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Comparison of Models for EEG-based Cross-Subject Movement Prediction

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Abstract

Brain-computer interfaces for robotic-assisted rehabilitation based on EEG recordings can play an important role in the rehabilitation of stroke patients. To effectively classify movement intentions from EEG signals, machine learning models are needed that can work with noisy and heterogeneous data. This work investigates four neural networks, namely the MLP, TKAN, EEGNet, and SincEEGNet, in their ability to predict movement intentions in intra- and cross-subject classification. Additionally, the amount of calibration data for adapting the pre-trained models of the cross-subject task to data of the target subject was explored. The model performance for intra-subject classification is highest with the EEGNet, however, SincEEGNet performs best in cross-subject classification. Calibrating the pre-trained models results in a performance gain with the overall highest accuracy of 88.1 % with SincEEGNet. Those results motivate to apply such models for EEG classification across subjects to reduce calibration times.

I. Introduction

Stroke is a worldwide cause of physical disability, affecting more than 12 million people around the world each year [1]. To increase their independence after a stroke, patients often participate in physical therapy where exoskeletons can be a supportive tool to enhance the process and outcome [2]. Such exoskeletons can be controlled with a brain-computer interface (BCI) by measuring the electrical activity of the brain as EEG signals and extracting human intentions from them. Indications for a planned movement can be found by detecting movement-related cortical potentials (MRCPs) from the human EEG [3]. Since EEG signals show high variability across different subjects, it is challenging to apply classification models on subjects without training the model on data from that subject. Alternatively, training data could be recorded from the target subject, having the disadvantage of needing long data recording and model training sessions before the classification model is applicable. Especially in stroke rehabilitation, long and tiresome data recording sessions must be avoided to provide efficient therapy while reducing preparation times to a minimum. One possible solution to this dilemma is to apply transfer learning, which offers approaches to improve cross-subject classification. An overview of approaches can be found in this review [4].

Machine learning techniques, particularly neural networks, have become increasingly popular in the field of EEG classification due to their ability to learn complex patterns from high-dimensional and noisy data such as EEG in an end-to-end architecture [5]. A popular model is EEGNet [6], a Convolutional Neural Network built to better generalize across different prediction tasks with small amounts of data. The model consists of layers for temporal and spatial feature extraction inspired by the filter-bank common spatial pattern (a common method for feature extraction in signal processing) [7] as well as separable convolutions. To further enhance EEGNet, an alternative first convolutional layer inspired by SincNet [8] was explored [9], allowing adaptable learning of band-pass filters, implemented by parametrized sinc functions. The resulting SincEEGNet is beneficial by having fewer adaptable parameters and by creating better interpretable temporal filters. Other approaches include Multilayer Perceptrons (MLPs). As an adaptation to MLPs, the Kolmogorov-Arnold Network (KAN) [10] was proposed, replacing the fixed activation functions of MLPs with learnable parametrized functions, and time-aware components were included by incorporating Long Short-Term Memory (LSTM) cells into the KAN structure [11], named temporal KAN (TKAN).

In this study, four different models were explored—MLP, EEGNet, TKAN, and SincEEGNet—regarding their classification capability to predict movement onsets from EEG data within and between subjects. Since recording calibration data from stroke patients takes time that could otherwise be spent on rehabilitation exercises, minimizing the amount of needed data would be beneficial. Therefore, the effect of different amounts of target data for calibrating the models was explored. The experiments in this study were conducted on data from healthy subjects, laying an important foundation for future studies on data of stroke patients.

The remainder of this paper is organized as follows: In Section II, the dataset, EEG pre-processing, model architectures, and classification tasks are introduced. The results are then summarized and discussed in Section III, followed by the conclusion of this work in Section IV.

II. Materials and Methods

The following methods were applied to predict movement onsets of self-initiated movements from recorded EEG signals, distinguishing between the two classes *movement intention* and *resting*.

II.I. Dataset

The utilized EEG dataset [12] includes data from eight healthy subjects performing different tasks. In this work, data of the unilateral reaching task was employed, where participants had to reach for a button with one arm and press it with their thumb by self-initiated movements. Each subject performed three measurement runs with 40 repetitions of the task, resulting in 120 trials in total. Each movement was preceded by at least 5 s of rest.

II.II. Train-Test Splits

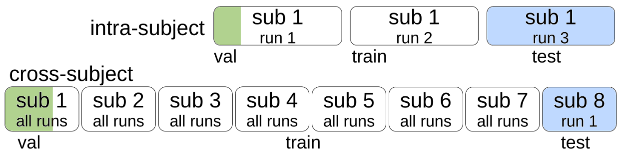

Figure 1: Exemplary train-test splits for intra-and cross-subject classification. For both settings, three models per subject were built, resulting in 24 trained models. For each model, one of three runs per subject was used for testing. The validation data (val) makes up 10 % of the training and validation data.

The data was split into train, test and validation data as displayed in Figure 1. Leave-one-run-out cross-validation was performed for the intra- and cross-subject scenario, however, for cross-subject classification, the data of the target subject was excluded from training. For calibrating the models, they are pre-trained equally to the cross-subject task and then calibrated similarly to the intra-subject scenario on different amounts of target data. Of the two runs to be used for calibration and validation, 10 % was left out for validation and 90 %, 70 %, 50 %, 30 %, and 10 % were each used once for calibration.

II.III. Pre-Processing

Of the 64 EEG channels, 32 were manually selected, covering relevant motor areas. Afterward, the EEG data is split into overlapping windows with a step size of 0.05 s and a length of 1 s. Since the brain potential of movement intention can be detected by MRCPs shortly before movement onset (at time-point 0 s) [3], the windows [-3.5, -2.5] s, [-3.2, -2.2] s, [-2.9, -1.9] s, [-2.7, -1.7] s, [-2.5, -1.5] s, and [-2.3, -1.3] s are selected as samples for the *resting* class and the windows [-1.1, -0.1] s, [-1.08, -0.08] s, [-1.06, -0.06] s, [-1.04, -0.04] s, [-1.02, -0.02] s, and [-1, 0] s as instances for *movement intention*. The pre-processing varies for each architecture because the networks process the data differently. The EEGNet and SincEEGNet are designed to extract spectral and spatial features. Hence, they are trained on windowed data and for EEGNet a Butterworth band-pass filter of order two is applied with the cutoff-frequencies 0.3 Hz and 40 Hz. For MLP and TKAN, the signals were filtered equally apart from differing cutoff frequencies of 0.3 Hz and 5 Hz. Time-domain features were extracted from the last 100 ms of the windows. Since TKAN processing is LSTM-like, it receives all 42 values from this interval. For MLP, 15 exponentially spaced time-point features are extracted. Additionally, frequency band powers are obtained channel-wise for each window from the original unfiltered signals to be combined with the time-domain features for MLP. The five selected frequency bands are the delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (>30 Hz) band.

10.18416/SCP.2025.1947

II.IV. Classification Models

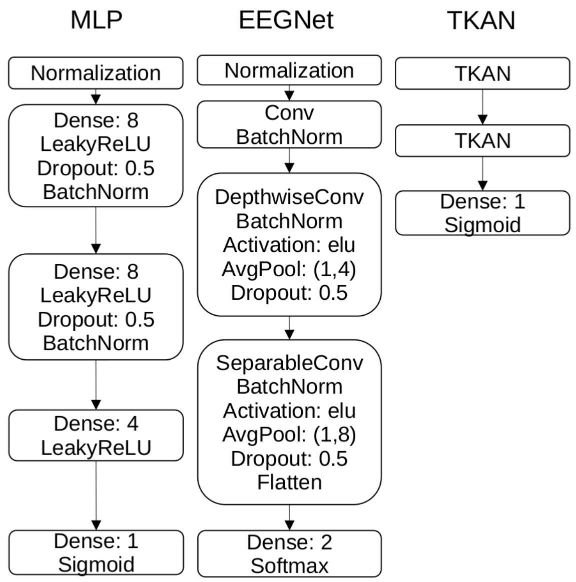

Figure 2: Architectures of MLP, EEGNet, and TKAN model. Legend of Layers: Dense: *output dimension*, Activation: *activation type*, AvgPool: *kernel shape*, Dropout: *dropout rate*.

Visualizations of the EEGNet, MLP, and TKAN model can be seen in Figure 2. Implementation details and parameter settings of EEGNet can be found the respective publication [6]. For the current work, an additional normalization layer was applied before the first convolution, and the kernel length of the first convolution was adapted to 50 samples due to a different EEG sampling rate and as a trade-off between long computation time and performance. SincEEGNet is built similarly to EEGNet but with a sinc convolution as the first convolution block [9]. Different to classical convolutions, it only adapts two parameters, the low cutoff frequency and the bandwidth of sinc-functions, describing band-pass filters. Therefore, only parameters of a specified function for signal filtering are learned instead of a whole convolutional kernel. Additionally, the kernel length of the sinc-functions was adapted to 63 samples, and it proved beneficial to set the number of filters for the first three convolution blocks to 16, 2, and 32, respectively, whereas EEGNet works better with 8, 2, and 16 filters. The implementation of the sinc convolution is based on the work of [8] (implementation used from `https://github.com/grausof/keras-sincnet/tree/master`).

The hyperparameters for training the MLP and TKAN are set similar to EEGNet as far as applicable. A minmax normalization was applied for TKAN to fit the signals to the interval [0,1], since the architecture itself does not include a normalization layer. Instead, the minmax normalization was selected after hyperparameter optimization. The output dimensions of the two TKAN layers are set to 100. A TKAN layer has a similar structure to an LSTM layer, whereby each input is processed by a linear KAN component which works with parametrized B-spline functions to learn the activation of the layers. The implementation of TKAN is based on [11].

III. Results and Discussion

The intra- and cross-subject classification performances are presented in Table 1. The accuracy score was chosen to evaluate the model performances. For intra-subject classification, EEGNet achieves the best performance, followed by SincEEGNet, then MLP and lastly TKAN being only slightly better than chance level. When classifying EEG signals cross-subject, SincEEGNet results in the highest accuracy, followed by EEGNet, then MLP and lastly TKAN, again with a low accuracy. Intra-subject classification generally leads to a better performance than training on data of non-target subjects. The distance between the scores of the two classification settings is most likely due to individual differences in the EEG data, resulting from varying anatomy and physiology. Even though cross-subject classification results in lower scores, it allows applying trained models without needing target data for model training, effectively reducing the preparation time. EEGNets superior performance in the intra-subject scenario could be caused by its effective way of learning spatial and spectral filters. However, it is outperformed by SincEEGNet when predicting cross-subject without calibration. This indicates superior generalization characteristics of sinc-functions compared to standard convolution kernels. The TKAN architecture seems to lack the capability of properly detecting movement intention from EEG data, indicating that convolution-based processing may work better for EEG classification than sequential processing. Presumably, the LSTM-like structure of TKAN hinders the proper extraction of features for EEG classification tasks. However, a more in-depth analysis of the architecture would be required to support this finding.

The results of testing different amounts of calibration data are displayed in Table 1. An overall increase in accuracy can be observed with more calibration data, as can be expected. Generally, SincEEGNet shows the highest performance, with exceptions at 10 and 30 % where it is outperformed by EEGNet. With 90 % of calibration data, SincEEGNet achieves the overall highest accuracy of 88.1 %. The settings when calibrating with an amount of 90 % equal the intra-subject classification with the distinction of training on pre-trained models instead of untrained ones. For the MLP and EEGNet, no performance increase can be observed when pre-training the models before applying the target data. However, for TKAN and SincEEGNet, considerably higher accuracy scores are reached. For all models, a trend towards superior results can be observed when using more target

10.18416/SCP.2025.1947

Table 1: Model performances, measured in % accuracy (median and standard deviation) of the 24 models for intra- and cross-subject classification. For the cross-subject setting, the results from different amounts of target data are displayed.

Model	intra-subject	cross-subject 0 %	10 %	30 %	50 %	70 %	90 %
MLP	81.5 ±8.8	67.0 ±8.0	71.7 ±8.4	78.3 ±9.6	79.6 ±9.6	80.4 ±9.6	81.0 ±8.5
TKAN	64.2 ±6.3	62.4 ±6.0	62.7 ±6.0	64.6 ±6.6	66.5 ±6.7	66.4 ±6.1	66.6 ±6.3
EEGNet	**86.8 ±7.7**	73.0 ±10.6	**80.1 ±7.9**	**82.4 ±9.0**	82.9 ±9.6	86.5 ±8.6	86.2 ±8.0
SincEEGNet	83.0 ±6.8	**78.5 ±10.1**	75.8 ±7.6	80.3 ±7.7	**83.8 ±7.3**	**87.0 ±6.5**	**88.1 ±5.3**

data. Already with only 10 % of training data from the target, the score of EEGNet is increased by about 7 %, involving only a fifth of the complete calibration data. This correlates with a considerable reduction of required data recording time. However, even with complete avoidance of calibration and therefore data recording and model adaptation, the pre-trained SincEEGNet is directly applicable to a new subject with a median performance of 78.5 %.

IV. Conclusion

Four machine learning models were tested for the prediction of movement intention from EEG data. Intra- and cross-subject classification settings were applied, and the calibration of pre-trained models was explored. Overall, the EEGNet and SincEEGNet provide the best results in all tasks, indicating that convolution-based processing is preferable for EEG classification. More precisely, EEGNet results in the best performance for intra-subject classification, whereas SincEEGNet is the best in most cross-subject tasks. Even without calibration, SincEEGNet provides a valuable tool for cross-subject classification of EEG data. Especially when working with stroke-affected patients, the usage of efficient cross-subject classifiers would save precious time. Avoiding data recording sessions for model training would allow an immediate start with the indispensable rehabilitation exercises.

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Author's statement

Conflict of interest: Authors state no conflict of interest. The study [12] with the used dataset was approved by the ethics committee of the University of Bielefeld according to the guidelines of the German Society for Psychology and the Professional Association of German Psychologists.

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