Research on ECG Classification Method Based on Convolutional Neural Network

Jin Tao[1(✉)], Jianting Shi[2], and Rongqiang Wu[2]

[1] Graduate College, Heilongjiang University of Science and Technology, Harbin 150022, China
taojin@usth.edu.cn

[2] School of Computer and Information Engineering, Heilongjiang University of Science and Technology, Harbin 150022, China

Abstract. The electrocardiogram reflects the temporal changes in the body's cardiac potential; This is also an important technology for diagnosing cardiovascular disease, so the classification of electrocardiogram has gradually become the focus of many scholars. This paper designs an ECG classification algorithm based on convolutional neural network, which aims to automatically classify ECG using artificial intelligence algorithm. The algorithm has the characteristics of less parameters and more layers, and the classification speed is faster and has very strong real-time performance. The experimental results show that the accuracy of the algorithm reaches 98.1%, which has strong advantages in medical diagnosis and application.

Keywords: Convolutional neural network · Electrocardiogram · Classification · Convolution kernel scale

1 Introduction

An electrocardiogram (ECG) is a visualization of the electrophysiological activity of the human heart recorded by electrodes placed on the skin. The data of heart rate, S-T segment, P wave, QRS complex shape and appearance position exhibited by the electrocardiogram can be use to diagnose the arrhythmia such as sinus tachycardia, sinus arrhythmia, ventricular premature beats and atrial fibrillation. Medical specialists have accumulated a large number of rules for ECG diagnosis in long-term practice, but since the large number of rules and empirical knowledge accumulated in ECG analysis, it is quite time-consuming to learn ECG analysis skills. Currently, The number of professional ECG analysis doctors is insufficient to cope with massive ECG data, so the computer-aided diagnostic classification is needed to improve diagnostic efficiency [1]. Based on this demand, various ECG automatic classification algorithms based on medical experience knowledge are proposed. KTateno et al. proposed an analysis of atrial fibrillation based on the sequence of R peak intervals; SONG Li and MENG Qingjian extracted five time domain features, 32 wavelet domain features and 18 high-order statistic features based on wavelet transform and QRS heartbeat detection algorithm,

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and used support vector machine to conduct classification. FA Elhaj, N Salim et al. used wavelet analysis and QRS complex group detection algorithm to extract linear and non-linear waveform features and then use support vector machine and neural network for classification [2]. However, such methods are extremely dependent on the accuracy of the extracted features. The existing waveform feature recognition algorithms perform well on the public dataset, but do not satisfactorily meet the requirements in terms of clinical data performance [3]. In recent years, some scholars have proposed automatic classification algorithms based on deep neural networks. For example, UR Acharya, H Fujita and others use convolutional neural networks to classify ECG signals on 2–5 s, which reduces the need for medical prior knowledge, but ECG signal processed by this method, since those time of data are too short and the data samples are small, resulting the classification effect is not very ideal [4].

2 Related Technology

2.1 Basic ECG Knowledge

Human heart activity is regular, such as the generation of electrical stimulation, the ECG signal occurs before the mechanical contraction of the heart, and can be transmitted to many parts of the body through the body tissue. If the human myocardium is stimulated, it will cause positive and negative ion movement inside and outside the membrane, so that different potential changes occur at different positions on the body surface, thereby forming an electrocardiogram of the human body. Therefore, the electrode information can be collected from the body surface, and the time, direction change of the information is Called electrocardiogram. When the data collecting electrodes are placed at different positions, different types of ECG signals are generated, and according to this division principle, 12 leads are divided. Usually, we have 6 limb leads, I, II, III, aVR, aVL, aVF; Six chest leads, V1–V6, usually, the ECG of the hospital examination also uses this 12-lead system. Electrocardiogram can reflect the related changes in human heart potential, so it has become an important technical means for doctors to diagnose cardiovascular disease. However, due to the complexity of the ECG data and the long analysis time, the traditional analysis method has low accuracy and long time; Therefore, in order to improve the accuracy of heart beat classification and shorten the analysis time, many scholars have proposed to introduce advanced pattern recognition, machine learning and other technologies, in order to use artificial intelligence technology to improve the analysis level for the heart beats, and provide strong support for medical diagnosis.

2.2 Convolutional Neural Networks

Convolutional neural network (CNN) is a deep feedforward artificial neural network that has been successfully applied to image recognition. CNN consists of two basic structures. The first is the feature extraction layer. The input of each neuron is locally connected with the previous layer. The local features of this part can be extracted. Once the local features are extracted, it is possible to determine the positional relationship between these features and other features; The second is the feature mapping layer. Each computing layer of the network can be composed of multiple feature maps. Each feature map can be described as a plane, and all the neurons on the plane have the same weight [5]. The mapping structure feature of CNN is to use the Sigmoid function as the activation function of the convolution network, in this way, the displacement of the feature maps can be made invariant, and the neurons on the same plane can share the weights; thus, the setting of the free parameters can be greatly reduced. Each convolutional layer of the convolutional neural network can be followed by a computational layer for local averaging and quadratic extraction, which can greatly reduce the feature resolution [6]. The CNN model has been known for many years and has not received enough attention in the years since it was reported; until recently, people intend to use the trained CNN model to achieve image classification, which can accurately distinguish each local feature. This result makes CNN technology widely accepted and applied in the fields of image classification, face recognition, and target detection. CNN's weight has common characteristics, which is convenient for high-dimensional data processing by reducing the number of training of free parameters. These characteristics are in line with the requirements of remote sensing images, and its classification calculation can obtain higher accuracy. The CNN structure is shown in Fig. 1.

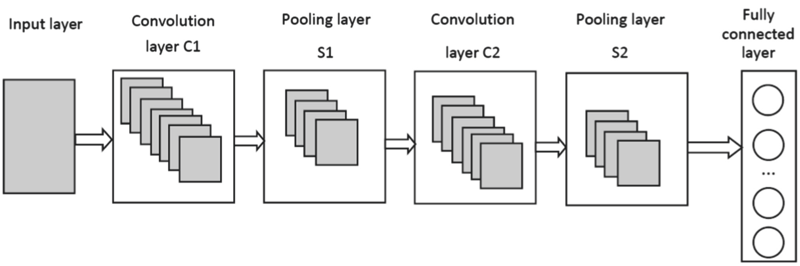

Fig. 1. CNN structure.

The main role of the input layer is to preprocess the original image data.

The convolution layer generally contains two operations. The first is to perform local associations, treating each neuron as a filter; the second is to perform window sliding, and the filter calculates local data. The key role of the convolutional layer is to acquire the local features of the image. Each convolutional layer can be used as a feature extraction layer, and the convolution accuracy can be improved by reducing the number of parameters set [7].

The main role of the pooling layer is to compress the amount of data and parameters and reduce overfitting. In other words, the pooling layer is used to compress images [8]. Based on the image features extracted by the convolutional layer, the pooling layer can calculate the average value of a local convolution feature, and can also calculate the maximum or minimum value; by reducing the dimension of the convolution layer feature, the classification can be continuously reduced. The computational complexity of the device reduces the burden on the classifier and also avoids over-fitting of the classifier.

The fully connected layer can output the classification result and function as a classifier, which can output the trained operation model so that the features of the image can be extracted.

3 Algorithm Design of Lead ECG Heart Beat Classification Based on Convolutional Neural Network

3.1 Algorithm Description

The electrocardiogram classification uses a convolutional neural network algorithm to include three key steps. First, it is necessary to obtain all the data images of the electrocardiogram, perform effective pre-processing operations on the data, and then perform electrocardiographic filtering and denoising operations to normalize the electrocardiogram so as to ensure that the results of the classification operation of the electrocardiogram are as Accurate and reliable. Secondly, the preprocessed data is input to the convolutional neural network, and the data features can be acquired through a series of convolution operations and pooling operations. Finally, the operation results of the convolutional neural network are output to form a classification result.

The convolutional neural network proposed in this paper consists of eight layers, five convolutional layers, two Pooling layers and one full connected layer. The setting parameters of the convolutional layer include the convolution kernel and the moving step size. For example, the convolutional layer C uses a convolution kernel of 7 * 1, the moving step size is set to 2, and the output result is 32X 18 * 1 feature vectors. The setting parameters for the pooling layer include the pooling kernel and the moving step size. For example, the pooling kernel used by the pooling layer B is 3 * 1, the moving step size is set to 2, and the output result is 32X 6 * 1 feature vectors. The fully connected layer uses the softmax classifier to output classification results. Detailed parameter settings are shown in Table 1. The convolutional neural network proposed in this paper consists of eight layers, five convolutional layers, two Pooling layers and one full connected layer. The setting parameters of the convolutional layer include the convolution kernel and the moving step size. For example, the convolutional layer C uses a convolution kernel of 7 * 1, the moving step size is set to 2, and the output result is 32X 18 * 1 feature vectors. The setting parameters for the pooling layer include the pooling kernel and the moving step size. For example, the pooling kernel used by the pooling layer B is 3 * 1, the moving step size is set to 2, and the output result is 32X 6 * 1 feature vectors. The fully connected layer uses the softmax classifier to output classification results. Detailed parameter settings are shown in Table 1.

3.2 Algorithm Design

The algorithm implementation proposed in this paper includes two key links. The first is the stage of training and learning for convolutional neural networks. The second is to test and verify the trained convolutional neural network. The specific description of each stage is as follows.

Table 1. Convolutional neural network structure

Name	Type	Number of convolution kernels	Step size	Feature vector	Output feature vector
1	Convolution layer	11 * 1	2	32	93 * 1
2	Convolution layer	9 * 1	2	32	85 * 1
3	Pooling layer	3 * 1	2	32	42 * 1
4	Convolution layer	7 * 1	2	32	18 * 1
5	Convolution layer	5 * 1	2	32	18 * 1
6	Pooling layer	3 * 1	2	32	6 * 1
7	Convolution layer	6 * 1	2	32	1 * 1
8	Fully connected layer			2048	11 * 11 * 256

(1) Training and learning stage.

The first step is forward calculation, and the selected training sample data D can be input into the network. The data is calculated by the convolution layer A, the convolution layer B, the pooling layer C, the convolution layer C, the convolution layer D, the pooling layer D, the convolution layer E, and the fully connected layer, and extract the ECG data characteristics of all intermediate layers.

The activation function of the convolutional layer is as described in formulas (1) and (2).

$$x_j^l = f\left(u_j^l\right) \tag{1}$$

$$u_j^l = \sum_{i \in M} x_j^{l-1} * k_{ij}^l + b_j^l \tag{2}$$

Among them, u_j^l is called the net activation of the jth channel of the convolution layer l, it is obtained by convolution summation and offsetting the previous layer output feature map x_j^{l-1}, x_j^l is the output of the jth channel of convolution layer 1. $f(\bullet)$ is called an activation function, and functions such as sigmoid and tanh can usually be used. M_j represents the input feature map subset used to calculate u_j^l, k_{ij}^l is the convolution kernel matrix, and b_j^l is the offset to the convolved feature map. For an output feature map x_j^l, The convolution k_{ij}^l core corresponding to each input feature map x_j^{l-1} may be different. "*" is a convolution symbol.

The pooling layer function is described in formulas (3) and (4).

$$x_j^l = f\left(u_j^l\right) \tag{3}$$

$$u_j^l = \beta_j^l down\left(x_j^{l-1}\right) + b_j^l \tag{4}$$

Among them, u_j^l is called the net activation of the jth channel of the pooling layer 1, which is obtained by downsampling weighting and offsetting the previous layer output characteristic map x_j^{l-1}, β is the weighting factor of the pooling layer, b_j^l is the offset term of the pooling layer. Symbol down (•) represents a downsampling function,It is divided into a plurality of non-overlapping $n \times n$ image blocks by sliding the window method on the input feature map x_j^{l-1}, The pixels within each image block are then summed, averaged, or maximized, and the output image is then reduced by n times in both dimensions.

The activation function of the fully connected layer classifier is as described in formulas (5) and (6).

$$x_j^l = f\left(u_j^l\right) \tag{5}$$

$$u^l = w^l x^{l-1} + b^l \tag{6}$$

Among them, u^l is called the net activation of the fully connected layer I, which is obtained by weighting and offsetting the previous layer output feature map x^{l-1}. w^l is the weighting factor of the fully connected network, b^l is the offset term of the fully connected layer I.

The second step is the back propagation of the error; The convolutional neural network calculation process is a step-by-step learning process. Therefore, the calculation process will produce errors, and the chain rule of back propagation can be adopted to calculate the gradient of each convolution layer.

The third step is to update the weight value of the convolutional neural network parameters, and use the gradient descent method to update the weight of the network. The calculation formula is as shown in (7).

$$w_l = w_l - \eta \partial J / \partial w_l \tag{7}$$

Among them, η is a balancing factor that controls the rate at which the gradient falls.

The fourth step is to loop through the first to third steps until the algorithm converges or reaches the set number of cycles. The conditions for experimental convergence in this paper are set as follows: Extract 100 running results and set the average accuracy. If the accuracy is greater than or equal to this, the algorithm converges and the operation ends.

(2) Test and verification stage.

After the convolutional neural network training and learning is completed, the actual data can be used for verification testing to see if the algorithm is accurate and reliable.

The first step is to load the trained and learned convolutional neural network model and remove the loss layer.

The second step is to perform classification, first input the test data into the convolutional neural network, then, perform the steps of the training learning stage; thus, a result of classifying the test data can be obtained, then, with the known clinical actual classification, to compare the analysis and calculate the accuracy of the algorithm.

4 Application Effect

In order to verify the effectiveness of the proposed algorithm, the experimental data in this paper uses the INCART data in the PhysioNet standard database. The data set includes 175,728 heart beats. The classification of heart beats adopts the international standard AAMI standard, which can divide the heart beat into F (Incorporating heart beat), N (normal heart beat), S (supraventricular ectopic beat), V (ventricular ectopic beat), Q (unclassified heart beat), totally five types, where F and Q are N, S, V Collection. The characteristic diagram of heart beat is shown in Fig. 2.

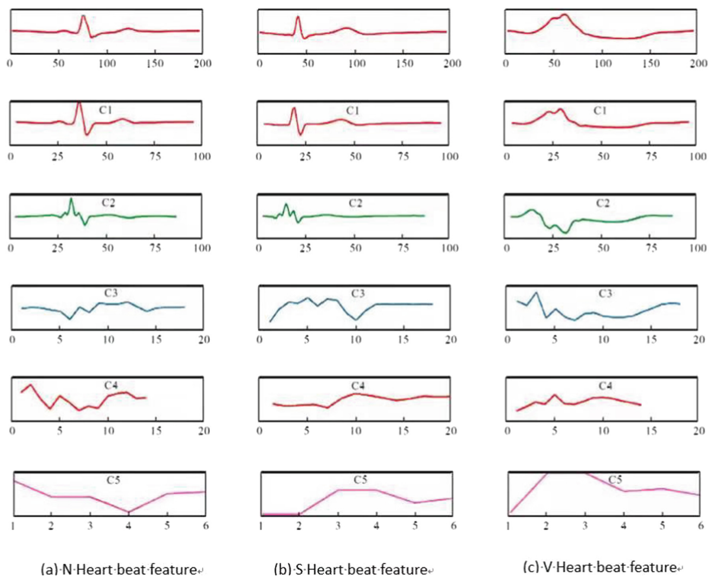

Fig. 2. Characteristic diagram of heart beat.

The specific data is shown in Table 2.

Table 2. Types and quantities of heartbeat data in the INCART database

Database name	Fusion heart beat	Normal heart beat	Ventricular ectopic beat	Supraventricular ectopic heart beat	Unclassified heart beat
INCART	219	153545	20000	1958	6

Because the number of fusion heart beats and unclassified heart beats in the database is very small, the heart beat data taken in the final experiment of this paper is normal heart beat, ventricular ectopic heart beat and supraventricular ectopic heart beat.

The experimental evaluation criteria are accuracy rate A, sensitivity S, and positive predictive value P. The accuracy formula A is calculated as the quotient of the correct classification number and the total number of samples. The sensitivity S is calculated as the average of the sensitivity of each category; The positive predictive values are the average of positive values for each category.

In order to be able to compare with the algorithm of this paper, this paper compares with the experimental results of support vector machine algorithm [9] and K-means algorithm [10] we found that each category data and average value of this paper are very high, detailed experimental results are shown in the Table 3.

Table 3. Comparative analysis of algorithm experiment results

Algorithm	N sensitivity	N positive predictive value	S sensitivity	S positive predictive value	V sensitivity	V positive predictive value	Overall sensitivity	Overall positive predictive value	Accuracy
K-means	95.4%	96.7%	76.2%	40.3%	79.6%	86.2%	83.4%	74.2%	89.5%
Support vector	98.1%	97.8%	87.3%	30.4%	89.6%	95.2%	88.7%	75.1%	92.3%
Our algorithm	99.3%	99.2%	76.8%	69.2%	95.4%	94.2%	91.4%	88.3%	98.1%

The experimental trend of support vector machine algorithm, K-means algorithm and the algorithm of this paper is shown in Fig. 3.

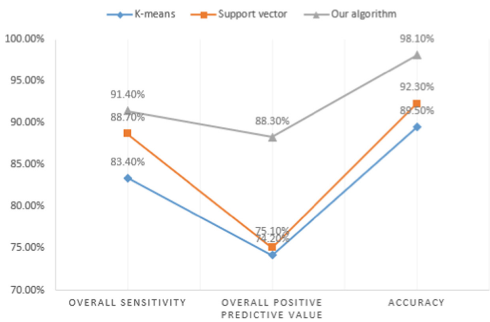

Fig. 3. Comparison of the experimental results of the algorithm.

5 Conclusion

Electrocardiogram classification is an important application field of artificial intelligence in the medical field, so it is very important to improve the accuracy of ECG classification. At present, the classification of team ECG has introduced some data algorithms: support vector machine, K-means algorithm, etc. However, due to the low accuracy of these algorithms, in this paper, we propose to introduce convolutional neural networks in ECG classification, which is more accurate than K-means algorithm and support vector machine; our principle conceivement is that the convolutional neural network uses a multi-level training model, including a 5-layer convolutional layer, which belongs to a deep convolutional neural network; and the scale of the convolution kernel is diversified, and it is better to obtain an accurate network structure through learning to improve the classification accuracy of the electrocardiogram; The experimental results show that the experimental accuracy of the algorithm reaches 98.1%. While, the convolutional neural network is the most advanced classification algorithm at present, which can utilize the structure of multi-level training and learning to greatly improve the classification accuracy of ECG.

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