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Classification of ECG Signals Based on 1D Convolution Neural Network

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***Abstract*—Recently, with the obvious increasing number of cardiovascular disease, the automatic classification research of Electrocardiogram signals (ECG) has been playing a significantly important part in the clinical diagnosis of cardiovascular disease. In this paper, a 1D convolution neural network (CNN) based method is proposed to classify ECG signals. The proposed CNN model consists of five layers in addition to the input layer and the output layer, i.e., two convolution layers, two down sampling layers and one full connection layer, extracting the effective features from the original data and classifying the features automatically. This model realizes the classification of 5 typical kinds of arrhythmia signals, i.e., normal, left bundle branch block, right bundle branch block, atrial premature contraction and ventricular premature contraction. The experimental results on the public MIT-BIH arrhythmia database show that the proposed method achieves a promising classification accuracy of 97.5%, significantly outperforming several typical ECG classification methods.**

***Keywords*—Cardiovascular disease; Convolution neural network; ECG signal classification; Wavelet transform**

I. INTRODUCTION

Cardiovascular disease is a chronic illness which is characterized by high risk and acute onset. It is a serious threat to people's health. Currently, there are more than 300 million patients with cardiovascular disease in china. The mortality of cardiovascular disease in rural areas and city are 44.8% and 41.9% respectively [1]. It ranks first of all chronic diseases and is enough to cause our attention. Electrocardiogram signals have the advantages of simple, convenient, safe and no trauma to the patients. ECG is commonly used to diagnose cardiovascular disease [2]. However, it is difficult for doctors to analyze the data comprehensively due to the huge amount and complexity of ECG data. Furthermore, the instability of ECG signals are not only reflected in the variability of its shape but also related to time, individual, environment and other factors closely. Therefore, it is the key step to extract the effective features of ECG signals more accurately [3].

ECG signals are mainly composed of QRS wave group, P wave, T-wave and other main wave forms. Different wave bands represent different cardiac activities, which is an important basis for analyzing ECG signals.

II. RELATED WORK

The traditional ways of ECG classification are to select the method to extract the features firstly and choose the technique for classification eventually. Of course, many researchers have done related work on classification of ECG signals, for instance, a patient adaptive heartbeat classification method is proposed in paper [4], which includes linear discriminant classifier and Expectation Maximization (EM) clustering algorithm that can work independently and perform feature classification or clustering efficiently; In literature [5], a heartbeat algorithm based on Artificial Neural Network (ANN) and fuzzy relation is adopted to get the accuracy of 85%. The result shows that the method of feature extraction needs to be improved; An effective classification system based on Machine Language Program (MLP) and Neural Network (NN) is proposed by M. K. Das et al. in reference [6], which getting better performance compared to other feature extraction techniques; What's more, a ANN-based method of ECG image classification is presented in the literature [7], which provide us a new research direction that studying signals with images; The article [8] is a detailed and comprehensive investigation about the processing, feature extraction and classification of ECG signals, in addition, it gives us a comprehensive overview about the progress of the research in recent years; The proposed weighted conditional random fields (WCRF) classifier is compared with the previous patient classification algorithms in [9] which shows that the WCRF classifier achieves better outcomes; An adaptive classification system is put forward in [10] and the classification accuracy can be improved to 91% by adjusting the classifier; In the reference [11], a new classification method based on the combination of morphology and dynamic features is presented. The wavelet transform (WT) and independent component analysis (ICA) are used to extract the morphological features together, while the support vector machine (SVM) classifier is selected for heart beat classification with an accuracy of 86.4%. The depth neural network method is presented in the literature [12] and the ECG data from three databases are divided into four classes achieving the considerable results. In the paper [13], principal component analysis (PCA), linear discriminant analysis (LDA) and ICA are used simultaneously to reduce the dimension of the data, meanwhile, three classifiers including support vector machine, neural network and probabilistic neural network are adopted to realize automatic diagnosis of ECG signals with an accuracy of more than 94%.

In fact, there are many methods adopted by researchers but still exist some defects, such as sensitive to noise, unable to retain local information, etc. In order to alleviate the above limitations and shortcomings, our study proposes a classification method about convolution neural network based on deep learning. Convolution neural network is an efficient identification method which has been developed recently and has attracted extensive attention especially in the field of pattern classification [14]. As the network inputs the original image directly instead of doing the complex pre-processing of images, thus it has been used widely. In our paper, the two-dimensional CNN model has .

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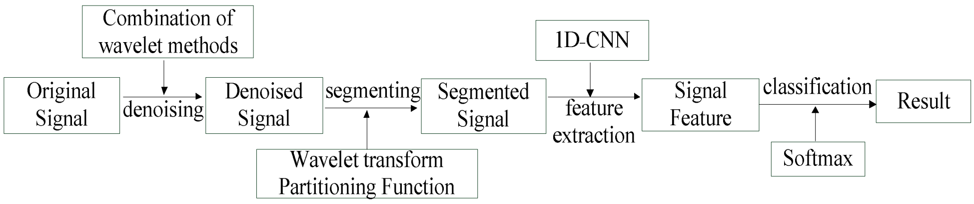

Fig. 1. The flow chart of model building

already been modified and optimized to a one-dimensional network structure. This model is used to classify and diagnose the following 5 arrhythmia signals directly, i.e., normal (N), left bundle branch block (L), right bundle branch block (R), atrial premature contraction (A) and ventricular premature contraction (V)

The remaining parts of our paper is organized as follows: section III mainly introduces the methods of data processing, the theory and the structure of CNN model; The data used in the experiment, the experimental procedure and the comparison with other algorithms are shown in section IV; The part V is a conclusion which summarizes the main point of the thesis.

III. METHODOLOGY

This section mainly introduces the methods of data processing, principles and applications. Fig.1 describes the detailed process of the whole method, which has 4 main steps, i.e., data pre-treatment, signal segmentation, feature extraction and classification. Firstly, the wavelet threshold method is used to filter the high frequency noise, while the wavelet transform and reconstruction algorithm is adopted to correct the baseline drift which is a low-frequency noise. Subsequently, the segmentation of ECG signals and the reduction of dimension are performed by using R peaks that were located by the method of wavelet transform. Finally, the processed heartbeat segments are used directly as input data of the CNN model to complete the feature extraction and classification of ECG signals.

A. Data Processing

ECG signals mainly include three kinds of noises, i.e., electromyographic noise, baseline drift and power line interference [15]. In order to extract the serviceable signal, the original ECG signals must be denoised. Thus the wavelet threshold method and wavelet decomposition reconstruction algorithm are applied together to reduce noises in this paper. On the one hand, wavelet threshold method can filter electromyographic noise and power line interference, on the other hand, the correction work of baseline drift can be completed by the approach of wavelet decomposition and reconstruction. Preliminary processing of the ECG signals is realized by using these two methods eventually. Among them, the wavelet threshold method is used to set the noise coefficient below threshold to zero by setting a threshold value while the signal coefficients above the threshold are reserved. After that, the inverse transform of the wavelet is implemented for obtaining the denoised signal. Moreover, the algorithm of wavelet decomposition reconstruction is adopted to decompose the original signals into several stages and each section is broken down into high frequency and low frequency information. Finally, the signals are reconstructed by determining the frequency range of the useful signals. Fig.2 shows the ultimate denoised results.

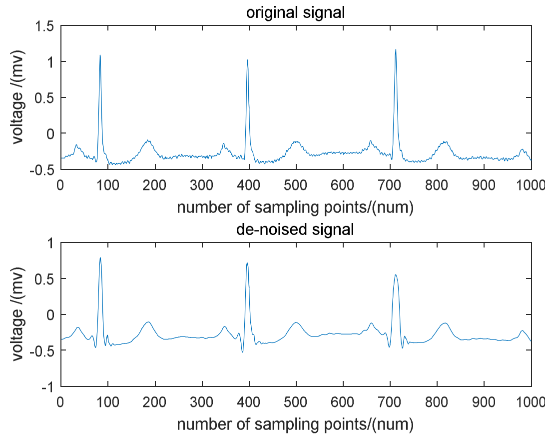

Fig. 2. The diagram of denoising effect

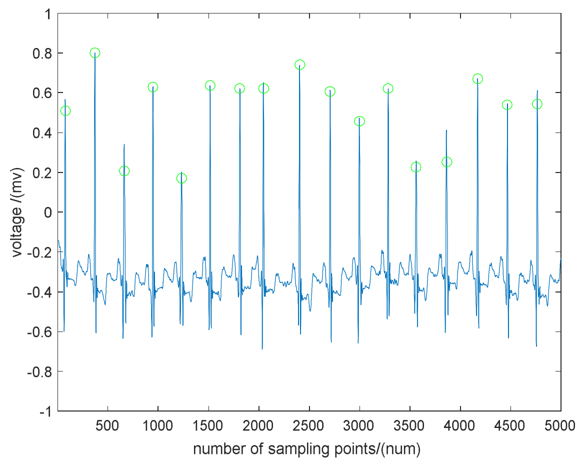

Fig. 3. The diagram of R wave peak location

As the R wave of the QRS wave group is a slope, therefore the method of wavelet transform can be utilized to detect R wave crest. However, singular point and modulus maximum of wavelet transform are used to analyze the ECG data, and the position of R wave crest is a pair of modulus maximum at zero point after the wavelet transform. In this paper, biorthogonal spline wavelet is chosen as wavelet function and the peak point of R wave is detected successfully on the 2^3 scale. As shown in Fig.3, the peak of the R wave is calibrated with a green ring and the ECG signals are segmented by taking the location of R point as a benchmark after locating the R point successfully. Meanwhile, we choose 100 sampling points on both left and right sides of the R peak. A segment of ECG signal with a length of 201 sampling points is obtained. Finally, the length of ECG data is reduced to 130 points by adopting the down sampling function and the processed

ECG signals are used as the input data of the CNN model directly.

B. Convolution Neural Network

Convolution neural network is mainly composed of two parts, feature extraction and classification. The section of feature extraction is responsible for extracting effective features from the ECG signals automatically, while the part of classification is in charge of classifying signals accurately by making use of the extracted features. In short, these two sections complete the main work of this paper cooperatively [16].

The part of feature extraction consists of convolution layers and down sampling layers. Convolution layers (C-layer) can be regarded as a fuzzy filter that can enhance the features of original signals and reduce noises. Convolution operation is performed between feature vectors of the upper layer and convolution kernel of the current layer. Finally, the activation function gives the results of convolution calculations. The output of the convolution layer can be represented by Eq.1:

$$x_j^l = \mathrm{f}(\sum_{i \in M_j} x_j^{l-1} * W_{ij}^l + b_j^l) \tag{1}$$

Where x_i^l is the characteristic vector corresponding to the j^{th} convolution kernel of the l^{th} layer and M_i is the receptive field of the current neuron, while W_{ii}^l indicates the bias coefficient appropriated to the j^{th} convolution kernel of the l^{th} layer and f is a nonlinear function.

Principle of local correlation is adopted by down sampling layer (S-layer) to reduce the dimension of ECG data and preserve useful information. At the same time, the pooling technology is utilized to keep the features that characterized by displacement, scaling and invariance. The down sampling layer has the function of further feature extraction, meanwhile, the spatial resolution between hidden layer and hidden layer is decreasing and its formula is as below:

$$x_j^l = \mathrm{f}(\beta_j^l \, \mathrm{down}(x_j^{l-1}) + b_j^l) \tag{2}$$

Where $\mathrm{down}()$ represents the down sampling function and β_i^l means the weighting coefficient, while b_i^l indicates the bias coefficient.

There are still input layers and output layers in addition to the C-layers and S-layers. The network model is initialized before training the network, then dividing the ECG signal as the input data and at the same time the output vector of the target is specified. The error is calculated according to the following Eq.3 compared with the given target output vector.

$$\mathrm{E} = \frac{1}{2}\sum_{k=0}^{n-1}(d_k - y_k)^2 \le \varepsilon \tag{3}$$

Where E is the total error function and y_k represents the output vector, while d_k is the target vector. If it is satisfied, the training is finished, meanwhile, the weights and thresholds are saved. It is considered that each weight is stable and the classifier is formed. Conversely, if the conditions are not reached, the iteration will continue.

The convolution neural network is originally designed to deal with two-dimensional data. However, we have to deal with one-dimensional signals. Thus, we need to adjust the structure of CNN model. The optimized model of CNN for ECG classification is shown in Fig.4. It consists of an input layer, two convolution layers, two down sampling layers, a full connection layer and an output layer. The input of each neuron is connected to the output of the previous layer which is used to extract local features. 18 convolution kernels with a length of 7 sampling points are distributed in the convolution layer C1, and its input is a segment of ECG signals with 130 sampling points. Moreover, it outputs 18 feature vectors which have 124 sampling points; The sampling layer S1 is used for pooling feature vectors from the C1 layer and the feature vectors are compressed into 62 sampling points; The C2 layer also contains 18 convolution kernels with a length of 7 sampling points, furthermore, its output is 324 feature vectors with 56 sampling points. The length of the feature vectors are changed into 28 sampling points when they are pooled again by S2 layer, which are finally sent to the output layer to calculate the classification results.

IV. EXPERIMENTAL RESULTS

A. Data Set

All ECG signals used in this paper are derived from MIT-BIH standard arrhythmia database [17]. It includes 48

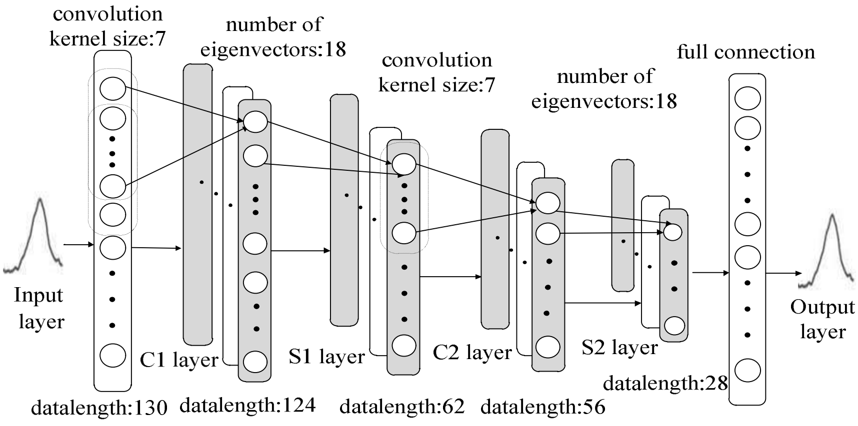

Fig. 4. Structure of proposed convolution neural network

two-channel dynamic ECG records. The first 23 records were extracted from the practice of regular outpatients, while the remaining 25 records were selected because of the presence of unusual complex ventricular, junctional and supraventricular arrhythmia. Each record is up to 30 minutes with a sampling frequency of 360HZ and 44 ECG records of the second lead were selected from the database to train and verify the feasibility of the method in this paper. According to the AAMI standard [18], (102, 104, 107, 217) the 4 beats were excluded because of their poor signal quality for post processing.

B. Parameter Optimization

In this paper, a total of 13200 beats were selected randomly as the training set, meanwhile, the other 13200 beats were chosen in the same way as the test set and there is no duplicate data between the two data sets. First of all, the training set is used to train the constructed network, then the well trained network is utilized to classify the test data.

1) The Optimization of Convolution Kernel

As the number and size of the convolution kernel have a great influence on the quality of the model, four groups of comparative tests were performed to make the model reach the optimal state in the case of learning rate is fixed. The sizes of convolution cores of two layers are set to 3*3, 5*5, 7*7 and 9*9 respectively in each experiment, and each group of tests has different numbers of convolution kernels. It is obvious that the error rate of the four sets of experiments changes with the increased numbers of convolution kernel as shown in Fig.5. Compared with the other two sets of experiments, the final trend of data changes is smooth relatively when the convolution kernel size is 7*7 and 9*9. In addition, the error rate almost reaches the minimum value when the number of characteristic vectors is 18. Lecun's recent remarks show that it is better to select smaller size of convolution kernels when the computing accuracy is equal. For avoiding the tedious computation caused by too large convolution kernels' size, we choose 7*7 as the size of convolution kernel eventually. We also draw a stacked line graph as shown in Fig.6 to further prove the stability of the chosen optimum point, which can intuitively show the developing trend of the sum of the values for the four data series in the same situation. Firstly, the change in the error rate all tends to be smooth. Moreover, the smaller the spacing between the four lines, the more stable the data changes. In conclusion, we select 7*7 as the convolution kernel size and the optimum number of eigenvector in per layer is 18.

2)The Setting of Learning Rate

For the sake of investigating whether the learning rate has an impact on the error rate, the learning rate of varying magnitude have been set in this section under the condition that the convolution kernel size and number are fixed. Moreover, we set different iterations to guarantee each experiment can achieve the state of convergence and specific experimental results are shown in table I. For one thing, when the learning rate is less than 0.1, the experimental results will achieve a state of convergence eventually and the error rates are all about 2.5%. However,

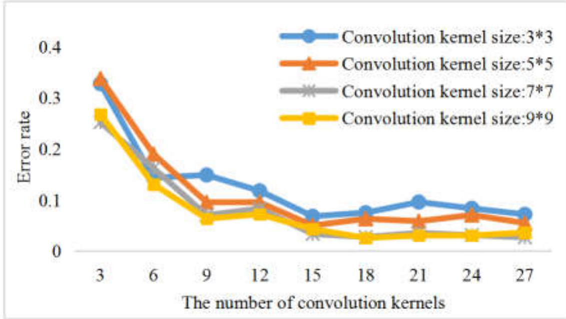

Fig. 5. The line graph for the regulation of convolution kernels

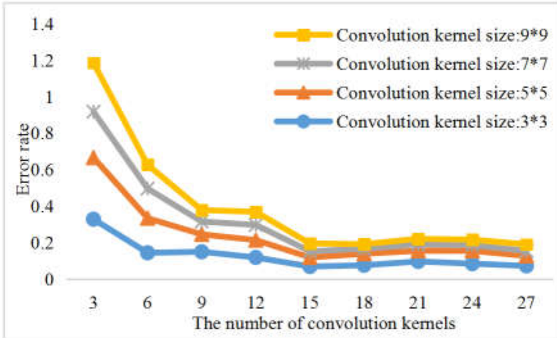

Fig. 6. The stacked line graph for the choice of convolution kernels

the time consumed decreases while the learning rate increases. For instance, the convergence speed is the slowest when the learning rate is 0.001. On the contrary, the data converges faster and takes the shortest time when 0.1 is set as the learning rate. For another, the error rate shows irregular changes while the learning rate is greater than 0.1. That is sometimes increasing and sometimes decreasing. It is believed that this phenomenon is due to the fact that the learning rate is too large for data to converge. In short, we should not only guarantee the recognition rate, but also select the appropriate learning rate to reduce the time consumption. That's why we select the learning rate of 0.1 and the data error rate is 2.5% as our final results.

TABLE I SELECTION OF LEARNING RATE IN STEADY STATE

Learning rate	**0.001**	**0.005**	**0.01**	**0.05**	**0.1**
Test error rate (%)	2.8	2.6	2.5	2.5	2.5
Training time(s)	280524	92302	51667	37676	14932

3). The selection of iterations

In order to observe the relationship between the number of iterations and the recognition rate of test data exactly, we evaluate the correct rate of the test set by adjusting the training times under the condition that the numbers of convolution kernel, size and learning rate are fixed. The experimental results show that the error rate reduces with the increase of the number of iterations and gradually keeps a stable state. When the number of iterations is 50, the error rate is as high as 11%, while the error rate is 2.5% at the time of iteration reach to 300. The detailed variation trend of error rate with the number of iterations is shown in Fig.7 and we can see clearly that the error rate remains changeless when the number of iterations is set to 300, 350, and 400. At this moment, the time of the training sample need to be considered. The time cost at each training step is similar when the other parameters are fixed, and the more training leads to the longer the time requirement.

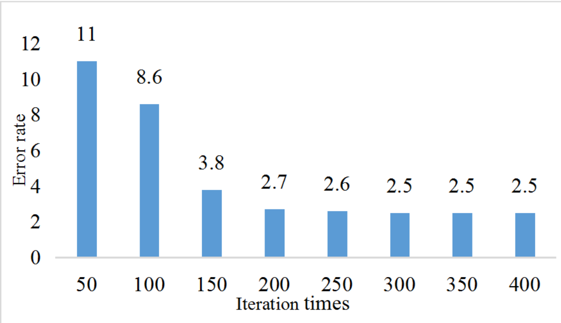

Fig. 7. Variation tendency chart of error rate

C. Performance Evaluation

A training model is obtained based on the above optimized parameters, in which the learning rate of the network model is set to 0.1 and the kernel size for the first and second convolution layer is 7. While the sampling factor of the two pooling layers is 2 for both the maximum pooling operation, the number of iterations is 300 times. The final test results show that the accuracy is 97.5%.

TABLE II. CONFUSION MATRIX OF CLASSIFICATION

	N	**L**	**R**	**A**	**V**
N	2951	0	0	49	0
L	26	2974	0	0	0
R	0	0	2977	23	0
A	84	39	59	2769	49
V	1	0	0	1	1198

From the Table I we known that the CNN algorithm is very cpu-consuming, moreover, any change in the neural network requires a new training, which will consume resources and time. This is an important aspect which needs to be optimized and valued. That’s why we choose the optimal parameters at all the stages. Table II gives the classification results of test data. We also preserve smooth sequence of historical error value and draw the mean squared error curve graph at the learning rate is 0.001, 0.01 and 0.1 as shown in Fig.8. The tendency of the error data eventually becomes stable when the learning rate is 0.1. This phenomenon indicates that the actual output coincides with the expected output, and it is further proved that the experimental results are optimal. But the data in the same state aren’t convergent when the learning rate is 0.01 and 0.001.

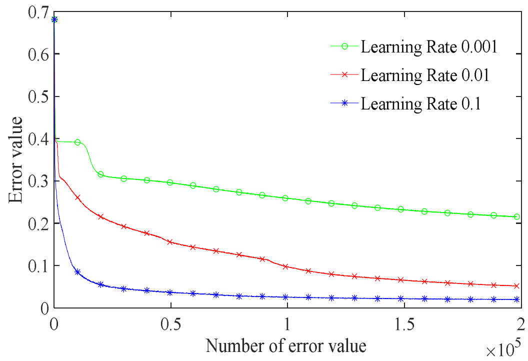

Fig. 8. Mean square error curve

The comparison of the current work with other existing algorithms is given in Table III. We can observe that the proposed method improves the accuracy of cardiac classification compared to the proposed methods and published experimental results. This is not only related to the idea of combining two algorithms to deal with the noisy of ECG data, but also shows that the optimized CNN model is also suitable for the classification of one-dimensional signals. In addition to the correct rate, the selected algorithms of the data pre-processing, feature extraction and classification parts in these comparative articles are described and compared in detail.

Moreover, what the types of "N.L.R.A.V" signals represent for in the "class" of Table III are introduced in the former part of the paper and each type represents a single arrhythmia signal, while "N.S.V.F.Q" these five types of signals are formed according to the AAMI standard rules, which recommends ECG signals are classified into the following five types: normal beats (N), supraventricular ectopic beats (S) ,ventricular ectopic beats (V), fusion beats (F), and unclassifiable beats (Q). A detailed description about these two different classification criteria for ECG signals is given in Table IV.

TABLE III. COMPARISON WITH OTHER ALGORITHMS

Article	**Class**	**Preprocessing**	**Feature Extraction**	**Classification**	**Accuracy**
R.J.Martis et al. [19]	N.L.R.A.V	Wavelet	Pan Tompkins + PCA	NN+ LS-SVM	93%
N. P. Joshi et al. [20]	N.S.V.F.Q	Wavelet	Wavelet+ PCA+ICA	SVM	86.4 %
Jose et al. [21]	N.L.R.A.V	Wavelet	Wavelet	PNN	92.7%
Zubair et al. [22]	N.S.V.F.Q	Bandpass filter	CNN	Softmax	92.7%
Ismaiel et al. [23]	N.L.R.A.V	Digital Filters	Discrete Wavelet	NNWs	94%
W. Jiang et al. [24]	N.S.V.F.Q	Bandpass filter	Hermite transform	Block based NN	96.6%
Zadeh et al. [25]	N.L.R.A.V	Bandpass filter	CWT	SVM +GA	97.2%
Proposed Method	N.L.R.A V	Wavelet combination	1D-CNN	Softmax	**97.5%**

TABLE IV. COMPARISON OF TWO CLASSIFICATION RULES

AAMI Class	MIT-BIH Hert Beat Types
Normal beats (N)	Normal beats (N), Left bundle branch block (L), Right bundle branch block (R), Atrial escape beat (e), Nodal (junctional) escape beat (j)
Supraventricular ectopic Beats (S)	Atrial premature contraction (A), Aberrated atrial premature beat (a), Nodal (junctional)premature beat (J), Supraventricular premature beat (S)
Ventricular ectopic beats (V)	Ventricular premature contraction (V), Ventricular escape beat (E)
Fusion beats (F)	Fusion of ventricular and normal beat (F)
Unclassifiable beats (Q)	Paced beat (/), Fusion of paced and normal beat (f), Unclassified beat (Q)

V. CONCLUSION

The classification of ECG signals is helpful to prevent and diagnose the cardiovascular disease and it is an important research subject in the process of fusing medicine and computer technology. In order to obtain higher quality ECG signals, there are two wavelet algorithms are employed in this paper. Then, it comes to the issues of using R crest's position and medical statistics to determine a candidate segment as the input data of CNN model. Finally, the optimized CNN model learns effective features and completes classification automatically. A good classification accuracy of 97.5% is obtained by comparing with the previous work. It is proved that the optimized CNN model, which was originally used to handle two dimensional data is also feasible in the field of processing one-dimensional signals.

It is well known that neural network algorithms are very central processing unit consuming and may jeopardize responsiveness. Moreover, any change in the CNN model requires a new training, which will consume resources and time. So the future work is to find a more simple and effective classification method to optimize convolution neural network and get better results. Besides, since this paper only tests the single lead signal of the database, the next step is to use the method proposed in this paper to test the multiple lead data to further enrich the experimental content.

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