EEG-Based Cognitive State Assessment Using Deep Ensemble Model and Filter Bank Common Spatial Pattern

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Outline

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- Performance analysis
- Conclusion

Basic terms

Common spatial pattern (CSP):

- It calculates spatial filters that maximize the ratio of the variance of one class while minimizing the variance of another.
- Classification performance is dependent on the selection of the proper frequency band of EEG.

Filter bank Common spatial pattern (FBCSP):

- It consists of four stages: frequency filtering, spatial filtering, feature selection and classification.
- The filter bank consists of multiple filtered signals with a specific frequency band of EEG, overcomes the band-specific dependency of CSP.

Cognitive state assessment using EEG:

- Cognitive state of a person is often expressed by mental workload, task demand.
- Mental workload can be measured by mental stress and strain during the task using EEG.

Framework of the model

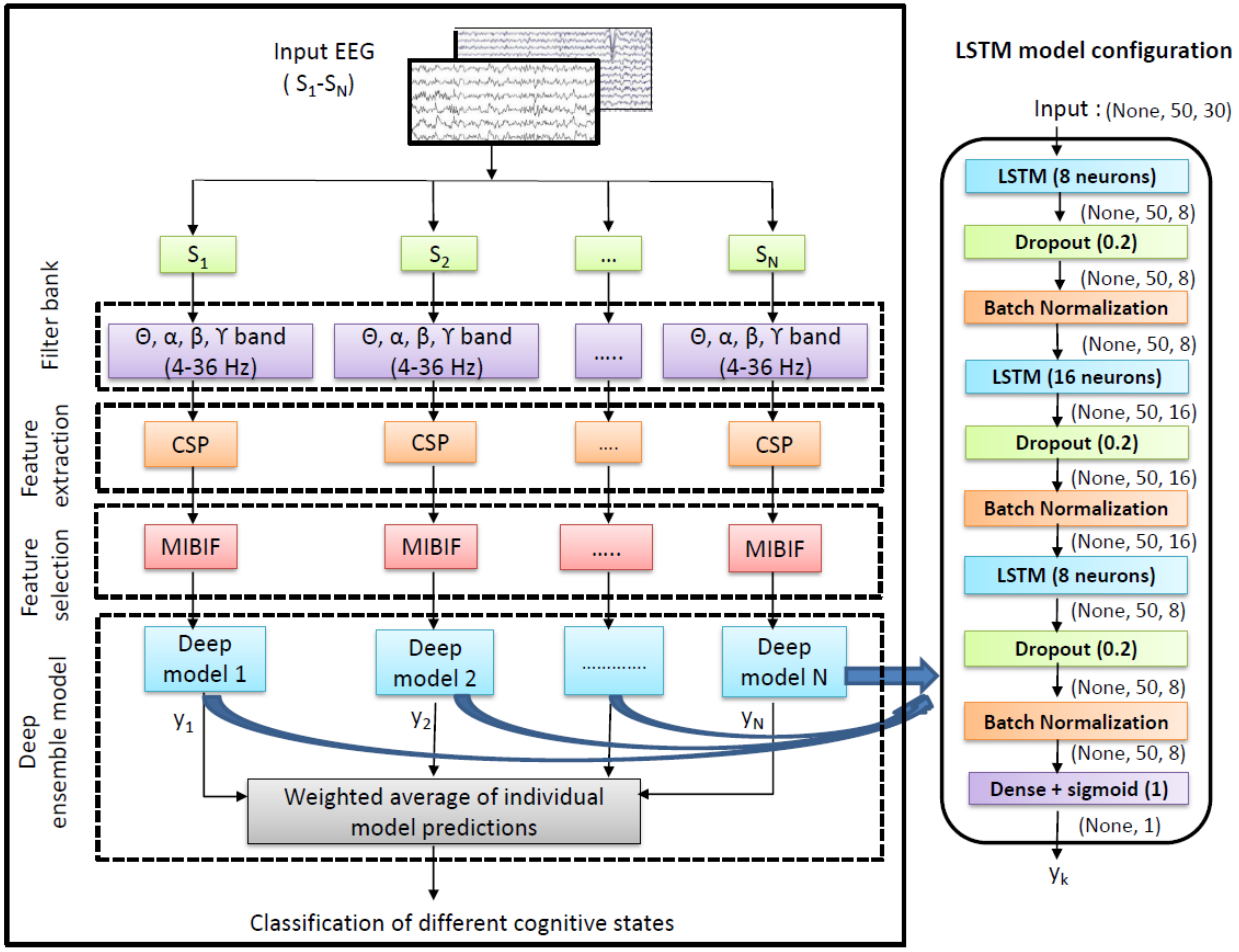


Fig.1: Framework of the proposed model

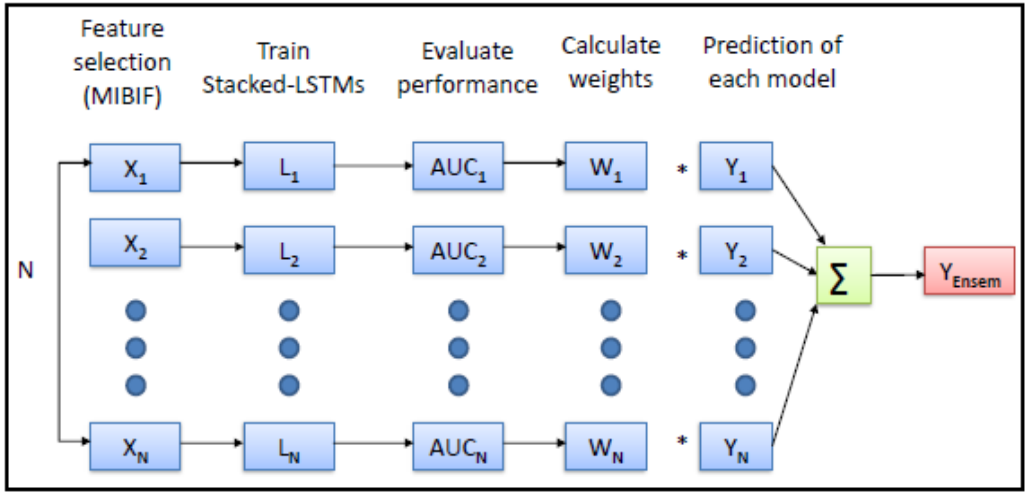
Framework (contd..)

- The proposed model consists of the first three stages of FBCSP & deep ensemble model.
- Subject-wise data distribution has been performed due to the execution of a large volume of data in a low computing environment.
- Filter bank is created by decomposing the EEG signal into eight equal-sized frequency bands, namely 4-8, 8-12, .., 32-36 Hz.
- CSP algorithm has been applied to extract the spatial features from each of those bands.
- Most discriminate CSP features from each filter bank have been identified using the Mutual Information-based Best Individual Feature (MIBIF) method.
- Subject-specific optimum CSP features have been fed into the LSTM model for cognitive state classification.

Framework (contd..)

Deep ensemble model

- The proposed deep ensemble model consists of multiple similar structured LSTM networks that work in parallel.
- The output of the ensemble model (i.e., the cognitive state of a user) is computed using the average weighted combination of the individual model prediction.



$$w_n^{(t)} = \frac{AUC(model^{(t)})}{\sum_{n=1}^{N} AUC(model_n^{(t)})} \quad (1)$$

$$y_{ensem}^{(t+1)} = \sum_{n=1}^{N} y_n^{(t)} . w_n^{(t)} \quad (2)$$

Fig.2: Proposed deep ensemble model

Experiment

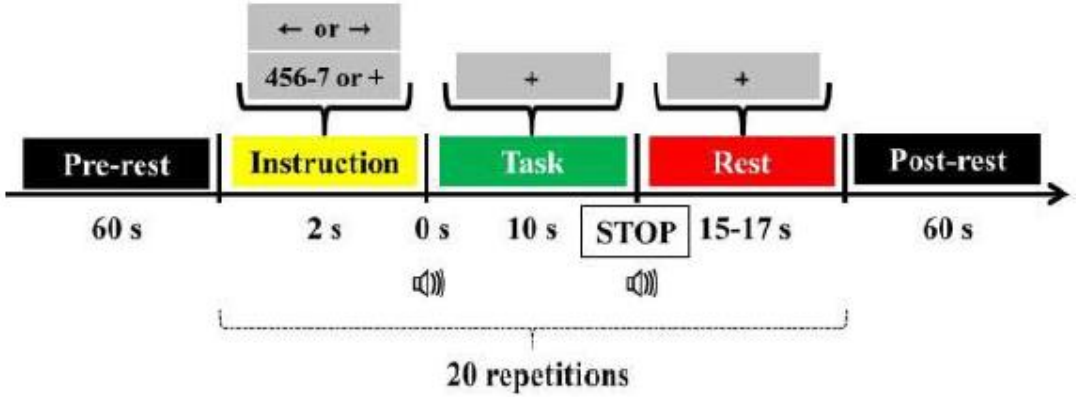


Fig 3: Mental arithmetic (MA) experiment. Each session consist of five steps: a) pre experiment of resting period (1min.), b) visual instruction of MA (2 sec.), c) task period of MA (10 sec.), d) resting period (15-17 sec.), e) post-rest experiment of 1 min. Each session consists of step (a), 20 repetitions of steps (b-d) and step (e).

Results & analysis

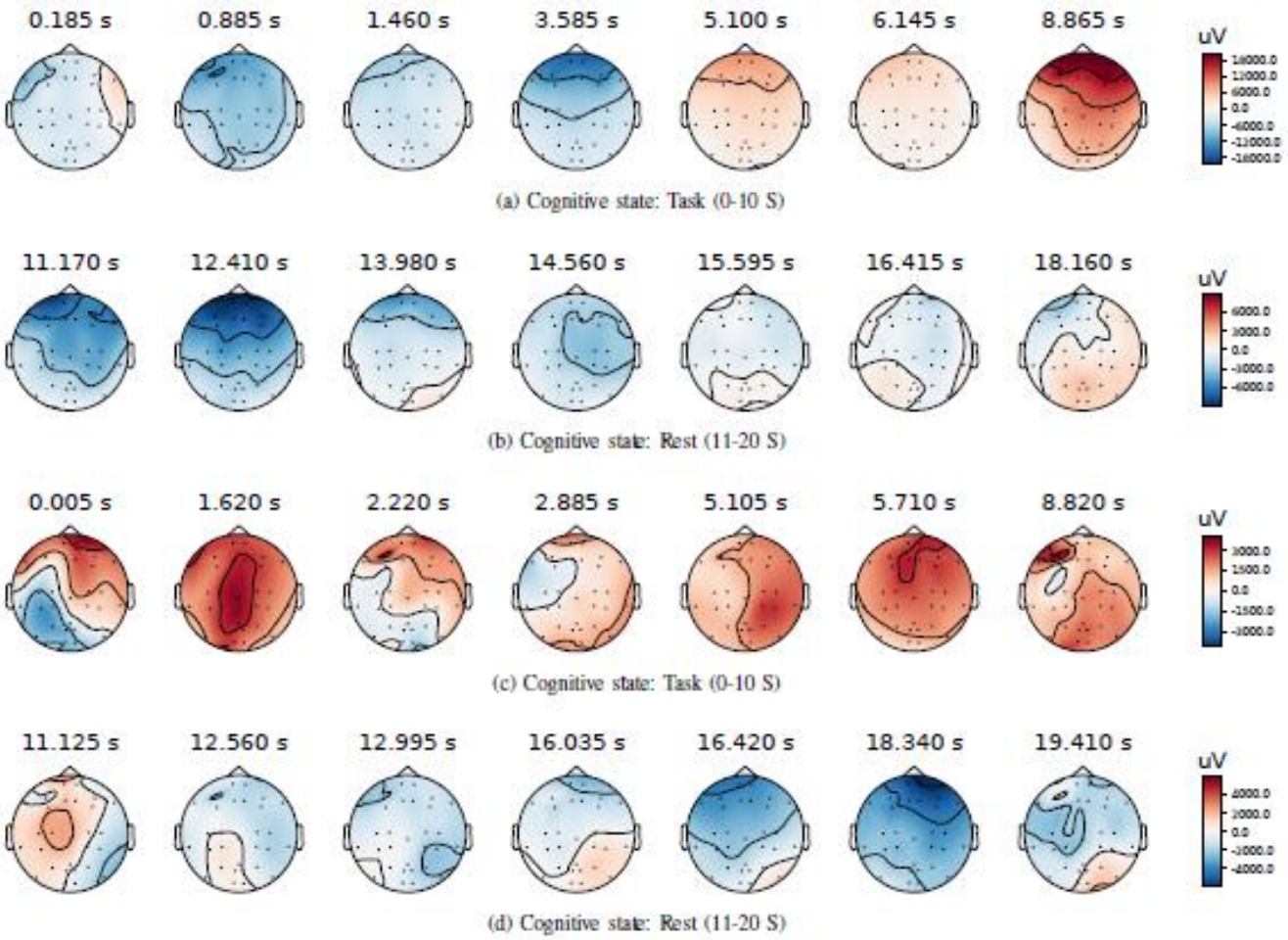


Fig.4: CSP filters (topographic map) of EEG bands for cognitive state task and rest: (a-b) theta band, (c-d) alpha band

Performance analysis

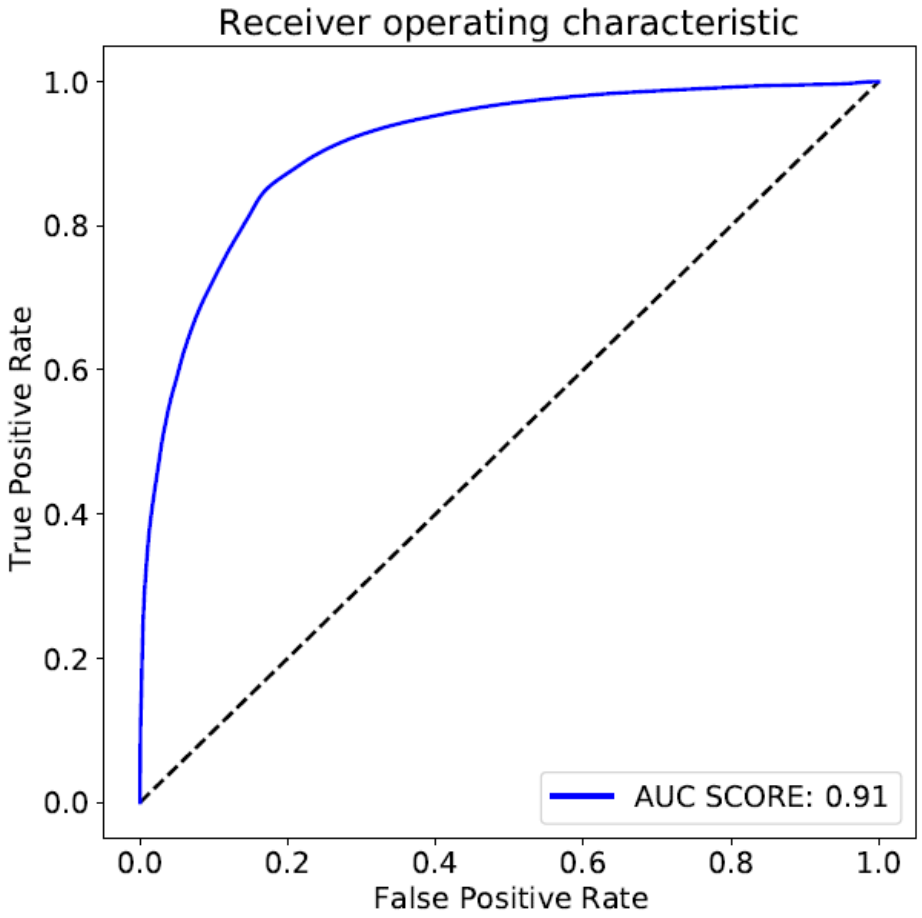


Fig.5: Model performance using ROC curve

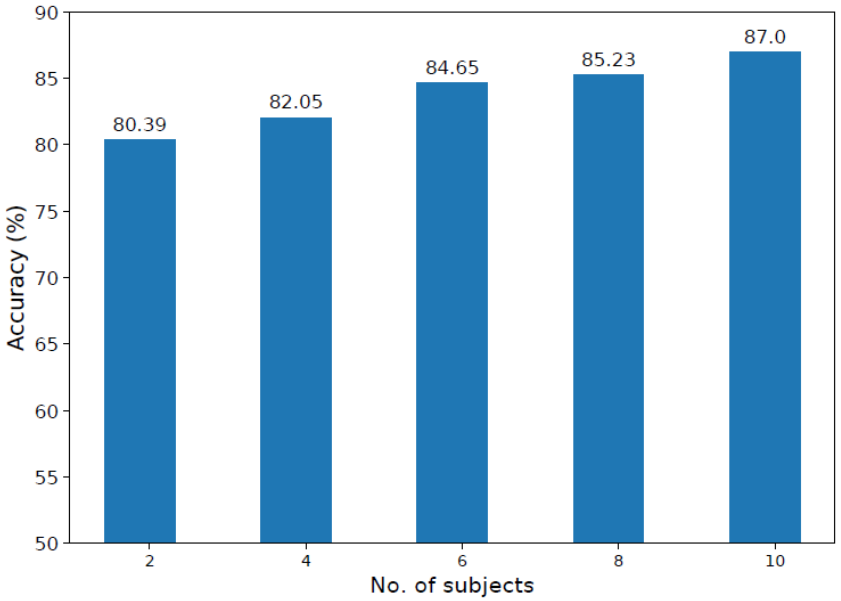


Fig.6: Scalability test of the model

Conclusion

- The proposed deep ensemble model can efficiently identify the cognitive state of a subject with 87% classification accuracy.
- The model can be effectively utilized for the execution of a deep model over a large volume of data in the low memory environment.
- The proposed ensemble model takes less computational time compared to an equivalent sequential model.