**Brain State Classification Using Liquid Neural Networks on EEG Data**

**Model comparison on EEG data –** this thesis includes a comparison of three deep learning architectures: GRUs, LSTMs, and Liquid Neural Networks (further LNNs), for classifying confusion based on EEG signals. Each model was trained using only EEG-based input, and their performance was evaluated across multiple metrics (accuracy, AUC, entropy) and data splits. The GRU model showed the best overall performance in terms of accuracy and efficiency, while the LNN model demonstrated competitive results with more stable training dynamics.

**Contribution to EEG-based confusion detection –** by focusing on EEG frequency band signals this study uses the neural signal as the only source of information for confusion prediction. This approach emphasizes the goal of understanding cognitive states directly from brain activity. The thesis demonstrates that meaningful distinctions in EEG signals can be captured by deep models. The findings validate the use of deep learning for subtle state recognition like confusion and support the use of EEG in many applications.

**Exploration of Liquid Neural Networks –** while LNNs required significantly more training time and had higher parameter counts, they showed competitive performance and much more stable metric dynamics during a training process. However, they could be also sensitive to some specific data combinations, which results in sudden quality drops. The thesis explores the strengths and limitations of LNNs in this context. Also, it suggests that their full potential may be realized in more complex or higher-dimensional EEG applications. Finally, the interpretability explanation using SHAP for these models seems to be challenging because of the recurrent nature of the liquid layers.

**Temporal embeddings –** another key contribution is the design and evaluation of temporal embedding strategies, including lag-based and convolutional embeddings. These techniques enhanced the temporal representation of the EEG signals and improved classification performance across all model types. The results show that even lightweight temporal transformations, like lag-1 embedding, can significantly increase predictive accuracy and training stability. This insight reinforces the importance of temporal context in EEG analysis and offers practical guidance for enhancing model inputs in future studies.

**Statistical and exploratory EEG signal analysis –** before modeling the thesis includes a statistical exploration of the EEG dataset. This includes frequency-band distribution comparisons between confusion classes, which suggests that Beta2, Gamma1, and Gamma2 bands might carry the most information about the confusion. However, the thesis highlights that strong inter-band relationships and temporal dynamics are more important, than single power values of different bands. A failed attempt to classify confusion using OLS regression supports the idea that static signal features are insufficient, and that only dynamic models can effectively capture the underlying patterns. This analysis confirms the dataset’s complexity and validates the need for sophisticated modeling approaches.

**SHAP-based interpretability –** to provide transparency into model behavior, SHAP analysis was applied to GRU and LSTM predictions. This revealed that model attention spikes at specific timestamps are often aligned with, presumably, challenging moments in the videos. These interpretability findings suggest that confusion is not uniformly distributed over time but may occur at key parts of a video. However more research on this topic is needed to confirm this finding.