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Detection of Arhythmia for Ballistocardiagram Based on CNN + RF

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Abstract

In order to solve the problem that the total accuracy of ballistocardiogram (BCG) signal in arrhythmia detection is not high, the synchronous electrocardiogram (ECG) and BCG clinical signals of patients with premature ventricular contraction (PVC) and atrial fibrillation (AF) were collected Taking ECG signal as the standard, an automatic arrhythmia recognition model is constructed by using the hybrid algorithm of convolutional neural network (CNN) and random forest (RF). The experimental results show that the overall accuracy of the algorithm can reach 97.2%, which provides a new idea for the early detection and timely screening of cardiovascular diseases under the condition of natural sleep.

Keywords*: BCG; CNN+RF; PVC; AF*

I. Introduction

Cardiovascular diseases have a high prevalence and mortality, and they have become major challenges for healthcare providers worldwide[1, 2]. Not just in the elderly, there is an upward trend for cardiovascular diseases in younger age.

Arrhythmia refers to a disorder involving the origin or conduction of cardiac activities that could cause abnormalities in the site of origin, frequency, rhythm, and conduction velocity of cardiac excitation. It can occur as a group of independent diseases, or occur combined with other cardiovascular diseases. Besides, it can even develop into malignant arrhythmias, which could induce heart failure (HF), thromboembolism, sudden death and so forth. This disease is characterized by repeated relapses, acute episode and poor prognosis, which would pose a serious threat to life and health[3]. For instance, the premature ventricular contraction (PVC) is a common cardiac arrhythmia, and it may occur in people under fatigue, anxiety and stress. If the number of heartbeats in patients with PVC exceeds 10% of the total number of heartbeats in a whole day, they are prone to suffer from heart failure and heart enlargement; In addition, patients with atrial fibrillation (AF) may easily feel dizziness, fatigue and chest pain, which may induce heart failure or myocardial ischemia[4]. Therefore, it is significant for the timely detection of arrhythmias.

Traditional arrhythmia detection is mainly performed to make a definite diagnosis by observing such characteristics as abnormal R-R intervals and disappearance of P waves in electrocardiography (ECG)[5, 6]. However, there is a lack of timeliness for ECG detection and the installation of electrodes on the human body surface is required during the detection process, which would restrict patients' activity and cause psychological stress to subjects, thus affecting the objectivity of detection results and hindering its application in the long-term and real-time monitoring. Therefore, there is an urgent demand for a non-restrictive detection mode to satisfy the long-term and daily monitoring.

BCG could demonstrate the kinetic characteristics of the human heart during mechanical motion. It could not only present the functional information of the heart, but also serve as a basis for evaluating changes in cardiac hemodynamic parameters. Compared with ECG, the detection method of BCG with unrestrained signal acquisition is more comfortable and suitable for daily monitoring.

Theories of machine learning (ML) and deep learning (DL) are increasingly adopted in the field of arrhythmia identification and classification. However, the focus of most BCG-based studies is placed on the identification of AF: Wen and Xin et al. calculated the variance, mean, skewness and kurtosis of BCG energy signals, extracted 16 features from each segment, and employed five ML algorithms for the identification of AF, among which SVM could achieve a favorable performance[7]. Jiang Fangfang et al. utilized a CNN approach to identify paroxysmal AF based on BCG signals, with an accuracy of 94.8%[2].

Inspired by the above research status, in this paper, an analysis was performed on the BCG by constructing a CNN+RF hybrid model, and the identification of PVC and AF based on BCG signals was achieved.

II. Research Methods

2.1 Data Collection

BCG and ECG were collected synchronously in clinical practice. BCG signals were collected by "DEEBCG" BCG recording pillow. Among these subjects, there were 21 healthy individuals (male/female ratio, 12/9; age range, 23-27), including 10 with long duration (60~100min) and 11 with short duration (5-6min). ECG data were collected by laboratory equipment (digital three-channel ECG machine) in a laboratory setting. The data of patients with arrhythmia were collected in the hospital ward by the prone position (put the pillow plate under the pillow), including the data of the whole night and the data found and detected during the physical examination. Participants' information is shown as in Table.1.

The ECG data of the whole night were collected by a 24-hour dynamic electrocardiograph, and the data of physical examination were collected by the equipment in the hospital. The ECG of heartbeats of patients with PVC and AF was marked and recorded for the appearance time of heartbeats by professional doctors, and the time of BCG signal corresponding to the relevant beat was searched by graphic viewer.

Table. 1 Participants' information

parameter	PVCS	AF
Number	9	6
Gender (M/F)	5/4	4/2
Age	45~73	50~65
All night(7~8 h)	7	2
Physical exaination (5min above)	2	2

The DEEBCG BCG signal recorder is composed of BCG signal acquisition system, collection and conduction device, BCG signal analysis system and communication module. “DEEBCG” BCG recording pillow includes: system of acquire BCG signals, device for collection and transmission, analysis system and communication module. The acquisition system of BCG signals is mainly composed of an extremely low frequency (ELF) micro vibration signal sensor; the device of collection and transmission consists of the panel, conductive sheet and pedestal that provide installation support for the panel; the device of collection and transmission collect the vibratory signals caused by the heart beats through the panel. The signals are delivered to ELF micro vibration signal sensor, are converted into electrical signals through the sensor, and are transmitted to analysis system; the signals are filtered, amplified, analyzed, sorted, AD converted by the analysis system. Finally, data that include status, strength and respiration are generated. The data that are processed by the arithmetic processed system, and are uploaded to computer through the communication module[8].

The physical diagram of pillow plate is shown in Fig. 1.

Fig.1: Physical diagram of pillow

In this paper, in order to integrate the data into the model, the data of the whole segment were divided into several groups in 15s (without overlapping). The ECG of heartbeats of patients with PVC and AF was marked and recorded for the appearance time of heartbeats by professional doctors, and the time of BCG signal corresponding to the relevant beat was searched by graphic viewer, and the file in 'csv' format was derived. The BCG data within 15s before and after this time point was intercepted. Due to the fact that the sampling frequency of this equipment is 1/0.0075 (133.33)HZ and the data within 15s includes 2,000 (integer) points, it is convenient for the data collection; Besides, in order to avoid the error caused by the asynchronous time of BCG and ECG collection equipment, the data within 15s is long enough to ensure that the graphic features of patients with PVC and AF can be included. Fig. 2 presents an example of BCG signal data for normal, PVC and AF subjects. It can be seen that there is a significant difference in BCG signals between patients with arrhythmia and normal individuals.

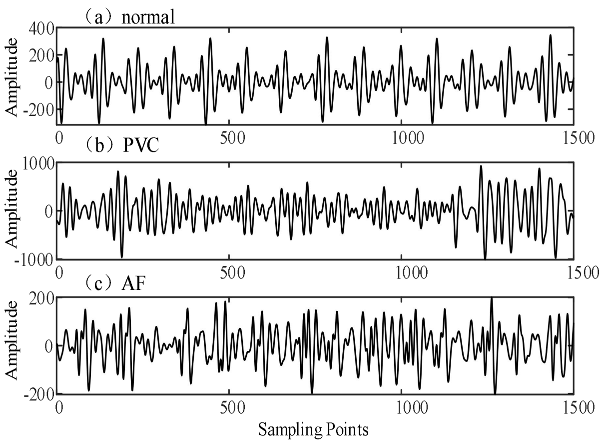

Fig.2: Example of BCG signals (a) normal (b) premature ventricular contraction (c) atrial fibrillation

2.2 Accuracy Experiment

In order to verify the effectiveness of the BCG collection equipment, the ECG and BCG of 21 healthy individuals were compared. An analysis was performed on the BCG signals of the subject in an attempt to obtain the heart rate (HR), which would be subjected to a comparison with HR obtained from ECG data. The results are shown in Table 2. The paired t-test was performed on 21 sets of data, and the P value was 0.658 (greater than 0.05). The calculation results showed that there was no significant difference between HR calculated by both signals, which laid a foundation for future studies based on the BCG equipment.

Table.2: Results of subject BCG and ECG heart rate calculations

subjects	HRmean(BCG)	HRmean(ECG)	subjects	HRmean(BCG)	HRmean(ECG)
1	78	76	12	78	77
2	77	77	13	65	67
3	76	75	14	70	68
4	70	71	15	75	73
5	74	74	16	70	70
6	69	70	17	69	70
7	75	76	18	71	70
8	68	67	19	68	68
9	72	74	20	74	73
10	69	66	21	72	73
11	72	74			

2.3 Construction of CNN+RF Hybrid Model

CNN is a DL algorithm developed by K. Fukushima from the original multi-layer network perceptron in the early 1980s[9, 10]. As a DL network architecture, it is widely used in such fields as visual processing and medical image processing[11]. The features of data can be extracted with this algorithm through multiple hidden layers, and the appropriate learning output can be generated through its fully connected layers. Besides, one-dimensional and two-dimensional signals can be processed by this network[12]. As for ECG signals, CNN model could not only cover the correlation of data before and after this time point, but also extract the features of the current time[2]. Therefore, BCG signals based on time series model can be subjected to effective learning through CNN. RF algorithm was first proposed by Breiman[13] in 2001. It is a statistical learning theory, including multiple decision tree classifiers. This algorithm possesses the favorable generalization ability and classification effect, and the high-dimensional data can be processed by this algorithm. Therefore, the combination of CNN model and RF model would contribute to the identification of PVC and AF.

The training process can be described as follows. The model is composed of convolution layer, pooling layer, flatten layer, fully connected layer and RF classifier.

(1) Load the new BCG data;

(2) Apply the convolution layer (the size of convolution kernel is 5×1);

(3) Apply the activation function (RELU);

(4) Apply the maxpool layer (the size of convolution kernel is 3×1);

(5) Repeat steps (2-4) four times to generate features that can be used for identification;

(6) Send the output to the flatten layer;

(7) Apply two fully connected layers;

(8) Apply RF classifier for classification.

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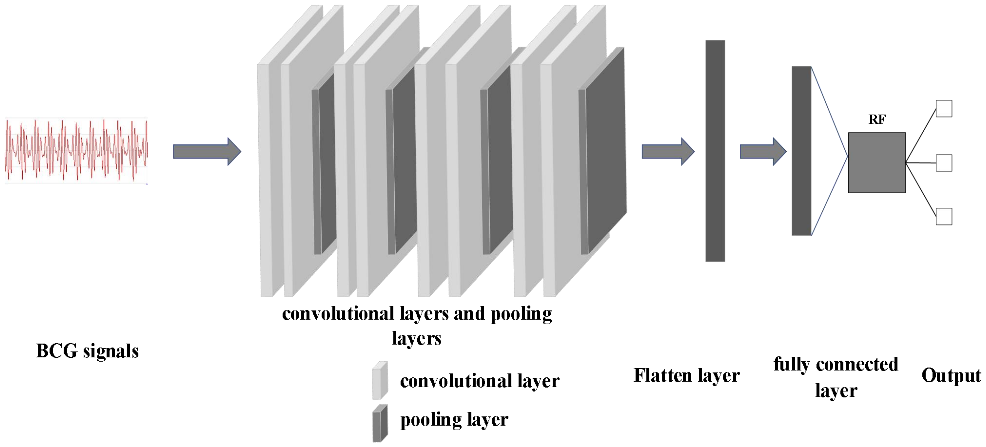

Fig.3: CNN+RF model

The above algorithm is applied to each set of data in the training stage. In the first stage of the algorithm, BCG is input into two convolution layers, followed by the pooling layer, in which the down-sampling operation would be performed, thus conducing to the reduction of the processing time and the identification and definition of new parameters. The next layer is the dropout layer, which is used to reduce the over-fitting (for training only). The above operations are repeated, the number of convolution kernels is changed, and then the flatten layer is accessed to flatten the data that can be used in the fully connected layers. The Adam optimization algorithm is employed to optimize the objective function, which further improves the performance of the model. Finally, it is input into the RF classification model for classification. As shown in Fig.3, the CNN constructed in this paper includes 8 convolution layers and 4 maximum pooling layers.

III. Experimental Results and Analysis

3.1 Network Training and Testing

As for the network training, the hardware of the experimental platform is based on Intel i7-10875H CPU, Windows system, RTX2060 graphics card, and 6G (RAM). In the whole research process, python programming platform and TensorFlow library were adopted to construct a DL model.

It could be found in the training process that the setting of learning rate (lr) and iteration times would exert significant impacts on the model effects and the convergence rate of training. Therefore, when starting to train the model, it is generally not appropriate to set lr too large, which may lead to the situation that the loss does not decrease but increases[14]. In this paper, a small lr was selected at the initial stage of model training, and subsequently it was slowly increased until the loss tended to be stable. The lr in the training process is shown in Table 3. With the increase of lr, the loss gradually decreases. The best learning rate of the model is 0.01. After 500 iterations, the loss of the model has been stabilized, which indicates that the model basically converges.

Table 3: Settings of learn rate

Iterations	lr	loss
200	0.00001	26.83
200	0.00005	19.65
600	0.0001	8.64
800	0.0006	4.38
1000	0.001	0.23
1000	0.0012	0.73
600	0.001	0.33
500	0.001	0.21

K-fold cross-validation was applied for the training of each model, which avoided the chance caused by the random division of data sets. According to the experimental results, the best fold number is 5. Fig. 4 presents the comparison of the total cross-validation accuracy of the three models.

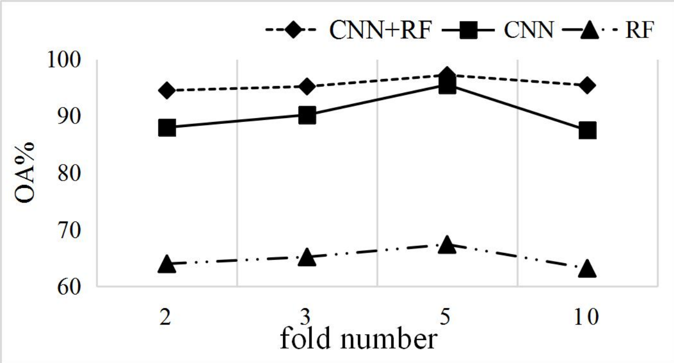

Fig.4: Comparison of cross-validation for CNN+RF, CNN, RF

3.2 Evaluation Indicators

In this experiment, confusion matrix, overall accuracy (OA), precision (P), sensitivity (sen) / recall (R), specificity (S) and F1 value were adopted to evaluate the classification results of CNN model.

OA refers to the ratio of the number of correctly classified heartbeats to the total number of samples (∑), and NN, VV and AA represent the number of correctly classified heartbeats of each type, respectively:

$$OA = \frac{N_N + V_V + A_A}{\Sigma} \tag{1}$$

P refers to the percentage of samples that are correctly predicted among all predicted or classified samples in a classification model.

$$P = \frac{\mathrm{tp}}{tp + fp} \tag{2}$$

R refers to the percentage of samples that are correctly predicted among all samples whose true labels are true in a classification model.

$$sen = R = \frac{tn}{tn + fp} \tag{3}$$

S refers to the percentage of samples that are correctly predicted among all samples whose true labels are untrue in a classification model.

$$S = \frac{tn}{tn + fp} \tag{4}$$

F1 value refers to the contradiction generated between P and R indicators under special conditions. Therefore, it is necessary to consider the results of these two indicators comprehensively. The range of F1 values is 0-1, and the larger the value, the better the

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$$F1 = \frac{2 \times P \times R}{P + R} \tag{5}$$

All the above information could be obtained by confusion matrix. In this paper, on the ground that a 3-classification condition is involved, the confusion matrix is three-dimensional.

3.3 Result Analysis

This data set consists of 2,672 groups of BCG signal segments and about 40,080 heartbeats, including 1,250 groups of normal BCG signals, 797 groups of PVC data and 625 groups of AF data. In the process of model learning, 80% of data sets are employed as the training sets, and the remaining 20% are employed as the test sets to verify the performance of the model after each iteration. Table 3 presents the confusion matrix after 5-fold cross-validation.

Table 4: Confusion matrix of RF, CNN, CNN+RF

		True								
	Type	RF			CNN			CNN+RF		
		N	PVC	AF	N	PVC	AF	N	PVC	AF
Predict	N	235	12	2	234	11	4	240	6	3
	PVC	0	0	157	2	148	7	2	152	3
	AF	0	0	125	0	1	124	0	1	124

Table. 4 presents the classification of the three types of data in the test sets, and the number of correctly classified samples accounts for the majority of the total samples. In the RF model, there are 12 normal BCG data predicted as PVC, and 2 as AF; The BCG data of PVC are completely predicted as AF. In the CNN model, there are 11 normal BCG data predicted as PVC, and 4 as AF; There are 2 BCG data of ventricular premature beat (VPB) predicted as normal, and 7 as AF; There is 1 BCG data of AF predicted as PVC. In the CNN+RF model, there are 6 normal BCG data predicted as PVC, and 3 as AF; There are 2 BCG data of PVC predicted as normal, and 3 as AF; There is 1 BCG data of AF predicted as PVC.

Table 5: The index results of three kinds of models

		P%			R%			S%			F1%		
Type	OA%	N	PVC	AF	N	PVC	AF	N	PVC	AF	N	PVC	AF
RF	67.8	94.4	0	100	100	0	44	49.2	72.1	50	97.1		61.1
CNN	95.3	94	94.4	99.2	99.2	92.5	92	95	97	99.7	96.5	93.4	95.5
CNN+RF	97.2	96.4	96.8	99.2	99.2	95.6	95.4	96.9	98.4	99.7	97.8	96.2	97.3

As shown in Table 5, CNN model is adopted to extract features and RF is adopted to replace softmax for classification. The OA reaches 97.2%, and other indicators exceed 95%, which indicates that the model can meet the basic requirements of arrhythmia identification. The classification effect of RF is poor. The OA is 67.8%, BCG signals of PVC type are all predicted as BCG signals of AF type. P value and R value are all 0, which indicates that the ability of RF to detect the BCG signals of PVC type is poor. In the CNN model, the OA is 95.3%, and other indicators are all over 90%. Therefore, the classification effect of this model is relatively favorable. However, compared with the CNN model, the OA of the CNN+RF model increases by 1.9%, P value increases by 1.6%, R value increases by 2.2%, S value increases by 1.1%, and F1 value increases by 2%. The results demonstrate that the performance of the CNN+RF model is obviously better than that of the CNN model and RF model.

IV. Conclusions

In this paper, an exploration is performed on the identification performance of the CNN+RF, CNN and RF models for PVC and AF based on BCG signals, respectively. As per the experimental results, the CNN+RF model could achieve better performance in the identification and accurate classification of BCG data for normal, PVC and AF subjects. Its OA could reach 97.2%, which is better than the CNN and RF models. Therefore, this model can basically meet the requirements of daily monitoring. The BCG detection method has the characteristics of non-binding and readiness compared with ECG; The CNN model can be adopted to automatically extract features, which effectively solves the problem that the traditional visual observation method of waveform could not avoid BCG with various artifacts and low signal-to-noise ratio. Besides, the adoption of RF for classification could improve the classification OA and generalization ability of the model. Through this study, the development orientation and possibility would be provided for the detection of daily cardiovascular diseases based on BCG signal analysis.

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