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Классификация состояний мозга с использованием жидких нейронных сетей на EEG данных

Brain State Classification Using Liquid Neural Networks on EEG Data

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# Brain State Classification Using Liquid Neural Networks on EEG Data

## Introduction

Understanding and classifying human cognitive states through non-invasive means has long been a compelling goal in neuroscience, education, and human-computer interaction. Among the many technologies developed for this purpose, electroencephalography stands out for its affordability, portability, and ability to capture dynamic brain activity in real time. EEG data, rich in temporal and spectral complexity, has proven useful in detecting mental states such as fatigue, attention, drowsiness, and confusion. However, effectively interpreting this data remains a technical challenge due to its susceptibility to noise, individual variability, and the intricacy of brain dynamics.

Recent advances in machine learning have considerably improved our ability to decode EEG signals. Traditional classifiers such as Support Vector Machines and Naive Bayes models have achieved high accuracy in detecting overt mental states like drowsiness and epileptic seizures. Yet, more subtle cognitive states – particularly confusion during learning – pose a harder problem. These require models that can account for temporal dependencies and nonlinear interactions within the EEG signal. Deep learning models such as Long Short-Term Memory networks and Gated Recurrent Units have shown promise in this regard by effectively modeling EEG sequences as time-series data. Their ability to retain and process long-range dependencies makes them especially useful for continuous monitoring applications like adaptive education platforms and brain-computer interfaces.

Nevertheless, even the most advanced recurrent architectures face limitations in adaptability and generalization, especially in the presence of non-stationary signals and context changes. This is where Liquid Neural Networks present a compelling alternative. Inspired by biological neuronal dynamics, LNNs feature continuously evolving internal states that allow them to adapt in real time to new patterns without requiring retraining. Their internal memory mechanisms and low parameter overhead make them particularly suitable for real-world, on-device EEG analysis where computational resources may be limited, and data conditions are unpredictable.

This thesis explores and compares the performance of three neural architectures – GRUs, LSTMs, and Liquid Neural Networks – on the task of classifying cognitive confusion from EEG recordings. The data used in this study comes from a controlled experiment in which students watched educational videos categorized as either confusing or non-confusing. EEG signals were recorded from the frontal lobe using a low-cost headset, capturing activity across eight standard frequency bands. The objective is to determine how effectively each neural network model can classify a student's cognitive state based solely on temporal patterns in their EEG signals.

In doing so, this work contributes to the broader effort of developing scalable, real-time brain state classification systems that can be used in personalized learning environments, mental workload monitoring, and future BCI applications. Particular attention is given to the adaptability and efficiency of Liquid Neural Networks, evaluating whether their biologically inspired architecture offers advantages over traditional recurrent models in capturing the complexity and variability of cognitive states in EEG data.

## Related papers

Electroencephalography (EEG) has long been established as a non-invasive and cost-effective method for monitoring brain activity, providing crucial insights into cognitive states such as confusion, fatigue, and mental workload. With the advent of machine learning and deep learning, the interpretation and classification of EEG signals have seen substantial improvements in terms of accuracy, scalability, and robustness. The integration of various neural network models, including GRUs, LSTMs, and Liquid Neural Networks, has opened new possibilities in decoding and understanding brain signals with greater fidelity.

The application of ML techniques to EEG data has historically produced significant results in detecting various mental and physiological states. Support Vector Machines, for example, have shown excellent performance in classifying driver drowsiness using features extracted from multiple EEG frequency bands, achieving accuracy as high as 99.3%. Similarly, they have been employed to detect epileptic seizures with perfect classification results in controlled studies. For more nuanced cognitive states like confusion, simpler classifiers such as Gaussian Naive Bayes have shown limited performance, achieving only moderate accuracy levels. These initial explorations emphasized the need for more advanced methods capable of modeling the temporal complexity and noise inherent in EEG signals.

The rise of deep learning brought transformative improvements. Deep Belief Networks, for instance, demonstrated the ability to extract high-level features from raw EEG data and outperformed traditional dimensionality reduction techniques such as PCA. When applied to driver cognitive state prediction, DBNs yielded better performance than earlier shallow learning methods. Convolutional DBNs went further by capturing spatial and temporal relationships within the EEG data, offering more reliable classification outcomes. Given that EEG signals inherently possess a sequential structure, Recurrent Neural Networks, and more specifically Long Short-Term Memory networks, emerged as a natural fit. These architectures are adept at modeling time-series data and have proven effective in identifying patterns over extended time windows, such as in early Alzheimer's detection and real-time confusion monitoring during MOOC learning sessions.

To accelerate model convergence and improve training stability, batch normalization techniques have been integrated into deep neural architectures. Applying batch normalization to recurrent structures like LSTMs has been shown to enhance both training speed and final performance, making deep models more practical for real-world EEG applications. This methodological advance is particularly important in scenarios that require real-time inference, such as in adaptive learning environments or brain-computer interface systems.

More recently, Liquid Neural Networks have emerged as a powerful alternative to traditional RNNs and LSTMs. These networks possess dynamic parameters that evolve with input data, allowing them to adapt to new patterns without retraining. This characteristic is especially valuable for EEG-based systems where input signals can vary significantly over time due to noise, external conditions, or individual differences. LNNs have demonstrated superiority over static models, particularly in environments with abrupt shifts in data distributions. Their performance in removing complex, noisy signals—such as those derived from aircraft magnetic fields—underscores their utility in filtering EEG noise, which is often a major challenge in brain signal analysis.

The use of LNNs has also extended beyond neuroscience. For example, they have been employed in optimizing urban communication networks and aeromagnetic compensation, consistently demonstrating their capacity to adapt and maintain performance without requiring frequent updates or retraining. These capabilities strongly parallel the demands of EEG signal processing, where robustness and adaptability are essential.

Architecturally, recent enhancements to LNNs have included the development of Neural Circuit Policies, which are built on the principles of biological nervous systems. NCPs utilize sparsely connected Liquid Time-Constant neurons, leading to efficient and interpretable models. Furthermore, Continuous-Time Liquid Neural Networks have simplified training and inference by eliminating the need for numerical solvers, thereby making real-time applications more viable. These innovations highlight the increasing relevance of LNNs in EEG research, particularly for applications that require quick adaptation and minimal computational overhead.

While traditional deep learning models such as LSTMs and GRUs have shown considerable promise in modeling EEG time-series, they often face limitations when dealing with non-stationary data streams or adapting to new contexts without retraining. LNNs, by contrast, offer a biologically inspired solution that inherently accommodates data variability and noise. Their dynamic temporal modeling capabilities suggest they may outperform static architectures in scenarios involving real-time EEG interpretation and cognitive state monitoring.

In addition to modeling innovations, addressing confounding factors remains a challenge in EEG data analysis. Approaches like Select-Additive Learning and confounder-aware training frameworks have been developed to mitigate the impact of irrelevant data components on model performance. While effective, these methods often require auxiliary models or significant architecture changes. LNNs may inherently possess an advantage here, as their dynamic nature allows them to filter extraneous patterns more organically, potentially simplifying the modeling process.

The integration of LSTM, GRU, and Liquid Neural Network models in EEG research marks a significant shift towards more adaptive, noise-resilient, and computationally efficient systems. Each of these architectures contributes unique strengths: LSTMs with their ability to handle long-term dependencies, GRUs offering computational efficiency with fewer parameters, and LNNs providing adaptability and robustness in dynamic environments. As this thesis progresses, the comparative evaluation of these models in the context of EEG-based cognitive state classification will highlight their respective advantages and potential for enhancing brain-computer interface technologies and educational cognitive monitoring systems.

## Data

This thesis is based on a publicly available dataset originally designed to explore cognitive responses—specifically confusion—in students viewing online educational video content. The data were collected under controlled experimental conditions, with the aim of studying how EEG signals reflect varying levels of cognitive load during learning.

The dataset includes recordings from ten college students, each of whom viewed a set of ten distinct educational videos. These videos were selected and categorized prior to the experiment into two groups:

* Non-confusing: Topics presumed to be familiar and readily understandable to the average student, such as introductory algebra or geometry.
* Confusing: Advanced topics such as quantum mechanics or stem cell research, selected for their potential to induce confusion in students unfamiliar with the material.

All students watched the same ten videos, evenly split between the two categories. Each video was approximately two minutes long, but only the central one-minute segment was used for EEG data analysis. The beginning and end of each clip were trimmed to minimize transitional and non-content-related cognitive responses.

EEG signals were recorded using a single-channel wireless EEG headset positioned to monitor activity over the frontal lobe. The headset recorded data using one electrode on the forehead and two reference electrodes placed near the ears. The device sampled neural activity every 0.5 seconds, resulting in approximately 120 EEG samples per video per participant.

Each EEG sample consists of power values across multiple standard brainwave frequency bands:

* Delta
* Theta
* Alpha1, Alpha2
* Beta1, Beta2
* Gamma1, Gamma2

These eight channels were the sole features used in this study. All other available information—such as participant demographics or specific details about the videos—was excluded from the analysis. The objective was to evaluate confusion purely from the perspective of neural signal data.

The primary label used in this thesis is the predefined confusion label, assigned based on the categorization of each video as either “confusing” or “non-confusing.” This classification was made independently of the participants' self-assessments and remains consistent across all viewers. The use of this label enables an investigation into whether confusion—operationalized at the video level—can be predicted from EEG features alone.

The dataset comprises over 12,000 EEG samples, corresponding to 100 individual recording sessions (10 participants × 10 videos). Each sample includes:

* A timestamp (0.5-second intervals)
* Eight EEG frequency band values (delta through gamma2)
* The predefined confusion label (binary)

These data were used to develop and evaluate predictive models aimed at distinguishing between confusing and non-confusing learning experiences based solely on patterns in brainwave activity.

## Methodology

### Training setup

The models in this study were trained using only EEG-derived features—specifically, the power values across eight standard frequency bands: delta, theta, alpha1, alpha2, beta1, beta2, gamma1, and gamma2. No participant demographic data or video metadata were included. This design choice allowed for an isolated exploration of how neural signals alone relate to cognitive confusion.

Each EEG time series corresponds to a one-minute segment, sampled at 0.5-second intervals, resulting in from 120 up to 144-time steps per recording. To ensure consistency across samples, each sequence was padded to a fixed length of 144-time steps, using zero-padding at the end of each signal. This allowed all models to accept uniform input dimensions while preserving the temporal structure of the original signals.

The dataset was split into training and testing subsets using a 70–30 ratio. For the final model evaluation, the split was performed by user, i.e. 7 users were used to train a model, the rest 3 were used for validation. To ensure robust and reliable evaluation, multiple distinct and fixed data splits were created. All models were trained and evaluated on the same series of partitions, ensuring comparability across experiments while mitigating the effect of variance due to random sampling. Each model was trained for the same number of epochs, standardizing training duration across all experiments.

In some experiments, a lagged embedding of the EEG signal was applied to enrich the input with temporal dependencies beyond the original sampling rate. This involved concatenating delayed versions of the input signal to provide the models with access to past temporal context within a given time window.

### Quality metrics

Model performance was assessed using a combination of three evaluation metrics:

* Accuracy: Measures the proportion of correctly classified samples out of all predictions. It provides a general measure of model performance across classes.

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

* AUC (Area Under the Receiver Operating Characteristic Curve): Evaluates the trade-off between true positive rate (sensitivity) and false positive rate across different classification thresholds. A higher AUC indicates better model discrimination between the classes.

TPR (True Positive Rate) =

FPR (False Positive Rate) =

* Entropy: Used as a measure of prediction uncertainty. Lower entropy indicates higher confidence in the model’s prediction. For binary classification, entropy of a prediction with probability is calculated as:

where is the Shannon entropy.

All metrics were averaged across the multiple fixed splits to obtain reliable, variance-reduced estimates of model performance.

### Models

The predictive models employed in this work consisted of three major types of neural network architectures, each with multiple internal variations:

* GRU-based networks: These models leveraged Gated Recurrent Units, which are well-suited for capturing temporal dependencies in sequential data while maintaining a relatively compact architecture. Several variations were tested with different numbers of layers and hidden dimensions.
* LSTM-based networks: Networks built with Long Short-Term Memory units were also explored due to their effectiveness in retaining long-range dependencies and mitigating vanishing gradient issues. As with the GRU models, multiple architectures were tested.
* Liquid State Neural Networks (LSNNs): Inspired by biologically plausible models, these networks incorporate liquid time-constant dynamics, allowing them to adapt their memory and response patterns over time. LSNNs were included to investigate whether models with non-static internal dynamics could outperform more traditional RNN variants on EEG time series data.

In each category, a range of architectures was evaluated to explore the design space and identify the most effective configurations for confusion detection.

All hyperparameters—including learning rate, batch size, number of layers, and hidden unit size – were manually selected based on preliminary testing and domain knowledge. These settings were held constant across similar models within each experimental group to ensure fair comparisons.

### Experimental Results

**Baseline**

As a baseline, a fully connected (FC) network architecture was implemented based on a previous study. This model flattened the EEG signal across time and frequency dimensions before feeding it into a deep multilayer perceptron. The architecture consisted of five sequential dense layers with decreasing units (200 → 100 → 50 → 16 → 1), each followed by a ReLU activation function except for the output layer, which used a sigmoid activation for binary classification.

This FC model achieved an average validation accuracy of 0.63, consistent with the source paper. However, the model contained 54,983 parameters, and its inability to account for temporal dynamics limited its effectiveness when compared to time-series-oriented approaches.

**Implemented models**

To better capture the temporal structure of the EEG signals, three categories of neural network models were evaluated: Gated Recurrent Units (GRU), Long Short-Term Memory networks (LSTM), and Liquid State Neural Networks (LSNN). All models were trained exclusively on the raw EEG frequency band features (delta, theta, alpha1, alpha2, beta1, beta2, gamma1, gamma2) and used the same training conditions:

* Adam optimizer with binary crossentropy loss
* Learning rate: 0.002
* Weight decay: 1e-7
* EMA (Exponential Moving Average): enabled
* Same number of training epochs and fixed data splits across models

Each model processed input sequences of 144-time steps per experiment, padded to a uniform length. Their architectures are described schematically below:

|  |  |  |  |
| --- | --- | --- | --- |
| **Name** | **GRU** | **LSTM** | **LSNN** |
| **Architecture** | Input: (144 time steps, 8 EEG features)  GRU(20 units, return sequences)  GRU(20 units, return sequences)  GRU(10 units, return sequences)  GRU(10 units, return final)  Dense(1 unit, sigmoid activation) | Input: (144 time steps, 8 EEG features)  LSTM(20 units, return sequences)  LSTM(20 units, return sequences)  LSTM(10 units, return sequences)  LSTM(10 units, return final)  Dense(1 unit, sigmoid activation) | Input: (144 time steps, 8 EEG features)  LTC layer configured with an AutoNCP topology of 64 neurons and 32 interconnections (return sequences)  LTC layer configured with AutoNCP topology of 32 neurons and 16 interconnections (return final)  Dense(1 unit, sigmoid activation) |
| **Dropout** | 0.2 | 0.2 | No |
| **Best Performance\*** | ACC: 0.893  ENT: 0.237  AUC: 0.971 | ACC: 0.840  ENT: 0.303  AUC: 0.946 | ACC: 0.813  ENT: 0.283  AUC: 0.927 |
| **Num parameters** | 5951 | 7691 | 27105 |

\* - this is the best performing epoch for each of the models on non-embedded validation data averaged by folds.

LSNN architecture leveraged the structure of NCPs to enhance temporal expressiveness while maintaining interpretability and compactness. Although the model had a relatively high parameter count, its performance remained competitive, suggesting that NCP-based LSNNs can effectively model cognitive states from EEG signals.

Overall, all three temporal models clearly outperformed the fully connected baseline across all evaluation metrics. Among them, the GRU-based model achieved the best performance while maintaining a relatively low number of parameters, making it an optimal choice in terms of both efficiency and accuracy. The LSNN, while having the highest parameter count, still demonstrated strong performance, indicating its potential for modeling complex temporal dynamics in EEG data.

**Temporal Embeddings for Enhanced Representation**

In addition to evaluating the models on raw EEG frequency-band signals, further experiments explored the integration of temporal embeddings to enrich the input representations. These embeddings were designed to expose temporal dynamics more explicitly by incorporating historical context into each time step.

The following types of lag-based embeddings were considered:

* Lag-1 embedding: Each timestamp was augmented with the feature values from the immediately preceding time step.
* Lag-2 embedding: The EEG signal at each timestamp was additionally augmented with the values from two steps before.
* Lag-1 + Lag-2 embedding: Both first and second-order lagged values were concatenated to each current timestamp, resulting in a broader temporal window for each input vector.
* First-order difference (Δlag-1): Rather than using raw lagged values, this embedding encoded the difference between the current timestamp and the one immediately before it, highlighting the change in brain activity over time rather than the absolute value.

These augmentations provided the models with richer temporal features, potentially aiding in the identification of subtle signal shifts indicative of cognitive states such as confusion.

**Convolutional Embedding**

In a parallel approach, temporal feature engineering was explored via causal convolution. A 1D convolutional layer with 50 filters, a kernel size of 3, ReLU activation, and causal padding was applied to the raw EEG signals. This method created new time-dependent embeddings that preserved the sequence’s chronological order while capturing short-term local patterns. The convolutional layer effectively summarized nearby temporal trends within the signal and passed the enriched representation to subsequent model layers.

To assess the impact of different temporal embeddings, performance metrics—accuracy, loss, and AUC—were monitored across training epochs for each embedding type and model architecture. These evaluations were conducted across GRU, LSTM, and LSNN-based models, allowing for a comprehensive comparison of embedding effectiveness. In the case of the best-performing LSNN architecture, not all embeddings were included in the final evaluation phase. This decision was based on earlier results, where certain embeddings consistently underperformed relative to others, and were therefore omitted to streamline experimentation.

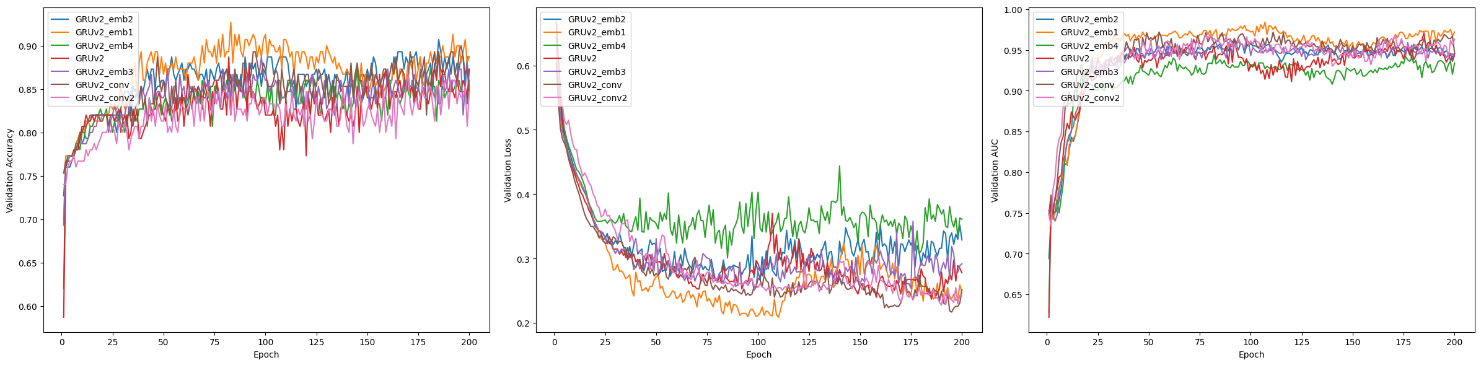


Figure 1. Best GRU performance

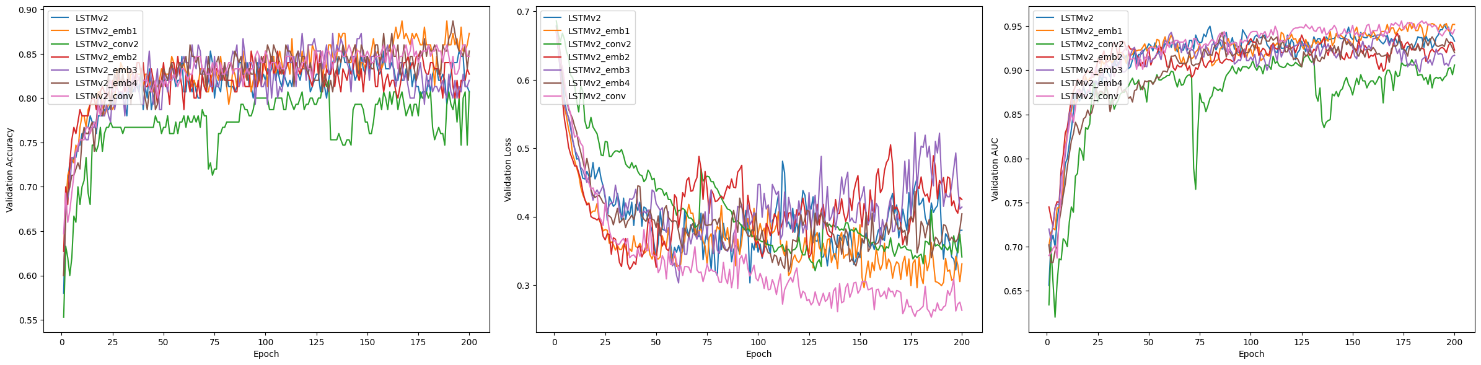


Figure 2. Best LSTM performance

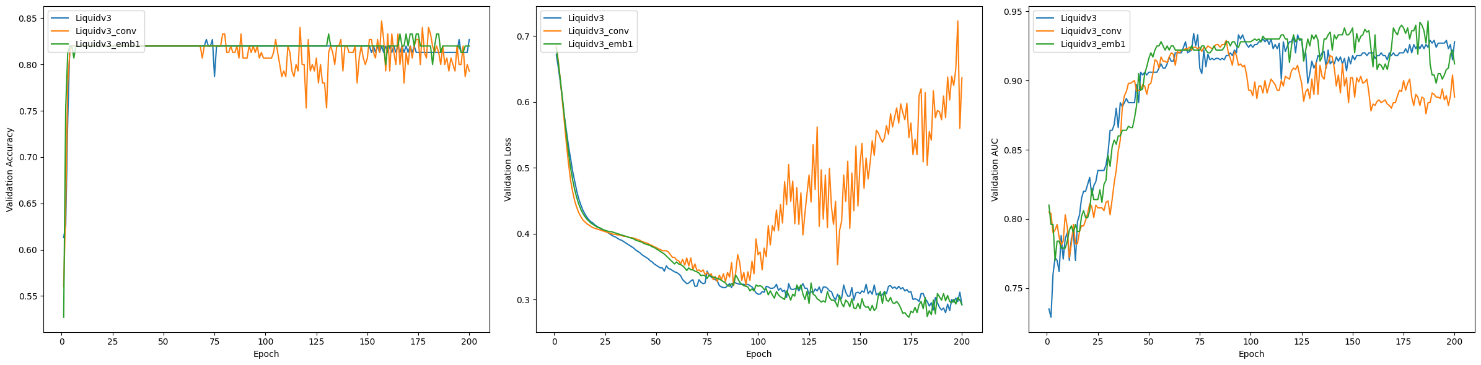


Figure 3. Best LNNS performance

Among all embedding strategies, the lag-1 embedding and the convolutional embedding consistently led to the most significant improvements across models. These two approaches not only increased predictive accuracy but also tended to stabilize the training process, reducing variance and preventing overfitting in several configurations.

The lag-1 embedding provided a minimal but meaningful temporal context, enriching the model’s ability to recognize transitions in brain signal patterns associated with cognitive states. Similarly, the convolutional embedding, by leveraging local temporal filters, effectively captured short-range dependencies that were often missed by raw features alone.

Overall, both of these embedding methods generally enhanced model performance, suggesting that even lightweight temporal transformations of EEG data can provide substantial benefits when predicting cognitive states like confusion.

**Summary of Final Model Performance**

To provide a comprehensive comparison, a summary graph is included that illustrates the final validation metrics—accuracy, AUC, and loss—for the best-performing configuration of each model type: GRU, LSTM, and LSNN. These models were selected based on their performance across all previous experiments, including variations with and without temporal embeddings.

The plotted results clearly show that GRU-based models significantly outperform the others across all metrics. Notably, the GRU model enhanced with lag-1 embedding achieved the best overall results, with accuracy exceeding 0.90 and AUC surpassing 0.95. This performance reflects a substantial improvement over the baseline fully connected model from the referenced paper, which reported an average validation accuracy of only 0.63.

While LSNN models (based on sparsely connected neural circuit policies) demonstrated competitive behavior, their overall performance was consistently lower than that of GRU and LSTM counterparts. Nevertheless, their results still validate the potential of biologically inspired recurrent architectures in EEG-based classification tasks.

These findings emphasize the importance of sequence-aware architectures and temporal embeddings when working with EEG signals. The GRU’s ability to model temporal dependencies effectively, especially when coupled with lightweight lagged context, appears to be particularly well-suited for confusion detection tasks using frontal EEG data.

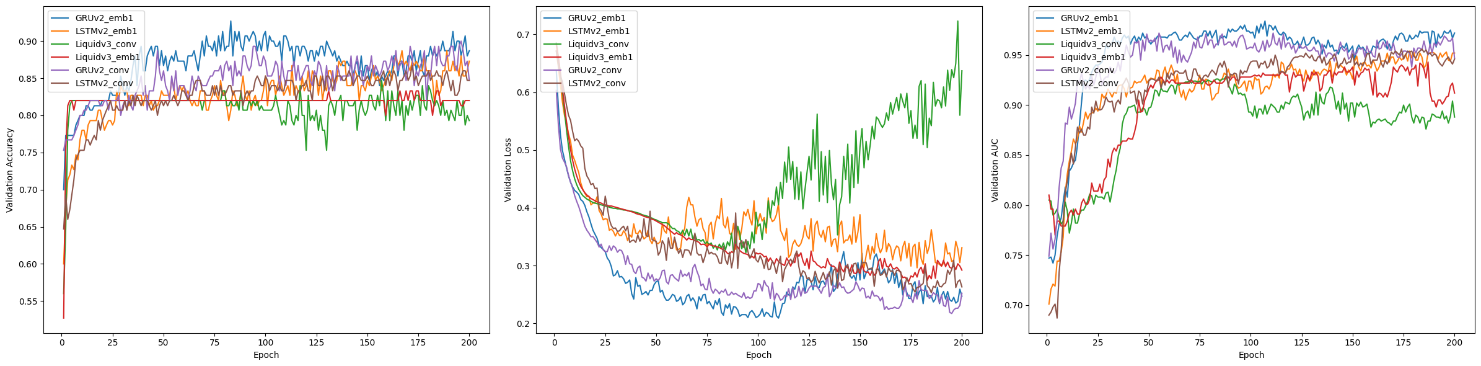


Figure 4. Final model performance

**Model Interpretability with SHAP Analysis**

To explore the interpretability of the trained models, I employed SHAP (SHapley Additive exPlanations) values, a widely adopted method for explaining predictions made by machine learning models. SHAP assigns an importance value to each feature for individual predictions, enabling insight into how specific EEG signals contribute to the final output.

In the SHAP summary plots, each point represents a feature contribution for a single sample. The size of the point corresponds to the absolute magnitude of the SHAP value, indicating the strength of that feature's influence. Red-colored points indicate positive SHAP values, meaning that the feature increased the model’s predicted probability of confusion, while blue-colored points reflect negative contributions, lowering the predicted probability.

To maintain clarity across signal types, the same EEG channel was consistently represented with the same shade of red or blue, allowing visual tracking of individual signal behavior across samples. This consistent color-coding helped highlight the relative importance of each frequency band (e.g., delta, theta, alpha1, etc.) throughout the dataset.

In experiments involving temporal embeddings, such as lagged values, I aggregated the SHAP values of the lagged features with their corresponding original features. This allowed for a more interpretable comparison across models and provided a clearer understanding of the role each signal type played in both its original and embedded forms.

A particularly striking observation from the SHAP summary plots is the presence of specific timestamps where all EEG signal features exhibit notably high importance. At these moments, the absolute SHAP values across all frequency bands increase sharply, suggesting that the model places disproportionate weight on certain temporal segments within the one-minute recording. This implies that cognitive confusion may manifest more strongly at specific points in the video, potentially aligning with moments of conceptual difficulty or topic transitions. While this observation is consistent across multiple samples and models, it warrants further investigation to verify whether these signal spikes consistently correspond to semantically confusing segments in the educational content itself.

Another consistent finding across experiments is the dominant importance of the theta band in predicting confusion. SHAP values frequently show that the theta signal contributes more significantly—both positively and negatively—to the model's decision-making process compared to other frequency bands. This trend is in agreement with prior research, which has linked increased theta activity in the frontal lobe with elevated cognitive load and attentional engagement, particularly in tasks that involve comprehension or problem-solving. The model's reliance on this band therefore provides additional validation for both the data and the model’s alignment with neuroscientific understanding of EEG signal interpretation.

While the GRU and LSTM models yielded interpretable patterns through SHAP analysis, LSNN models unfortunately did not provide useful insights into feature importance. The SHAP value distributions for LSNNs were generally less consistent, lacked clear structure, and often failed to highlight meaningful temporal or spectral patterns. This may be attributed to the architectural sparsity and internal dynamics of neural circuit policies, which, although biologically inspired, can obscure direct attribution of output predictions to individual input features. As a result, while LSNNs demonstrated reasonable predictive performance, their interpretability remains limited, reducing their utility for detailed signal-level or time-resolved analysis in this context.

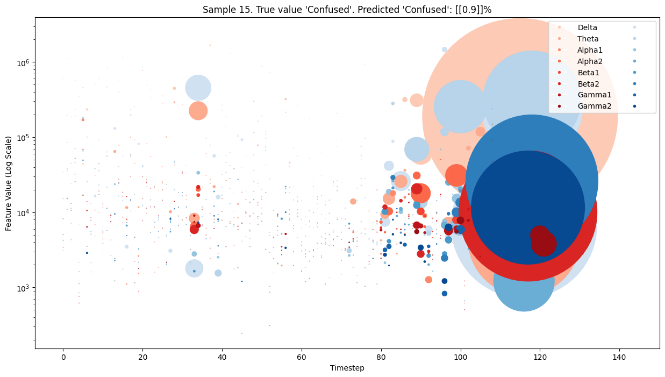
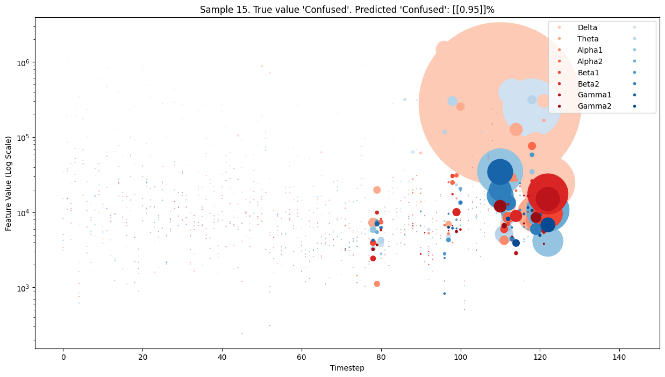
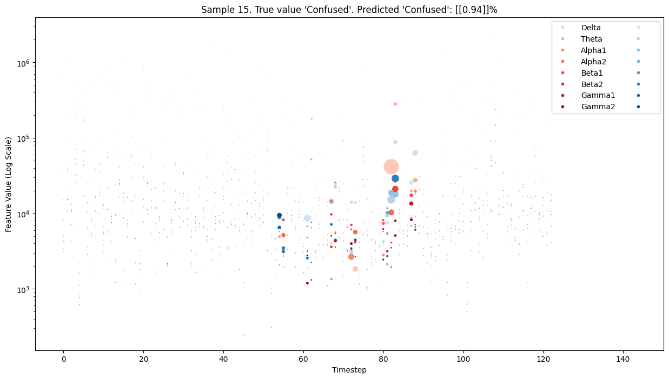
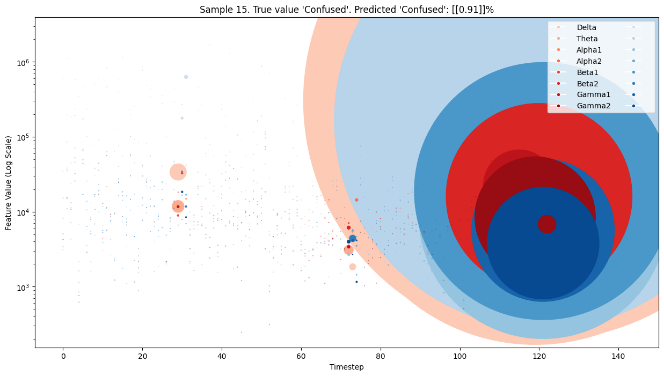
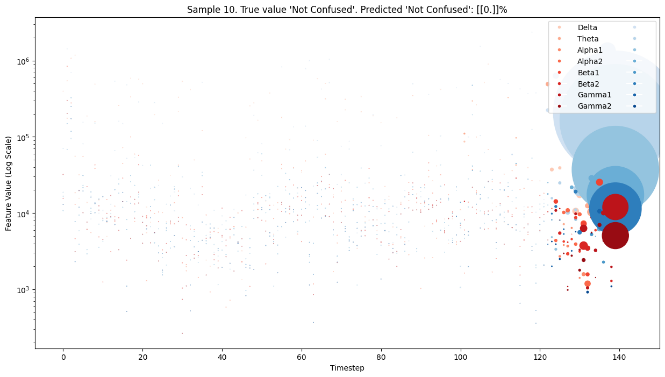
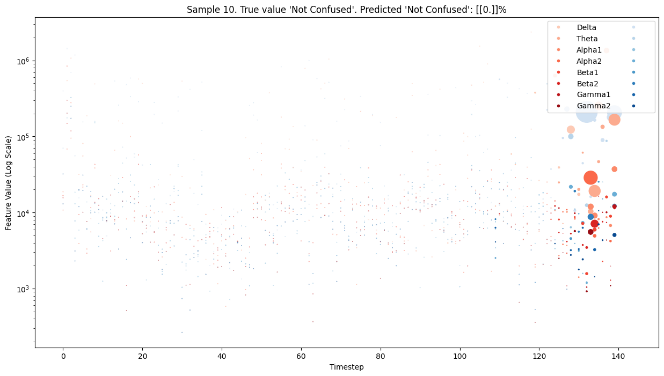
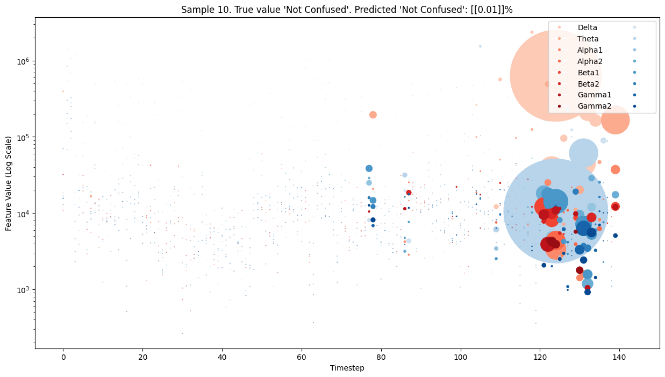
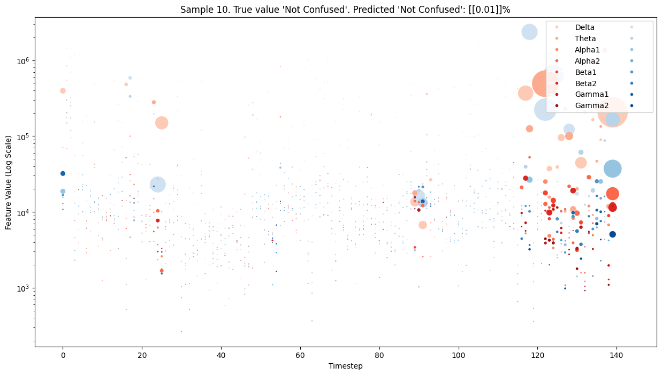
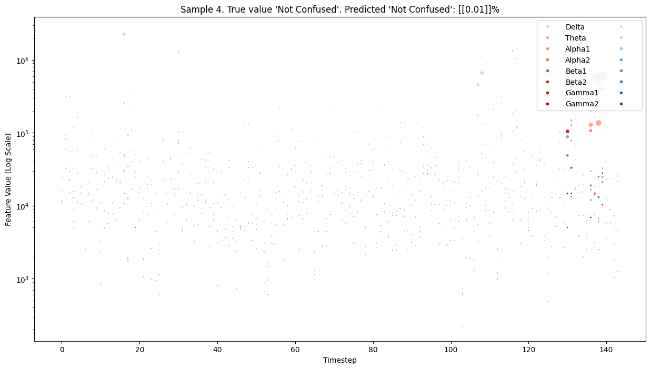
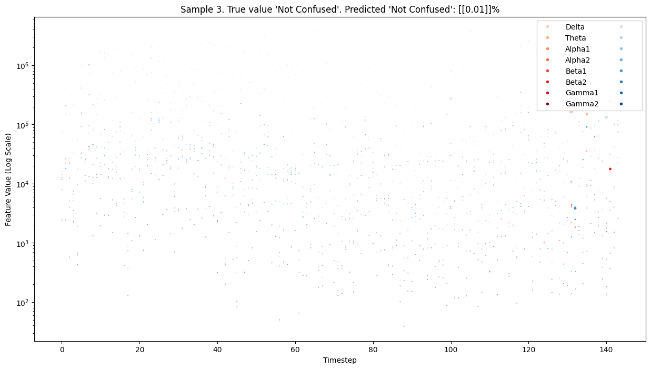
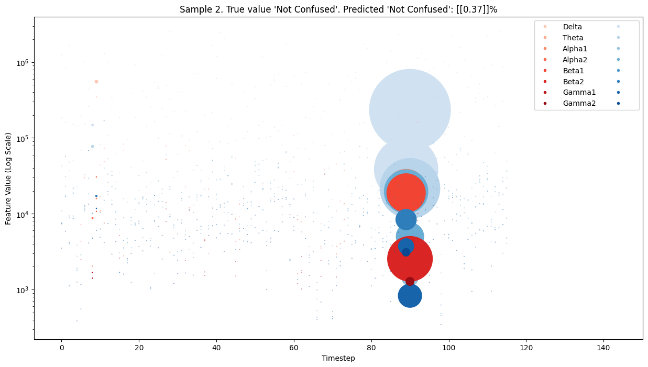
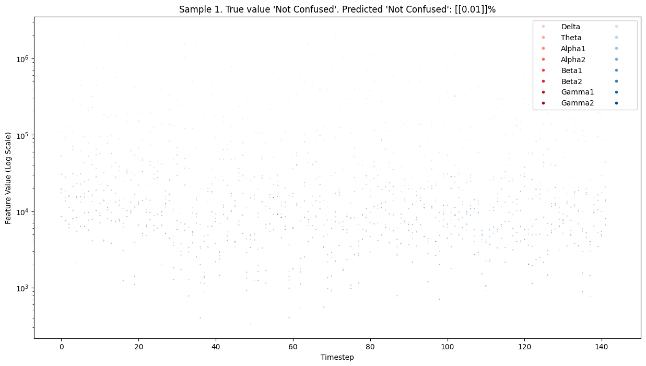
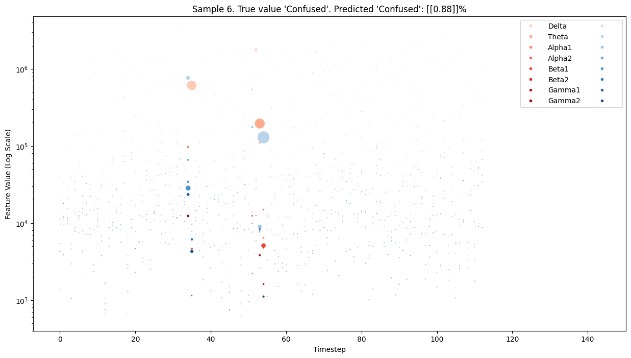
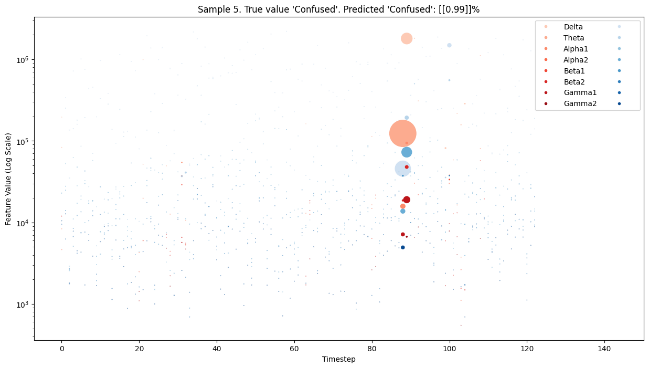


Figure 5. SHAP for Samples 10 and 15 for GRU and LSTM with lag-1 embeddings and convolution





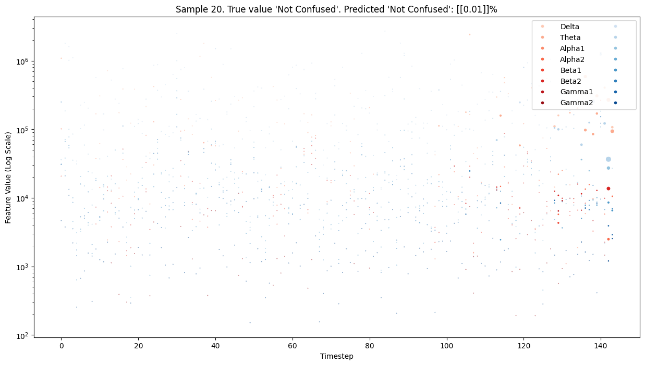
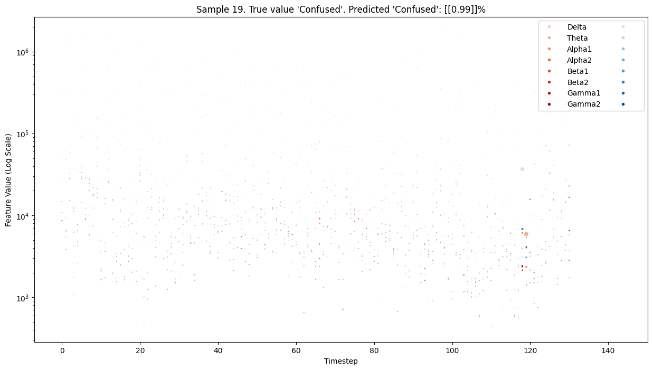
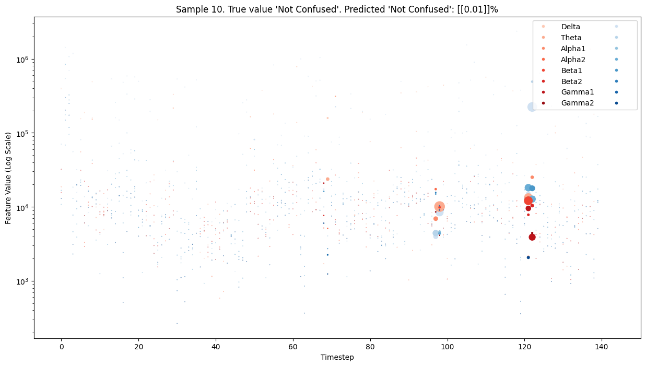
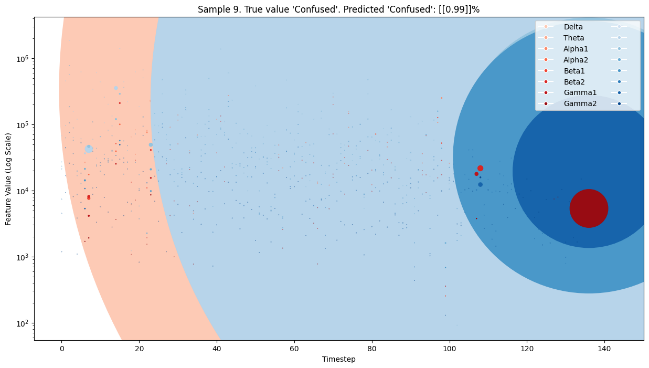


Figure 6. SHAP for GRU with embeddings (best model)

## Conclusions

## References

1. **Ayoub, O., Andreoletti, D., Knapińska, A., Goścień, R., Lechowicz, P., Leidi, T., Giordano, S., Rottondi, C., & Walkowiak, K.** (2024). Liquid Neural Network-based Adaptive Learning vs. Incremental Learning  for Link Load Prediction amid Concept Drift due to Network Failures. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2404.05304>
2. **Bidollahkhani, M., Atasoy, F., & Abdellatef, H.** (2023). LTC-SE: Expanding the potential of Liquid Time-Constant Neural Networks for scalable AI and embedded systems. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2304.08691>
3. **Hasani, R., Lechner, M., Amini, A., Liebenwein, L., Ray, A., Tschaikowski, M., Teschl, G., & Rus, D.** (2022). Closed-form continuous-time neural networks. Nature Machine Intelligence, 4(11), 992–1003. https://doi.org/10.1038/s42256-022-00556-7
4. **Hasani, R., Lechner, M., Amini, A., Rus, D., & Grosu, R.** (2021). Liquid Time-constant Networks. Proceedings of the AAAI Conference on Artificial Intelligence, 35(9), 7657-7666. <https://doi.org/10.1609/aaai.v35i9.16936>
5. **Huang, Z., Contreras, L. F. H., Leung, W. H., Yu, L., Truong, N. D., Nikpour, A., & Kavehei, O.** (2024). Efficient Edge-AI models for robust ECG abnormality detection on Resource-Constrained hardware. PubMed. <https://doi.org/10.1007/s12265-024-10504-y>
6. **Lechner, M., Hasani, R., Amini, A., Henzinger, T. A., Rus, D., & Grosu, R.** (2020). Neural circuit policies enabling auditable autonomy. Nature Machine Intelligence, 2(10), 642–652. <https://doi.org/10.1038/s42256-020-00237-3>
7. **Lechner, M., Hasani, R. M., & Grosu, R.** (2018). Neuronal circuit policies. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.1803.08554>
8. **Nerrise, F., Sosanya, A. S., & Neary, P.** (2024). Physics-Informed Calibration of Aeromagnetic Compensation in Magnetic Navigation Systems using Liquid Time-Constant Networks. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2401.09631>
9. **Nye, L.** (2023). Digital twins for patient care via knowledge graphs and Closed-Form Continuous-Time liquid neural networks. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2307.04772>
10. **Yang, J., Shi, R., & Ni, B.** (2021). MedMNIST Classification Decathlon: A Lightweight AutoML Benchmark for Medical Image Analysis. In 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI) (pp. 191-195). Nice, France. doi: <https://doi.org/10.1109/ISBI48211.2021.9434062>
11. **Zheng, Z., & Jia, X.** (2023). Complex Mixer for MEDMNIST Classification Decathlon. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2304.10054>
12. **Zhu, F., Wang, X., Huang, C., Jin, R., Yang, Q., Alhammadi, A., Zhang, Z., Yuen, C., & Debbah, M.** (2024). Robust Continuous-Time Beam Tracking with Liquid Neural Network. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2405.00365>