Predicting Recovery from Coma After Cardiac Arrest Using EEG Recordings and a CNN-LSTM Network

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Patients surviving initial resuscitation after cardiac arrest can often suffer from brain injury leaving them comatose. Physicians may rely on long term electroencephalogram (EEG) to estimate the chances of patient's recovery. This can however be time-consuming and lead to erroneous prognoses that can have tragic consequences. An automatic and reliable method to analyze such EEG recordings is urgently needed.

This paper proposes a method to predict good and poor patient outcome for patients comatose after cardiac arrest. The proposed method uses sequences of short (5 min) multichannel EEG signals recorded every hour during the first days after cardiac arrest. The sequence of recordings is input to a predicting function that consists of three units. First, each short recording is processed through a compact convolutional neural network that reduces it to a vector of features. The resulting sequence of features is input to a network of long short-term memory (LSTM) cells able to take the time-dependency between recordings into account. Finally, the outcome is predicted by combining the output of the LSTM network with the patient's metadata. This approach is robust against missing recordings and can be applied to sequences of arbitrary length.

We evaluated the proposed method using 10-fold cross validation on the training data of the 2023 PhysioNet Challenge. The performance is assessed using the challenge score, i.e., the true positive rate for predicting a poor outcome, for a given maximum false positive rate. Initial results yield a score of 0.33, outperforming the score of 0.22 obtained by the baseline on the same folding. The Challenge team evaluated the method on the (hidden) validation data of the challenge, yielding a score of up to 0.36. Further development to assess the full potential of the proposed method will include tuning of hyperparameters and of the regularization used during training.