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Zero-shot Deep Learning for Calibration-free Motor Imagery BCIs

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Introduction: Despite the potential of motor imagery (MI) BCIs, their usability outside of laboratory settings is limited due to the need for frequent system calibration and user training. A promising direction to create more user-friendly, plug-and-play BCIs is **zero-shot learning** [1]. This approach enables models trained on data from a set of subjects or tasks to generalize and perform classification on unseen subjects/tasks. While this approach has been previously attempted on task-to-task learning [2,3], very few studies have applied it to cross-subject learning for calibration-free MI-BCIs, and those that have suffer from limitations such as relying on small datasets and hand-crafted machine learning models [4]. Contrary to past research, this study aimed to leverage end-to-end deep learning (DL) to evaluate the robustness of zero-shot learning on a large dataset, which included MI EEG signals from **142 participants**. Our RQ was: Is calibration-free MI BCI feasible if zero-shot learning is applied to a large group of users?

Methods and Results: To obtain a large dataset, we aggregated two existing datasets; Leeuwis et al. (55 subjects, 2021) [5] and Dreyer et al. (87 subjects, 2023) [6], both employing the same EEG device and right- vs. left-hand MI protocol. The signals were resampled and overlapping electrodes relevant to MI task were selected (C3, C4, Cz, CP1, CP2). For each subject, the available trials (min 120, max 320) were included. From each trial, 4 seconds of MI was selected for model training. Five models were selected for zero-shot learning; an SVM trained with ERD/ERS patterns (used as the baseline) and 4 DL models namely, EEGSimpleConv [7], EEGNet, Deep and Shallow ConvNets [8] trained with raw EEG data. The training pipeline consisted of leave-one-subject-out cross-validation (LOSO-CV), where models were trained on all subjects except one, and then tested on the left-out subject. The obtained accuracies per model are presented in Figure 1.

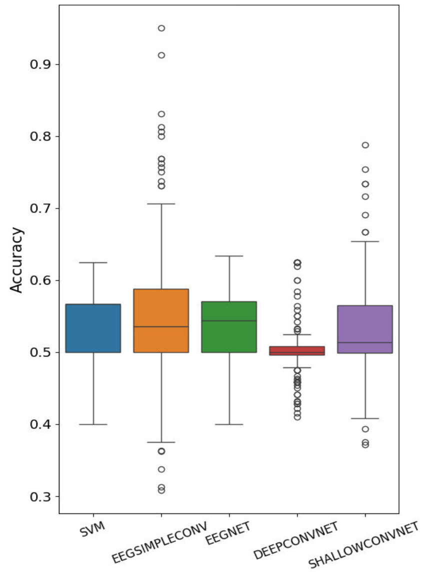

Figure 1: Comparison of model accuracies.

Conclusion: While for some subjects, EEGSimpleConv and Shallow CovNet models achieved noticeably better performance compared to the baseline, the overall results show that calibration-free MI BCIs remain a challenging task due to the high inter-subject variability of MI patterns. Future research could explore the benefits of one-shot or few-shot learning, allowing pre-trained models to adapt to new users with minimal data.

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