Study on abnormal detection of ecg signal base on DCNN

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Abstract. In this paper, the Dropout deep convolutional neural network based on ecg signal anomaly detection method is proposed. Then, the double threshold method is used to detect the R wave and calculate the width of corresponding QRS wave group and the position of QRS wave is taken as the reference to include several points forward and backward respectively. These data points are intercepted and made into data sets for training and testing of deep convolutional neural network. Finally, the data set is read into deep convolutional neural network for abnormal measurement, and the test results are statistically analysed. In this paper, the detection rate of QRS composite wave is up to 99.5%, and the classification accuracy of abnormal signals can reach 99.26%. Experimental results show that the algorithm has the characteristics of high implementation rate, high accuracy, convenient and fast.

1. Introduction

With the increasingly pace and pressure of people's life, cardiovascular diseases have seriously threatened people's life and health [¹]. Electrocardiogram (ECG) is a common method to record the cardiac electrical signal, which can reflect the basic state of human heart [²]. By analyzing the ECG data, medical personnel can make more accurate judgment of people’s health state. At present, a large number of scientific researchers have begun to use computer technology to analyze ECG data, thus realizing real-time the monitoring of individual heart conditions without medical supervision. Construct a self-organized neural network to realize unsupervised clustering of ECG signals [³]. 16 types of ECG data in MIT arrhythmia database are used to obtain accurate classification results. Benali R [⁴] research group combined wavelet transform and neural network to classify 5 kinds of ECG signals, and also obtained higher accuracy. Acir N [⁵] et al. proposed to classify ECG signals by Least Squares Support Vector Machine (LSSVM). This method classifies ECG data by fast LSSVM algorithm on the basis of dimension reduction in feature vector space. In [⁶], Shen CP uses an adaptive algorithm to extract data functions, and then combines support vector machine (SVM) and K-means clustering to ECG data sets for classification. It improves the classification accuracy, but these methods only carry out simple pretreatment on the data, resulting in high error detection and waveform error detection rates. Deep convolution neural network (DCNN) is suitable for pattern detection and classification tasks [⁷]. In recent years, theoretical research on in-depth learning has received attentions ever than before. DCNN has made great achievements in various applications such as image recognition [⁸], natural language processing [⁹], video recognition [¹⁰] and speech processing [¹¹]. ECG data is regarded as a special kind of one-dimensional image which can use depth volume and neural network to study and analyze ECG signals. However, with the increase of convolution and pooling layers, there will be over-fitting phenomenon in training. In order to solve the over-fitting phenomenon and the problems of missing
detection, wrong detection and abnormal ECG signal detection of R wave in ECG signals, this paper proposes an ECG signal anomaly detection method based on Dropout depth convolution neural network.

2. Anomaly Detection

2.1 Algorithm flow
A complete ECG consists of several groups of ECG waveforms. The complete ECG waveform period includes P wave, QRS wave and T wave. Each waveform has certain physiological significance\cite{12}. QRS wave group generally has more energy with higher amplitude than P wave and T wave in RR interval (interval between two adjacent R waves). The particularity of QRS wave group in ECG signals determines that it is the key to ECG signal detection. Discrimination of other waveform morphological characteristics should be based on this.

![Diagram](image1)

Figure1. The flow chart of this algorithm

The neural network training data set in this paper is from MIT-BIH arrhythmia database. According to the pathological labels marked in the database, it selects a total of 110238 data. The training set data are labeled as 4 categories: normal (N), left bundle branch block (LB), right bundle branch block (RB), ventricular premature beat (PVC). It proposes the ECG anomaly detection method based on Dropout deep convolution neural network. The method firstly preprocesses the data, uses the adaptive double threshold method to detect the peak value of the R wave, and then determines the QRS wave group width. Based on the position of QRS wave group, each of the left and right waves includes several sampling points to determine one sampling point including one cycle. Complete candidate sections of ECG signal waveforms and create data sets. Finally, the constructed data set is input into the designed deep convolution neural network to complete anomaly detection of ECG signals. The flow chart of this algorithm is shown in Fig.1.

2.2 Data pre-processing
In the process of making ECG data set, as ECG signals are affected by power frequency interference, baseline drift, electromyography interference and electrode movement during the acquisition process. In order to better complete the work of feature extraction, this paper preprocesses the original data by FIR band-pass filtering to remove noise so as to avoid the influence of noise on ECG data feature extraction. Since the peak value of the R wave in one cycle of the ECG signal is the most obvious and easy to identify, the peak value position of the R wave in each cycle is marked in the preprocessing process at the same time.

There are four main steps in pretreatment. Step 1: The algorithm first performs FIR band pass filtering (40 steps) on the original ECG signal data containing various noises and complex redundant information. Through experimental tests, the band-pass frequency is 15-25Hz, noise and other clutters (P wave, T wave) can be eliminated after the band-pass filtering, and the signal information of QRS.
wave group is well saved. Step 2: After the band-pass filtering in the previous step, the ECG signal has the problem of "double slope" (two peaks). In order to solve this problem, find the maximum average slope value and the maximum slope value of septum integration on both sides of the center point (0.015s-0.060s), multiply by 0.6 and 0.5 respectively, then subtract the maximum slope value of septum on the right from the maximum value on the left, and finally find the average slope value. In this step, the waveform pattern becomes simple and clear, which highlights the QRS complex signal. Step 3: The remaining ECG signals are processed by low-pass filtering with a cut-off frequency of 6Hz. At this time, the e waveform is very smooth, which is more conducive to accurate detection of R waves. Step 4: The pretreatment of the waveform in the first three steps make the obtained small amplitude value of the ECG waveform small, which is not conducive to the R wave detection. In this step, the designed sliding window integration method with a width of 18 sampling points is used to increase the absolute amplitude of the ECG waveform and further smooth the waveform. After the pretreatment of above four steps, the original complex ECG signals only have groups of peak signals with single mode. Fig. 2 is a comparison diagram of the original signal and the preprocessed signal. Compared with the original signal, the preprocessed signal has smoother waveform, single mode, and easier location detection.

2.3 Detection of QRS wave group

2.3.1 Design the self-adaption double thresholds to defect the R wave

The self-adaption double-threshold operation on the characteristic signal after pretreatment is to detect the R wave. In order to enable the designed adaptive double threshold to change stably in real time with the signal and reduce the error detection and missed detection rate, this research designs a high-low double threshold method. When the peak value exceeds the low threshold value, it is believed that it accurately detects the R wave. Then, by comparing the relationship between peak amplitude and high and low threshold, the threshold is adjusted to detect the next R wave. Since the energy of ECG waveform is mainly concentrated in QRS wave group, the R peak value can be regarded as the energy peak value of each waveform. By dividing the time window of each waveform and finding the maximum and minimum values in the window, it makes the R wave peak position of each heartbeat waveform, and then completes the R wave detection of all data. Fig.3 is an R wave detected by data recorded as number 100.

![Figure 3. R wave detected by data recorded as number 100](image)

2.3.2 Analysis of detection result

According to the designed self-adaption threshold method, the detection results of R wave is as Table 1. The total data is 110238, the correct detection result of the algorithm is 109250, the algorithm has 620 errors and 368 missed ones, the overall sensitivity (Se) reaches 99.44%, and the positive prediction rate (P+) reaches 99.66%. The definitions of Se and P+ are shown in Formula (1) and Formula (2) respectively:

\[ Se = \frac{TP}{TP + FN} \]

\[ P+ = \frac{TP}{TP + FP} \]

Where TP represents the correct number of tests, FN represents the number of unchecked tests, and FP represents the number of error checks.
2.3.3 Extracting ECG data characteristics
After marking the R wave peak position of each waveform, the ECG data of a certain length is taken as the candidate segment of the data set with the R wave peak as the reference point. As can be seen from Table 1, the R wave data detected in this paper have the situations of wrong detection and missing detection. For these two situations, the processing method in this paper is to detect the original data three times and select the data result with the lowest error detection rate to extract ECG characteristics. Based on the medical statistics and position of QRS wave detected before, this research includes 100 sampling points (about 0.28 seconds) forward and 150 sampling points (0.42 seconds) backward respectively, in total of 250 sampling points (0.7 seconds), and then intercepts this segment of data points as a data sample in the data set. Then, take data in this segment as a data sample in a data set. Divide the data sample into training data sets and detected data sets in ratio of 3:1. Then, put the prepared training data set into the designed deep convolution neural network for training.

| Signal record number | Experts marking QRS wave | Correct detection QRS wave | wrong detection | missing detection | Sensitivity (Se) | predicting rate (P+) |
|----------------------|--------------------------|-----------------------------|-----------------|------------------|-----------------|---------------------|
| 100                  | 2273                     | 2272                        | 0               | 1                | 0.9996          | 1                   |
| 111                  | 2124                     | 2123                        | 4               | 1                | 0.9995          | 0.9981              |
| 121                  | 1863                     | 1863                        | 3               | 0                | 1               | 0.9984              |
| 210                  | 2650                     | 2604                        | 15              | 46               | 0.9826          | 0.9943              |
| 220                  | 2048                     | 2048                        | 0               | 0                | 1               | 1                   |
| 234                  | 2753                     | 2751                        | 0               | 2                | 0.9993          | 1                   |
| Total                | 110238                   | 109586                      | 648             | 380              | 0.9965          | 0.9941              |

3. Abnormal Detection Based on Droupt DCNN
According to the experimental results, the deep convolution neural network (DCNN) is used to detect abnormal ECG signals. Generally, DCNN is a multi-layer convolution neural network model formed by alternating multiple convolution layers and pooling layers. The complete DCNN performs a one-to-many complete connection between neurons in adjacent layers. The deep convolution neural network structure designed in this research consists of two convolution layers, two pooling layers and a two-dimensional CNN full connection layer. Fig.4 is a complete depth convolution neural network model convolution layer C1, also known as a feature extraction layer, applied to the classification of four ECG waveforms. It is used as a fuzzy filter in convolution neural network, receives feature vectors from input layer, performs convolution operation on convolution kernel, and calculates convolution feature mapping result through activation function RELU. The size of the convolution kernel receptive field directly affects the size of the neuron receptive field. In this research, the convolution kernel is set to 31 in the convolution layer C1, and the pooling layer S1 is connected to the convolution layer C1. The down-sampling function realizes data sampling to keep the characteristics unchanged. Convolution layer C2 extracts features again, sets the convolution kernel size to 6, extracts feature values obtained by down-sampling S1 layer, and outputs feature mapping vectors through convolution operation. The pooling layer S2 performs down-sampling again, and the calculation process is similar to that of S1. The output layer is set to contain 4 neurons, and the output layer describes the classification results of ECG signal data through the classifier and its parameters.
The complete depth convolution neural network mentioned has two convolution layers and two pooling layers. The structure of this neural network is relatively simple, but the convolution coordination is very complex and over-fitting phenomenon often occurs. In the practical application of DCNN, this over-fitting phenomenon often leads to the results of weakening generalization ability of the neural network, lowering the accuracy and taking too long training time. Excessive training time limits the operability of ECG signal data analysis of DCNN in clinical application. In order to solve the over-fitting problem of ECG waveform data classification based on DCNN, this research designs one new network structures to reduce over-fitting, this is the abnormal ECG signal classification algorithm based on Dropout deep convolution neural network. The algorithm is based on the complete depth convolution neural network model described above. The model of randomly discarding certain neurons and related connections based on probability during training is equivalent to training multiple sub-networks simultaneously. Figure 5 show a neural network based on Dropout depth convolution, in which several neuron are randomly discarded. Dropout Deep Convolution Neural Network is a simplification of the complete Deep Convolution Neural Network. That is, a sub-network that randomly forms a plurality of neurons to form a complete network. For a network with m neurons, 2m subnets can be theoretically generated. In the sample training process, it can reduce the subnet each time for training. In this paper, each neuron is activated according to the probability $P \in [0.5, 1.0]$, and propagation calculation is performed according to the forward BP model. The parameter settings of convolution layers $C_1^1$, $C_2^1$ and merging layers $S_1^1$, $S_2^1$ are the same as those of the above-mentioned full-depth convolution neural network. Compared with the complete DCNN, the waveform classification algorithm based on Dropout DCNN reduces the network structure through probability, which can improve the generalization ability of the neural network to a certain extent. Reference points out that this neural network based on Dropout has higher applicability and robustness in terms of sample training time and training results. The experimental classification results are shown in Table 2. There are four main types of test results, as shown in Figure 6, which are "normal (N)", "left bundle branch block (LB)", "right bundle branch block (RB)" and "ventricular premature beat (PVC)".

| Test categorization | N   | LB  | RB  | PVC |
|---------------------|-----|-----|-----|-----|
| N                   | 7665| 5   | 8   | 10  |
| LB                  | 12  | 5514| 46  | 17  |
| RB                  | 8   | 44  | 6852| 25  |
| PVC                 | 9   | 17  | 16  | 7168|
4. Experimental results and performance analysis

4.1 Accuracy of ECG abnormality classification

The number of R waves detected after pretreatment is 109,586, which are divided into training and detection based on a ratio of 3:1. The detection and classification data are mainly 27,400 and then divided into four types of pathological features. Table 2 shows that the normal detection accuracy is the highest, the detection accuracy of ventricular premature beat is relatively low, and the left bundle branch block and the right bundle branch block are easy to cause misjudgment. The main reason is that the two types of pathologies that are misjudged have little difference in early ECG data. Although the data are preprocessed, there is still the possibility of misjudgment. Calculate the classification accuracy of these four types’ case detection results, and then the average calculation accuracy rate. It is clear that the algorithm accuracy can reach 99.26%. As a preliminary diagnostic method for clinical diagnosis and ECG data, it can meet the needs of practical application.

4.2 The number of iterations selection

In order to better select the number of iterations of the deep convolution neural network, this research discusses the relationship between the number of iterations of the deep convolution neural network training and the accuracy of the test classification, fixes the number of convolution kernels to 3, adjusts the number of iterations of the network, and analyses the classification accuracy of ECG signals. The relation between the number of experimental iterations and the recognition rate of the test set is shown in Fig. 10. It can be found that with the increase of training times, the ECG signal classification and recognition rate increases, but when the number increases, the iteration times exceed 500, the ECG signal classification and recognition accuracy rate increases very slowly, and the training difficulty and training duration increase at the same time. Therefore, this paper selects 500 as the experiment iteration times, and the test set accuracy rate reaches 99.26%.

4.3 Compared with other networks

For the data of making ECG signal, this research uses the typical neural network (BP), cyclic neural network (RNN) and convolution neural network based on residual network (Res-Net CNN) to train samples and classify and identify test sample waveforms. Then, compare them with the classification results of this experiment, and the experimental comparison results are shown in Table 3. From the comparison results, it can be seen that the classification and identification rate of Droup-based deep convolution neural network is 99.26%, which is higher than that of other neural networks.
5. Conclusion Remarks

This research proposes the abnormal ECG signal detection method based on Dropout deep convolution neural network. The method firstly preprocesses the data, then locates and detects the QRS wave and calculates the heart rate. Then, based on the position of the QRS wave, it includes several points forward and backward respectively, which takes out the data point of this segment as convolution neural network training and testing data. It finally reads the data into the deep convolution neural network for abnormal determination and the detection results are counted to evaluate the algorithm. In order to solve the problem of over-fitting, this research compares the excellence and classification accuracy of the two algorithms of the deep convolution neural network based on Dropout and the deep convolution neural network based on residual network. The experimental results show that the deep convolution neural network algorithm based on Dropout can better solve the problems of error detection, missed detection and classification of four abnormal ECG signals, effectively improving the generalization ability of the deep convolution neural network and improve the usability of the algorithm. Finally, the research compares the classification accuracy of the algorithm with typical neural network (BP), cyclic neural network (RNN) and convolution neural network (Res-Net CNN) based on residual network. It is concluded that the algorithm in this research is due to other algorithms in solving the problem of abnormal ECG signal classification. However, due to the limitation of data sources, only standard database data can be used for experiments. It is still possible to misjudge similar data in early pathology, and some of which need improvement. The experiment is only for the diagnosis of four types of ECG abnormalities. On the basis, the research group will further study the diagnosis of various cases.

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