Final Project in: Machine Learning and Neural Networks for Neuroscience

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A. The Learning Problem:

This project addresses a time series prediction problem using resting-state EEG data collected from three groups: Alzheimer's Disease (AD) participants, Frontotemporal Dementia (FTD) participants, and healthy participants. Rather than focusing on traditional classification models, which are common in dementia-related EEG studies (Rostamikia et al., 2024), our goal is to evaluate whether the predictability of resting-state EEG signals differs across these groups, potentially reflecting different neural dynamics for neurodegenerative and healthy participants, and how well these dynamics can be predicted.

We explore whether the temporal dynamics and spectral patterns of EEG signals differ between these groups by measuring how well a segment of the EEG signal (for each group) can be predicted based on earlier brain activity. The learning problem is a supervised learning problem, where the model learns to predict a 5-second segment of EEG from a 50-second input segment. First, we trained the model on one electrode and then proceeded to a fixed set of six frontal electrodes, common across all subjects, to capture neural activity in brain regions that are typically affected early in both AD and FTD.

B. Previous Solutions:

Most of the prior work using EEG data and machine learning in the context of neurodegenerative disease has focused on classification tasks, where models are trained to classify groups- such as AD, FTD, and healthy participants. A recent study used the same dataset as ours and focused on a classification approach, where EEG recordings were analyzed to distinguish between AD, FTD, and healthy participants (Rostamikia et al., 2024)[1]. In that study, the authors extracted a wide range of features including time-domain, frequency-domain, and connectivity-based measures while demonstrating high classification performance using traditional machine learning models. We felt inspired by their work and asked a different question: if EEG features are enough to support classification, can they also support prediction? Rather than focusing solely on whether certain features differ across AD, FTD, and healthy participants, our aim was to explore whether and how these differences affect predictability. If the brain's temporal and spectral dynamics change differently in each group, we hypothesized that this would be reflected in group-specific patterns of signal predictability.

C. Methods:

Dataset: We used a publicly available EEG dataset (from Openneuro) consisting of resting-state, eyes-closed recordings from a total of 88 participants: 36 with AD, 23 with FTD, and 29 healthy controls. The data was recorded by an EEG device with 19 electrodes with a sampling rate of 500 Hz. Preprocessing included a 0.5–45 Hz Butterworth band-pass filter, re-referencing to A1–A2, and artifact correction using Artifact Subspace Reconstruction (ASR). Independent Component Analysis (ICA) was then applied, and components labeled as eye or jaw artifacts by the ICLabel algorithm were removed.

Previous research has shown that frontal electrodes are significantly correlated with cognitive performance in both Alzheimer's disease and frontotemporal dementia patients, highlighting their importance in assessing executive functions, attention, and working memory (Azargoonjahromi et al., 2024)[3]. Thus, for our project, only six frontal electrodes (Fp1, Fp2, F3, F4, F7, F8) were selected.

From each participant, 50-second input segments were extracted from the cleaned EEG signal, resulting in multiple samples, each being a matrix of 2500 timestamps long time series per channel.

Architecture: We implemented a two-layer LSTM model, a type of recurrent neural network (RNN) designed to capture long-range temporal dependencies in sequential data. Previous research has shown that LSTM networks are well-suited for EEG signal analysis, successfully capturing temporal dependencies in tasks such as seizure prediction (Tsiouris et al., 2018)[2]. The model receives a 6-channel time-series of 50 seconds input and outputs a sequence of 2500 values per channel, matching the raw EEG signal length. The architecture is as follows:

- Layer 1: LSTM with 128 hidden units.
- Layer 2: LSTM with 64 hidden units.
- Each layer is followed by batch normalization, ReLu activation function was used between them.
- Output Layer: Fully connected linear layer that maps to 2500 output points per sample.

As training parameters, we set batch size to 32, used 0.5 overlap between windows, and trained the model for 20 epochs. We used Adam optimizer, which adjusts learning rates during training.

Evaluation: We used permutations tests for validating the model's performance, by comparing Pearson correlation scores between actual and predicted signal against a null distribution created by shuffling labels 1000 times. This helped us understand whether the model's predictive performance was statistically significant beyond chance.

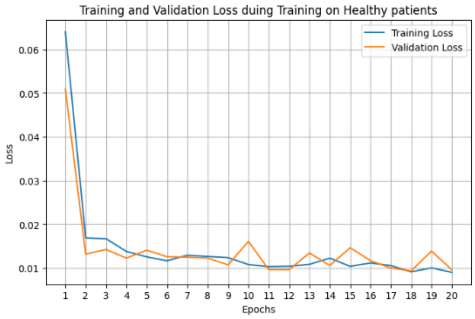
Spectral Evaluation: In addition to time-domain comparisons, we evaluated the similarity between the predicted and true EEG signals in the frequency domain using Fast Fourier Transform (FFT). This analysis aimed to determine whether the model could preserve key spectral features, such as power in the delta, theta, alpha, and beta bands, which are known to differ across AD, FTD, and healthy individuals (Hachamnia et al., 2025)[4]. For each sample, we computed the FFT of both the predicted and real signals and visualized their power spectrums.

Feature extraction: To further evaluate the performance of the model, we extracted from the data both time domain and frequency domain features. Time domain features include the mean, std, skewness, kurtosis, and signal power of the time series, while the frequency domain features are the power of each band: Delta $(0.5 - 4_{hz})$, Theta $(4 - 8_{hz})$, Alpha $(8 - 13_{hz})$, Beta $(13 - 30_{hz})$, and Gamma $(30 - 45_{hz})$. In total we extract 10 features per sample, as we had flattened the matrix beforehand.

SVM Classification: Lastly, to evaluate the quality of the predicted data, we trained an SVM model to classify the prediction window of predicted data and of the true data from the recordings. We tried several different model options and have decided to ultimately use a model that was trained on predicted EEG data of healthy patients, as it achieved the best performance. The SVM model was developed using an 'RBF' kernel known to be efficient in classification of EEG data and was also used in previous research on the same dataset (Rostamikia, M., at al., 2024)[1]. The performance of the SVM was presented in the form of confusion matrices and a report table specifying accuracy for each group of data – 'AD', 'FTD', and 'Healthy'.

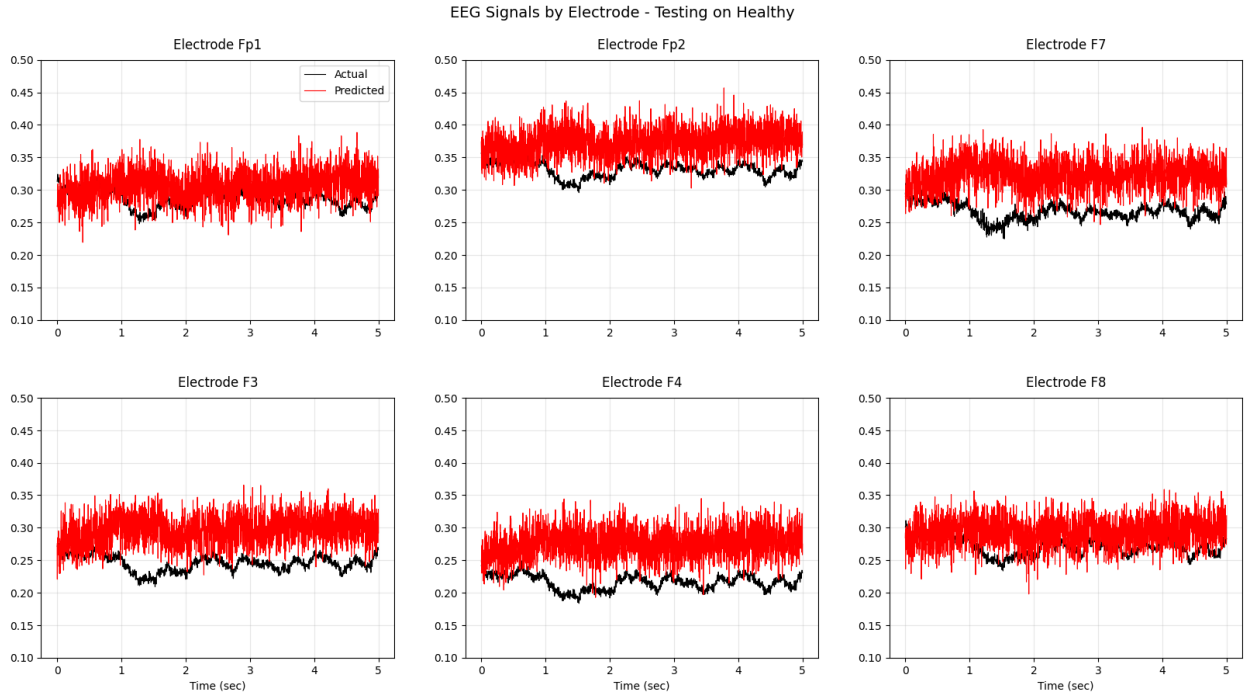
D. Results:

Losses: To track the model's learning process, we plotted the training and validation loss curves over 20 epochs. The graph shows the error decreased across epochs on both training and validation sets. The training loss curve decrease indicates that the model was learning the data well, and the validation loss curve decrease and stabilization indicates that the model generalized well.

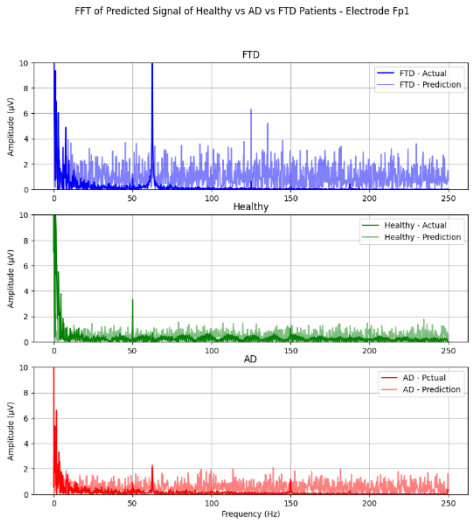


Prediction: To visually assess the quality of the model's predictions, we plotted one example of actual and predicted EEG signals for a 5-second window from a healthy participant. The plot shows the six frontal

electrodes comparing the actual EEG recordings (black lines) against predictions from our model trained on healthy participants (red lines), using one recording sample 0 from our healthy test dataset.

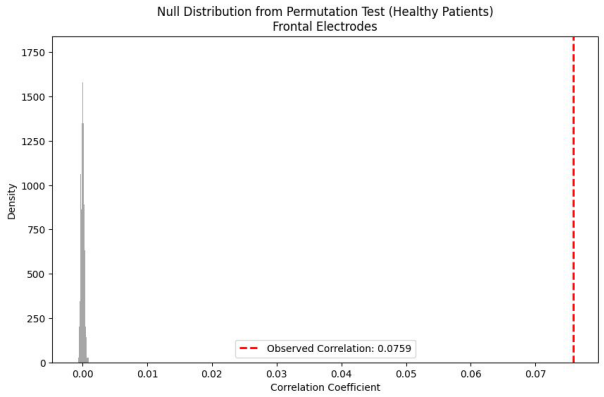


In addition to time-domain comparisons, we evaluated the similarity between the predicted and true EEG signals in the frequency domain using Fast Fourier Transform (FFT). The FFT analysis allows us to evaluate the model. This spectral analysis provides an additional layer of validation by evaluating the model's success in preserving frequency specific information, as abnormalities in EEG frequency components, particularly in the delta, alpha, and beta bands, are known to differ across AD, FTD, and control groups (Hachamnia et al., 2025).



Pearson correlation: The average Pearson correlation for healthy participants was the highest- 0.0759, compared to 0.0312 in the FTD participants and 0.0241 in the AD participants. The fact that the healthy participant's predicted signal was at least twice as accurate as the AD and FTD groups can support our hypothesis, that neurodegenerative participant's EEG signal can consist of irregular, constantly changing patterns that are more difficult to predict. This also suggests that temporal patterns in healthy participants are more consistent and easier to predict.

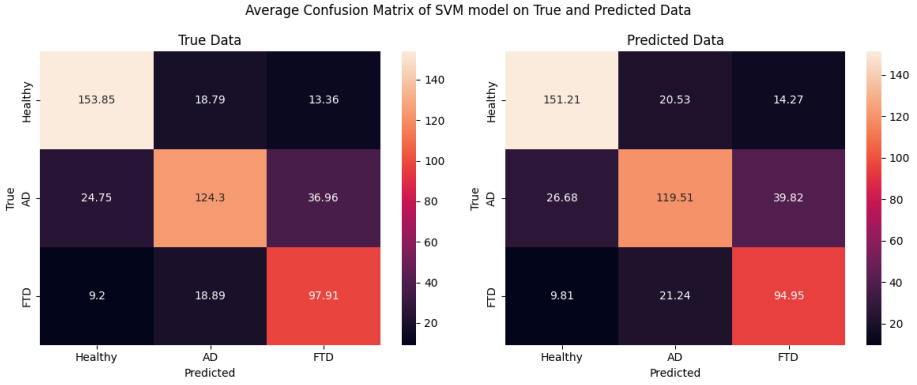
Model predictions are significantly higher than the null distribution: Due to the low correlation of the prediction, we used a permutation test to evaluate prediction success. After shuffling the true labels of the prediction window and computing the Pearson correlation factor for each shuffle, we've compared the actual prediction of the model to true data to the z-scored null distribution we got of the permutations that represent random prediction. We then tested to see if the true correlation falls within the distribution and saw that the model predicted the true data significantly better than the null distribution.



SVM Classification Performance

	Predicted data			*True data*		
Label	**F1 Score**	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**
Healthy	0.81	0.81	0.81	0.82	0.82	0.83
AD	0.69	0.74	0.64	0.71	0.77	0.67
FTD	0.69	0.64	0.75	0.71	0.66	0.78
	F1 score – 0.73			*F1 score – 0.75*		

An SVM model trained on generated predicted data can classify actual data: To evaluate the model's performance in encountering the main learning problem we've tackled, we developed an SVM model and trained it to classify a time series to the medical label of its patient using the extracted features of both time domain and frequency domain of the predicted data our model generated. We tested it on both test data of predicted time series as well as the actual time series recordings. The model has achieved the f1 score of 0.73 on predicted data, with accuracy differing between groups. Unexpectedly, the model performs similarly on True data (F1 score – 0.75), suggesting the model might be preserving patterns in the actual recording that differ between the groups in its predictions, allowing the SVM model to classify the actual data similarly. Interestingly, the recall of 'AD' is low, while the precision of 'FTD' is low as well, suggesting the model exhibits bias towards 'FTD' on classification of 'AD' time-series. However, this bias can also be seen in classification of true data, supporting the suggestion that the model manages to incorporate real patterns and features of the actual data into the prediction.



References:

1) Rostamikia, M., Sarbaz, Y., & Makouei, S. (2024). EEG-based classification of Alzheimer's disease and frontotemporal dementia: A comprehensive analysis of discriminative features. Cognitive Neurodynamics, 18, 3447–3462.

2) Tsiouris, K. M., Pezoulas, V. C., Zervakis, M., Konitsiotis, S., Koutsouris, D. D., & Fotiadis, D. I. (2018). A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals. Computers in Biology and Medicine, 99, 24–37.

3) Azargoonjahromi, A., Nasiri, H., & Abutalebian, F. (2024). *Resting-State EEG Reveals Regional Brain Activity Correlates in Alzheimer's and Frontotemporal Dementia* [Preprint]. medRxiv.

4) Amir Hossein Hachamnia, Ali Mehri, Maryam Jamaati (2025). Integrating neuroscience and artificial intelligence: EEG analysis using ensemble learning for diagnosis Alzheimer's disease and frontotemporal dementia, Journal of Neuroscience Methods, Volume 416.