A Method with Time-sensitive Features for the Automated Prognosis Prediction of Cardiac Arrest Patients Based on EEG

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Abstract

Aims: As part of the George B. Moody PhysioNet Challenge 2023, we proposed a method for the neurological recovery of patients following cardiac arrest by a convolutional neural network with time-sensitive features to realize the automated prognosis prediction for these patients after cardiac arrest.

Methods: Firstly, we selected EEG records for the first 72 hours to build the input signal. During the data preprocessing, we used 3 strategies to get EEG segments including FFT EEG segments, time EEG segments, and enhanced time EEG segments. In our model, we designed 3 stacked Conv Blocks to extract features in each hour respectively. Then we designed the Time-sensitive Learning Block to learn the time-sensitive weights of these 72 hours. The features extracted by Conv Blocks were scaled by the time-sensitive weights so that we got the time-sensitive features. Then these features were sent into 3 Residual Blocks to get the final features which were used to predict the output of the model.

Results: The model with the enhanced time EEG segments as the input and the SE Block in the Time-sensitive Learning Block performed best in the 5-fold cross validation experiments. Our team, Aircas, achieved the Challenge score of 0.45±0.13 on the open training set and 0.475 on the hidden testing set with a rank of 20/36.

1. Introduction

These patients who are successful in resuscitation from cardiac arrest (CA) are facing the risk of severe brain injury due to cerebral hypoxia and ischemia [1, 2] which could cause a terrible result like death. There is a need for prognosis to predict their recovery consciousness of them. EEG is an objective tool which reflects the brain activity by potentials. Poor outcomes with low false-positive rates of prognosis always occur when the EEG keeps persistent EEG background suppression, burst suppression with identical bursts, and seizure-like, i.e. ictal interictal activity on a suppressed background.

The traditional method to get a prognosis from EEG depends on neurologists with advanced training in neurophysiology. However not all medical centers hold neurologists. The method of artificial intelligence has been used in the field of intelligent diagnosis of the brain, such as epilepsy detection [3], seizure prediction [4], Parkinson's disease recognition [5], and achieves good performance. The George B. Moody PhysioNet Challenge 2023 [6] provides access to a large database [7] assembled by the International Cardiac Arrest REsearch consortium (ICARE), and hope the participants provide the prognosis prediction of good and poor patient outcomes after cardiac arrest by automated analysis without experts [6,8].

In this study, we proposed a convolutional neural network to extract time-sensitive features of sequence signals to provide an automated prediction for patients after cardiac arrest.

2. Methods

2.1 Dataset

The dataset used in this study was shared by the work [7]. It was collected by the ICARE from seven hospitals in Europe and the U.S. During the ICARE dataset, all records came from 1020 adult patients who were comatose but the return of heart function after cardiac arrest with the data of electroencephalography (EEG) group, electrocardiography (ECG) group, a reference (REF) group, and another (OTHER) group. Data recording started within hours of cardiac arrest. The time of monitoring may last for several hours to days depending on the patients' condition.

In our study, only the data of the EEG group from 19 channels ('Fp1', 'Fp2', 'F3', 'F4', 'C3', 'C4', 'P3', 'P4', 'O1', 'O2', 'F7', 'F8', 'T3', 'T4', 'T5', 'T6', 'Fz', 'Cz', and 'Pz') were used to build the input.

2.2 Data preprocessing

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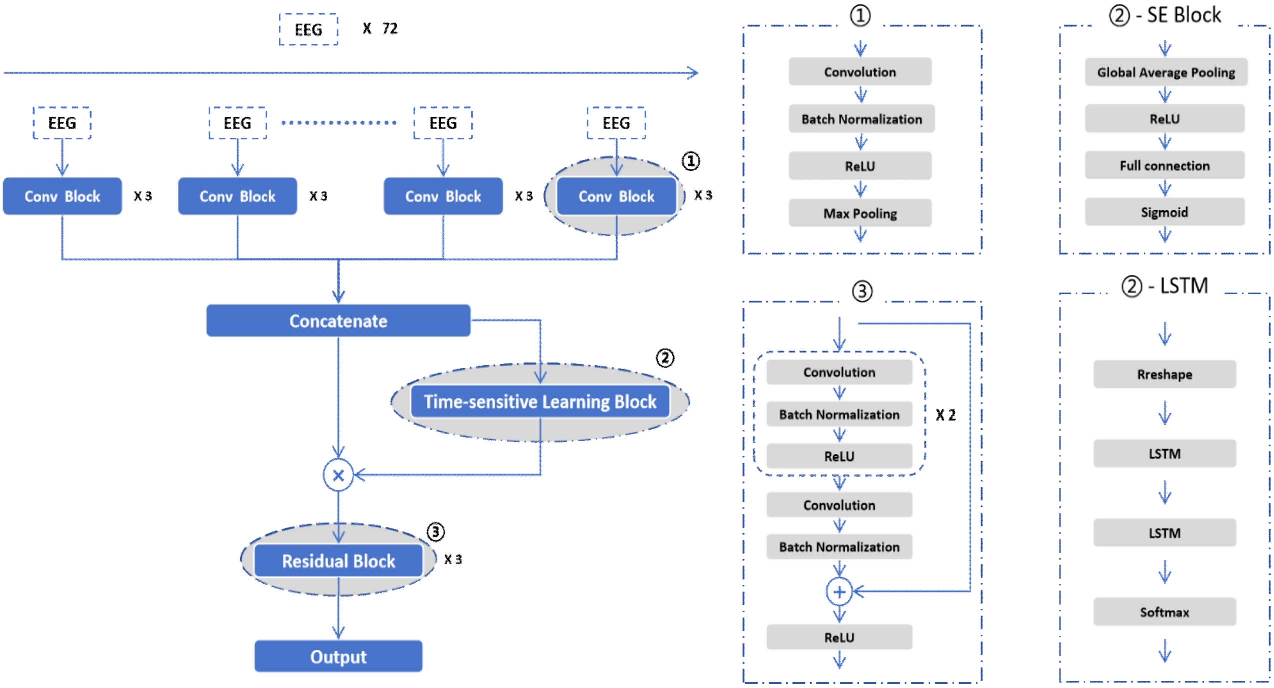

Figure 1. The architecture of our model.

The steps of data preprocessing were as follows:

1. Adjust the length of recording hours. Because EEG records came from different persons with different continued care. The recording hours were not the same for these recordings. In this step, we cut off EEG records after the 72nd hour. Other records were abandoned.
2. Resample the data to 100 Hz. The EEG records were collected in seven hospitals by different facilities with different sampling frequencies. We resampled them to the same frequency.
3. Remove noise by a band-pass Butterworth filter from 0.5 to 30 Hz. Due to there were some special components in EEG signals including the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) rhythms, all EEG data were filtered by a band-pass filter.
4. Segment EEG records. The length of the EEG records was very long. In this step, we designed 3 operations to get EEG segments. If there were no EEG records we used 0 to fill the missing value.
   A. Apply the Fast Fourier Transform (FFT) to EEG data in each channel. Then the FFT samples between the frequency from 0.5 and 30 Hz were picked up as EEG segments.
   B. Choose the first 20s data in each hour as EEG segments.
   C. Cutting 5 different EEG epochs with the length of 20s as EEG segments to achieve data enhancement. One record generated 5 samples. The training samples had increased.
5. Resample EEG segments to 1000 points. The three EEG segments in step 4 had different sample points. We resample them with the same length to get a fixed input shape of (19,1000).
6. Normalize EEG segments for each EEG segment in the channel dimension.

2.3 The architecture of model

The architecture of model is shown in Figure 1. First of all, we designed Conv Blocks to extract features in 72 hours respectively. Then, features were concatenated together. After that, we designed a block named Time-sensitive Learning Block to learn the time-sensitive weights of the 72 hours from the concatenated features. The time-sensitive weights were used to adjust the concatenated features by multiplication to get the time-sensitive features. Next, we applied three Residual Blocks to extract depth features from the time-sensitive features. The output of the Residual Block was flattened and sent to a fully connected layer to get the predicted label.

Conv Block	1	2	3
Convolutional kernel	3*3@16	3*3@16	3*3@16
Convolutional stride	1*1	1*1	1*1
Batch normalization	default	default	default
Activation	ReLU	ReLU	ReLU
Max pooling	3*3	1*3	-

Table 1. The parameter setting in the 3 stacked Conv

Blocks. processed by 3 stacked Residual Blocks.

Model	Score	Accuracy	AUROC	AUPRC	F-measure
FFT EEG segments + SE Block	0.41±0.06	0.59±0.10	0.62±0.08	0.77±0.08	0.53±0.07
Time EEG segments + SE Block	0.42±0.06	0.64±0.05	0.64±0.07	0.80±0.06	0.48±0.09
Time EEG segments + LSTM	0.41±0.06	0.59±0.10	0.62±0.07	0.78±0.08	0.53±0.07
Enhanced time EEG segments + LSTM	0.45±0.13	0.64±0.06	0.45±0.07	0.80±0.07	0.63±0.07

Table 2. Average results of 5-fold cross validation on the training data.

As shown in Figure 1, there were 4 layers in the Conv Block including a convolution layer with the kernel size of (3,3) and a stride of (1,1), a batch normalization layer, an activation layer with a function of ReLU, and a max pooling layer. In our model, we stacked 3 Conv Blocks and the parameter setting was slightly different in each Conv Block, especially the number of the convolutional kernels in the convolution layer and the setting in the max pooling layer. In the third Conv Block, there was no max pooling layer. The concrete parameters are listed in Table 1.

The Conv Block output 72 groups of feature maps with the shape of (64, W, H). All of them were concatenated into one. We got a group of feature maps with the shape of (72, 64, W, H) and sent it into the Time-sensitive Learning Block. To learn the time-sensitive features, we designed 2 structures, the time-sensitive Squeeze-and-Excitation (SE) Block and the time-sensitive Long Short-Term Memory (LSTM).

SE block was proposed by [9] with the aim of learning the dependency of feature channels to recalibrate the features. As shown in Figure 1, the time-sensitive SE Block was made up of a global average pooling layer, a fully connected layer, and two activation layers. After being processed by the global average pooling layer, the shape of concatenated feature maps changed to (72, 64). Then we used a fully connected layer to learn the time dependence of the 72 hours and we got the feature maps with the shape of (72, 1). Then we got the output of this block with the shape of (72,1) when feature maps were processed by the activation function of the Sigmoid.

LSTM [10] was a special recurrent neural network that had shown noteworthy ability to process time series. As shown in Figure 1, the keys in the time-sensitive LSTM were two LSTM layers. Before being sent into the LSTM layers, the feature maps were reshaped from (72, 64, W, H) to (72, 64*W*H). In the LSTM layers, the output length in every time step is 1. Hence, all the outputs at each time step formed a group of features with the shape of (72,1) after the two LSTM layers. Then we got the output of this block with the shape of (72,1) when these features were processed by the activation function of the Softmax.

We regarded the outputs of the block Time-sensitive Learning as the weights to scale the concatenated feature maps by multiplication to enhance the time-related features. After that, the scaled feature maps were processed by 3 stacked Residual Blocks.

The implementation of the 3 Residual Blocks was the same, including 3 convolution layers with the kernel size (1,1) and the stride (1,1), 3 batch normalization layers, and 3 activation layers with the function of ReLU. The shortcut connection was placed between the input of this block and the position where before the last activation layer.

Due to the unbalanced numbers of positive samples and negative samples, we chose the Focal Loss [11] as the loss function during model training.

3. Results

The George B. Moody PhysioNet Challenge 2023 proposed the Challenge score to evaluate the model performance. The Challenge score was defined as the true positive rate at a false positive rate of 0.05. Besides the Challenge score, the metric accuracy, AUROC, AUPRC, and the F-measure were computed in the experiment. We conducted a 5-fold cross validation experiment on the open training set. We tested different combinations of the EEG segments and model architectures:

1. Use the FFT EEG segments as input and use the time-sensitive SE Block as the Time-sensitive Learning Block.
2. Use the time EEG segments as input and use the time-sensitive SE Block as the Time-sensitive Learning Block.
3. Use the time EEG segments as input and use the time-sensitive LSTM as the Time-sensitive Learning Block.
4. Use the enhanced time EEG segments as input and use the time-sensitive SE Block as the Time-sensitive Learning Block.

The average results of 5-fold cross validation on the training set are shown in Table 2, and the results of our model on the hidden validation set and the hidden testing set are listed in Table 3.

Training	Validation	Test	Ranking
0.45±0.13	0.269	0.475	20/36

Table 3. The scores of our team on the open training set (5-fold cross validation), the hidden validation set, the hidden testing set, and the final ranking.

4. Discussions

As described in Section 2.3, we designed two structures to learn time-sensitive features. We conducted experiments to evaluate the performance of the two structures by keeping the input the same but changing the Time-sensitive Learning Block. As shown in Table 2, when using the time EEG segments as the input, the average score of the model with the SE Block was higher than that of the model with the LSTM. The SE block learned better time-sensitive features about the changes in the long records of 72 hours.

As described in Section 2.2, we designed three methods to generate EEG segments from raw EEG. We used the SE Block in the Time-sensitive Learning Block but changed the input. As shown in Table 2, the score of the FFT EEG segments was lower than that of the time EEG segments. It can be inferred that time characters were vital for the task of automated prognosis prediction.

Besides, we compared the effect of data enhancement. As shown in Table 2, the model with the enhanced time EEG segments as input achieved the highest score (0.45±0.13) on the training data. Data enhancement expanded the training set and improved the generalization of the model.

We tested the model with the combination of the enhanced time EEG segments and SE Block on the hidden validation set obtaining a score of 0.269 and on the hidden testing set obtaining a score of 0.475 which ranked 20/36 in Challenge 2023.

5. Conclusions

In this study, we proposed a convolutional neural network by learning time-sensitive features and depth features to realize the automated prognosis prediction for these patients after cardiac arrest. The time series are more suitable than the frequency series for this task. The SE block showed better performance than the LSTM to learn time-sensitive features of the data from 72 hours. Finally, our team Aircas obtained a score of 0.269 on the hidden validation set, a score of 0.475 on the hidden testing set, and a ranking of 20/36 in Challenge 2023.

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