

# Classification and Analysis of EEG Signals for Brain-Computer Interface



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This work presents an approach how a small data set of EEG-MI data can be used to train a Deep Learning model for classification of motor imagery of left and right arm movements for stroke rehabilitation.

### Introduction

### Stroke Rehabilitation - Why are BCI systems relevant?

Stroke is one of the main causes of long-term disability like motor impairments or limb paralysis [1]. Imagining a movement, called Motor Imagery (MI), activates the same area in the brain (motor cortex) as when the movement is actually performed. Brain-Computer Interface (BCI) is an effective method for motor neurorehabilitation by translating EEG-MI brain signals into motor intentions that can be used to control robotic systems to perform the passive movement [2].

#### Challenges

EEG signal characteristics:

- Low signal-to-noise ratio (SNR)
- Many artefacts (blinking, interference,...)
- Large variability in signal between different subjects/trials

#### **Current Research**

Deep Learning (DL) methods attracted attention by combining feature extraction and classification in one model, leading to superior performances [3] → requires a large amount of data

### **Research Goal**

Evaluate methods for training a DL classifier while overcoming the challenges of limited data and variety in EEG-MI data for different subjects

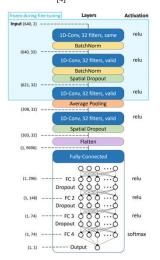
#### Focus of Channel this Work **Training Phase** Application Predict Class Train Classifier Trainingset Pre-processing Predict Class Validate Trials left right left Compare to Ground Truth Class Signal Aquisition Exoskeleton

Subject

### **Experimental Setup**

### Datasets:

- Own recordings (11 subjects, 125 Hz, 16 ch) → total: 480 trials per class
- Open-Source PhysioNet [5] (105 subjects, 160 Hz, 64 ch) → total: 2205 trials per class
- Network Architecture



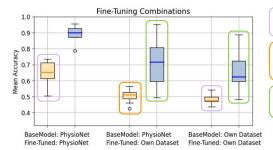
#### Approach:

1. Adapting PhysioNet to our own recording settings (resampling, channel selection)

2. Train base-model PhysioNet Fine-tune on individual subjects

### Results

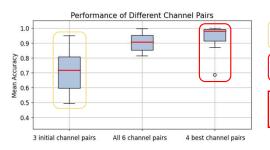
Subject-independent evaluation of the base-model without fine-tuning Subject-specific evaluation of the adapted models after fine-tuning



Size of dataset is crucial when classifying unseen subjects

Knowledge of PhysioNet model can't be directly transferred on new data from our dataset

Better results with PhysioNet base-model than training only with own data



High variance with 3 initial channel pairs (bad connectivity, noise)

Choosing 4 channel pairs with the most robust results

→ 98% accuracy after fine-tuning (averaged over all 11 target subjects)

## Summary

- Individualized BCI-system with accurate DL classification, providing a simple and practical solution with only few EEG channels required
- New insights into fine-tuning PhysioNet with subjects from different dataset
- Future Work: Data variety within a person → record & evaluate multiple sessions
  - Promising architecture: CNNs and Transformer models combined

### References

Assentini Salinalis Set al. Liestyre and so sixole lisk. a ferrew, 2009.

Mahmad Ahmed Khan et al. "Review on motor imagery based bot systems for upper limb post-stroke neurorehabilitation: From designing to application," 2020. exander Craik et al. 'Deep learning for electroencephalogram (eeg) classification tasks: a review," 2019.

Mattoli, et al. "At donn for high accuracy classification and transfer learning in motor imagery eeg-based brain-computer interface," 2022.

L. Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," 2000.