Classification of Motor Imagery Tasks based on BCI Paradigm

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Declaration

It is hereby declared that

1. The thesis submitted is 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.

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Abstract

Motor imagery tasks are mental processes by which individual practices a set of actions in their mind without actually performing the physical movements. Research in the motor imagery tasks allow us to acquire critical information on how the human brain works, which further enables us to integrate the knowledge with brain-computer interface (BCI) technologies to improve neurological rehabilitation along with, commercial uses such as communication, entertainment, etc. Electroencephalogram (EEG) is a commonly used process to observe and classify brain activities. However, EEG signal is non-stationary in nature, therefore, feature extraction based on EEG signals is quite hard. In our thesis, empirical mode decomposition (EMD) was used to break down the original signal into intrinsic mode functions (IMFs) in order of higher frequency to lower frequency. Convolution neural network (CNN) is then used on IMFs' feature vector and classify different motor imagery tasks. Our proposed model achieves around 78% accuracy, where the dataset was captured from nine participants.

Keywords: EEG, EMD, IMF, CNN, BCI.

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Nomenclature

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

ϵ Epsilon

υ Upsilon

AI Artificial Intelligence

$BNCI$ Brain Neural Computer Interaction

CNN Convolutional Neural Network

EEG Electroencephalogram

EMD Empirical Mode Decomposition

EOG Electrooculography

HCI Human Computer Interaction

IMF Intrinsic Mode Functions

NLP Natural Language Processing

SVM Support Vector Machine

VR Virtual Reality

Chapter 1

Introduction

1.1 Motivation

Our prime drive is to conduct the research solely relied on enhancing the field of motor imagery actions using BCI which can be advantageous for the remote controlled systems. We find out that brain signals can tell us movement and determining the imagination of a motor action without movement of limbs. Systems based on motor imagery generally involve the imagination of movements of different body parts[1]. Our approach will be able to serve the purpose of various applications like c robotic and avatar control, stroke rehabilitation, cog assessment and communication by extension. Also, in the short term, noninvasive headsets will be the next generation of BCI that allow the control of video games. There are some premises of games already where as an input modality, BCI is used [2]. Various research papers tells us that BCI is a developing technology which uses signals exclusively to deal with computer-aided control and has found applications in neuroprosthetics and biotech fields [3]. Hence, we decided to work to help the user by activating cortical related motor areas and generating the signals that we can read by the classifier and training and helping them to operate without making movement externally with a decent accuracy level using our own proposed method. In the future, we would like to use our proposed approach for the benefits of disabled people and also for entertainment purposes (i.e. VR games) and apply this conception in various educational institutions of our country. We presume that our results are significant to the BCI community and can be used for real-world applications.

1.2 Thesis Overview

Human brain and the computer are connected through a channel for communication provided by BCI. The history of BCI starts with Hans Berger's invention of the human brain's electrical activity and the advancement of EEG. The field of BCI research and development has since concentrated on neuroprosthetics applications that focus on recovering damaged hearing, movement and sight. Our thesis gives an overview of this small subset of HCI emphasising on BCI . In theory, this approach is not only limited to take input for the computer but also may include some processes for the computer to provide feedback by stimulating neurons to the user. The neurons operate in complex logic and control our bodies by producing thoughts and signals. A voltage change of around 100mv across the cell is activated when the neuron fires which a variety of devices can read. The frontal lobe generates command for various voluntary actions. The surface of the brain originates the signals. These electric brain signals are separate in frequency and magnitude. We can comprehend the working procedure of the brain by analyzing and monitoring these brain signals. Small signals are generated in different areas of the brain whenever we imagine ourselves doing something. These small signals are, however, measurable [4]. In BCI, the most convenient mean is to record brain electrical activity through EEG which is prominently noisy [3]. However, it is notoriously difficult to analyze the motor imagery BCI. After implementing the EMD algorithm, we are supposed to get the IMF from the feature extraction. Subsequently, we used IMF on a machine learning algorithm called CNN. We then applied this method for the classification process with four different feature combinations. The functions were exerted for several times on our proposed model to escalate the efficiency and accuracy level of our experiment. In this thesis paper, we tried to highlight the importance of a human user in the BCI systems.

1.3 Thesis Orientation

The alignment of the subsequent sections of our thesis paper is as follows. Chapter 2 features the adhering work gathered from our research and existing approaches related to our proposed method. Chapter 3 discloses a detailed analysis of the background information and the learning methods we need to acquire related to our experiment. Chapter 4 introduces the proposed model of our experiment along with the dataset and algorithms we used after feature extraction that defines our approach for recognizing imagery motion signals. Chapter 5 provides the results of our experiments and explains our work in company with related discussions. To terminate, Chapter 6 concludes and summarizes the thesis.

Chapter 2

Literature Review

To start with, we went through different research on Brain-Computer Interfacing and it came to our knowledge that, studies has gauged the possibility that brain signals recorded from inside the brain could provide new rising technology [5]. iBMIs recording of neural activities are using for controlling neural prostheses [6].People are late stages of ALS capable of utilizing BCIs that depends on signals generated by the motor system. Thus it also explored novel BCI paradigms that are independent of motor signals [7]. Applying EMD on a signal decomposes into a limited number of signs into IMFs. First few IMFs are supposed to be enough to classify signals successfully [8]. Data can be classified by analyzing EEG signals using CNN. The quality of this classifier depend on the data [9]. EEG information filed during motor imagery is used to recreate a non-concurrent BCI and also to optimize the findings a dwell time and refectory period were introduced in this paper [10]. EEG is the most opportune resource for BCI, and is particularly noisy. This paper introduced low signal-to-noise ratio, MEMD and narrowly spaced frequency bands [11].
Schalket al. [5] developed a general-purpose BCI research and progress platform called BCI 2000. It can integrate in combination of any brain signals. The thoughts of the BCI 2000 system is based on examples of successful BCI system.
Zhang et al. [6] alongside studied, iBMI record neural activities that used for the paralyzed people. LFP recorded via microelectrode arrays. The time and frequency of the high-frequency LFP signals was removed by wavelet Packet. Again, this research used SVM to classify discrete reaching and grasping postures. The result showed, high accuracy can be get by different transforms method.
Hill & Schölkopf[7] researched, while BCIs were initially conceived as devices for communication for the disabled. This system enabled to detect the movement intent of severely impaired stroke patients in real-time and translates this intent into actual movements through haptic feedback provided by the robotic arm. According to them modulation of SSAEPs was not satisfactory for single-trial BCI communication. This paper was very informative for us as we came to learn many new things from this which leads us to do what we did in our thesis.we came to know about different type of signals.
Parvez & Paul [8] stated that IMFs' can be utilized in grouping applications where the first flags are nonlinear and nonstationary and recognizing highlights exist on the diverse frequencies/amplitudes.EMD is a versatile time-domain investigation technique appropriate for handling arrangement that is non-stationary and nonlinear. EMD performs activities that segment an arrangement into IMFs without leaving

the domain. Through the study, it was found that each IMF fulfilled two conditions and the first four IMFs provide the best results. It was also observed that the first IMF of ictal signal carries a highest amplitude .
Takahasi et al. [9] used EMD to create the new artificial EEG signals. It bearks the main signal into a finite number of IMFs. Then randomly combine some IMFs to get new artificial EEG signals. The paper found a new artificial signals from 60 real signals data for each subject and used them for the CNN training process.This paper was very informative for us as we came to learn many new things from this which leads us to do what we did in our thesis.we came to know about different type of signals and how they works.
Townsend et al. [10] in their study showed that, the amplified brain signals was a bandpass filter from 0.5 to 50 Hz. They divided each session into four experimental runs each containing 40. It was also found that, the comportment of this SIMULINK model was used to deliver the simulated asynchronous analysis where 27 EEG channels are filtered from 8 to 30 Hez. This is very good way to model some data they said.
Park et al. [11] proposed that, improved frequency information in EEG can be obtain by using MEMD directly with the mix of multi-channel processing, especially, its NA - MEMD mode is claimed to provide better time and frequency representation.

Chapter 3

Background Analysis

3.1 Human Brain

The human brain is the most significant organ of a body that allows us to feel, think, see, move, hear, smell and taste. The relation between intelligence and brain size has been a particularly intriguing question [12]. The brain commands the nervous system to monitor and coordinate system which is responsible for judgment,intelligent and memory. This system in each animal varies from one another and therefore each animal have their own level of those capability. Because of this, some animals are more advanced than the other. They learn to adapt with their environment and learn new things about their surroundings so that they can come up with a strategy to solve when there is any crisis. Among all the animals with brain, us humans are much more superior in level of judgment, intelligence, memory. creativity, emotions etc. The structure of the human brain is most complex then any other animal. The human brain is very bigger compared to other mammals in this world. The spinal cord runs from the neck to the hip area and connects the brain. Our life support systems are controlled by the autonomic nervous system that we cannot control consciously such as breathing, blood circulation, digesting food etc [12]. The brain controls all the organs that are inside of our body. It also controls the all the voluntary and involuntary muscles of our body, the involuntary muscle such as heart and lungs cannot be stopped consciously by us but it is controlled by the brain which keeps it functional even when we sleep the brain does not shut down. Along with some other organs like heart, lungs, kidney the brain does not shut down and it functions in a low energy consumption state, Neuronal activity produces local changes in cerebral blood oxygenation, flow and volume [13]. Although the brain is the processor of the body, the brain itself is very delicate and can be easily damaged from external force or practicals and so therefore the brain is surrounded and protected by the cranium (the top of the skull). The brain has three main parts which are the cerebrum, the cerebellum and the brain stem. The brain is divided into regions that control specific functions.Each part works in unity with each other and operates the brain and the body.

3.1.1 The Cerebrum

It is the largest part of the brain that contains both the right and left hemispheres [14]. Each hemisphere has their own role to play in the brain, The cerebrum is formed of two cerebral hemispheres that are left and right hemispheres. The sides of the hemispheres are connected by a progression of strands which is called as corpus callosum that transfers data to every other sides. Then each of this data is processed by cerebral. Every part of the hemispheres controls the contrary portion of the body. For example, the right flank of the hemisphere controls imagination, melodic aptitudes, spatial capacity, while the left hemisphere oversees discourse, composing, counts and perception. when we do something creative like painting a piece of art or composing a song or understanding a poetry the right side of cerebral takes this data and then processes it to our understanding. While on the other hand the left side of the cerebral controls where we compare information and come to a conclusion based on the processing power of the brain. Each hemisphere can be classified into four different sections that are known as lobes - frontal, parietal, occipital and temporal lobes [15]. Every lobe is responsible for performing a explicit and specic kind of capacity [16].

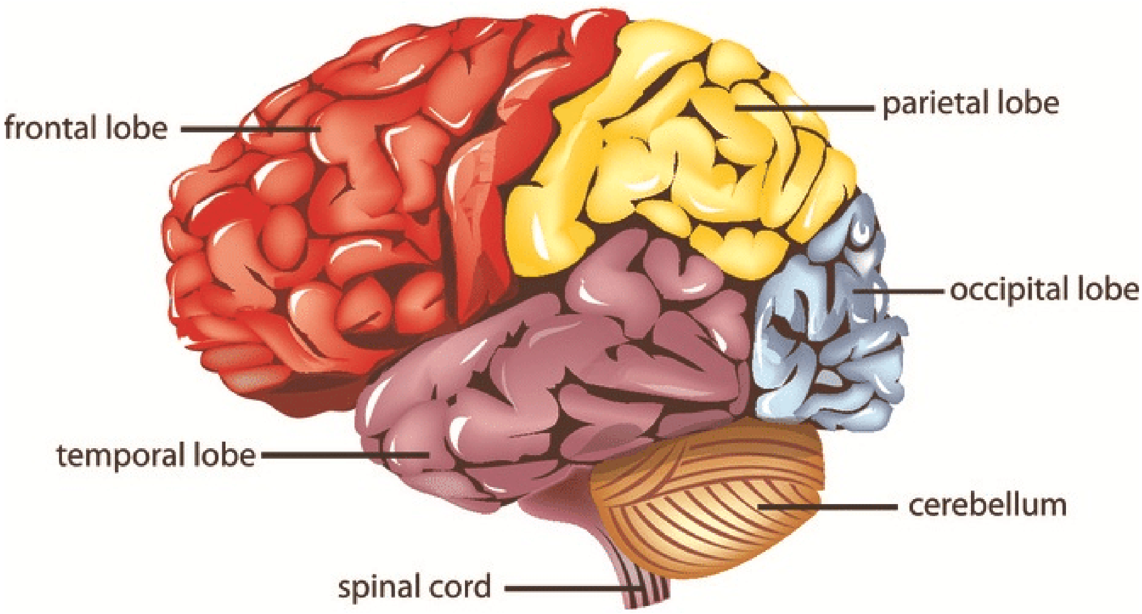

Figure 3.1: Four different types of lobes and locations [17]

Frontal Lobe

The frontal lobe is an essential part which generates the major skills and emotions. Because of this our skills vary from one another and we react to each situation differently. By practicing a certain skill over and over again we can sharpen that skill and our frontal lube can process this more faster. This lobe shapes human intellect, reection, behavior, creative thought, abstract thought process, some specic emotions, inhibition, physical reaction, skilled movements, physical reaction, libido (sexual urges), judgment and some motor skills. But not all the reaction and thinking of all human is same as others. It also coordinates muscle movements, some eye movements, generalized and mass movements and cooperates in taking initiative, sensing of smell [18].

Occipital Lobe

The paired occipital lobes are at the back which are required exclusively for visual processing, including perceiving colors and shapes.Without this lobe we could not see with our eyes. We would see everything distorted and colourless. We would be colour blind and would not be able to tell the difference between sizes if we did not have this lobe. This lobe is connected with vision and also helps in reading.We could not read properly if this lobe is somehow damaged. Distorted vision can be caused by damage to these lobes. [19].

Parietal Lobe

The parietal lobe responses to internal stimuli, some language, reading and visual functions, influences the sensation of touch, appreciates the formation through touch, sensory combination and comprehension [20]. It helps us understand visuals and combine them with other parts of the brain to identify the object. We found from recent research data that the motor acts such as grasping, are studded in a particular way by the nature of action in the parietal lobes which tends to give a neural scheme [21].

Temporal Lobe

The temporal lobe conducts visual memories, few vision pathways, some hearing, auditory memory and other memories. Without the help of temporal lobe we can memorise the visual structure of an object and can identify it. We can also sense and remember sounds that we hear and identify it by using this lobe. It can also help us remember memories which can be either short term memory or long term memory. By using it we can have feelings towards someone or an object. We can also learn the sound, music, beats of a song by using it. It helps us identify languages that we know and processes words into a sentence and then deliver it with our mouth.It also makes us fear an object or individual and think that they will do harm to us. It also controls some behaviour of our characteristics. It helps in identifying an object or an individual. Overall it lets us feel and learn about music, fear, languages, speeches, some behaviors, emotions and sense of identity .[22].

Right Hemisphere (The Representational Hemisphere)

The left portion of the body is controlled by the right hemisphere. It builds a relationship between temporal and spatial lobe. The right hemisphere analyzes non-verbal information and also communicates through emotion. It helps us process non-verbal information and also processes our emotions. [23].

Left Hemisphere (The Categorical Hemisphere)

The right portion of the body is controlled by the left hemisphere which produces and understands language. With the help of it we can understand each and every single word and come up with an answer by using words that are stored inside our brain by making them altogether to form meaningful sentences. [23].

3.1.2 The Cerebellum

Cerebellum is small in size but serves important functions for movements of the body, maintaining posture equilibrium and tone. Without it our body could not function properly and would have collapsed on itself. it also helps maintain the posture of the equilibrium tone. It is the largest part of the hindbrain and called the little brain. It is called the little brain because it covers a large portion of the brain and processes and stores a lot of information there. It is located in the posterior cranial fossa. Voluntary movements of the body are coordinated by cerebellum but the involuntary muscles can not be controled by the cerebellum. [24]. There is cumulative recognition that the cerebellum contributes to emotional control and cognitive processing along with its role in motor coordination. It keeps the control of the emotions and moves all the voluntary muscles of the body but the involuntary muscles can not be moved due to the cerebellum has no control of the involuntary muscles. [25].The cerebellum performs the following functions like posture, balance, respiratory, cardiac and vasomotor centers. I helps us to maintain the backbone posture of our body. It also helps us take breath by our lungs.

3.1.3 The Brain Stem

The brainstem is the eldest part of the brain that regulates the general level of alertness and warns the organism of essential incoming information as well as operates basic bodily functions necessary for survival [26]. The pons, the medulla oblongata and the midbrain construct the brain stem. Cerebrum is connected to the spinal cord by the brainstem. The cells of stem have the malleability to create, alter and repair the functions of nervous system [27]. It connects the brain with the spinal cord which is the most subordinate section of the brain. The brain stem contains gray matter (40%) and white matter (60%) inside the skull which shapes the body's muscle tone and controls the cycle of waking and sleeping of brain. Furthermore, the brain stem oversees functions identified with oxygen levels, circulatory strain, homeostasis, sneezing, vomiting, coughing and swelling reflexes.

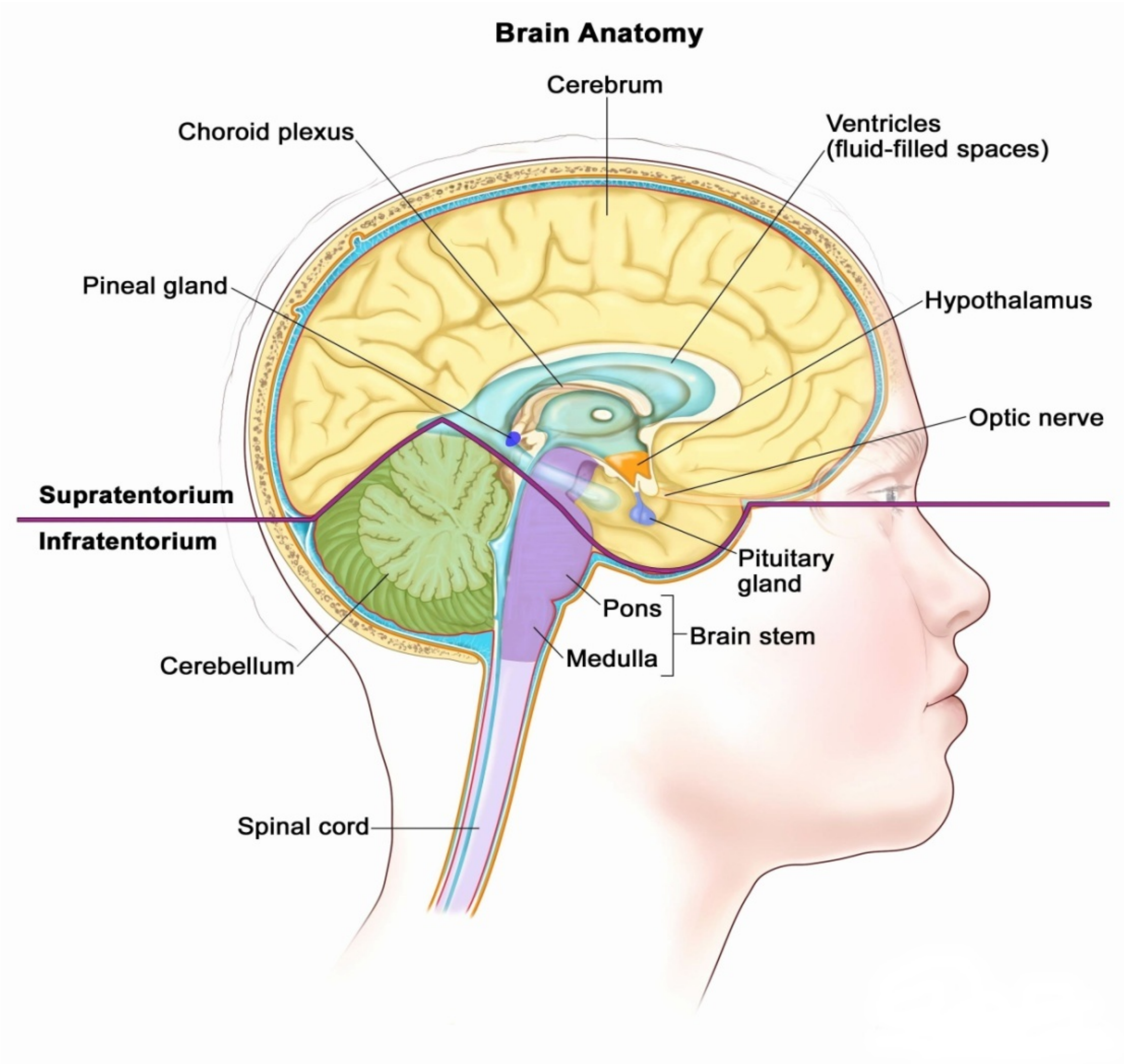

Figure 3.2: Basic structure of human brain [28]

3.2 Machine Learning

ML is a developing part of computational calculations that are intended to copy human knowledge by gaining from the encompassing condition. It seems like a subset of AI. Strategies dependent on machine learning have been connected effectively in assorted fields extending from example acknowledgment, computer vision, rocket designing, money, stimulation, and computational science to biomedical and therapeutic applications [29]. Brain data is hard to model and impose difficulties from perspective of a data scientist. It is portrayed by critical preliminary to preliminary and subject to subject fluctuation. Because of this inconstancy handling ability, ML techniques have turned very famous [30]. Application of ML in the real world is very important nowadays. Our world is now day by day becoming data driven. All information we use is under the necessity of ML. ML makes our life easy. It is the future of the earth. Next generation will be AI generation and ML is the biggest part of that future. ML opens a new way to look at data. It makes us realise how important data is. How data can lead to future where everyone will be happy to get what they want. Everyone will be able to have prediction of their problems and will be able to solve it. ML gives that ability for the prediction of future based on current data that we have. So, we can see that this will lead us to assume any future problem like rain prediction, deforestation, over-fishing , natural resource etc. So that we can take action to fix those problems.

3.2.1 Supervised Learning

This learning is the AI errand of learning which maps a yield dependent on model information yield sets[31]. The information is called as training data. Each training example has at any rate one data source and a perfect yield generally called a supervisory signal. Because of semi-directed learning estimations, a bit of the readiness models are feeling the loss of the perfect yield. In the logical model, every readiness point of reference is addressed by the testing data and branch by a system, iterative improvement is used to get better results [32]. A perfect limit will empower the estimation to successfully choose the yield for data sources that were not a bit of the preparation information. A calculation that upgrades the precision of its yields or desires after some time is said to have made sense of how to play out that errand [33]. Similitude learning is a zone of the coordinated machine adjusting solidly related to backslide and gathering, be that as it may, the goal is to pick up from points of reference using a likeness work that evaluations how near or else related two things are. It has different applications [34].This learning use in the real world is very important now a days. Our world is now day by day become data driven. All information we use is under the need of this learning. this learning make our life easy. It is the future of the earth. Next generation will me AI generation and this learning is the biggest part of that future. this learning open a new way to looks data. It make us realise how important data it. How data can lead to future where everyone will be happy get what they want. Every one will be able to prediction their problem and will able to solve it. this learning gives that ability prediction future based on current data. So , that we can fix or get what we want in our future can be get by the help of this learning.

3.2.2 Unsupervised Learning

This learning algorithm takes a ton of data that contains just wellsprings of perceives and data an example in the data, for instance, assembling or gathering of data centers. The counts along these lines gain from the test data that has not been named, requested o grouped. As opposed to responding to analysis, solo learning estimations perceive shared attributes in the data and react reliant on the closeness [35], in any case, this learning encompasses various regions. Pack examination is the errand of plenty of observations (gatherings), so discernments inside a comparative bundle are similar according to at any rate one predesignated criteria, while recognitions drawn from different bundles are extraordinary. Assorted gathering frameworks make particular suppositions on the structure of the data, much of the time portrayed by some equivalence metric, for example, the closeness between people from a comparable bundle, and parcel, the differentiation between gatherings. Various strategies rely upon evaluated thickness and graph arrange [34]. This learning is very important for our real life. In real life all the data are mostly come under this learning. This teach us how to work with nonleanear data which we get from real world or from the nature. This kind of learning is very useful for the future. We all ready have seen that the future will based data and real life data is very important to solve by this learning. As learning gives is a way to categorize real world data into pattern so that we can gain info from them and use them in the machine so that we get the result we want to get from that data. That's why this learing is so impontant we came to know from our findings.

3.2.3 Reinforcement Learning (RL)

This learning is a zone of AI worried about how to programming authorities should take exercises in a circumstance so as to grow a few musings of consolidated reward. In light of its broad explanation, the field is examined in various requests, for instance, delight theory, control speculation, assignments investigate, information theory, diversion based headway, multi administrator structures, swarm knowledge, estimations and innate calculations [36]. Support learning counts are used in self-overseeing transport or else in making sense of how to play a diversion against a human adversary [37]. RL is important part of ML as it is going to change the world in a way that we cannot imagine. RL has a very different way to learn thing it work on the basis of points. It see how the world is behaving ,what it can do , how this will benefits the world and based on that it will get points and this is how it learn what to do what not to do. SO, we can understand it actully work as a any human do. we human do work for some kind of reward in the case of RL it is points. This is going to change the world in future as we already see in other parts of this thesis.RL is the newest part of ML and it is here to change our future for better [38].

3.2.4 Convolutional Neural Network (CNN)

This is a sort of counterfeit neural system used in picture acknowledgment and han dling that is unequivocally planned to process pixel information [39]. CNNs are solid picture taking care of Artificial knowledge (AI) that use profound figuring out how to make sense of how to perform both generative and drawing in endeavors, habitually utilizing mama chine vision that consolidates picture and video acknowledgment, close by prescribed structures and normal language handling (NLP). it is an excellent method to get result from extraction of data which works better if it is a data of image. A neural system is an organize of equipment and programming designed after neuron's movement cerebrum. Customary neural system is not good for picture preparing and ought to be bolstered pictures in diminished goal pieces. CNNs has their "neurons" planned progressively like those of the frontal flap, the territory accountable for getting ready visual boosts in people and various creatures. The layers of neurons are engineered to cover the entire visual field [39].

3.2.5 Electroencephalogram (EEG)

The EEG is a broadly utilized non-obtrusive strategy for observing the mind. It depends on putting metal anodes on the scalp which measures the little electrical possibilities that emerge outside of the head because of neuronal activity inside the mind [40]. This is a very good procedure to read signals which sends electrical waves via wires. One piece of EEG-put together BCI is based with respect to the chronicle and grouping of encircled and transient EEG changes during various sorts of engine symbolism, for example, e.g., creative mind of left-hand, right-hand, or foot development [41].

3.2.6 Entropy

The entropy is portrayed as an extent of the level of confusion. In the con content of informed speculation, the entropy is a pointer of the proportion of data taking care of an undeniably wide likelihood of conveyance. It is a proportion of the multifaceted nature of time arrangement. The non - linear parameters can be useful to the components of the EEG signals [42].

Chapter 4

Proposed Model

In this research, an EEG dataset was collected from the Brain Neural Computer Interaction (BNCI) website [43] where four-class motor imagery tasks have been defined. Bandpass filter was used between 0.5hertz and 100hertz on this dataset. In this thesis, we used EMD method to analyze the non-stationary EEG signals [8]. After applying EMD on the raw data it broke down the original signal into IMFs which were ordered from higher frequency components to lower frequency components[8]. After that we used CNN [44] for the classification of the four motor imagery tasks (Left hand, right hand, feet, and tongue). The entire process illustrated in Fig. 4.1.

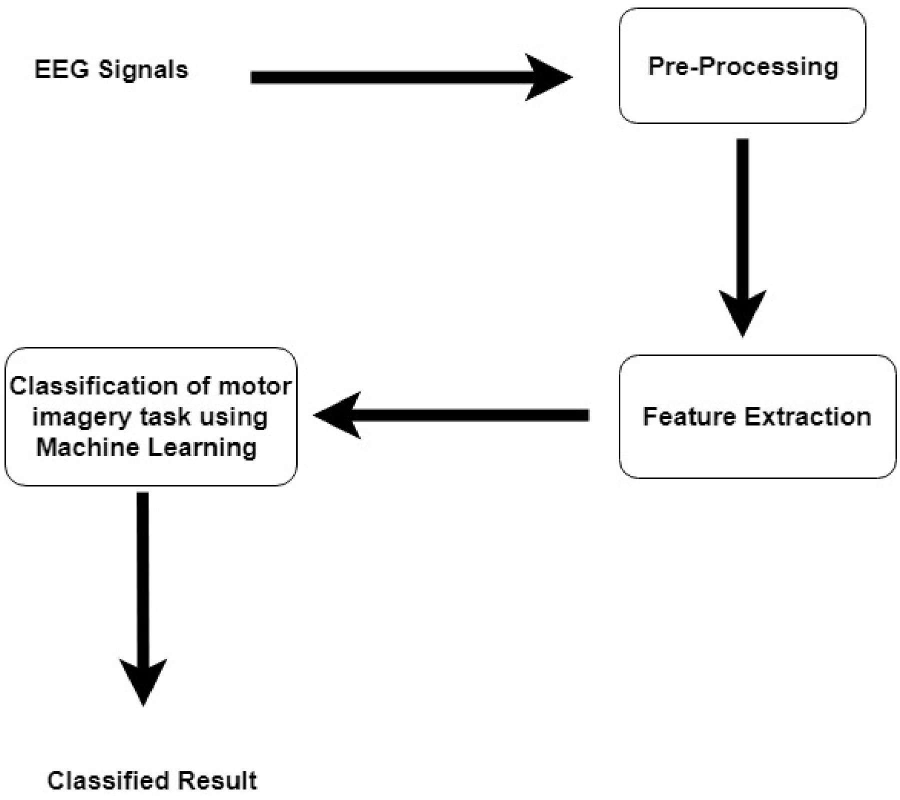

Figure 4.1: Work flow of the proposed model.

4.1 EEG Signals Description

4.1.1 Experimental Setup

AS we mentioned before the dataset was collected from online source. This give us some problem and also help us in various form. In the further discussion we will explain how this all happened. According to the description of dataset contains information from 9 subjects.[45] Each of them were given four motor imagery tasks to perform they are the creative mind of development of the tongue (class 4), feet (class 3), right hand (class 2) and left hand (class 1). For every day on different days two sittings were recorded. For every sittings, there are six division isolated by brief breaks. Forty eight preliminaries is in one division (twelve for every one of the four potential classes), and aggregate there are 288 preliminaries for each sittings.[45]

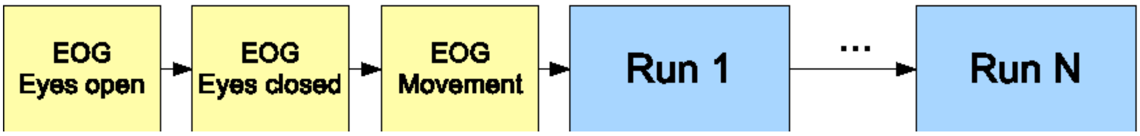

Figure 4.2: Timing scheme of one session [45]

Toward the start of every sittings, to appraise the EOG influence, an account of around 5 minutes was performed. There were 3 squares while recording: (1) one moment with eye developments, (2) one moment with eyes shut, and (3) eyes open for two minutes (taking a gander at an obsession cross on screen).[45] In Figure 4.2, the planning plan of one sitting is represented

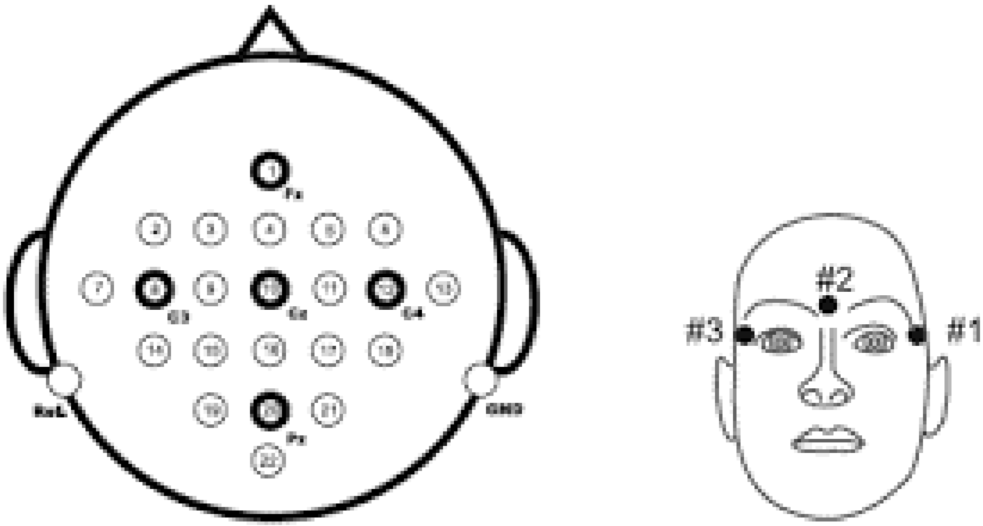

Figure 4.3: Right: Electrode positioning of the 3 monopolar EOG channels. Left: Electrode positioning to the international system. [45]

With this, three monopolar EOG channels were recorded to the twenty two EEG channels and sampled with 250Hz (see Figure 4.3 right image). With the 50hertz notch filter enabled the signals were filtered between 100hertz and 0.5hertz. During the capturing process the amplifier was fixed at 1mV.

4.2 Pre-processing

For recording, EEG twenty-two Ag / AgCl cathods (with between anode separations of 3.5cm) were utilized.[45] All signals was recorded where signals were separated between 0.5 hertz and 100 hertz and examined with 250 hertz.This was very important for the processing, this give us the ability to work with this data in a efficent way. As it was pre prcessed in a certain band it was easy to work with. The affect ability of the intensifier was set to 100mV and furthermore to stifle line commotion, an extra 50 hertz step channel was empowered [46].

4.3 Features Extraction

In this research, our goal is to classify brain signals so that we can further develop a control system which can be used to move a device both horizontally and vertically.So, in order to achieve our goal we are working on EEG signal data. Our first step was collecting the data. After collecting the data we started working on collecting feature from the data which is very hard to understand, non-stationary and unsystematic in behavior. All though signals can be viewed as stationary signal within a short period of time but in case of long duration, they are non-stationary. Due to this drawback, many linear feature extraction methods use a brief windowing process. However, in the cases of motor imagery tasks following these methods are not endurable, which is why we used the EMD to analyze this erratic signals [8]. After applying EMD on the signals, we get our IMFs.[47]. From our dataset we got nine IMFs from each trials. After that, we used three statistical methods - means, the maximum and standard deviation to establish relation between the nine IMFs. The purpose of using the statistical method was to represent the original signal by using the relation between the IMFs. For this research, we also used spectral entropy for feature extraction to evaluate the performance of IMF as a feature vector.

4.3.1 Empirical Mode Decomposition

As mentioned before the main advantage of using EMD is that it can be applied directly to the EEG signals. This decomposes the signal into a finite number of Functions which are known as IMF. These IMFs are structured in a descending order. This attribute makes every IMF vital to recognize the features of the original signal. Since this IMFs are the portrayals of the original signal and the distinctive highlights among the four motor imagery classes like left arm, right arm, feet and tongue, EEG signals lie on the frequency/amplitude. We can conclude that any feature extracted from IMFs will be an effective feature to classify the four motor imagery classes successfully[8].In our thesis we were able to collect nine IMFs from each trials .The algorithm we used for the EMD function is given below [47].
EMD decomposes a signal X(t) into k number of IMFs, and residual

$$r_k(t)$$

using the sifting process [47].The total process can be summarized as following steps :

1. Find local maxima and minima for signal X(t) to construct an upper cover and a lower cover expression respectively [48],

$$s_+(t) \ and \ s_-(t)$$

2. Compute mean cover for ith iteration,

$$m_{k,i}(t) = \frac{1}{2}[s_+(t) + s_-(t)] \quad .... \quad (4.1)$$

3. For the first iteration With,

$$c_k(t) = X(t) \quad .... \quad (4.2)$$

subtract mean cover from residual signal,

$$c_k(t) = c_k(t)m_{k,i}(t) \quad .... \quad (4.3)$$

If Ck(t) does not match the standard of an IMF, steps 4 and 5 are not used. The procedure is iterated again at step 1 with the new value of,

$$c_k(t)$$

4. If Ck(t) matches the standard of an IMF, a new residual is computed. To update the residual signal, subtract the k'th IMF from the previous residual signal,

$$r_k(t) = r_{k1(t)c_k(t)} \quad .... \quad (4.4)$$

5. Then begin from step 1, using the residual obtained as a new signal rk(t), and store ck(t) as an intrinsic mode function.

For N IMFs [49], the original signal is represented as,

$$X(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad .... \quad (4.5)$$

The example picture of generating IMFs of left hand is shown in Fig 4.4. The original signal x(t) can be represented as a combination of IMFs and residual component:

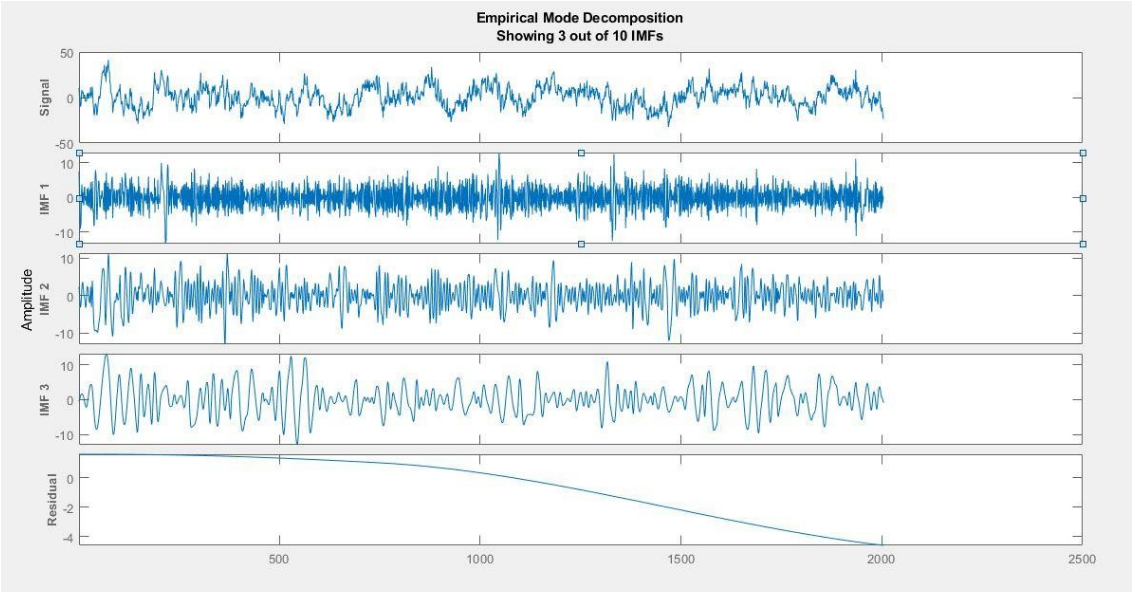

Figure 4.4: Example IMF of left hand signals

We further applied statistical methods consisting mean value, the maximum value and standard deviation value to get a better result.

4.3.2 Spectral Entropy

Spectral entropy is a feature vector which is calculated by finding the spectral power distribution of a time domain signal. This concept was derived from Shannon entropy [50]. This feature represents the data signals normalized power distribution in the frequency domain as a probability distribution and calculates entropy [51]. However, for this feature to perform optimally the knowledge of original signal's bandwidth is crucial. The data also have to go under specific filters such noise filter , bandwidth filter etc to perform well.In our research the data we collected was pre-processed. Moreover, the channel for motor cortex was not specified so we could not apply further filtering processes.

4.4 Motor Imagery Task Classification

There are several numbers of machine learning algorithms available; among them, we chose to use CNN. CNN is a neural network used in image recognition [39]. This is very help full for our thesis, it make easy to get pattern using this from and image but we tried to do it in our brain signals. In our thesis, after feature extraction, we get IMF which is the one of the resultant feature of Empirical mode decomposition (EMD) algorithm. We used 2D vector matrix of those IMF rather than an image to apply convolution neural network with the matrix having dimension of 1000x25x1 of those IMF rather than an image to apply convolution neural network. After that, we used the Batch Normalization Layer function in the input layer [52]. Furthermore, we applied Relu Layer function which performs a operation to the input, where any value less than zero is set to zero [53]. Apart from this, we also applied Softmax Layer function to perform neural transfer for calculating a layer's output from its net input [54]. After that, we used Max pooling 2d layer on our model which performs down-sampling by dividing the input into rectangular pooling regions and computing the maximum of each region [55].

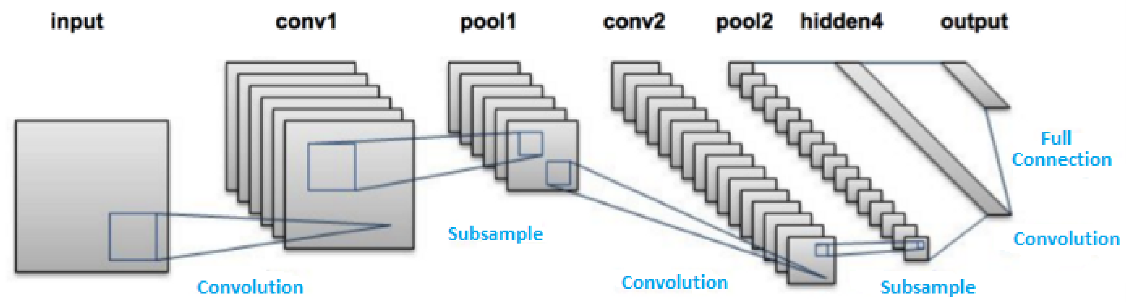

Figure 4.5: Visual representation of 2d convolutional neural network(CNN) model [56]

Next, to make our model more optimized, we used ADAM(adaptive moment estimation) as training options including learning rate information, L2 regularization factor and mini-batch size [57]. This mini-batch size helps to run our model more efficiently than ever before. To reach higher accuracy, we need to increase our hidden layer of the modal to 400, where each 100 layers were fully connected layers. This makes the model to be trained well to perform better while training and testing. Then, Classification layer is used to compute the entropy [58]. Afterwards, for training, we used train Network function with parameter train, target, layer and options. All these functions we applied in our model were needed to be applied several times in our proposed model to make sure that we get the accuracy as high as possible. Lastly, we used the basic equation of sum to find out the accuracy of our model.

Chapter 5

Results and Discussions

We have calculated four different feature sets which are mentioned below. Each feature set was subsequently splitted into training set and test set and then CNN was used to classify four motor imagery tasks.

1. Feature set A : Spectral Entropy
2. Feature set B : Maximum value from IMFs
3. Feature set C : Mean value from IMFs
4. Feature set D : Standard deviation value from IMFs

It was observed from Table 5.1, some feature sets did not perform well compared to other feature set. In contract, we can observe that feature set C perform better than other sets which provide us with highest accuracy with 78%. Table 5.1 give us an overview of all results along with their accuracy, sensitivity and specificity we get for all feature sets.

Table 5.1: Accuracy, Sensitivity and Specificity for different feature set.

Feature Set	Accuracy (%)	Sensitivity (%)	Specificity (%)
A	33	33	33
B	42	42	42
C	78	78	78
D	33	33	33

From the observed result, we came up with several hypothesis for the variation in results for each feature set.
For feature set A, it gives us such low accuracy is because lack of pre-processing on the raw EEG data. Spectral entropy gives better features only if the data was pre-processed several times [59].
For feature set B, it gives us result better than A and D because of IMFs.In feature set B, we used the maximum value from the IMFs which fails to represent the original signal completely. Reason for this is that only using maximum ignores the rest of values which might also represent a good feature [60].
For feature set D, it performs as poorly as feature set A is because standard deviation for the IMFs can not represent a signal of particular task properly because EEG

data from one type of task to another type of task gives poor standard deviation which in result gives us bad feature [61].
For feature set C, it performs better than other feature set is that it uses the mean value of IMF which can represent the original better than other feature set. Benefit of using mean value of IMF is that it can perform well with less amount pre-processing. Using only the mean value provides us a better showcase of the original signal rather using just the maximum value or standard deviation [62].
In order to get the accuracy, the formula is defined as:

$$Accu = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} * 100\% \quad \ldots\ldots\ldots\ldots\ldots \quad (5.1)$$

It can be noticed from Table 5.1 that the feature set with Mean value of IMF delivers us the highest accuracy among all the sets. At the same time, the sensitivity and the specificity of the feature set C are much higher than others.
In order to get the sensitivity, the formula is defined as :

$$Sen = \frac{TruePositive}{(TruePositive + FalseNegative)} \quad \ldots\ldots\ldots\ldots\ldots \quad (5.2)$$

In order to get the specificity, the formula is defined as :

$$Spec = \frac{TrueNegative}{(FalsePositive + TrueNegative)} \quad \ldots\ldots\ldots\ldots\ldots \quad (5.3)$$

The confusion matrices shown in Fig 5.2, 5.4, 5.6 and 5.8 are used to calculate True Positive, True Negative, False Positive, and True Negative for all feature sets.

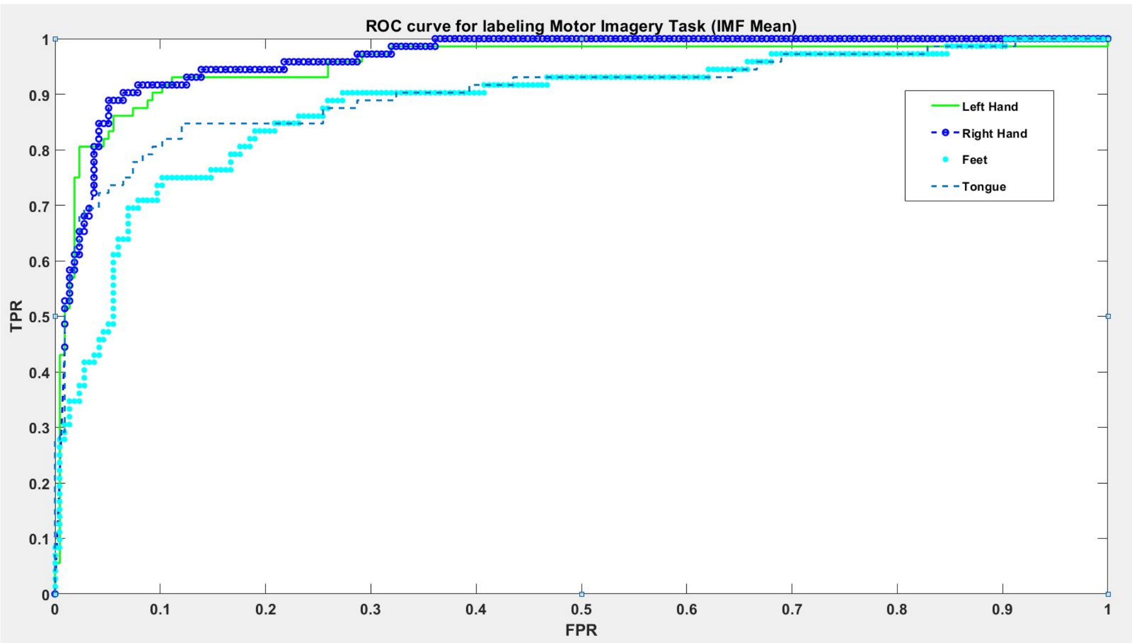

Figure 5.1: ROC curve for labeling Motor Imagery Task (IMF Mean)

For feature set C, we can see Fig 5.1 and 5.2. Where the Receiver operating characteristic (ROC) curve and confusion matrix are shown. ROC curve from Fig 5.1 shows that curve is closer to the upper left corner means accuracy will be higher [63], because of this we get the highest accuracy for this feature set C in our thesis.

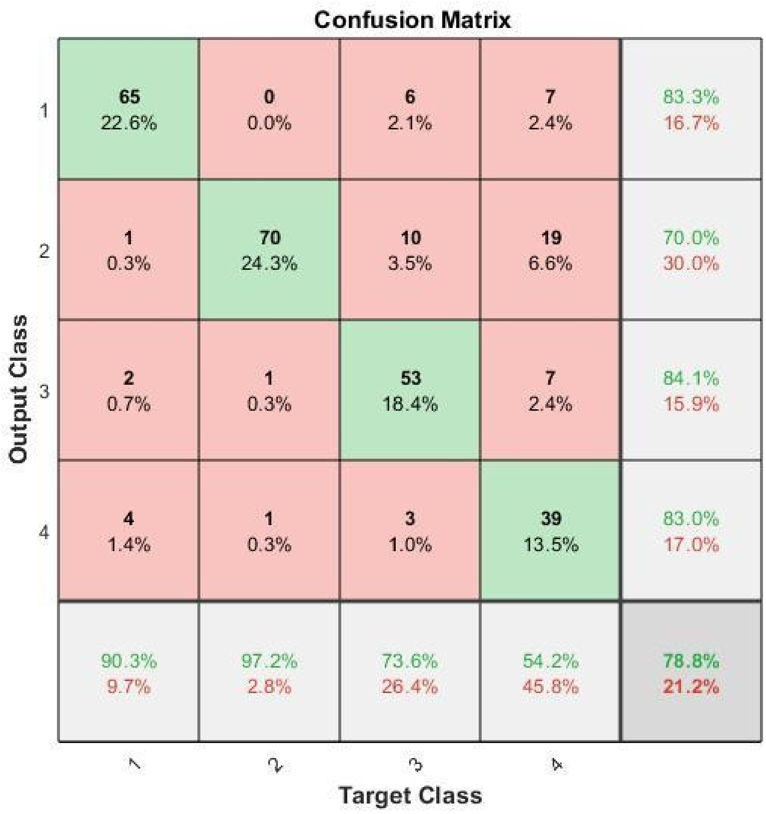

Figure 5.2: Confusion Matrix for IMF Mean

Fig 5.2 show us the corresponding confusion matrix that we used to calculate the value of sensitivity and specificity which can be seen in table 5.1.
It can be noticed that Fig 5.3 and 5.4 having ROC and confusion matrix for feature set A. ROC curve from Fig 5.3 clearly shows that the curves are somewhere in the lower side of the graph near to false positive side of curve and that is the reason the result of this feature set is lowest[63].

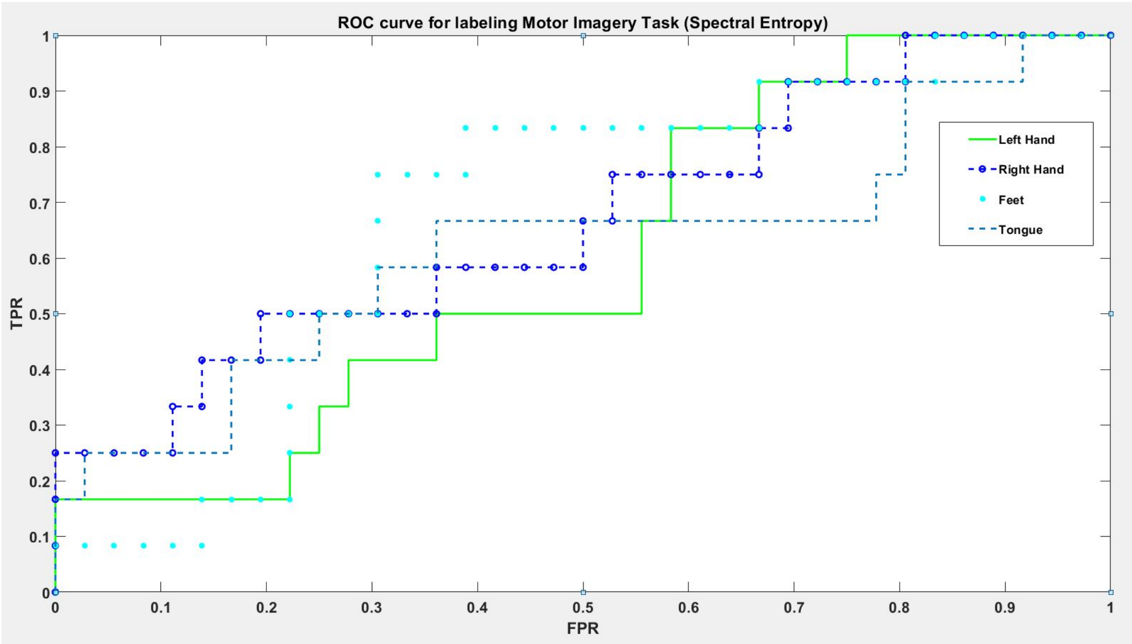

Figure 5.3: ROC curve for labeling Motor Imagery Task (Spectral Entropy)

The ROC curve in Fig 5.3 clearly showed that the spectral entropy was an inferior feature sets to get the high accuracy. From the Fig 5.4, the calculated value of sensitivity and specificity were unsatisfactory which can be seen in table 5.1.

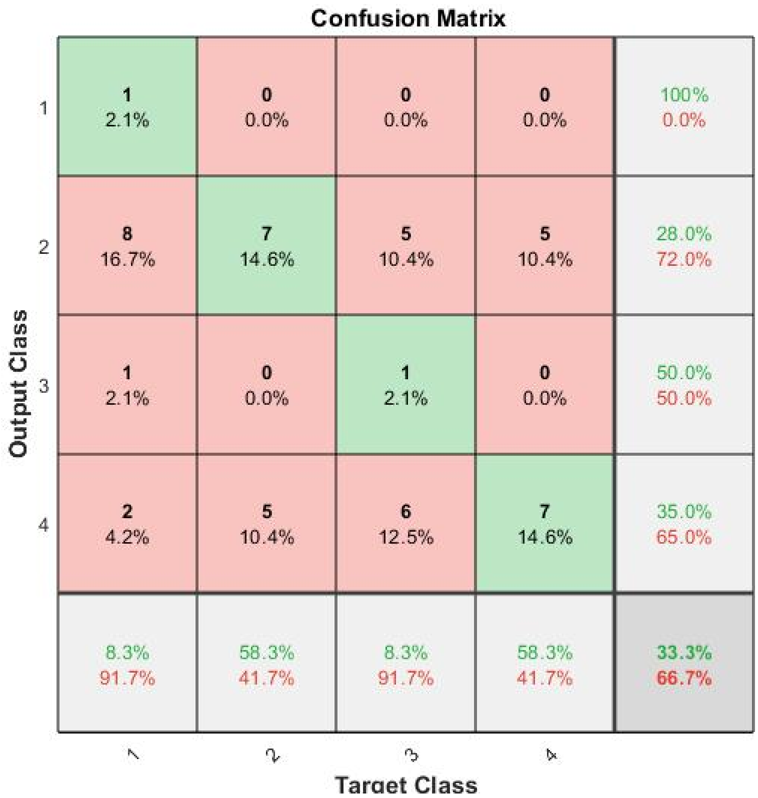

Figure 5.4: Confusion Matrix for Spectral Entropy

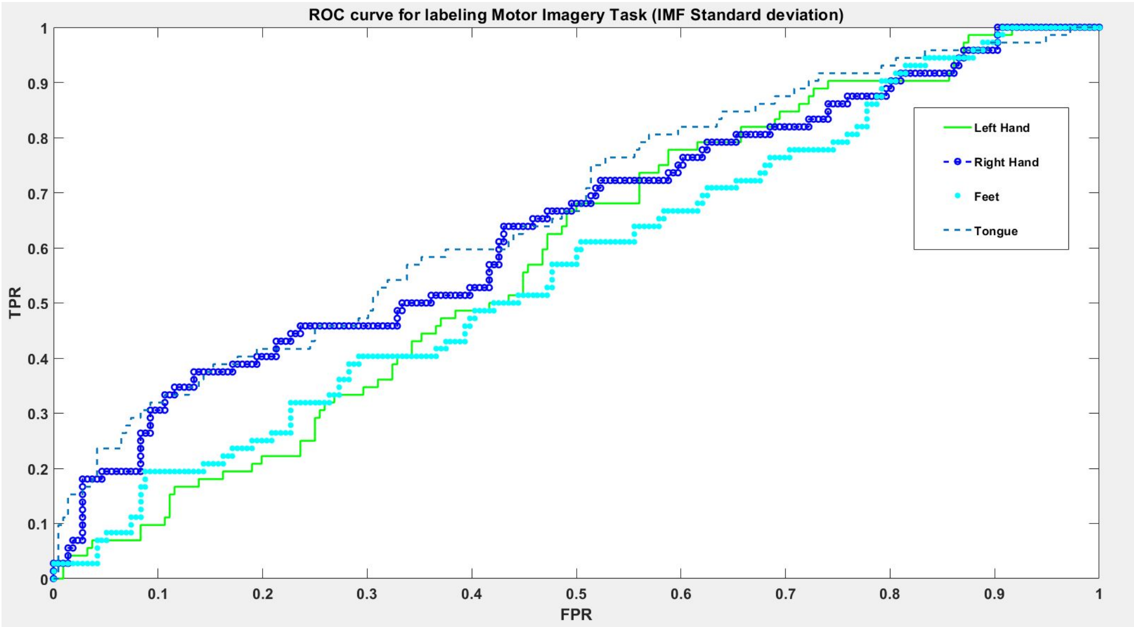

Figure 5.5: ROC curve for labeling Motor Imagery Task (IMF Standard deviation)

Now, from Fig 5.5 and 5.6, for feature set D, we can see that the ROC is more likely to be similar as feature set A because both of them are having almost same accuracy of 33% and the sensitivity and specificity has calculated from the Fig 5.6's confusion matrix.

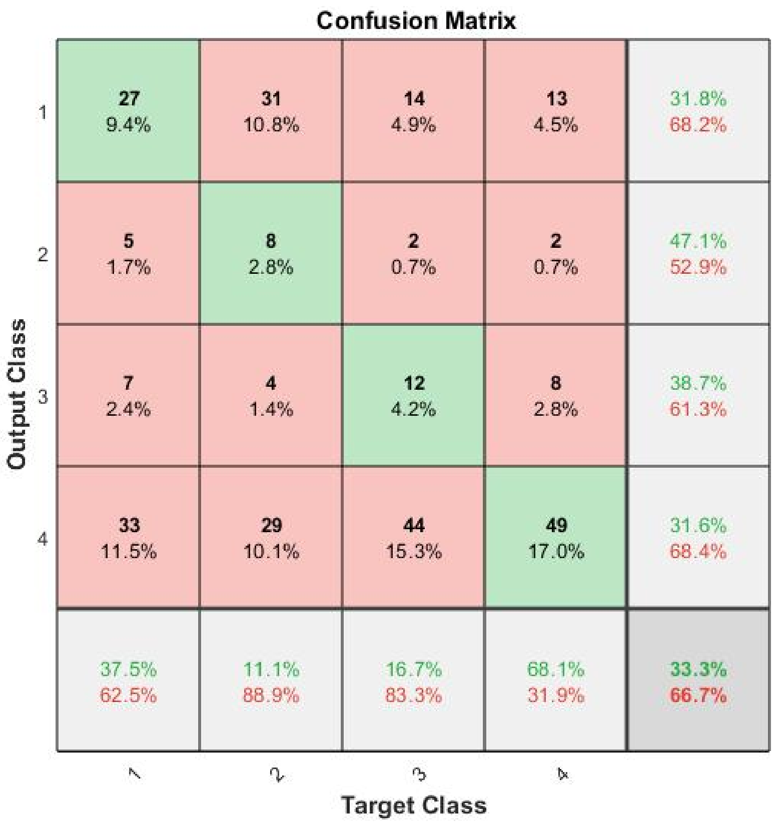

Figure 5.6: Confusion Matrix For IMF Standard deviation

In feature set B, it can be noticed that the ROC curve in Fig 5.7 has more points close to true positive than feature sets A and D.

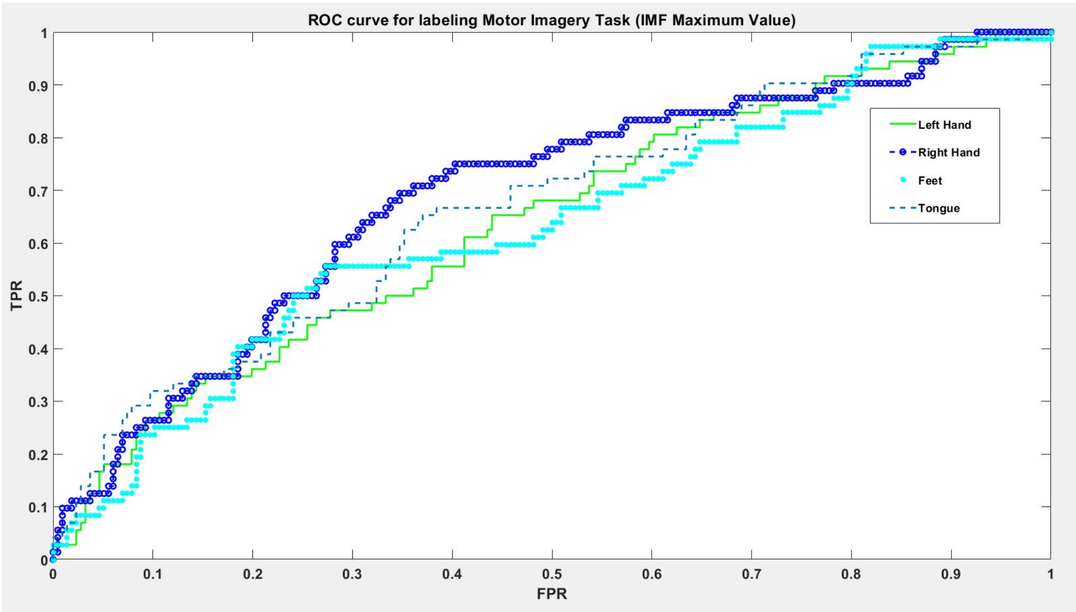

Figure 5.7: ROC curve for labeling Motor Imagery Task (IMF Maximum)

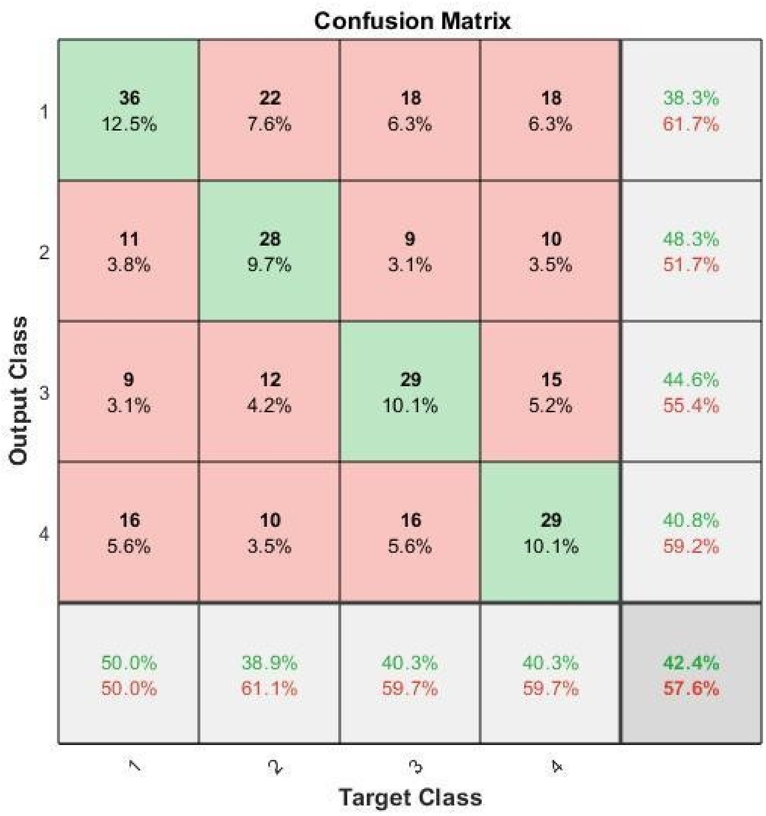

Figure 5.8: Confusion Matrix for IMF Maximum

But not as close as feature set C. The curve is little upper from middle points towards true positive side which leads to a higher accuracy [63] than feature set A and D with the accuracy 42% can be seen in table 5.1. From Fig 5.8 we calculated the sensitivity and specificity around 42% .
After examining all the feature sets, it is ensured that Mean value of IMF or feature set C is the best among all feature sets and it can be spotted from the table as well . So it can be said that by averaging all the IMFs values and trains them with CNN gives us highest the accuracy, sensitivity and specificity of 78%.

Chapter 6

Conclusion

In this thesis, EEG signals were used in order to distinguish among different motor imagery tasks. From the EEG signals, IMFs were extracted based on EMD method. We derived the resultant IMFs from EMD application and set out for different combinations to estimate the accuracy level to be retrieved from the experiments. After that, a set of algorithms were applied on those IMF to get the features. We attempted with the IMF Max on CNN which gives us the accuracy of 42%. Later, we took the IMF Mean value and tried on CNN with 78% which was satisfactory. Afterwards, we applied Spectral Entropy and IMF Standard Deviation with CNN that gave us an accuracy of around 33% each. Our result shows that, among all these four combinations, the mean of IMF implemented with CNN can provide the better result with highest accuracy compared to all of them. Our study is one among very few delivering a detailed comparison among the four combinations using the classification of EEG signals where we can clearly get an idea that the feature set (mean value of IMFs) achieves better result.

From our research, we found out that the implementation of CNN was not conventional on few other existing methods of feature extraction and motor imagery applications using BCI technology which we applied in our experiment as a significant method to get the final outputs.

BCI applications have interested the research community all over the world and several studies that have been presented in our thesis, raise attraction in BCI application fields such as security, organizational, transportation, medical, VR games and entertainment and authentication fields. We plan to conduct our study results and apply further implementations to create a wheelchair which can be controlled by brain signal, make a brain signal controlled game and robot, detect mental disorder, communicate with people and build a low cost software available to mass people.

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