Comparison Between a Classical Feature-Based AI Model and a Foundation Model for the Analysis of EEG Brain Signals

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Background

This project builds on the EEG Challenge 2025, part of the NeurIPS 2025 Competition Track. The challenge is organized by Université Paris-Saclay, UC San Diego's Swartz Center for Computational Neuroscience, and the Child Mind Institute. Its overarching objective is to improve the generalizability of EEG-based predictive models across subjects and tasks. More broadly, the initiative aims to identify robust and interpretable neural biomarkers linking brain activity to cognitive traits and psychopathology [1].

Definitions

The following latent dimensions are defined and used in the EEG Foundation Challenge [1]:

- **P-factor**: A latent dimension capturing the shared variance across all forms of psychopathology, reflecting a general liability to mental disorders.
- **Attention problems**: A construct representing deficits in sustained attention, concentration, and cognitive control.
- **Externalizing factor**: A broad domain including outward-directed behavioral dysregulation such as impulsivity, aggression, and rule-breaking.
- **Internalizing factor**: A latent dimension capturing inward-directed emotional dysregulation, including anxiety, depressive symptoms, and social withdrawal.

Aim

The goal of this project is to compare two approaches for predicting the four latent factors: the P-factor, attention problems, externalizing, and internalizing.

The first approach relies on traditional EEG signal analysis, where meaningful features are manually extracted from the power spectrum. Specifically, I compute FOOOF parameters, the alpha-peak frequency, and frequency band powers. These features are then used to train a classical machine-learning model based on a multilayer perceptron (MLP), which predicts the four latent dimensions [3, 4].

The second approach involves training a foundation model directly on raw EEG signals, followed by fine-tuning to predict the same four factors. This allows the model to learn relevant representations directly from unprocessed data, avoiding manual feature engineering.

Ultimately, the project compares the two approaches in terms of performance, robustness, and interpretability.

Methods

The analysis uses only the resting-state EEG data from the HBN-EEG dataset [2]. Although multiple tasks are available, the project focuses exclusively on resting-state recordings consisting of alternating "eyes open" and "eyes closed" periods. Resting-state provides a simple and controlled setting, allowing the study of spontaneous brain activity without task-related interference.

The EEG data were collected using a 128-channel HydroCel net and follow the standardized BIDS format [2].

For the first method, raw EEG signals are preprocessed and their power spectral density (PSD) is computed. From the PSD, I extract the alpha-peak frequency, FOOOF parameters, and band-power values, which serve as inputs to a multilayer perceptron trained to predict the target factors [3, 4].

For the second method, I employ a pretrained foundation model developed at IMT Atlantique. After loading the pretrained architecture, I fine-tune it on the same resting-state dataset to predict the four target dimensions. Using identical data for both pipelines enables a direct comparison of their predictive performance.

Expected Results

By the end of the project, I expect to compare the performance of the two models using the R^2 score and the normalized mean square error (NMSE), following the metrics defined in the EEG Challenge 2025 [1].

For the feature-based model, I anticipate identifying explicit relationships between EEG-derived parameters and the four latent dimensions (Attention, Externalizing, Internalizing, and P-factor). Due to its simplicity and interpretability, this model may help highlight which EEG features are the most informative [3, 4].

The foundation model may capture more subtle or complex patterns present in raw EEG signals—patterns that manual feature extraction may overlook. Ideally, it will provide complementary insights into neural signatures related to the four target factors.

A major limitation of the project is the relatively small amount of usable EEG data, which may restrict performance and limit generalization [2].

References

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