ANALYSIS OF MENTAL IMAGERY BASED COGNITIVE TASKS FOR BRAIN COMPUTER INTERFACE

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A project report submitted in partial fulfilment of the requirements for the award of the degree of Bachelor of Engineering (Honours) Electronic Engineering

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"ANALYSIS OF MENTAL IMAGERY BASED COGNITIVE TASKS FOR BRAIN COMPUTER INTERFACE"** was prepared by **TANG CHEE HOE** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Hons) Electronic Engineering at Universiti Tunku Abdul Rahman.

Approved by,

Signature : _________________________

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Date : _________________________

Specially dedicated to

my beloved grandparents, family and friends.

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ABSTRACT

By representing the EEG signals (brain waves) recorded during mental imagery in terms of features and classifying them using an appropriate classifier, the mental imagery tasks performed can be identified accurately and thus be used for BCI in full applications. The optimal electrodes for mental imagery applications are the C3, Cz and C4 electrodes that are not present in low cost EEG acquisition devices like the Emotiv EPOC+ headset. However, this limitation is overcome in this study. In fact, not all the electrodes available are needed. Most of the information necessary for the mental imagery applications is present at the FC5, FC6, P7, P8, AF3 and AF4 electrodes. Moreover, it is found that the combination of features is able to improve the average cross validation accuracy further. By classifying the Band Power and ApEn features from the electrodes mentioned above using the KNN classifier, an average cross validation accuracy of 99.75% is achieved. If the same features from the FC5, FC6, AF3 and AF4 electrodes are classified, an average cross validation accuracy of 98.55% can be attained. Hence, it is deduced as the best model that meets the aim of this study, requiring only four instead of all the electrodes with a little compromise on the average cross validation accuracy. Based on the model selected, it can be concluded that out of the four mental imagery tasks (LEFT, RIGHT, PUSH and PULL), the PULL mental imagery task is the hardest to be classified, with a classification error of 2.4%.

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LIST OF SYMBOLS / ABBREVIATIONS

mph	miles per hour
Hz	Hertz
s	seconds
α	alpha waves
β	beta waves
C	Cost (hyperparameter of SVM classifier)
$C_i^m(r)$	correlation intergral
δ	delta waves
γ	gamma waves
θ	theta waves
ALS	Amyotrophic Lateral Sclerosis
ApEn	Approximate Entropy
BCI	Brain Computer Interface
BP	Band Power
C	Central
CMS	Common Mode Sense
CSP	Common Spatial Pattern
CVA	Cross Validation Accuracy
CWT	Continuous Wavelet Transform
db4	Daubechies wavelet with order 4
DRL	Driven Right Leg
DT	Decision Tree
DWT	Discrete Wavelet Transform
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography

ERS	Event-Related Synchronization
ERD	Event-Related Desynchronization
F	Frontal
FFT	Fast Fourier Transform
GNB	Gaussian Naïve Bayes
ICA	Independent Component Analysis
KNN	K-Nearest Neighbours
LDA	Linear Discriminant Analysis
MI	Mental Imagery
NN	Neural Network
O	Occipital
P	Parietal
PSD	Power Spectral Density
PSO	Particle Swarming Optimization
QSA	Quaternion-based Signal Analysis
RF	Random Forest
SD	Standard Deviation
SMR	Sensorimotor Rhythm
SVM	Support Vector Machine
T	Temporal
WT	Wavelet Transform

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CHAPTER 1

INTRODUCTION

1.1 Background

Human brain is known to be the most unique yet mysterious structure in the universe. It allows us to think, to speak, to move, to solve problems and so forth. It also responds to the stimuli in the surroundings through information perceived by the sensory organs, such as the eyes, nose, ears etc. In short, it is the control centre that controls and regulates all conscious and unconscious facets of human’s daily life.

With the objective to unlock mysteries of the human brain, numerous studies and researches have been done to understand human brain better. One of the key research area is the Electroencephalography (EEG). As the brain processes information and reacts to it, electrical signals travel between nerve cells in the brain. However, some of the electrical signals escape while traveling between neurons and EEG is the method that detects these escaped signals. According to Jais *et al.* (2017), even the imagination of performing a task produces EEG signals and these signals are somewhat similar to that of executing the task in reality. This phenomenon is known as mental imagery or more specifically, motor imagery.

Brain Computer Interface (BCI) is a system that enables direct communication between the human brain and computers or any other external devices. With proper signal processing methods, it is believed that the mental imagery based EEG signals can be utilised for BCI applications. These signals reflect the user’s intention and thus can be used as the input for BCI systems. After processing the signals, BCI system sends out signal that controls the external devices according to the user’s intention.

As a matter of fact, BCI is a neurotechnology initially developed for biomedical applications. With the development and advancement in BCI, the potential and future of BCI has been foreseen by researchers, leading to a wider scope of research that includes non-medical applications which target normal individuals. Particularly, BCI can improve on the current human computer interface (HCI), resulting in its contribution in numerous fields such as medical, communication, mental state monitoring as well as entertainment (Abdulkader, Atia and Mostafa, 2015).

1.2 Problem Statement

According to Mak and Wolpaw (2009), there are millions of people around the globe who suffer from motor disabilities such as people with head injuries, spinal-cord injuries, stroke, amyotrophic lateral sclerosis (ALS) and other severe neuromuscular diseases. The loss of neuromuscular function and the ability to communicate greatly impacts the daily life of these less fortunate people. Therefore, the restoration of basic communication abilities for these people would be a gift to them as it can improve their quality of life considerably and reduce their dependence on others.

BCI devices appear to be one of the possible solutions for them but these devices usually come with a hefty price tag that keeps them away. This is due to the fact that most of the BCI devices available in the market utilises a high cost EEG acquisition device in order to achieve a higher accuracy (Zhang *et al.*, 2013). Low cost EEG acquisition devices like Emotiv EPOC+ are seldom used due to the lesser number of electrodes, especially the lack of electrodes covering regions essential for motor imagery applications. Use of these acquisition devices may lead to a lower accuracy, therefore affecting the user experience.

1.3 Aims and Objectives

This study aims to propose a cost effective yet high accuracy method that is able to interpret the user’s mental imagery based on the EEG signal acquired. The objectives of this thesis are shown as follows:

i) To pre-process the mental imagery EEG signals acquired from a low cost EEG acquisition device
ii) To identify the features that can be used to represent the user’s intention precisely
iii) To classify the EEG signals into four different classes, i.e. left, right, push and pull based on the features extracted

1.4 Research Questions

Can the cognitive tasks performed by users be classified into different classes based on the mental imagery based EEG signals acquired?

1.5 Research Hypothesis

1. The cognitive tasks performed by users can be classified by using features extracted from the EEG signals which represent information embedded in the signal.
2. Different combinations of features extracted and classifier used will give different classification accuracy.

1.6 Significance of Study

Fundamentally, BCI serves as a bridge that enables human brain to communicate directly with the external world, bypassing the normal information delivery method. From the brain signals obtained, it is able to interpret a person's silent thought, thus helping handicapped people to express their mind. Moreover, BCI also enables the mind-controlling of devices, further enhances the user experience of hands-free applications. Neuromuscular output channels are no longer required and brain signals alone are sufficient to complete a set of commands. As a result, through the use of BCI assistive robots, the life of those with motor disabilities would be easier as they can handle practically everything on their own.

In addition, BCI can also be a logical measuring tool that identifies a person's emotional, cognitive or affectiveness state. Other than controlling external devices like in the passive BCI, the state monitoring function of BCI brings a variety of different applications. For instance, it is used to improve HCI by adapting the HCI based on the user's emotion or cognitive state. This allows the best control to be implemented in a particular condition (Abdulkader, Atia and Mostafa, 2015). An example being the use of state monitoring in workplace. It ensures that the lighting and air condition is adjusted such that a conducive working condition is provided.

All the applications mentioned would not come into reality without accurate classification of the cognitive tasks performed. Hence, this study aims to propose a cost effective yet accurate way of analysing the user's mental imagery based on the EEG signals acquired so that BCI are available and affordable by the masses.

CHAPTER 2

LITERATURE REVIEW

2.1 Brain Anatomy

Undeniably, as the center of the nervous system, brain is the most complex organ in the human body. Generally, the brain can be divided into 3 main parts, which are cerebrum, cerebellum and brain stem as shown in Figure 2.1.

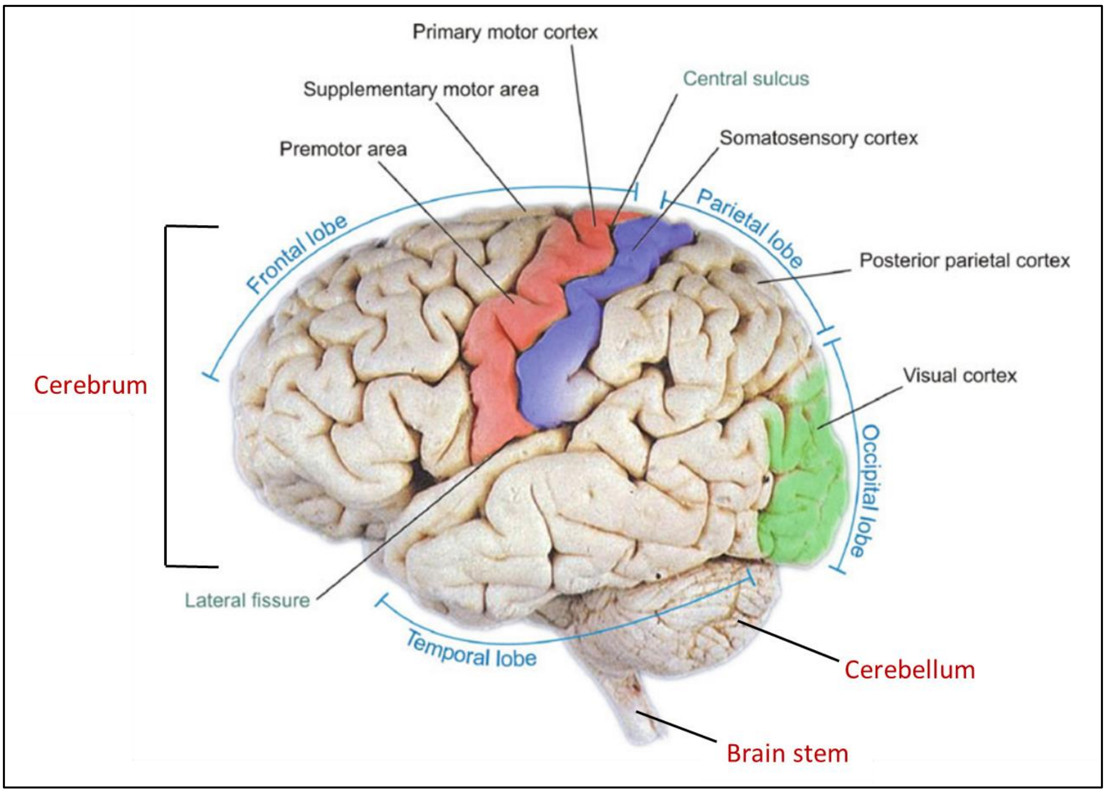

Figure 2.1: Brain Anatomy (Graimann, Allison and Pfurtscheller, 2010)

Cerebrum, which is the largest among the three, consists of the left hemisphere and the right hemisphere. Each cerebral hemisphere can be further divided into four lobes, which are frontal, parietal, occipital and temporal lobe with their functions tabulated in Table 2.1. As shown in the Figure 2.1, the frontal lobe is separated from the parietal lobe by the central sulcus while the temporal lobe is separated from the parietal lobe by the lateral fissure (Graimann, Allison and Pfurtscheller, 2010).

Table 2.1: Function of the Lobes

Lobe	Functions of the lobe
Frontal lobe	Higher level cognitive functions: • Problem solving • Concentration • Speaking • Writing
Parietal lobe	• Sensation • Spatial perception • Language and words interpretation
Occipital lobe	• Visual processing center
Temporal lobe	• Memory • Hearing

Located below the cerebrum, cerebellum is accountable for maintaining posture and balance besides coordinating muscle actions. Connecting the cerebrum and cerebellum to the spinal cord, brain stem acts as a relay centre and it is responsible for self-regulating functions, such as breathing, digestion, heart rate, swallowing etc. (Alnemari, 2017).

2.2 Electroencephalography (EEG)

Neuron or nerve cell as shown in Figure 2.2, is the basic unit of brain and the nervous system. When a person is performing a task such as focusing on something, moving or performing mental calculations, nerve signals travel from neuron to neuron up to a speed of 250mph. In fact, nerve signals are basically electrical signals, generated due to the changes in concentration of charged potassium (K+) and sodium (Na+) ions in the neurons (Kamel and Malik, 2015). Even though the path travelled by the nerve signals are insulated by myelin, some of the electric signal still escapes (Anupama, Cauvery and Lingaraju, 2014). Electroencephalography (EEG) is a technique that detects and monitors these escaped signals by placing small flat metal discs known as electrodes on the scalp (Alnemari, 2017).

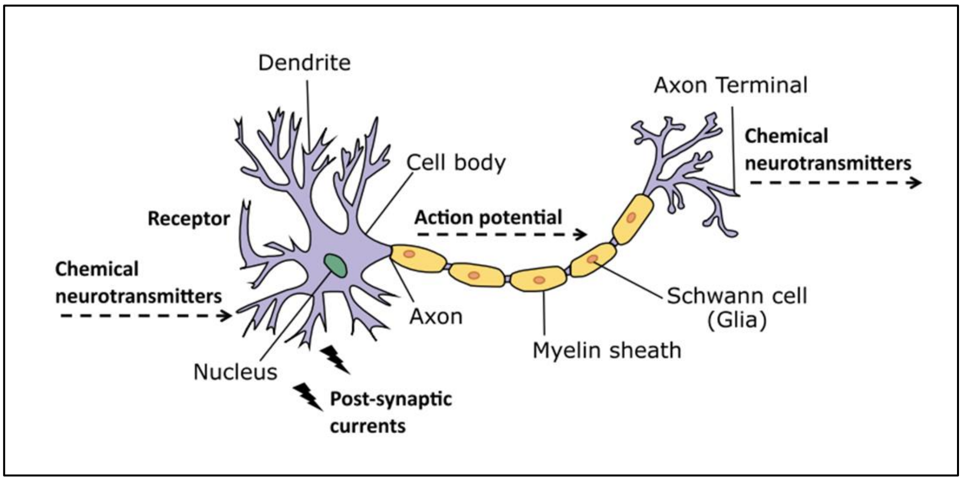

Figure 2.2: Structure of a neuron (Tiziano D'Albis, 2008)

Human EEG was first discovered by a German scientist, Hans Berger in 1924. He recorded the first EEG signal of human brain and identified oscillatory activity in the brain, which was the alpha wave through analysis performed on the recorded EEG signal (Anupama, Cauvery and Lingaraju, 2014). Hence, alpha wave is also known as Berger's wave. Since then, EEG has been developed and new methods for exploring every possibility of it have been found. All of these efforts lay the groundwork for neuroscience and Brain Computer Interfaces (BCI).

2.3 Brain Waves

EEG waveforms can be classified in terms of amplitude, frequency, shape and the site of recording electrical signals on the scalp (Nanditha and A, 2017). In fact, brain waves are commonly categorized based on their frequency range (bandwidth). The five major waves are delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) waves. These brain waves are in sequence from lowest frequency (highest amplitude) to highest frequency (lowest amplitude) as shown in Figure 2.3.

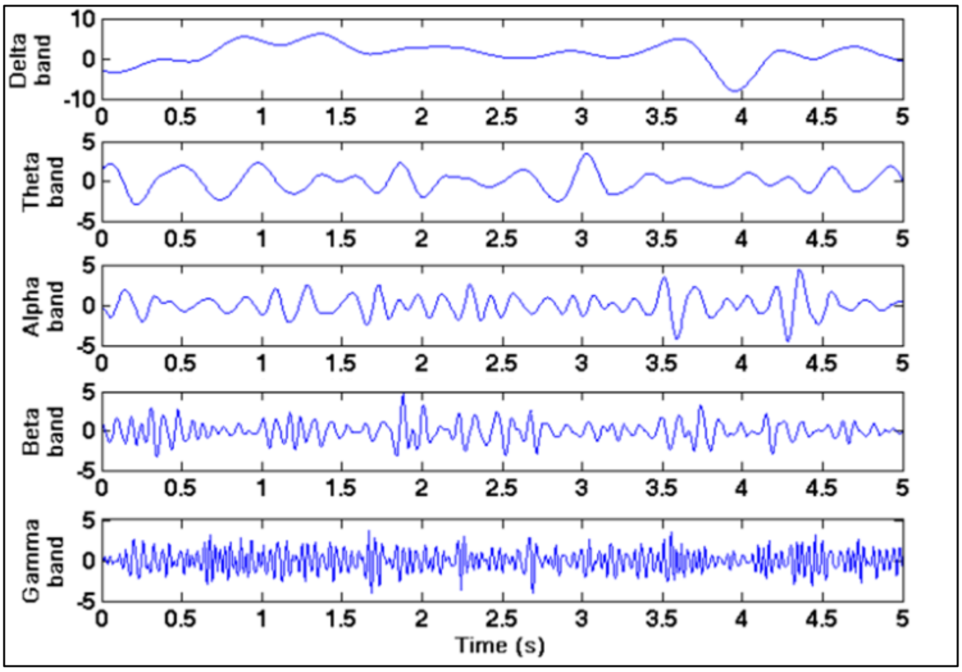

Figure 2.3: Waveforms for the different types of EEG signal (Abo-Zahhad, Ahmed and Abbas, 2015)

Delta wave is the lowest frequency brain wave in the range of 1 – 4 Hz. However, it has the highest amplitude among all the other brain waves. It is usually observed in adults or babies in deep or dreamless sleep (Shakshi and Jaswal, 2016).

Theta wave ranges from 4 – 7 Hz. It is often associated with inefficiency, daydreaming, as well as a state between being awake and falling asleep (Larsen and

Wang, 2011). This brain wave usually appears with the closing of eyes and disappears with the opening of eyes (Shakshi and Jaswal, 2016). High level of theta waves are said to be abnormal in adults.

Alpha wave which ranges from 7 – 13 Hz, is produced when a person closes his eyes or when he is relaxed. In other words, thinking something peaceful with the eyes closed will increase the alpha activity in the brain (Larsen and Wang, 2011). This brain wave is mostly found in the occipital lobe of the human brain.

Beta wave on the other hand, has a frequency range of 13 – 30 Hz. It is the characteristic of an active thinking or focused mind (Aparna Ashtaputre, 2016). This means that when the brain is aroused or actively engaged in mental activity, beta wave is generated, especially in the frontal and parietal lobe.

Gamma wave is the fastest and has the lowest amplitude among all brain waves, with frequency between 31 – 100 Hz. It is believed that gamma wave is the one that binds different population of nerve cells together when the brain processes simultaneous information from different parts of the brain. Hence, an optimal level of gamma waves is often associated with good memory whereas a lack of gamma waves result in learning disabilities (Warner, 2013). Typically, it is engaged in higher level tasks, for instance learning, memory and processing of information.

Mu wave has frequency ranges from 7 Hz to 13 Hz, which overlaps with the alpha wave's frequency band. As opposed to alpha wave which usually presents in the occipital region, mu wave is normally found in the sensorimotor cortex, which is where the C3, Cz and C4 electrodes are located. This wave is "suppressed" or "desynchronized" whenever a person moves or has the intention to move (Garcia-Rill, 2015). Summary of the above brain waves are shown in Table 2.2.

Table 2.2: Summary of Brain Waves (Alshbatat *et al.*, 2014)

Brain Waves	Frequency Range (Hz)	Location	Associated with
Delta (δ)	1 – 4	• Frontal region (adults) • Posterior region (premature babies)	• Dreamless sleep • Coma
Theta (θ)	4 – 7	• Parietal region • Occipital region	• Daydreaming • Drowsiness • Dream Sleep
Alpha (α)	7 – 13	Occipital region	• Relaxed state of mind • Closing of eyes in awake condition
Beta (β)	13 – 30	• Frontal region • Parietal region	• Problem solving • Judgement • Decision making • Concentration
Gamma (γ)	30 – 100	Every part of the brain	• Learning • Processing of information • Concentration • High energy state, e.g. when afraid
Mu (μ)	7 – 13	Sensorimotor cortex (C3, Cz and C4 electrodes)	• Actual movement • Intention to move

CHAPTER 3

METHODOLOGY

3.1 Introduction

The flow of this project is based on the implementation of a BCI system as shown in Figure 3.1. EEG data was recorded using Emotiv EPOC+ headset by a previous researcher. The EEG signal acquired is first pre-processed using EEGLAB in order to remove artifacts present in the signal. After removing artifacts in the signal, relevant features are extracted from the EEG signals using MATLAB. Next, classification of the features will be done by using the Weka software. The flowchart as shown in Figure 3.2 illustrates the flow of this study.

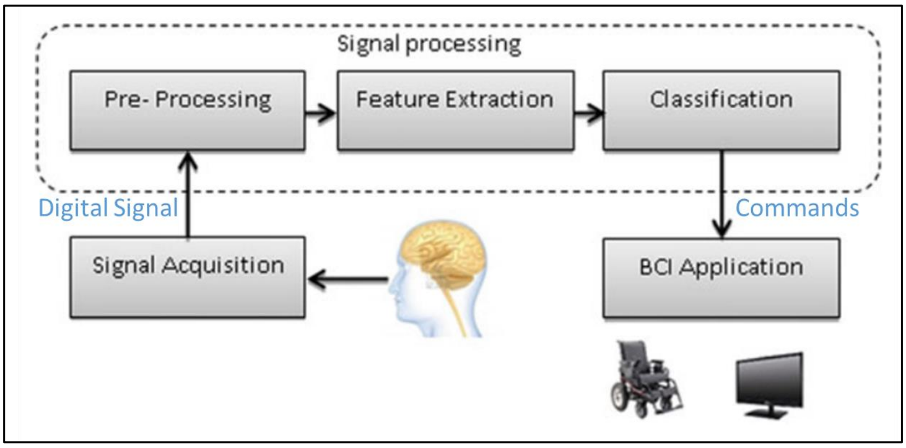

Figure 3.1: A Brain Computer Interface (BCI) system (Ramadan *et al.*, 2015)

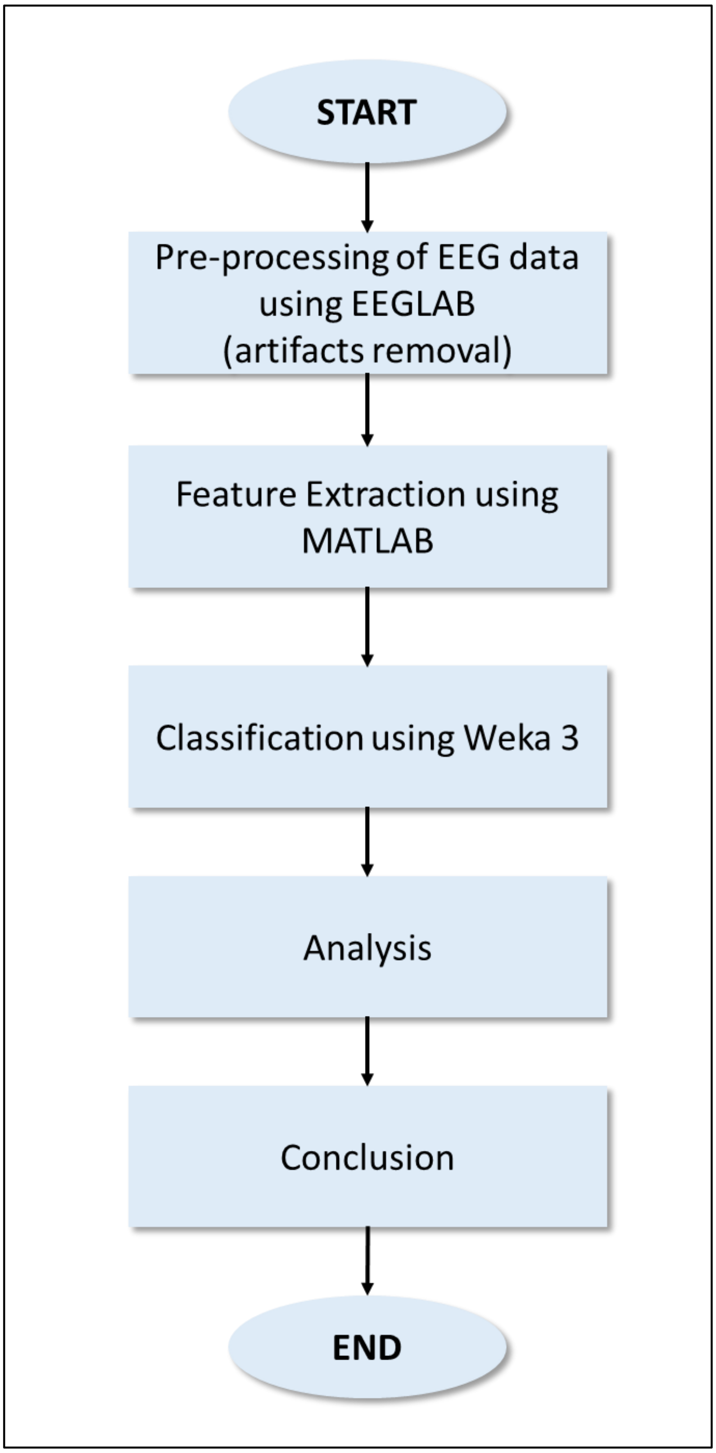

Figure 3.2: Generic Flowchart of the Project

3.2 Equipment and Tools

3.2.1 Hardware

i. Personal Computer

3.2.2 Software

i. EEGLAB (Version 14)
ii. MATLAB (Version R2014a)
iii. Weka (Version 3.8)
iv. Microsoft Excel

3.3 Description of Data Set

The EEG data used in this study is adopted from a previous researcher who developed a BCI system which controlled the robot using motor imagery. Listed below are the steps carried out by the researcher to record EEG signals from 13 subjects:

1. The subject is first given some time familiarizing with the Emotiv headset and then he/she is asked to relax and close his eyes, in order to record the EEG signal for 5 minutes.

2. Next, the subject is asked to relax again with eyes open and EEG signal is recorded for another 5 minutes.

3. After some rest, the subject is introduced to the Emotiv Cognitive suite as shown in Figure 2.10 where the subject is required to undergo training of two actions, i.e. mental imagery of push and pull on the animated cube.

4. Step 3 is repeated three times so that the system obtain a better signal from the subject.

5. Rest is given after the training phase.

6. 5 minutes is given to the subject to apply the push action on the animated cube.

7. Step 6 is repeated for pull action.

8. Step 3 to step 7 are repeated for mental imagery of left and right action on the animated cube.

3.4 Pre-processing of EEG Signal

As frequencies higher than 30Hz belong to the gamma band which is not the band of interest for mental imagery applications, EEG signals are filtered from 1 – 30Hz at the beginning of the pre-processing stage. In addition, EEG signals acquired are normally noisy with some artifacts being introduced. Examples of artifacts include muscle activity – Electromyography (EMG) artifacts, eye movements – Electrooculography (EOG) artifacts, interferences from electrical equipment and cables etc. as shown in Figure 3.3 (Alnemari, 2017). Hence, there is a need for artifact removal before extracting features from the signals and classifying them. A technique commonly used to remove artifacts from the EEG signals is the Independent Component Analysis (ICA) (Rak, Kołodziej and Majkowski, 2012). However, in this study, the removal of artifacts in EEG signal is done manually by using an open source MATLAB toolbox known as EEGLAB. All the artifacts are removed first before proceeding to the feature extraction stage.

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APPENDICES

APPENDIX A: Normalized Feature Values

The normalized values of the features used in this study is shown in following pages (Table A.1 to A.4)

Table A.1: Normalized Band Power values

Features	**Mental Imagery Tasks**			
	LEFT	RIGHT	PUSH	PULL
Alpha Power (AF3)	0.0463	0.0422	0.0877	0.0536
Alpha Power (FC5)	0.0401	0.0519	0.0280	0.0454
Alpha Power (FC6)	0.0558	0.0695	0.0536	0.0729
Alpha Power (AF4)	0.0558	0.0779	0.0507	0.0621
Beta Power (AF3)	0.0829	0.0679	0.1346	0.0853
Beta Power (FC5)	0.0995	0.0695	0.0830	0.0835
Beta Power (FC6)	0.0947	0.0531	0.0942	0.0760
Beta Power (AF4)	0.1002	0.0666	0.0937	0.0870
AVERAGE	0.0719	0.0623	0.0782	0.0707

Table A.2: Normalized ApEn values

Features	Mental Imagery Tasks			
	LEFT	RIGHT	PUSH	PULL
AF3	0.4857	0.4660	0.4516	0.4570
FC5	0.5907	0.5562	0.5279	0.5015
FC6	0.5097	0.4724	0.5164	0.4738
AF4	0.4774	0.4166	0.5023	0.4208
AVERAGE	0.5159	0.4778	0.4995	0.4633

Table A.3: Normalized Statistical feature values

Features	Mental Imagery Tasks			
	LEFT	RIGHT	PUSH	PULL
Mean (AF3)	0.602	0.606	0.615	0.589
Mean (FC5)	0.563	0.549	0.560	0.543
Mean (FC6)	0.531	0.535	0.533	0.520
Mean (AF4)	0.743	0.734	0.753	0.728
SD (AF3)	0.106	0.108	0.133	0.137
SD (FC5)	0.060	0.061	0.061	0.101
SD (FC6)	0.085	0.085	0.094	0.115
SD (AF4)	0.096	0.101	0.080	0.112
1st diff (AF3)	0.345	0.331	0.399	0.368
1st diff (FC5)	0.053	0.029	0.080	0.098
1st diff (FC6)	0.054	0.025	0.089	0.099
1st diff (AF4)	0.063	0.034	0.091	0.103
Normalized 1st diff (AF3)	0.358	0.354	0.329	0.320
Normalized 1st diff (FC5)	0.320	0.269	0.322	0.301
Normalized 1st diff (FC6)	0.268	0.208	0.298	0.289
Normalized 1st diff (AF4)	0.223	0.172	0.268	0.235
2nd diff (AF3)	0.321	0.308	0.371	0.344
2nd diff (FC5)	0.055	0.031	0.082	0.100
2nd diff (FC6)	0.056	0.028	0.091	0.102
2nd diff (AF4)	0.069	0.039	0.095	0.109
Normalized 2nd diff (AF3)	0.379	0.372	0.353	0.342
Normalized 2nd diff (FC5)	0.345	0.293	0.348	0.326
Normalized 2nd diff (FC6)	0.294	0.232	0.324	0.316
Normalized 2nd diff (AF4)	0.246	0.195	0.294	0.257
AVERAGE	0.260	0.237	0.278	0.273

Table A.4: Normalized Wavelet-based feature values

Features	Mental Imagery Tasks			
	LEFT	RIGHT	PUSH	PULL
D2 Mean (AF3)	0.453	0.447	0.452	0.434
D2 Mean (FC5)	0.525	0.533	0.544	0.523
D2 Mean (FC6)	0.490	0.497	0.505	0.483
D2 Mean (AF4)	0.530	0.534	0.540	0.518
D2 SD (AF3)	0.272	0.248	0.329	0.288
D2 SD (FC5)	0.068	0.038	0.090	0.106
D2 SD (FC6)	0.070	0.036	0.101	0.109
D2 SD (AF4)	0.081	0.046	0.102	0.112
D2 Energy (AF3)	0.122	0.097	0.170	0.137
D2 Energy (FC5)	0.022	0.005	0.061	0.079
D2 Energy (FC6)	0.025	0.004	0.067	0.080
D2 Energy (AF4)	0.028	0.006	0.064	0.076
D1 Mean (AF3)	0.500	0.483	0.490	0.473
D1 Mean (FC5)	0.641	0.646	0.641	0.629
D1 Mean (FC6)	0.710	0.711	0.695	0.690
D1 Mean (AF4)	0.519	0.500	0.509	0.491
D1 SD (AF3)	0.288	0.259	0.337	0.293
D1 SD (FC5)	0.055	0.029	0.083	0.098
D1 SD (FC6)	0.052	0.023	0.089	0.097
D1 SD (AF4)	0.056	0.026	0.086	0.095
D1 Energy (AF3)	0.140	0.106	0.179	0.147
D1 Energy (FC5)	0.014	0.002	0.057	0.076
D1 Energy (FC6)	0.016	0.002	0.065	0.078
D1 Energy (AF4)	0.016	0.002	0.059	0.072
AVERAGE	0.237	0.220	0.263	0.258

APPENDIX B: Results of Classification based on a Single Feature

The average cross validation accuracies of using a single feature are shown in following pages (Table B.1 to B.4).

Table B.1: Average Cross Validation Accuracy of Band Power Features

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	49.87%	59.85%	69.38%	60.09%
P7, P8	60.33%	65.62%	63.70%	61.77%
AF3, AF4	52.40%	60.45%	57.93%	57.09%
FC5, FC6, P7, P8	66.34%	81%	84.61%	81.49%
FC5, FC6, AF3, AF4	61.53%	77.76%	82.93%	80.04%
P7, P8, AF3, AF4	65.50%	83.65%	86.65%	82.57%
FC5, FC6, P7, P8, AF3, AF4	69.23%	87.98%	92.30%	89.18%
All	76.20%	93.87%	95.91%	93.62%

Table B.2: Average Cross Validation Accuracy of ApEn Features

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	53.60%	59.85%	57.69%	60.21%
P7, P8	49.03%	49.27%	48.91%	54.20%
AF3, AF4	56.85%	60.69%	59.85%	61.17%
FC5, FC6, P7, P8	72.47%	81%	88.58%	85.21%
FC5, FC6, AF3, AF4	78.36%	88.34%	94.23%	93.50%
P7, P8, AF3, AF4	73.31%	86.41%	91.34%	91.70%

FC5, FC6, P7, P8, AF3, AF4	82.69%	94.83%	98.67%	98.67%
All	82.45%	98.19%	99.87%	99.75%

Table B.3: Average Cross Validation Accuracy of Statistical Features

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	61.41%	72.83%	63.70%	63.82%
P7, P8	59.97%	73.67%	66.82%	67.42%
AF3, AF4	67.42%	77.04%	76.08%	74.39%
FC5, FC6, P7, P8	68.26%	86.89%	81.61%	81%
FC5, FC6, AF3, AF4	72.83%	87.98%	85.45%	84.25%
P7, P8, AF3, AF4	72.23%	89.54%	87.01%	86.17%
FC5, FC6, P7, P8, AF3, AF4	74.15%	92.78%	91.70%	88.82%
All	79.92%	95.55%	95.67%	94.35%

Table B.4: Average Cross Validation Accuracy of Wavelet-based Features

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	51.92%	62.86%	49.03%	46.63%
P7, P8	58.53%	66.34%	53.72%	53.12%
AF3, AF4	56.85%	67.30%	57.45%	61.29%
FC5, FC6, P7, P8	65.26%	80.76%	66.34%	63.34%
FC5, FC6, AF3, AF4	68.99%	82.21%	66.82%	68.99%
P7, P8, AF3, AF4	66.94%	81.73%	75.12%	74.75%
FC5, FC6, P7, P8, AF3, AF4	74.03%	88.82%	79.68%	80.88%
All	80.16%	95.07%	88.46%	90.14%

APPENDIX C: Results of Classification based on Combinations of Features

The average cross validation accuracies of using combination of features are shown in following pages (Table C.1 to C.11)

Table C.1: Average Cross Validation Accuracy of Combination 1 (Band Power and ApEn Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	73.31%	89.18%	92.66%	91.94%
P7, P8	70.31%	84.61%	82.93%	84.13%
AF3, AF4	70.79%	85.69%	90.26%	90.50%
FC5, FC6, P7, P8	80.64%	94.23%	98.07%	96.15%
FC5, FC6, AF3, AF4	82.09%	96.75%	98.55%	98.67%
P7, P8, AF3, AF4	78.72%	96.99%	98.19%	97.83%
FC5, FC6, P7, P8, AF3, AF4	83.89%	97.83%	99.75%	99.27%
All	84.73%	98.31%	100%	99.75%

Table C.2: Average Cross Validation Accuracy of Combination 2 (Band Power and Statistical Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	61.53%	80.28%	73.07%	74.51%
P7, P8	62.74%	79.80%	74.39%	75.12%
AF3, AF4	64.30%	81.85%	79.80%	79.20%
FC5, FC6, P7, P8	69.23%	89.66%	87.86%	81.73%
FC5, FC6, AF3, AF4	75.48%	89.90%	87.86%	87.25%

P7, P8, AF3, AF4	71.75%	91.58%	90.74%	89.06%
FC5, FC6, P7, P8, AF3, AF4	77.04%	94.11%	93.02%	90.74%
All	82.21%	96.63%	95.91%	95.07%

Table C.3: Average Cross Validation Accuracy of Combination 3 (Band Power and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	60.93%	74.03%	63.34%	62.01%
P7, P8	63.10%	76.56%	67.66%	65.50%
AF3, AF4	62.01%	73.43%	67.42%	66.10%
FC5, FC6, P7, P8	67.66%	86.17%	81.12%	79.08%
FC5, FC6, AF3, AF4	71.51%	87.5%	77.40%	80.64%
P7, P8, AF3, AF4	73.19%	87.37%	86.89%	82.93%
FC5, FC6, P7, P8, AF3, AF4	73.43%	92.42%	89.30%	87.5%
All	80.04%	95.79%	93.62%	93.75%

Table C.4: Average Cross Validation Accuracy of Combination 4 (ApEn and Statistical Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	77.76%	90.14%	86.41%	85.45%
P7, P8	69.83%	85.33%	85.21%	87.13%
AF3, AF4	74.27%	90.14%	92.06%	91.10%
FC5, FC6, P7, P8	82.09%	96.99%	94.95%	96.63%
FC5, FC6, AF3, AF4	83.41%	96.27%	96.87%	96.39%
P7, P8, AF3, AF4	78.36%	96.15%	96.99%	96.99%

FC5, FC6, P7, P8, AF3, AF4	85.93%	97.83%	98.43%	97.71%
All	87.37%	98.43%	99.39%	99.87%

Table C.5: Average Cross Validation Accuracy of Combination 5 (ApEn and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	79.68%	90.26%	81.49%	83.77%
P7, P8	70.07%	81.97%	80.76%	79.56%
AF3, AF4	72.83%	86.17%	86.17%	87.37%
FC5, FC6, P7, P8	79.44%	95.31%	96.51%	93.87%
FC5, FC6, AF3, AF4	85.33%	96.63%	95.91%	97.35%
P7, P8, AF3, AF4	81%	94.95%	96.63%	96.39%
FC5, FC6, P7, P8, AF3, AF4	84.01%	97.95%	98.91%	99.03%
All	84.13%	98.91%	99.39%	99.51%

Table C.6: Average Cross Validation Accuracy of Combination 6 (Statistical and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	64.54%	79.08%	66.34%	64.54%
P7, P8	68.14%	78.72%	75.36%	74.15%
AF3, AF4	66.22%	79.80%	76.08%	74.27%
FC5, FC6, P7, P8	67.78%	88.94%	85.21%	82.21%
FC5, FC6, AF3, AF4	73.31%	89.66%	86.05%	84.73%
P7, P8, AF3, AF4	75.36%	91.10%	90.38%	89.66%

FC5, FC6, P7, P8, AF3, AF4	74.87%	93.62%	91.70%	90.86%
All	81.85%	96.27%	95.55%	95.79%

Table C.7: Average Cross Validation Accuracy of Combination 7 (Band Power, ApEn and Statistical Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	76.44%	93.87%	91.22%	88.70%
P7, P8	67.66%	87.62%	88.94%	87.37%
AF3, AF4	71.39%	91.10%	93.14%	91.46%
FC5, FC6, P7, P8	80.40%	97.23%	96.75%	96.87%
FC5, FC6, AF3, AF4	81.85%	97.11%	97.11%	96.63%
P7, P8, AF3, AF4	81%	96.27%	97.59%	96.63%
FC5, FC6, P7, P8, AF3, AF4	84.97%	97.71%	98.79%	98.31%
All	88.34%	98.43%	99.51%	99.87%

Table C.8: Average Cross Validation Accuracy of Combination 8 (Band Power, ApEn and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	74.51%	93.02%	92.54%	91.46%
P7, P8	70.55%	85.57%	86.65%	86.29%
AF3, AF4	73.19%	89.06%	89.90%	90.50%
FC5, FC6, P7, P8	80.40%	95.31%	97.71%	97.11%
FC5, FC6, AF3, AF4	84.49%	98.07%	97.35%	98.07%
P7, P8, AF3, AF4	78.96%	95.19%	97.23%	97.23%

FC5, FC6, P7, P8, AF3, AF4	80.88%	98.19%	99.03%	98.67%
All	82.09%	98.55%	99.15%	99.63%

Table C.9: Average Cross Validation Accuracy of Combination 9 (Band Power, Statistical and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	64.42%	82.09%	74.15%	75.60%
P7, P8	67.54%	80.52%	79.08%	78.24%
AF3, AF4	64.66%	83.17%	79.44%	77.88%
FC5, FC6, P7, P8	70.55%	89.54%	88.46%	87.62%
FC5, FC6, AF3, AF4	73.67%	91.94%	87.74%	86.17%
P7, P8, AF3, AF4	73.19%	92.90%	92.06%	91.10%
FC5, FC6, P7, P8, AF3, AF4	73.91%	94.95%	93.02%	91.94%
All	83.41%	96.39%	96.39%	96.03%

Table C.10: Average Cross Validation Accuracy of Combination 10 (ApEn, Statistical and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	75.96%	91.22%	87.13%	87.13%
P7, P8	70.19%	83.65%	87.98%	85.33%
AF3, AF4	72.95%	89.54%	91.34%	89.78%
FC5, FC6, P7, P8	80.64%	96.63%	96.15%	95.91%
FC5, FC6, AF3, AF4	80.28%	96.39%	96.63%	95.91%
P7, P8, AF3, AF4	80.64%	96.27%	96.87%	95.07%

FC5, FC6, P7, P8, AF3, AF4	84.49%	97.59%	98.67%	98.55%
All	86.53%	98.43%	98.91%	99.51%

Table C.11: Average Cross Validation Accuracy of Combination 11 (Band Power, ApEn, Statistical and Wavelet-based Features)

Electrodes Used	Decision Tree	Random Forest	KNN (k = 1)	SVM
FC5, FC6	75.12%	92.18%	91.10%	88.46%
P7, P8	70.91%	86.05%	90.26%	86.41%
AF3, AF4	71.51%	89.18%	92.06%	90.98%
FC5, FC6, P7, P8	79.80%	95.67%	96.87%	95.91%
FC5, FC6, AF3, AF4	81.25%	96.51%	96.87%	95.79%
P7, P8, AF3, AF4	80.16%	95.67%	96.99%	95.91%
FC5, FC6, P7, P8, AF3, AF4	85.81%	96.99%	98.55%	98.67%
All	86.17%	98.31%	99.15%	99.27%

APPENDIX D: Source Code for Extracting Band Power Features

```
filename = 'bp_features.csv';
sampRate = 128; % sampling rate of your data
lowerFreq = 7; % lower bound of alpha band
higherFreq = 13; % upper bound of alpha band

length = 20;    % desired length of EEG signal in seconds
window_size = 5;    % size of sliding window in seconds
overlap = 0.25;  % overlapping ratio of sliding windows
loop = ((length-window_size)/((1-overlap)*window_size)) + 1;      % Number of windows (features) extracted from a signal

abspower=0;
nbchannel=EEG.nbchan;
inter_ar=zeros(1,nbchannel);
window_bp = zeros(int16(loop),nbchannel);

for chanNr = 1:nbchannel; % channel number of your specific lead

   start_index = 1;
   end_index = start_index + window_size*sampRate - 1;
   data = EEG.data(chanNr,1:length*sampRate);

   for i = 1:loop
      window_data = data(start_index:end_index);

      % computing log spectrum for different frequencies
      [power, freq] = spectopo(window_data, 0, sampRate);%(chanNr, :)

      % average power within the predefined frequency range
      AlphaIdx = find(freq == lowerFreq) : find(freq == higherFreq);
      temp = 10^(mean(power(AlphaIdx))/10);

      % Saving data for sliding window
      window_bp(i,chanNr) = temp;
      start_index = int16(start_index + window_size*sampRate*(1-overlap));
      end_index = int16(end_index + window_size*sampRate*(1-overlap));
   end
end

%Writing the features extracted into a csv file
dlmwrite(filename,window_bp,'delimiter',',','-append');
```

APPENDIX E: Source Code for Extracting ApEn Features

```
filename = 'apen_features.csv';
sampRate = 128; %sampling rate of your data

length = 20;    % desired length of EEG signal in seconds
window_size = 5;    % size of sliding window in seconds
overlap = 0.8;  % overlapping ratio of sliding windows
loop = ((length-window_size)/((1-overlap)*window_size)) + 1;     % Number of windows(features) extracted from a signal

apen=0;
nbchannel=EEG.nbchan;
channel_ar=zeros(1,nbchannel);
window_apen = zeros(int16(loop),nbchannel);
h = waitbar(0,'Please wait...');
for chanNr = 1:nbchannel; % channel number of your specific lead

    fprintf('%d ', chanNr);
    perc = fix((chanNr/nbchannel)*100);
    waitbar(chanNr/nbchannel,h,sprintf('%d%% done...',perc))

    start_index = 1;
    end_index = start_index + window_size*sampRate - 1;
    data = EEG.data(chanNr,1:length*sampRate);

    for i = 1:loop
        window_data = data(start_index:end_index);

        r = 0.5 * std(data);       % tolerance value
        % Computing approximate entropy for single channel
        apen = ApEn( 2, r, window_data, 1 );

        % Saving data for sliding window
        window_apen(i,chanNr) = apen;
        start_index = int16(start_index + window_size*sampRate*(1-overlap));
        end_index = int16(end_index + window_size*sampRate*(1-overlap));
    end

end
close(h);

%Writing the features extracted into a csv file
dlmwrite(filename,window_apen,'delimiter',',','-append');
```

APPENDIX F: Source Code for Extracting Statistical Features

```
filename = 'stat_features.csv';
sampRate = 128; % sampling rate of your data

length = 20;    % desired length of EEG signal in seconds
window_size = 5;    % size of sliding window in seconds
overlap = 0.8;  % overlapping ratio of sliding windows
loop = ((length-window_size)/((1-overlap)*window_size)) + 1;     % Number of
windows(features) extracted from a signal
h = waitbar(0,'Please wait...');

abspower=0;
nbchannel=EEG.nbchan;
inter_ar=zeros(1,nbchannel);
window_mean = zeros(int16(loop),nbchannel);
window_std = zeros(int16(loop),nbchannel);
window_1st = zeros(int16(loop),nbchannel);
window_2nd = zeros(int16(loop),nbchannel);
window_1stnorm = zeros(int16(loop),nbchannel);
window_2ndnorm = zeros(int16(loop),nbchannel);

for chanNr = 1:nbchannel; % channel number of your specific lead

   fprintf('%d ', chanNr);
   perc = fix((chanNr/nbchannel)*100);
   waitbar(chanNr/nbchannel,h,sprintf('%d%% done...',perc))

   start_index = 1;
   end_index = start_index + window_size*sampRate - 1;
   data = EEG.data(chanNr,1:length*sampRate);

   for i = 1:loop
      window_data = data(start_index:end_index);
      norm_window = (window_data - mean(window_data))/std(window_data);

      % Saving data for sliding window
      window_mean(i,chanNr) = mean(window_data);
      window_std(i,chanNr) = std(window_data);
      window_1st(i,chanNr) = mean(abs(diff(window_data)));
      window_1stnorm(i,chanNr) = mean(abs(diff(norm_window)));
      window_2nd(i,chanNr)          =          mean(abs(window_data(3:end)          -
window_data(1:end-2)));
      window_2ndnorm(i,chanNr)        =        mean(abs(norm_window(3:end)        -
norm_window(1:end-2)));
```

```
        start_index = int16(start_index + window_size*sampRate*(1-overlap));
        end_index = int16(end_index + window_size*sampRate*(1-overlap));
    end
end

close(h);
stat_feature = [window_mean window_std window_1st window_1stnorm
window_2nd window_2ndnorm];

%Writing the features extracted into a csv file
dlmwrite(filename,stat_feature,'delimiter',',','-append');
```

APPENDIX G: Source Code for Extracting Wavelet-based Features

```
filename1 = 'D1_features.csv';
filename2 = 'D2_features.csv';
sampRate = 128; % sampling rate of your data

length = 20;    % desired length of EEG signal in seconds
window_size = 5;    % size of sliding window in seconds
overlap = 0.8;  % percentage of overlapping between windows
loop = ((length-window_size)/((1-overlap)*window_size)) + 1;      % Number of windows(features) extracted from a signal

waveletFunction = 'db4';    % Mother wavelet - db4
level = 3;      % Level of decomposition

nbchannel=EEG.nbchan;
h = waitbar(0,'Please wait...');

d1window_mean = zeros(int16(loop),nbchannel);
d1window_std = zeros(int16(loop),nbchannel);
d1window_energy = zeros(int16(loop),nbchannel);

d2window_mean = zeros(int16(loop),nbchannel);
d2window_std = zeros(int16(loop),nbchannel);
d2window_energy = zeros(int16(loop),nbchannel);

for chanNr = 1:nbchannel; % channel number of your specific lead

   fprintf('%d ', chanNr);
   perc = fix((chanNr/nbchannel)*100);
   waitbar(chanNr/nbchannel,h,sprintf('%d%% done...',perc))

   data = EEG.data(chanNr,1:length*sampRate);
   start_index = 1;
   end_index = start_index + window_size*sampRate - 1;

   for i = 1:loop
      window_data = data(start_index:end_index);

      %Computing wavelet coefficient for single channel
      [C,L] = wavedec(window_data,level,waveletFunction);
      cD1 = detcoef(C,L,1);         % D1 wavelets
      cD2 = detcoef(C,L,2);         % D2 wavelets
      cD3 = detcoef(C,L,3);         % D3 wavelets
      cA3 = appcoef(C,L,waveletFunction,3);       % A3 wavelets
```

```
        d1norm_window = (cD1 - mean(cD1))/std(cD1);
        d2norm_window = (cD2 - mean(cD2))/std(cD2);

        %Saving D1 wavelets features for sliding window
        d1window_mean(i,chanNr) = mean(cD1);
        d1window_std(i,chanNr) = std(cD1);
        d1window_energy(i,chanNr) = sum(abs(cD1).^2);

        %Saving D2 wavelets features for sliding window
        d2window_mean(i,chanNr) = mean(cD2);
        d2window_std(i,chanNr) = std(cD2);
        d2window_energy(i,chanNr) = sum(abs(cD2).^2);
        start_index = int16(start_index + window_size*sampRate*(1-overlap));
        end_index = int16(end_index + window_size*sampRate*(1-overlap));
    end

end
close(h);
d1stat_feature = [d1window_mean d1window_std d1window_energy];
d2stat_feature = [d2window_mean d2window_std d2window_energy];

%Writing the features extracted into a csv file
dlmwrite(filename1,d1stat_feature,'delimiter',',','-append');
dlmwrite(filename2,d2stat_feature,'delimiter',',','-append');
```

APPENDIX H: Procedures of Classifying the Features Extracted

Step 1: Load the features extracted into the Weka interface

First of all, open the Weka 3 software and select the Explorer application. From the Weka Explorer window that appeared, click the “Open file” option and select the features (with the file format .csv) to be classified.

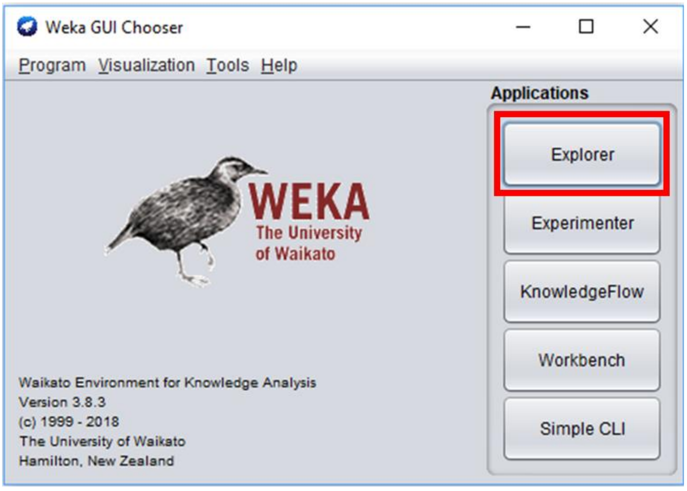

Figure H1: Weka Interface

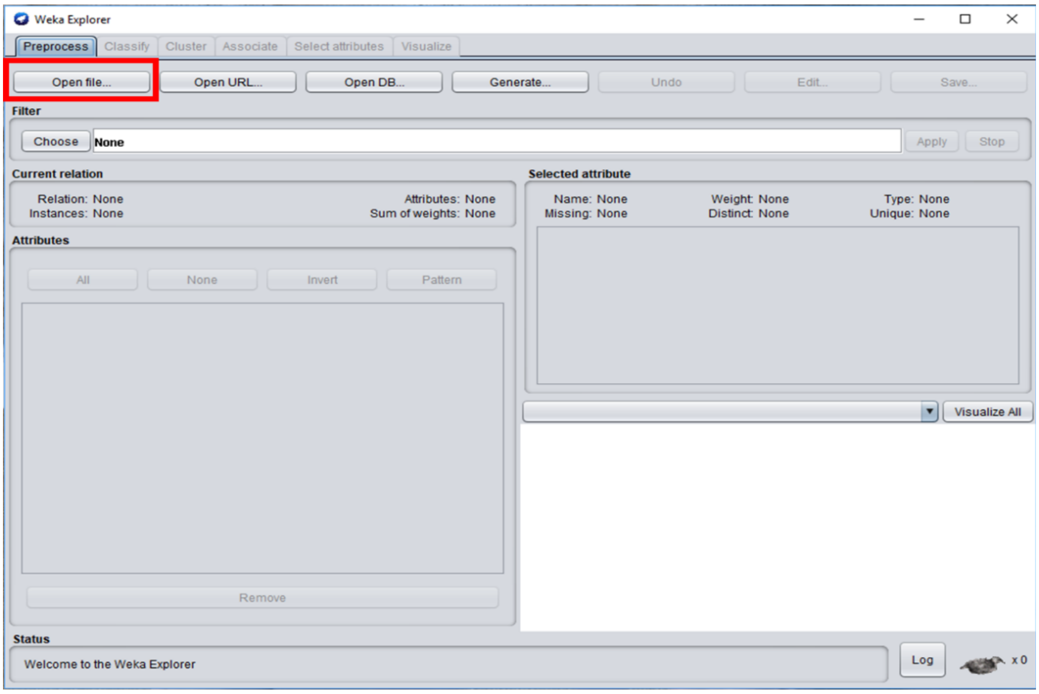

Figure H2: Weka Explorer window

Step 2: Normalizing the data before classify

The features have to be normalized before the classification process begins. At the filter section, click the “Choose” button → select filters > unsupervised > attributes → select Normalize. Then, click on the “Apply” button to normalize the features.

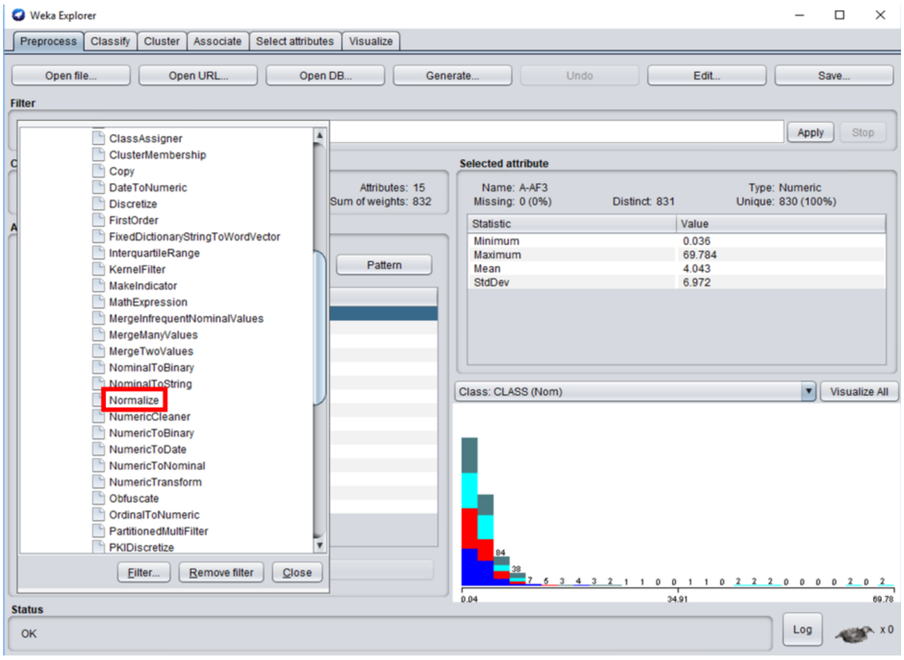

Figure H3: Normalizing the features

Step 3: Choose the classifier

Click on the “Classify” tab to proceed to the classification process. At the classifier section, click the “Choose” button and select lazy > IBk for the KNN classifier. Make sure that the “Cross-validation” option is selected in the Test Option section and the number 10 is entered. Then, press the “Start” button to begin the classification process.

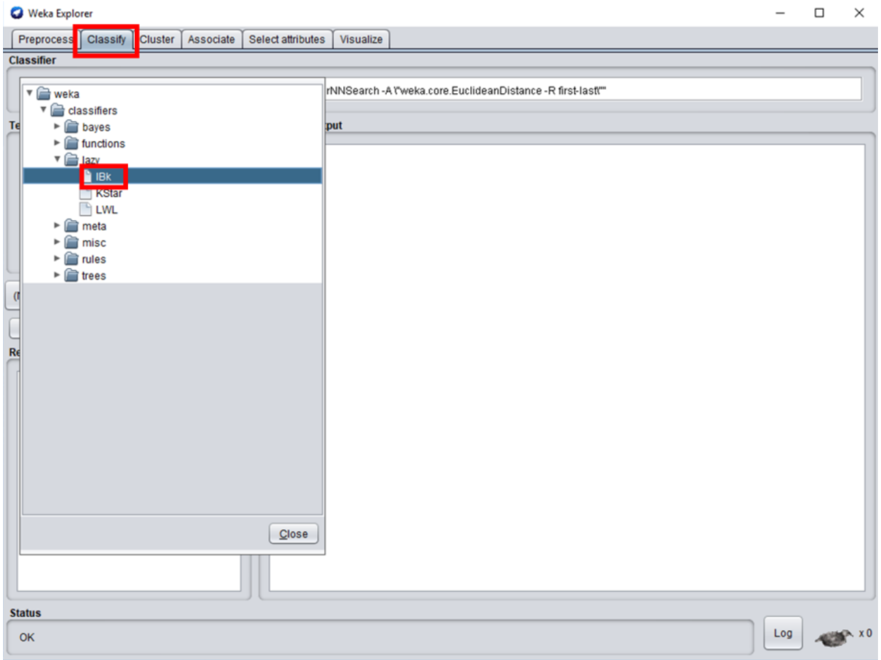

Figure H4: Choosing the classifier to be used

<u>Step 4: Record the average cross validation accuracy</u>

Lastly, the classification results are displayed and the average cross validation accuracy can be obtained from the "Correctly Classified Instances" section.

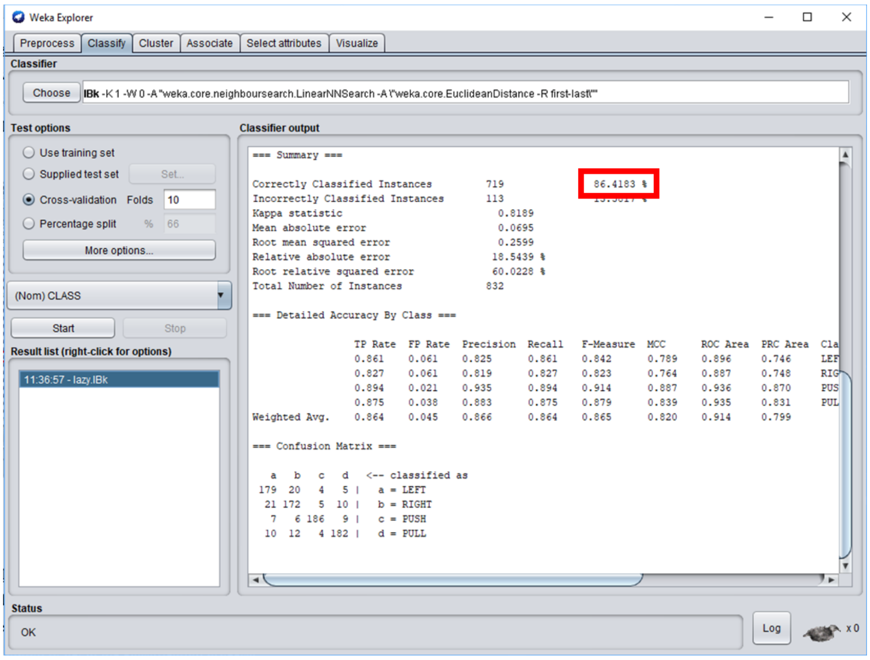

Figure H5: Recording the classification results