Atrial Fibrillation Prediction Algorithm Based on Attention Model

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Abstract. Atrial Fibrillation is a common arrhythmia. when the heart is in the state of atrial fibrillation, can not deliver enough oxygen rich blood to the body. It may be asymptomatic when AF occurs. The patient does not know that AF has occurred. If the patient is not treated in time, the consequences of AF may be fatal. The diagnosis of AF needs a doctor with rich clinical experience, because the ECG signal of AF type is similar to that of other types of heart rate, which is difficult to confirm. The purpose of this paper is to train a better model through machine learning method, to realize the automatic detection of long-term AF ECG signal, to predict AF in advance, to automatically classify, recognize and inform patients. In this way, even if the patient himself can know the physical condition in time, early treatment. Automatic prediction and diagnosis of AF by machine learning method can play a positive role in the treatment of AF, but the existing scheme is not ideal for the detection and recognition rate of AF type. This paper proposes a deep learning framework based on attention mechanism. The segmented data are sequentially input into the deep convolution neural network for feature extraction, and then input into the two-way recurrent neural network with attention layer to predict the AF signal. The accuracy of 99.1% in the existing data set is better than the existing deep learning classification algorithm, which proves the validity and feasibility of the model.

1. Introduction
In recent years, many papers have proposed the method of automatic prediction of AF using ECG signals. These methods try to solve the shortcomings of automatic prediction of AF in traditional methods. In general, the paper analyzes the characteristics of ECG signals, including P-wave [1] RR interval [2] and P-wave and R-wave [3] extraction of parameters and characteristics dependent on AF attack. Then, the extracted parameters are applied to various classifiers, such as support vector machine (SVM), and a general algorithm is used to predict or diagnose AF.

Goldberger al [4] proposed a method based on the analysis of arrhythmic characteristics. By looking at the characteristics of all signals before, when and after PAF, it was pointed out that the frequency of atrial premature beats (APCs) was a useful feature for the prediction of PAF, and the accuracy of the experiment was 80%. At first, van alst é [5] used the traditional ECG signal preprocessing technology, P-wave correlation variability evaluation and statistical rules to predict atrial fibrillation. Through the coherent averaging of the corresponding signal parts of all regular beats, a representative P-wave template was generated, which matched all the regular beats with this template, and finally achieved 82% specificity. This method obviously can not achieve a high recognition rate. Alistair EW [6] proposed a method based on heart rate variability (HRV) analysis. Short term HRV analysis requires 5 minutes of data, and each data set is divided into 5 minutes of data segments. The HRV characteristics of each segment are calculated from time-domain and frequency-domain measurements using the power spectral density estimation of fast Fourier transform, Lomb
scargle and wavelet transform. Different HRV feature combinations are selected by genetic algorithm and applied to k-nearest neighbor classification algorithm. The sensitivity, specificity and accuracy of this method were 92%, 88% and 90%, respectively. Juan Pablo [7] also estimated PAF by using 30 minute RR interval signals to observe the number of ectopic atrial and ventricular beats. It is pointed out that the atrial ectopic beats increased significantly before PAF. Using the RR data of 1-min, 5-min, 10-min and 30-min, Qiao Li [8] estimated PAF by using 1-6 correlation coefficients, time-domain measurement, frequency-domain measurement and P-wave and spectral density. It was found that the power spectral density and p-ported property of RR interval have obvious characteristics. In another study, Xu K [9] found that before PAF, spectral components increased statistically, while sample entropy and approximate entropy decreased. H. Li [10] used spectral, bispectral, and nonlinear measurements from 30 minute heart rate variability (HRV) data. The results show that the spectral power of LF and HF band increases before PAF event. In bispectrum measurement, phase coupling is observed in the data far away from PAF events, but decreases with the approaching of PAF events. Poincare measurement may be a key PAF event indicator [11].

In this chapter, on the basis of the existing algorithm research, the problem of insufficient learning of timing information in the method of ECG signal recognition using only one-way cyclic neural network (RNN) is improved, and the two-way cyclic neural network (BRNN) is proposed to learn the timing characteristics of the front and back directions of ECG signal at the same time, in order to improve the accuracy of the prediction of AF, we realized the effective learning of the whole signal timing characteristics. In combination with convolutional neural network (CNN) to extract image spatial features, the automatic prediction method of atrial fibrillation based on brnn mechanism has achieved high recognition accuracy. Combined with the idea of multi-scale learning, the attention mechanism is increased, and the importance of the region corresponding to the feature is automatically learned, which makes the algorithm tend to pay attention to the key region in the AF signal, reduce the influence of invalid or even interference information, and improve the effectiveness of model feature extraction. Finally, the performance evaluation results of the proposed model are compared with those of the conventional methods, and a higher accuracy is obtained. The performance of the classifier is calculated by 10 times cross validation. Within 30 minutes before the PAF event, the sensitivity, specificity and accuracy of the method were 98%, 98% and 97%, respectively. Compared with the similar research in literature, this method has better performance. Through the comparison of existing studies, the method proposed in this paper provides a better choice for the prediction of PAF events.

2. Data Set
ECG signals were collected from two AF datasets. The AFDB and PAFDB provided 100 ECG records of 98 groups of subjects. Each group consists of two records, each 30 minutes long. Subjects were divided into two groups with equal signal length. All subjects in the first group had a history of PAF and had an irregular heart rate. The two ECG records provided by each group consist of one record before the onset of PAF and another record from any such record (> 45 minutes). Another group of "normal" subjects had no history of PAF, and each group provided two ECG records. PhysioNet provides a label for the learning set to indicate whether the record is immediately prior to the onset of PAF.

|                      | Sampling rate (Hz) | signal length (min) | signal before AF | Other time AF signal |
|----------------------|--------------------|---------------------|------------------|----------------------|
| PAFDB                | 128                | 100 *2* 30          | 53               | 147                  |
| MIT-BIH AFDB         | 250                | 23*10*60            | 21               | 0                    |

3. Algorithmic Process
Attention mechanism was first applied in computer vision, and then it began to be widely used in NLP field. In this paper, attention is improved, and attention is further combined with CNN. Firstly, features are acquired automatically through CNN. In CNN, dual channel mode is adopted, and
convolution cores and steps of different sizes are adopted for two channels. On this basis, experiments are carried out continuously to find the most suitable number of network layers. Then we use brnn to analyze the features extracted by CNN in time order, and predict the possibility of AF from the window spanning 30 seconds. In addition, we also implement a soft attention mechanism on brnn, so that the algorithm can prioritize the ECG segments of predictable AF (considering the paroxysm of AF). According to the calculation area, information used, structure level, convolution network and Different combinations of attention compared with different attention models, the proposed method can predict AF patients or normal subjects by using short-term normal ECG signals. The whole process of the model is shown in Figure 1.

3.1. Data Processing and Segmentation
The ECG signal is preprocessed to train and evaluate the AF automatic prediction method based on the attention model. In order to preprocess, band-pass filter and discrete wavelet transform are used to eliminate baseline drift and high frequency components of ECG signal. The fifth order Butterworth filter is used to filter the low-pass of each ECG channel to remove the frequency above 40 Hz. Because they come from two different ECG data sets, the sampling rate is not the same, so all ECG signals are divided into 30 seconds duration.

3.2. CNN
CNN uses two channels to extract features, one uses a small filter to extract time information, the other uses a large filter to extract frequency information, and the other uses a large filter to weigh between the extracted time and frequency domain features which helps to benefit from the classification task. After repeated experiments, a smaller convolution kernel (20,1) step size (4,1) was used on one side and a larger convolution kernel (100,1) step size (25,1) on the other side.

CNN structure is shown in Fig. first, convolutional layers generate intermediate feature vectors using convolution kernels through input signals. The one-dimensional (1 D) convolution is used experimentally in convolutional layers because the input ECG signal is a one-dimensional time series. One-dimensional convolutions can be represented by equation 1 as follows:

\[ x_k = b_k + \sum_{i=1}^{N} w_k \times y_i \]  

(1)
Where $x_k$ is the k-th feature map, $b_k$ is the deviation of k-th feature map, $w_k$ is all features of k-th feature map, and $y_i$ is the i-th feature map. Secondly, the pool layer reduces the size of the middle feature map to select representative features. The maximum pooling is used in the pooling layer to reduce the intermediate feature map. In addition, this paper also uses other functions to design CNN model to optimize the model and avoid divergence, including normalizing the input ECG records before training CNN model, limiting the processed data to a certain range, dropout and reLu. As shown in formula 2:

$$x_b = \alpha \cdot \left( \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}} \right) + \beta$$

(2)

Where $\varepsilon$ is a small random noise, and are mean and standard deviation of sample data, respectively. $\alpha$ is the learning rate, $\beta$ is the shift parameter. Both alpha and beta are trainable and updated in a step-by-step manner. Dropout is a technique used to avoid over fitting and divergence. Relu shows great training performance, which helps with gradient based learning. Finally, the features are combined and output. In order to find the best architecture of CNN model, three to thirteen layers of convolution are designed, and finally seven layers model is adopted to achieve better results.

3.3. BRNN

Compared with other RNN variants, the two-way recurrent neural network can get the forward and backward information of current nodes. The output of bidirectional loop network structure is determined by forward and backward output.

For feedforward neural network, the input sequence is input in normal time sequence, $t$ from 1 to $t$. For the feedback network, the input order is from $t = t$ to 1. Finally, the weighted sum of the outputs of the two networks is used to calculate the output of brnn. The formula of this method is as follows:

$$h_t = \tanh(W x_t + V \bar{h}_{t-1} + \bar{b})$$

(3)

$$\bar{h}_t = \tanh(W x_t + V \bar{h}_{t+1} + \bar{b})$$

(4)

$$y_t = (U[\bar{h}_t; \bar{h}_t] + b_y)$$

(5)

Among them, $\bar{h}_t$ is the hidden state of feedforward network, $\bar{b}$ is the deviation of feedforward network, $\bar{h}_t$ is the hidden state of feedback network, and $\bar{b}$ is the deviation of feedforward network. $X$ and $y$ are the input and output of birnn respectively. The above figure shows the brnn framework with $t$ time steps.

3.4. Attentional Layer

Attention has been widely used in the field of natural language processing before, but rarely in physiological signal recognition. This time, attention mechanism is applied to predict atrial fibrillation signal. At the same time, as a powerful tool, it is integrated into various models to deal with the corresponding tasks. Before the extensive use of attention mechanism, seq2seq model has been widely used. Seq2seq model is mainly an encoder decoder architecture.

In this experiment, soft attention is used. The attention mechanism makes the model learn the most relevant part of the input sequence in the decoding stage. In the sequence to sequence model without attention mechanism, the decoder part depends on the RNN (or brnn) hidden vector of the decoder. In the sequence to sequence model with attention mechanism, the target is generated by paying attention to the most obvious attention area.
4. Experimental Result
AF automatic prediction method based on attention model. On the test set, analyze the results of short-term normal (less than 60 seconds) ECG signal training to find the best length and iteration times. The experimental results are shown in Table 5 and table 6. First, the length of the model is trained by training different length (10-60 seconds) ECG signal segments, and then, the number of iterations of the training set is increased. The results show that the performance is relatively high in the duration of 30 seconds, and the performance can be improved by increasing the number of iterations. Finally, an ideal seven layer CNN architecture is chosen as a part of the model to predict AF automatically. For the test set, the evaluation method shows 99.1% accuracy.

Table 2. Effect CNN different layers.

| CNN Layer Number | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|------------------|-----|-----|-----|-----|-----|-----|-----|
| Sensitivity      | 92.1| 93.5| 94.6| 98.9| 99  | 98.5| 97.5|
| Specificity      | 89.1| 92.4| 95.1| 96.8| 98.7| 96.5| 96.4|
| Accuracy         | 90.7| 96.4| 94.1| 96.4| 99  | 97.2| 95.6|

Table 3. Effect of Different Iterations.

| Number of iterations | 100 | 200 | 400 | 600 | 800 | 1600 | 2000 |
|----------------------|-----|-----|-----|-----|-----|------|------|
| Sensitivity          | 85.2| 92.8| 94.8| 95.8| 96.1| 97.6 | 98.5 |
| Specificity          | 85.2| 91.5| 93.5| 94.8| 97.2| 98.4 | 98.5 |
| Accuracy             | 84.2| 93.2| 94.6| 95.7| 95.8| 98.2 | 98.1 |

Table 4. Effect of Different Input Signal Lengths.

| Number of iterations | 100 | 200 | 400 | 600 | 800 | 1600 | 2000 |
|----------------------|-----|-----|-----|-----|-----|------|------|
| Sensitivity          | 85.2| 92.8| 94.8| 95.8| 96.1| 97.6 | 98.5 |
| Specificity          | 85.2| 91.5| 93.5| 94.8| 97.2| 98.4 | 98.5 |
| Accuracy             | 84.2| 93.2| 94.6| 95.7| 95.8| 98.2 | 98.1 |

Besides the above experimental studies, there are several other methods used to predict PAF automatically by ECG signal. Table 8 presents a summary of the different automatic prediction PAF, outlining the experimental results of N methods and their sensitivity and specificity. Apply any normal ECG signal to the proposed model and automatically predict whether atrial fibrillation will occur later in the ECG signal. Sensitivity of 99.0%, specificity of 98.7% and accuracy of 99.1% in this experiment, it is proved that this model has great effect on AF prediction and detection.

In this study, we proposed a model for automatic prediction of AF using short-term normal ECG, found the optimal architecture of the model, and demonstrated the optimal length of short-term ECG segments. The proposed CNN model can not only exclude the use of complex manual feature extraction to perform well in automatic prediction AF. However, the current model has some limitations. First of all, we can not detect the starting point where AF start to happen. Second, the proposed method can only predict the potential AF of the object. Altogether, a attention model-based
approach to automatic prediction of atrial fibrillation by short-term normal electrocardiogram.
provides the possibility of more accurate prediction and diagnosis for AF patients. in further studies,
the proposed model should be trained using a type of electrocardiogram from arrhythmia patients as
well as a large number of electrocardiograms.

5. Experimental Summary
When a large amount of data is available, the performance of the deep learning model will be better.
However, in practice, especially in the medical field, access to such data is limited or impractical
because of the considerable work required. When the distribution of input features and labels changes,
but the task substance remains the same, we can apply methods adapted to different fields. for a given
dataset, we aim to detect pre-occurrence signals of af from ECG records. the experimental deficiency
is that the dataset is relatively small. obtained high accuracy indicates the feasibility of this method. if
further study of this method can be feasible in a larger patient population, this method can take
the first step towards achieving reliable af prediction studies and eventually be used to guide the
preventive treatment of af detection.

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