Neurodesign competition - ICRA 2024: EEG movement detection for robotic arm control

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***Abstract*—This research introduces a novel approach to the construction of an online BCI dedicated to the classification of motor execution, which importantly considers both active movements and essential resting phases to determine when a person is inactive. Then, it explore the best Deep Learning architecture suitable for motor execution classification of EEG signals. This architecture will be useful for control an external robotic arm for people with severe motor disabilities.**

I. Introduction

This research investigates the use of active brain-computer interfaces (BCIs) for managing devices like robotic arms via human neurophysiological signals. Within the realm of BCI, recognizing movements is vital for operating external devices such as robotic arms, assisting people with disabilities, or enabling remote activities in dangerous settings. The study presents a new method for developing an online BCI that focuses on classifying motor execution, taking into account both active movements and crucial resting periods to identify when an individual is not active. This initial study aims to identify the most effective Deep Learning (DL) architecture for classifying motor execution (ME), using data from two public EEG datasets focused on ME. This is depicted in Fig. 1. It includes a comparison of three distinct DL architectures, each trained from the ground up, with the datasets processed uniformly to ensure comparability. This approach ensures that the comparison is not skewed by biases from feature cleaning, extraction, or selection processes. Several studies have explored decoding ME tasks, primarily for applications in telerehabilitation and controlling robotic arms for individuals unable to use hand-based sensors.

II. Materials and methods

The public dataset [1] used are the following: (1) PhysioNet [2] and (2) Upper Limb Graz Dataset [3] for ME and the three DL architectures used are: (1) EEGnetv4 [4], (2) Deep4Net [5] and (3) EEGITnet [6]. These networks were chosen because they were already implemented in the Braindecode library and were suitable for these types of applications and data. Moreover, the Common Spatial Pattern (CSP) algorithm are evaluated to improve the classification. For each participant in the two datasets used, the same preprocessing pipeline was applied. Following some general rules about EEG preprocessing, we applied the following pipeline to preprocess the data using EEGLAB. A simple diagram of the preprocessing pipeline in the first part of Fig. 2 is shown. In this study, the categories considered from the Physionet and Upper Limb datasets included “open and close left or right fist”, “rest”, “hand close”, “hand open”, and “rest”, respectively. For the Physionet dataset, only right-hand movement signals were selected, maintaining heterogeneity between the datasets as the Upper Limb dataset involves right-handed participants. The training was divided into two categories: “rest” and “open/close” for the right hand. Similarly, for the Upper Limb dataset, training involved the “rest” and “hand open/close” categories. The “open/close” category was formed by merging the “hand close” and “hand open” categories from the dataset to address the differences between the two datasets.

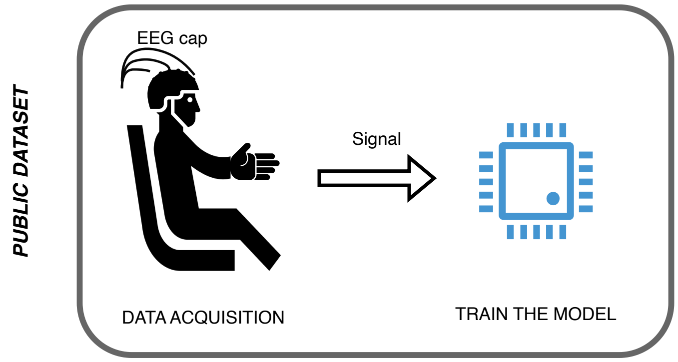

Figure 1. The purpose of this work.

III. Results

For evaluating the model, Accuracy, Precision, Recall, and F1 metrics were used. They are based on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). EEGNET yielded the most advantageous results without needing the CSP transformation for any dataset. The results demonstrate that the Upper Limb dataset, when using the same DL model with CSP transformation, performs better than the Physionet dataset. It implies that the movements labeled as “open” and “close” are significantly correlated and distinctly different from the “rest” state. This distinction also explains EEGnet’s effective discrimination between the “open/close” and “rest” categories in the Physionet dataset. The results for all trained models are shown in Tab. I

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Parts of this work is already submitted to one other conference.

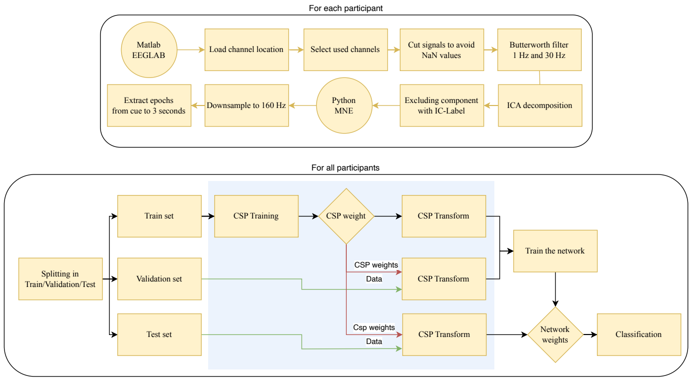

Figure 2. In the upper part, the pipeline applied to clean the signals is shown performed for each participant. The training and test phases are shown in the lower part after merging all samples in one set. The processes in the blue box are skipped if the CSP transformation is not applied.

Table I
PREDICTION METRICS TABLE FOR ALL NETWORKS USED IN *Physionet* AND *Upper Limb* DATASET WITHOUT CSP. IN BOLD, THE BEST ACCURACY FOR EACH DATASET AND MODEL.

Dataset	Network	Class	Support	Precision	Recall	F1	Accuracy
Physionet	EEGnet	Rest	589	0.66	0.81	0.73	**0.70**
		Open/Close	593	0.76	0.58	0.66	
Upper Limb	EEGnet	Rest	237	0.80	0.76	0.78	**0.77**
		Open/Close	213	0.74	0.79	0.77	

IV. CONCLUSION

This study focused on assessing three deep learning (DL) models: (1) EEGnetv4, (2) Deep4Net, and (3) EEGITnet, for EEG signal classification under ME in real-time brain-computer interfaces (BCI). The networks were trained from scratch, utilizing identical datasets and hardware to enhance comparison accuracy and minimize preprocessing biases. The findings indicated that EEGnet, which does not employ the CSP in feature extraction and processes raw EEG data, emerged as the most effective classifier for both datasets. Future work should include an evaluation of the classification with EEGNet in the real-time domain and apply the same conceptualization in the Transformer architecture to find the best model to apply our method in a real-time BCI to control robotic hands for rehabilitation. Furthermore, integrating the Virtual Glove system [7] along with its kinematic data could significantly enhance the effectiveness of the system's information gathered through EEG, thereby aiding in more accurate decoding, as illustrated in Fig. 3.

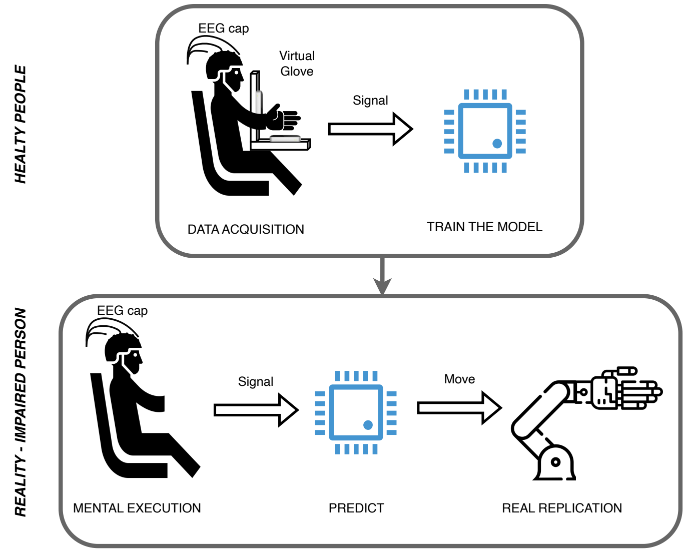

Figure 3. A simple scheme of the scenario composed by Virtual Glove and EEG system device.

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