A Temporal-Spectral Based Single-lead Electroencephalogram Feature Fusion Network may Provide Potential Clinical Biomarker for Cardiac Arrest

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Abstract

Cardiac arrest is a fatal condition requiring rapid identification and intervention. Our team "SHE Lab" develops a deep neural network for automated detection from single-lead electroencephalogram (EEG) as part of the 'Predicting Neurological Recovery from Coma After Cardiac Arrest: The George B. Moody PhysioNet Challenge 2023'. Our model comprises complementary time-domain and spectral-domain to extract prognostic biomarkers. The adaptive time-domain convolution block directly analyzes the EEG waveform. The multi-resolution wavelet decomposition block captures discriminative spectral bands. Feature fusion integrates this multi-modal information before final classification. While our team was unable to be scored on the test set, experiments demonstrate good performance with accuracy 78.1%, AUROC 0.914, AUPRC 0.942, F1-score 0.841 on our held-out subset of the training set. Compared to methods based on multi-lead EEG, our automated single-lead interpretation model can achieve accessible and scalable monitoring, providing a powerful and universal method to explore the predictive function of EEG. The proposed biomarkers demonstrate the low-cost, rapid diagnosis, real-time care in clinical practice. Therefore, the biomarkers may provide important value for the prognosis evaluation and timely treatment of patients with cardiac arrest.

1. Introduction

Cardiac arrest is a life-threatening condition that occurs when the heart suddenly stops pumping blood to the body's vital organs. It is a leading cause of death worldwide, with survival rates below 10% in out-of-hospital cardiac arrests even with cardiopulmonary resuscitation (CPR) and defibrillation attempts. Rapid and accurate identification of cardiac arrest is critical to enable early interventions and improve outcomes. Previous studies have shown the utility of electroencephalography (EEG) in evaluating brain function and predicting recovery in comatose survivors of cardiac arrest[1][2]. However, the above studies are all based on multi-lead EEG data. It is known that multi-lead EEG data is very expensive to collect compared to single-lead EEG.

With the development of deep learning, there are emerging opportunities for automated EEG interpretation. Convolutional neural networks (CNNs) can directly analyze EEG raw signal and perform feature extraction and classification end-to-end. While multi-lead EEG provides spatial information, single-lead EEG has the advantages of wide availability and simple acquisition. Effective learning from single-channel EEG remains a challenge. The George B. Moody PhysioNet Challenge 2023[3,4] offers a chance to make progress in predicting outcomes for coma patients following cardiac arrest by granting access to a substantial international multicenter database comprising over 1,000 subjects who collectively underwent more than 50,000 hours of EEG monitoring collected by the International Cardiac Arrest REsearch consortium (I-CARE)[5].

In this study, we develop a deep neural network model comprising time-domain and frequency-domain blocks to extract prognostic information relatd biomarker from single-lead EEG recordings. The adaptive time domain block performs feature extraction from raw waveform. The multi-spectral representations block transforms the signal to spectrogram representations to analyze critical frequency bands. The complementary information is integrated through concatenation before final classification. Our model aims to accurately predict neurological outcomes based on early coma EEG after cardiac arrest. The learned EEG features can potentially inform patient-specific pathology and recovery processes. This biomarker has the potential to be used as a clinical biomarker for real-time monitoring and timely intervention in cardiac arrest patients.

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2. Method

2.1. Preprocessing

For this challenge, the database[3, 5] consisted of data from 1,020 adult patients with out-of-hospital or in-hospital cardiac arrest who recovered cardiac function ("return of spontaneous circulation", ROSC) but remained in a comatose state. All patients were admitted to the ICU and their body activity was monitored with continuous 18-channel EEG and 1-channel ECG. Monitoring usually begins within hours of cardiac arrest and continues for hours to days depending on the patient's condition. Therefore, the start time and duration of the record varied for each individual. The labeling results were determined prospectively by telephone interview (6 months after ROSC) for clinical outcomes and chart review (3-6 months before ROSC) for the remaining hospitals. Neurologic function was also measured using the Cerebral Performance Category (CPC) scale.

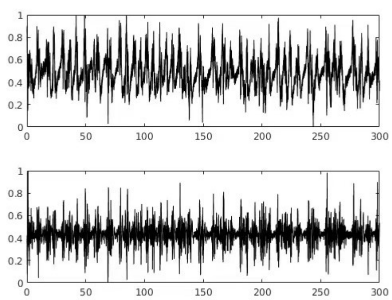

Figure 1. 300 seconds of EEG signals before and after preprocessing.

All EEG data were preprocessed using bandpass filtering (0.5-20 Hz) and then resampled to 100 Hz. For the latest release of raw data, the training process requires 60 to 72 hours of data for training as data augmentation, and 5 minutes of signal with better quality is selected for each hour. The preprocessing results are shown in Figure 1.

2.2. Network Structure and Experiment

The overall network architecture is shown in Figure 2, consisting of the following modules: 1) preprocessing, 2) adaptive time domain block, 3) multi-spectral representations block, and 4) classification block. The network is trained end-to-end, jointly optimizing the parameters of all modules, to extract both temporal-domain and spectral-domain from the EEG signals simultaneously, improving classification performance. Our proposed model uses the RMSprop optimizer with an initial learning rate of 0.001, batch size of 256. The experiments are implemented using Python 3.8.15, PyTorch 1.13.1 and NVIDIA 3090 GPU.

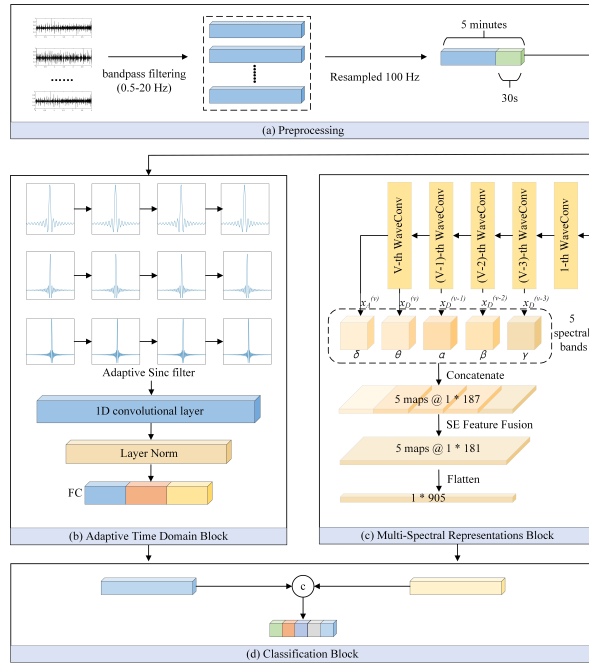

Figure 2. The architecture of the temporal-spectral based single-lead eeg feature fusion network. (a) Preprocessing, (b) Adaptive Time Domain Block, (c) Multi-Spectral Representations Block, (d) Classification Block.

2.3. Adaptive Time Domain Block

CNNs learn low-level representations from waveforms, whereas traditional filtering functions can discover more meaningful and effective features. Based on SincNet[6], which is used in the speech speaker recognition task, the filter bank is efficiently customized by implementing adaptive bandpass filters to learn the low cutoff frequency and high cutoff frequency directly from the data. The first layer of the CNN performs a set of time-domain convolutions between the input waveform and finite impulse response (FIR) filters. The convolution operation is as follows:

$$y[n] = x[n] * g[n] = \sum_{l=0}^{L-1} x[l] \cdot g[n-l] \tag{1}$$

where $x[n]$ is the corresponding signal, $g[n]$ is a filter of length L, and $y[n]$ is the filtered output. The elements of CNN filter are learned from the row data. Instead, the adaptive bandpass filter forms a convolution with a pre-defined function g that depends on only a few learnable parameters:

$$y[n] = x[n] * g'[n, \theta] \tag{2}$$

where fs denotes the sampling frequency of the input signal and the cutoff frequency is initialized at random in the range [0, fs/2]. And using the cutoff frequency of the Mayer filter bank to initialize the filter, many key signal features can be better captured.

In addition, the weights of the filters are trained by subsequent layers so that different levels of importance can be assigned to the output of each filter. The ideal bandpass filter needs to be of infinite length, characterized by ripples in the passband and finite attenuation in the stopband. Therefore, window strategy is adopted, which is achieved by multiplying the truncation function g with the windowing function w. The experiment takes Hamming windows:

$$w[n] = 0.54 - 0.46cos(\frac{2\pi n}{L}) \tag{3}$$

Hamming windows are particularly well suited to achieve high frequency selectivity [36]. The overall network structure is shown in Figure 2(b). The adaptive filter is taken for convolution, then standard pooling, normalization, activation and drop out layers are taken. Finally full connectivity extraction is taken to target the time domain feature extraction of EEG signals.

2.4. Multi-Spectral Representations Block

Due to the non-stationary nature of EEG, the effective extraction of EEG spectral components is challenging. Inspired by Li et al[7]., we introduce a multi-spectral representations block (MSR-block) block by using a series of wavelet convolutions to obtain multi-spectral representations corresponding to five clinical frequency bands and further concatenate them into multi-spectral features.

Specifically, MSR-block achieves wavelet decomposition of EEG representations by applying a convolution operator called Wavelet Convolution (WaveConv). Daubechies order-4 (Db4) wavelet have high correlation coefficients with brain signals, have good orthogonality and efficient filter implementation[8], and do not involve learnable parameters in WaveConv, so the Db4 wavelet is chosen for this module for spectral feature extraction. After a series of WaveConv layers in MSR-block, the EEG representation is decomposed into coefficients corresponding to five frequency subbands that satisfy the clinical interest: δ subband (0-4Hz), θ subband (4-8Hz), α subband (8-12Hz), β subband (13-30Hz), and γ subband (30-50Hz). Assuming the input EEG is $\mathbf{X}$ x, the WaveConv at time sample t is defined as follows:

$$x_A\left(t\right) = \sum_{r=0}^{R} x\left(s \times t - k\right) \times u\left(r\right) \tag{4}$$

$$x_D\left(t\right) = \sum_{r=0}^{R} x\left(s \times t - k\right) \times v\left(r\right) \tag{5}$$

The WaveConv uses approximation and detail wavelet filters u and v to generate approximation and detail coefficients x_A and x_D from EEG signals. The number of WaveConv layers V depends on sampling rate fs to obtain 5 subbands. WaveConv has stride of 2 and kernel size of 8, matching the Db4 wavelet. x_A and x_D are computed together then separated, so output channels are 2R (R is input channels). x_A and x_D are separated by formula:

$$x_A = \{x_w(c)|c = 1, 3, \ldots, 2R - 1\} \tag{6}$$

$$x_D = \{x_w(c)|c = 2, 4, \ldots, 2R\} \tag{7}$$

Distortion is reduced by periodic padding on x_A. In summary, WaveConv generates multi-band spectral representations of EEG signals. The MSR-block applies WaveConv in parallel to extract spectral features within each band.

3. Results

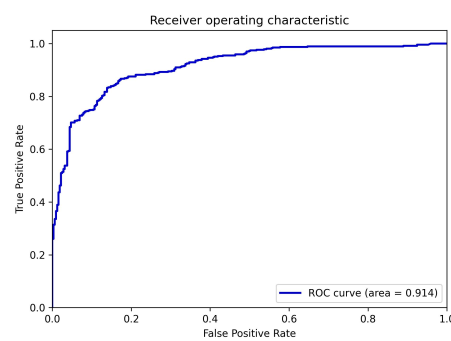

Figure 3. Receiver-operating characteristic curves.

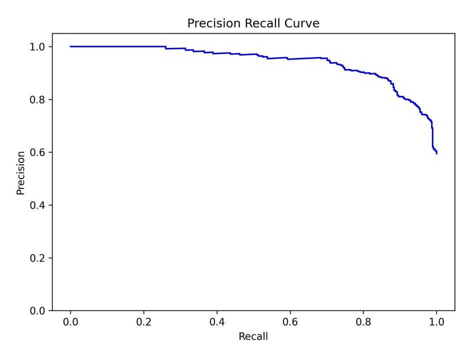

Figure 4. Precision-recall curves.

Our proposed model demonstrates good performance for cardiac arrest detection on the held-out subset of the training set. We would like to emphasize that our team did not achieve any scores in both the unofficial and official phases, all the results reported in this paper were obtained

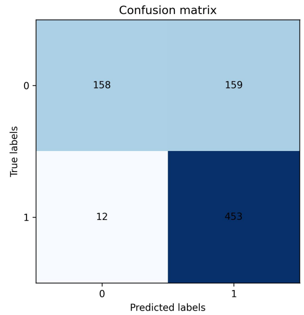

Figure 5. Confusion matrix for the outcome prediction for comatose patients post cardiac arrest.

on the public training set. As shown in Figure 3 and 4, our model achieves accuracy of 78.1%, F1-score of 0.841, AUROC of 0.914, AUPRC of 0.942, and a challenge score of 0.701 on the 20% held-out subset of the training set that has been data augmented. Additionally, the confusion matrix in Figure 5 provides insight into the true/false positives and negatives. These results on key classification metrics reflect the model's effectiveness at distinguishing cardiac arrest cases from normal EEG signals. The performance on our held-out subset of the training set highlights the potential of our proposed temporal-spectral feature fusion approach as an effective biomarker for cardiac arrest detection from single-lead EEG.

4. Discussion and Conclusion

Our proposed temporal-spectral feature fusion model achieves good cardiac arrest detection performance from single-lead EEG, obtaining good classification metrics on the held-out subset of the training set. The complementary time and frequency domain features effectively capture pathological EEG patterns. Our automated single-lead EEG interpretation is more convenient and clinically applicable than multi-channel EEG studies, and therefore has the potential to enable real-time monitoring and timely intervention. The learned representations show potential as practical biomarkers for rapid and real-time diagnostics. Although we demonstrate good performance, further validation and extension to out-of-hospital cardiac arrest is needed to predict more fine-grained outcomes to better assess real-world impact.

In conclusion, we present a deep learning model integrating time-domain and multi-spectral EEG features to accurately detect cardiac arrest, showing the promise of automated EEG-based biomarkers. Our adaptive modeling of raw waveform and spectral bands from single-lead EEG may provide an important step toward patient-specific assessment and timely treatment. This study may offer a practical, low-cost and real-time approach to leverage EEG's prognostic capabilities for cardiac arrest care. Future research may reveal clinically relevant biomarkers that allow for more accessible neurological prognostication.

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