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ORIGINAL RESEARCH ARTICLE

Arrhythmia classification based on convolution neural network feature extraction and fusion

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ABSTRACT

This study proposes a new automatic classification method of arrhythmias to assist doctors in diagnosing and treating arrhythmias. The convolution neural network is constructed to extract the features of ECG signals and wavelet components of QRS complex. The ECG signal features and wavelet features extracted by the network and the artificially extracted RR interval features are input to the full connection layer for fusion, and the softmax function is used to classify the beats in the output layer. The network is trained and tested using the mil lead data in MIT BIH arrhythmia database. The overall classification accuracy of this method is 98.12%, the average sensitivity is 87.32%, and the average positive predictive value is 90.37%. This method can quickly identify different types of arrhythmias, and has certain reference value for the application of computer-aided diagnosis of arrhythmias.

Keywords*:* arrhythmia; single lead; feature extraction and fusion; classification; convolutional neural network

1. Introduction

Arrhythmia is the most significant manifestation of cardiovascular disease. Severe arrhythmia may lead to cardiac arrest or even death. Portable wearable devices can realize long-term monitoring of patients and achieve the purpose of early recognition of arrhythmias, but they must meet the requirements of high recognition accuracy, light weight, low energy consumption and fast recognition speed. Therefore, it is of great significance to improve the classification accuracy of arrhythmias on the basis of reducing the computational complexity.

With the development of technology, machine learning methods have been applied to arrhythmia classification [14]. Mond é jar Guerra et al. [2] extracted RR interval features, small baud sign, high-order statistical features, etc. Of ECG signals and input them into support vector machine, obtaining an accuracy of 95.9%. However, manual feature extraction is highly dependent on experience, it is difficult to extract hidden features, and a large number of calculations will be introduced, which can not meet the requirements of simple calculation. Later, convolutional neural network (CNN) was applied to arrhythmia classification [56]. The method based on CNN has the ability to learn and classify

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features independently from input. Rajpurkar et al. [5] trained a 34 layer CNN, which can automatically classify arrhythmias, and its sensitivity and accuracy exceed the average level of cardiologists. If a shallow CNN is used, it is difficult to learn the deep-seated features in ECG signals. When the network depth increases, the network parameters will increase exponentially and the computational burden will increase [7].

This study combines the advantages of artificial feature extraction and CNN automatic feature extraction, and proposes an anti noise automatic arrhythmia classification method based on CNN. CNN is used to extract the features of the original ECG signal and wavelet components and fuse them with RR interval features. Softmax function is used to automatically classify the beats. In order to verify the effectiveness of feature fusion, the performance of the network before and after feature fusion is evaluated and compared.

2. Experimental data

The experimental data are from MIT BIH arrhythmia database [8]. The database contains 48 pieces of data, each data lasts for 30 minutes, the sampling frequency is 360 Hz, and provides about 110000 beats [9]. During the medical interval, the device Promotion Association (AAMI) divides arrhythmias into five categories: normal beat (n), superior ectopic beat (s), ventricular ectopic beat (V), fusion beat (f) and unknown beat (q). Unknown beats are those that cannot be accurately identified due to low signal-to-noise ratio. Therefore, only N, s, V and f beats are studied.

Lead II is one of the most commonly used leads for diagnosing heart disease [10]. The modified lead II data (mlii) were used in the study.

3. Method

3.1. Data set division

Remove 4 pieces of ECG data (102, 104, 107 and 217) using cardiac pacemakers. Divide the data into two data sets DS1 and DS2 that do not contain the same patient information [11]. DS1 data number is: 101、106、108、109、112、114、115、116、118、119、122、124、201、203、205、207、208、209、215、220、223、230.   DS2 data number is: 100、103、105、111、113、117、121、123、200、202、210、212、213、214、219、221、222、228、231、232、233、234.

This study uses the training method of active learning [12]. The training set is divided into global training set and individual training set. Use the global training set to train a model. When a new patient is encountered, make a label for a part of the data of the new patient, fine tune the model as an individual training set, and use the fine-tuned model to predict the remaining data. In the study, DS1 data set acts as a global training set. The first 5 minutes of DS2 data set were used as individual training sets to introduce patient specificity. DS2 data in the first 5 minutes of removal shall be taken as the test set. This practice complies with AAMI standards.

3.2. Beat segmentation

Before feature extraction, the complete ECG signal needs to be divided into a single beat. The R peak position marked in the database is used to segment the ECG signal. In order to characterize a complete beat cycle, this study took 100 points before the R peak and 150 points after the R peak, a total of 250 points to represent a beat, and made labels.

3.3. Artificial feature extraction

RR interval refers to the time interval between two adjacent r peaks, which can effectively distinguish the types of arrhythmias [13]. The pre RR interval and post RR interval were used to characterize the time domain information of ECG signals. Calculate RR interval characteristics according to equations (1) and (2).

$$\mathrm{rr}_{\mathrm{pre}} = \mathrm{r}_{\mathrm{cur}} - \mathrm{r}_{\mathrm{pre}} \tag{1}$$

$$\mathrm{rr}_{\mathrm{post}} = \mathrm{r}_{\mathrm{post}} - \mathrm{r}_{\mathrm{cur}} \tag{2}$$

Where, represents r_{cur} the position of the current R peak, represents r_{pre} the position of the previous adjacent r peak, represents r_{post} the position of the subsequent adjacent r peak, r_{pre} represents the pre RR rr_{post} interval, and represents the post RR interval.

QRS complex contains the most information in ECG signals. Wavelet feature extraction is performed on this part. Taking the R peak as the center, 44 points were selected to represent the QRS complex. Discrete wavelet transform (DB4) is used to decompose QRS complex signal into four scales, namely D2, D3, D4 and A4, and the wavelet components of each scale are reconstructed.

3.4. Network structure design

CNN can automatically extract the effective features of ECG signals. In the study, a CNN for arrhythmia classification is proposed. The network structure is shown in **Figure 1**. The network is divided into four modules: input, feature extraction, feature fusion and classification.

Input module. The network consists of three inputs: size 250 × 1 beat signal, 4 sizes 44 × Wavelet feature of 1, size 2 × 1.

Feature extraction module. The network is constructed to extract the beat waveform features and deep wavelet features. When extracting the characteristics of the beat waveform, the convolution kernel of the beat waveform is 9 × 1. After the convolution results are normalized in batch, the nonlinear activation processing is performed. The nonlinear activation function uses the relu function. The maximum pool operation is carried out on the obtained feature map, and the step size is 4, which can reduce the number of features and reduce the amount of calculation. The size of the obtained feature map is 9 × 1, batch normalization and relu activation. To prevent over fitting, add a drop-out layer. The final size is 45 × 16 eigenvector; when extracting deep wavelet features, the four wavelet components D2, D3, D4 and A4 are convoluted respectively, and the convolution kernel size is 9 × 1. After the convolution operation, the relu activation function is used. After the average pooling, 22 4 are finally obtained × 4.

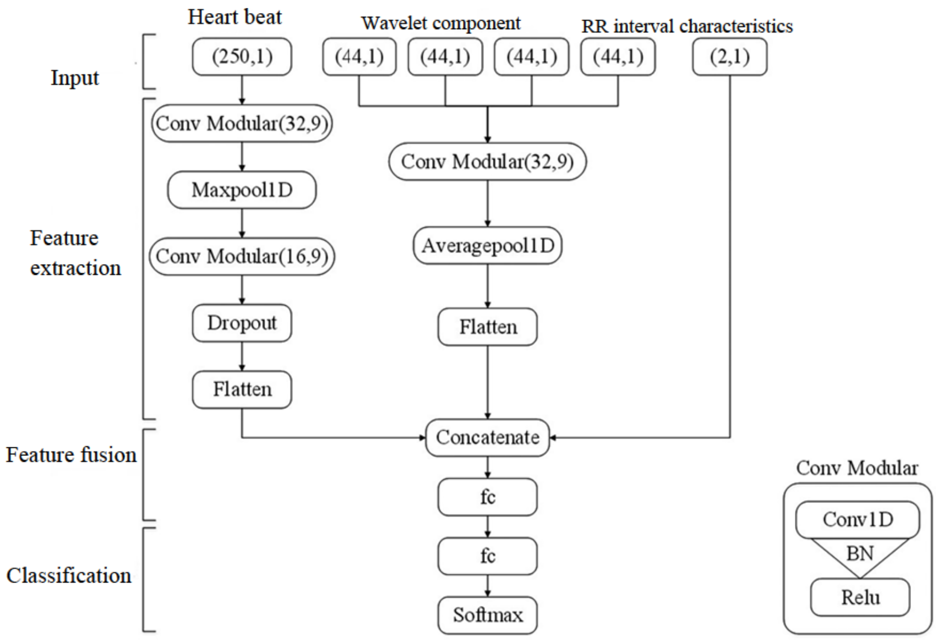

Figure 1. Network structure diagram.

Feature fusion and classification module. After the feature vectors extracted from the network and RR interval features are spliced, they are input to the full connection layer for fusion, and softmax function is used in the output layer for classification. See **Table 1** for specific configuration parameters of CNN structure.

3.5. Network training

Using the cross-entropy loss function, the weight and offset are optimized by Adam optimizer in the training process. When the loss value does not decrease within 20 iterations, stop the iteration and save the model with the highest accuracy.

Table 1. Specific configuration of convolutional neural network structure

	***n*-th layer**	**Network layer**	**Convolution kernel number convolution kernel size**		**Step activation function**		**Loss rate (%)**
ECG signal	1	Conv1D	32	9x1	1	Relu	--
	2	Maxpool	--	2	4	--	--
	3	Conv1D	16	9x1	1	Relu	--
	4	Dropout				--	20
	5	Flatten				--	--
Wavelet component	1	Conv1D	4	9x1	1	Relu	--
	2	Averagepool	--	2	2	--	--
	3	Flatten				--	--
Fuse	1	Concatenate				--	--
	2	Fully connected layer	20	--	--	Relu	--
Classification	1	Output layer	4	--	--	Softmax	--

3.6. Evaluation index

The proposed algorithm has been verified in MIT BIH arrhythmia database. The accuracy (ACC), sensitivity (SE) and positive predictive value are selected to (P^+) evaluate the performance of the model. The calculation formula is as follows:

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{3}$$

$$\mathrm{Se} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{4}$$

$$\mathrm{P}^+ = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{5}$$

Where TP (true positive) is the true positive quantity, FP (false positive) is the false positive quantity, TN (true negative) is the true negative quantity, and FN (false negative) is the false negative quantity.

4. Experimental results

4.1. Comparison of experimental results before and after feature fusion

The test set was used to test the networks before and after feature fusion, and the sensitivity, positive predictive value, overall accuracy, average sensitivity and average positive predictive value of various heart beats before and after feature fusion were calculated, as shown in **Table 2**. Only CNN was used for feature extraction of cardiac beats, and the results were poor in class F cardiac beats, with a sensitivity of only 37.15%. CNN is used to extract and fuse the features of heart beat and wavelet components, which mainly improves the classification performance of class V and makes it reach 91.03% sensitivity. When CNN is used for feature extraction of cardiac beats and fused with RR interval features, the best S-class sensitivity is achieved. After fusing all the extracted features, the overall accuracy of the network has reached 98.12%, and all kinds of heart beats have achieved high sensitivity and positive predictive value, and the classification performance has been greatly improved compared with that before fusion.

4.2. Impact of noise on classification results

In order to evaluate the influence of noise on the classification results, four kinds of Gaussian white noise with different signal-to-noise ratios were added to the original ECG data, and db8 wavelet was used to denoise the original signal. Taking a single beat as an example, the original waveform and the processed beat waveform are shown in **Figure 2**. The constructed CNN is used to classify the signals after adding and removing noise. The results are shown in **Table 3**.

Table 2. Performance evaluation results

		N (%)	S (%)	V (%)	F (%)	Mean (%)	Acc (%)
Heart beat	Se	99.57	70.26	8358	3715	7264	96.67
	P $^{+}$	97.31	90.00	97.23	66.88	8786	
Beat + **wavelet Weight**	Se	99.63	6911	9103	57.99	7944	97.60
	P $^{+}$	97.96	9113	97.64	7167	8964	
Heart beat +rr **Interval**	Se	98.75	83.94	8641	7830	8685	97.21
	P $^{+}$	98.36	8425	95.23	5873	8414	
Heart beat **+ wavelet score Volume** + RR **interval**	Se	99.51	7430	95.27	8021	8732	9812
	P $^{+}$	98.66	9227	9628	74.28	9037	

According to the data in Table 3, when 10 db signal-to-noise ratio noise is superimposed, each performance index of the network decreases. It can be seen from Figure 2 (c) that the beat waveform superimposed with 10 db noise is seriously distorted. Although the classification effect has decreased, the overall accuracy can still reach 95.69%, which is of certain reference value.

When the superimposed signal-to-noise ratio is greater than or equal to 20 db, the overall accuracy has no significant change, and the performance evaluation indicators of each category have little difference. The network has the highest overall accuracy for signal classification after removing baseline drift and high-frequency noise.

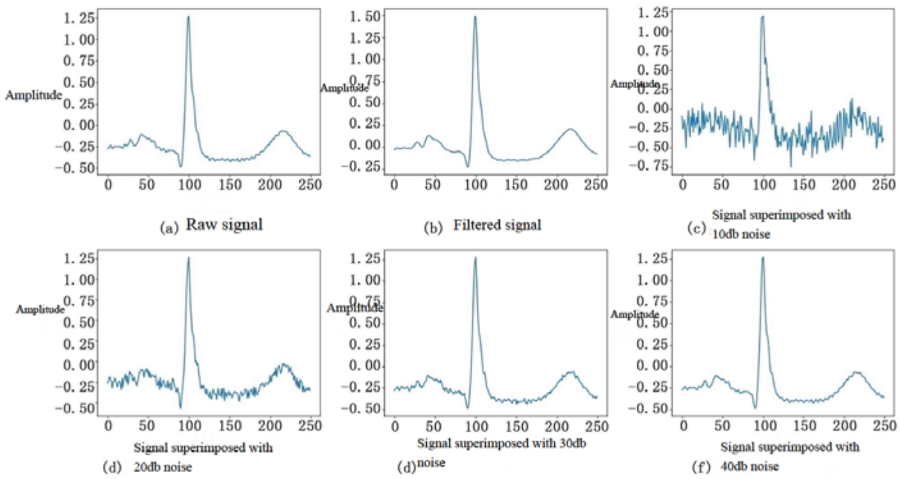

Figure 2. Original heartbeat and heartbeat waveform after adding and removing noise.

Table 3. Noise immunity test results

Signal	**N(%)**		**S(%)**		**V(%)**		**F(%)**		**Average (%)**		
	Se	**P $^{+}$**	**Se**	**P $^{+}$**	**Se**	**P $^{+}$**	**Se**	**P $^{+}$**	**Se**	**P $^{+}$**	
Original signal	99.51	98.66	74.30	92.27	95.27	96.28	80.21	74.28	8732	90.37	98.12
Denoised signal	99.39	98.71	75.11	92.63	96.57	96.25	80.21	81.05	8782	9216	98.24
+ 10 dB	99.50	96.06	40.26	89.86	8206	94.84	29.51	5000	6286	8269	95.69
+ 20 dB	99.56	98.46	7237	92.67	93.86	96.29	76.39	73.83	85.55	90.31	97.98
+ 30 dB	99.52	98.65	74.18	92.33	95.23	96.31	79.86	75.92	8720	90.80	98.12
+ 40 dB	99.51	98.66	74.49	92.22	95.01	96.23	79.51	73.16	8713	90.07	98.11

4.3. Comparison with other arrhythmia classification methods

Table 4 shows the performance evaluation index results of other classification methods that also meet the AAMI standard, and the best results of each index are displayed in bold. Kiranyaz et al. [12] used one-dimensional CNN to test 24 ECG data in MIT BIH database, and obtained an overall accuracy of 95.13%; luo et al. [14] used a method of frequency slice wavelet transform to generate the time-frequency map of heart beat, built a deep neural network to extract the characteristics of heart beat and classify it, and achieved an overall accuracy of 97.5%; xiang et al. [15] proposed a two-level feature extraction method based on attention mechanism, and obtained an overall accuracy of 96.74%. By comparison, the N and s sensitivity, positive predictive value and overall accuracy of this research method are higher.

Table 4. Arrhythmia classification methods and performanceevaluation indicators

Literature	N(%)		S(%)		V(%)		F(%)		Acc (%)
	Se	P +	Se	P +	Se	P +	Se	P +	
Thisstudy	99.51	98.66	74.30	92.27	95.27	96.28	8021	74.28	98.12
Kiranyaz[12]	97.09	98.02	64.60	6202	94.99	88.09	76.11	8055	95.13
Luo[14]	99.0	98.4	71.4	94.9	93.3	93.3	827	585	97.5
Xiang[15]	98.27	98.47	8630	7990	93.42	92.98	5918	79.69	96.74

5. Discussions

In this study, CNN is constructed to automatically extract the features of heart beat and QRS complex wavelet components, fuse RR interval features, and use softmax function to classify heart beat. By comparing the evaluation index results obtained before and after feature fusion, it is proved that the feature fusion method proposed in this study can effectively improve the classification ability of the network.

In order to evaluate the anti-interference ability of the constructed network to noise, the network is tested by adding or filtering noise to the test set signal. According to the test results, it can be considered that the network constructed in this study has certain anti-interference ability to noise.There are two main reasons for this anti noise ability: (1) The batch normalization layer used in the network structure can eliminate part of the noise; (2) In this study, no pretreatment such as de-noising and normalization was performed on the ECG data input to CNN. While preserving the integrity of ECG signal to the greatest extent, the network was trained in the case of noise. The trained CNN model can extract effective features from the noisy signal.

In the follow-up work, it is necessary to combine QRS complex detection, optimize the network structure and training process, and further improve the classification accuracy. In addition, the amount of abnormal beat data in the study is less, so more data need to be collected for the experiment.

6. Conclusions

Based on CNN, this paper proposes an anti noise automatic arrhythmia classification method for feature extraction and fusion of single lead ECG signals. The proposed method reduces the preprocessing process and the computational burden. Combining the advantages of manual feature extraction and CNN automatic feature extraction, the classification accuracy is effectively improved. After the anti-interference ability test, it is proved that the classification method in this study has a certain anti-interference ability to noise. In addition, this research method only needs single lead data to realize the classification of cardiac beats. It has fast processing speed for ECG data and small amount of calculation. It has certain clinical significance and value, and can be used as an ECG screening tool.

Conflict of interest

The authors declare no conflict of interest.

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