Prediction Comatose Patient Outcomes Using Deep learning -based Analysis of EEG Power Spectral Density

Kyungmin Choi [1], Gi-Won Yoon[1], Sanghoon Choi[1] and Hyeon-Hwa Choi[1], Segyeong Joo[1]

[1]Department of Biomedical engineering, Asan Medical Institute of Convergence Science and Technology, Asan Medical Center, University of Ulsan College of Medicine, Seoul, Republic of Korea

Abstract

The EEG signal is capable of detecting changes in brain activity with millisecond-level precision. However, due to the high dimensionality and non-stationarity of EEG signals, various features, such as Power Spectral Density (PSD), are extracted instead of using EEG signals directly in deep learning models. One potential advantage of analyzing PSD in EEG analysis is that it provides information about the frequency components of the signal, which can help identify patterns and abnormalities in brain activity. Therefore, our team extracted PSD from comatose patients' recordings 12 hours post-cardiac arrest to predict neurological outcomes within 72 hours. This is part of the George B. Moody PhysioNet Challenge 2023

Since the number of recorded data varies for each patient, we extracted the available dataset within 12h after cardiac arrest. The EEG feature selected was the PSD in major frequencies, including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-15 Hz), and beta (15-30 Hz). Therefore, we calculated the PSD and combined the values for each of the four frequency ranges. Each PSD was classified using a ResNet model, and the average predicted values were used for binary classification in the Outcome model and for estimating CPC scores in the CPC model.

We evaluated the performance of two models: the Outcome Model and the CPC Model. In Challenge submission system, our team, EEG pz lmn sqz achieved a challenge score of 0.584 for 72 hours in test set and ranked 11th according to the result of challenge leaderboard.

Our team proposed a novel deep learning method using PSD to predict outcomes in comatose patients. Future work includes exploring various time intervals for PSD extraction and segmentation to further enhance model performance.

1. Introduction

Coma state is a common clinical condition that arises after successful resuscitation from cardiac arrest (CA) [1]. The most comatose patients undergone after CA have typically showed significant abnormalities, with changes in EEG patterns. [2, 3] Recently, the studies with prognostication after CA suggested that early reactive (12h after CA) related important to predict outcome of patients [4, 5].

The EEG signal is an exceptionally powerful tool for detection changes in brain activity with millisecond-level precision. However, EEG signal has substantial challenges that is high dimensionality and non-stationarity [6]. In addition to, EEG signal include its susceptibility to noise interference and variations in signal quality and individual differences. Therefore, analyzing EEG signal need for sophisticated processing techniques to extract meaningful patterns such as power spectral density (PSD). The PSD is the feature that represents the power distribution of EEG signal in the frequency domain, which is easily capturing for abnormalities of EEG signal.

The prediction outcome from comatose patients in ICU: The George B. Moody PhysioNet Challenge 2023 presented large new large data of various signals included EEG [7, 8]. Also, the dataset was labelled good and poor for Cerebral Performance Category (CPC), which determined good outcome at CPC score of 1-2 and poor outcome at CPC score of 3-5.

Our team, EEG pz lmn sqz, suggests a novel approach for prognosticating outcomes within 72 hours for comatose patients. We employ deep learning to analyze EEG signals obtained at 12 hours post-cardiac arrest. This involves calculating their Power Spectral Density (PSD) to predict prognosis.

2. Method

Our aim was to extract PSD from specific time of EEG signal segmented 5 minutes for voting method. We developed two model, outcome model and CPC model for predicting outcome from comatose patients. The outcome model is for classification good or poor and the CPC model is multi class classification model for estimating CPC score. The Figure1 presented overview in detail.

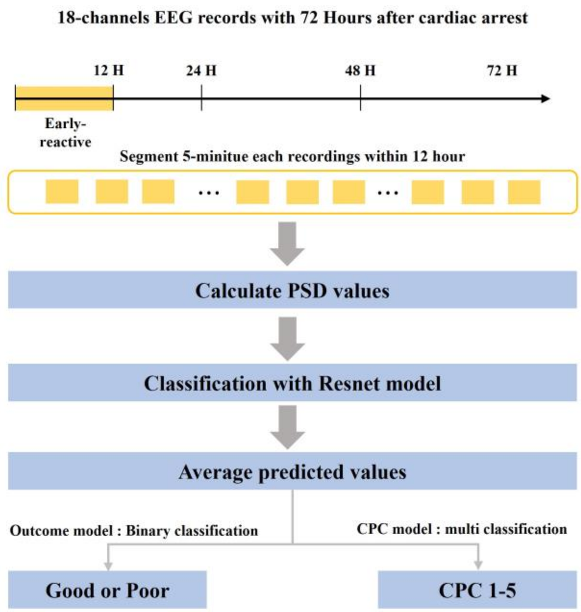

Figure 1. Overview of proposed method.

Label	Class	Number
Outcome	Good	225
	Poor	382
CPC score	1	181
	2	44
	3	353
	4	20
	5	9

Table 1. number of dataset for outcome and CPC scores.

2.1. Datasets and Preprocessing

The dataset contains 607 patients, and the recordings of each patient were extracted within 72 hours. We used only an EEG signal from the patients who had return of spontaneous circulation after cardiac arrest but were still comatose. The dataset was split 8:2 for train and test set for model training and evaluating. The test set is held-out subset of the training set. Table1 shows the dataset in detail.

The EEG signal contains 19 channels, which included Fp1, Fp2, F7, F8, F3, F4, T3, T4, C3, C4, T5, T6, P3, P4, O1, O2, Fz, Cz, Pz, Fpz, Oz, and F9. We utilized the 18 channels of bipolar EEG signal calculated from 19 channels. All EEG signals were downsampled to 100Hz and included records with a minimum duration of at least 15 minutes. Also, since the start point of time is different in all patients, we extracted data based on the patient's EEG measured record, not the EEG record recorded within 12 hours after ROSC to address missing data.

The preprocessing and normalization applied all dataset. We used a Butterworth 4th order bandpass filter with cut-off frequency set at 0.1Hz and 30Hz to remove low and high frequency noise. And min-max normalization was used for ensuring the EEG signal scaling within -1 to 1 as follow (1):

$$Scale = \frac{data - \min(data)}{\max(data) - \min(data)} \times 2 - 1 \qquad (1)$$

The normalization was applied for EEG recordings of each patient within 12 hours. The *data* in equation (1) means EEG recordings of each patient.

After preprocessing and normalization, each recording was segmented into 5 minutes for voting each minute.

And we calculated PSD of each segment, which was performed for four main frequency bands of the EEG signal: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-15 Hz), and beta (15-30 Hz) (Figure 2). We utilized the MNE Python library, a widely recognized used open-source tool for analysis of neurophysiological data. And it employs the Welch method for PSD estimation, which is a classical technique used in frequency domain analysis. It involves dividing the signal segmented 5 minutes and calculating the power spectrum and then averages them to obtain the main frequency spectrum. This method reduces the effect of noise and highlights frequency components.

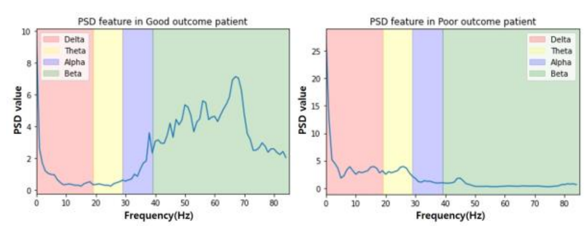

Figure 2. Example for PSD value of single channel extracted from the first EEG signal after cardiac arrest for each label.

After calculated, the PSD values of four main frequency were concatenated for training model. Finally, The input size is 18x85, which contains channels and PSD.

2.2 . Model description

Figure 3 illustrates the ResNet architecture. Each block consisted of a convolutional layer, followed by max pooling, and two residual blocks. A total of five such blocks were stacked. The first layer and the initial two blocks utilized 16 convolution filters. The number of filters doubled with each subsequent block. The kernel size decreased by a factor of two, starting from nine. The learning rate was set at 0.009, while a dropout rate of 0.1 was applied. The model underwent training for a total of 150 epochs.

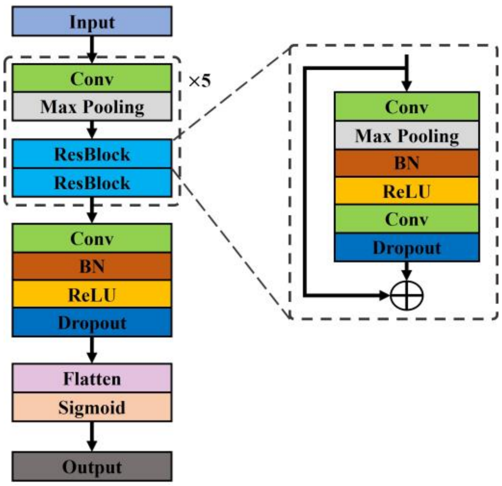

Figure 3. The ResNet model for classification

2.3 Evaluation model

We evaluated the output model for classification as AUROC, AUPRC, Accuracy, and F1 score. The evaluate metrices are calculated as :

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1\ score = \frac{2\times(Precision\times Recall)}{Precision+Recall} \quad (6)$$

TP denotes true positive, FP denotes false positives, FN denotes false negatives, and TN denotes true negatives. The predicted values from 12 recordings within 12h after CA are average for each patient.

Also the CPC model was evaluated as mean squared error(MSE) that is different between predicted CPC scores(X) by the model and . These score are calculated as (7) :

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(X_k - Y_k)^2 \quad (7)$$

Also, Challenge score is calculated by true positive rate at a false positive rate of 0.05.

3. Results

The Table 2 presented the performances of two model, outcome model and CPC model on held-out subset of the training set. In the results of outcome model, The AUROC, AUPRC, accuracy, and F1 score are 0.774, 0.856, 0.7 and 0.683 respectively. Especially, the AUPRC of model is best score, which highlights its proficiency in correctly identifying positive instance (Poor outcome) and its emphasis on recall. In addition to, the MSE score from CPC model was 0.3404. Figure 4 shows confusion matrix for classification outcome of 120 patients of our test set. In Challenge system, our team's submission was evaluated using the Challenge scoring system with hidden test dataset. Table 3 shows challenge score for 72 hours as training, validation, and test dataset. Our team, EEG pz lmn sqz, received challenge scores for training set, validation set, and test set of 0.987, 0.582, and 0.584 respectively, and ranked 11th out of 36 teams.

Model	Score	
Outcome	AUROC	0.774
	AUPRC	0.856
	Accuracy	0.7
	F1 score	0.683
CPC	MSE	3.404

Table 2. The results of model performances in held-out subset of the training set.

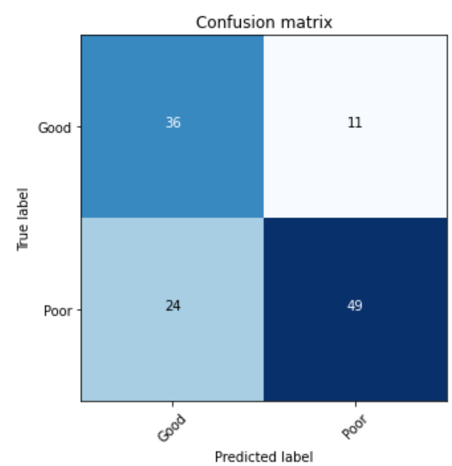

Figure 4. Confusion matrix of in held-out subset of the training set.

Team	Training	Validation	Test	Rank
EEG pz lmn sqz	0.987	0.582	0.584	11/36

Table 3. The Challenge score of each dataset at 72 hours after ROSC.

4. Discussion and Conclusions

Our team proposed a novel method for predicting outcome of comatose patients using deep learning with PSD. Instead of using the PSD of all recordings within 72 hours after CA, we extracted the meaningful recordings within 12 hours after CA for predicting outcome. Also, by using 5-minute segmented PSD calculations instead of hourly records in a deep learning model offers enhanced temporal granularity, improving the model's sensitivity to short-term variations and enabling more precise detection of transient patterns.

When evaluating the performance of the Outcome Model, the high AUPRC indicates its proficiency in effectively capturing the positive cases as intended by the challenge, reflecting a high level of recall in real medical scenarios. In contrast, for the CPC Model, the low MSE score suggests that the model encountered challenges due to severe data imbalance, resulting in lower overall performance.

In the future, we plan to enhance model performance by extracting PSD from various time intervals, and not limiting the segmentation process to just 5 minutes. We will consider segmenting data into intervals such as 10 seconds, 1 minute, and 3 minutes, aiming to compare and optimize the model's performance.

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Address for correspondence:

Kyungmin Choi
rudals300@gmail.com

Segyeong Joo
sgjoo@amc.seoul.kr