Decoding EEG Signals with Visibility Graphs to Predict and Understand Mental Workload

COMPUTER SCIENCE
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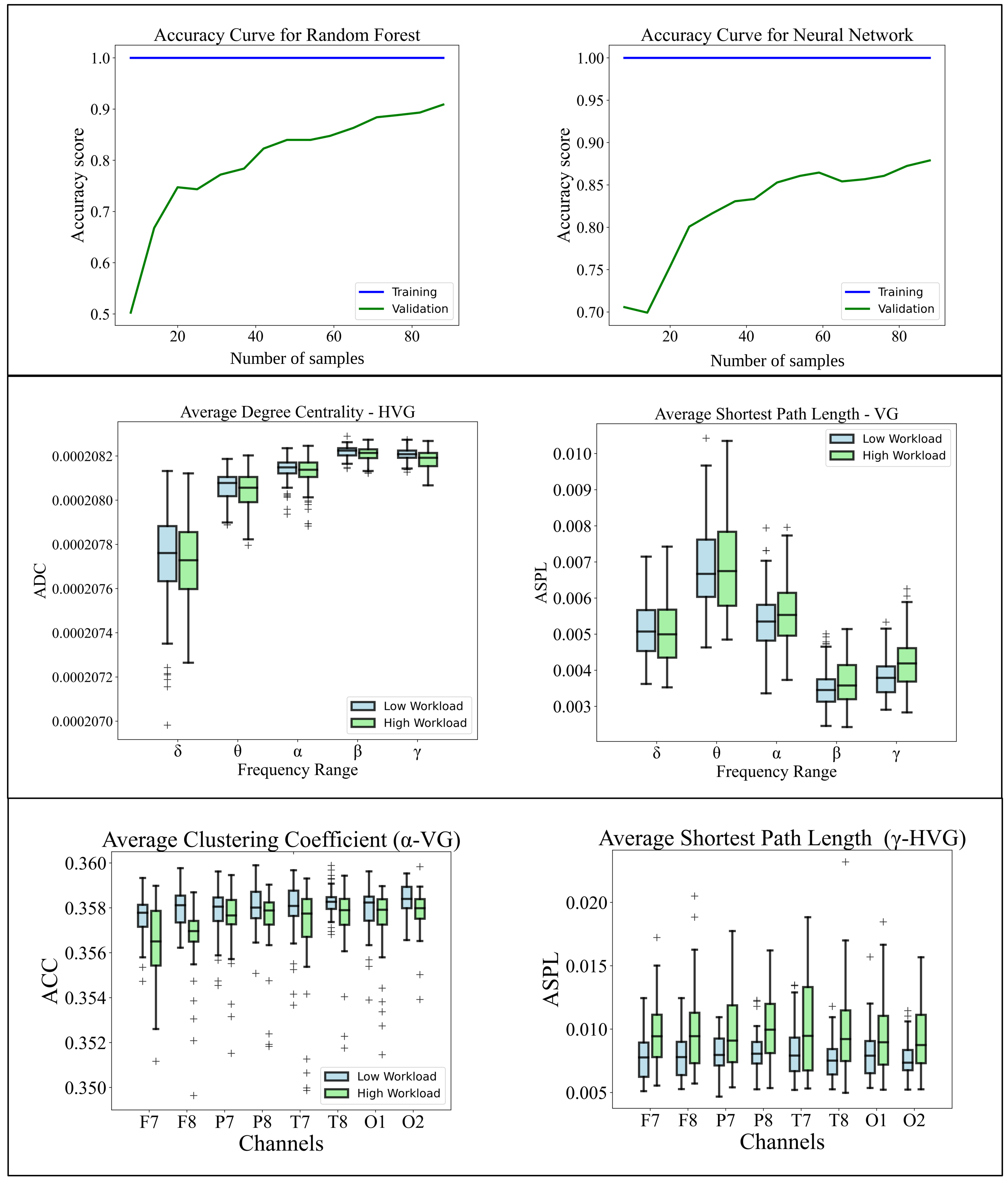
Introduction

- Very little research on mental workload classification with electroencephalography (EEG) has focused on graph-based features.
- Functional connectivity measures have been explored in prior work, but the use of visibility graph algorithms has been very limited.
- This research investigated the effectiveness of graph-based features for classification of mental workload levels. Two types of visibility graph algorithms and six different graphical features were compared in the analysis.

Methods

- Data was acquired from a public dataset [1].
- In the study, 48 subjects completed two activities. In the first activity, subjects were at rest and did not complete any tasks. In the second activity, subjects completed the simultaneous capacity multi-tasking task as a measure of mental workload.
- The two activities to the study were denoted as *low* and *high* mental workload, respectively. There were 96 times series files, 48 for each level of workload.
- The visibility graph (VG) algorithm transforms the time series into a graph that contains nodes and edges [2]. Nodes correspond to collected EEG samples.
- Edges are formed when two nodes can reach each other in a straight line, not touching any other nodes.
- A variant of the VG is the horizontal visibility graph. In this algorithm, two nodes form an edge only if their values are larger than all other values of the nodes between them [3]. This project used the original VG.
- From the resulting graphs, the clustering coefficient, average degree centrality, and average shortest path length were extracted.
- The features are fed to two machine learning (ML) algorithms, random forest and neural network.
- Random forest makes predictions using multiple decision trees, a type of ensemble learning.
- A neural network is trained by optimizing an activation function and minimizing the error.

Results



References

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2. Lacasa, L., Luque, B., Ballesteros, F., Luque, J., & Nuno, J. C. (2008). From time series to complex networks: The visibility graph. *Proceedings of the National Academy of Sciences*, *105*(13), 4972-4975.
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Discussion

- Both ML models showed high accuracy (89-91%) in predicting mental workload.
- The results of the machine learning classifiers suggest the graph-based approach was accurate in predicting mental workload. See the two learning curves in the top row of the results section.
- It is important to consider there were only 96 total samples. A small dataset size makes it more difficult to consistently maintain high classification accuracy.
- The graphical analysis showed features from higher frequency ranges (α, β, γ) were largely able to distinguish between levels of mental workload.
- Lower frequency ranges such as δ and θ had less discriminatory features. See the two boxplots in the second row of the results.
- Two of the best feature sets were average clustering coefficient in the alpha band and average shortest path length in the gamma band. For both sets, the features were statistically significant for all channels. See the two boxplots in the bottom row of the results.
- These findings suggest that graph algorithms perform better with time series of higher frequencies.
- The HVG algorithm was more time-efficient than VG.
- However, the VG algorithm produced nearly twice as many discriminatory features.
- In general, graphs of lower frequencies were less time-efficient than graphs of higher frequencies.

Conclusion

- The preliminary results suggest a graph-based approach is effective and accurate in classifying mental workload from EEG signals.
- The results suggest visibility graphs perform better with data from higher frequency ranges.
- This work can potentially be applied to brain-computer interfaces, which use machine learning to make predictions from brain activity.
- We recommend validating the graph-based approach with different cognitive tasks and other ML classifiers.