Predicting Neurological Recovery from Coma with Longitudinal Electroencephalogram Using Deep Neural Networks

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Aim: This work studies the problem of predicting neurological recovery from coma with longitudinal electroencephalogram (EEG) recordings raised by the George B. Moody PhysioNet Challenge 2023. This problem is crucial for continuous brain monitoring for patients after cardiac arrests.

Methods: Deep neural network (DNN) models were trained to predict cerebral performance category (CPC) scale, ranging from 1 to 5, from EEG waveforms which were rescaled to have zero mean and unit variance. The prediction was treated as a 5-class classification task. The models adopted a bottleneck SE-ResNet backbone with optional long short-term memory (LSTM) and global attention modules on its top. Neural architecture searching was performed to find the optimal model. Further study will focus on self-supervised representation learning methods and models from EEGs.

Via stratified splitting on clinical attributes (age, sex, etc.) and prediction targets of the patients, 20% of the public training data were left out as a validation set for model selection. Recordings were randomly sliced to lengths of 180 seconds every 5 epochs during training. The AdamW optimizer along with the OneCycle scheduler with maximum learning rate of 0.004 was used to optimize the model weights on the asymmetric loss of the training data.

Predictions of multiple EEG recordings from one patient were merged via manually designed rules to give final CPC and clinical outcome prediction. In cases where no EEG recording was available, random forest regressor and classifier trained using only the clinical attributes replaced DNNs to make predictions.

Results: The best entry submission of our team "Revenger" received a Challenge score of 0.537 on the hidden test set. The highest score on the left-out validation set was 0.462.

Conclusion: Our solution offers a practical way to continuously monitor the brain after cardiac arrest using EEGs, with room and potential for further enhancements.