UNIVERSITY OF TARTU
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# Development of EEG-Based BCI Application Using Machine Learning to Classify Motor Movement and Imagery

**Bachelor's Thesis (9 ECTS)**

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## Elektroentsefalograafial põhineva aju-arvuti liidese loomine kasutades masinõpet, et klassifitseerida motoorset liikumist ja kujutlust


**Lühikokkuvõte:**

Aju-arvuti liides (AAL) on süsteem, mis tõlgendab ajulaineid inimese ja arvuti vaheliseks suhtluseks. Ajulaineid on võimalik tuvastada erinevate peaaju aktiivsuse mõõtmise meetoditega, näiteks kasutades elektroentsefalograafiat (EEG). AAL süsteemi eesmärk on võimaldada kasutajal välise seadmega suhelda või seda juhtida ainuüksi mõttetegevusega. Seda tehnoloogiat kasutatakse peamiselt meditsiinis, et aidata piiratud liikumisvõimega patsientidel oma keskkonnas paremini toime tulla.

Siiski on AAL süsteemide arenduses mitmeid väljakutseid, mis takistavad kasutaja tegevuse täpset klassifitseerimist. Näiteks on inimeste ajulained väga individuaalsed ja seetõttu on universaalse klassifitseerija loomine keeruline ülesanne. Selle töö eesmärk oli luua olemasolevatest mudelitest parem elektroentsefalograafial põhinev masinõppe mudel, mis oleks võimeline klassifitseerima motoorset liikumist ja kujutlust, ning AAL süsteem, et hinnata loodud klassifitseerija võimekust.

Valminud klassifitseerija tugines mitme haruga konvolutsioonilistele närvivõrkudele ning kasutas erinevate harude tunnuste kokkusulatamist. Klassifitseerija loodi kasutades Tensorflow masinõppe raamistikku, AAL loodi programmeerimiskeeles Python kasutades PyQT raamistikku ning signaalihõiveks kasutati Emotiv EPOC EEG seadet.

Töö tulemusena loodud klassifitseerijat katsetati andmestikul, mis koosnes 103 vabatahtliku katsealuse andmetest. Klassifitseerija saavutas 84.1% täpsuse parema ja vasaku käe liigutuste ennustamisel ning 83.8% täpsuse parema ja vasaku käe ettekujutatud liigutuste ennustamisel.



**Võtmesõnad:**

Aju-arvuti liides (AAL), elektroensefalograafia (EEG), konvolutsiooniline närvivõrk (CNN), siirdeõpe, sügavõpe

**CERCS:** P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria).

## Development of EEG-Based BCI Application Using Machine Learning to Classify Motor Movement and Imagery

**Abstract:**

A brain-computer interface (BCI) is a system that implements human-computer communication by interpreting brain signals. The signals can be recorded through different neuroimaging techniques that can read brain activity, such as electroencephalography (EEG). The goal of BCI technology is to enable the user to communicate with or control an external device using their mind. BCIs are widely used in medicine to help patients with limited motor abilities to communicate with their environment.

However, there are many challenges faced when building a BCI capable of classifying the subject's intention, such as the highly individualized nature of brain waves, which makes the development of a universal classifier difficult. This work aimed to develop a better electroencephalography (EEG) based machine learning classifier model capable of cross-subject motor movement and imagery classification and to build a BCI system to validate the performance of the developed classifier.

The classifier was based on convolutional neural networks (CNN) with a multi-branch feature fusion approach. The classifier was developed using Tensorflow machine learning framework, the BCI system was developed in the Python programming language using the PyQT framework, and the Emotiv EPOC EEG device was used for signal collection.

The resulting classifier was tested on a publicly available dataset of 103 subjects. The classifier achieved an accuracy of 84.1% when predicting executed left- or right-hand movement and an accuracy of 83.8% when predicting imagined left- or right-hand movement.

**Keywords:**

Brain-computer interface (BCI), convolutional neural network (CNN), deep learning, electroencephalography (EEG), transfer learning

**CERCS:** P170 Computer science, numerical analysis, systems, control

# Contents

# 1 Introduction

Ever since electronics first entered our homes and daily lives our quality of life has improved noticeably as many tasks that required manual labor can now be executed through automation. Currently these technologies have become so intertwined with our lives that it is difficult to imagine a society without electricity and electronic devices. The most common way of interfacing with them relies on our ability to move and touch as an input for these systems. However, according to the World Health Organization there is a considerable population of people with limited motor abilities who are unable or find it difficult to operate these devices without external assistance [1].

To improve on existing technology researchers have long been interested in combining the fields of computer science, engineering, and medicine to enable humans to interface with machines without the need for executed motor tasks. This is illustrated by the fact that the first such device was proposed by University of California, Los Angeles professor Jacques J. Vidal already in 1976 [2].

Brain-computer interface (BCI) or brain-machine interface (BMI) is a system composed of software and hardware components with the purpose of interpreting the human brain signal patterns to control electronic devices with input from the brain or the spinal cord [3]. Brain activity can be collected through many different technologies that can identify the chemical, electrical, or magnetic activity of the brain. Electroencephalography (EEG) is often preferred over other methods as a less complex way to detect electrical activity in the brain through sensors placed on the scalp that are used to sense the electrical potentials generated by neurons [4].

In recent years, the progress in developing these BCI systems has been increasing rapidly with breakthrough advancements in the fields of machine learning and engineering being applied to BCI development. A recent example of this is the Neuralink BMI platform developed by Elon Musk and his team [5] that is capable of interfacing with the brain through thousands of channels.

## 1.1 Introduction to the Problem

The potential for improvements to the quality of life and the commercial value of BCI systems is unquestionable. However, it is evident that for BCI systems to be adopted to a wider general use, the accuracy of classifying the brain activity of the subjects operating the system needs to be near 100%. Achieving this target is made more difficult by the fact that brain waves are documented to be highly individualized to the subject [6]. To achieve a more generalized cross-population classifier there is a need for improvement in the preprocessing methods used for removing noise from the EEG data, as well as developing better classifier architectures. In this regard the field of neural network based deep learning has shown significant promise [7].

## 1.2 Purpose and Overview of the Thesis

The purpose of this thesis is to develop a neural network based classifier to improve the accuracy of existing classifiers and build a BCI application based on the developed classifier that is capable of interpreting the brain waves of subjects performing various motor movement and imagery tasks. The classification is based on a public EEG motor movement and imagery dataset which was collected using the BCI2000 system and published by Schalk *et al.* [8]. The main goal of developing this application is to improve the classification accuracy of motor movement and imagery tasks and as a result help accelerate the development of a universal BCI capable of helping people with limited motor abilities to interact and communicate with their environment.

The second chapter gives a detailed overview of modern methods for brain signal collection and processing, different brain wave classification methods and state-of-the-art classifiers, and various applications of BCI systems in the scientific literature.

The third chapter describes the overall architecture of the developed BCI system, introduces the dataset used for classifier training, gives a detailed description of the proposed neural network based classifier and data preprocessing methods used in the produced software, and outlines the chosen hardware solution.

In the fourth chapter the experimental validation of the developed system, the benchmark studies used for comparison, the results and analysis of the experiments, and proposals for future work in the field of BCI development are presented.

Finally, a summary of the thesis and evaluation of the goals achieved are given.

# 2 Overview of the Problem

As described by the developers of the BCI2000 system [8], the design of a BCI system involves two major parts: the data processing stage and designing the hardware controls and software application for collecting the brain signals.

The overall procedure behind data processing in BCI system development involves two phases:

1. The signal collection phase where new data is acquired from subjects, and
2. The signal processing phase where the data is interpreted to machine commands.

The signal processing stage can be further divided into signal preprocessing where different techniques are applied to reduce noise and remove artifacts from the raw signals, feature extraction where a set of features are extracted from the raw signals for classification, and the classification stage where the signals are classified as an output of commands or intentions of the user of the BCI system. Figure 2.1 represents the different stages of signal processing.

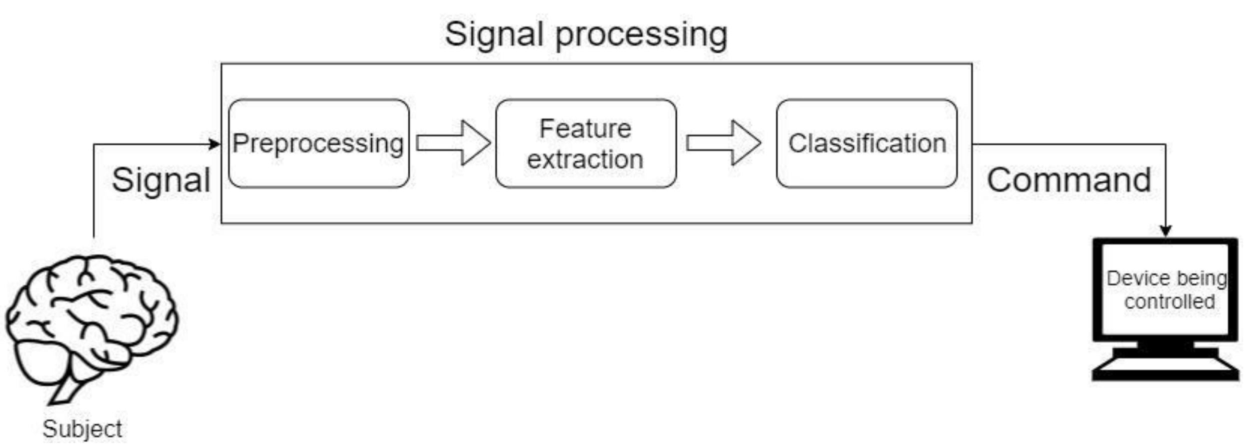


*Figure 2.1: Signal processing stages.*

In the following chapter the various signal collection methods used for brain signal collection and the common preprocessing and classification methods are described. In addition, an overview of BCI system development in the literature is given with a focus on smart environments and medical applications.

## 2.1 Signal Collection

One of the most important stages of BCI development is the signal collection stage. Brain signal collection methods can be divided into two main categories: invasive and non-invasive. According to Zhang *et al.* [7], invasive signals are collected from places over and below the cortex surface, while non-invasive signals are collected by external sensors. Invasive methods include signals like intracortical signals and electrocorticography (ECoG). Non-invasive signals can be divided into electrooculography (EOG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS) and electroencephalogram (EEG).

### 2.1.1 EEG

One of the most common ways of collecting input from the brain is a process called electroencephalography (EEG). EEG is the process of reading the brain waves of subjects using a device capable of electrophysiological measuring of the electrical activity of the brain [9]. Typically this is achieved by placing fixed electrodes on the scalp in the international 10-20 standard system for electrode placement [10]. According to Bougrain *et al.* [3], electroencephalography provides measurements of electrical potential over time for each electrode placed on the subject's scalp. Furthermore, the authors note that although these measurements only partially reflect the brain's underlying electrophysiological phenomena, they nevertheless contain significant information for use in clinical diagnosis and cognitive sciences, as well as in BCI development.

Due to its relatively low cost, ease of use and sufficiently high temporal resolution, EEG-based BCI development has seen a wide range of use in medical applications such as neurorehabilitation [11] and disorder diagnosis [12] and entertainment applications such as smart environments [13] and biofeedback-based games [14]. For the same reasons, EEG was chosen as the signal collection method in this thesis.

## 2.2 Preprocessing Methods

The main purpose of a BCI system is to interpret computer system control commands from brain activity. Achieving this requires extracting the user's intention from a wide range of brain activity signals. During the signal collection process, the acquired data is commonly contaminated with noise and various artifacts related to eye movement or other bodily functions and external electrical signals. In the case of EEG as a data source, these various artifacts can be similar in amplitude to the EEG signals. Thus, it is important to clean the raw signals of noise to be able to extract reliable features from the data.

### 2.2.1 Signal filtering

The most common method to remove noise from raw data is to apply a band-pass filter to the signals which removes all signals lower and higher in frequency to the specified values. These values can be varied depending on the type of classification that the BCI system is intended to perform [15]. In tasks related to motor movement and imagery, the frequencies of interest are usually in the range of 7-30 Hz (i.e. Alpha (7.5-13 Hz) and Beta (14-30 Hz) waves) [16]. Furthermore, a notch filter is commonly used to remove the alternating current electrical line noise on the 50 Hz or 60 Hz frequency [17].

Biological signals like eye-blinking (EOG), heartbeat (ECG), and other muscle movements (EMG) can also be present in the raw data. These types of signals have a similar bandwidth to EEG signals and as such it is important to find a technique that can remove these signals without losing important EEG data. Some possibilities for this type of filtering are principal component analysis (PCA) and independent component analysis (ICA) [18]. In this thesis, ICA is used for eye-movement artifact removal.

### 2.2.2 Feature extraction

Even after the signal filtering stage, the artifact-free EEG signals still contain a lot of redundant information that is not relevant for most BCI system purposes. A feature extraction algorithm is commonly used to distinguish the important data from noise and to filter out the information that indicates the user’s intentions.

One of the most used methods for feature extraction in the BCI domain is the common spatial pattern (CSP) filter [19]. The CSP algorithm calculates spatial filters that maximize the ratio of the variance of data between the different classification classes. As a result, the extracted signals optimally discriminate between the different EEG classes and reveal their spatial patterns [20].

However, the performance of the CSP algorithm depends on the operational frequency band of the EEG. To address this issue, the filter bank common spatial pattern (FBCSP) algorithm could be used to perform an independent selection of important temporal-spatial discriminative EEG features. This algorithm relies on bandpass-filtering the EEG data into multiple frequency bands and applying CSP filters on the filtered data [21].

In motor-imagery related studies, further experiments with alternate methods of manual feature selection have been performed by extracting the event-related desynchronization (ERD), event-related synchronization (ERS) and movement-related cortical potentials (MRCP) and calculating the mean, power, and energy of the activations as features for classification [22, 23].

## 2.3 Classification Methods

In a BCI system, the objective of classification is to determine the intentions of the user based on a feature vector that describes the user's brain activity [24]. For example, the purpose of binary classification might be to determine if the user is moving their left or right hand. The classifier could be something simple such as a fixed threshold for each feature, or a more complex method, like a machine learning algorithm.

Although many classical approaches have been successfully used to classify EEG based brain activity data, this thesis focuses on a machine learning approach and more specifically artificial neural networks as a modern method of classification with promising results in many different classification tasks [25].

### 2.3.1 Artificial neural networks

An artificial neural network (ANN) is a network of artificial neurons or nodes [26]. According to Graupe [27], ANNs are computational networks that crudely attempt to simulate the decision process of nerve cells (neurons) of the biological central nervous system. Even though a conventional digital computer can perform the same tasks as an ANN, the importance of an ANN lies in its ability to use very simple computational operations, like additions, multiplications, and fundamental logic elements, to solve complex tasks such as nonlinear or stochastic problems.

There are many different types of ANNs, from simpler structures like feedforward and backpropagation neural networks to more complex architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [28]. A neural network is sometimes also called a deep neural network when the network architecture contains more than one hidden layer [29].

### 2.3.2 Convolutional neural networks

According to Goodfellow [29], convolutional networks were originally inspired by biological processes, in that the connectivity patterns between the artificial neurons resemble the organizational structure of the visual cortex. The first convolution-based neural network architecture was proposed by Kunihiko Fukushima in 1980 when he introduced the “neocognitron” [30].

A CNN consists of several convolutional and subsampling layers that are optionally followed by one or more fully connected layers. The CNN architecture takes advantage of the two-dimensional structure of input data like images, speech, or other signals with similar structure. The EEG data used in this thesis are also two-dimensional because the signals have a temporal (data points over time) and a spatial (number of electrode channels) dimension. CNNs have been shown to be effective in image [31] and video recognition [32], as well as signal [33] and natural language processing [34]. They became more well-known in 2012 when the research team led by Krizhevsky [31] won the ImageNet [35] image recognition competition using a novel CNN architecture.

Morabito *et al.* [36] describe the two main parts of a CNN as the feature extractor, containing multiple convolution and pooling layers, and the trainable component, containing the fully connected multilayer perceptron. The convolution layers extract features from the raw data automatically, while the pooling layer performs the downsampling of the data. The perceptron performs the classification based on the learned features from the previous layers.

Convolutional networks were chosen to be the focus of this thesis, because of their ability to automatically extract higher-level features from the input data and the generally good classification accuracies reported in the literature for this type of architecture [37]. It has been shown that the CNN architecture can in some cases produce better results than traditional EEG classification approaches [25].

### 2.3.3 Current state-of-the-art classifiers

In this thesis, three state-of-the-art classifiers are used for performance comparison. In a pioneering study deep and shallow CNN architectures with various design decisions were explored [38]. The DeepConvNet architecture utilizes four convolution blocks with max pooling, with the first block designed to handle the spatial and temporal features of EEG data, followed by three standard convolutional blocks and a dense softmax classification layer.

Similarly, in the ShallowConvNet architecture the first two layers perform a temporal convolution followed by a spatial filter, but with larger kernel sizes. These layers are followed by a square root activation function, an average pooling layer, and a logarithmic activation function. In addition, utilizing novel advances in the field such as batch normalization and the exponential linear unit (ELU) activation function, the authors reached within-subject accuracies of 70.1% and 71.9% on the BCI Competition IVa [39] dataset for ShallowConvNet and DeepConvNet, respectively.

In a separate study, a neural network architecture named EEGNet that is suited for cross-paradigm BCI problems was introduced [40]. EEGNet is designed to be capable of accurately classifying EEG signals from many different BCI paradigms including sensory-motor rhythms (SMR) and MRCP. In addition to normal convolutional layers, the network utilizes depthwise and separable convolutional layers, ELU activations, average pooling, batch normalization, and dropout layers. This approach resulted in 70% within-subject and 40% cross-subject accuracies for the BCI Competition IVa dataset. The authors also evaluated the ShallowConvNet and DeepConvNet architectures for cross-subject classification on the same dataset achieving 40% accuracy with both approaches.

## 2.4 Applications of Brain-Computer Interfaces

Although brain-computer interfaces were first proposed over 40 years ago [2], more recent advances in the domains of machine learning based EEG classification and BCI development have led to many novel applications for such systems. These systems could help us solve a wide variety of tasks such as the development of smart environment solutions which would enable us to control the lighting, TV or other electronic applications in our homes [41], while also being portable [13] and interactive through augmented reality devices [42]. Some studies have investigated the possibility of using brain waves to help people who are movement impaired to control their wheelchairs [43] and prosthetics [44]. In other cases there have been successful attempts to fly drones [45] and operate robots [46]. In the medical field, some promising studies have shown BCIs to be effective in helping patients with limited motor abilities [47] or neurodegenerative diseases [48, 49] to communicate more easily or even in some cases rehabilitate stroke victims [50, 51].

### 2.4.1 Smart environments

For many years now, the demand for smart environments to improve the quality of our everyday life has been on the increase. Their value is not only in entertainment and convenience, but also increased accessibility for people with limited motor abilities, like the elderly or the disabled.

While smart homes have been an active research topic since the early 2000s, the feasibility of such applications has not been widely researched. Kosmyna *et al.* [41] were one of the first groups to evaluate the feasibility of smart environments when they studied 12 healthy subjects between the ages of 23 and 45 and two subjects with motor disability in a smart home setting. The goal of the study was to evaluate the potential interest of users about BCI usage in smart homes. The subjects were given control of the lighting and window shutters in all the rooms, a TV set, a kettle, and a coffee machine while wearing a 16-channel standard 10-20 EEG cap. They were then briefed on the layout of the smart home, trained in using the system, and instructed to perform various tasks using the BCI to interact with their smart home environment. To evaluate the user experience, the subjects were given a questionnaire with four categories of Usefulness, Ease of Use, Ease of Learning, and Satisfaction with answers on a scale from 1 to 7. The results showed that in these four categories the subjects scored high, with slightly less than 6/7 on average with their answers to the questionnaire. In addition, the brain-computer interface managed a task accuracy of 77% and a mean correct activation time of 2 seconds, which was in the range of state-of-the-art performance for smart home BCI systems.

Another approach to portability was proposed by Saboor *et al.* [42] in using a BCI system combined with smart glasses for an augmented reality smart home experience. The study group used a BCI system composed of EPSON Moverio BT-200 smart glasses with actiCHamp EEG amplifier and actiCAP electrodes on 7 healthy volunteers with the majority having previous BCI experience. The goal was to simulate a smart home scenario by using a quick response technology QR-code to identify controllable items in the environment such as lights, a coffee machine, and an elevator. The subjects could use their wearable smart glasses to scan the QR-code on these objects, which activated an options screen on their glasses. They could then select their option by thinking about their choice and this selection was sent to a central processing server to perform the selected action. As a result of each of the 7 participants performing 7 different actions an average command classification of 85.70% was achieved.

### 2.4.2 Medicine

Advances in the field of medicine have always been of the highest importance in improving our lifespan and quality of life. However, for many elderly or disabled people everyday tasks such as interacting or communicating with their environment have been unnecessarily difficult.

Locked-in amyotrophic lateral sclerosis (ALS) patients may find great benefit from BCI development, as they are fully dependent on caregivers in their daily needs. Spataro *et al.* [47] developed a BCI robot system to allow ALS patients who have lost most of their motor function to control a humanoid robot by directing it to grab a glass of water. As part of the study 4 healthy subjects in the control group and 4 ALS patients performed 3 experimental sessions of 9 runs each with one session for calibration of the system, one online session with a simulated robot, and one session with an actual robot being controlled by the subjects. Three out of the four ALS patients, as well as all healthy controls were able to complete the tasks after minimal training. The researchers concluded that besides the obvious economic benefit of reducing the need for daily assistance, the control of a robotic alter-ego may also yield invaluable psychological significance to the subjects by giving them back some basic forms of independence.

Similarly, it was shown by Ang *et al.* [51] that patients who have experienced stroke could potentially benefit from EEG-based BCI technology by inducing activity-dependent brain plasticity and as a result, restoring motor function. The goal of this study was to compare the effects of EEG-based BCI with robotic feedback versus manual robotic training using the Massachusetts Institute of Technology (MIT) Manus robot and to test the safety and efficacy of the BCI-Manus compared to Manus therapy on stroke victims. Their experiments were performed on 26 subjects who received a total of 18 hours of intervention therapy delivered over 4 weeks and of whom 11 patients were subject to BCI-Manus therapy. As a result, both groups demonstrated significant gains in the primary outcome, the total Fugl-Meyer Assessment of Motor Recovery After Stroke (FMMA) score, compared with their baseline FMMA score. This is in accordance with other results in neurorehabilitation that have demonstrated new neural connections appearing in the brains of paralyzed patients as a result of thinking about movement while observing a robot performing this movement [50].

Furthermore, Alzheimer's disease (AD) patients in advanced stages, who are not able to communicate verbally, could be enabled to express basic thoughts and emotions through the means of a BCI system designed for this purpose. One such interface was hypothesized by Libertati *et al.* [48] to allow AD patients to convey information related to their mental states, such as emotions (happiness or sadness) and cognitive states ("yes" or "no" thinking). Libertati *et al.* [49] developed the hypothesized system in a later study with 6 Alzheimer's patients and 7 healthy control subjects. The central intention for this research was to confirm if brain activations relative to congruent and incongruent word-pairs, that respectively elicit affirmative ("yes") and negative ("no") responses could be classified by linear support vector machines (SVM) after a specified conditioning process. The participants were instructed to listen to simple word-pairs and to think "yes" if the word-pair was congruent (e.g. "Animal-Cat") or "no" if it was incongruent (e.g. "Animal-Apple"). The results gave a reassuring outlook for future developments in this area as the classification accuracies for AD patients reached up to 85%, with an average of 71% over all patients, while the accuracies for healthy controls were up to 83%, with an average of 69%.

# 3 Brain-Computer Interface Architecture

In the following chapter the overall process and architecture of the proposed BCI system are described. Furthermore, the hardware and software choices for the classifier and BCI application are outlined and the methodology for EEG signal preprocessing is given.

## 3.1 Overall Process

The overall process for classifying motor movement and imagery EEG data in this thesis is depicted in Figure 3.1.

The first step in any classification task is data preprocessing. This means taking the EEG data from the chosen dataset and processing it using the chosen filtering methods and splitting the dataset into training, testing, and validation subsets.

The training subset of the processed data is then given as an input to the classifier model for training while the model is validated after each training epoch by running the model on the validation set. This is followed by testing the fully trained model on the testing set. After the classifier results for the given model are clear, the model architecture and hyperparameter tuning can be applied before going through the training and testing process again until the best classification results are achieved.

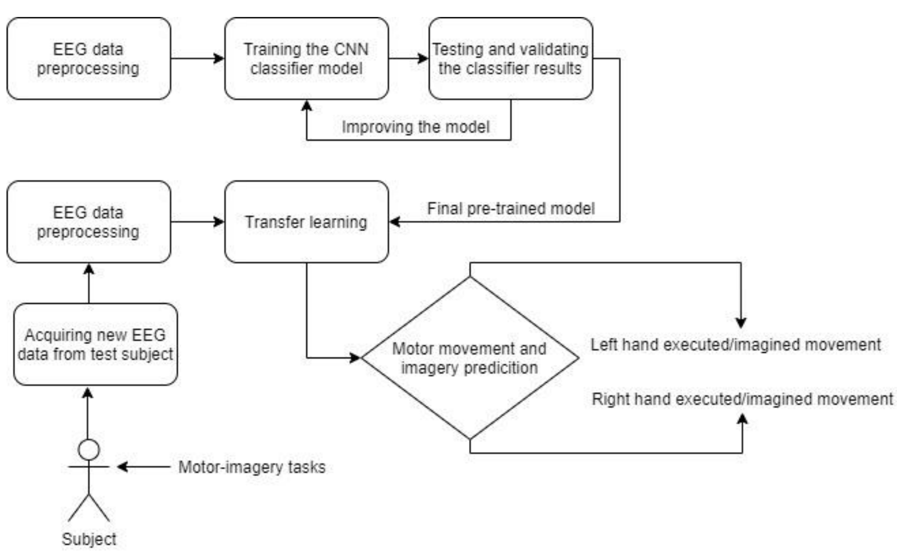


*Figure 3.1: Overall process for motor and imagery EEG classification.*

The next stage is to test the BCI system on EEG data from a new test subject. The subject wears a device capable of reading their EEG signals while they go through the same tasks as were performed in the original dataset. The collected data is given as input to the preprocessing and prediction pipeline where the performed actions are classified into two categories. Subjects can see the prediction results of their performed tasks on the screen in front of them as a form of biofeedback. The results are stored, and accuracy results are calculated to evaluate the performance of the pre-trained classifier model on new data.

## 3.2 Classifier

The classifier was the core research focus of this thesis as the need for improvement in the classifier architecture and methodology is one of the main challenges in BCI development [3]. The classifier was developed with a focus on cross-subject classification and transfer learning.

### 3.2.1 Hardware

All the classifier models were tested using the resources provided by the High Performance Computing Center (HPC) of the University of Tartu. For each classifier preprocessing, training, and testing task 64GB of RAM, 16 cores of CPU and a Tesla P100 GPU were used.

### 3.2.2 Dataset

The dataset used for this thesis was provided to PhysioNet [52] by the developers of the BCI2000 [8] research and development platform. It is made up of over 1500 EEG recordings, collected from 109 volunteer subjects. The dataset is publicly available at [53]. The subjects in the experiment performed different motor movement and imagery tasks while EEG data was recorded using the BCI2000 system. As described by the authors [53], each subject performed a total of 14 experimental runs of one of the following types:

- A one-minute run where the subject keeps their eyes closed
- A one-minute run where the subject keeps their eyes open
- A two-minute run where the subject opens and closes their left fist if the target appears on the left side of the screen or right fist if the target appears on the right

- A two-minute run where the subject imagines the opening and closing of their left fist if the target appears on the left side of the screen or right fist if the target appears on the right
- A two-minute run where the subject opens and closes both of their fists or both of their feet depending if the target appeared on the top (both fists) or the bottom (both feet) of the screen
- A two-minute run where the subject imagines the opening and closing of both of their fists or both of their feet depending if the target appeared on the top (both fists) or the bottom (both feet) of the screen

The data is provided in European Data Format plus (EDF+) [54] format and contains 64 EEG channels sampled at 160 Hz and an annotation channel. Each annotation includes one of three codes: T0 corresponds to the rest state, T1 corresponds to the real or imagined onset of motion of the left fist or both fists and T2 corresponds to the real or imagined onset of motion of the right fist or both feet. The EEG signals were collected using 64 electrodes of the international 10-20 system, excluding the electrodes FT9, F9, F10, FT10, P9, P10, A1, A2, TP9, TP10, and Nz, as it is depicted in Figure 3.2.

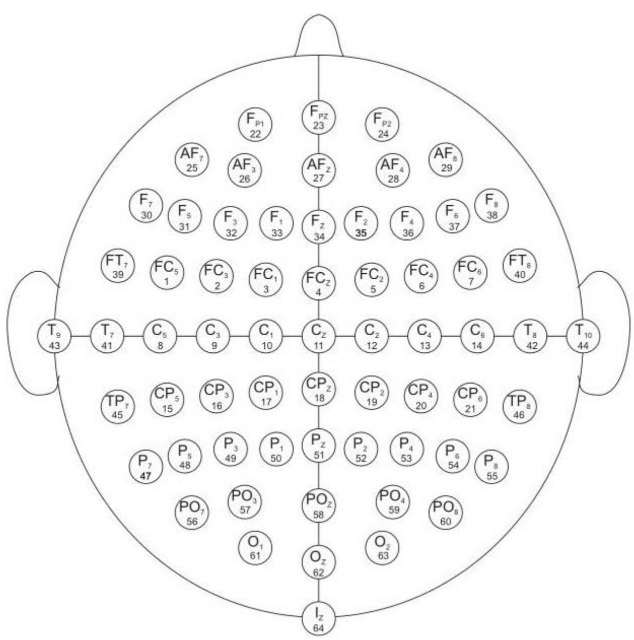


*Figure 3.2: Placement of electrodes in the PhysioNet motor movement and imagery dataset* [53].

In this thesis, a subset of the data was used corresponding to the six two-minute runs where the subjects performed either task 1 (opening and closing the left or the right fist) or task 2 (imagining the opening and closing of the left or the right fist). The corresponding runs in the dataset are numbered as 3, 4, and 7 for executed tasks and 8, 11, and 12 for imagined tasks. There is an equal proportion of left- and right-hand tasks in the dataset.

During the inspection of the dataset it was determined that 6 out of the 109 subjects had incorrectly annotated data with some subjects having trials lasting longer and some subjects having fewer trials than specified. As a result, the subjects numbered 38, 88, 89, 92, 100, and 104 were omitted from the final set of subjects, and only data from 103 subjects was used for training and testing.

### 3.2.3 Preprocessing

Data preprocessing is an important step for achieving better classification results. In this thesis data preprocessing was conducted in the following manner.

The input data for each subject was sliced into dimensions (64, W), where W denotes the temporal dimension and 64 is the number of EEG channels. Different values of W were tested and the value with the best possible training and testing results was determined as 80. This means that each task consisting of 640 data points (160 data points per second for 4 seconds of continuous task execution) was sliced into 8 non-overlapping chunks of 80 data points and each chunk was given the same label as the original task. This approach effectively helps to increase the number of samples available for training and testing the model by 8 times the original size and is an effective method of increasing classifier accuracy [55].

A second-order infinite impulse response (IIR) notch filter with a quality factor of 30 was applied to the data to remove the alternating current (AC) noise in the 60 Hz frequency line. It is worth noting that two of the studies used for comparison in this thesis mistakenly used the same technique on the 50 Hz frequency line, even though the data was collected in the United States where AC line noise is present in the 60 Hz frequency [56].

Next, a band-pass filter was applied to the result of the previous steps in the range of 2-60 Hz with the order value of 5 to effectively remove any frequencies below 2 Hz and any frequencies above 60 Hz. The goal of the filtering was to remove noise and to leave only frequencies related to motor movement and imagery in the resulting data.

Finally, the filtered data was subject to artifact removal using the Gumpy [57] library, which is based on the FastICA method of the Scikit-learn [58] machine learning framework. The goal of the artifact removal is to remove any ocular artifacts that were present in the raw data due to eye movement of the subjects.

### 3.2.4 Model architecture

The proposed CNN architecture is based on a cross-paradigm EEG classifier called EEGNet [40]. According to the authors, the architecture of EEGNet (see Figure 3.3) is well suited for any type of EEG-based classification problem and has achieved high accuracy on the PhysioNet motor movement and imagery dataset. However, for cross-subject classification there is room for improvement. It has been shown that the CNN hyperparameters such as kernel size and the number of filters that work the best for each subject can vary as each subject's brain signals are individual and for different subjects, the best-performing architectures and hyperparameters can differ [3].

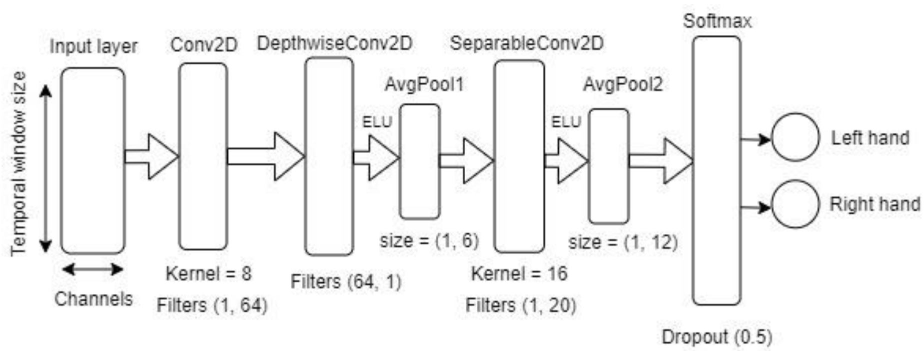


*Figure 3.3: EEGNet classifier model architecture.*

In EEG-based classification, fusion networks have shown promise in overcoming the problem of poor classification of cross-subject data. Several research groups [59, 60] have utilized fusion networks to increase overall network classification accuracies by enabling the network to extract features from multiple branches with differing architectures or hyperparameters and fusing the features in a fusion layer. As a result, the overall architecture of the network becomes more flexible for data from different subjects.

The proposed network termed EEGNet Fusion consists of three different branches with each branch given the same input. The overall structure of each branch is the same as the structure of the EEGNet architecture, but the kernel size and the number of convolutional filters in the depth-wise and separable convolutional layers are different for each branch. The basic structure of the branches can be described as follows.

The input layer is followed by a two-dimensional convolutional layer with kernel sizes 4, 8, and 16, and filters with sizes (1, 64), (1, 128), and (1, 256) for the three branches, respectively. Next there is a depth-wise convolutional layer with (64, 1) filters for all branches. This is followed by a separable convolutional layer with kernel size 16 for all branches and (1, 8), (1, 16), and (1, 32) filters for the three branches, respectively. Each convolutional layer is also followed by batch normalization which is an effective method for reducing overfitting and improving the training speed of the network.

Furthermore, each depth-wise and separable convolutional layer is followed by an exponential linear unit (ELU) activation function, which is a popular alternative to the rectified linear unit (ReLU) activation function and is more computationally efficient in CNN-based classification [61]. ELU applies the activation function given by the formula (Eq. 3.1):

$$R(z) = \left\{ \begin{array}{cc} z & z > 0 \\ \alpha.\,(e^{z} - 1) & z <= 0 \end{array} \right\}$$

*Eq. 3.1: ELU activation function*

Average pooling was preferred for the pooling function over other pooling methods for its simplicity. The objective of the pooling function is to down-sample an input representation by reducing its dimensions. This in effect reduces the computational cost by having fewer parameters for learning. An example of applying a 2x2 filter with a stride of 2 on a 4x4 input matrix can be seen in Figure 3.4.


*Figure 3.4: Average pooling with filter size (2, 2) applied to a 4x4 input matrix.*

Each pooling layer is followed by a dropout function with the value 0.5. Dropout is a technique that helps to avoid overfitting on training data by ignoring randomly selected neurons during the model training phase [62].

After the final pooling layer, a feature fusion layer is used to merge the weights of the three CNN branches and its output is given as input to softmax classification layer producing the probabilities for each of the two classes (left- or right-hand executed movement in one experiment and left- or right-hand imagined movement in the second experiment). The final architecture of the proposed convolutional network is depicted in Figure 3.5.

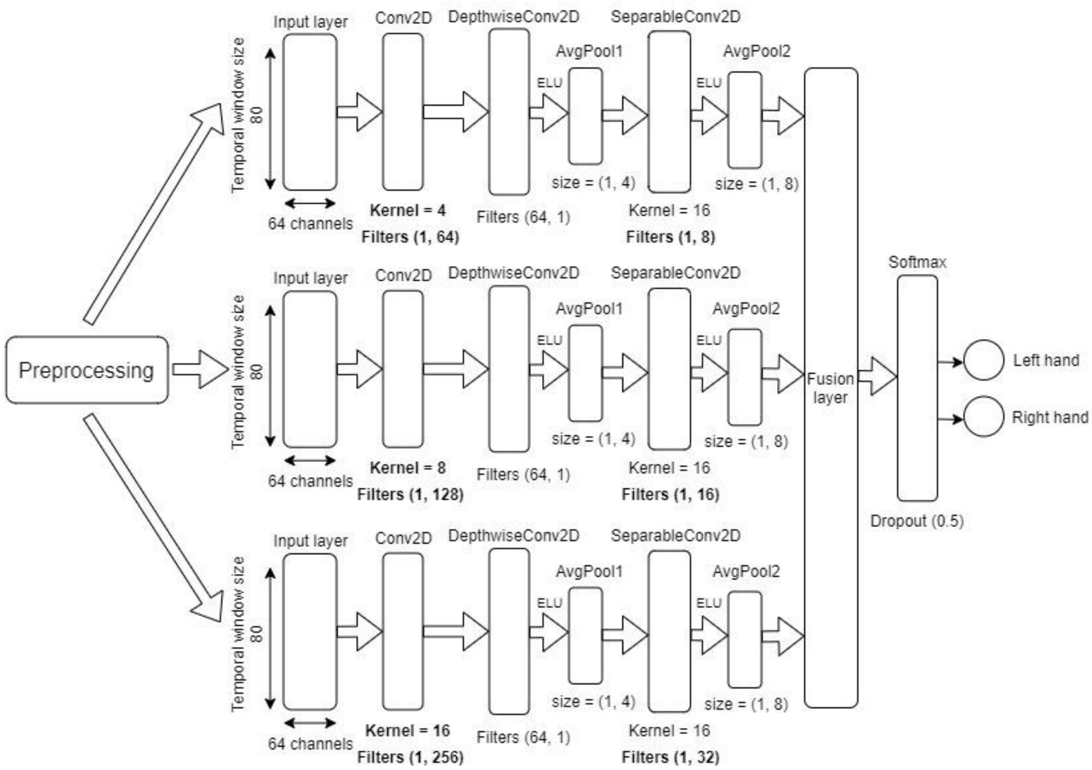


*Figure 3.5: The architecture of the proposed classifier model EEGNet Fusion with differences in the three branches highlighted in bold.*

## 3.2.5 Transfer learning

A major issue when working with EEG data from different subjects is that the differences in each subject's brains make it difficult to generalize the classifier over many subjects. Furthermore, the nonstationary nature of EEG means that the brain waves of people are subject to change over time, and as such the classification accuracy for a subject can dramatically change between experiments that are performed days apart [63].

Several studies have shown the transfer learning method to be an effective way to overcome the issue where the model is unfamiliar with a new subject's EEG signals by re-training it with some samples from the subject [64, 65]. The basic process of transfer learning is that after the initial model has been pre-trained on training data, some layers from the model are disabled. This means that the weights of these layers are fixed and will not be updated on further training of the model [64]. As the next step, some samples from a new subject are given to the model as input and as a result the weights of the remaining active layers are adjusted accordingly. This way the re-training of the model is computationally much more efficient while retaining information about the subjects used for pre-training the model and adjusting itself to the new subject.

## 3.3 Real-Time Application

The real-time BCI application was developed to validate the performance of the proposed classifier compared to the state-of-the-art models on new data. The goal of the application was to be easily usable with the chosen EEG headset and to perform experiments with left- and right-hand executed and imagined movement. Figure 3.6 outlines the overall flow of the developed application in an experimental setting.

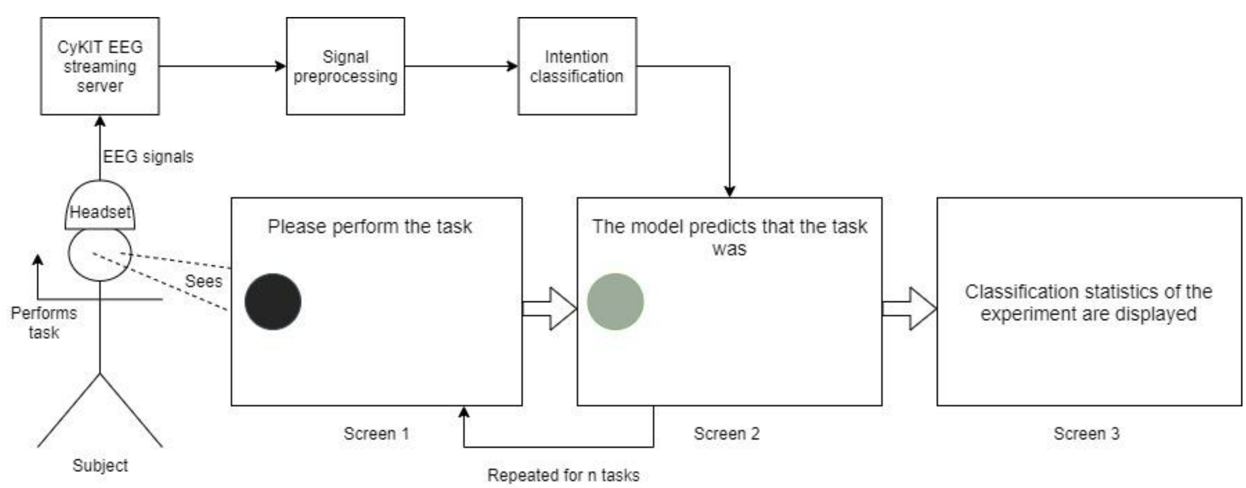


*Figure 3.6: Flow diagram of the developed BCI application.*

### 3.3.1 Hardware

The Emotiv EPOC® [66] headset was chosen over the Muse [67] headset as the device for EEG data collection for the BCI application. This choice was made due to the Emotiv EPOC® headset having 14 electrode channels compared to the 4 electrode channels of the Muse headset. Furthermore, all the 14 channels of the Emotiv EPOC® headset were present in the original dataset while none of the channels provided by the Muse headset were present. The 14 channels used by the Emotiv EPOC® headset for data collection in the 10-20 international system are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 [66]. Figure 3.7 shows the placement of the electrodes according to the international 10-20 system for electrode placement. The chosen device records each channel at a sample rate of 128 Hz. The application was developed, and the experiments were performed on a Lenovo ThinkPad laptop running 64-bit Windows 10 operating system with 16GB of RAM and an Intel 8-core i5-8250U processor.

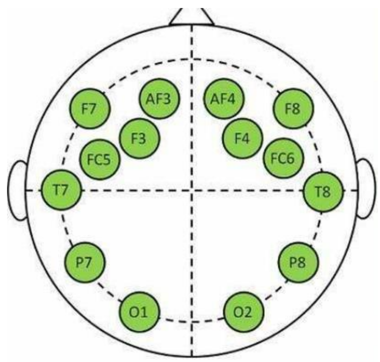


*Figure 3.7: Emotiv EPOC electrode placement in the 10-20 system* [68].

### 3.3.2 Software

The application was developed using the Python [69] programming language version 3.7.7, PyQT [70] graphical user interface (GUI) framework version 5.9.2, Tensorflow [71] machine learning framework version 2.1.0, Scikit-Learn [58] machine learning framework version 0.22.2, Gumpy [57] BCI toolbox and CyKIT [72] EEG streaming library version 3.0. The download link for the software developed as a result of this thesis is presented in Appendix I.

### 3.3.3 Signal processing and classification

When a new experiment is started using the BCI application, the EEG signals from the Emotiv EPOC device are processed by the CyKIT EEG streaming server and sent to the BCI application for preprocessing.

As the sample rate of the Emotiv EPOC device is 128 Hz, unlike the 160 Hz sample rate of the dataset used for pre-training the classifier model, each task is recorded for 5 seconds of continuous data. This way the resulting number of samples for each task is 640, as it was after preprocessing each task for the pre-trained models. The artifact removal and filtering of the EEG signals are conducted in the same manner as described in Chapter 3.2.3. Similarly, each task is divided into 8 equal chunks of 80 samples corresponding to 0.5 seconds of executed or imagined activity. Each chunk is given the same target label as the original task to preserve consistent methodology with the preprocessing of the classifier evaluation.

Each of the 8 chunks of the recorded data is used to make predictions and the accuracy of the predictions is evaluated against the target labels. The user is shown the prediction of the whole task by calculating the most common prediction among the 8 chunks of samples.

Transfer learning is performed after the end of the experiment if the relevant option was enabled. The transfer learning model is saved for each subject separately and will be loaded the next time an experiment with the same subject ID is started. If the evaluation of all models option was chosen along with the transfer learning option, then each of the models will be used for transfer learning and saved separately.

### 3.3.4 User interface

The graphical user interface of the BCI application consists of 3 main views:

- The settings view
- The experiment view
- The statistics view

The settings view (see Figure 3.8) enables the user to specify settings relevant to the experiment. The user can specify the subject ID used for the experiment, the number of tasks to perform, the run type (executed or imagined movement), the classifier model to be used in the experiment, if predictions should be shown to the subject after each task, if transfer learning should be used, and if all classifier models should be evaluated simultaneously. The state-of-the-art models used for classifier evaluation and the proposed EEGNet Fusion model are loaded for selection by default. The user can also load new models by opening the “Load new model” menu dialog. When pressing the “Start” button the experiment view is displayed to the user.

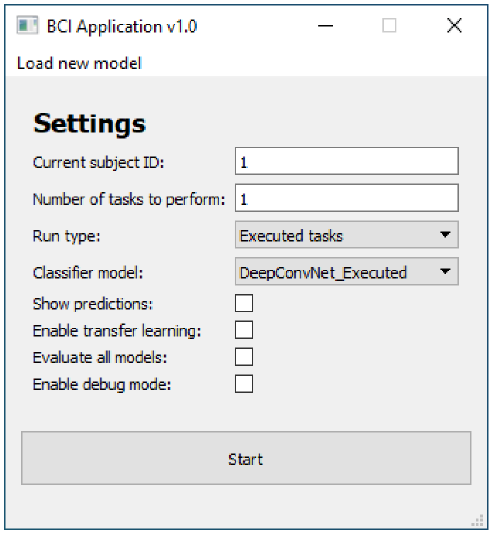


*Figure 3.8: The settings view of the BCI application.*

The experiment view (see Figure 3.9) is where the user is shown a circle either on the left or the right side of the screen and is instructed to either execute or imagine left- or right-hand movement depending on the chosen experimental run type. The EEG signals from the subject are recorded for 5 seconds and if the relevant option was enabled in the settings view, the user is shown the prediction for the performed task or is instructed to rest if the prediction option was not selected. This task-rest cycle is continued until the number of specified tasks have been performed. At the end of the experiment or if the "Stop experiment" button is pressed, the statistics view is displayed to the user.

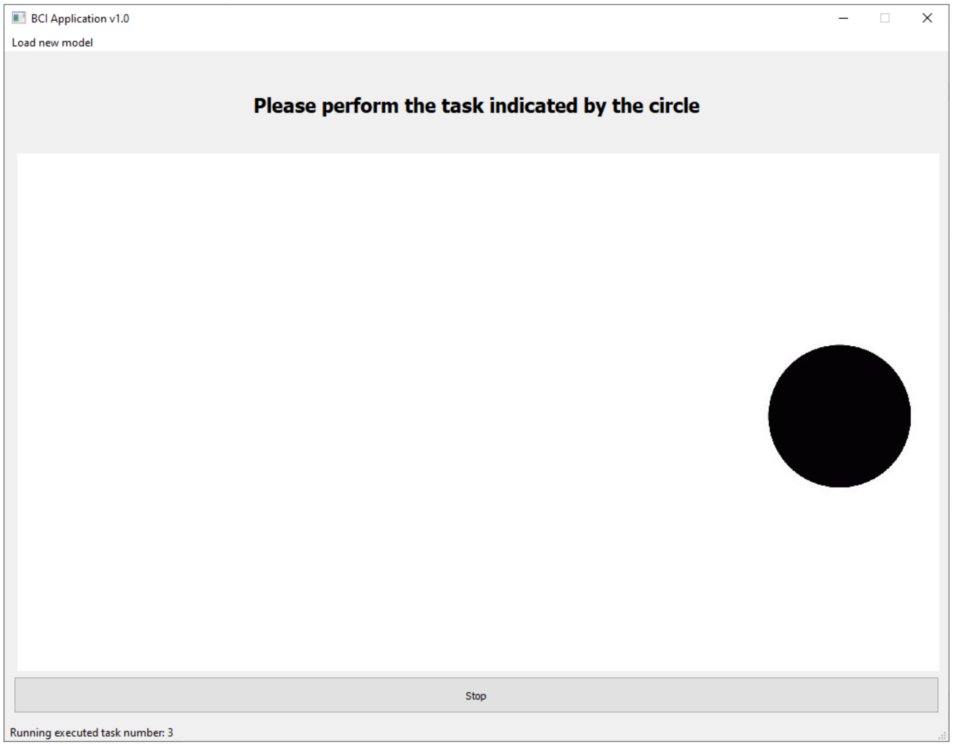


*Figure 3.9: The experiment view of the BCI application.*

In the statistics view (see Figure 3.10) the user is shown relevant statistics from the performed experiment. The statistics contain the correct and incorrect predictions made for each of the 8 chunks from each task, the total time taken, and the calculated classification accuracy. The user can switch between the statistics of different models if the option to evaluate all models was chosen. All the statistics displayed, and the predictions of the different classifiers are saved into a CSV file that can be imported to Excel for analysis.

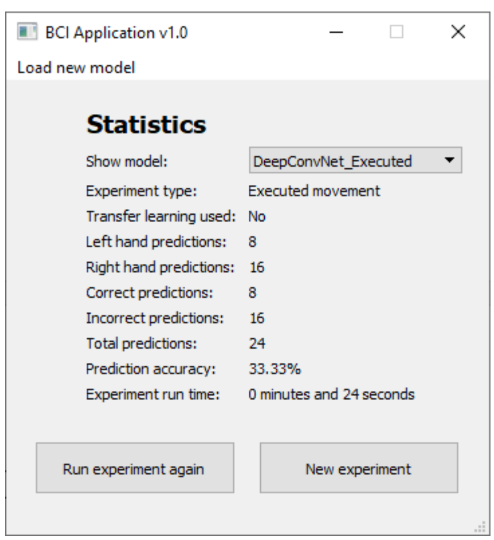


*Figure 3.10: The statistics view of the BCI application.*

# 4 Experimental Validation and Analysis

In this chapter the experimental validation methodology is described and the experimental results are presented and analyzed. Three state-of-the-art classifiers – DeepConvNet, ShallowConvNet, and EEGNet - with publicly available and reproducible code [73] were chosen to evaluate the proposed preprocessing method and to compare the classification results with the proposed classifier EEGNet Fusion. The experimental validation in this thesis consists of three parts:

1.) First, the proposed classifier EEGNet Fusion and the benchmark CNN models EEGNet, ShallowConvNet, and DeepConvNet were trained and tested on the motor movement and imagery dataset, and the accuracy and p-values were calculated. Each model was trained and tested on both executed and imagined movements separately. The models were evaluated on the first 6 subjects, first 20 subjects and all 103 subjects of the dataset separately to compare the results with chosen benchmark studies.

2.) Secondly, the models were tested with the transfer learning method, where the first 100 subjects were used for training the model and the remaining 3 subjects were used for testing and transfer learning.

3.) Finally, the EEGNet Fusion, EEGNet, ShallowConvNet, and DeepConvNet models were evaluated on new data from a new subject using the BCI application developed for this thesis. The performance of the models on new data was also evaluated with the transfer learning approach.

## 4.1 Statistical Significance

It is common practice to evaluate the classification methods using 10-fold cross-validation and use the paired Student's t-test to check if the difference in the mean accuracy between the two models is statistically significant. However, in the k-fold cross-validation procedure, a given observation is used in the training dataset k-1 times. As such, the estimated skill scores are not independent and it has been shown that this approach has an elevated probability of type I error [74].

The statistical significance of the experimental results in this thesis is evaluated using McNemar's statistical test [75]. McNemar's test is a paired nonparametric or distribution-free statistical hypothesis test. The test evaluates if the disagreements between the two evaluated classifiers match. The test statistic is calculated by forming a 2x2 contingency table which summarizes the number of samples that the two models both predicted correctly, both predicted incorrectly, or one model predicted correctly and the other predicted incorrectly (see Table 4.1).

*Table 4.1: Contingency table for the McNemar's test.*

| | Classifier 2 correct | Classifier 2 incorrect |
|---|---|---|
| Classifier 1 correct | Yes/Yes (a) | Yes/No (b) |
| Classifier 1 incorrect | No/Yes (c) | No/No (d) |

The test statistic is given by the formula (Eq. 2):

$$\chi^2 = \frac{(b-c)^2}{b+c}.$$

*Eq. 2: McNemar's test statistic.*

Under the null hypothesis the two classifier models compared should have the same error rate. We can reject the null hypothesis if the two models make different errors and have a different relative proportion of errors on the test set. This type of test is shown to have a low type I error and can be used to show statistical significance when not using cross-validation [74].

## 4.2 Classifier Validation

In the following subchapters, the benchmark studies used for comparison are described and the results and analysis of the classifier validation are given.

### 4.2.1 Benchmark studies

Two cross-subject studies with left- and right-hand executed movement classification for the first 6 subjects [22] and 103 subjects [23] of the PhysioNet BCI2000 dataset were chosen for classification accuracy comparison. Also, one cross-subject study with left- and right-hand imagined movement classification for the first 20 subjects on the same dataset was chosen [76]. These studies were of interest due to their use of the same cross-subject data and different machine learning and feature extraction methods where the features used for training the classifier were handpicked by creating customized feature vectors.

In the first study, published by Alomari *et al.* [22], the data were preprocessed using a bandpass filter in the range 0.5 Hz to 90 Hz and a notch filter was applied to remove the 50 Hz line noise. Furthermore, automatic artifact removal was performed using the MATLAB AAR toolbox to remove the eye and muscle movement artifacts. After preprocessing, specific time-locked events were extracted from the continuous EEG data. Event-related desynchronization (ERD) and event-related synchronization (ERS) of the mu and beta rhythms and movement-related cortical potential (MRCP) data of the delta rhythms were extracted before and after the sustained movement. Finally, the power, mean, and energy of the activations were calculated and used as features for the neural network (NN) and support vector machine (SVM) classifiers. The NN classifier achieved an accuracy of 89.8% and the SVM classifier achieved an accuracy of 97.1%.

In the second study, published by Huong e*t al.* [23], the overall preprocessing and feature selection is performed in the same manner as in the first study, but all of the 109 subjects were used for training and testing and only a neural network approach is evaluated with the best classification accuracy of 67%.

In the third study, published by Alomari *et al.* [76], the preprocessing steps were the same as for the previous two studies. However, for feature extraction, discrete wavelet transform (DWT) was used. For classification both SVM and NN methods were evaluated using the MATLAB NN toolbox and 80% of the samples were used for training and 20% for testing. For the NN approach the best accuracy of 82% was achieved with 9 hidden layers. For the SVM approach the best accuracy of 84.5% was achieved with degree parameter 7 and gamma parameter 3.

It is important to note that these three studies utilized a different approach to preprocessing than proposed in this thesis and as such the comparisons are made to the whole process including preprocessing and classifier selection.

### 4.2.2 Experimental results

The performance of the proposed classifier was evaluated in the following manner. The 103-subject dataset was tested on EEGNet, ShallowConvNet, and DeepConvNet architectures, and the results were recorded for comparison with the results of the proposed EEGNet Fusion model. Additionally, a subset of the dataset consisting of the first 6 subjects was used to evaluate the models. For all datasets, if not specified otherwise, 70% of the samples were randomly chosen for training, 10% for validation, and 20% for testing.

The testing accuracy and the p-value[1] relative to the proposed EEGNet Fusion model for executed movement tasks for all evaluated models can be seen in Table 4.2.

Table 4.2: Executed motor task results for the classifier experiments.

| **Model** | **Subjects 1-6** | | **Subjects 1-103** | |
|---|---|---|---|---|
| | Accuracy | p-value | Accuracy | p-value |
| EEGNet | 99.5% | 1 | 65.8% | < 0.001 |
| ShallowConvNet | **100%** | 1 | 77% | < 0.001 |
| DeepConvNet | **100%** | 1 | 76% | < 0.001 |
| **EEGNet Fusion** | 99.8% | 1 | **84.1%** | 1 |

In addition to the executed movement tasks, the same state-of-the-art models were evaluated on the dataset with only imagined tasks. Imagined tasks were additionally evaluated on a subset of the original dataset with the first 20 subjects for comparison with a benchmark study. The results of the experiments with imagined tasks can be seen in Table 4.3.

Table 4.3: Imagined motor task results for the classifier experiments.

| **Model** | **Subjects 1-6** | | **Subjects 1-20** | | **Subjects 1-103** | |
|---|---|---|---|---|---|---|
| | Accuracy | p-value | Accuracy | p-value | Accuracy | p-value |
| EEGNet | 71.5% | < 0.001 | 92.5% | < 0.001 | 68.2% | < 0.001 |
| ShallowConvNet | 99.5% | 0.5 | 95.6% | < 0.001 | 77.8% | < 0.001 |
| DeepConvNet | **100%** | 1 | **98.9%** | 0.70 | 75.8% | < 0.001 |
| **EEGNet Fusion** | **100%** | 1 | 98.7% | 1 | **83.8%** | 1 |

### 4.2.3 Analysis

For the 6-subject dataset on executed movement tasks, the proposed EEGNet Fusion model achieved slightly lower accuracy than two benchmark classifiers. However, the differences

[1] The *p*-value or probability value is the probability of obtaining test results at least as extreme as the results observed during the test. In this thesis the p-values were calculated relative to the proposed model EEGNet Fusion. That means each of the other models under evaluation were evaluated against the proposed model and the p-value can be used to show statistical significance of the difference of the two models.

between the proposed model and the benchmark classifiers were not statistically significant. All the evaluated models outperformed the benchmark study that achieved the SVM classifier accuracy of 97.1% [22]. On imagined movement tasks of the same dataset, the proposed model achieved 100% accuracy. However, only the difference with the EEGNet model was statistically significant. The generally high accuracies on this dataset for both executed and imagined tasks suggest overfitting on the training set due to the small size of the dataset.

For the 20-subject dataset on imagined movement tasks, the proposed EEGNet Fusion model performed statistically significantly better than the EEGNet and ShallowConvNet models ($p < 0.001$). However, the difference with the DeepConvNet model was not statistically significant ($p = 0.7$). In addition, the evaluated models outperformed the benchmark study that achieved the SVM classifier accuracy of 84.5% [76].

For the 103-subject dataset on executed movement tasks, the proposed EEGNet Fusion model performed better than the benchmark classifiers with statistically significant result ($p < 0.001$) of 84.1% accuracy. On imagined movement tasks on the same dataset, the proposed model performed also better than the benchmark classifiers with statistically significant result ($p < 0.001$) of 83.8% accuracy. Furthermore, all the evaluated models except for EEGNet outperformed the benchmark study that achieved 67% accuracy [23]. These results suggest that the EEGNet Fusion model is well-suited for cross-subject classification when used in combination with the proposed preprocessing methodology.

## 4.3 Transfer Learning Validation

In the following subchapters, the experimental results and analysis of the transfer learning validation are given.

### 4.3.1 Experimental results

To evaluate the transfer learning method, the first 100 subjects out of the 103 valid subjects in the PhysioNet dataset were used for pre-training the models, and the last 3 subjects were used for individual transfer learning and testing.

The models were pre-trained on 90% of the data from 100 subjects, while 10% of the data was used for validation. Each of the 3 test subjects were evaluated separately on the pre-trained model before transfer learning was applied. The subject's data were randomly split into 45% training, 10% validation, and 45% testing data.

The model layers where learning was disabled for the transfer process were layers 1-8, 15-22, and 29-36 of the EEGNet Fusion model, layers 1-8 of the EEGNet model, layers 1-2 of the ShallowConvNet model and layers 1-15 of the DeepConvNet model.

The accuracy and p-value relative to the proposed EEGNet Fusion model on executed motor tasks for subjects numbered 107, 108, and 109 are seen in Table 4.4.

Table 4.4: Executed motor movement task results for transfer learning experiments.

| **Model** | **Subject 107** | | | | **Subject 108** | | | | **Subject 109** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Before TL | | After TL | | Before TL | | After TL | | Before TL | | After TL | |
| | Acc. | p | Acc. | p | Acc. | p | Acc. | p | Acc. | p | Acc. | p |
| EEGNet | 62.8% | 1 | 66.5% | 0* | 49.7% | 0.04 | 55.1% | 0* | 45.6% | 0.04 | 53.2% | 0* |
| ShallowConvNet | 60.3% | 0.69 | **100%** | 1 | 46.9% | 0.01 | 99.4% | 1 | **52.8%** | 0.84 | **98.6%** | 1 |
| DeepConvNet | **65.2%** | 0.21 | 63.9% | 0* | 51.1% | 0.09 | 43.7% | 0* | 45.6% | 0.04 | 52.5% | 0* |
| **EEGNet Fusion** | 61.7% | 1 | **100%** | 1 | **56.4%** | 1 | **100%** | 1 | 51.9% | 1 | 97.2% | 1 |

* - *p-value < 0.001*

Similarly, imagined tasks were evaluated for the same transfer learning method and the results are seen in Table 4.5.

Table 4.5: Imagined motor movement task results for transfer learning experiments.

| **Model** | **Subject 107** | | | | **Subject 108** | | | | **Subject 109** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Before TL | | After TL | | Before TL | | After TL | | Before TL | | After TL | |
| | Acc. | p | Acc. | p | Acc. | p | Acc. | p | Acc. | p | Acc. | p |
| EEGNet | **53%** | 0.21 | 38.9% | 0* | **45.6%** | 0.02 | 62.5% | 0* | 38.6% | 0.34 | 52.8% | 0* |
| ShallowConvNet | 45% | 0.23 | **100%** | 1 | 41.4% | 0.27 | 99.4% | 1 | 38.3% | 0.44 | **100%** | 1 |
| DeepConvNet | 50.1% | 0.63 | 36.1% | 0* | 35.8% | 0* | 56.9% | 0* | **41.9%** | 0.03 | 41.7% | 0* |
| **EEGNet Fusion** | 48.9% | 1 | **100%** | 1 | 38.1% | 1 | **100%** | 1 | 40.8% | 1 | **100%** | 1 |

* - *p-value < 0.001*

### 4.3.2 Analysis

All the transfer learning experiments showed a significant increase of up to 100% classification accuracy for the proposed EEGNet Fusion model and the ShallowConvNet model after transfer learning was used on the 3 subjects under evaluation. However, the differences between the EEGNet Fusion and ShallowConvNet models were not statistically significant ($p = 1$). The EEGNet model also showed an increase in accuracy after transfer learning was performed on all but one subject, but the DeepConvNet model produced generally mixed results. These results suggest that the EEGNet Fusion, EEGNet and ShallowConvNet models are well-suited for the transfer learning approach. However, the DeepConvNet model might rely on a larger training set to produce better results.

## 4.4 Brain-Computer Interface Validation

The developed BCI was evaluated using a similar experiment to the method used for data collection for the PhysioNet dataset. However, since the used EEG device had fewer channels available than were included in the original dataset, the models used for evaluation were trained on a reduced channels version of the dataset. The dataset used was the same 103-subject dataset described in Chapter 3.2.2, but the number of channels was reduced to 14 (channels AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4). The data used for the following BCI experiments were randomly split as 90% for training and 10% for validation.

### 4.4.1 Experimental results

The author of this thesis performed 5 runs consisting of 8 left-hand tasks and 8 right-hand tasks each for a total of 80 tasks to evaluate the performance of the classifiers under observation. Before each task, there were 4 seconds for rest and during the task the subject was instructed to perform 5 seconds of left or right hand executed or imagined movement.

Additionally, 5 more runs of the same tasks were performed to evaluate the effect of transfer learning. The data collected from the initial runs were used to re-train the models for the transfer learning experiment.

Predictions were made on each of the evaluated classification models - EEGNet, ShallowConvNet, and DeepConvNet – and the results were compared to the EEGNet Fusion model. For all experiments the accuracy of the predictions made and p-value from McNemar's test statistic were calculated.

The results of the experiments for executed movements are seen in Table 4.6.

Table 4.6: Executed motor movement task accuracies for the BCI experiments.

| **Model** | **Before TL** | | **After TL** | |
|---|---|---|---|---|
| | Accuracy | p-value | Accuracy | p-value |
| EEGNet | 51.4% | 0.46 | 53.1% | 0.44 |
| ShallowConvNet | 50.9% | 1 | 50.3% | 0.89 |
| DeepConvNet | 50% | 1 | 50% | 1 |
| **EEGNet Fusion** | **51.6%** | 1 | **53.7%** | 1 |

The same models and experimental setup were used for imagined movements and the results of the experiments are seen in Table 4.7.

Table 4.7: Imagined motor movement task accuracies for the BCI experiments.

| **Model** | **Before TL** | | **After TL** | |
|---|---|---|---|---|
| | Accuracy | p-value | Accuracy | p-value |
| EEGNet | 45% | 0.14 | **52%** | 0.06 |
| ShallowConvNet | 50% | 0.15 | 50.2% | **1** |
| DeepConvNet | **51%** | 0.15 | 50% | 0.02 |
| **EEGNet Fusion** | 45% | 1 | 50.5% | 1 |

### 4.4.2 Analysis

None of the transfer learning experiments with the BCI application showed a statistically significant difference between the EEGNet Fusion and the evaluated state-of-the-art models before or after transfer learning was applied.

These results could be explained by the difference in data quality produced by the 14-channel Emotiv EPOC headset compared to the 64-channel device used for data collection for the PhysioNet motor movement and imagery dataset. It might be that the channels containing relevant features for motor movement and imagery classification were not present in the data acquired for the BCI experiments.

It is also possible that performed experiments did not produce enough samples for the classifiers to achieve better results. In this regard further experiments with more subjects are necessary to draw any definite conclusions.

## 4.5 Future work

In the process of writing this thesis, numerous occasions were identified that require further research and experimental investigation. In this subchapter ideas for future improvements to the methodology of the classifier and BCI application development are presented.

While the proposed EEGNet Fusion model was tuned for best performance for the transfer learning experiment, the other state-of-the-art models under evaluations were not. It is possible that tuning the hyperparameters of these models could change the outcome of the experiments and needs to be considered in future work in this field.

The evaluation of statistical significance could be improved by reducing the chance of type I errors. This could be achieved by performing 5x2-fold cross-validation [75] or standard 10-fold cross-validation using the corrected paired Student's t-test as described by Nadeau *et al.* [77].

The transfer learning methodology could be improved by performing leave n-subjects out cross-validation. That means instead of testing the models on the last 3 subjects, the dataset can be split into 102 training subjects and one test subject and evaluated for 103 iterations until all subjects have been evaluated separately.

The BCI application developed in this thesis could be improved by adding functionality to analyze and plot the experimental results in a convenient way. Currently the results being saved to CSV must be post-processed in other ways for meaningful analysis of the results. Furthermore, the BCI application could be extended to support other types of experiments in the EEG experimental paradigm.

The device used for evaluation of the BCI application had clear limitations with the reduced number of channels. A device capable of recording higher quality data could be used to achieve better results with the BCI experiments.

Finally, the BCI application could be used to develop a practical navigation system where the user is thinking about movement to the left or right and the user is displayed the previous or the next page in a book or a document.

# Summary

A brain-computer interface is a system that interprets brain signals for human-computer communication. The signals can be recorded through different neuroimaging technologies that can identify the chemical, electrical, or magnetic activity of the brain, such as electroencephalography. The goal of BCI technology is to enable the user to communicate with or control an external device using their mind.

In this thesis an overview of modern EEG signal collection, processing, and classification methods, as well as various BCI applications used in medicine and the development of smart environments were given. Furthermore, a novel classifier model architecture termed EEGNet Fusion was proposed and experimentally validated in comparison to three state-of-the-art models – EEGNet, ShallowConvNet, and DeepConvNet.

The proposed model consists of three parallel branches with varying hyperparameters and the weights of the branches are combined in the final fusion layer. Additionally, a BCI application was developed to further validate the performance of the proposed model on data from a new subject and compare it to the performance of the state-of-the-art models.

The classifier performance was validated on left- and right-hand executed and imagined movement data from 103 subjects. Additionally, the classifiers were evaluated on new data from a new subject using the developed BCI application and the Emotiv EPOC device.

The results of the experiments suggest that the proposed preprocessing methodology and the classifier model EEGNet Fusion are well-suited for EEG motor movement and imagery task classification given enough data. The experiments showed statistically significant improvement over several state-of-the-art classifiers with accuracies of 84.1% and 83.8% on executed and imagined tasks, respectively. Furthermore, the proposed model performs significantly better on data from new subjects when transfer learning is applied. However, the experiments with the BCI application did not yield expected results and further experiments are needed to make definite conclusions.

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# Appendices

## I. Software Download and Installation Instructions Link

The software used for classifier validation and the BCI application developed in this thesis along with installation instructions can be accessed at https://github.com/rootskar/MotorImageryBCI

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