A Semi-supervised Algorithm for Atrial Fibrillation Attack Prediction Using Convolution Auto-encoder of Time Series Signal

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***Abstract*—At the beginning of the attack, atrial fibrillation (AF) usually presents as paroxysmal atrial fibrillation (PAF), and may be further transformed into persistent AF that may cause high-risk diseases such as ischemic stroke and heart failure. Under considerations of current machine learning algorithms for AF predictions that manure extraction of features and tag electrocardiograph (ECG) data are time consuming and labor-intensive processes, a novel two-stages of semi-supervised algorithm for AF attack prediction is proposed in this paper. With the input of the time series signal of RR interval, the first stage is designed as an unsupervised learning based on convolution auto-encoder (CAE) network and the second stage is a supervised learning based on Long short-term memory (LSTM) model. A total of 855,882 heartbeat activities including 30 segments of PAF and 30 segments of normal heart rate were collected so as to evaluate the performance of the CAE-LSTM combination model. The obtained results showed that the averaged accuracy and the root mean square error (RMSE) of ten-fold cross-validation are 90.16% and 0.0113, respectively. In summary, the preliminary results suggested that the combination of the unsupervised CAE model and of the supervised LSTM model could reduce the dimension of the input data meanwhile perform the subsequent classification with a small amount of labeled data as input. Moreover, the proposed algorithm could be useful to predict AF when the sample is scarce, and potentially prevent the occurrence of a paroxysmal atrial fibrillation.**

***Clinical Relevance*— Compared with common supervised methods, our proposed method only requires a small number of tagged ECG signals, which can reduce the workload of clinicians to complete the task of atrial fibrillation attack prediction.**

I. Introduction

In the world, atrial fibrillation (AF) is the most common arrhythmia with irregular heartbeat, and its incidence rate and mortality are very high, so it has a serious impact on patients, clinical work and society [1].

At present, there are two main measures to manage and treat the clinical symptoms of hospitalized patients with atrial fibrillation, namely, the control of ventricular rate and the control of rhythm [2]. However, the above methods have certain risks. The drug has a good effect on the treatment of newly diagnosed patients with atrial fibrillation, and the control of rhythm can reach about 50% of the treatment success rate [3].

For patients with persistent atrial fibrillation, the drug treatment effect is not only poor, but also may produce adverse reactions, Leading to other arrhythmia and even fatal complications. Therefore, in order to prevent the irreversible changes of the atrium [4] and prevent the further development of atrial fibrillation through rhythm control at the early stage, the prediction of atrial fibrillation attack becomes particularly important [5]. Similar to the automatic detection algorithm of atrial fibrillation based on the traditional machine learning method, the automatic prediction of atrial fibrillation can also be realized based on the atrioventricular conduction characteristics such as P wave shape change, RR interval difference, etc. Some studies show that up to 40% of patients with atrial fibrillation do not find atrial fibrillation in the early morning [6]. Yang Ping et al. [9] used probabilistic symbolic pattern recognition method combined with convolution neural network and short-term memory network to predict atrial fibrillation 45 minutes in advance using l segment. The Acc on the MIT-BIH paroxysmal atrial fibrillation prediction challenge database were 91.26%, respectively. Heo et al. [10] achieved 85.03% accuracy by directly inputting ECG output text into CNN model. The specific information of atrial fibrillation prediction methods in recent years is shown in Table 1.

TABLE I. Information of the Dataset

Author	Prediction methods of atrial fibrillation		
	Year	***method***	***Classification results***
Attia et al. [7]	2019	5-layer convolution CNN	98.7%
Erdenebayar et al. [8]	2019	CNN	83.3%
Ping Yang et al. [9]	2020	Pattern recognition + integrated CNN-LSTM	91.26%
Heo et al. [10]	2021	ECG output text + CNN	85.03%

Given the above studies, supervised algorithms are usually used for automatical AF detections and predictions, and these algorithms usually need a large number of ECG tagged by senior clinicians as support, which will undoubtedly be a time-consuming and tedious work. As such, this paper propose a novel semi-supervised automatic monitoring algorithm for atrial fibrillation prediction based on CAE-LSTM, which only uses a small number of tagged ECG to predict atrial fibrillation. And, the evaluated prediction results of atrial fibrillation of the network model

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that would be encourage to predict the AF when the sample is scarce, and potentially prevent the occurrence of a paroxysmal AF.

II. Materials and Methods

A. Database

This paper uses the database of Paroxysmal Atrial Fibrillation Prediction Database (AFPDB), MIT-BIH Atrial Fibrillation Database (AFDB) and MITBIH Normal Sinus Rhythm Database (NSRDB)from Physionet website.

The training set of this study adopts the training set of AFPDB. The training set contains 50 ECG record sets from 48 patients' long-term records. Each record set contains two 30-45minute ECG records (such as p01 and p02), and two 5-minute ECG records with names ending with "c" (such as p01c and p02c, which are not used in this study). The records with names beginning with "p" are from patients with paroxysmal atrial fibrillation, the odd number at the end indicates that the corresponding 30-minute ECG recording is at least 45 minutes away from any paroxysmal atrial fibrillation segment, and its category is recorded as "PAF_N". The ECG record with the name beginning with "n" is from the subject with atrial fibrillation, and its category is recorded as "N"; The test set of this study uses the AFDB database and the NSRDB database. The AFDB database contains 23 ECG records with annotations. These records are from the Holter monitor of patients with AF. The duration of each record is about 10 hours, including 317 atrial fibrillation episodes with an average duration of 115 seconds and 288 normal heart rates with an average duration of 174 seconds. The NSRDB database contains 18 and long-term ECG. This paper intercepts 30 minutes of ECG records.

B. Preprocessing

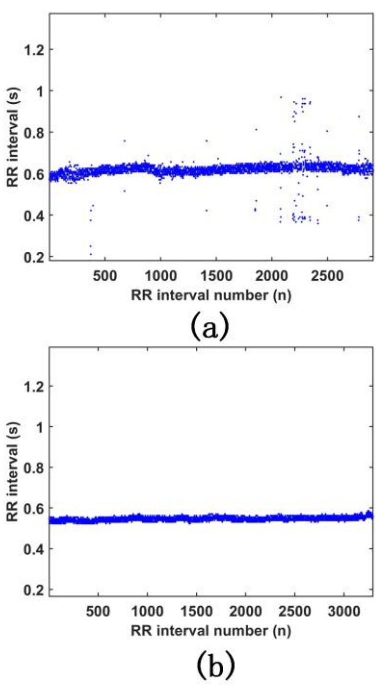

Fig. 1: RR interval as input. (a) RR interval of PAF, (b) RR interval of sinus rhythm.

Based on three common ECG databases, a set of ECG signal database for algorithm model training and performance evaluation testing was created.

Because one of the characteristics of ECG during atrial fibrillation attack is the uneven distribution of RR interval, this study uses the RR interval of each ECG as the input of the network and can reduce the calculation time as shown in Fig.1. The data set information is shown in Table II. The data of AFPDB in the training set is re-divided according to the tenfold cross-validation method, that is, the data of AFPDB is divided into ten pieces on average, 90% of the data of each training is used for training, and 10% of the data is used for validation. The test set selects 10 sinus rhythm ECG signals and 10 PAF patients ECG signals selected from NSRDB and AFDB respectively as cross-database tests to verify the generalization ability of the model in different databases. Finally, the average accuracy of the ten models is taken as the result, and the RMSE of the accuracy of the ten models is taken as the stability evaluation index.

TABLE II. Information of the dataset

Database	Database information			
	Time (min)	*AF*	*Normal*	*Sampling (Hz)*
AFPDB	600	20	20	250
AFDB	30	10	0	128
NSRDB	1500	0	10	128
Total	-	30	30	-

C. Model Description

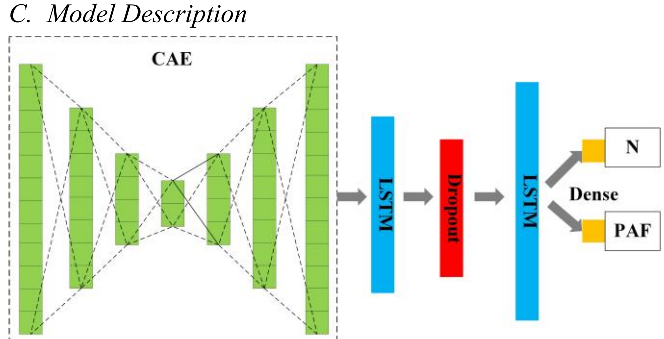

Fig. 2: The CAE-LSTM semi-supervised network model studied in this paper.

The semi-supervised network model proposed in this paper is shown in the Fig. 2. The semi-supervised network model is divided into two stages of learning. The first stage is unsupervised learning based on convolution autoencoder (CAE). The CAE network compresses and reconstructs the input data. The Encoder module encodes the RR interval sequence of 50 * 1 into a size of 7 * 128 through three convolution modules (including convolution layer, activation function, normalization layer and maximum pooling layer).

The function of the encoder is to encode the input RR interval into a low-dimensional hidden variable h to force the neural network to learn the most informative feature, namely

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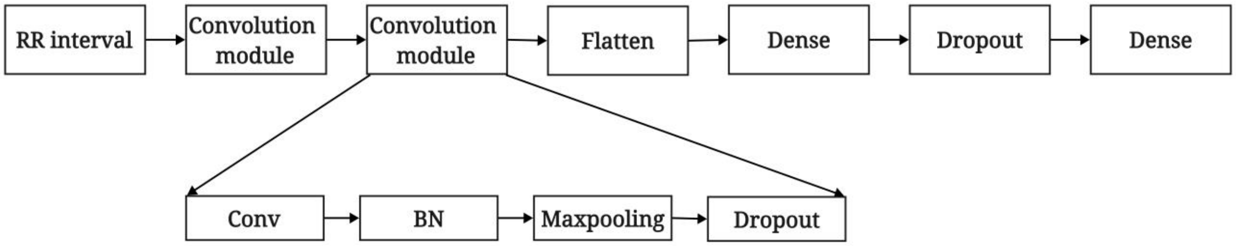

Fig. 3: CNN network model for comparison.

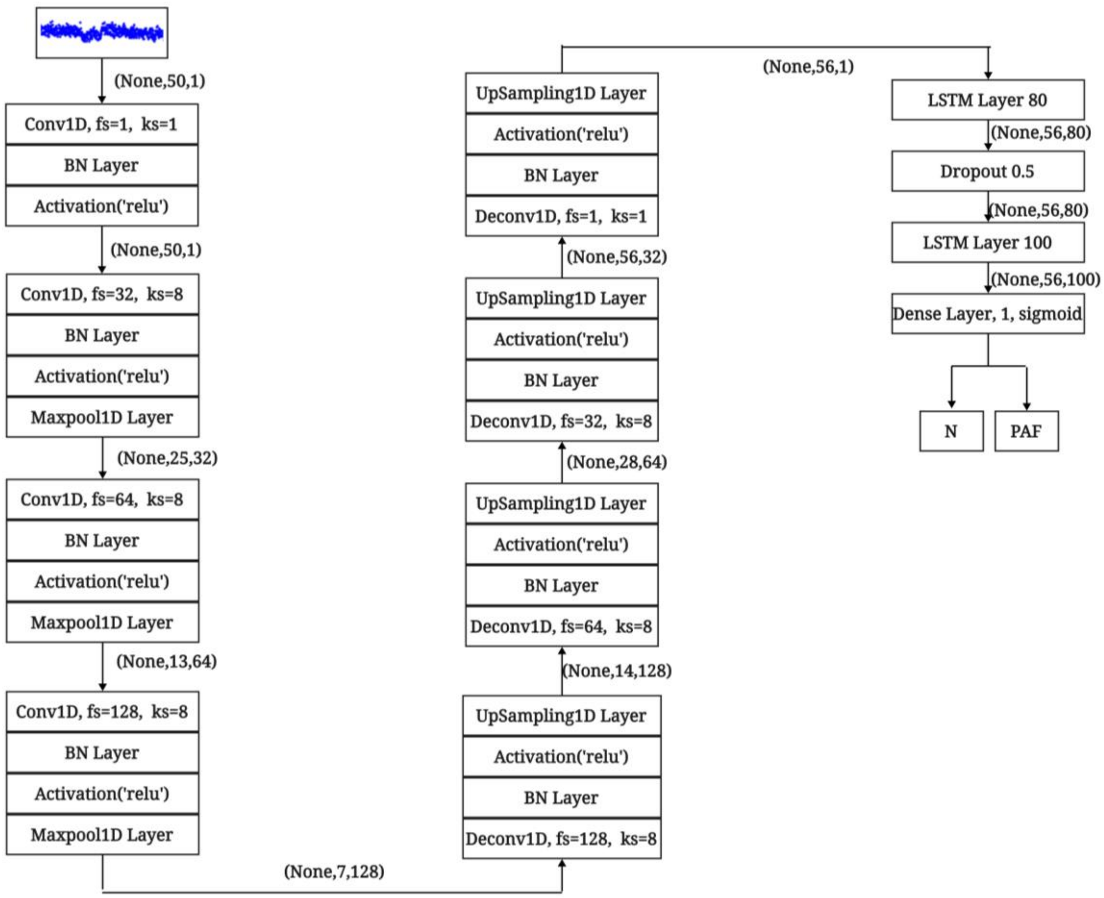

Fig. 4: CAE-LSTM parameter setting and input/output model diagram of each layer.

feature extraction The Decoder module then restores the size to 56 * 1 through three deconvolution modules (including deconvolution layer, activation function, normalization layer and maximum pooling layer) The decoder is used to restore the hidden variables of the hidden layer to the initial dimension. The second stage of supervised learning, the output of the previous stage as input, and the addition of LSTM layer, Dropout layer, LSTM layer and Dense layer to complete the classification of supervised learning. The LSTM layer is an improved cyclic neural network that is more sensitive to time series. Compared with the RNN model, it solves the Vanishing Gradient problem caused by gradual reduction in the gradient reversal process, and is used to realize high-level feature learning. Specific network parameter settings and input/output methods are shown in Fig. 4.

In order to avoid the reduction of accuracy caused by over-fitting, the Dropout layer is added to the two-layer LSTM in supervised learning, and the drop rate is set to 0.5.

In this study, binary cross entropy is used as the loss function because of binary classification. The unsupervised learning part uses the RMSprop optimizer, and the supervised learning part uses the Adam optimizer.

The model proposed in this study was built through Tensorflow2, and our model was trained on NVIDIA GeForce GTX 3080Ti GPU. The learning rate was 0.001, the batch size was 512, and 50 epochs were trained.

D. Evaluation Metrics

Finally, the evaluation index of the network model is the classification accuracy rate and the RMSE of cross-validation with ten-fold, respectively evaluating the classification performance and model stability of the model. The calculation formula of RMSE is as follows, where N is the fold number of cross validation, $f(x_i)$ is the result of each fold, and Y_i is the average value of cross validation accuracy rate of ten-fold.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - f(x_i))^2} \quad (1)$$

III. Results and Discussions

In terms of the selection of RR interval, this paper sets the RR interval as 50, 100, and 200 respectively into the semi-supervised network. The specific results are shown in Table III. From Table III, we can see that when the RR interval is 50 (30-45 second ECG data), the network classification accuracy is the highest, and when the input data only accounts for 10% of the total data (8268 data with RR interval of 50), the classification accuracy is the highest, 90.16 and the RMSE value is 0.0113.

For performance comparison, this study uses two models for training to verify the superiority of the semi-supervised network model when the labeled data is scarce. One is the Fourteen layers of convolution neural network (CNN) model, the specific model structure is shown in Figure 3 and the other is the semi-supervised network model described above. This study uses the same amount of labeled Input 10% data as input to compare the classification accuracy of the two models of the data (8268 data with RR interval of 50) into the CNN network, and the accuracy rate is only 77.95%. Therefore, when there is only a small amount of labeled data, the semi-supervised network can better complete the classification and recognition task.

TABLE III. Comparative results of different RR interval values and the number of training inputs

Accuracy (%)	RR interval		
	50	***100***	***200***
100% data	88.19	86.02	86.45
10% data	90.16	85.68	86.07
1% data	88.02	85.19	83.15
0.1% data	87.89	85.11	83.76

TABLE VI. Comparison of results of different epoch values when RR interval is 50

Accuracy (%)	epoch		
	40	***50***	***60***
rr interval=50	85.55	90.16	87.21

IV. Conclusions

In summary, three main contributions of this work would be clear as below. First, with the ECG characteristics of AF, RR intervals was designed as the input of the proposed network only that in this work, which shows an encouraged improvement in the training efficiency and shortening the calculation time. Second, in order to solve the problem of the scarcity of clinical data with labels in real life, the CAE-LSTM semi-supervised network is proposed, with AFPDB as the training set, AFDB and NSRDB as the test set to improve the generalization ability of network classification. When the input RR interval is 50 and the epoch is 50, the network showed the best classification with the accuracy of 90.16 and RMSE of 0.013. In addition, a 14-layer CNN network is developed for further comparisons. When the same amount of sparse data is input, the accuracy rate is only 77.95, far less than the CAE-LSTM semi-supervised network proposed in this paper. In the future work, we hope to simplify the network structure, so that we can apply this network to single-lead ECG detection equipment, and provide patients with security assurance for atrial fibrillation prediction.

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