Method of diagnosing heart disease based on deep learning ECG signal

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Abstract

The traditional method of diagnosing heart disease on ECG signal is artificial observation. Some have tried to combine expertise and signal processing to classify ECG signal by heart disease type. However, the currency is not so sufficient that it can be used in medical applications. We develop an algorithm that combines signal processing and deep learning to classify ECG signals into Normal AF other rhythm and noise, which help us solve this problem. It is demonstrated that we can obtain the time-frequency diagram of ECG signal by wavelet transform, and use DNN to classify the time-frequency diagram to find out the heart disease that the signal collector may have. Overall, an accuracy of 94 percent is achieved on the validation set. According to the evaluation criteria of PhysioNet/Computing in Cardiology (CinC) in 2017, the F1 score of this method is 0.957, which is higher than the first place in the competition in 2017.

Keywords: Electrocardiogram; Machine learning; Neural Network; Wavelet transform.

1. Introduction:

Cardiovascular disease is the leading killer threatening human life and health. The electrocardiogram (ECG) is a graph of voltage versus time, representing the electrical activity of myocardium during contraction and relaxation, which is the main diagnostic tool for this kind of disease. Traditional ECG recognition relies on the experience of clinicians, but this method is limited by time and space. Therefore, a better classification of ECG is a necessary means for clinicians to get a message of pathogenetic condition. Atrial fibrillation (AF) is the most common arrhythmia and a major part of cardiovascular disease. However, most of the existing algorithms follow the traditional preprocessing, feature extraction and classification processes. The deep learning (DL) technology can provide a promising framework for end-to-end classification, and the deep neural network can learn the inherent characteristics.

Pranav Rajpurkar used a deep neural network to detect arrhythmias by the method of training a 34-layer convolutional neural network (CNN). The result of recall (sensitivity) and precision (positive predictive value) excee the average performance of 6 individual cardiologists. But the method can’t detect Ventricular Flutter or Fibrillation which do not necessarily exhibit as arrhythmias [1]. In the same way, Antônio H. Ribeiro and his research team use convolutional neural network a model for predicting electrocardiogram (ECG) abnormalities in short duration 12-lead ECG signals which used the database of a large telehealth network and built a novel dataset with more than 2 million ECG tracings. The average F1 score of the result is 0.886 [2]. Meanwhile, Li Guo tried to use other conventional neural network likes the densely connected convolutional neural network (DenseNet) and gated recurrent unit network (GRU) for addressing the inter-patient ECG classification problem [3]. Tae Joon Jun and his teammates tried to analyze ECG signal from a unique perspective. They used spectrograms to transformed data into an image and got features by CNN transferred to study the identification and classification of four ECG patterns. Nonetheless, the paper selected 7008 data which is considerably small in popular image classification tasks [4]. In the same way, Zheng Zhao improved the method by classifying the 2D spectro-temporal based on deep convolutional neural network, with Kalman filter and smoother to estimate the time-varying
coefficients of Fourier series, stochastic oscillator to accelerate signals spectro-temporal representation estimation. However, the dataset in this paper limits the medical significance because the data in the dataset doesn’t suit the typical AF detection [5].

In order to make up for this research gap and obtain more features to diagnose heart disease, we proposed the combined research method of signal processing and deep learning. Compared with the short-time Fourier transform, the wavelet transform, which provides a “time-frequency” window that changes with frequency, can perform multi-scale refinement on the signal. Through refinement, signal localization can be analyzed and feature mapping of ECG can be enriched. In addition, we use the method of transfer learning to the two-dimensional region, which transforms the extraction coefficient of the signal into a time-frequency diagram through the wavelet transform. Since the training data volume of image classification and target recognition is rich, these can be applied in the diagnosis of heart disease. From our results, it is in line with the most advanced level.

The structure of this paper is as follows: in the second part, we will focus on introducing our basic theory; in the third part, we will discuss our experimental results; in the fourth part, we will summarize the paper.

2. Methodology

In order to classify the ECG signals better, we use the classification method that combines signal processing and deep learning. The ECG input is first filtered and then the R waves of each segment of the signal is extracted (the background contains the content explaining the PQRST wave). According to the number and location of the R waves extracted from each recording, a signal of a certain length is intercepted as the characteristic wave of the signal for this segment. The time-frequency diagram of each characteristic wave is obtained by continuous wavelet transform of different scales. In the end, time-frequency diagrams are then fed into pre-trained Resnet34 to get the classification results. The classification steps are shown in Fig.1.

![Fig.1 Overall frame diagram](image)

2.1 Noise removal filtering

The data used is ECG of a single lead. Under normal circumstances, the frequency range of the signal is between 0.5~100Hz and mainly concentrated between 5~35Hz, which is a very weak low-frequency physiological signal. ECG signals are collected by electrodes placed on the surface of the skin. The movement of the electrodes, poor contact between the electrodes and the skin and other physiological electrical signals will interfere with the measured ECG signals. At the same time, the electromagnetic environment we are in will also interfere with the ECG signal. After studying the noise signal that may cause interference, we designed a six-order Butterworth low-pass filter to filter out the high-frequency noise of the original ECG signal.

2.2 Feature wave extraction

Because the length of the ECG signals in the data set is different, and the characteristics of each ECG signal are generally reflected by one or more complete heart beats. Therefore, we try to extract characteristic waves of the same length for each ECG segment, and replace the original
signal with characteristic wave for the subsequent processing and classification.

2.2.1 R wave extraction

According to medical research, a full beat of normal ECG signals should include P, Q, R, S, T waves, and heart disease may cause patients to lose some waves of their ECG signals. For example, AF can cause the disappearance of P waves in the ECG of patients. We find that heart disease generally does not result in the disappearance of R waves in the ECG. We use the modified Pan-Tompkins algorithm to identify R peaks in the ECG signals.

Pan-tompkins algorithm includes low-pass filter, high-pass filter, differential, square, integral, adaptive threshold and searching. Low-pass filter and high-pass filter are used to filter the noise and reduce the drift of the signal at low frequencies. The transfer function of these two filter are shown below as followed:

\[ H_{lp}(z) = \frac{1}{32} \left( 1 - z^{-1} \right)^2 \]  

\[ H_{hp}(z) = z^{-16} - \frac{1}{32} \left( 1 - z^{-1} \right)^2 \]  

The differential filter is used to enhance the slope of the R wave. The transfer function is shown below:

\[ H(z) = \frac{1}{8} \left( 2 + z^{-4} - z^{-3} - 2z^{-4} \right) \]  

To ensure that each sample is positive, pan-tompkins algorithm uses squared filter. The input and output relationship is shown below:

\[ y(n) = x^2(n) \]  

Also, to smooth the output, pan-tompkins algorithm uses integration filter to accomplish this. The input and output relationship is shown below: (If the value of N is too large, the wave group will be flooded. If the value of N is too small, other clutters will be generated, so N takes 30 here.)

\[ y(n) = \frac{1}{N} \left[ x(n - (N - 1)) + x(n - (N - 2)) + \cdots + x(n) \right] \]  

Finally, the adaptive threshold is used to determine the peak amplitude to identify R peaks. The threshold update formula are as follows: (SPKI is the QRS peak amplitude, NPKI is the non-QRS peak amplitude, \( THRESHOLD I_1 \) is the threshold for distinguishing the detected peaks. If the peak is larger than threshold, it is considered as SPKI, otherwise it is NPKI)

\[ SPKI = 0.125\text{PEAKI} + 0.875\text{SPKI} \quad \text{if PEAKI is signal peak} \]  

\[ NPKI = 0.125\text{PEAKI} + 0.875\text{NPKI} \quad \text{if PEAKI is noise peak} \]  

\[ THRESHOLD I_1 = NPKI + 0.25(\text{SPKI} - \text{NPKI}) \]  

2.2.2 characteristic wave interception

In the previous step, we can get the R peaks of the signals. According to the length of the sampling time, we set the value range for the total number of R waves of each signal. If the total number of R waves of each signal exceeds or is less than the value range, it can be considered as a noise signal. In order to avoid the interference of random noise signals to the subsequent processing and classification, zero sequence is taken as the characteristic wave of the noise signal. For normal ECG signals, through the observation of the signals, we find the front of some signals will appear irregular vibration, and then the signals tend to be stable and manifests certain rules. Random oscillations may come from the adjustment of the acquisition equipment and the patient's posture in the early stage of signal acquisition. These signals cannot reflect the characteristics of the whole
ECG signal. We take the R point nearest to the middle point of the signal and use it as the starting point to intercept a signal of a certain length as the characteristic wave of this signal. Since the effect of some heart diseases on patients' ECG signals requires more than one complete heartbeat to be reflected, the characteristic wave we intercepted contains four complete heartbeats.

2.3 time-frequency diagram conversion

In signal processing, the time-frequency characteristics of the signal can be obtained by using wavelet transform, and the time resolution and frequency-domain resolution of the signal can be obtained by wavelet transform of different scales. The wavelet transform formula is as follows:

$$W_f(a, b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{a}} \int_{k\Delta t}^{(k+1)\Delta t} f(t) \times |a|^{-\frac{1}{2}} \varphi \left( \frac{t-b}{a} \right) \Delta t$$  \hspace{1cm} (9)

In this formula, $\langle *, * \rangle$ is expressed as dot product, $a$ is expressed as scale factor, $b$ is expressed as displacement factor, $*$ is expressed as complex conjugate and $\psi_{a,b}(t)$ is expressed as wavelet basis function.

In order to apply the above formula to programming, we can achieve integration by discretizing the integral function and summing it. The discrete formula is as follows:

$$W_f(a, b) = \sum_k \int_{k\Delta t}^{(k+1)\Delta t} f(t) \times |a|^{-\frac{1}{2}} \varphi \left( \frac{t-b}{a} \right) \Delta t$$

$$= |a|^{-\frac{1}{2}} \Delta t \sum_k f(k\Delta t) \times \varphi \left( \frac{k\Delta t-b}{a} \right)$$  \hspace{1cm} (10)

At the same time, in order to use CNN network designed for image classification in ECG signal, we need to convert the one-dimensional signals into two-dimensional images first, because the training data and ways of two-dimensional image classification and target recognition is more abundant than one-dimensional signals. Meanwhile, the feature of the signal after time-frequency diagram conversion will be clearer as time-frequency diagram conversion expends the information intersected in the one-dimensional signal. We use the fourth-order Daubechies wavelet of different scales to carry out continuous wavelet transform on the feature waves, extract the coefficients of the wavelet transform, and store the coefficients in each row of the transformation matrix in order according to the size of the wavelet scale. The characteristic wave of each ECG signal corresponds to a transformation matrix, which can be regarded as a single-channel image. We call this image the time-frequency diagram corresponding to the characteristic wave. The time-frequency diagrams obtained from the conversion of ECG signals of different categories have different characteristics. Examples of time-frequency diagrams corresponding to each kind of signal are shown in Fig.2.
As can be seen from Fig.2, the textures of images of are quite different after the different types of ECG signal feature waves are converted into time-frequency diagrams. According to medical knowledge, compared with normal signals, ECG signals of AF patients have the characteristics that p-waves disappear and RR interval change. Due to the interference of noise and other factors, it is difficult to extract the characteristics of the signals by combining signal processing and expert knowledge. However, as can be seen from the converted time-frequency diagrams, AF disease has an obvious influence on the textures of the time-frequency diagrams. Since other heart diseases are all classified in the other rhythm, we can see that the time-frequency diagram has different textures after the signal conversion of this type, which are different from the normal, AF and noise categories. Most of the noise signals have been replaced by zero signals in the preliminary processing, so the converted time-frequency diagrams are pure black images. The feature waves of the signals can be extracted from a few images, but there is a big difference between the textures of the converted time-frequency diagrams and that of the ECG signals. Using wavelet transform of different scales to transform the characteristic waves into time-frequency diagrams can not only reflect the time-frequency characteristic of the signals and have the advantage that the wavelets of different scales have the resolution characteristic of different frequency bands, but also use the adequate and accurate image method to classify the time-frequency diagrams.

2.4 Classification via ResNet

Deep convolutional neural network can extract deep features of images, which is helpful to improve the accuracy of image classification. Resnet has been proved to have a good performance in image classification. We use Resnet 34 network to classify time-frequency diagrams of signals. We find that time-frequency diagrams of different categories have different textures, and the depth features of time-frequency diagrams can be extracted by a using convolutional neural network. In
order to improve the classification, the time-frequency features and depth features of the time-frequency diagrams are combined for classification.

3. Experimental result

We use a database of competitions to train and evaluate our methods. ECG recordings were collected using the AliveCor device. The training set contains 8528 single lead ECG recordings lasting from 9 seconds to more than 60 seconds, and the test set contains 3658 ECG recordings of similar lengths. The sampling frequency of ECG recordings was 300 HZ. We applied our method to the data set of the competition, and evaluated our method according to the evaluation criteria of the competition and compared it with the method of the several top competitors. As can be seen, our method can improve the accuracy of classification.

We used the training set to train our model, used the trained model to classify the signals of the test set, and compared the result with the test set labels published officially. Figure 4 is the confusion matrix of the classification results.

![Confusion Matrix](image)

Fig 4 the classification results of using resnet34

We calculated the precision and recall of each category according to the prediction label and real label of the test set. The results are shown in table 1. According to the results, we can see that the model can learn the different categories of ECG signals well and classify them. The irregular noise signals can interfere with the classification of the signal to a certain extent and affect the classification accuracy of the model. When we classify the signals after removing the noise signals, the classification accuracy can reach more than 98.6%.

Table 1: the results on the test set

| Class           | Precision | Recall  |
|-----------------|-----------|---------|
| Normal          | 99.32%    | 96.67%  |
| AF              | 97.83%    | 90.00%  |
| Other rhythm    | 98.44%    | 90.00%  |
| Noise           | 68.18%    | 100%    |
According to the evaluation criteria of the competition, the classification results of the experiment were scored. The F1 score of the experiment and the score of the top five of the competition are compared in Table 2.

| Participant       | F1 score |
|-------------------|----------|
| 1st  Guangyu Bin  | 0.86     |
| 2nd  Zhaohanx      | 0.85     |
| 3rd  Tomas.teijeiro| 0.85     |
| 5th  Fplesinger    | 0.85     |
| 5th  Rmaka08       | 0.84     |
| **Our method**    | **0.9593**|

Our method is significantly improved compared with the top three methods in the competition in F1 score. From the open source data, we know that the Tomas group uses LSTM to extract the characteristics of signals and use XGBoost for classification, the Guangyu Bin group uses traditional signal processing methods for signal classification, and the zhaohan group uses shallow convolutional neural network for signal classification. From this, we can see that our method combining signal processing method and deep convolutional neural network performs well in the classification task of ECG signals, which can improve the accuracy of ECG signals classification of different categories.

4. Conclusion

In this paper, we propose a classification model of ECG signals combining signal processing and deep learning. We use the wavelet transform to obtain the time-frequency diagrams of the signals and convert the one-dimensional signal classification to the two-dimensional image classification. Subsequently, we use resnet34, which performs well in image classification, to classify time-frequency diagrams. The experimental results show that wavelet transform can represent the time-frequency characteristics of signals and deep learning can extract the depth characteristics of time-frequency diagrams, which can greatly improve the accuracy of ECG signal classification with fewer sample data.

Due to the excellent performance of this method in the task of the four classification of ECG signals, we expect this method to distinguish more types of heart disease. So we will experiment on a larger, more abundant data set. In addition, since different wavelet bases have different results when using wavelet transform, the performance of different features of the signal is different. We will try to use other wavelet bases to transform the signals, and synthesize different wavelet bases in wavelet transform. The advantages of signal feature representation to achieve a more accurate classification of the signal.

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