A Deep-Learning Based Decoded EEG Neurofeedback Platform Using Muse-S

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Introduction

Decoded neurofeedback (DecNef) enables the induction of targeted neural activity patterns (Shibata et al., 2011) and offers a promising, non-invasive alternative to traditional neurofeedback approaches. Wireless EEG devices, such as the cost-effective and mobile Muse (Krigolson et al., 2017), provide a scalable and practical solution. In this study, we developed an open-source, deep learning–driven decoded EEG neurofeedback platform leveraging Muse. For decoder training and real-time EEG prediction, we employed EEGNet (Lawhern et al., 2018), a compact convolutional neural network specifically designed for EEG-based brain–computer interfaces.

Methodology

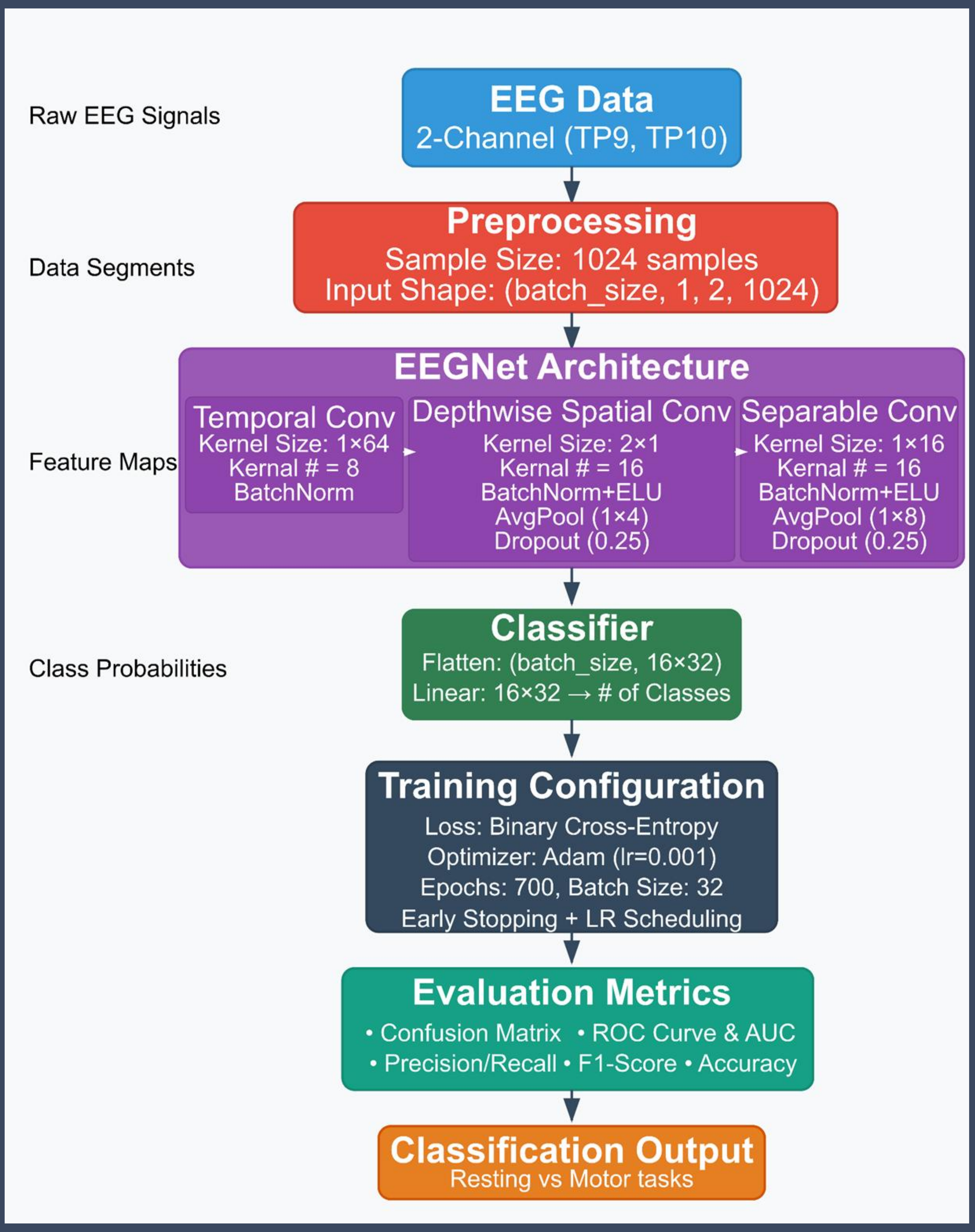

Figure 1. EEGNet Architecture for Decoded EEG Neurofeedback platform.

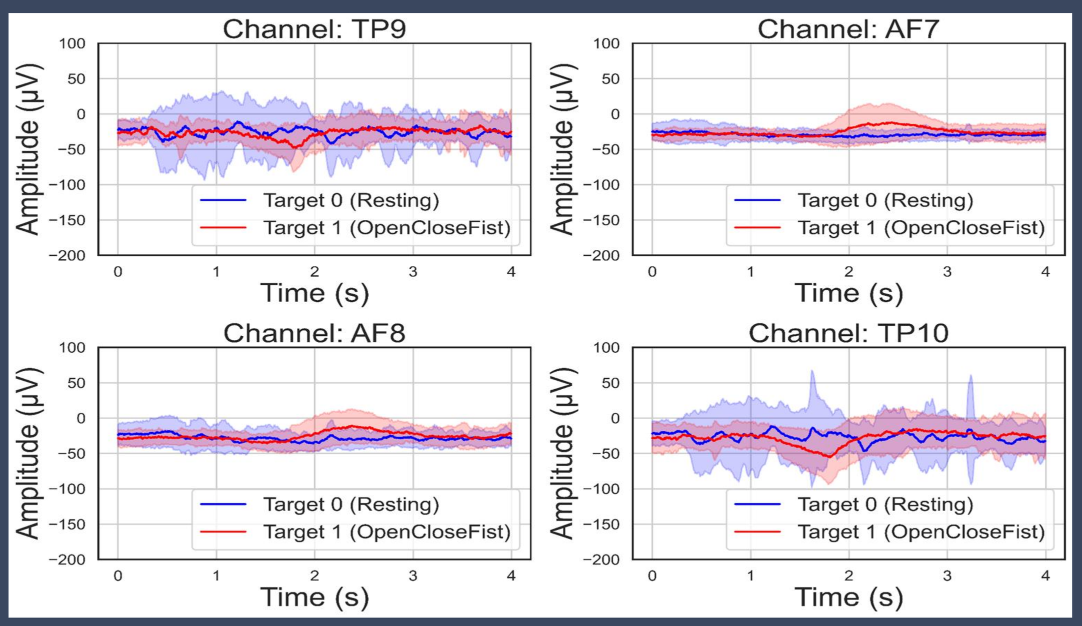

Figure 2. Raw EEG Signals.

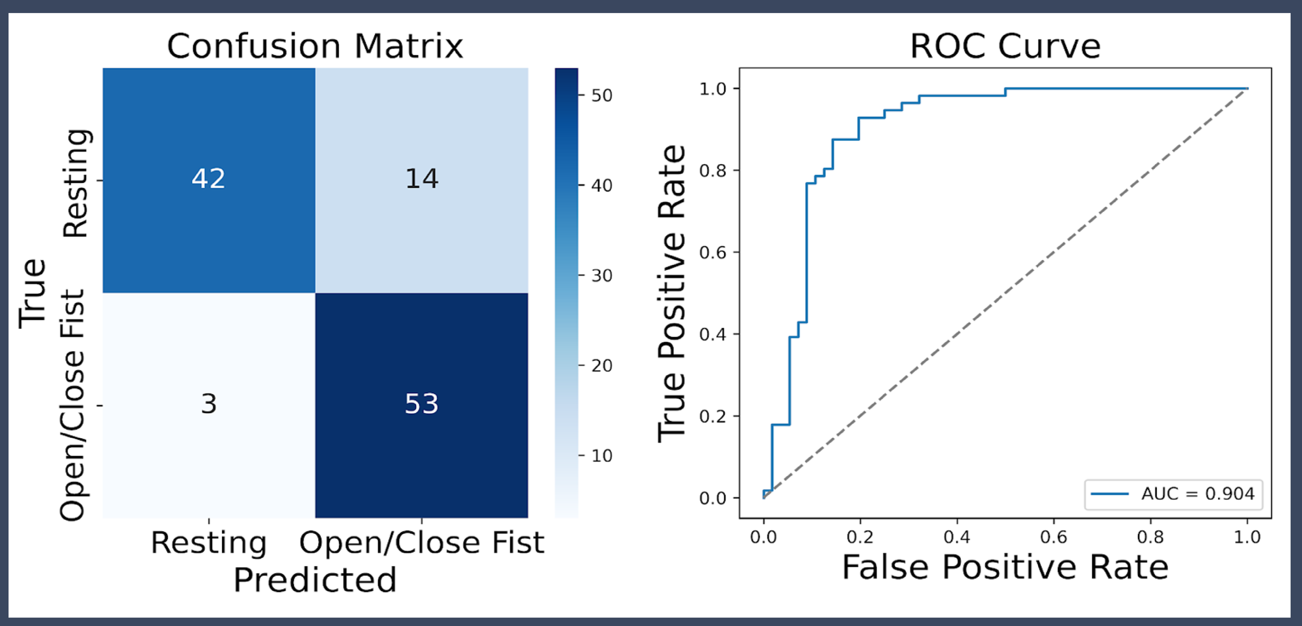

Figure 3. Model Performance of Decoder Construction.

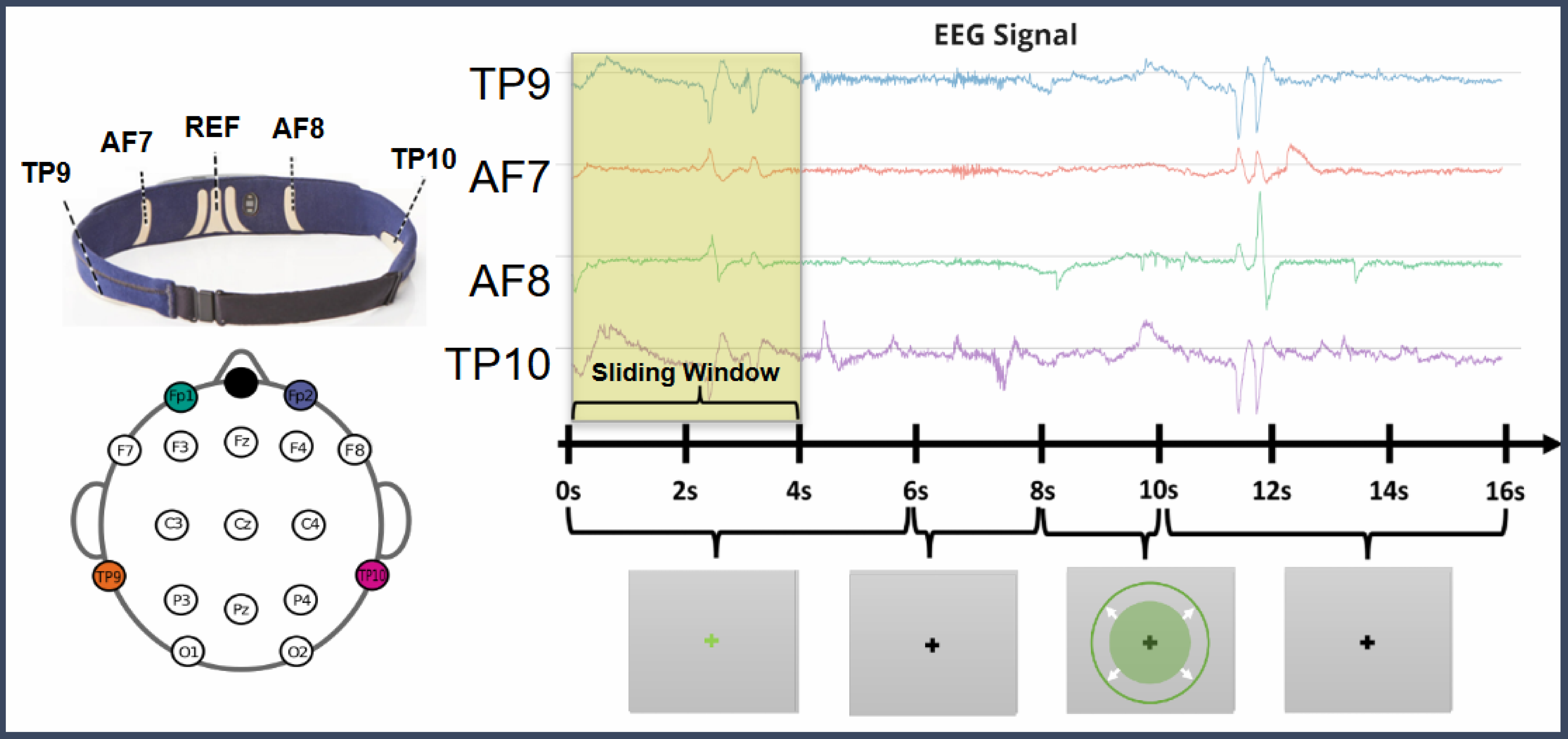

Figure 4. Trial Structure of Induction which is adapted from DecNef.

Decoder Construction (Offline Modeling)

- **Model Architecture:**

The EEGNet architecture (Fig. 1) consists of three main processing blocks:
Block 1: Temporal Convolution — 8 filters with kernel length 64 learn frequency-specific patterns.
Block 2: Depthwise Spatial Convolution — depthwise filters capture spatial patterns per frequency band, followed by Exponential Linear Unit (ELU) activation, batch normalization, average pooling (factor 4), and dropout.
Block 3: Separable Convolution — 16 filters combine spatial-temporal features efficiently, followed by ELU, batch normalization, average pooling (factor 8), and dropout.
A fully connected classification layer with max-norm constraint outputs the final prediction.

- **Model Training and Evaluation:**

The model was trained using binary cross-entropy loss with class balancing. The optimizer and scheduler followed EEGNet training guidelines, using Adam with learning rate scheduling (ReduceLROnPlateau) and max-norm weight constraints applied at each step to prevent overfitting. The model performance was evaluated using standard classification metrics including ROC curves, AUC, precision, recall, F1-score, and accuracy. Confusion matrix analysis was used to visualize class-level performance.

- **Data Preparation and Feature Extraction:**

EEG data were recorded using a Muse-S headset from four electrodes while participants performed motor tasks, for example, opening and closing fists. Only two channels (TP9 and TP10) were used in subsequent analysis, as the amplitudes of the other two channels (AF7 and AF8) were too low to reveal discernible differences (Fig. 2). The raw EEG signals were normalized on a per-channel basis using the mean and standard deviation computed from the training set. The final input segments had a shape of (2, 1024). Each EEG segment was then reshaped to (batch_size, 1, 2, 1024) to accommodate the EEGNet configuration, where “2” corresponds to the two EEG channels.

Induction (EEG neurofeedback)

The induction trial structure was adapted from the DecNef paradigm, consisting of a 6-second induction period, a 2-second fixation, a 2-second feedback phase, and a 6-second inter-trial interval. During the induction period, a 4-second sliding window was applied to the 6-second EEG signals for decoding, producing three overlapping segments and enabling the analysis of frequencies as low as 0.5 Hz. EEGNet performed binary classification of each segment against the predefined target pattern. The predicted scores from the three segments were averaged and mapped onto a visual feedback disk, whose size was proportional to the likelihood that the current brain pattern matched the target. The platform was validated on a motor task involving hand movements (opening and closing fists) and is designed to be easily adapted to other experimental or clinical applications.

Results & Conclusions

To evaluate generalization performance, we employed a cross-session design: data from session one were used for training, and data from session two were used for testing. Each session comprised 50 trials in total, each trial including a 4-second motor task (opening and closing fists) followed by a 4-second fixation period. The EEGNet-based decoder demonstrated good generalization, achieving an AUC of 0.904 (Fig. 3), precision of 0.791, recall of 0.946, F1-score of 0.861, and accuracy of 0.848. The confusion matrix in Figure 3 further illustrates clear separation between the resting state and hand movement. The Python-based, open-source platform has been made publicly available on GitHub*, demonstrating its feasibility in a lightweight laboratory environment. Future work will explore clinical applications and extend this approach to therapeutic settings, such as neurofeedback therapy for children with ADHD.

References

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*https://github.com/xinyanghe08/DecNef-EEG