Predicting Neurological Outcome from Electroencephalogram in Patients after Cardiac Arrest with Multi-Channel Transformer

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Aims: This study aims to improve prognostic accuracy for comatose patients by using longitudinal electroencephalography (EEG) recordings to predict good and poor patient outcomes after cardiac arrest, thus guiding appropriate levels of care and treatment decisions.

Methods: We proposed a multi-channel convolutional transformer model that utilized continuous EEG recordings to predict the neurological recovery of unconscious cardiac arrest patients. The collected EEG signals were fed into a convolutional module to extract the Hourly Clear Five Minutes (HCFM) features from the clearest five-minute signals per hour. The inter-channel and temporal correlation were modelled using a parallel Channel-Temporal Alternating Transformer (CTAT) module. The Temporal Transformer (TTR) module extracted the temporal correlation of features from HCFM over the 72-hour period, while the Channel Transformer (CTR) module computed the correlation between HCFM across channels. CTR and TTR were alternately fused to obtain the final prediction results. Data augmentation such as noise injection, scaling, and shifting were used to address the issue of insufficient and imbalanced training data.

Results: Our team, ZJUT-Luckycloud, participated in the PhysioNet/CinC Challenge 2023 using a dataset of 607 EEG recordings which we augmented to 3000 samples. The model was trained and evaluated using 10-fold cross-validation and achieved challenge scores of 0.05, 0.21, 0.72, and 0.96 for 12, 24, 48, and 72 hours, respectively. However, due to the limited computing resources of competition, we could only augment the dataset to 807 samples, resulting in 0.09, 0.19, 0.21, and 0.25 at 12, 24, 48, and 72 hours, respectively, in the unofficial phase.

Conclusion: The proposed algorithm provides a promising solution for clinical decision-making in unconscious cardiac arrest patients by utilizing continuous EEG recordings. In the official phase, we plan to enhance the model performance within limited computational resources and incorporate basic clinical information to improve prediction accuracy.