Short-term heart rate prediction approach based on CNN-GRU model with an attention mechanism

Yongjun Zhang1,2*, Yufu Ning1,2, Zhang Huan3, Baotian Li1 and Yanfeng Liu1

1 School of Information Engineering, Shandong Youth University of Political Science, Jinan, Shandong, 250103, China
2 Key Laboratory of Intelligent Information Processing and Information Security in Universities of Shandong, Jinan, Shandong, 250103, China
3 School of International Studies, Shandong Youth University of Political Science, Jinan, Shandong, 250103, China

*Corresponding author’s e-mail: Yongjunzhang@sdyu.edu.cn

Abstract. An accurate short-term heart rate (HR) prediction approach can provide safe, reliable, and efficient early warning for human health, and reduce the occurrence of harmful events. Traditional heart rate prediction methods cannot meet the requirements of high-precision dynamic prediction, and the wide application of machine learning algorithms provides a series of accurate methods for HR short-term prediction. In this study, one kind of a hybrid model, the CNN-GRU model with an attention mechanism, for HR prediction is designed, which is facilitated by the convolutional neural network (CNN) as well as the gated recurrent unit (GRU) with an attention mechanism. This model can realize more precise prediction and early warning for short-term HR changes with full consideration of its dynamic features. To prove the accuracy of our forecasting method, the college students’ HR trends in their daily life are acquired by the wireless HR monitoring devices. This hybrid prediction algorithm is been proved to be effective when compares with other commonly-used prediction models (CNN, LSTM, GRU, SVM, Random Forest). Through experiments, our proposed model is proved to has higher accuracy in HR prediction and early-warning application.

1. Introduction

Heart Rate (HR) is one of the most important health indicators for the risk of cardiovascular diseases, which is the principal cause of morbidity worldwide. Improving the prediction accuracy of short-term heart rate prediction is an effective means to protect human health and prevent the occurrence of hazardous events [1-2]. The traditional HR prediction methods are not suitable for such complex time series prediction. At present, the HR trend prediction methods mainly include support vector machine (SVM) and neural network, which can better deal with nonlinear problems [3]. However, SVM and Random Forest have some difficulties in processing large-scale data, and the convolutional neural network (CNN) method can fully solve the nonlinear problem in large health monitoring data to some extent. Therefore, it is widely applied in physiological parameters prediction [4-7]. CNN model is used to extract the characteristics of input data to predict HR and point out that this method has higher accuracy in learning heart rate data of nonlinear sequence. However, the single CNN model is uneasy to learn the variation of peak features when the acquired data series has great volatility and instability. In reference [8], a short-term HR prediction method based on Long Short-Term Memory (LSTM) is
designed, and the effectiveness of this method in monitoring and extracting HR series features is illustrated. In addition, one kind of short-term heart rate prediction model merging CNN and LSTM was proposed to solve the problem that the accuracy of LSTM decreased due to too long input. Literature [9,10] also points out that the LSTM-CNN model is better than CNN or LSTM model in training speed and fitting effect. Given the above problems of those methods, this paper proposes a CNN-GRU model with an attention mechanism, which gives different probability weights to the hidden layer of GRU, to handle the losing issue for long input HR series, and improves the accuracy of HR prediction. Through real experiments, the results show that our proposed method manifests higher prediction accuracy than other traditional models.

2. Methodology

2.1. Convolutional neural network

The main function of a convolutional neural network (CNN) is to extract basic features from the dynamic HR series. The convolution layer, pooling layer, and full connection layer establish the basic structure of the CNN model. The structure of the CNN model is demonstrated in the following figure 1.

![Figure 1. Structure of CNN model.](image)

In addition, the rectified linear unit (ReLU) is explored as the activation function to abandon the irrelevant features. The activation function is as the following formula (1).

$$ReLU = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases} = \max(0,x) \quad (1)$$

Nevertheless, it is uneasy for the CNN model to comprehensively learn the features of HR trends. Therefore, we appropriately merge the CNN and GRU technology for further improvement of more accurate predictions.

2.2. Gated recurrent unit

A gated recurrent unit (GRU) is a kind of recurrent neural network that is designed and modified with a simpler structure. The training parameters are reduced because the number of control doors is reduced to 2, and its training speed is also greatly improved. The training process of the GRU neural network is as follows equations (2) to (5):

\[
\begin{align*}
\tilde{s}_t &= \sigma_{\text{tanh}} (W_r (r_t \odot s_{t-1}) + U_r x_t + b_s) \\
s_t &= (1 - z_t) \odot s_{t-1} + z_t \odot \tilde{s}_t \\
z_t &= \sigma_{\text{sig}} (W_z s_{t-1} + U_z x_t + b_z) \\
\end{align*}
\]

(2) (3) (4) (5)
Where $\odot$ stands for the product formula of elements; $W_z$ and $W_r$ are the weight matrix of the gate $z_t$ and $r_t$; $W_{s}$ is the weight matrix of the output state; $x_t$ is the input data at time $t$; $s_t$ and $s_{t+1}$ are candidate states and output states at time $t$, respectively; $b_z$, $b_s$, and $b_r$ are the constants. $\sigma$ and $\phi$ are respectively sigmoid and tanh activation functions, which are used to activate control gates and candidate states. To minutely explain the working procedures of the GRU model, figure 2 illustrates the data processing as follows.

Figure 2. Structure of GRU model.

### 2.3. Attention mechanism

The function of the attention mechanism is to capture more key features and improve the accuracy of classification. It assigns probability weight to each feature vector to obtain more key feature information, improve the quality of feature extraction and obtain a better classification effect. The calculation formula of the attention mechanism is as following equations (6)-(8).

\[
S = \sum_{m=1}^{l} a_m h_m 
\]  

\[a_m = \exp(e_m) \sum_{k=1}^{n} e_k\]  

\[e_m = v_m \tanh(w_m h_m + b_m)\]  

Where $h_m$ is the original hidden layer state, $S$ is the new hidden layer state, $a_m$ is the proportion of each original hidden layer state in the new hidden layer state, $e_m$ represents the vector after the hidden layer state vector $h_m$ is processed, $v_m$ is the weight at time $m$, and $b_m$ is the offset at time $m$.

### 2.4. Attention-based CNN-GRU model

Figure 3 shows the whole forecasting process of this hybrid CNN-GRU model with an attention mechanism. This combined deep learning prediction model preserves the advantages of both feature
extraction and HR series forecasting ability. The original HR series were combined and converted to a specific and normalized data format. The specific description of the HR prediction process in this study is described as follows.

- **Data pre-processing.** Data pre-processing includes HR series normalization as well as the supplement of missing HR values.
- **The training procedures of this model.** The inputted HR series of training set into the CNN-GRU model for training, extract features from CNN layer, and next model of GRU further earns the HR series features of data peaks and trends with large changes, and use dropout method to suppress over-fitting problems.
- **The output of prediction.** The attention mechanism determines the weight value of output to get the predicted output of HR results.

![Image of process](https://example.com/image.png)

Figure 3. The prediction processing of the CNN-GRU model with an attention mechanism.

The setting of the main parameters in the attention-based CNN-GRU model is described as follows. In the CNN processing part, the convolutional layer feature maps are set to 128. *ReLU* is utilized inactivation function and dense layer activation function. The spatial dropout ratio is set to 10%. Adam technology is taken as an optimization method in CNN procedures. In GRU part, *ReLU* is also used in the layer activation function and dense layer activation function. The dropout ratio of the GRU process is set to 20%.

3. **Results and discussion**

The prediction is to estimate the forthcoming HR data according to the current real-time HR series sampling and acquisition. An effective HR prediction model can effectively predict and prevent some cardiovascular diseases. Our research tests are developed by Python language 3.9. All of the training
and prediction tests are implemented by the NumPy, and Scikit. The attention-based CNN-GRU, CNN, LSTM, GRU, SVM, and Random Forest models are constructed by Keras on TensorFlow. All those HR series are acquired by the intelligent wearable wristbands device (YUNHUI technology, Shenzhen, China) for daily health monitoring and evaluation. The HR series is about 10 hours sampling data set (From AM 8:00 to PM 18:00) and experiments are carried out in this data set.

3.1. Data acquisition and preprocessing
A total of 50 undergraduate students on our campus were tested and divided into modeling groups (n = 30) and verification groups (n = 20) to participate in the test. The HR series of subjects was collected in our university. During the test period, there were no chronic diseases, no skeletal muscle injury, and no drugs affecting health. According to the test arrangement, the subjects did not participate in high-intensity physical activities on the day before the test. The short-term prediction test and the evaluation time step are set to 10 minutes because long-term HR is prone to be influenced by external environmental factors. The basic information of the subjects is shown in Table 1.

| Items       | Modeling group | Validation group |
|-------------|----------------|------------------|
|             | Male (n=16)    | Female (n=14)    | Male (n=10) | Female (n=10) |
| Age (year)  | 21.00 ± 1.76   | 21.86 ± 1.12     | 21.90 ± 0.84 | 21.92 ± 1.25 |
| Heigh (cm)  | 176.77 ± 3.78  | 162.39 ± 5.93    | 176.13 ± 4.95 | 164.75 ± 6.73 |
| Weight (kg) | 68.78 ± 6.13   | 54.11 ± 6.04     | 75.12 ± 12.03 | 59.58 ± 14.01 |
| BMI         | 21.77 ± 2.17   | 20.82 ± 2.60     | 24.16 ± 3.48 | 22.06 ± 3.45 |

The HR data is pre-processed, including missing value filling and data normalization. Through the preliminary analysis of the data, it is found that with the changes of the period, the HR series shows obvious periodical changes, and there are large fluctuations during the working condition. The HR sequence diagram of different periods is shown in Figure 4.

![Figure 4. The HR changing trends.](image)

3.2. Evaluation measures
In this paper, the mean absolute percentage error, root means square error, and coefficient of determination are used as evaluation indexes.

- Mean absolute percentage error (MAPE) is as the following formula (9).

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|\hat{y}_i - y_i|}{y_i}
\]  

(9)

- The root means square error (RMSE) root is as the following equation (10).
\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}
\]  

(10)

- The determination coefficient \( R^2 \) is used to judge the fitting degree of the regression equation and is expressed in the following formula (11).

\[
R^2 = 1 - \frac{\sum (\hat{y}_i - y_i)^2}{\sum (y_i - \bar{y}_j)^2}
\]

(11)

Where, \( y_i \) is the actual value. \( \hat{y}_i \) is the predicted value. \( \bar{y}_j \) is the average value. \( N \) is the number of samples.

3.3. Discussion

To verify the superiority of the method proposed in this paper, figure 5 shows the comparison results between the prediction error of the proposed model and the other typical algorithms (CNN, LSTM, GRU, SVM, Random Forest). The prediction accuracy is evaluated by the criteria of MAPE, RMASE, and \( R^2 \). The specific improvements are illustrated in figure 6. It can be concluded from the evaluation result that the proposed method has a small prediction error and shows good expected results for HR trends prediction.

![Figure 5. The contrast of prediction performance by using different models](image)

![Figure 6. The evaluation of prediction error](image)

After analyzing the comparison of prediction results, several discussions for model performance are described as follows in detail.
GRU and LSTM predictions are slightly smaller than CNN under the criterion of RMSE. While in MAPE, the CNN model is slightly better than predictions of LSTM and GRU. The convolution kernel of CNN is competent to extract the basic characteristics of HR trends. Moreover, LSTM and GRU pay more attention to the overall characteristics, so the fitting degree on the trend of the overall curve is also very excellent.

Compared with CNN, LSTM, GRU, SVM and Random Forest model, the MAPE of our proposed model reduces by 24.3%, 25.3%, 26.7%, 32.3% and 35.2% respectively, and RMSE by 52.2%, 43.2%, 42.6%, 55.4% and 53.2% respectively. To compared with those traditional models, the determination coefficient is improved by 4.2%, 5.3%, 3.2%, 7.4%, and 8.9% separately.

From the above contrast results, our hybrid model has greatly enhanced the fitting degree, and can accurately judge the short-time HR trends (less than 10 minutes). At the same time, the prediction of individual mutations is also better than other prediction methods.

4. Conclusions
This paper fully considers the characteristics of HR variation in different periods and the difficulty of CNN inaccurately learning data characteristics when the data fluctuates greatly. Our designed model can easily extract the features of HR changes through CNN, and then uses GRU combined with an attention mechanism to complete HR precise prediction by deep learning the features of HR trends. The attention-based CNN-GRU method combines the advantages of CNN and GRU to a great extent and greatly improves the short-term HR prediction accuracy ten minutes in advance, which is sufficient to implement effective rescue measures. In addition, the prediction error is measured smaller than the models of CNN, LSTM, GRU, SVM and Random Forest by the error measures MAPE, RMSE, and R². Through the verification of actual experiments, our proposed short-term HR prediction model can facilitate user’s routine self-testing by providing accurate healthcare recommendations.

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