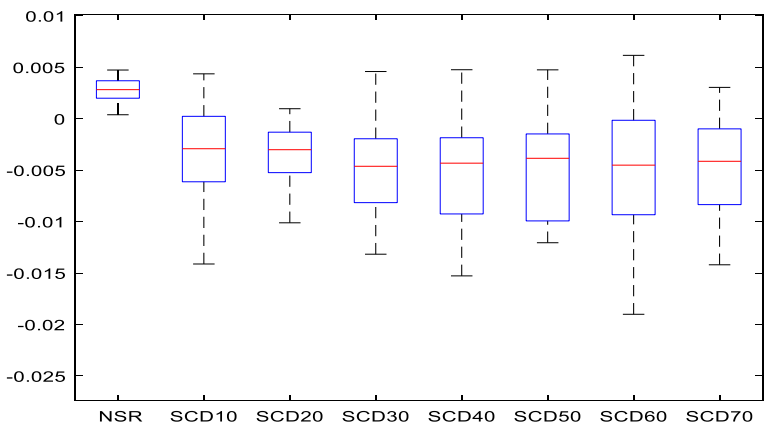


Fig. 5 Boxplot analysis of S_v

Table 2 Mean ± standard deviation of S_v 70 min before SCD

Time	Feature	Mean ± standard deviation		*P*-value
		Normal	SCD	
SCD10	S_v	0.0029 ± 0.0021	− 0.0036 ± 0.0057	5.9619e−05
SCD20	S_v	0.0025 ± 0.0018	− 0.0039 ± 0.0040	2.3831e−07
SCD30	S_v	0.0024 ± 0.0017	− 0.0051 ± 0.0045	7.2757e−08
SCD40	S_v	0.0028 ± 0.0021	− 0.0053 ± 0.0057	1.5355e−06
SCD50	S_v	0.0021 ± 0.0030	− 0.0061 ± 0.0078	1.6377e−04
SCD60	S_v	0.0020 ± 0.0031	− 0.0047 ± 0.0064	2.8929e−04
SCD70	S_v	0.0023 ± 0.0023	− 0.0046 ±0.0046	1.7450e−06

Table 3 Classification accuracy of feature S_v 70 min before SCD

Time	Acc	Spe	Sen
SCD10	86.79%	86.67%	83.33%
SCD20	90.00%	93.33%	87.00%
SCD30	**92.14%**	95.00%	**91.00%**
SCD40	89.29%	90.00%	88.33%
SCD50	81.43%	82.00%	88.00%
SCD60	82.50%	88.33%	80.33%
SCD70	87.50%	**100%**	77.00%
Mean ± standared deviation	87.09% ± 3.92%	90.76% ± 5.91%	85.00% ± 4.98%

The bold part represents the best result among different time parts for Acc, Spe and Sen

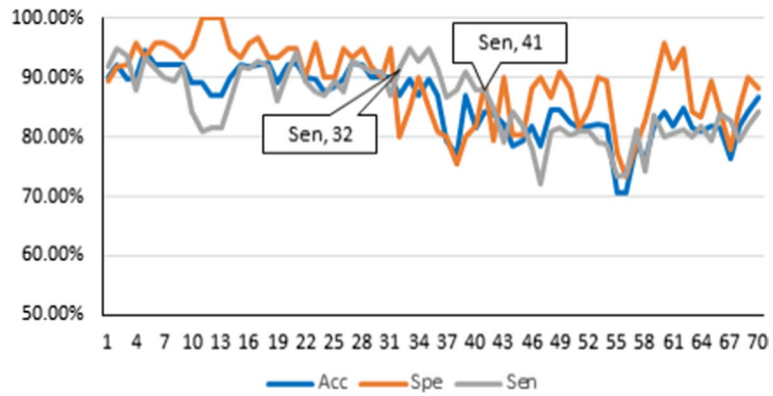


Fig. 6 Accuracy of feature S_v per minute before SCD

of this feature in SCD prediction. From the classification results of each time period, 0–40 min before sudden death has a higher prediction accuracy.

Figure 6 shows the prediction results of SCD in each minute before sudden death by using multiscale variation feature. It can be seen from the figure that although the prediction accuracy tends to decrease with the increase of time, the overall prediction stability is good.

Table 4 gives the prediction accuracy with different feature combinations. From the statistics in the table, it can be seen that after adding time domain features, the specificity has been significantly improved, the accuracy has not changed significantly, and the

Table 4 Prediction accuracy with different feature combinations

Feature	Time	Acc	Spe	Sen
S_v and time domain	SCD10	87.50%	95.00%	80.00%
	SCD20	86.43%	95.00%	80.33%
	SCD30	92.14%	100%	86.67%
	SCD40	92.50%	100%	89.33%
	SCD50	86.79%	91.00%	87.00%
	SCD60	78.21%	92.00%	71.33%
	SCD70	90.00%	100%	85.33%
	Mean ± standared deviation	87.65% ± 4.84%	96.14% ± 3.89%	82.86% ± 6.15%
S_v and entropy	SCD10	87.50%	93.33%	82.00%
	SCD20	87.14%	96.67%	81.33%
	SCD30	92.50%	100%	86.67%
	SCD40	95.00%	100%	90.00%
	SCD50	87.50%	83.81%	89.33%
	SCD60	84.28%	89.33%	81.67%
	SCD70	90.00%	100%	84.67%
	Mean ± standared deviation	89.13% ± 3.64%	94.73% ± 6.29%	85.10% ± 3.65%
Combined	SCD10	90.00%	100%	85.00%
	SCD20	90.00%	100%	85.00%
	SCD30	94.29%	100%	91.00%
	SCD40	95.00%	100%	93.33%
	SCD50	90.00%	86.67%	90.00%
	SCD60	86.43%	96.00%	85.33%
	SCD70	92.50%	100%	88.33%
	Mean ± standared deviation	91.17% ± 2.97%	97.52% ± 5.01%	88.28% ± 3.32%

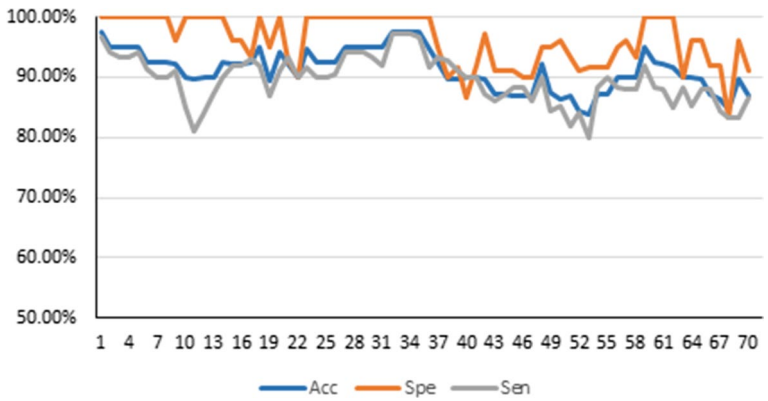


Fig. 7 Classification result of SCD in each minute using the combined features

sensitivity was decreased. After adding the entropy feature, the accuracy and specificity increased, but the sensitivity did not decrease significantly. The three feature combinations achieved the best results, and shown better prediction stability for HRV in different time periods.

Figure 7 shows classification result of SCD in each minute using the combined features. Compared with the single feature analysis in Fig. 6, the specificity is significantly improved and the stability for the next 30 min is improved. In the combined feature

analysis, the accuracy is higher than the sensitivity most of the time, while in the single feature analysis, the sensitivity is significantly higher than the accuracy in the interval of 32–41 min.

In order to further verify the stability of the algorithm in this paper, we use the data of SCD20 to train the SVM and use the data of other periods for testing. The results are shown in Table 5. From the perspective of prediction accuracy, this still has higher prediction accuracy and better algorithm stability.

Table 6 presents the experimental comparison with other methods for predicting SCD using ECG and HRV signals. Ebrahimzadeh et al. [9] and Lopez-Caracheo et al. [10] used ECG signals to predict SCD. Ebrahimzadeh et al. [9] proposed a local feature extraction method and extracted nonlinear, time–frequency, and classical features from local ECG signals, which could enhance the feature expression of ECG. Lopez-Caracheo et al. [10] introduced fractal dimension (FD) into SCD prediction and achieved an average accuracy of 91.4% at 14 min before the onset of SCD. Aiming at solving the problem that the prediction result is greatly affected by individual difference in ECG signal, Heng et al. [14] extracted linear and nonlinear features of HRV signal to predict SCD. It achieved an accuracy, sensitivity, and specificity of 94.70%, 100%, and 88.90% only using two nonlinear features for four minutes before the occurrence of SCD. Ebrahimzadeh et al. [15] used a local feature subset selection method to select the optimal features in each minute HRV signal to predict SCD and promoted the prediction time to 13 min before the onset. Shi et al. [16] further promoted the prediction time to 14 min before the onset of SCD by using EEMD-based entropy and classical linear features with accuracy of 96.1%. In this paper, through developing high specific feature of HRV signal, accurate prediction results of 91.22% are achieved by only using three simple features and the prediction time is promoted to 70 min before the occurrence of SCD. In addition, the prediction accuracy of the proposed algorithm shows good stability for different HRV segments before sudden death.

4 Conclusions

In this paper, an intelligent prediction algorithm for SCD based on multi-domain feature fusion is proposed. By extracting time-domain feature, entropy, and multiscale variation feature S_v in the multiscale Poincare plots from the HRV signal, the accurate prediction of SCD is achieved. The advance prediction time of SCD is increased to 70 min before the occurrence of sudden death. HRV signals in different time periods before sudden

Table 5 Classification accuracy with selected segment of HRV for training and testing

Time	Acc
SCD10	92.11%
SCD30	92.11%
SCD40	92.11%
SCD50	86.84%
SCD60	84.21%
SCD70	92.11%
Mean ± standared deviation	89.92% ± 3.5%

Table 6 Comparison with other methods

Author	Signal type	Method	Classification	Results
Ebrahimzadeh et al. [9]	ECG signals	Linear (time, frequency domain), TF domain, and nonlinear methods (Poincare, detrended fluctuation analysis)	MLP	12 min: Acc = 83.88% Sen = 82.67% Spe = 85.09%
Lopez-Caracheo et al. [10]	ECG signals	Nonlinear methods (Higuchi fractal dimension, Box dimension, Katz fractal dimension)	MLP-NN	14 min: Acc = 91.40%
Heng et al. [14]	HRV signals	Linear (time domain) and nonlinear methods (Hurst Exponent, SD1)	SVM	4 min: Acc = 94.70% Sen = 100% Spe = 88.90%
Ebrahimzadeh et al. [15]	HRV signals	Linear (time, frequency domain), TF and nonlinear methods (Poincare and detrended fluctuation analysis)	KNN, SVM, ME, and MLP	13 min: Acc = 84.28% Sen = 85.72% Spe = 82.86%
Shi et al. [16]	HRV signals	EEMD, linear (time, frequency domain), TF domain, and nonlinear methods (Rényi entropy, fuzzy entropy, dispersion entropy, Rényi distribution entropy and improved multiscale permutation entropy)	KNN	14 min: Acc = 96.1% Sen = 97.5% Spe = 94.4%
Ours	HRV signals	Linear (SDRR) and nonlinear methods (Shannon entropy, S_v)	SVM	Acc for 5, 20, 35, 60 min: 95.00%, 94.29%, 97.50%, 92.50% Average: Acc = 91.22% Sen = 96.15% Spe = 89.59%

death have good stability. In addition, the multiscale variation feature proposed in this paper has extremely high sensitivity and specificity for SCD, and the average prediction accuracy of the single feature reaches 85.83%. The algorithm utilizes HRV signals, has low requirements on the number of leads and signal acquisition accuracy in the signal acquisition process, and is suitable for real-time monitoring systems for cardiac status. At the same time, the three features proposed by this paper have low computational complexity and are easy to integrate into single-chip programmable devices, which can be directly applied to real-time monitoring and warning of SCD and have broad application prospects.

Abbreviations

SCD	Sudden cardiac death
HRV	Heart rate variability
VF	Ventricular fibrillation
ECG	Electrocardiogram
SCA	Sudden cardiac arrest
SCDI	SCD index
KNN	K-nearest neighbor
SVM	Support vector machine
DT	Decision tree

NB	Naive Bayes
RF	Random forest
EMD	Empirical mode decomposition
FD	Fractal dimension
EEMD	Ensemble empirical mode decomposition
CNN	Convolutional neural network
RCN	Recurrence complex network
MSP	Multiscale poincare
SDRR	Standard deviation of RR intervals
RBF	Radial basis function
Acc	Accuracy
Spe	Specificity
Sen	Sensitivity

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Author contributions
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Availability of data and materials
The database used in this study is public and can be found in https:// physionet.org/.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare that they have no competing interests.

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