

Fine-Tuning a Foundation Model for Motor Imagery Pediatric Brain-Computer Interfaces (BCIs)

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Introduction: Previous research has shown that BCI classification accuracy heavily relies on the availability of sufficient training EEG data for each participant. However, limited EEG recording durations—especially in pediatric populations—pose significant challenges. Furthermore, variations in brain responses between users and across multiple BCI sessions hinder the generalizability of models, often necessitating lengthy calibration sessions [1]. Recent advancements in foundation models and self-supervised learning offer potential solutions to these challenges. Foundation models are large-scale, pre-trained neural networks designed to generalize across multiple tasks by learning from extensive, unlabelled datasets. They can be fine-tuned for specific downstream classification tasks using minimal labelled data. These models have achieved groundbreaking results in fields like natural language processing, setting new performance benchmarks. This research is the first to explore the application of foundation models in pediatric BCIs, addressing the critical issue of limited training data in this population.

Material, Methods: This study utilized a dataset comprising left/right hand Motor Imagery (MI) EEG data from 32 typically developing pediatric participants (ages 5–17). The dataset included 19 EEG channels following the standard 10-20 electrode placement system. We employed a pre-trained foundation model, EEGPT [2], which outperformed alternative models due to its pre-training on a large, multi-task adult EEG dataset. After preprocessing the pediatric dataset for compatibility with EEGPT, we developed a pipeline to fine-tune the model for the downstream classification task using a linear probing approach. Classification accuracies for the training and test sets were calculated for all participants and compared to those achieved by a Convolutional Neural Network (CNN) trained from scratch.

Results: Fig. 1 presents the classification accuracy for the 32 pediatric participants using the fine-tuned foundation model ($58\% \pm 3.7$) compared to a CNN classifier trained from scratch ($48\% \pm 5.8$). Early results demonstrate that the foundation model pre-trained on adult data and fine-tuned for pediatric data classification yields acceptable performance and outperforms the CNN model.

Conclusion: This study highlights the potential of foundation models in pediatric BCI systems, representing a significant step toward practical, high-performance pediatric BCI applications.

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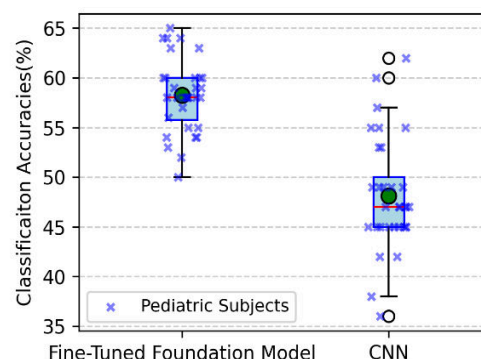


Figure 1. Box plot with scatter points showing classification accuracies for the Motor Imagery task across 32 pediatric subjects.

References:

- [1] Guetschel P, Ahmadi S, and Tangermann M. Review of deep representation learning techniques for brain-computer interfaces. *Journal of Neural Engineering*, 2024.
- [2] Wang G, Liu W, He Y, Xu C, Ma L, and Li H. EEGPT: Pretrained Transformer for Universal and Reliable Representation of EEG Signals. presented at The Thirty-eighth Annual Conference on Neural Information Processing Systems, 2024.