

EEG Signals Analysis for Motor Imagery Brain–Computer Interface

by

Lafiz Maruf Rahman

14201006

Zawad Alam

15101098

Md. Musta-E-Nur Rahman

15101089

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
August 2019

© 2019. Brac University
All rights reserved.

Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Lafiz Maruf Rahman
14201006

Zawad Alam
15101098

Md. Musta-E-Nur Rahman
15101089

Approval

The thesis/project titled “EEG Signals Analysis for Motor Imagery Brain–Computer Interface” submitted by

1. Lafiz Maruf Rahman (14201006)
2. Zawad Alam (15101098)
3. Md. Musta-E-Nur Rahman (15101089)

Of Summer, 2019 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on August 28, 2019.

Examining Committee:

Supervisor:
(Member)

Dr. Mohammad Zavid Parvez
Assistant Professor
Department of Computer Science and Engineering
Brac University

Program Coordinator:
(Member)

Dr. Jia Uddin
Associate Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Dr. Mahbub Alam Majumdar
Professor
Department of Computer Science and Engineering
Brac University

Ethics Statement (Optional)

This is optional, if you don't have an ethics statement then omit this page

Abstract

A brain–computer interface is a medium for communication which converts neuronal signals into commands towards controlling external system. This thesis presented the process of classifying three motor imagery tasks using EEG signals which can be further evolved into BCI system that can remotely control external devices. Different bands are filtered from EEG signals in order to extract different frequency distributed features. These features are used to classify different motor imagery tasks based on SVM and ANN. Experimental results show that SVM carried higher accuracy (i.e., 80%) compared to other machine learning algorithms where seven subjects participated in this experiment.

Keywords: EEG, BCI, MI, SVM, ANN.

Dedication (Optional)

We would like to dedicate this thesis to our parents and honorable Supervisor Dr. Mohammad Zavid Parvez for their endless support and patience.

Acknowledgement

All praises goes to The Almighty Allah, The Most Gracious and The Most Merciful for the endless blessing and provide us good health and well being to complete this thesis.

Our deepest gratitude goes to our Supervisor, Dr. Mohammad Zavid Parvez for his supporting us, helping us and guiding us in every possible way for completion of this thesis. Whenever we face a problem we find his door open for helping us. He consistently helped us by providing us the dataset, which algorithm we should use and to write the paper in a better way. His behavior, kindness and guidance steered us in the right path whenever we thought we needed it.

And finally, we would like to express our love and gratitude to our parents and siblings and all those friends who tried to inspire and motivate us in every way throughout our years of study and continuous support for writing this paper.

This would not have been possible and accomplished without any one of them.

Table of Contents

Declaration	i
Approval	ii
Ethics Statement	iii
Abstract	iv
Dedication	v
Acknowledgment	vi
Table of Contents	vii
List of Figures	ix
List of Tables	x
Nomenclature	xi
1 Introduction	1
1.1 Motivation	2
1.2 Thesis Overview	2
1.3 Thesis Orientation	3
2 Literature Review	4
3 Background Analysis	7
3.1 Human Brain	7
3.1.1 Brain Stem	7
3.1.2 Cerebellum	8
3.1.3 Cerebrum	8
3.1.4 Lobe and its functions	8
3.1.5 Brain functions	9
3.2 Brain Waves	9
3.2.1 Gama Waves	10
3.2.2 Beta Waves	11
3.2.3 Alpha Waves	11
3.2.4 Theta Waves	11
3.2.5 Delta Waves	11

3.3	EEG Signals	12
3.4	Motor Imagery task	13
4	Data and Method	15
4.1	Dataset	15
4.2	Algorithm	16
4.2.1	Band Extraction	16
4.2.2	Feature Extraction	16
4.2.3	Classification	19
5	Proposed Model	23
5.1	Pre-processing	23
5.2	Band Extraction	24
5.3	Feature Extraction	24
5.4	Classification	25
6	Results and Discussions	26
7	Conclusion and Future work	29
7.1	Conclusion	29
7.2	Future Work	29
	References	35

List of Figures

3.1	Lobes and its functions.	9
3.2	Different frequencies of brain waves.	10
3.3	Ag/AgCl electrode cap.	13
4.1	Electrode position.	16
4.2	SVM.	19
4.3	Confusion Matrix.	22
5.1	Work flow of proposed model.	23
5.2	Splitted train and test set.	25
6.1	ROC curve using SVM classifier for all Subjects.	28

List of Tables

4.1	Dataset details.	15
5.1	Dissection of feature set.	24
5.2	The size of the feature sets.	25
6.1	Classification Results.	26
6.2	Performance Overview of classification algorithms	27

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ANN Artificial Neural Network

BCI Brain Computer Interface

DCT Discrete Cosine Transform

DWT Discrete Wavelet Transform

EEG Electroencephalograph

FFT Fast Fourier Transform

FN False Negative

FP False Positive

PCA Principal Component Analysis

ROC Receiver operating characteristic

STFT Short-time Fourier Transform

SVM Support Vector Machine

TN True Negative

TP True Positive

WT Wavelet Transform

WVD Wigner Vile Distribution

Chapter 1

Introduction

Everyone needs the capacity to conduct fundamental daily living activities. If the functions and structures of the body are disrupted for some reason, the capacity may be decreased or even wasted, and we call it disability. In the era of the 21st century both technology and society is changing at an astonishing pace. However, the number of disable people are also increasing with the population but as the family structures are changing joint to nuclear family, the life of a disabled person is also getting worse. This research proposes classification of motor imagery tasks in particular for persons with severe handicaps [1].

Human brain is the most important and central organ within the skull among all other organs of the body. It receives information through the sensory organs of the body, then analyzes and processes it and sends various tasks to the various areas of the body. Brain gets electrical pulse data. There is a technique called electroencephalography (EEG), detecting electrical signals in order to comprehend for conduct [2]. EEG signal is measured in micro volts (mV). EEG relates to the spontaneous electrical activity of the brain over a period of moment when several electrodes are placed on the skull [3].

EEG is a method for diagnosis epilepsy, abnormalities, coma etc. Brain signals are classified as brain waves which correspond for multiple scalp states. The frequencies of these signals varies from 0.1Hz to more than 100 Hz. Understanding the functional behavior of the brain is an interesting factor for the medical researchers. Based on the signal frequencies EEG signals are classified for different states such as hand or foot movements, finger clenching, eye ball open or close etc. Due to these motor images, human conduct can be visualized [4].

Millions of people worldwide suffer from loss of motor function as a result of accident or disease. These people life are dependent on other individuals. In the past, many aids have been created to integrate handicapped people into society, but the effectiveness of these aids for people with serious disabilities restricted by brain computer interface. An advance interface can be developed if a disabled people can move his arm or leg through motor imagery. This paper primarily focused on motor imagery for different states of the human body using EEG signals.

1.1 Motivation

Almost 15% of the world population is carrying some sort of disability as stated in the consensus of the WHO [5]. In Bangladesh it is not an exception. According to the National Taskforce on Disabilities-friendly Disaster Management Affairs, in Bangladesh there are 1.6 million registered disabled people [6]. This huge number of the population live a really miserable life as they can not do the works to lead their life lonely. Or they can do all of their works with so difficulties. Though the government try to give them special facilities over the normal people, it can not give the ability to lead their life like a normal people. Specially with the change of the family structure mentioned above, for a disable person leading a solitary life is almost impossible. Our working provocation for this research came from them. The rehabilitation of the disabled people is very costly even in the developed countries. The technology used for the rehabilitation of disabled people is not available in all countries specially in the under developed ones. We, in our work tried to develop a system in which the cost will be low with more accuracy so that the technology will be available to all the poor people. Going through multiple research papers we found out that the movements of hand or leg are strongly linked to motor cortex region. Therefore, we decided to work on classifying the motor imagery tasks using EEG signals as it reflects various brain electrical activity.

1.2 Thesis Overview

Recently, Brain-computer interface (BCI) has become an interesting research and important subject for broad applications [7]. BCI is a way of communicating between the computer and the brain to command an external work. For example, through BCI a prosthetic limb movement can be possible. Hans Berger's innovation began the history of brain computer interfaces. It was found by Berger in 1924. His first brain signal recording device was not that successful. The BCI system initially tested on animal in 1970s. After 1980s it was applied on the human brain [8]. After the application started on human being it started to develop year by year. It is now used to many other purposes along with the disabled people's rehabilitation. Many games have been created in the past several years where the player is controlled by an invasive EEG signal that was made possible by BCI. Electroencephalogram evaluates voltage changes in the skin region and simply placing the electrodes on the skin [9]. It is used to evaluate the neural activity of neurons with comparable spatial orientation that matches the electrical activity. The BCI's task is to convert these signals into an appropriate order. Later, various EEG signal processing algorithms are executed to distinguish the commands.

The process of collecting the data was done by the motor imagery task [10]. In this method a human thinks of a work and the brain signals are generated as if he is executing the work in real life. The signal is then recorded and kept for further use. The physiological processes underlying the motor imagery process are similar to motor control systems and this can be used to rehabilitate motion disabled patients. Many of the neuro-imagery research have shown the association between motor imagery and the specific activation in the early motor control point of the neural circuits. It covers primary motor cortex, the lower parietal cortex and some

sub-cortical area i.e. the basal ganglia, and the cerebellum [11]. Motor imagery can be the only technique to restore motion in patients with serious paralysis. This has resulted to a growing interest in motor imagery function research over the last 10 years [12].

In this research we worked with a recorded signal dataset from Berlin Institute of Technology [13]. Seven subjects are participated in this experiment. EEG signals were collected from these subjects using Brain Amp MR plus amplifiers. We are classifying three motor imagery tasks which are right hand, left hand and foot. Fifty-nine electrodes used over the sensory motor areas which was densely distributed. The filtered band pass was implemented between 0.05-200 Hz for the removal of additional noises from the signal and was digitized at 1000Hz. Next, we did the band extraction using the 1-D Wavelet Transformation. By the band extraction, we got the signal bands alpha and beta from five bands. We worked with only alpha and beta signals. After extracting the bands, we used five entropy features. We divide these five features into two feature sets. In feature set 1, we applied WVD and STFT. And for feature set 2, we used FFT, DCT and DWT. After that, we applied machine learning algorithms for classifying data. For classification we used five algorithms - ANN, Decision tree, SVM, Logistic regression and Naive Bayes. We applied these five algorithms on these two feature sets. Now for training we used 80 percent of feature set and 20 percent for testing. As a result, it is seen that SVM, ANN and decision tree produces better classification results than Naive bayes and Logistic regression. Furthermore, feature set 1 gives better results than feature set 2. As EEG signals are stationary in nature, its accuracy varies from subject to subject. Subject 1, subject 5, subject 6, and subject 7 are giving better motor imagery tasks compared to the other three subjects.

1.3 Thesis Orientation

The thesis started with the intensive study on several different techniques. All approaches and process used for thesis work are broadly organized in this paper. Chapter 2 represents the work involved and the previous works done by the researchers. Chapter 3 presents about the background analysis on the human brain and different types of brain waves. Chapter 4 describes the dataset used on our research papers and also gives a description on algorithms and classification that are implemented for motor imaginary tasks. Chapter 5 introduces how the proposed model works by using band and feature extraction and classified by using machine learning algorithms. Chapter 6 shows the experimental results that we found out through our research along with some discussion. Finally, Chapter 7 concludes our work with a conclusion.

Chapter 2

Literature Review

Primarily, a lot of research's and projects have been conducted on this topic. Many researchers have worked extensively in this field. They tried to developed a non-invasive system that outputs a set of signal which allows the movement of robotic arm. Our focus is on developing a system for identifying limbs during motor imagery tasks. Various methods and algorithms have been used by many researchers and tried to develop a model.

G. Townsend in his project deals with simulated asynchronous and synchronous BCI [14]. He used left and right imagery to simulate an asynchronous BCI using EEG signals for three subjects. Refractory period and a dwell time is used for classification. Band pass filters was applied between 8–30 Hz. Two sessions applied for three subjects using five weight vectors (WV) and four common spatial filters (CSP) were set up. In the application of TP and FP rates, subject g3 showed the lowest FP rate and the highest TP rate among three subjects (g3, g7 and i2). Using 1.0, 1.25 and 1.35s refractory times and 0.25s dwell time for each subject, the highest outcomes for subject g3 are shown to be 1.00 to 1.25 s refractory period for the correct imagery. There was a significant improvement on left imagery of subject g7.

A number of literature's has been devoted to make a prototype of robotic arm for helping physically disabled people. A neural interface system has been created by John Donoghue's study group of Brown University consisting 100 electrodes and implemented on patient's motor cortex. A prosthetic neuromotor device made up of hundreds silicon micro-electrodes was used. The signals were converted into an output that allowed a robotic multi-joint arm motion of an item. But, the system is invasive [15].

Howida *et al.* developed a non-invasive system that outputs a set of signal which allows movement of robotic arm but the movements were very limited. EEG signals linked to three arm movements for the control of the robotic arm. Four electrodes AF3, F3, F7, FC5 were used in experiment. The feature extraction was carried out by FFT, PCA and wavelet transformation (WT). For classifying the three tasks, Neural Network was used which was trained by back propagation algorithm. While experimenting with the outcomes, the suggested system was shown to achieve a greater classification with a frequency of 91.1%, 86.7% and 85.6% for the three methods featured [16].

For moving a cursor in the computer screen, four topics with EEG-based cursor control were used. Signals were evaluated and categorized online by a neural network using particular frequency bands. In off-line analysis AAR model was used for improvement. The main goal of G. Pfurtscheller was to establish whether adaptive auto regressive parameter (AAR) is an appropriate method for BCI based on the EEG. Linear discriminant analysis was used to separate for left and right motor imagery. On average the error rate was better which was between 5.8 and 32.8% than the online results. It was also showed that reactive beta rhythms can increase the rate of communication for brain computers than the alpha rhythms compared to the subjects. In the future, the AAR model with a classification delay of around 1 s can be expected to improve the error rate for online classification [17].

H. Sun propose a method by using different mental tasks through EEG signals. So he took mental tasks for three movements for classifying the EEG signals online in a BCI system combining CSP and SVM. Three male subjects participated in the experiment. At a frequency of 500 Hz, EEG signals were digitized and band-pass filtered between 0.1 Hz and 100 Hz. Sixty – two channels have been registered on the subjects in a protected room. For feature extraction, CSP algorithm was used and SVM was applied for the classification for completion and training velocity. The primary objective was to monitor an individual's intentions in a complex and concentrated 3D game setting so that it can adapt motor imaginary in an online training system. Using CSP, the precision for subjects A, B and C is about 86.3%, 91.8% and 92.0% respectively for movements on the right and left hands of three subjects. Among all other subjects, the lowest online error rate of subject C was 4% under 5 seconds [18].

For controlling and identifying the movements of a human based small robot, Rakesh Rao's team at the Neural Systems Laboratory in Washington created a BMI machine. Using a non-invasive machine holds a cap equipped with 32 electrodes, signals were collected from pre-motor and motor cortices. These signals were sent to the robot. The device cannot perform professional instructions, but can do the basic tasks like pick an object and to move in which direction [19].

Stroke rehabilitation is now one of the most successful brain computer interface application. Hand movements are widely used for motor imagery. For their proposed model, A.Suwannarat choose three wrist and hand movement tasks. In the experiment eleven subjects participated comprised of eight sessions of MI tasks. For extraction of features, CSP algorithm was used. For classification, linear discriminant analysis (LDA) and (SVM) gives comparable classification accuracy. It is seen that the precision of the classification of wrist and forearm tasks was greater than the classification of hand opening / closing tasks for all subjects [20]. Also, FB acquired an accuracy of higher classification compared to WB. A.Suwannarat also stated that most subjects could lead to better accuracy if there were more training sessions.

By studying the works of many researchers it is seen that they tried to work on the motor imagery tasks by using EEG signals. We learn how to analyze the EEG

signals by using specific frequency bands and extract the data from it. Since our aim is to discriminate between the movements of the foot, the left and the right motions, we learn which algorithms and classifiers we can use for our thesis.

Chapter 3

Background Analysis

The brain is made up of brain stem, cerebellum, cerebrum and lobes [21]. Brain receives information from the environment through the sense organs, process, analysis and integrates the information and sends the instructions to the rest of the organs. Besides there is a communication between billions of neurons within the brain for emotion, thoughts and behaviour [22]. As a result, brainwaves are produced by thousands of electrical signals from millions of neurons that interact with one another. Using sensors positioned on the scalp, brainwaves are identified. To define their tasks, they are splitted into bandwidths. We will address various components of the brain and its functions shortly in this article. Likewise, how the brain waves operate and how these brain waves generate the signals.

3.1 Human Brain

Main organ of the human body is human brain which is located in our head. Brain receives much data from the neurons as electrical signals. When the information comes, it detects whether it is relevant or irrelevant [23]. If it is irrelevant we are not conscious about it and it just faded away. But if it is relevant, the brain amplifies the signal and sends the signals to different parts of the body making a conscious experience. The central nervous system, which is main control center, constitute of brain and spinal fluid which is accountable for various tasks and body motion. By producing a steady stream of sensory signals, the brain also makes the body conscious of the inner and outer environment [21]. The brain collects data from the surrounding through hearing, sight, taste, smell and touch.

3.1.1 Brain Stem

The brain is highly compact. Information transmission speed range from 3 to 300 feet/sec. For beating of the heartbeat and breathing automatic internal actions are processed through brainstem modules. The spinal cord represents the reduced part of the central nervous system which connects cranial cavity as well as peripheral organs [21]. Multiple upward as well as downward tracts pass through the three parts – the midbrain, the medulla oblongata, and the pons. Medulla contains the respiratory and vasomotor centers while the midbrain holds nuclei of oculomotor and trochlear nerves [24]. The brainstem also manages tasks associated with home-

ostasis, oxygen levels, vomiting, coughing, swelling and blood pressure.

3.1.2 Cerebellum

Cerebellum is small in size. It is located behind the pons and the medulla in the posterior cranial fossa. It is hemispherical in shape [25]. The main functions of the cerebellum is coordinating voluntary movements of the body, posture equilibrium and maintaining muscles activities [24]. The primary motor cortex receives messages through the cerebellum for conscious operations, hands and legs motion. The Cerebellum synchronizes and improves motor operations.

3.1.3 Cerebrum

Cerebrum is the brain's biggest component. In the upper part of the cranial cavity the brain is located inside the top of the scalp. It's made up of two hemispheres of the brain, left and right [26]. The lobes that are frontal, temporal, parietal and occipital are divided into four hemispheres. To communicate with each other, this control is performed through some cells, known as corpus callosum. The cerebrum obtains information from the environment, analyzes the knowledge, hold the instructions and give decision what will happen next [21]. The right hemisphere regulates imagination, musical skills, and spatial capacity, whilst the left hemisphere is accountable for speech, writing, calculation, and comprehension.

3.1.4 Lobe and its functions

The cerebrum is split into four areas that regulate senses, ideas, and motions, called lobes [21]. The four lobes are the occipital, temporal, frontal, and parietal lobes (Figure 3.1). Even though each lobe has to undertake a distinct job, they all have to work together. For planning, reasoning, intelligence and concentration, the frontal lobe is linked with these executive functions. Emotions and memory may affect if the frontal lobe is damaged [27]. It is also responsible for your personality, behavior, emotion and the movements of the voluntary muscles. The temporal lobe is located to close to your ears. Its primary function is auditory so that you can pronounce a word or learn a new sentence. It is responsible for language comprehension, visual memory and emotion association. The occipital lobe is involved in vision processing of the brain like light, color. If the occipital lobe gets injured it can cause visual and perceptual problems [28]. The parietal lobe integrates sensory information and helps us to feel pain, temperature and touch. It's also helps to translate messages through sensory, vision and hearing through the signals it received from the environment.

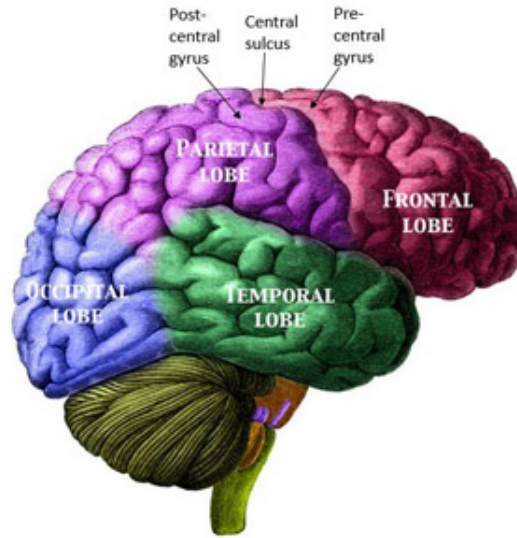


Figure 3.1: Lobes and its functions.

3.1.5 Brain functions

The brain consists of about 1000 billion cells. Approximately 10% are sophisticated electrical cells that send signals which are called neurons. These several thousand neurons are connected with each other through synapses [29]. They carry billions of signal pulses and communicate with other neurons through long protoplasmic fibers called axons. Although the signals happens to be electrical, a chemical called neurotransmitters is responsible for transmission of signals between cells. This transmission of the signal enables brain functions make choices and differ from any other body process [21]. An important question is that how these electrical signals turns into experience or movements. Every sense organ, such as eyes, is susceptible to light, ears collect sound waves, etc. receive incoming information from outside and sends to the brain. The brain process the signals determines what type of information it will generate such as thoughts, actions or emotions.

3.2 Brain Waves

Brain is like an electrochemical organ, it has billions of neurons and they are connected with each other. It's like if you make a connection of wires you can light a bulb. Transmission of chemical and electrical information is occurred through these neurons. These electrical activity makes the neurons active which in result measured in the form of brainwaves. This activities can be enhanced, evaluated and visualized by putting electrodes on the scalp. This process is called electroencephalography (EEG). A certain brain wave will dominate over the others, depending on what one does at that moment. These synchronized electrical pulses create Brainwaves [30]. Depending on the level of consciousness and cognitive processing, one's brain waves pattern changes. A way of conveying data from EEG's brainwaves is by their repetition frequency (Figure 3.2). According to the scientist who proved electromagnetic

waves, these cycles are measured in Hz or hertz known as frequencies. Certain oscillations are likely to happen on a scalp over 30 cycles per second.

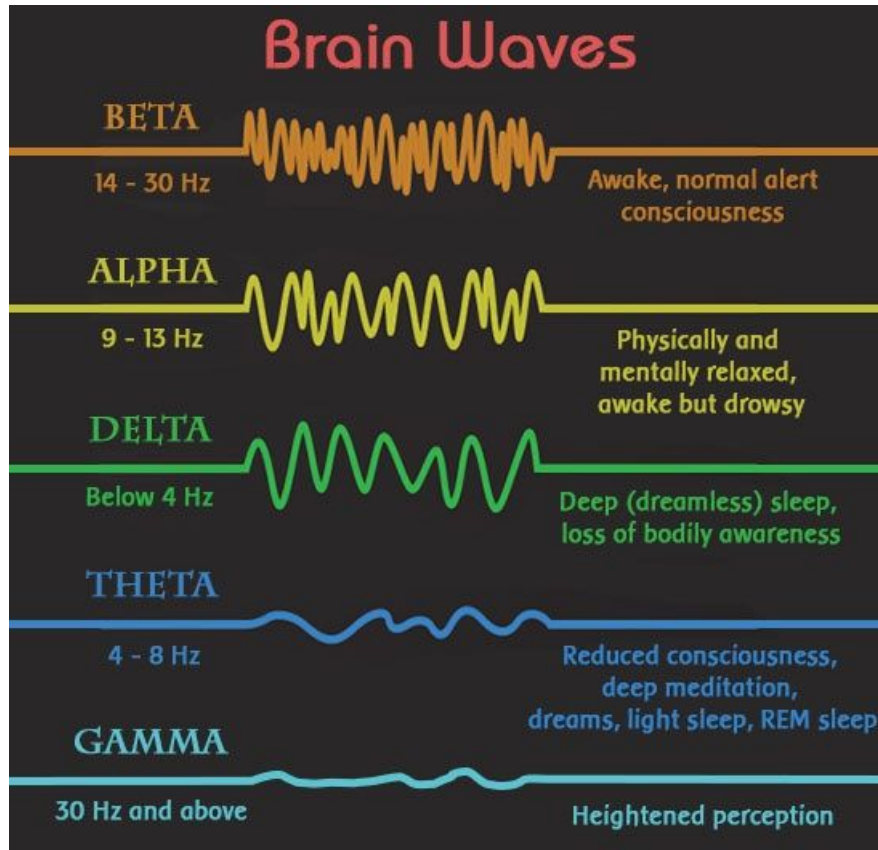


Figure 3.2: Different frequencies of brain waves.

Brainwaves may be classified by activity level or frequency [31]. Slow activity relates to a reduced frequency and elevated amplitude such as a drum's profound beat. Fast activity relates to a greater frequency and often smaller amplitude such as high pitched flute [32]. According to the mental states and different behaviour of the brain, the frequencies of the brain waves also differs [33]. There are five types of brainwaves, from fastest activity levels to slowest, which are narrated below –

3.2.1 Gama Waves

Gamma waves are associated with higher levels of consciousness. When the brain tries to store memories or tend to learn new information, these waves are generated. The gamma waves smoothly transfer information [34]. In order to achieve those waves, the mind must be in peaceful condition. The frequencies of gamma waves is 32- 100 Hz [30]. These waves are often associated with insight, hyper focus, heightened perception, data processing and problem-solving tasks (Figure 3.2). During researching, gamma brainwaves are noted to be much stronger and more frequently. Distress, elevated excitement and pressure can also be caused.

3.2.2 Beta Waves

Beta are the most common pattern which is experienced most of the time. These waves occur when one is focused on problem solving or is concentrated on some hard tasks. The frequencies of beta waves is from 13 – 32 Hz. These waves is related with active conservation, solving a problem, making decisions or focusing on a task (Figure 3.2). Beta waves have a downside in which they can draw our energy and lower our feelings of emotion and creativity. An elevated beta-wave concentration leads adrenaline to increase, leading to stressful thinking, elevated excitement and a lack of relaxation [35].

3.2.3 Alpha Waves

During calm, thoughtful moments are the reasons of alpha waves. Alpha waves were the first to be found among all the other brainwaves. They become different when the mind is lighten and eyes are off. Therefore, the Alpha wave promotes mental sync, alertness and knowledge. The alpha waves involves of a frequency between 7.50 to 13.0 Hz. These waves are accompanying with deep states, dreams, insight, deep meditation, reduced consciousness (Figure 3.2). A person becomes loosen up if there are a number of alpha waves stimulates in the brain and that person can not concentrate and dream constantly [36]. When the frequency of alpha is less than one, however, elevated stress, nervousness is present.

3.2.4 Theta Waves

One can experience theta waves in sleep and during relaxation. They are a sign of an interior focus and in this state dreams and vivid illustrations happen. The range of theta waves is between 3 to 8 hertz. Theta waves show profound relaxation and happen more often in extremely practiced meditation [30]. The origin is probably frontal parts of the brain that are linked to other mental operations [33]. During the theta wave stage, people are dreaming or outside of ordinary consciousness. It is also producing a nightmare, a fear of any object, a disturbed past. This wave helps to understand, learn and remember (Figure 3.2). Extensive theta wave rate can regulate depression, impulsiveness and attention.

3.2.5 Delta Waves

The brain waves of delta are the slowest waves. They are produced in profound meditation and in a dreamless state we enjoy restorative sleep. Delta wave is more prominent in adults, although dominant in infants. It consists of a frequency between 0.5 -4 Hz [30]. It's speed wave is slow, that is, more like a drum beat. A large quantity of delta wave can harm the brain seriously, failure to think and problems with learning (Figure 3.2). This is also the situation where rejuvenation and healing are encouraged, which is why sleeping is so important every night.

Brain creates wave-like signals which helps for identification of motor imagery tasks.

From above we know that the waves are divided into five frequency bands. [37]. It is found in previous researches that alpha and beta waves represent the identification of motor imagery tasks than the other three frequency bands.

3.3 EEG Signals

The elaboration of EEG is Electroencephalogram. The brain cells act with each other for a successful motor action to happen. These electrical impulses of the brain cells is recorded as analogue signals for determining the normal or abnormal brain cell activity detection. A German psychiatrist Hans Berger proclaimed it for the first time [38]. He tested the brain signal for different human activity such as sleep, epilepsy arm movement, leg movement etc. The way he paved has now become a vast area of research.

Scientists are working in this sector to understand the working technique of the human brain and to use it for the well being of the mankind. They are trying to establish a connection between human and computer interaction [39]. EEG machines have become the best devices to work with for its easy to use and for its low cost and maintenance [40]. To work with the EEG of a human brain, the signal is taken by electrodes which are small flat metal disks with wires. The EEG signal can be extracted by two method. One is invasive and another is non invasive [41]. Typically all the signal extraction are done by non invasive method. In non invasive a cap with various electrodes is worn on the head (Figure 3.3). There are variations of the channels in the cap. Some cap has lower and some has as high as 128 channels. In our research 59 channels are used. Recorded signal through electrodes are saved in the computer for further processing. The signals are registered in micro-volts that are subsequently amplified by analog signal amplifier and used for signal processing as analog to digital converter. By taking these signals and processing it many activities can be done as per the brain signal command.



Figure 3.3: Ag/AgCl electrode cap.

For physically disabled persons it is very helpful that their brain signal can lead to a motor execution task and they can regain their ability to work in close to normal state. Many brain signal detection caps constructed with many electrodes have been used to detect human brain defects in hospitals or health organisations, but use has declined with the advent of latest enhanced science. If the brain signal is abnormal then it is difficult to rehabilitate them. On the other hand, if a person loses his control over the organs by accident or the muscular failure then it is possible to give him a prosthetic arm controlled by his brain [42].

3.4 Motor Imagery task

Every action of living creatures is driven by the brain signals. The neurons act differently for different type of tasks. It is very astonishing that Jeannerod and Decety about three decades ago proved these brain signals can be acquired by not only executing the tasks but also imagining about it. It has been researched by the technique of introspection and mental chronometry. Through these techniques, it is specified that motor imagery signals reveal many characteristics in terms of temporal regularity, programming rules and bio-mechanical limitations discovered in the actual execution of an action.[43]. They proved that the accuracy of the imagery signals are as equal to the signals when the subject actually do the task. This imagining brain signal can lead to real life execution of that task. Motor imagery is a dynamic state where a person executes a motion without actually executing the motion. In other words, motor imaging needs motion to activate brain areas consciously [44]. By taking the imagery signals from EEG, many real life work command can be generated such as prosthetic arm movement, leg movement, wheel

chair control, extra hand movement etc. Moreover, the accuracy of the imaginary brain signal and the physically executed brain signal is the same means it is very usable for the rehabilitation of physically disabled people. It helps for improving motor learning and rehabilitation in patients where motor imagery is broadly used. It is also used for sport training as mental state of action.

Chapter 4

Data and Method

4.1 Dataset

For our research we got the dataset from BCI competition IV website and it was recorded by Berlin Institute of Technology [45]. This data included a continual 32-minute EEG recording of seven healthy subjects. 2 classes of motor imagery were chosen randomly from 3 classes left hand, right hand and foot for each subject. The recording was done with BrainAmp amplifiers and an electrode cap Ag / Ag-Cl. The electrodes with small amount of Ag-Cl are applied [46]. For this experiment 59 electrodes were used which were densely distributed over the sensory motor areas (Figure 4.1). The signals denoised and band-pass filtered between 0.05 and 200 Hz and then digitized at 1000 Hz. During recording soft acoustic stimuli (words left, right, and foot) were provided to the subjects as cues for the motor imagery tasks for periods of 8 seconds [45].

Table 4.1: Dataset details.

Number of recordings	7
Number of cues	200
Class	Left and right Left and foot Right and foot
Record duration per subject	32 minutes
Electrode used	59
Data (data x channels)	1905940x59

The dataset provided by BCI competition 4 is in (.mat) format and in a 1905940x59 array. The (.mat) files also includes vector position for the cues, the vector target class for the related cues, 2D location of the electrodes, electrode names, and class labels.

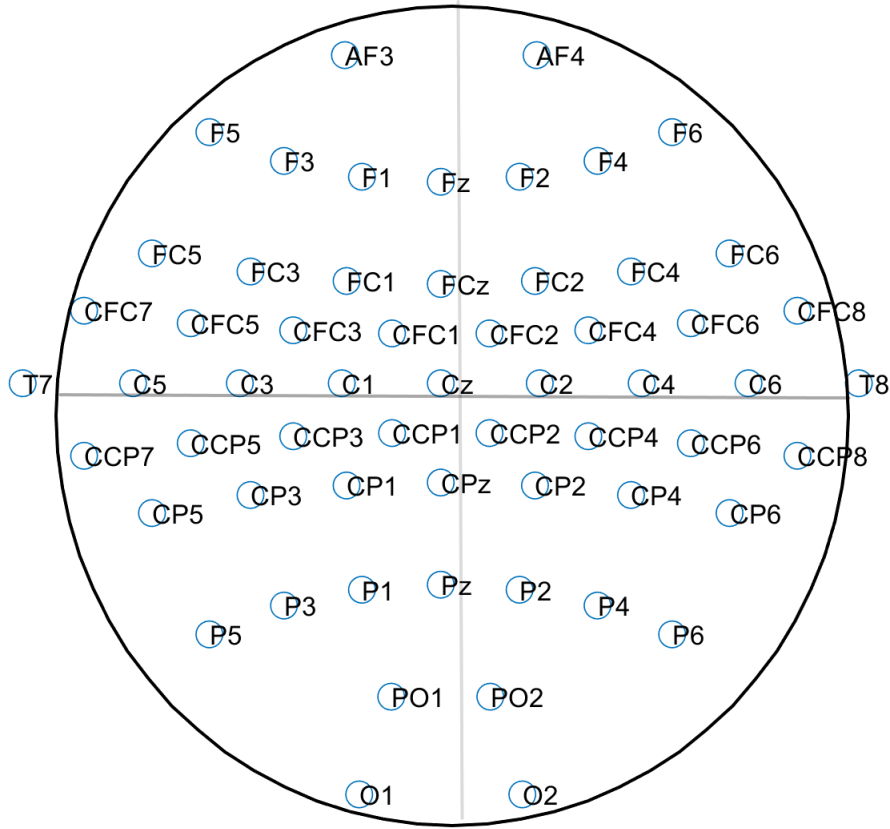


Figure 4.1: Electrode position.

4.2 Algorithm

4.2.1 Band Extraction

EEG headset gives raw brain signal data. It is so difficult to analyze these data without processing it. Band extraction is used to process the data for further use of the signals. By band extraction the signals are splitted into different frequency bands.

1-D Wavelet Decomposition

1-D wavelet decomposition is a one-dimensional wavelet algorithm of multilevel analysis. It's similar like a Fourier transform. It separates a wave into multilevel signals [47]. With this signal analysis the data is filtered by a specific pair of wavelet decomposition filters. This algorithm takes a signal and a level n . It then gives a result of decomposition which is a vector c containing the number of coefficient by level n . It returns results with certain low-pass filters and high-pass filters if provided as input parameter [48].

4.2.2 Feature Extraction

For feature extraction, two types of feature sets were used. In feature set 1, Short-time fourier transform (STFT) and Wigner ville distribution (WVD) was used. In

feature set 2, we applied three algorithms which are fast fourier transform, discrete cosine transform and discrete wavelet transform.

Wigner-Ville distribution

We add parts of the signal product to get Wigner distributed multiplied at some point at a certain point at a certain time by the signal, since past was equal to future. So we mentally fold the left part of the signal to the right and see if there are a simultaneous overlaps for determining Wigner distribution properties. If there is, then at the time t , those properties will now be present. Wigner Vile distribution compared the information of the signal with its own information at other times and frequencies [49]. If this easy point is kept in mind, the distribution of Wigner becomes apparent with many problems and outcomes. For the frequency domain, Wigner distribution in both domains is essentially identical [50]. Another significant point is that the distribution of Wigner is equally weighing the distant times to the close moments. The distribution of Wigner is therefore extremely non-local [51]. If a signal is $s(t)$, the corresponding Wigner distribution equation becomes

$$W(t, w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S^*(t - \frac{1}{2}\tau) S(t + \frac{1}{2}\tau) \exp^{-j\tau\omega} d\tau \quad (4.1)$$

The distribution of wigner implies, that the signal is split in a left and a right portion in relation to time t , and the right portion is folded over the left portion (equal to the spectrum because in both domains it is formally equal). The result is that, if the signal is always 0 before t or is always null after t , the Wigner distribution is undoubtedly 0 at t time, so the weak form is respected [52]. For such a phenomenon, the word interference or cross term is used and illustrated by the following statistics.

Short-time Fourier Transform

For analysis and modelling of slowly changing signals, Fourier analysis have been widely used [53]. We highlighted the desire in a short time of Fourier transformation to study frequency characteristics at moments t . Conversely, at a given frequency we might want to examine time characteristics. We then window the spectrum, $S(w)$ and take the time transform with the frequency window function $H(w)$ that is also inverse Fourier. Here-

$$s_w(t) = \frac{1}{\sqrt{2\pi}} \int e^{j\omega't} S(\omega') H(\omega - \omega') d\omega' \quad (4.2)$$

When we relate the window feature in time $h(t)$ to the frequency $H(w)$ window feature

$$H(\omega) = \frac{1}{\sqrt{2\pi}} \int h(t) e^{-j\omega't} dt \quad (4.3)$$

It does not join the phase factor $e^{-j\omega t}$ and either the short-term transformation of Fourier or the short-frequency transformation can be used to describe the joint distribution. This shows that the spectrum can be used at a certain frequency to study the behavior of time features. This can be accomplished by choosing a tiny $h(w)$ or equivalently taking a broad $H(t)$ [51].

Discrete Wavelet Transform

The goal of the DWT is transforming time signal to a discrete wavelet representation [54]. For processing Biological signals such as EEG, EMG in discrete wavelet transform digital filtering is used. DWT algorithm gives octave-scale frequency as well as spatial timing of the given signal. For this reason it is always used to address and resolve many sophisticated and complicated issues. In this process, Low Pass Filter (LFP) [55] and High Pass Filter (HPF)[56] are extracted. Scaling function can be acquired from the LPF while the wavelet function can be acquired from the HPF. The filter bank level varies with the availability of the bandwidth. The high frequency is analyzed by HPF and the low frequency is analyzed by LPF. Signal resolution is found by the filtering and scaling process. The equation of the filtering process is given as follow:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n - k] \quad (4.5)$$

Here x an input signal. This means that a series of filters can be used to measure the DWT of a signal x. Here g is impulse response of sample passing through LPF and h is the decomposition of the signal through HPF. n is the level of transform and the k is the type of the transformation. The detailed coefficient is found from the HPF and the approximation coefficients can be found from the LPF. These filters are also processed by another filters to step for achieve final signal resolution [57].

Discrete Cosine Transform

DCT is used primarily for signal extraction features. In terms of a sum of sinusoids at multiple frequencies and amplitudes, it sends a signal like any linked Fourier transform. It was first introduced in 1974 in a research paper of Nasir Ahmed et al. In 1977 Wen-Hsiung Chen paved the way of this algorithm by developing it to work very fast. In 1987, Peincen, Johnson and Bradley suggested further adapted DCT. It is a way for transforming a frequency into different frequencies for summation of cosine functions [58]. In this method the relevant coefficients of a signal is transformed from a whole signal [59]. It performs energy compaction and decorrelate the data for the image [60]. After decorrelation of every data, the coefficient can be cipher individualistic. The transformed signal is categorized in low, mid and high frequency each contains different details and information about the signal.

Fast Fourier Transform

FFT is a kind of transforming from the basic Fourier that is much quicker [61]. This is used to turn a signal from the time domain into a frequency domain. The inverse FFT does the opposite conversion. FFT is mostly used for signal processing as it consumes significantly less time than other feature extraction methods [62]. It is an efficient algorithm of the (FT). It takes N^2 multiplication to process a signal where the FFT takes only $N \log_2(N)$. It is obtained by reducing the multiplication needed in the Fourier transform. The transformation of Fourier from N discrete points can be written as two N/2 discrete points. Thus if the number N is a power of two it is possible to divide the points until there is only one point left. It greatly reduces the

time complexity. If we take the even points by dividing the points by two then the equation should be as follow [63]:

$$X[k] = \sum_{n=0 \text{ even } n}^{N-1} x(n)e^{-2\pi jnk/N} \quad (4.6)$$

Here, the transform points are $x(n)$ and the amount of points is N . And other half of the equation would be

$$X[k] = \sum_{n=0 \text{ odd } n}^{N-1} x(n)e^{-2\pi jnk/N} \quad (4.7)$$

If both of the equations are added and let the X of even points be X_1 and the odd point X_2 then the equation becomes

$$X[k] = X_1(k) + e^{-2\pi jnk/N} X_2(k) \quad (4.8)$$

Thus N point discrete Furrier transform can be obtained from two $N/2$ transforms.

4.2.3 Classification

Five machine learning algorithms were used to classify motor imagery tasks. These are - Artificial neural network, Support Vector Machine, Decision tree, Logistic regression and Naive Bayes.

Support Vector Machine (SVM)

(SVM) is mainly a binary classifier which is divided by hyperplane [64]. A level of selection separates a group of objects with separate class membership (See 4.2). Consider the figure below for a distinct kind of insight where x represents positive training cases, o indicates adverse training examples, a border of selection (which represents the line indicated by $\theta^T x = 0$ equation, and is also called a separating hyper-plane) and A, B, and C points have also been shown.

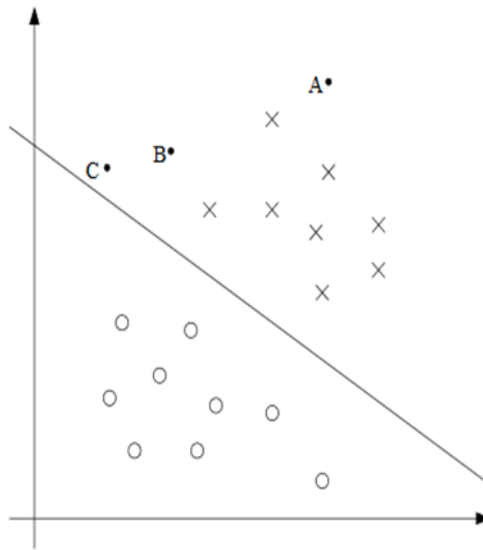


Figure 4.2: SVM.

Note that point A is far from the limit of the choice. If the value of y on point A is requested to, it appears that most probably you will get $y=1$. Point C, on the other side, is very close to the limit of choice, while it is on the edge where we have to predict $y=1$, and although we note that a slight change at the edge of decision could lead to the prediction that $y=0$ would be $y=0$. We therefore believe in our forecast much more in A than in C. Point B is between A and B and we have discovered that our predictions can be significantly more precise if one point is far away from the hyperplane [65]. Again, with the training set, we think it would be good if we managed to find the boundary for the choice that makes it possible for us to take all predictions correct and accurate (i.e. far from the choice limit) on the training examples.

Decision Tree

Monitoring method for machine learning from training data is known as decision tree. It is a method that can predict outcomes on its target value by monitoring an object. It classifies information objects into a finite amount of classes that are predefined. Leaves constitute classifications (also called labels) in tree structures, non-leaf nodes are characteristics, and branches represent conjunctions of characteristics leading to categories. Decision trees are used to find solutions in the machine learning community to classification applications. Deciding that will eventually lead to a leaf and a response based on the values of each function. Two distinct operating areas operate in a decision tree: one to produce the tree and the other to take on the understanding, i.e. classification.

1. Generating the tree: The process of constructing up-down is decision tree. It starts with the complete root training. The objective is to determine the best test attribute of every decision node in the tree in order to minimize the mixture of classes between every sub-set generated by the test. This method will proceed until leaves are reached and their respective classes are fixed for each sub-decision tree.
2. Classification: Classification works on induction of the decision tree. So we begin from the root to classify an item, evaluate the test attribute comparative and matches the results by using the branch. Repeat the method until a leaf has been found. Then fresh item happens to be new into the leaf labeling class [66].

Suppose N is a collection of products. These products have two categories, label 1 is n and label 2 is $m = N-n$. For grouping them by labels in order to get our information a little more organized. We introduce the ratio-

$$p = \frac{n}{N} \text{ and } q = \frac{m}{N} = 1 - p \quad (4.10)$$

The entropy of our set can then be determined by the next equation:

$$E = -p \log_2(p) - q \log_2(q) \quad (4.11)$$

Sets are clever if they contain only items on the same label and unclear if they are a mixture of products on distinct labels. Now see the entropy feature above. If the set has no label ($p=0$), or the set has reached a label 1 threshold ($p=1$) entropy will

be null.

Artificial Neural Network

ANN considered as computing system [67]. These systems can take decisions for any action by considering examples. The system trains itself for necessary action. This is not programmed for any specific action rather than it is designed in a way that it can learn by examples and take action according to the analysis result of that examples. For example, if it is given to the system to distinguish between a monkey and a human being the system will distinguish analyzing the previous model of human being and a monkey. In this process it will try to match the characteristics, behavior, features and the structure of the previous model of monkey and human being.

Logistic Regression

Logistic regression is an algorithm for a supervised classification [68]. For a classification issue, for certain characteristics, Y can only accept discrete values for certain functions, X. Logistic regression is of three categories based on the number categories. The categories are binomial, multinomial and ordinal. The simplest form of Logistic Regression is given below:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + + \beta_n X_n \quad (4.12)$$

Where dependent variable is y and explanatory variable are $X_1, X_2, X_3,, X_n$ and β_i is the coefficient of the variables. The sigmoid function then can be defined as

$$p = \frac{1}{1 + e^{-y}} \quad (4.13)$$

The p of the equation 4.21 implies the probability of the event. The Sigmoid feature provides an 'S' curve that can be used to map any real amount in a value of 0 to 1. If the curve reaches positive Infinity and is expected to be 1 and the curve reaches negative Infinity and predicts to be 0 [69].

Naive Bayes

A Naive Bayes used to classify based on Bayes. It is simple to implement because of strong and independence between the attributes of data points. Text analysis, spam filters and medical diagnosis are some of the uses of Bayes classifier. Due to the presumption of independence, the parameters for each attribute can be learned individually, which makes learning much easier, particularly when the amount is big. The naive aspect of a Bayes classifier is that it is presumed that every attribute of a given data point is autonomous from each other [70]. Naive Bayes precision does not depend on the degree of feature dependencies that are the class-conditional reciprocal data between characteristics. Instead, the assessment of the algorithm's precision relies on the amount of data about the class lost due to the assumption of independence [71].

Confusion Matrix

Confusion matrix is an efficiency measurement for the classification issue, where the output may be two or more classes. The number of correct and incorrect predictions is abridged and divided into count values for each class. This is the key to the matrix of confusion. The data will be more scattered if the number of attributes is larger [72]. The table consists of four different expected and real values combinations.

		True Class	
		P	n
Hypothesized class	Y	True Positive	False Positive
	N	False Negative	True Negative

Figure 4.3: Confusion Matrix.

For model-generated class projections we used the labels (Y,N) to distinguish between real class and predicted class [73]. Given a classifier and an instance, there are four possible results (Figure 4.3).

Chapter 5

Proposed Model

In this thesis, we have classified different motor imagery tasks based on EEG signals. We have collected the dataset from BCI competition 4 [45]. The EEG signals were recorded by BrainAmp MR plus amplifiers with a Ag/Ag-Cl electrode cap and it was recorded from seven healthy subjects [45]. Three class of movements such as left hand, foot(left or right were chosen by subjects randomly) and right hand have been defined. They have used bandpass filter to remove unwanted signals. Then we have extracted different features based on time-frequency distributions. These extracted features are then considered to classify motor imagery tasks using SVM, ANN, Logistic regression, Decision tree, and Naive Bayes classifier.

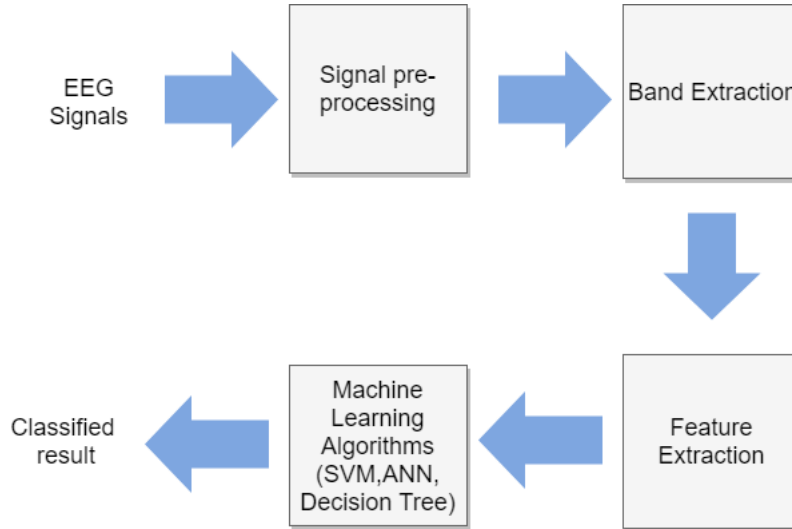


Figure 5.1: Work flow of proposed model.

5.1 Pre-processing

Preprocessing is a noise removal technique where different filter has been used [4]. It helps to remove noise also to make the signal further smooth and remove trends in signals to prepare them to get better and accurate results. Preprocessing also enhances signals for patterns to be visualized and discovered. The EEG signal was carried through the 0.05Hz and 200Hz band pass filter. Then data is preprocessed by digitizing the signals into 1000Hz (Figure 5.1). The average size of epochs in our

experiments is 8s.

5.2 Band Extraction

For our research, EEG signals were recorded on a time domain. As mentioned in the previous chapters, electrical activity makes the neurons active which in results measured in the form of brainwaves. Repetitive frequency can be obtained by conveying data from EEG's brainwaves. These brainwaves can be subdivided (Figure 5.1). Among these five bands, two bands - alpha and beta waves Literature shows that alpha and beta bands can specifically represent the motor imagery tasks than the other three bands [74]. Therefore, we have used only alpha and beta band for feature extraction. For band extraction, we used 1-D continuous wavelet transformation with 8-level decomposition.

5.3 Feature Extraction

Researchers suggested that frequency distribution is carrying discriminant features for EEG signals. In our research, two different sets of features are considered to get better accuracy (details in Table 5.1). EEG signals is non-stationary in nature [2], therefore, we have used entropy features based on WVD and STFT for first set of feature. To justify our results, we have further explore our experiment by extracting entropy features from DWT, DCT and FFT.

Table 5.1: Dissection of feature set.

Feature set 1	Feature set 2
Wigner-Vile distribution(WVD) entropy	Discrete Wavelet transform(DWT) entropy
Short Time Fourier transform(STFT) entropy	Discrete Cosine transform(DCT) entropy
	Fast Fourier transform(FFT) entropy

After feature extraction, the size of feature vector for set 1 and set 2 are 200x238 and 200x354, respectively (Figure 5.2). Here, 200 is epochs no. and 238 is attribute no. for feature set 1 and 354 is attribute count of feature set 2.

Table 5.2: The size of the feature sets.

Feature	Size
Feature Set 1	200x238
Feature Set 2	200x354

5.4 Classification

Classification techniques are used to classify different motor imagery task [75]. There are many existing machine learning algorithms available for supervised learning. Among them, researchers showed that most efficient algorithms are ANN and SVM [76]. SVM classifier works based on the notion of decision hyperplanes defining the limits of the choice. For determining a decision hyperplane, SVM classifies data samples into two cases. Maximize the margin between two of the closest class points, it is possible to identify the best possible hyperplan for differentiating two groups. We have used 80 percent of the data from each feature set for training and remaining 20 percent is our test dataset (Figure 5.2) through evaluation function. In addition, we have used other machine learning approaches such as decision tree algorithm, logistic regression, and naive bayes.

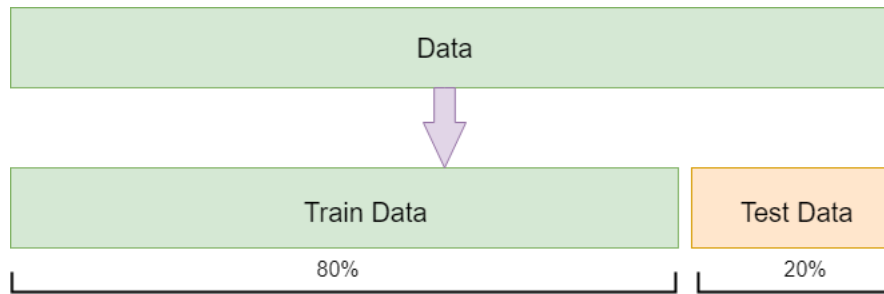


Figure 5.2: Splitted train and test set.

We got the maximum result from five electrodes (C5, C3, Cz, C2, C4) and the first 50% of the indexes. We then used both feature set 1 and feature set 2 related to electrodes mentioned and applied selected classification algorithms on them.

Chapter 6

Results and Discussions

The chapter's primary goal is to define outcomes and their analysis based on extracted features from EEG signals and machine learning algorithms.

Table 6.1: Classification Results.

	subject1		subject2		subject3		subject4		subject5		subject6		subject7	
	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2
SVM	82.23	83.3	77.77	78.57	76.47	76.47	71.58	75.0	80.0	81.25	82.60	75.0	83.5	82.3
D_tree	85.71	63.15	72.0	73.33	76.19	80.0	73.91	68.0	71.42	76.0	83.33	68.0	70.58	69.23
ANN	77.77	82.35	73.68	73.68	73.68	70.58	68.0	61.11	81.48	68.42	76.47	62.96	80.76	80.76
Naive	50.0	64.28	50.0	53.57	64.28	28.57	59.09	46.4	59.09	57.14	68.18	35.71	50.0	67.85
Logistic	58.23	55.88	39.39	64.71	45.45	38.24	42.42	50.0	45.45	55.88	45.45	41.18	66.66	55.88

Table 6.1 displays the overall classification results using five machine learning algorithms where F1 is feature set 1 consisting entropy features from WVD and STFT transformation and F2 is feature set 2 from DWT, DCT and FFT transformation. It is demonstrated from Table 6.1 that SVM, Decision tree and ANN are carrying better classification results compared to naive bayes and Logistic regression classifier. Between the feature sets, feature set 1 shows more better results than feature set 2. However, the results varied from subject to subject as different subject may concentrated differently. In the SVM, subject 1, subject 5, subject 6, and subject 7 are getting more distinguishable motor imagery task compared to subject 2, subject 3, and subject 5.

Table 6.2: Performance Overview of classification algorithms

Algorithms	Feature set 1	Feature set 2
SVM	79.17	78.84
Decision Tree	76.16	71.10
ANN	75.97	71.40
Naive Bayes	57.23	50.50
Logistic Regression	49.0	51.68

From the above table, we tried to show the performance overview of classification algorithms. We average the results of the feature sets 1 and feature sets 2 by the seven subjects. It is seen that from the five algorithms that has been used for classification, SVM, Decision tree and ANN gives the best performance results among all other algorithms for both the feature sets. The polynomial kernel of SVM is better for non-linear data and SVM also performs well for binary class problems which is the reason behind SVM classifier's performance. Moreover decision tree also specializes in binary class problems while ANN is suitable for any kind of data type also it can handle both continuous and discrete values. For these reasons these 3 algorithms performed better than others.

The sensitivity, specificity and accuracy of machine learning algorithms are used for performance analysis. However, we have shown only performance accuracy in the Table 6.1. Besides, sensitivity and specificity outputs are presented in the Figure 6.1.

$$Sensitivity = \frac{TP}{(TP + FN)}$$

$$Specificity = \frac{TP}{(TP + FP)}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100\%$$

Where TP means true positive number, TN means true negative number, FP means false positive number, and FN means false negative number.

Receiver operating characteristics or (ROC) curve describes all feasible thresholds for the results of a classification. The True Positive Rate (Y-Axis) is compared to the False Positive Rate (X-Axis), as the limit for the assignment of observations to a given class [15]. The most common way of viewing the performance of the binary classifier is to use a ROC curve, and AUC is (perhaps) the best way to summarize its efficiency in a single number. ROC graphs are two-dimensional graphs where Y-axis plots tp rate and X-axis plots fp rate.

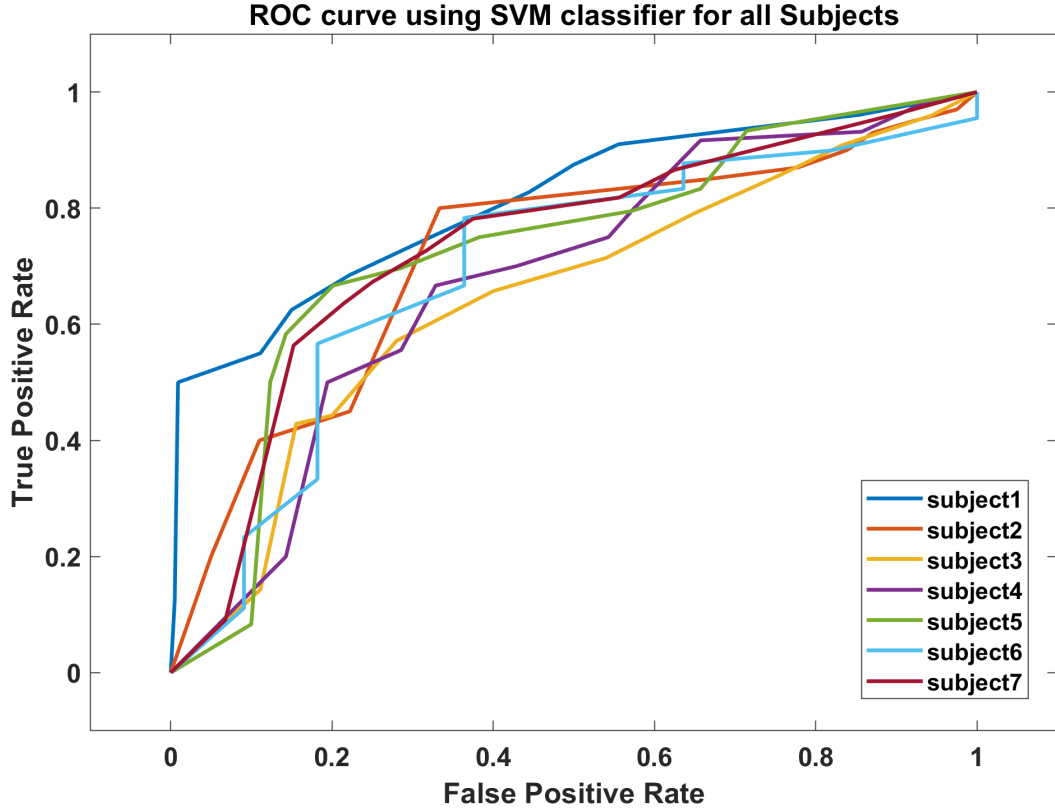


Figure 6.1: ROC curve using SVM classifier for all Subjects.

In Figure 6.1, the ROC curve of SVM classifier for all subjects are shown. ROC indicates the performance of a binary classifier by plotting TRP as y axis and FRP as x axis with different threshold settings. From the Figure 6.1, its shown that subject 1 gives good results considering SVM classification results.

We have demonstrated the overall comparison of three motor imagery tasks of seven subjects (i.e., subject specific) using two feature sets and five machine learning algorithms. However, it is noticeable that the EEG signal and its accuracy varies from person to person because EEG signals contain high level of noises and non-stationary in nature.

Chapter 7

Conclusion and Future work

7.1 Conclusion

BCI systems extensively explored for around two decades to restore features for motor impairments. Researchers want to make this technology available to everybody though it is too expensive for end-users. BCI has become an interesting research and important subject for broad applications. It is a way of communicating between the computer and the brain to command an external work. BCI replaces the nerves and muscles and produces motor tasks with EEG signals and combined with hardware and software translating these signals into physical behavior. We wanted to develop a system that will distinguish between three motor imagery signals. For minimizing cost with more accuracy so that the technology will be available to all the people. As a result, disabled people can move his arm or leg with less difficulty through motor imagery.

In our experiment, we have taken seven healthy subjects. The signals has been obtained from alpha and beta bands. The extracting features were using various frequency distribution methods, followed by five algorithms for classifying the distinct motor imagery functions. Experimental results show that SVM carried higher classification accuracy (i.e., 80%) compared to other machine learning algorithms.

7.2 Future Work

The current model is identifying limbs during motor imagery tasks. Our goal is to develop a prototype robotic arm by implementing the proposed model. We will also try to make the prototype robotic arm cheaper and user- friendly. Accuracy that we get from the classification is not so high. In future, accuracy improvement task will be done by doing more research in this area.

Bibliography

- [1] M. Reaz, M. Hussain, M. Ibrahimy, and F. Mohd-Yasin, “Eeg signal analysis and characterization for the aid of disabled people”, *WIT Transactions on Biomedicine and Health*, vol. 12, pp. 287–294, 2007.
- [2] M. Z. Parvez and M. Paul, “Seizure prediction by analyzing eeg signal based on phase correlation”, in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, 2015, pp. 2888–2891.
- [3] D. L. Schomer and F. L. Da Silva, *Niedermeyer’s electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins, 2012.
- [4] J. S. Kumar and P. Bhuvaneswari, “Analysis of electroencephalography (eeg) signals and its categorization—a study”, *Procedia engineering*, vol. 38, pp. 2525–2536, 2012.
- [5] W. H. Organization, “World report on disability”, 2011. [Online]. Available: https://www.who.int/disabilities/world_report/2011/report/en/.
- [6] T. D. Star, *16 lakh registered as disabled in bangladesh*, 2018. [Online]. Available: <https://www.thedailystar.net/city/news/16-lakh-registered-disabled-bangladesh-1643995>.
- [7] J. Sleight, P. Pillai, and S. Mohan, “Classification of executed and imagined motor movement eeg signals”, *Ann Arbor: University of Michigan*, vol. 110, 2009.
- [8] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “Bci2000: A general-purpose brain-computer interface (bci) system”, *IEEE Transactions on biomedical engineering*, vol. 51, no. 6, pp. 1034–1043, 2004.
- [9] E. Maiorana, G. E. Hine, D. La Rocca, and P. Campisi, “On the vulnerability of an eeg-based biometric system to hill-climbing attacks algorithms’ comparison and possible countermeasures”, in *2013 IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, IEEE, 2013, pp. 1–6.
- [10] J. F. D. Saa and M. Çetin, “A latent discriminative model-based approach for classification of imaginary motor tasks from eeg data”, *Journal of neural engineering*, vol. 9, no. 2, p. 026 020, 2012.
- [11] J. Decety, D. Perani, M. Jeannerod, V. Bettinardi, B. Tadary, R. Woods, J. C. Mazziotta, and F. Fazio, “Mapping motor representations with positron emission tomography”, *Nature*, vol. 371, no. 6498, p. 600, 1994.

- [12] O. A. Mokienko, L. A. Chernikova, A. A. Frolov, and P. D. Bobrov, “Motor imagery and its practical application”, *Zhurnal vysshei nervnoi deiatelnosti imeni IP Pavlova*, vol. 63, no. 2, pp. 195–204, 2013.
- [13] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. E. Ramsey, I. Sturm, G. Curio, *et al.*, “The berlin brain–computer interface: Non-medical uses of bci technology”, *Frontiers in neuroscience*, vol. 4, p. 198, 2010.
- [14] G. Townsend, B. Graimann, and G. Pfurtscheller, “Continuous eeg classification during motor imagery-simulation of an asynchronous bci”, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 2, pp. 258–265, 2004.
- [15] M. Costandi, *A bigger role for the little brain?*, May 2019. [Online]. Available: <https://neurophilosophy.wordpress.com/2015/05/10/a-bigger-role-for-the-little-brain/#more-4708>.
- [16] H. A. Shedeed, M. F. Issa, and S. M. El-Sayed, “Brain eeg signal processing for controlling a robotic arm”, pp. 152–157, 2013.
- [17] G. Pfurtscheller, C. Neuper, A. Schlogl, and K. Lugger, “Separability of eeg signals recorded during right and left motor imagery using adaptive autoregressive parameters”, *IEEE transactions on Rehabilitation Engineering*, vol. 6, no. 3, pp. 316–325, 1998.
- [18] H. Sun, Y. Xiang, Y. Sun, H. Zhu, and J. Zeng, “On-line eeg classification for brain-computer interface based on csp and svm”, in *2010 3rd International Congress on Image and Signal Processing*, IEEE, vol. 9, 2010, pp. 4105–4108.
- [19] L. Blain, “Honda’s brain-machine interface: Controlling robots by thoughts alone”, *gizmag magazine*, April, 2009.
- [20] A. Suwannarat, S. Pan-ngum, and P. Israsena, “Comparison of eeg measurement of upper limb movement in motor imagery training system”, *Biomedical engineering online*, vol. 17, no. 1, p. 103, 2018.
- [21] R. S. Frackowiak, *Human brain function*. Elsevier, 2004.
- [22] J. LeDoux, *The emotional brain: The mysterious underpinnings of emotional life*. Simon and Schuster, 1998.
- [23] N. Jadhav, R. Manthalkar, and Y. Joshi, “Effect of meditation on emotional response: An eeg-based study”, *Biomedical Signal Processing and Control*, vol. 34, pp. 101–113, 2017.
- [24] J. C. Eccles, *The cerebellum as a neuronal machine*. Springer Science & Business Media, 2013.
- [25] M. Ito and M. Itō, *The cerebellum and neural control*. Raven press, 1984.
- [26] C. Chiron, I. Jambaque, R. Nabbout, R. Lounes, A. Syrota, and O. Dulac, “The right brain hemisphere is dominant in human infants.”, *Brain: a journal of neurology*, vol. 120, no. 6, pp. 1057–1065, 1997.
- [27] Y. Gil, S. Seo, and J. Lee, “Eeg analysis of frontal lobe activities by decision stimuli”, in *2008 Second International Conference on Future Generation Communication and Networking*, IEEE, vol. 3, 2008, pp. 30–34.

- [28] E. Goldberg, *The executive brain: Frontal lobes and the civilized mind*. Oxford University Press, USA, 2002.
- [29] W. Gerstner and W. M. Kistler, *Spiking neuron models: Single neurons, populations, plasticity*. Cambridge university press, 2002.
- [30] R. Horlings, D. Datcu, and L. J. Rothkrantz, “Emotion recognition using brain activity”, in *Proceedings of the 9th international conference on computer systems and technologies and workshop for PhD students in computing*, ACM, 2008, p. 6.
- [31] P. L. Nunez and R. Srinivasan, “A theoretical basis for standing and traveling brain waves measured with human eeg with implications for an integrated consciousness”, *Clinical neurophysiology*, vol. 117, no. 11, pp. 2424–2435, 2006.
- [32] T. Matlovic, P. Gaspar, R. Moro, J. Simko, and M. Bielikova, “Emotions detection using facial expressions recognition and eeg”, in *2016 11th international workshop on semantic and social media adaptation and personalization (SMAP)*, IEEE, 2016, pp. 18–23.
- [33] N. Birbaumer, T. Elbert, A. G. Canavan, and B. Rockstroh, “Slow potentials of the cerebral cortex and behavior.”, *Physiological reviews*, vol. 70, no. 1, pp. 1–41, 1990.
- [34] *Brain anatomy, anatomy of the human brain*, 2015. [Online]. Available: <http://www.mayfieldclinic.com/pe-anatbrain.htm>.
- [35] N.-H. Liu, C.-Y. Chiang, and H.-C. Chu, “Recognizing the degree of human attention using eeg signals from mobile sensors”, *Sensors*, vol. 13, no. 8, pp. 10 273–10 286, 2013.
- [36] C. W. Hughes, “Emotion: Theory, research and experience”, *The Journal of Nervous and Mental Disease*, vol. 170, no. 5, pp. 315–316, 1982.
- [37] K. Kalimeri and C. Saitis, “Exploring multimodal biosignal features for stress detection during indoor mobility”, in *Proceedings of the 18th ACM International Conference on Multimodal Interaction*, ACM, 2016, pp. 53–60.
- [38] J. G. Webster and J. W. Clark, *Medical instrumentation: application and design*. John Wiley & Sons, 1995, vol. 200.
- [39] K. Schaaff and T. Schultz, “Towards emotion recognition from electroencephalographic signals”, in *2009 3rd international conference on affective computing and intelligent interaction and workshops*, IEEE, 2009, pp. 1–6.
- [40] M. Singh, M. M. Singh, and N. Singhal, “Emotion recognition along valence axis using naive bayes classifier”, *International Journal of Information Technology & Knowledge Management*, vol. 7, no. 1, pp. 51–55, 2013.
- [41] F. Cincotti, D. Mattia, F. Aloise, S. Bufalari, G. Schalk, G. Oriolo, A. Cherubini, M. G. Marciani, and F. Babiloni, “Non-invasive brain–computer interface system: Towards its application as assistive technology”, *Brain research bulletin*, vol. 75, no. 6, pp. 796–803, 2008.

- [42] R. Kottaimalai, M. P. Rajasekaran, V. Selvam, and B. Kannapiran, “Eeg signal classification using principal component analysis with neural network in brain computer interface applications”, in *2013 IEEE International Conference on Emerging Trends in Computing, Communication and Nanotechnology (ICECCN)*, IEEE, 2013, pp. 227–231.
- [43] G. Pfurtscheller and C. Neuper, “Motor imagery and direct brain-computer communication”, *Proceedings of the IEEE*, vol. 89, no. 7, pp. 1123–1134, 2001.
- [44] M. Lotze and L. G. Cohen, “Volition and imagery in neurorehabilitation”, *Cognitive and behavioral neurology*, vol. 19, no. 3, pp. 135–140, 2006.
- [45] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, “The non-invasive berlin brain–computer interface: Fast acquisition of effective performance in untrained subjects”, *NeuroImage*, vol. 37, no. 2, pp. 539–550, 2007.
- [46] P. Tallgren, S. Vanhatalo, K. Kaila, and J. Voipio, “Evaluation of commercially available electrodes and gels for recording of slow eeg potentials”, *Clinical Neurophysiology*, vol. 116, no. 4, pp. 799–806, 2005.
- [47] C.-H. Yeh, T.-C. Shen, and F.-C. Wu, “A case study: Passive component inspection using a 1d wavelet transform”, *The International Journal of Advanced Manufacturing Technology*, vol. 22, no. 11-12, pp. 899–910, 2003.
- [48] A. Cohen, “Ten lectures on wavelets, cbms-nsf regional conference series in applied mathematics, vol. 61, i. daubechies, siam, 1992, xix+ 357 pp.”, *Journal of Approximation Theory*, vol. 78, no. 3, pp. 460–461, 1994.
- [49] J. L. Semmlow, *Biosignal and medical image processing*. CRC press, 2008.
- [50] S. Qian and D. Chen, “Decomposition of the wigner-ville distribution and time-frequency distribution series”, *IEEE Transactions on Signal Processing*, vol. 42, no. 10, pp. 2836–2842, 1994.
- [51] L. Cohen, *Time-frequency analysis*. Prentice hall, 1995, vol. 778.
- [52] D. P. Scarpazza, “A brief introduction to the wigner distribution”, *Dipartimento di Elettronica e Informazione, Politecnico di Milano*, 2003.
- [53] R. Crochiere, “A weighted overlap-add method of short-time fourier analysis/synthesis”, *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 28, no. 1, pp. 99–102, 1980.
- [54] C. E. Heil and D. F. Walnut, “Continuous and discrete wavelet transforms”, *SIAM review*, vol. 31, no. 4, pp. 628–666, 1989.
- [55] G. L. Fredendall, *Low-pass filter system*, US Patent 2,472,798, Jun. 1949.
- [56] S. Randall and D. A. Bates, *High frequency band pass filter with coupled surface mount transition*, US Patent 9,490,768, Nov. 2016.
- [57] Y. S. Rohmah, I. Dinata, and D. A. Nurmantris, “Performance comparison of orthogonal wavelet division multiplexing (owdm) system using discrete wavelet transform and wavelet packet transform on rayleigh channel”, in *2016 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob)*, IEEE, 2016, pp. 104–108.

- [58] A. B. Watson, “Image compression using the discrete cosine transform”, *Mathematica journal*, vol. 4, no. 1, p. 81, 1994.
- [59] K. Manikantan, V. Govindarajan, V. S. Kiran, and S. Ramachandran, “Face recognition using block-based dct feature extraction”, *Journal of Advanced Computer Science and Technology*, vol. 1, no. 4, pp. 266–283, 2012.
- [60] S. A. Khayam, “The discrete cosine transform (dct): Theory and application”, *Michigan State University*, vol. 114, pp. 1–31, 2003.
- [61] W. T. Cochran, J. W. Cooley, D. L. Favon, H. D. Helms, R. A. Kaenel, W. W. Lang, G. C. Maling, D. E. Nelson, C. M. Rader, and P. D. Welch, “What is the fast fourier transform?”, *Proceedings of the IEEE*, vol. 55, no. 10, pp. 1664–1674, 1967.
- [62] P. Welch, “The use of fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms”, *IEEE Transactions on audio and electroacoustics*, vol. 15, no. 2, pp. 70–73, 1967.
- [63] W. Huang and D. L. MacFarlane, “Fast fourier transform and matlab implementation”, *The University of Texas at Dallas. Dr. Duncan L. MacFarlane. Web*, vol. 24, 2016.
- [64] B. Scholkopf and A. J. Smola, *Learning with kernels: support vector machines, regularization, optimization, and beyond*. MIT press, 2001.
- [65] A. Ng, “Cs229 lecture notes”, *CS229 Lecture notes*, vol. 1, no. 1, pp. 1–3, 2000.
- [66] N. B. Amor, S. Benferhat, and Z. Elouedi, “Qualitative classification with possibilistic decision trees”, in *Modern Information Processing*, Elsevier, 2006, pp. 159–169.
- [67] J. M. Zurada, *Introduction to artificial neural systems*. West publishing company St. Paul, 1992, vol. 8.
- [68] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, “Supervised machine learning: A review of classification techniques”, *Emerging artificial intelligence applications in computer engineering*, vol. 160, pp. 3–24, 2007.
- [69] S. Menard, *Applied logistic regression analysis*. Sage, 2002, vol. 106.
- [70] A. McCallum, K. Nigam, *et al.*, “A comparison of event models for naive bayes text classification”, in *AAAI-98 workshop on learning for text categorization*, Citeseer, vol. 752, 1998, pp. 41–48.
- [71] I. Rish *et al.*, “An empirical study of the naive bayes classifier”, in *IJCAI 2001 workshop on empirical methods in artificial intelligence*, vol. 3, 2001, pp. 41–46.
- [72] S. Visa, B. Ramsay, A. L. Ralescu, and E. Van Der Knaap, “Confusion matrix-based feature selection.”, *MAICS*, vol. 710, pp. 120–127, 2011.
- [73] T. Fawcett, “An introduction to roc analysis”, *Pattern recognition letters*, vol. 27, no. 8, pp. 861–874, 2006.
- [74] E. Iáñez, J. Azorin, E. Fernández, and R. Morales, “Electrooculography-based human interface for robot controlling”, in *Proceedings of the 13th Annual Conference of the International Functional Electrical Stimulation Society (IFESS)*, vol. 53, 2008, pp. 305–307.

- [75] W. Kaneko, E. Phillips, E. Riley, and C. Ehlers, “Eeg findings in fetal alcohol syndrome and down syndrome children”, *Electroencephalography and clinical neurophysiology*, vol. 98, no. 1, pp. 20–28, 1996.
- [76] W.-H. Chen, S.-H. Hsu, and H.-P. Shen, “Application of svm and ann for intrusion detection”, *Computers & Operations Research*, vol. 32, no. 10, pp. 2617–2634, 2005.