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ECG diagnosis based on one-dimensional convolutional neural network

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Abstract. At present, cardiovascular disease has become the "first killer" endangering human life and health. Arrhythmia is one of the common diseases and frequently-occurring diseases. It is one of the main causes of death, and it is often accompanied by many complications. It can cause serious heart disease or even death, so it is very important to find a timely diagnosis of arrhythmia [1]. This article is based on the ECG data which is obtained from long-term monitoring to perform classification diagnosis on the occasional irregular heartbeat. It can be summarized as a series of features extraction and automatic classification diagnosis after a series of preliminary processing of the obtained long-term ECG data. This method is based on one-dimensional convolutional neural network to classify the normal heart rhythm and five abnormal heart rhythms according to the single lead data.

1. Introduction

In recent years, due to people's unhealthy lifestyles, the probability of suffering from cardiovascular diseases has increased, the hospital load is getting bigger and bigger, doctors may have overloaded work, and it is inevitable that many patients will be diagnosed with energy every day. It is difficult to accurately identify the small morphological changes of the ECG signal, which may result in the loss or misinterpretation of important information during diagnosis. At this moment, effective auxiliary diagnosis methods are particularly important.

For arrhythmias, diagnosis by electrocardiogram is the fastest, cheapest, and non-invasive method. ECG signals contain a wealth of physiological and pathological information, each of which may imply a cardiac condition, and each abnormal change is considered an arrhythmia, so the ECG signal is considered to determine the individual's heart rhythm condition and pathology. An important basis for sexual change.

In a normal cardiac cycle, a typical ECG waveform is a P wave, a QRS complex, a T wave, and a U wave that may be seen in 50% to 75% of the ECG. The classification techniques for ECG signals can be divided into two categories from the perspective of characteristics. One is to extract features



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manually. It is necessary to understand the structure of ECG and extract features from as many angles as possible, such as data features and morphological features, and then feature selection of features. Finally, the appropriate classification model is used for classification diagnosis, but in the case of abnormal heart rhythm, artificial features are more difficult to extract. The other type is the extraction of automatic features. Select the appropriate deep learning algorithm, let the algorithm extract the features by itself, obtain more accurate description of the data, and then select the appropriate algorithm for classification, but the model is constructed when the data set is large. And training takes a long time. Since the extraction of artificial features determines the quality of the whole system to a large extent, this paper adopts the dual features, that is, the automatic features of artificial features and higher-level representation of data as the basis for ECG diagnosis.

In 2015, V.K. Malhotra and others conducted a research to assess the prevalence of abnormal ECG in trained Indian athletes and correlate it with the nature of sports training, that is endurance or strength training [2]. In 2015, Wan Jing et al. used wavelet transform for preconditioning and 2D-PCA feature extraction, and based on mean square error attribute weighted genetic simulated annealing K-means improved clustering algorithm for classification diagnosis [3]. In 2017, Om Prakash Mahela and others proposed a method on S-transform and Fuzzy C-means (FCM) clustering initialized by decision tree to detect and classify the power quality disturbances [4]. In 2018, Mohammad S. Refahi et al. used a semi-automated method based on maximum and minimum for ECG feature extraction and a classification diagnosis using LS-TSVM [5]. In 2018, G. Sannino et al. used two median filters and a low-pass filter for signal denoising on arrhythmia, using WFDB tools to detect R points, taking points for signal segmentation, extracting time domain features, and finally using deep neural networks (DNN) for classification diagnosis [6].

In this paper, the data collected by the standard 12-lead bipolar II lead is selected as the basic data of the diagnosis. The lead measures the potential difference between the left leg and the right hand, and is the most clearly display in the 12-lead Ventricular electrical signal. A typical standard normal II lead ECG waveform is shown in Figure 1. Most of the papers use the features extracted after ECG segmentation as the characteristic parameters, so that only the local features of ECG can be reflected. In the process of automatic feature extraction, the whole record is taken as input, considering the globality of features and extracting segmentation. The post-artificial features also take the locality of the features into account.

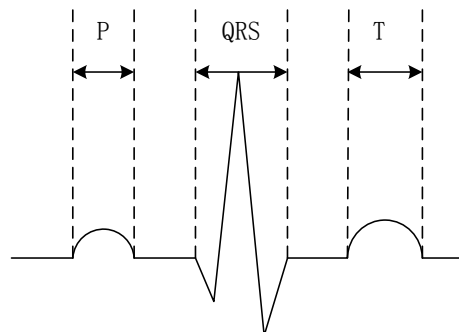


Figure 1. Typical standard normal II lead waveform.

2. ECG classification model

The ECG data classification model is established based on real ECG data. The general process is as follows:

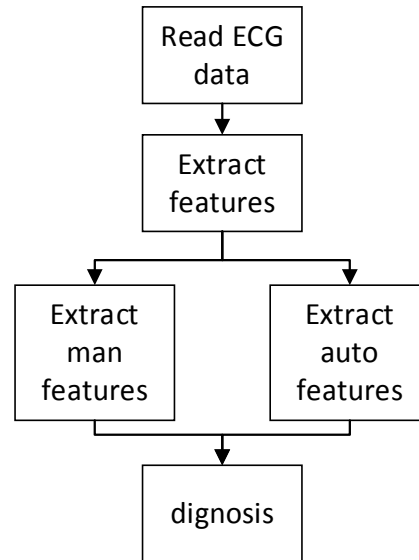


Figure 2. ECG data classification model design flow.

Firstly, certain data preprocessing operations are carried out for ECG datasets, then automatic feature extraction is performed by CNN, and weights are updated by backpropagation, high-dimensional features are extracted, and feature fusion is performed with artificial features to diagnose ECG. And perform performance evaluation on this classification model.

3. Algorithm framework

3.1 Artificial feature extraction

The diagnosis of heart disease is usually based on heartbeat, and the ECG signal is a non-stationary signal. Its amplitude is very low, in a small range, which brings certain difficulties to ECG feature extraction. The obtained data set is the ECG detection data for a long period of time, and thus the extraction of artificial features involves signal segmentation and extraction of artificial features.

There are three categories of artificial features, one is the age of a single sample, the other is the gender of a single sample, and the last is the time domain feature extracted from the data set based on the characteristics of the standard ECG. It can be seen from the typical standard normal II lead waveform that the QRS wave is significantly different from the other parts of the ECG signal, and the frequency variation at the QRS wave is also quite obviously compared to other parts. According to medical knowledge, the appearance of each R peak corresponds to a new rhythm cycle, so effective R peak detection is very necessary.

In this paper, based on the squared signal point, the Lagrange's five-point interpolation method is used to find the second-order derivative [7] to detect the R-peak position. This method mainly shows the change in the slope of the QRS region of the ECG data. From the typical standard normal II lead waveform, it is observed that the slope change of the QRS region has a positive value and a negative value, so we consider squaring the sample first to enhance the QRS region. And Lagrange's five-point interpolation can effectively prevent the amplification of high-frequency noise, which is very

necessary for our signal. The Lagrange's five-point interpolation expression is:

$$g'_0 = \frac{1}{12h} (g_{-2} - 8g_{-1} + 8g_1 - g_2) \quad (1)$$

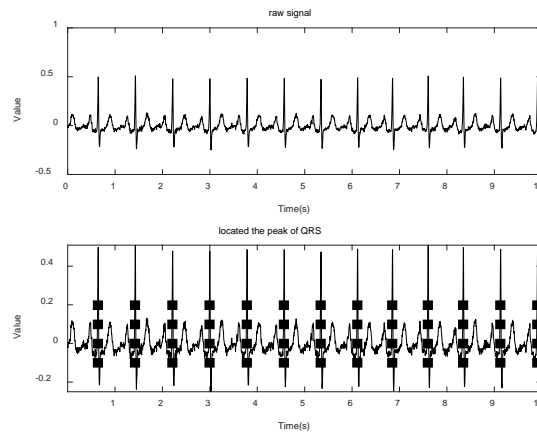


Figure 3. R peak detection.

3.2 Automated feature extraction network framework

Since the data set has periodic ECG data, a convolutional neural network [10] is constructed to process the one-dimensional ECG data. A typical convolutional neural network is composed of multiple levels of convolutional layers, pooled layers, and fully connected layers. It is mostly used in image processing and pattern recognition. The convolutional layer performs a convolution operation on the input data to enhance signal characteristics and reduce the effects of noise. The pooling layer performs the down sampling operation, and uses the data local correlation principle to sample the data, which reduces the amount of data and retains certain useful information. The fully connected layer is classified and diagnosed based on the extracted features.

In this paper, a five-level convolutional neural network [8] is used, and feature extraction and classification diagnosis multi-task learning are performed at the same time. The overall can be divided into 8-Net, 8-Net, 16-Net, 16-Net, and 32-Net. Modules, according to this cascading these five network modules, achieve the process of feature extraction from wide to fine. The fifth network module in this paper is different from other modules. It uses global pooling instead of average pooling to avoid over-fitting caused by direct connection to fully-connected networks and greatly reduces network parameters. The proposed approximate network structure can be as shown in Figure 4 below:

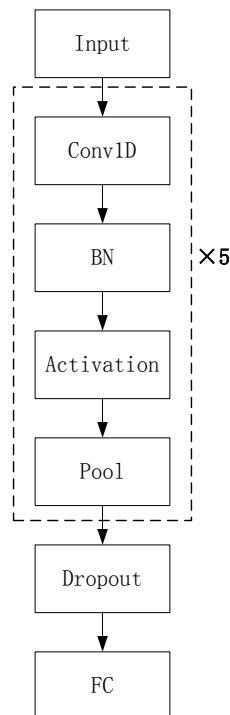


Figure 4. ECG feature extraction network structure.

Table 1 shows the specific structure of the proposed one-dimensional convolutional neural network model, which has an 11-layer network, including five convolutional layers, four averaged pooling layers, one global pooling layer, and one fully connected layer. The convolution kernel size set for each convolution layer (Layer 1, Layer 3, Layer 5, Layer 7, Layer 9) is 27, 15, 13, 9, and 7 in order. The first four convolutional layers use the average pooling to down sample the feature map to reduce computational complexity and prevent overfitting. Let the convolutional layer and the pooling layer have a step size of 1, and perform a zero-fill operation on the convolutional layer.

Table 1. ECG model structure

Layers No.	Type	Kernel size	No. Kernels	Stride	Output shape
Layer1	Conv1D	27	8	1	(None,3000,8)
Layer2	Pool	3×3	1	1	(None,1000,8)
Layer3	Conv1D	15	8	1	(None,1000,8)
Layer4	Pool	3×3	1	1	(None,333,8)
Layer5	Conv1D	13	16	1	(None,333,16)
Layer6	Pool	3×3	1	1	(None,111,16)
Layer7	Conv1D	9	16	1	(None,111,16)
Layer8	Pool	3×3	1	1	(None,37,16)
Layer9	Conv1D	7	32	1	(None,37,32)
Layer10	Pool	-	-	-	(None,32)
Layer11	FC	-	-	-	(None,6)

4. experimental results and analysis

4.1 Experimental environment and data set introduction

The experiment was performed on an algorithm evaluation on a 16G 1050Ti Nvidia notebook. The data set is derived from the first physiological signal challenge competition, and six types of data are selected for classification diagnosis. The specific information can be known from Table 2. After a series of considerations and processing, the sampling frequency of the data set is 200 Hz, and the length of each record is 3000. Sixty percent of the data was selected as the training set, 20% of the data was used as the verification set, and 20% of the data was used as the test set. The sample distribution in each set is unbalanced. For example, there are 366 normal samples in the test set, 420 AF samples, 297 I-AVB samples, 82 LBBB samples, 653 RBBB samples and 66 STE samples.

Table 2. Mapping between dataset categories and annotations.

Category	Annotation
N	normal
AF	Atrial fibrillation
I-AVB	I-type Atrioventricular resistance
LBBB	Left bundle branch block
RBBB	Right bundle branch block
STE	ST segment elevation

N refers to normal heart rhythm; AF is called atrial fibrillation, which has a high incidence in the elderly and is a sign of human aging; I-AVB is called type I atrioventricular block, and is a complication caused by other diseases. This type of less complication, but it is more serious, such as fatal arrhythmia ventricular fibrillation, so it is very important for this type of diagnosis; LBBB called left bundle branch block, more common in organic Heart disease, and RBBB refers to right bundle branch block, which can be seen in organic heart disease or normal people. Both bundle branch block are caused by severe heart disease; STE is called ST segment lift High, can be seen in patients with acute myocardial infarction, can also be seen in normal adult male or other clinical diseases, but the diagnosis of ST-segment elevation is very important, because for patients with acute myocardial infarction, time is the heart muscle, myocardium is life.

4.2 Model training

Set the Batch-size to 32 by verifying the set debugging, and set the epoch to 60 to achieve better results. Since the back-propagation weight update will change the distribution of network layer input, and thus need to reduce the learning rate and good weight initialization, this paper uses batch standardization in the training process, that is, input to each network layer. Batch standardization is performed to ensure uniformity of input distribution and to reduce the network's dependence on parameter initial value settings. In this paper, parameter initialization is performed using a normal distribution with a mean of 0 and a standard deviation of 0.01. The initial learning rate is set to 0.1. If the loss value of the verification set does not decrease in 10 rounds, the update learning rate is 0.1 times of the previous learning rate. The Dropout module is added to the visible layer of the network. The probability of each node having 0.4 in each round of weight update is randomly ignored, so that the network model is not overly dependent on the weight, and the generalization ability of the model is improved.

4.3 Performance evaluation

The number of samples in each category in the entire data set is unequal, that is, the data set diagnosed by ECG is classified as unbalanced. Thus, we list the confusion matrix of the proposed ECG diagnostic algorithm in Table 3. It can be clearly seen from Table 3 that our ECG diagnostic algorithm can achieve comparable classification accuracy for each category.

Table 3. Confusion matrix of ECG diagnostic algorithm.

	Predicted						
		N	AF	I-AVB	LBBB	RBBB	STE
Actual	N	300	2	13	0	23	28
	AF	2	378	9	8	23	0
	I-AVB	2	3	283	1	7	1
	LBBB	1	3	2	71	4	1
	RBBB	72	38	38	7	479	19
	STE	13	2	3	2	9	37

TP: The prediction is true, the actual is true;

TN: The prediction is false, the actual is false;

FP: The prediction is true, the actual is false;

FN: The prediction is false, the actual is true.

(i) Define the sensitivity, which refers to the proportion of all symptoms that are predicted to be in a certain class.

$$\text{sensitivity} = \frac{TP}{TP + FP} \quad \#(2)$$

(ii) Define recognition, which refers to a symptom of a certain class, and the algorithm successfully predicts the proportion of the class.

$$\text{recognition} = \frac{TP}{TP + FN} \quad \#(3)$$

(iii) The definition of F1 is a harmonic averaging of sensitivity and recognition. It is characterized by more focus on lower values, which is highly valued for each indicator.

$$F1 = \frac{2 \times \text{sensitivity} \times \text{recognition}}{\text{sensitivity} + \text{recognition}} \quad \#(4)$$

(iv) Define acc, which refers to the classification accuracy.

$$\text{acc} = \frac{\text{samples of correct classification}}{\text{all samples}} \quad \#(5)$$

Each category of sensitivity, recognition, F1 can be seen in Table 4.

Table 4. Values of each evaluation indicator.

	Sensitivity	Recognition	F1	Samples
N	0.77	0.82	0.79	366
AF	0.89	0.9	0.89	420
I-AVB	0.81	0.95	0.88	297
LBBB	0.80	0.87	0.83	82
RBBB	0.88	0.73	0.80	653
STE	0.43	0.56	0.49	66

The recognition accuracy of the whole test sample set is 0.82, and it is obvious from the confusion matrix and Table 4 that the ECG diagnosis algorithm proposed in this paper is insensitive to the ST-segment elevation of this heart rhythm abnormality, and the ST segment is the level of the typical cardiac cycle. In the segment extraction, when the feature extraction is performed, the measurement benchmark cannot be found to judge the level or not, and because the imbalance of various sample sets in the test set, the sample of the most category is approximately 10 times that of the ST segment elevation sample, so this may be The reason for the low accuracy of ST segment elevation recognition. In addition, from the confusion matrix, the diagnosis results of normal sample, right bundle branch block and ST segment elevation are misdiagnosed to some extent. As mentioned in the previous introduction, ST segment elevation can also be seen in normal people and other clinical diseases. Therefore, there will be a certain degree of misdiagnosis between the three categories.

5. Conclusion

Due to the performance of various anomaly categories, it is difficult to extract features manually, and the data set is long. The abnormal heart rhythm usually only occurs in a short time, which further increases the difficulty of feature extraction. Therefore, the extraction is based on one-dimensional convolution. For the ECG diagnosis of the neural network, each record of the obtained numerical type is taken as a feature into the designed network, and the automatic feature extraction is performed to obtain the deep meaning of the representation feature, and the ECG classification diagnosis is performed, but the designed algorithm is designed. The sensitivity to one of the categories is not high, and the algorithm will continue to be optimized to improve the universality of the algorithm.

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