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Development of Brain-Computer Interfaces by using Deep Learning Technologies

Theses of the PhD Dissertation

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1. Introduction

Brain-Computer Interfaces (BCIs) represent a rapidly evolving interdisciplinary research field that holds significant potential for developing systems that allow individuals to communicate, control, and interact with technology using only their brain activity, bypassing the need for motor control or other physical input devices. This technology has the potential to greatly improve the quality of life for individuals with disabilities such as impaired vision, hearing, movement, or communication, and could be particularly beneficial for those with Locked In Syndrome, a condition resulting from illness or injury that prevents individuals from using their neuromuscular channels to move their body, despite being in a cognitively intact state.

However, despite the great potential of BCIs, there are still significant challenges to overcome. One of the main challenges is to improve the accuracy and reliability of the BCI systems, particularly in real-world scenarios with varying environments and user states. Additionally, BCIs based on communication systems may be significantly slower than traditional communication channels, but restoring the ability to communicate via these systems can have a profound impact on quality of life, irrespective of communication speed.

This dissertation aims to present a BCI System, which can be used by subjects with tetraplegia, to control a video game. In addition, it aims to investigate and compare different classification methods to further advance the field of BCI technology. The study involves the development of signal processing algorithms and machine learning models.

2. Methods

I designed a BCI system for the Cybathlon [1] 2020 competition. As a first step of my system the Fully Automated Statistical Thresholding algorithm (FASTER), published by Nolan et al. [2], was employed for the purpose of artifact rejection. The Python implementation of the algorithm was derived from the work of Vliet [3]. After the removal of artifacts, such as eye blinks, eye movements, and facial expressions, the feature extraction signal processing step was followed in the frequency domain. The absolute value of the complex Fast Fourier Transformation [4] (FFTabs) was calculated for 1-second-long EEG windows as a feature. From this FFTabs data, I calculated multiple averages from 2 Hz wide, non-overlapping frequency bins (referred to as the range40 method). For signal classification multiple SVMs [5] were trained, each receiving only one frequency bin. The final decision was determined by taking the maximum vote of all SVM units. We refer to this ensemble classifier as Voting SVM. To the best of my knowledge, Voting SVM combined with my range40 method based on FFTabs has not been previously investigated and compared statistically on MI datasets or used to control a computer game as part of a BCI application.

To conduct the statistical comparison analyses I utilized the EEG Motor Movement/Imagery Dataset, accessible via PhysioNet (Physionet) [6], which represents one of the biggest repositories of MI task-based data, acquired using the BCI2000 system [7]. The Physionet dataset contains EEG recordings from 109 subjects, obtained using a 64-channel 10-20 EEG system.

In parallel I designed a so-called Two Choice Paradigm to simplify the execution of the Physionet task as two subjects with tetraplegia (referred to as pilots), having C5 or higher spinal cord lesions, reported difficulty in performing four-limb imagination during some experimental trials.

Prior to each experiment, pilots were instructed to avoid blinking, swallowing, clenching, or making any movements or facial expressions unrelated to the task during task periods. They were asked to repeatedly perform only the required MI tasks while the fixation cross was displayed on the screen. During rest periods, the paradigm control program presented the next task on the screen in written form. During these periods, pilots were permitted to blink, swallow, and make any necessary movements to prepare for the next task. Pilots were instructed to perform motor tasks for 4 seconds and rest tasks for 3 seconds.

The Two Choice Paradigm, illustrated in Figure 2.1, began with a one-minute period during which subjects were required to open their eyes and focus on the cross displayed on the screen. This was followed by a one-minute period during which subjects were instructed to close their eyes. In both cases, subjects were required to sit as calmly as possible, both physically and mentally, without engaging in any thoughts. This introductory ses-

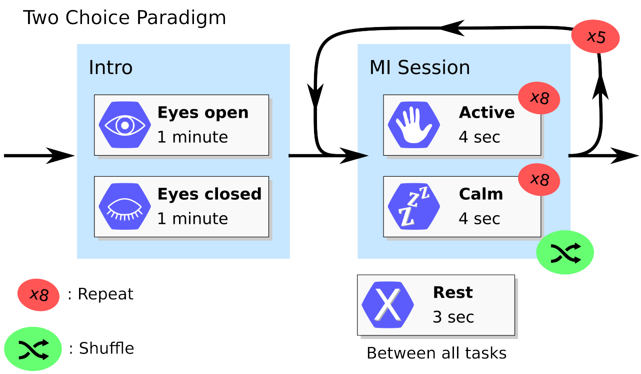

Figure 2.1: **Two Choice Paradigm** – It started with a one-minute open-eye and a one-minute closed-eye task, which served as a baseline and aimed to get the pilots' full attention, preparing them for the MI sessions. Under one MI session, 8 active and 8 calm mental tasks were required from the pilots. The order of the tasks was randomized. The MI session was repeated 5 times under one experiment.

sion served as a baseline for the experiments and aimed to capture the pilots' full attention in preparation for the MI sessions.

Following the introductory session, the experiment consisted of 5 MI sessions. Each MI task was presented 8 times per session in a randomized order. After each completed session, subjects were allowed to take a self-defined break without leaving the experimental setup.

For the active MI tasks, pilots were permitted to select and combine any hand and foot motor movements. However, these movements had to be decided upon and fixed prior to the start of the experiment. Pilot B selected Left Hand movements for the active task, while pilot C selected Both Feet movements. The calm task required subjects to sit with their eyes open and refrain from making any movements or engaging in any thoughts or other potential sources of artifacts.

I compared my range40 feature extraction method, combined with my Voting SVM classifier with state-of-the-art EEGNet [8] algorithm to provide a broader perspective on my findings within the BCI community. To receive reliable classification accuracy results I conducted 5-fold cross-validations for each subject in each database and these cross-validated results were averaged. Accroding to the Wilcoxon statistical tests, my method significantly outperformed EEGNet on the Physionet dataset. Repeating these tests on my Two Choice Paradigm dataset yielded less significant results. (Figure 3.1)

After conducting these comparisons, I developed a real-time BCI system that includes a unique control protocol called the Toggle Switch. This algorithm allowed the pilots to control the BrainDriver computer game using only two mental commands instead of four. This approach was inspired by Perdikis et al. [9], who developed an algorithm that classified two MI signals using a thresholding technique. When a third active game control command was required, their pilot initiated two different active MI tasks within a given time window. In contrast, my method cycles through active control commands one after another when the pilots initiate an active MI task, allowing for easy extension with additional commands.

Using the developed BCI system, I conducted real-time BCI experiments with the pilots using the BrainDriver game developed for the BCI discipline of the Cybathlon 2020 competition. During these gameplay sessions, pilots received immediate feedback from the computer about the correctness of their mental commands.

To further investigate the effect of different classifiers, used database and transfer learning I conducted other comparisions utilizing additional databases, namely BCI Competition IV 2a [25], Giga [26], and the TTK dataset [Au6]. From the EEGNet family presented in Table 2.1 I arbitrarily selected Shallow and Deep ConvNet [10] as predecessors of EEGNet, the EEGNet itself [8], the EEGNet Fusion [12], and the MI-EEGNet [16] from the EEGNet family. As best to my knowledge the effect of transfer learning on these selected neural networks has not been presented before.

For within-subject classification, 5-fold cross-validation was performed on a subject-wise basis, with the database split at the epoch level to ensure that windows originating from the same epoch were used exclusively in either the training or testing set. Approximately 10% of the training data was used as a validation set, with the split performed at the epoch level.

In case of transfer learning test subjects were selected as distinct groups of 10, with the remaining subjects designated as pretrain subjects and used to establish the initial optimal weights for the neural networks. A validation set was separated from the pretrain data for use with my modified early stopping and model-saving strategy. Upon convergence of the pretraining phase, either through reaching the maximum number of training epochs or through early stopping, the best network weights were stored. For each test subject, 5-fold within-subject cross-validation was

Table 2.1: EEGNet family and the used MI EEG databases

Nerual Network	**Used MI EEG database**
Shallow ConvNet [10]	BCI Competition IV dataset 2a, BCI Competition IV dataset 2b
Deep ConvNet [10]	BCI Competition IV dataset 2a, BCI Competition IV dataset 2b
EEGNet [8]	BCI Competition IV dataset 2a
S-EEGNet [11]	BCI Competition IV dataset 2a
EEGNet Fusion [12]	PhysioNet
TCNet Fusion [13]	BCI Competition IV dataset 2a, High Gamma Dataset
Sinc-EEGNet [14]	BCI Competition IV dataset 2a
TSGL-EEGNet [15]	BCI Competition IV dataset 2a, BCI Competition III dataset IIIa
MI-EEGNet [16]	BCI Competition IV dataset 2a, High Gamma Dataset
Channel-Mixing-ConvNet [17]	BCI Competition IV dataset 2a, High Gamma Dataset
AMSI-EEGNet [18]	BCI Competition IV dataset 2a
ATCNet [19]	BCI Competition IV dataset 2a
FFCL [20]	BCI Competition IV dataset 2a
MTFB-CNN [21]	BCI Competition IV dataset 2a, BCI Competition IV dataset 2b, High Gamma Dataset
TCACNet [22]	BCI Competition IV dataset 2a, High Gamma Dataset
FB-EEGNet [23]	No MI databases are utilized
CRGNet [24]	BCI Competition IV dataset 2a

performed as described in case or within-subject classification. Prior to each cross-validation step, the saved model weights were loaded and the selected training set for the test subject was used as fine-tuning data for the neural networks. During fine-tuning, validation sets were again employed in conjunction with early stopping and model-saving strategies.

3. New Scientific Results

3.1. Thesis Points

Thesis group I – Development and Testing of a Real-Time Working BCI System
Corresponding publication: [J1]

Thesis I: *I developed a novel feature extraction and classification pipeline, utilizing Fast Fourier Transformation and Support Vector Machine algorithms for real-time processing and classification of motor imagery EEG signals for Brain-Computer Interface purposes.*

Thesis Ia: *I compared my implemented range40 feature extraction method, combined with my Voting SVM classifier, to the state-of-the-art EEGNet using the Physionet dataset and found that it significantly outperformed it according to the Wilcoxon statistical test.*

The range40 feature extraction method calculates the absolute of the Fast Fourier Transformation from a given EEG window and averages the values in 2 Hz wide frequency ranges (2-4 Hz,

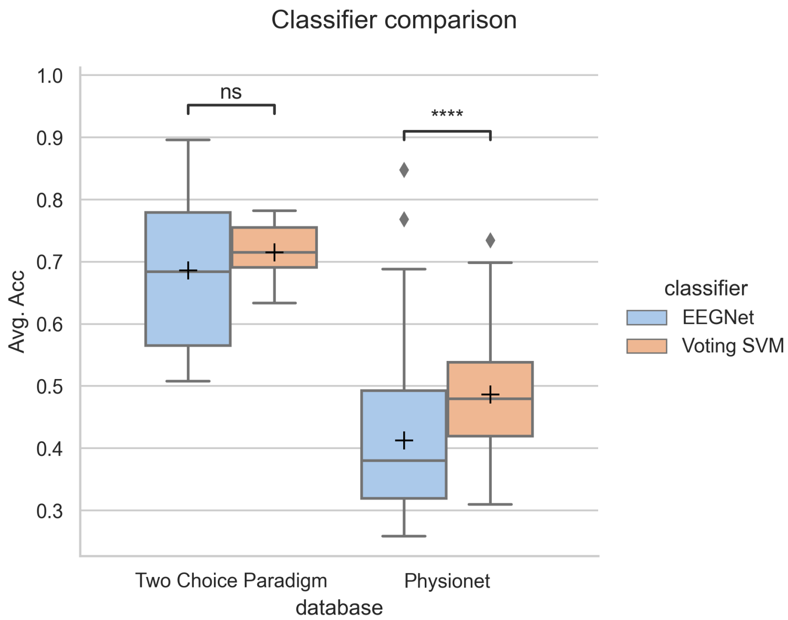

Figure 3.1: 5-fold cross-validated accuracy level comparison of range40 + Voting SVM with EEGNet. The p-value annotation legend is the following: non-significant (ns): $5 \times 10^{-2} < p$; ****: $p \leq 10^{-4}$. The mean of the data is presented with the '+' symbol. The horizontal line in the box represents the median of the data. The box shows the quartiles of the dataset while the whiskers extend to show the rest of the distribution, except for individual points that are determined to be outliers.

4-6 Hz, . . . , 38-40 Hz) for each EEG channel. The 19 $\times$ *channel number* generated features are used to train 19 RBF kernelled SVMs. Each SVM learned distinct characteristics of brain signals concerning the 2 Hz wide frequency ranges. Each SVM made its own decision, and the final decision was generated as the max vote of the SVM units. This ensemble SVM classifier is called as Voting SVM. The complete signal processing pipeline is presented in Figure 3.2

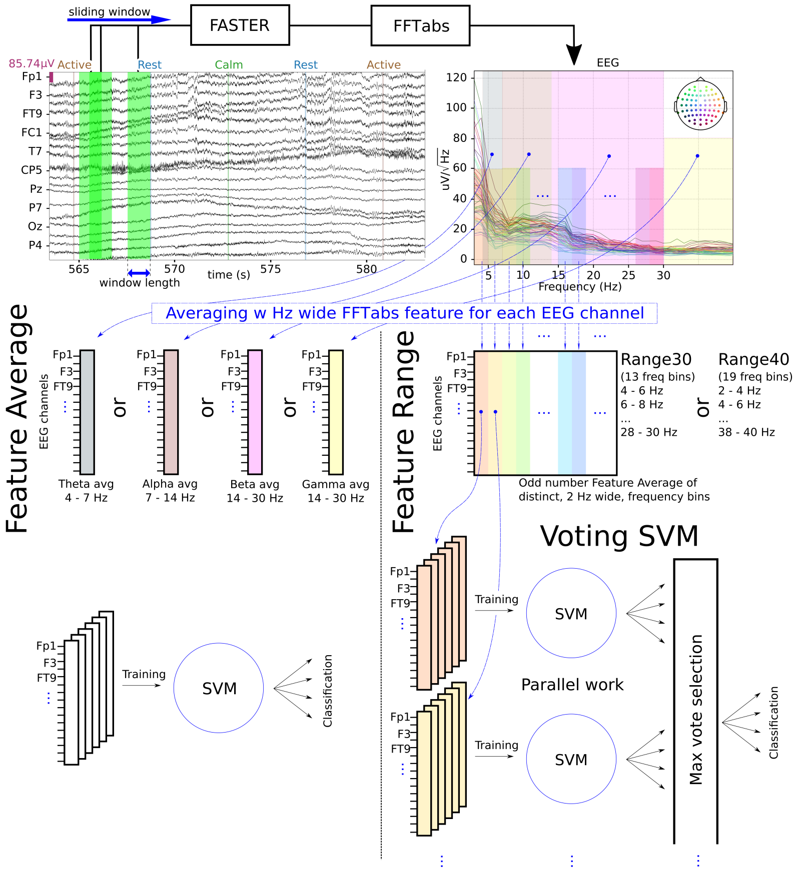

Figure 3.2: BCI pipeline

Thesis Ib: *I developed a unique control protocol, called the Toggle Switch, to extend the 2-class output of my BCI System to control a video game requiring 4 commands. My method circulates active control commands one after the other during active motor imagery till the subject selects the required command by initiating the calm mental state. This approach can easily be extended to have more than four control commands.*

The BrainDriver program required four input commands from the user (three active commands plus the absence of any commands), but the Two Choice Paradigm was designed to elicit only two. To bridge this gap, a unique mechanism called the Toggle Switch was introduced, inspired by the Brain Tweaker team [9]. When an active MI task was performed by the user, game control commands were cycled through in sequence at a predefined frequency. When the desired control command was reached, the user had to initiate a calm mental task to maintain that command and send no further commands to the game. This mechanism is illustrated in Figure 3.3.

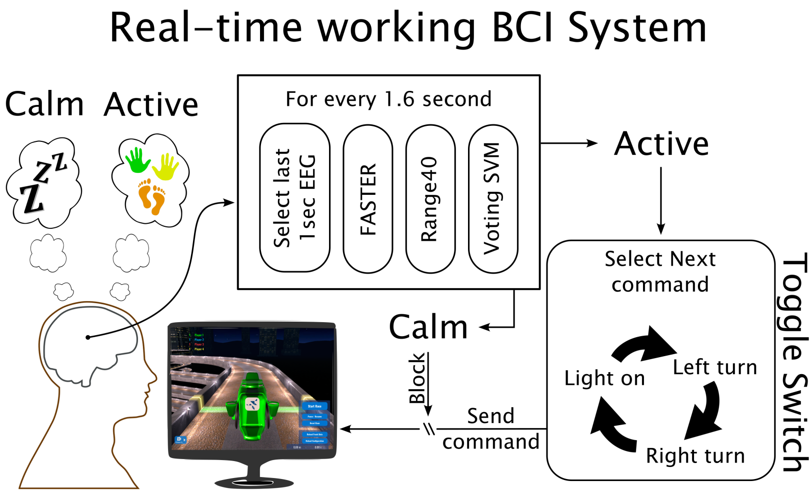

Figure 3.3: Components of the real-time BCI System and the Toggle Switch control mechanism.

Thesis Ic: *With the aid of my complete BCI System, I successfully conducted a total of 59 video game control experiments, involving two pilots diagnosed with C5 or higher spinal cord lesions. The results, in terms of online gameplay, were comparable to those of other teams participating in Cybathlon 2020.*

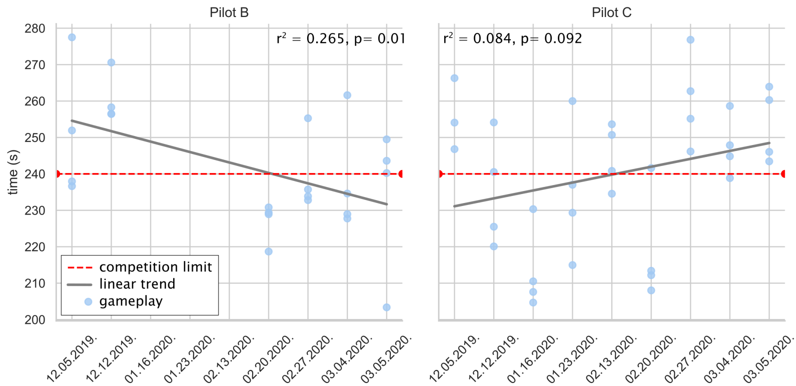

Figure 3.4: Gameplay performance of pilots per experimental day. 240 seconds were marked with a red line, which is the time limit defined by the organizers. The gray lines present the learning curves.

The pilots completed the game with varying runtimes between 200 and 280 seconds, as shown in Figure 3.4. Pilot B showed a significant learning curve; however, due to pandemic-related restrictions, we were only able to conduct 9 experimental days resulting in a total of 59 gameplay trials for both pilots.

Thesis group II – Deep Comparisons of Neural Networks from the EEGNet Family
Corresponding publication: [J2]

Thesis II: *I selected and compared the classification and transfer learning capabilities of Shallow ConvNet, Deep ConvNet, EEGNet, EEGNet Fusion, and MI-EEGNet on artifact-rejected EEG data from four databases with varying numbers of subjects.*

Thesis IIa: *I showed that transfer learning on the selected neural networks can significantly improve classification accuracy, even after artifact rejection, compared to within-subject classification.*

Upon obtaining five-fold cross-validated accuracy levels for all combinations of the four databases, five neural networks, and two learning methods (within-subject and transfer learning), normality tests indicated a non-normal distribution of the data. Consequently, the Wilcoxon statistical test with Bonferroni correction was employed for significance analysis. The results are presented in Figures 3.5. Transfer learning was found to significantly improve performance across all databases except for BCI Competition IV 2a.

Thesis IIb: *I also demonstrated that significant comparison cannot be evaluated on databases with less than or equal to 10 subjects.*

Databases were ranked based on the number of significant differences observed between them. Table 3.1 presents the sum of significance ranges (corresponding to the number of stars in figures) and count of significant differences alongside the number

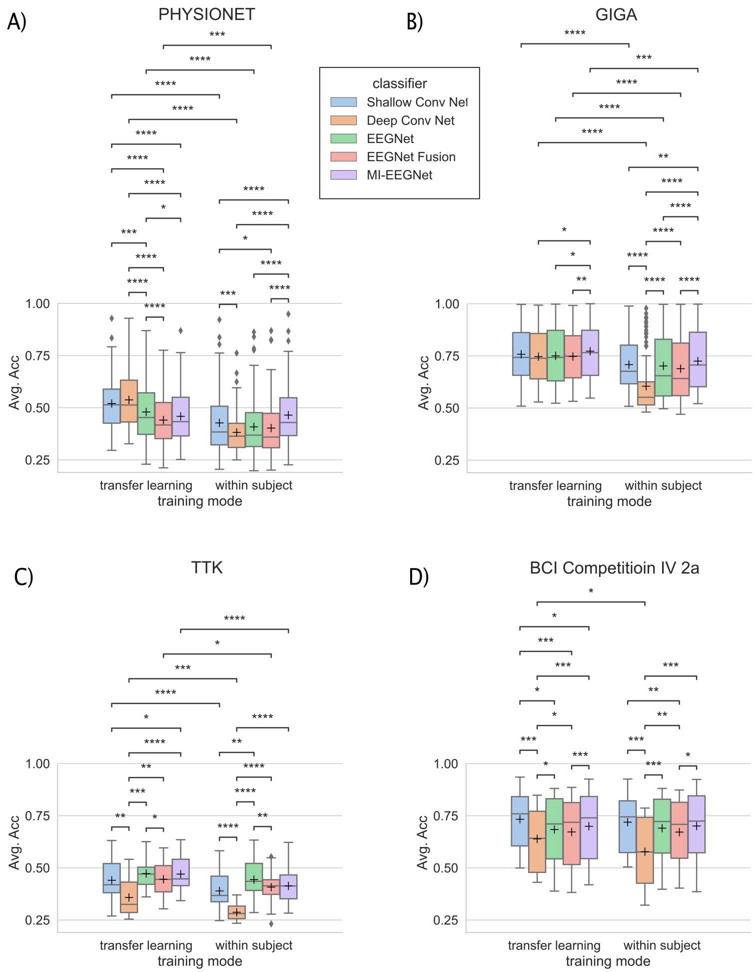

Figure 3.5: EEGNet family comparison on 4 databases handling the datasets in independent days configuration.
The p-value annotation legend is the following: *: $10^{-2} < p <= 5 \times 10^{-2}$; **: $10^{-3} < p <= 10^{-2}$; ***: $10^{-4} < p <= 10^{-3}$; ****: $p <= 10^{-4}$. The mean of the data is presented with the '+' symbol. The horizontal line in the box represents the median of the data. The box shows the quartiles of the dataset while the whiskers extend to show the rest of the distribution, except for individual points that are determined to be outliers.

of subjects in each database. The sum of significance ranges was found to be strongly correlated with the number of subjects in each database (r(3) = 0.7709), although this correlation was not statistically significant (p-value = 0.127014 > 0.05).

Table 3.1: Significance investigation.

	Significance Level		
Database	**Sum**	**Count**	**Subjects**
Physionet	63	18	105
Giga	49	15	108
TTK	45	16	25
BCI Comp IV 2a	31	15	18
BCI Comp IV 2a-merged subject data	0	0	9

Thesis IIc: *In order to compare the neural networks, I used two metrics, "Improvement from chance level" and "Improvement by transfer learning". These metrics indicated that Shallow ConvNet and Deep ConvNet outperformed more recently published networks from the EEGNet family and highlighted the importance of considering multiple factors when ranking the performance of neural networks beyond generally used accuracy differences between networks.*

Table 3.2: Ranking the performance of neural networks on all the databases concerning the independent days configuration.

	Classifier	Avg. Acc. Improvement from Chance Level	Rank
Within subject	Shallow ConvNet	0.2071	2
	Deep ConvNet	0.1249	5
	EEGNet	0.1997	3
	EEGNet Fusion	0.1871	4
	MI-EEGNet	0.2306	1
Transfer learning	Shallow ConvNet	0.2721	1
	Deep ConvNet	0.2598	2
	EEGNet	0.2521	4
	EEGNet Fusion	0.2312	5
	MI-EEGNet	0.2537	3

Table 3.3: Classification improvements by transfer learning on databases with independent day configuration.

Rank	Neural Networks	Physionet	Giga	TTK	BCI Comp IV 2a	Avg. Impr.
1	Deep ConvNet	0.1557	0.1418	0.0708	0.0614	0.1075
2	Shallow ConvNet	0.0928	0.0497	0.0509	0.0141	0.0519
3	EEGNet	0.0716	0.0487	0.0288	−0.0065	0.0357
4	EEGNet Fusion	0.0381	0.0586	0.0379	0.0007	0.0338
5	MI-EEGNet	−0.0058	0.0475	0.0564	−0.0015	0.0241

3.2. Potential Applications and Benefits

The BCI System was designed for a concrete application called the BCI discipline in the Cybathlon 2020 competition, where pilots with quadriplegia compete in a car-racing-like computer game by controlling their avatar using well-timed imagined mental commands recorded by EEG.

In addition, this work was prepared with the professional support of the Doctoral Student Scholarship Program of the Co-operative Doctoral Program (hungarian abbreviation: KDP) of the Ministry of Innovation and Technology financed from the National Research, Development and Innovation Fund. The so-called KDP grant aims to implement scientific research to industrial purposes. Therefore the gained knowledge was transferred to the domain of electromyographycal signal processing, where a small, portable, affordable EMG armband was used. The complete study is presented in [Au4] and [Au5].

I highlighted by the comparison of members of the EEGNet family, that it is vital for presenting new classification methods for EEG signal processing to use databases with large numbers of subjects, such as Physionet or Giga. I also highlighted the importance of considering multiple factors when ranking the performance of neural networks. Relying solely on accuracy differences between networks and using unfiltered datasets with small numbers of subjects may lead to inconclusive results. Ideally these findings could lead to a new comparison procedure when a new neural network is presented for EEG signal classification.

Publications related to the thesis

[J1] **Cs. Köllőd**, A. Adolf, G. Márton, M. Wahdow, W. Fadel, and I. Ulbert, "Closed loop BCI system for Cybathlon 2020", *Brain-Computer Interfaces*, vol. 10, no. 2, pp. 114–128, 2023. DOI: 10.1080/2326263X.2023.2254463.

[J2] **Cs. Köllőd**, A. Adolf, K. Iván, G. Márton, and I. Ulbert, "Deep Comparisons of Neural Networks from the EEGNet Family", *Electronics*, vol. 12, no. 12, p. 2743, 2023. DOI: 10.3390/electronics12122743.

Other publications of the author

[Au1] M. Wahdow, M. Alnaanah, W. Fadel, A. Adolf, **Cs. Kollod**, and I. Ulbert, "Multi frequency band fusion method for EEG signal classification", *Signal, Image and Video Processing*, 2022. DOI: 10.1007/s11760-022-02399-6.

[Au2] W. Fadel, **Cs. Kollod**, M. Wahdow, Y. Ibrahim, and I. Ulbert, "Multi-Class Classification of Motor Imagery EEG Signals Using Image-Based Deep Recurrent Convolutional Neural Network", in *2020 8th International Winter Conference on Brain-Computer Interface (BCI)*, 2020, pp. 1–4. DOI: 10.1109/BCI48061.2020.9061622.

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