Predicting Neurological Recovery After Cardiac Arrest from Electroencephalogram Using Residual Network and Random Forest

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Abstract

The goal of Predicting Neurological Recovery from Coma After Cardiac Arrest: The George B. Moody PhysioNet Challenge 2023 is to use longitudinal electroencephalogram (EEG) and electrocardiogram (ECG) recordings to predict patient prognosis after cardiac arrest (CA). As part of the Challenge, our team, UCASFighters, introduced an approach that fuses an 18-layer residual network and a random forest to predict patient prognosis after CA. This fusion prevents overfitting and improves the performance. We also introduced an improved focal loss function to handle class imbalance in classification task and improve model training. Finally, our approach received a Challenge score of 0.599 (ranked 10th out of 36 teams) on the hidden test set.

1. Introduction

Currently, cardiac arrest (CA) has one of the highest mortality rates among all diseases. Due to the severe neurological damage caused by hypoxic-ischemic brain injury after CA, some patients will still face death after active treatment [1]. To avoid waste of medical resources, early prediction of comatose patients after CA is necessary.

Electroencephalogram (EEG) provides information on neurological function by recording functional activities in different parts of the brain. It is valuable for evaluating the prognosis of acute brain injury. Machine learning (ML) methods have been used to utilize EEG data to predict the neurological prognosis of comatose patients after CA [2]. However, ML usually uses only artificially predefined features. Other potentially relevant features of EEG may be lost. Furthermore, deep neural networks perform well in the predicting of comatose patients' prognoses and have the potential to utilize long-term trends in EEG [3].

In *The George B. Moody PhysioNet Challenge 2023* [4, 5], we introduced an approach that fuses an 18-layer residual network and a random forest to predict patient prognosis after CA. We also introduced a focal loss function that incorporates the false positive rate as a penalty term. More details are shown below.

2. Method

2.1. Datasets and Preprocessing

Researchers from the International Cardiac Arrest Research consortium(I-CARE) collected 19-channel EEG data from 1,020 CA patients from seven academic hospitals in the U.S. and Europe. The I-CARE dataset includes EEG data up to 72 hours after CA, demographic information and functional neurological outcome from 3 to 6 months after CA. The cerebral performance category (CPC) score of 1 or 2 (minimal to moderate neurologic dysfunction) was defined as good neurologic prognosis, whereas the CPC score of 3-5 (severe neurologic dysfunction, persistent coma or vegetative state, or death) at 3-6 months was defined as poor prognosis [6].

The EEG data were preprocessed by applying digital bandpass filters (0.5-30Hz), resampling to 128 Hz, scaling to the interval ([-1,1]). EEG's 19 channels are Fp1, Fp2, F7, F8, F3, F4, T3, T4, C3, C4, T5, T6, P3, P4, O1, O2, Fz, Cz, and Pz. The EEG was processed to 18 channels: Fp2-F8, F8-T4, T4-T6, T6-O2, Fp1-F7, F7-T3, T3-T5, T5-O1, Fp2-F4, F4-C4, C4-P4, P4-O2, Fp1-F3, F3-C3, C3-P3, P3-O1, Fz-Cz, Cz-Pz. For data up to 72 hours, we intercepted the first five minutes (38400 points) of each hour and filled in the missing data with zeros. Then, the 72 five-minute data segments were cached as intermediate files.

2.2. Feature Extraction

Since EEG signals are characterized by randomness, non-stationarity and nonlinear, a single class of features cannot analyze EEG signals, so we analyze the data from the last hour in the time, frequency, and nonlinear domains. We extracted six statistical features in the **time domain** including mean, standard deviation, variance, root mean square, kurtosis, and power for each channel.

Frequency domain analysis has been proved to be effective in the classification of EEG signals related to other neural systems [7], so making full use of the characteristics of EEG signals in the frequency domain is conducive to improving the classification accuracy of the model. The **frequency domain** features extracted by us are as follows:

Power Spectral Density (PSD). In the frequency domain, the PSD in the $\delta(0.5-4Hz), \theta(4-8Hz), \alpha(8-14Hz)$ and $\beta(14-30Hz)$ bands are computed using the fast fourier transform (FFT) of the autocorrelation function, respectively. [7] $x(t)$ of an EEG signal of length N is set to have a value of t ranging from 0 to $N-1$, and the autocorrelation function is as follows:

$$\hat{\gamma}(i) = \frac{1}{N}\sum_{t=0}^{N-1-i} x(t)x(t+i), \tag{1}$$

where $i = 0, 1, ..., N-1$. The autocorrelation function is an even function, so there is:

$$\hat{\gamma}(-i) = \hat{\gamma}(i). \tag{2}$$

The PSD function is as follows

$$\mathrm{PSD} = \sum_{t=-(N-1)}^{N-1} \gamma(t)\mathrm{e}^{-\mathrm{i}\omega_\mathrm{k}\mathrm{t}}, \tag{3}$$

where $k = -(N-1), ..., 0, 1, ..., N-1, \omega_k = 2\pi k/N$.

For a single data, we can get a PSD feature sequence in 4×18 dimensions, where 4 represents the number of frequency bands and 18 represents the number of channels.

Petrosian Fractal Dimension (PFD). To a time series, PFD is defined as

$$\mathrm{PFD} = \frac{\log_{10} N}{\log_{10} N + \log_{10}(N/(N+0.4N_\delta))}, \tag{4}$$

where N is the series length, and N_δ is the number of sign changes in the signal derivative [8]. PFD is a scalar feature. Thus, for a signal 18-channel EEG data, we obtained 18-dimensional PFD features.

The neural activity of the brain is a complex activity with nonlinear dynamics, and the method of nonlinear feature extraction and analysis helps to understand and explain the dynamics of EEG signals and the corresponding neural activity process in the brain. In this study, we extracted the **nonlinear domain** features as follows:

Permutation Entropy (PE). As a parameter to measure the complexity of time series [9], PE is widely used in the detection of chaotic systems, especially in the research of EEG signals. The following is the calculation process:

Assuming that $(x(1), ..., x(N))$ is a one-dimensional EEG sequence of a single channel, the embedded data dimension is $m(m > 1)$, and the time delay is t $(t > 0)$, which constitutes a window (m, t) capable of allowing the current sequence to pass through it sequentially, phase space reconstruction is performed on this time series to obtain a matrix Y:

$$Y = \begin{bmatrix} x(1) & x(1+t) & \cdots & x(1+(m-1)t) \\ x(2) & x(2+t) & \cdots & x(2+(m-1)t) \\ \vdots & \vdots & \ddots & \vdots \\ x(K) & x(K+t) & \cdots & x(K+(m-1)t) \end{bmatrix}. \tag{5}$$

Each row of matrix Y is a reconstruction component:

$$Y_j = [x(j), x(j+t), ..., x(j+(m-1)t)], \tag{6}$$

where $j = 1, 2, ..., K, K = N-(m-1)t$.

The reconstructed components are arranged according to the ascending order of the value, and there are $m!$ kinds of arrangement. $P_1, P_2, ..., P_k$ represents the probability of occurrence of each permutation, and PE is defined as:

$$\mathrm{PE} = -\sum_{i=1}^{k} P_i \ln(P_i). \tag{7}$$

We can get 18 dimensional PE features for a single data. Finally, we can get 12×18 dimensional EEG features.

2.3. Model Description

As shown in Figure 1.(a), we proposed a method that fuses residual network (ResNet) and random forest (RF). This fusion leverages the deep neural network's ability to extract intricate features and RF's robustness and interpretability, mitigating overfitting and enhancing performance. The ResNet and RF are trained independently.

Random Forest (RF)

For a single sample, we extracted 12×18 dimensional EEG features from the last hour EEG data. The dataset also provides 5-channel ECG data, we extracted two features, mean and standard deviation for each channel in the first hour ECG data. Thus, for a single sample, we obtained 2×5 dimensional ECG features. We utilized six clinical features including Age, Gender, ROSC (return of spontaneous circulation), OHCA (out-of-hospital cardiac arrest), Shockable Rhythm and TTM (targeted temperature management) from the demographic information.

Then we flatten all the features obtained above into a 232-dimensional feature vector, which is used as the input

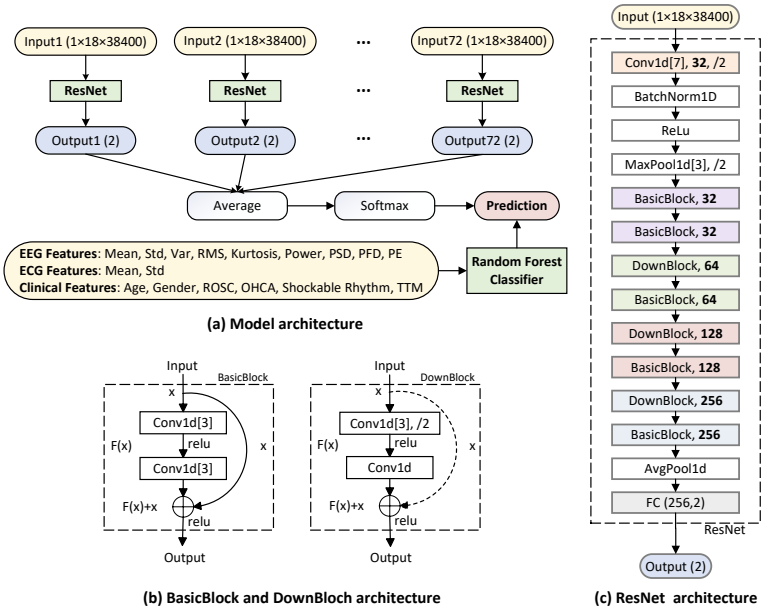

Figure 1. The architecture of our architecture. **(a)** The overall architecture of our approach. **(b)** BasicBlock and DownBlock of the ResNet. **(c)** Architecture of the 18-layer ResNet built by our team, the number in [] represents the kernel size, the bolded number represents the number of channels, and "/2" means that the stride is 2, i.e., the data is downsampled.

to the RF classifier. Set the parameters of RF including the number of estimators, max leaf nodes and random state to 100, 100 and 789 respectively. The output of RF is 0 or 1, representing good or poor outcome. In addition, we can get the probability of poor prognosis and the CPC by mapping the probability to a value in the range of 1 to 5. These are the outputs that the Challenge requires.

Residual Network (ResNet) [10]

Figure 1.(b) illustrates the two blocks of ResNet. The BasicBlock comprises two identical convolutions (kernel=3, stride=1) with matching input and output dimensions. In contrast, the first convolutional layer of DownBlock has a stride of 2, and output dimension twice that of the input. Refer to Figure 1.(c), by employing BasicBlock and DownBlock, we constructed an 18-layer ResNet tailored for one-dimensional convolutions, ideal for processing time series data. In Figure 1.(a), we processed each hour's data individually using ResNet, generating a two-dimensional output for each hour. With 72 hours of data, we obtained 72 outputs. These outputs were then averaged, consolidating the results for each hour. Subsequently, we applied a softmax layer to obtain the probability for each category. Finally, the outcome is the category with highest probability, the CPC is obtained by the same way above.

In prediction, the neural function of the patient is predicted independently using random forest classifier and residual network respectively, the probability of each category is output, the probability is averaged then the category with the highest probability is taken as the final prediction.

2.4. Loss Function

Due to sample imbalance problem in dataset, we used a focal loss function to train ResNet, which is defined as:

$$FL = \begin{cases} -\alpha(1-p)^{\gamma}\log(p), & y=0 \\ -(1-\alpha)p^{\gamma}\log(1-p), & y=1 \end{cases} \tag{8}$$

where y is the true label, p is the estimated probability of the model for label 0 (minority category). The hyperparameter α is the balanced parameter and the non-negative hyperparameter γ is known as the focusing parameter.

For *The George B. Moody PhysioNet Challenge 2023*, the scoring metric is the true positive rate for predicting an poor outcome with a false positive rate (FPR) less than or equal to 0.05 at 72 hours. In clinical practice, prognostic assessment influences whether to continue treatment. False-positive predictions of adverse outcomes are therefore very serious and may cost patients who could regain consciousness their lives. Therefore, we add the FPR as a penalty term to the focal loss function. The final loss function is as follows:

$$Loss = FL + \beta \cdot FPR, \tag{9}$$

where β is the hyperparameter that regulates FPR's weight.

2.5. Model Training

ResNet model is trained 80 epochs with single-sample update method. Adam with an initial learning rate of 0.001

was applied for model optimization. The hyper-parameters were adjusted according to the model 5-fold cross validation performance on the public training dataset to achieve optimal performance. Finally, we set α, γ and β to 0.63, 2 and 0.0002, respectively. In addition, the parameters including the number of estimators, max leaf nodes and random state of the RF classifier were set to 100, 100 and 789.

3. Results

We evaluated our approach through 5-fold cross-validation on the public training set with the Challenge evaluation metric. Then our approach was evaluated by Challenge organizer on the hidden validation and test set. The results are shown in Table 1.

Training	Validation	Test	Ranking
0.552 ± 0.09	0.687	0.599	10/36

Table 1. True positive rate at a false positive rate of 0.05 (the official Challenge score) for our final selected entry (team UCASFighters), including the ranking of our team on the hidden test set. We used 5-fold cross validation on the public training set, repeated scoring on the hidden validation set, and one-time scoring on the hidden test set.

4. Discussion and Conclusion

We introduced an approach that fuses an 18-layer residual network and a random forest (RF) to predict patient prognosis after CA. The results show that our method is effective and feasible.

There are some limitations of our work. Firstly, we only utilized the first 5 minutes EEG data for each hour. And we only extract features as RF's inputs from the last hour's EEG data and the first hour's ECG data. We did not fully utilize the dataset. Secondly, we have not identified a more effective data preprocessing method, so the data contains a lot of noise, which could potentially influence the final predictions. Thirdly, we have not fully harnessed the temporal changes in EEG data, the potential of deep neural networks has yet to be explored.

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