# Predicting Neurological Recovery from Coma with Longitudinal EEG Using Deep Neural Networks

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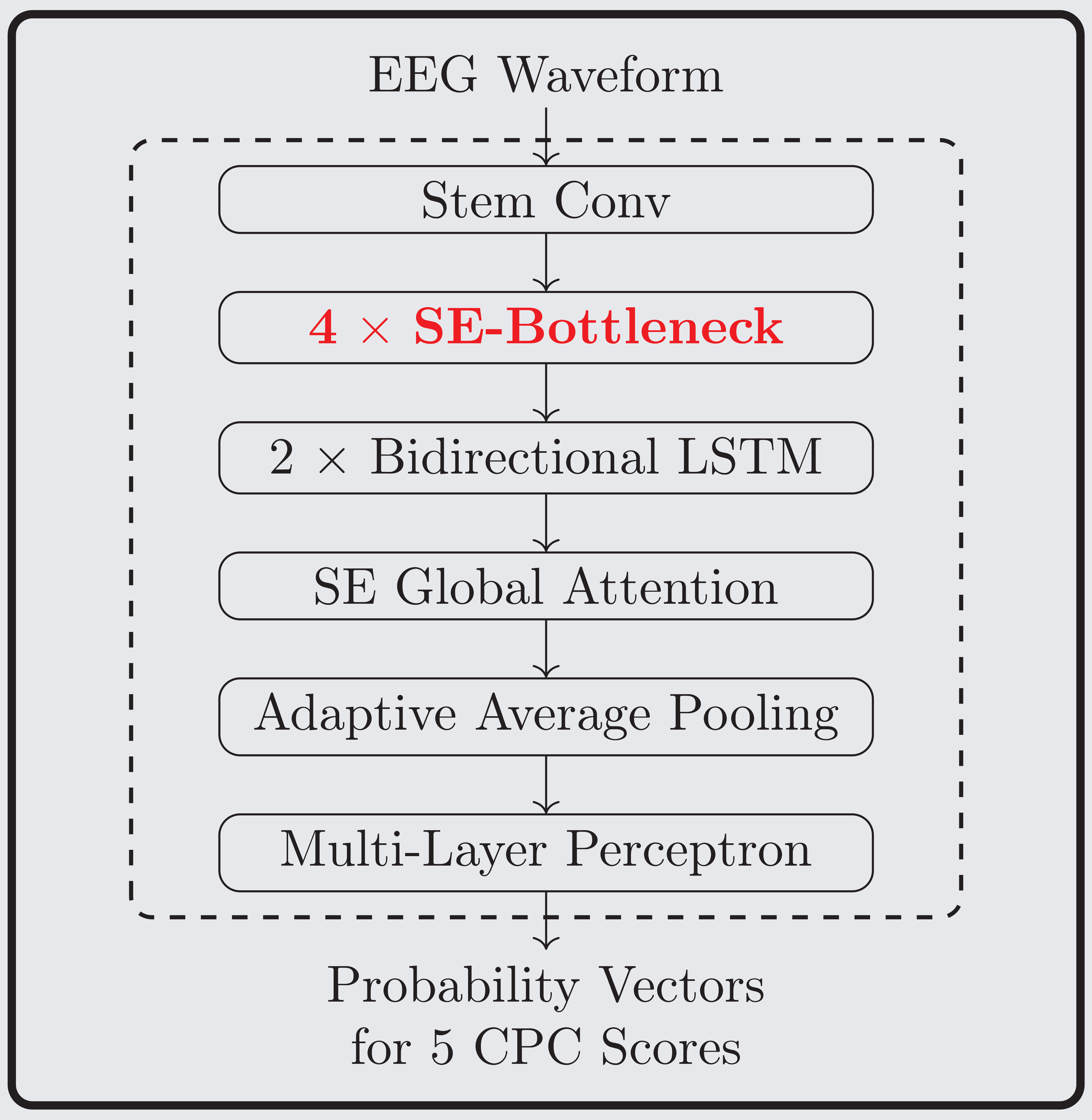
## Introduction

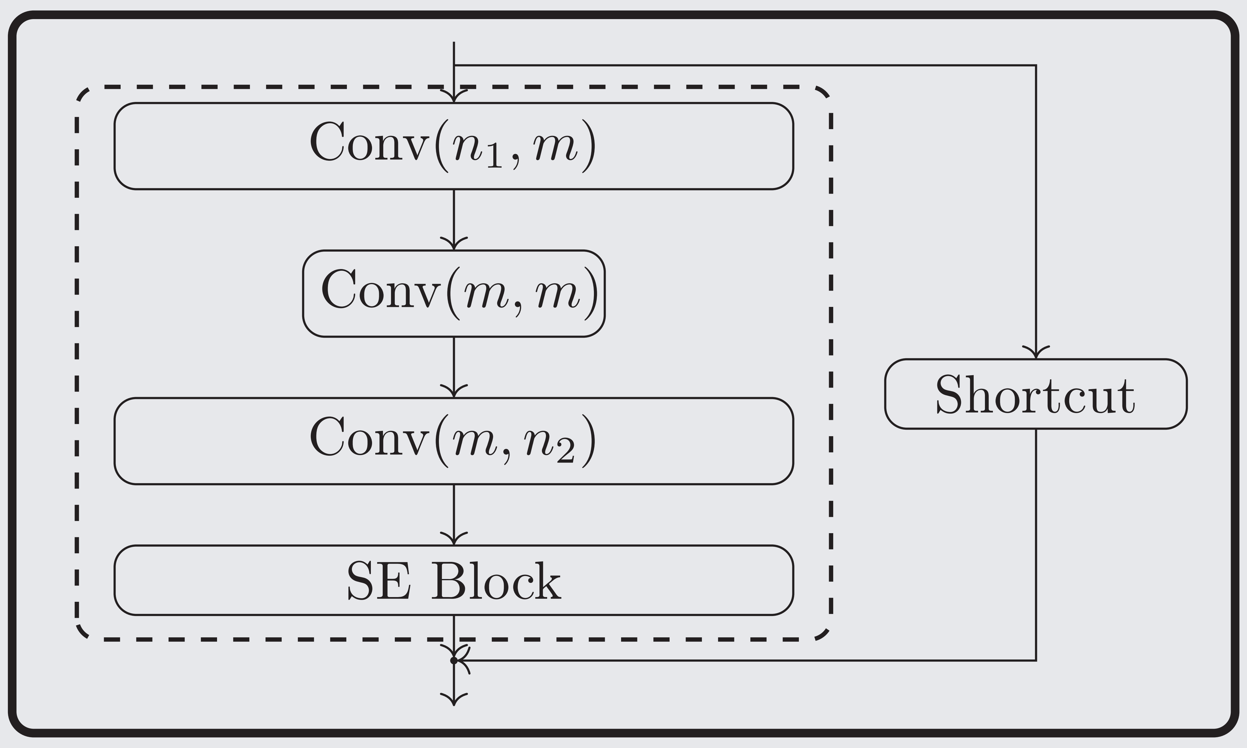
- We modeled the problem as a **classification problem** where the learning objective is the discrete CPC scores (1 - 5). The final clinical outcome prediction is obtained via the mapping: CPC = 1 or 2 → "Good outcome"; CPC = 3, 4, or 5 → "Poor outcome".
- Offline signal quality index (SQI) was computed offline for EEG recordings. A part of EEGs was selected for training based on SQI.
- We used a **time-incremental convolutional recurrent neural network (TiCRNN model** to make per-recording probability vectors, which were averaged and re-normalized via `Softmax` to obtain per-patient predictions from multiple EEG recordings.

## Main Model: TiCRNN




We used a Time-incremental Convolutional Recurrent Neural Network (TiCRNN) model to predict probabilities of CPC scores for the EEG recordings.

## Neural Network Backbone




The neural network backbone is a convolutional network whose building blocks are SE-Bottleneck blocks. The mainstream in the dashed box consists of 3 convolutional blocks (actually compositions of convolution, batch normalization, and activation) followed by an SE block. The channels $n_1, n_2$ are typically several times of $m$, hence giving the name "bottleneck". The shortcut is typically convolutions of kernel size 1, whose stride and input/output channels match the mainstream.

## Training Strategies

- Optimizer: AMSGrad variant of AdamW with OneCycleLR scheduler.
- Stratified train-validation split (split among patients): 80 % – 20 %.
- Batch size 32; epoch number $\leq$ 55 with early stopping patience 25 epochs.
- Input length 180s, randomly sliced from one recording and reloads every 5 epochs.

## Preprocess Pipeline

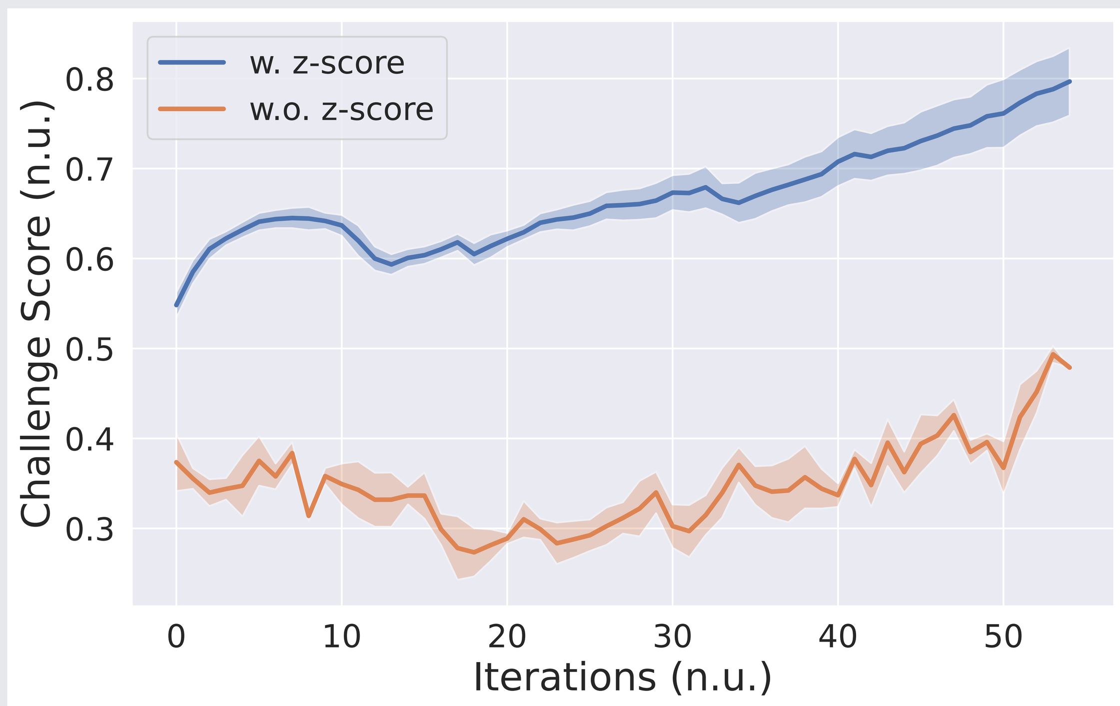
- Select at most one 5-minute window from each recording by offline-computed SQI.
- Butterworth bandpass filtering of order 4 and cutoff frequencies 0.5 - 30 Hz.
- Resampling to 100 Hz using polyphase filtering.
- Rescaling (Z-score normalization) to zero mean and unit variance.

## Submission Results

| | Challenge Scores | | | |
|---|---|---|---|---|
| | **72 hours** | 12 hours | 24 hours | 48 hours |
| Training | 0.814 ± 0.070 | - | - | - |
| Cross-validation | 0.424 ± 0.026 | - | - | - |
| Hidden validation | **0.701** | 0.33 | 0.40 | **0.75** |
| Ranking | **5 / 270** | - | - | - |

- Challenge score and ranking evaluated on the hidden validation set, scores on its truncated 12h / 24h / 48h subsets, and scores on the training and cross-validation sets.
- Scores on the train and cross-validation sets are of the form $mean \pm std.dev.$ from all our offline experiments with z-score normalization included in the preprocessing pipeline.

## Importance of Rescaling




Mean curves of challenge scores on the training set. Shaded areas are error bounds.

## Discussions and Limitations

- Our team provided a solution that is relatively simple and lightweight, but still able to attain a TPR as high as 0.701 with FPR suppressed to a very low level ($\leq$ 0.05) for poor clinical outcome prediction.
- Our team made too much trade-off for the limited computation resources by dropping a large proportion of the EEG data by SQI thresholding and random slicing. The data amount (counting by time length) we really used for training the NN models merely constitutes 6 % of the total EEG data. The potential of this extraordinarily big data had not yet been fully explored.
- Our team had planned to make full use of the data to train a larger model that learns latent representations from EEGs via unsupervised contrastive learning. However, due to the constraints of time and computation resources our team owns, we finally decided to stick to the simpler TiCRNN model. Architecture design and unsupervised training mechanisms for large EEG models are left as future research directions.
- The computation of SQI for EEGs is time-consuming. This prohibited us from adding a similar selection procedure in the pipeline of model evaluation on the hidden data and is highly probable to have a negative influence on our overall performance, especially for EEGs heavily contaminated with artifacts. Therefore, developing a faster and end-to-end SQI computation method would also be a meaningful research problem.

## Acknowledgements

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*Code, configs, etc. available at https://github.com/DeepPSP/cinc2023, and based on https://github.com/DeepPSP/torch_ecg.*