Classification of Modulated Motor Cortex Based on Anodal and Cathodal tDCS

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A thesis submitted to the Department of Computer Science and Engineering
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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.

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Abstract

Over the centuries, humans have wished to achieve the ability to understand the inner functions of the mind and brain. Neurofeedback is the procedure which has an influence on physiological brain conditions that takes place by allowing self-regulation. It has been obtaining momentum as a feasible treatment method for a number of mental disorders and additionally serves as an experimental methodology for researchers to manipulate brain activity in the aims to persuade specific conditions of mind. The purpose of the research is to classify the usage of transcranial direct current Stimulation (tDCS) to overcome and reduce the limitations of neurofeedback. The treatment method of neurofeedback often leads to complications like extremely diffused sensation of anxiety, discontent and discomfort, which is often recognized as an impulse to vomit, dizziness, and photophobia as it redirects and regulates the brain function, which is a fragment of the process. Thus for this purpose in this research, anodal and cathodal tDCS based neurofeedback were applied and then classified to achieve a better result in the application of neurofeedback. The proposed method showed a higher percentage of accuracy (98.67%) for both anodal and cathodal readings using Electroencephalography(EEG) based neurofeedback data for 20 subjects.

Keywords: Neurofeedback; Brain; Mental disorders; Transcranial Direct Current Stimulation (tDCS); Electroencephalography(EEG); Anodal; Cathodal

Dedication (Optional)

A dedication is the expression of friendly connection or thanks by the author towards another person. It can occupy one or multiple lines depending on its importance. You can remove this page if you want.

Acknowledgement

First and foremost, we thank the Almighty for showering us with His blessing and mercy, and providing us with strength, knowledge, capability and opportunity to take on and complete this thesis acceptably on time. This achievement would not have been attainable without His blessings and will.

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Chapter 1

Introduction

1.1 Motivation

The study of neurofeedback has become prominent in different research fields and is increasing rapidly where the primary focus is to improve the lifestyle of human beings. Neurofeedback is a type of biofeedback [27] that prepares the brain to function in complete self control, in condition to count and estimate the brain waves and send a feedback signal to the brain [13] [62]. Neurofeedback generally comes up with audio and video feedbacks. It usually generates positive and negative feedbacks in order to supply favourable or unfavourable brain activities. One of the most important uses of neurofeedback is the treatment of patients suffering from ADHD [16]. ADHD represents consideration deficiency hyperactivity issue [39]. It is being used for treatment of depression [19], anxiety [29], schizophrenia [20] and others that people suffer from. Besides medical field, neurofeedback is also being used in the fields of music, dance, acting and so on. It is observed in a study that alpha-beta training helps to increase the performance of musicians substantially.

Furthermore, transcranial direct current stimulation (tDCS) is also considered to be made use of neurofeedback. It is an immediate and transferable neuromodulatory process that supplies small, pulsed and low electric current to targeted areas of the brain in order to help patients who are suffering from brain injuries or mental illness; they have good potentiality to cure major depressive disorders [37]. On the other hand, tDCS uses another form of neuromodulatory method to come in effect, which is known as CES (Cranial Electrotherapy Stimulation). This also provides low and alternating current via electrodes to the scalp. No dangerous side effects has been reported yet that tDCS can cause.

As it has been reviewed that tDCS is a process used to show how to train brain to function directly, it can be said that it is just another way to make the brain function efficiently and systematically, using neurofeedback. Both are based on electrical brain activity, because their major aim is to provide fast brainwaves, that will allow the brain to function at its best. In other words, it can be said that tDCS using neurofeedback, has the ability to make people ‘smarter’. It is basically a device that contains electrodes, which uses mild and useful electrical currents, provided for obliterating the brain through the skull.

One of the main reasons why this field seems so attractive is it's process of succeeding in the cure of patients mental problems, memory and focus and other benefits just through the usage of neurofeedback. The machine assisted programs like neurofeedback helps people to grow self-regulation, and the potential to overcome disorders such as insomnia, anxiety, depression, epilepsy or brain damage from stroke.

1.2 Thesis Overview

This research paper is segmented into multiple sections which helps to provide a detailed scheme on how the research has been conducted to achieve the outcome. The very first section proposes the incentive for choosing the topic and simultaneously displays a brief idea about what has been actually done in this study. The next section consists of a Literature review, which presents the previous research that has been conducted on similar topics and concurrently, the limitation and obstacles, that aided to make the study more efficient. In the background study, different brain waves and EEG signals were analysed, that are usually used to collect the neuro feedback from the human brain. In addition, it also gives an idea of several different machine learning algorithms and their competency with EEG signals. Next, in the proposed model section, the complete workflow of the study is introduced, where the detailed explanation of the feature extraction, dataset and classification techniques are provided. Moving onto the next section, the results obtained from the study with appropriate graphs are conferred to prove the effectiveness of the study. Lastly, in conclusion, the future implementation procedure and essentiality of tDCS in the neurofeedback research has been provided.

1.3 Major Contribution

The major purpose of this study was to classify the modulated motor cortex based on anodal and cathodal tDCS simulation. The motor cortex is usually situated on the frontal lobe [58], which is right anterior to the central sulcus, that also makes sure that the parietal lobe is separated from the frontal lobe. It is considered as a gateway for outgoing motor commands, which essentially includes sending information down to motor neurons of different parts. It has been known as the most developed part of the brain, as it provides superior functions like thinking, speaking, planning, controlling movement, increased sensation and emotions. Motor cortex, in the nervous system of human body, deemed a great success in controlling human behaviour, execution of voluntary movements and taking out cognitive tasks.

As mentioned earlier, the dataset used for the study contained data of neurofeedbacks that were recorded from multiple different subjects.The neurofeedback data had 3 stages: before tDCS, during tDCS and after tDCS. There were significant changes of data for each stages, which was recorded in different channels subjected to anodal vs sham and cathodal vs sham data readings. After extracting the motor imaginary period from the dataset, the anode, cathode and sham were labelled next. Afterwards multiple features were extracted from the data as well. For the feature extraction, different features like the statistical features and time-frequency domain features were calculated from the data as well. Furthermore, the energy level for the time-frequency domain features was determined which aided in attaining a better accuracy level.

The extracted features were classified using the Support Vector Machine (SVM) to achieve a satisfactory result. Additionally , the Receiver Operating Characteristic (ROC) curve was utilised to ascertain the accuracy.

The next chapter will state the further points about the research conducted previously on relevant topics and the limitations faced which made this study more efficient.

Chapter 2

Literature Review

A literature review was carried out to classify and summarize the results relating to the classification of modulated motor cortex based on anodal and cathodal tDCS. This review explored the practicality of a methodology where the application of tDCS has been done at the time of neurofeedback-guided motor imagery training to the to the contralateral motor cortex but not ipsilateral [30].

Since tDCS has showed up to regulate Event-Related Desynchronization (ERD), motor symbolism's neural mark recognized for neurofeedback, the suggestion of a mix of the strategies was made. tDCS might meddle with nearest EEG (electroencephalographic) cathodes. Thus this investigation was to examine if there could have been any interhemispheric impacts on the unstimulated hemisphere's spectral power caused by the contralateral tDCS, that the transcallosal connection potentially intercedes, and if any such impacts could be utilized in upgrading ERD sizes [30]. A contralateral incitement method would undoubtedly encourage co-enlistment, since it would be a long way in between the incitement cathode and the chronicle destinations [30].

An experiment was conducted using twenty volunteers who were healthy and their age ranged from 21 to 32: cathodal stimulation was given to ten, anodal versus sham stimulation to the rest ten. The hemisphere's predominant (left) side was given stimulation, and evaluated ERD and phantom control over the hemisphere's non-dominant (right) side was applied. tDCS's impact was assessed after a specific period. Spectral power was evaluated under both MI and rest states in alpha, beta and theta groups, while the assessment of ERD was performed in only alpha and beta groups. Two fundamental outcomes developed: (1) there was a decrease in contralateral alpha-ERD ($p = 0.0147$)[30] after anodal, yet not improved after cathodal tDCS; (2) the spectral power of the contralateral side of the hemisphere was affected dimly by the two stimulations, especially in the theta and alpha groups (the land t-value maps had notable contrasts) [30]. So it was concluded that the non-attendance of contralateral cathodal ERD improvement recommends that the convention is not completely relevant with regard to MI preparing. In any case, ERD after effects of anodal and spectral power consequences of the two incitements supplement late discoveries on the far off tDCS impacts between practically related regions. The limitation faced during the procedures included the unavailability of a balanced ERD improving impact through contralateral cathodal incitement, which proposed that this arrangement is not relevant in the recovery circumstances [30].

In another study, past information on the neurophysiological premise of tDCS was complemented by putting in similar TMS(Transcranial Magnetic Stimulation) and EEG(Electroencephalography) co-enlistment to investigate the impacts incited using cathodal tDCS. Tending to the cortical impacts of cathodal tDCS obtains a basic importance thinking about that the conduct results of this incitement are increasingly questionable in contrast with those instigated by anodal tDCS. Normally, it has been seen that anodal tDCS upgrades the directed cognitive function, though cathodal incitement is accounted for as less compelling or is not investigated in any way [34]. For example, lately the rules based on proofs for clinical utilization of tDCS do exclude cathodal incitement for any ailment [34]. However, the lack of noteworthy differences in between the conditions of before, during-and after tDCS without anyone else gives no proof that there is any equivalence in beteween these three conditions. To additionally check this opportunity, a legitimate test of the invalid theory, that says there's no difference in between the three conditions, was done by performing a Bayesian analysis. Regardless of unpretentious contrasts, every one of the consequences of the Bayesian investigation unite in recommending an average sign towards the null hypothesis.

The main ideas of tDCS modulation of motor learning was also applied on the evolving brains of children to see if they have any effect on them. Regardless of the proofs of adequacy and security in grown-ups, tDCS involvement with kids has been restricted. It has been comprehended from two directed tests that repetitive transcranial magnetic stimulation can upgrade motor learning treatment in hemiparetic children with perinatal stroke. Stimulation from these early outcomes is tempered by affirmation that the essential standards of the effects of tDCS for motor learning in the growing brain have not been characterized. But this procedure of tDCS application on children was restricted by the pragmatic phenomenon of the trial, since keeping up concentration and cooperation was fundamental in case of children. Moreover, the security of tDCS has been set up in grown-ups, with less than 20,000 sessions performed, yet information are constrained in pediatric populaces. The security of tDCS is restricted to presently applied tDCS conventions in a controlled research and clinical settings only.

An investigation was carried out to build up the viability of utilizing a patent's reaction to motor cortex rTMS (repetitive transcranial magnetic stimulation) as a screening technique for tDCS intended for in-home use and to evaluate the possibility and adequacy of utilizing in-home tDCS treatment in two groups of patients (responders versus nonresponders to rTMS) who are suffering form neuropathic pain. The objective was to develop a complete preliminary to test whether tDCS over the primary motor cortex (M1) diminishes pain scores in subjects known to have recently picked up comfort from high-frequncy rTMS of M1 cortex. The theory was that rTMS responders would get more prominent advantage by anodal tDCS than nonresponders. Moreover, we proposed that there would be no contrast among responders and nonresponders in help with discomfort from cathodal or sham tDCS. One of the contraints faced was, since patients were approached to perform self-managed tDCS incitement at home and as incitement was not legitimately seen by a researcher, variance in electrode position may have occurred. Moreover, there is a likelihood that earlier presentation to rTMS could have influenced ensuing reaction to tDCS. While association of these two unique types of incitement has been documented [17][18], these discoveries have been in connection to tDCS preparing preceding TMS. Besides, given the brief span of impact of tDCS, any preparing wonders are just obvious if the two are consolidated inside a short time allotment [31].

In an experiment a numerous TMS conventions known was applied for investigating the human motor cortex's explicit cortical neuronal frameworks, by uncovering any differences at the time of tDCS just as the tDCS's short-lasting and long-lasting consequences on motor-cortex volatility. The objective was to get familiar with the incitement changes' initialization during tDCS just as the consequences [53].

Two things were investigated in another study about the effects of tDCS on human motor cortex: 1) whether lessening the incitement cathode size and 2) whether expanding the reference terminal size centers the impacts of tDCS in the human motor cortex tDCS convention as a model. Here the incitement cathode is fixed over the hand region of the essential motor cortex, though the reference terminal is arranged contralaterally over the frontopolar cortex [8]. For the first investigation it was noticed that the impact on motor cortex tDCS was not affected by the the increase in the size of the reference electrode, while the second investigation's results showed that increase in the size of the frontopolar reference reference removes its impacts on probabilistic classification learning [55]. However, the obstacle faced was that the large incitement electrodes did not permit in a number of occasion a particular incitement of the cortical zones of interest. Motor cortex incitement with these terminals caused incitement of the contiguous somatosensory and premotor cortices and accordingly limit the translation of tDCS-actuated movements of execution as far as cortical regions included, for example, in motor learning.

The practicality of a methodology where tDCS was exercised during neurofeedback-guided MI preparing to the right motor cortex was examined [30]. The plan was to check if it was conceivable to improve the ERD prompted by motor imagery on the M1 (primary) motor cortex by abusing the wonder of interhemispheric hindrance. The hypothesis was that tDCS might impact the contralateral motor cortex's ERD with a contrary indication regarding the left (ipsilateral) adjustment, for example that cathodal incitement would realize help while anodal incitement would create a restraint of right (contralateral) ERDs, and anodal incitement of the correct motor cortex would expand both the right-hand and left-hand motor imagery's ERD [30].

A number of previous studies and researches regarding tDCS applied on adults and children for different motives, like mitigating pain or diseases in patients and discovering the stimulation's effects on human brain and motor cortex, along with the constraints and limitations that have been faced by the investigators have been brought into account. This will help in guiding the study carried on in this paper and also take any possible restraints into consideration that might come up during the study. The following chapter discusses about the different brain signals and machine learning algorithms.

Chapter 3

Background Study

In this chapter, it is discussed about the human brain and different parts of the brain and their functions. There different types of brainwaves generated from the brain with different frequency range. EEG Signal which is the most important part of this study is also explained. For classification Machine Learning has been used for obtaining better accuracy and different machine learning algorithms has been discussed.

3.1 Human Brain

The human brain is considered as the command and control centre for the human nervous system, as it has the ability to control many functions of the body; which includes thoughts, memory, speech, movements of body parts, etc [46]. It produces information to the muscles as it acquires signals from all the sensory organs of the body. It is almost similar to all the other mammal brains in fundamental structures but only differs in the body size, as human brain is usually very large in size. Our five senses-sight, hearing, smell, taste and touch, lets the human brain collect information. It constructs all the information together in a way where it tends to be significant and additionally stocks the information in our brain. The figure 3.1 [45] exhibits different pats of the human brain.

The brain consists of three important parts which are known as the cerebrum, cerebellum and brain-stem.

1.Cerebrum:

This covers the largest part of the brain, and is divided into two halves- right and left cerebral hemispheres as well. It processes information from our five sense organs and is in charge of all the voluntary functions that takes place in our body, which can be for example, explaining the meaning of touch, hearing, vision, etc [41].

2.Cerebellum:

It is a part of the brain that is situated right under the cerebrum. It plays an important role in all the physical voluntary movements; that includes motor skills, coordination of muscle movements and balance [41].

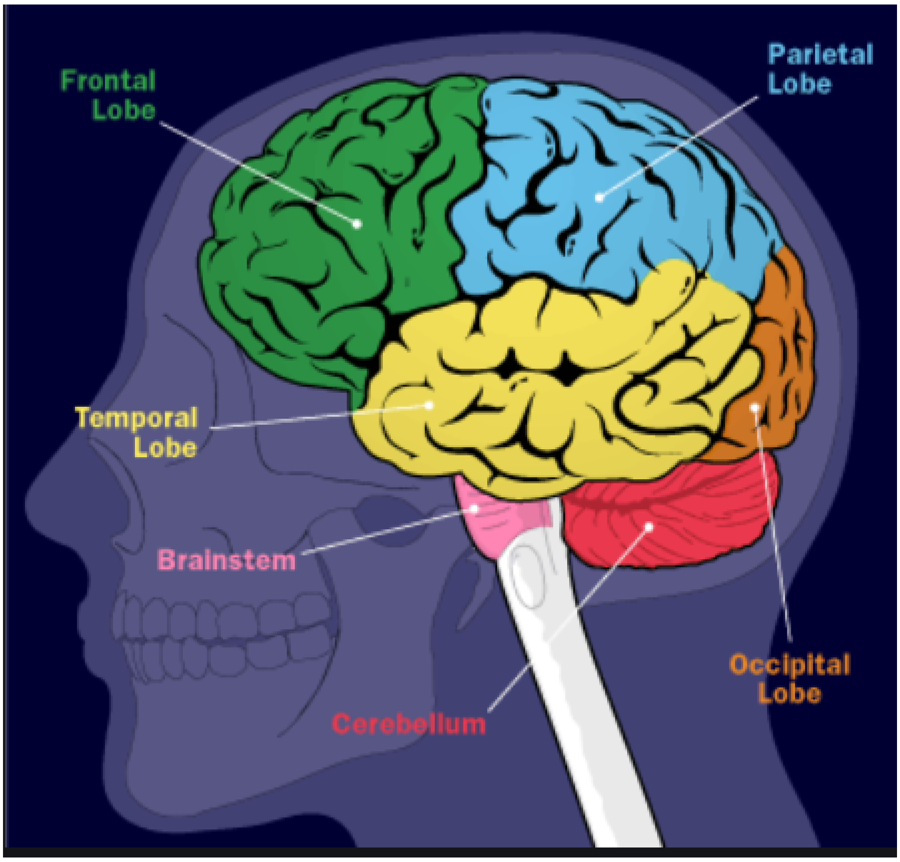

Figure 3.1: Human Brain.

3.Brainstem:

It is the main tool which allows the cerebrum and cerebellum connect with the spinal cord, that eventually leads to regulating the messages between the brain and the rest of the parts. It also performs and controls few basic functions that includes swallowing, breathing, coughing, vomiting, etc [41].

3.1.1 Right brain and left brain

The cerebrum is broken down into two parts- the right and left hemispheres. Corpus callosum, a bunch of fibres, connects these two parts and transfers information from one part to another. The function of each hemisphere is controlling the other part of the body [49]. For example, if a stroke occurs in the left side of the brain, the right arm will be affected and vice versa. However, all the functions of both hemispheres aren't the same and hence, there are separate roles that they play. For instance, the left hemisphere is more supreme in the hand use of humans, which consists of controlling writing, speech, comprehension etc. On the other hand, the right hemisphere is in charge of innovation, artistic and other creative skills like musical, etc.

3.1.2 Lobes of the brain

The cerebral hemispheres consists of some prominent fissures, which splits the brain into lobes. Each hemisphere contains four types of lobes, which are, frontal, temporal, parietal, and occipital lobes. Each of the lobes has their own clearly defined functions [50]. However, its not possible for them to function by themselves alone. The frontal lobe involves planning and coordinating movements of the body. The parietal lobe is responsible for processing information from different organs of the body, basically through sense organs. The temporial lobe helps in processing information regarding hearing, languages, memory, emotions, etc. Lastly, the occipital lobe manages and interprets all the visual information.

3.2 Brainwaves

Brainwaves (i.e., different bands) consists of different sorts of electrical activities that takes place in the human brain. Our emotions, behaviour, thoughts and all other factors are transmitted through neurons within the brain. They happen to take place at many different frequencies, some tend to be speedy and some steady. In addition, they are constructed by synchronised electrical pulses through piles of neurons communicating with each other. The figure 3.2 [44] presents different types of brainwaves are Delta, Theta, Alpha, Beta and Gamma, which are arranged from fastest to slowest frequencies [43]. They are measured in cycles per second or hertz (Hz).

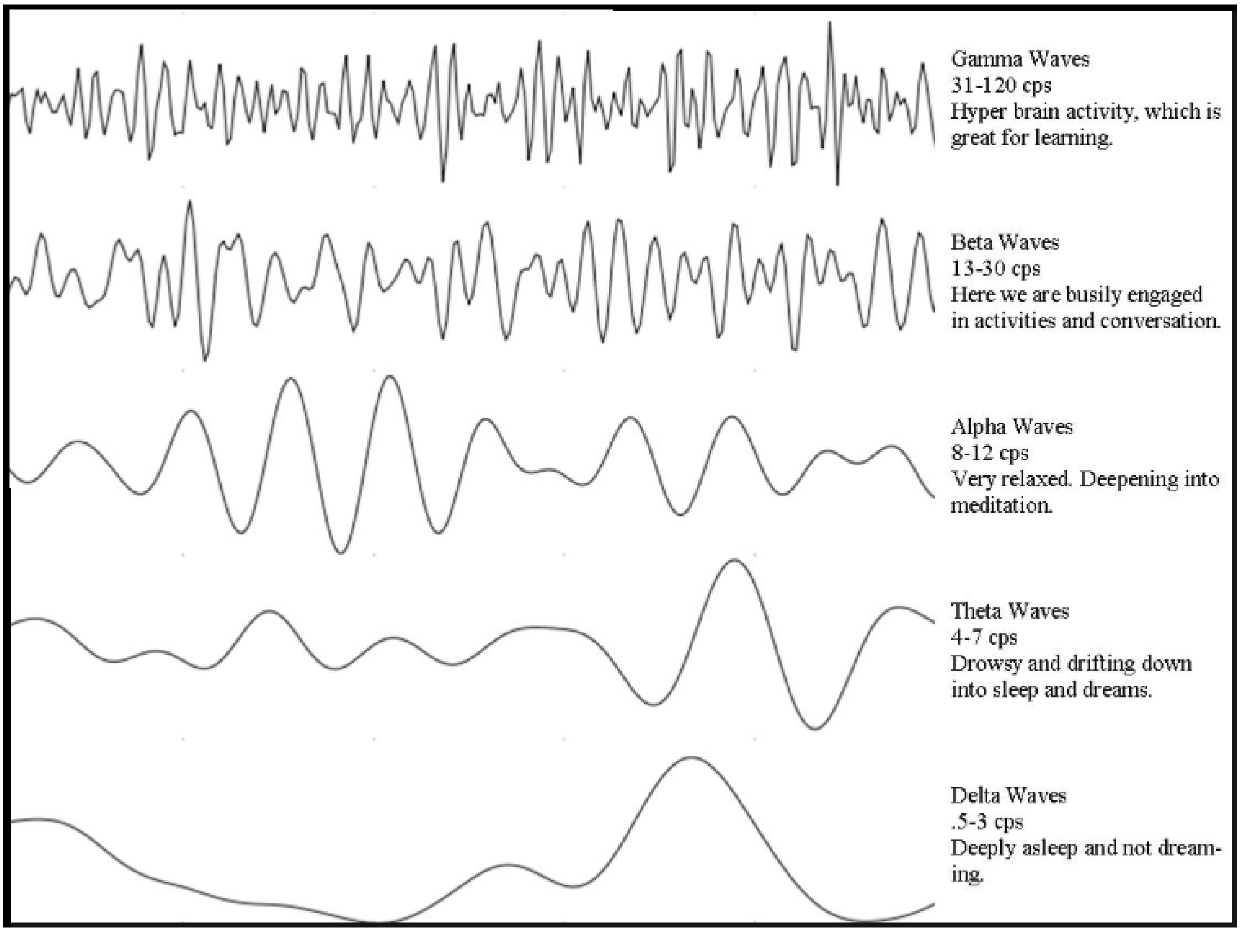

Figure 3.2: Different EEG bands extracted from EEG signals.

Delta Wave

Delta waves have a frequency range less than 4 Hz and are related to deep sleep without dreaming and loss of consciousness of the body [61].

Theta Wave

Theta waves have a frequency range between 4 to 7 Hz and are associated with deep meditation and relaxation [61].

Alpha Wave

Alpha waves frequency ranges between 7 to 13 Hz and help to stay relaxed and calm yet in alert condition [61].

Beta Wave

Beta waves frequency ranges between 13 to 39 Hz and are associated with fast, busy thinking, fast diagnosis, active focus, arousal and attention [61].

Gamma Wave

Gamma waves have a frequency range greater than 40 Hz and are associated with higher mental function, perception , problem resolution, and awareness [61].

3.3 EEG Signal

Electroencephalography(EEG) is a procedure intended to detect all the issues related to the brain's electrical activities and measure the brains wave patterns [10]. With the aid of EEG, it is possible to diagnose few conditions such as seizures, epilepsy, head injuries, dizziness, headaches, brain tumors and sleeping problems. Moreover, it also comes in function during the evaluation of patients with brain deaths.

To carry out this test, electrodes are put down alongside the scalp, so it is considered as a non-invasive technique. Later on, each set of electrodes transfers a signal to any one of many recording mediums of the electroencephalograph, more like the neurofeedback, which is a tool that quantifies, measures and tracks the patterns of the brain wave and provides a feedback signal [12]. Nonetheless, its usefulness being an important tool for further investigation is restricted because it measures only a small portion of electrical activity from the brain.

The study of neurofeedback raised the concern of researchers since several years. Therefore, in addition, as it is also involved in the whole procedure of Electroencephalography as an important tool, this research is solely constructed upon EEG based neurofeedback.

3.4 Machine Learning

Machine learning is a data analysis method that imbrutes analytic model building. It uses algorithm which help to build software applications to predict the results with better accuracy without the need intensive programming.The underlying principle of machine learning is to create algorithms which receives data as input and predicts the results using statistical analysis while refreshing the results according to the new data [4]. It is a subdivision of artificial intelligence on the basis of idea that programs can self learn , recognise patterns by searching through data and can make decisions on their own with the minimal need of human intervention.

Supervised and unsupervised learning are the two wings of machine learning algorithms. Supervised learning analyzes the input data and uses an algorithm to create an inferred function which can be used to learn the mapping function from input to the output [11].

3.4.1 Supervised Learning

It is called supervised learning as the training data set is considered supervisory, for example, this supervises the algorithm or regulates the process of learning. Supervised learning algorithms are sub grouped into classification and regression. So if the algorithm makes a false prediction, it is rectified by the training dataset. Therefore, the system is learning from the data set of training or supervision [63].

1. Regression:

It is when the output variable holds a number, for example "height" or "age".

2. Classification:

It is when the output variable is in a group, for example "colourful" or "colourless" or "green" and "red".It is used to differentiate objects based on particular features.

Some techniques of supervised learning include:

Support Vector Machine(SVM):

SVM or Support Vector Machine provides a linear model on classification and regression problems. It has the capability to provide a solution for both linear and non-linear problems. SVM divides the data into groups or classes by creating a line. Support vector machine can be used for both regression and classification SVMs look for a separate line (known as hyperplane) between two classes of data at first approximation. SVM's algorithm uses the data to generate a line which separate the classes [57]. It transform the data using a technique known as kernel trick and based on these transformation it figures out a suitable boundary between the desirable outputs.We have used SVM for our classification of anodal vs sham tDCS group and cathodal vs sham tDCS [26]. SVM is the most commonly used technique among the numerous algorithms used to identify EEG signals. This is due to its higher performance of generalization of different types of data [32]. The data used

for this experiment were not linearly separable, so the radial basis kernel in SVM have been used [7].
The equation for radial basis is,

$$K(s, s\prime) = exp(-|x - x\prime|^2/2\sigma^2) \tag{3.1}$$

where, x and $x\prime$ are the two samples represented as feature vectors in the input space, σ is free parameter and $|x - x\prime|^2$ is the squared euclidean distance [9].

KNN:

It stands for K-Nearest Neighbours. It is a classification algorithm. It is simple to use and still a fundamental algorithm. It does not assume any distribution of data so, it is known as non-parametric [48].

Naive Bayes Classifier:

It is also a classification algorithm. It is a machine learning model that is used to classify tasks according to certain features [6].

Bayes Theorem:

$$P(A|B) = P(B|A)P(A)/p(B) \tag{3.2}$$

By the help of Bayes theorem, we can find the probability of A happening, where it is given that B has occurred. Here, B is the evidence and A is the hypothesis [54].

3.4.2 Unsupervised Learning

Unsupervised learning happens when data or training set is not labelled. Unsupervised learning's objective is to show the trend in the data to learn much more about data [54]. Like supervised learning, unsupervised learning does not require training data set [54] [56]. Instead, unsupervised learning solely uses the data from input.

Unsupervised learning can be sub-grouped into:

1. Clustering:

In a clustering problems groups of data doing a particular behaviour is discovered.

2. Association:

It discovers the rules which explains the data. For example, people who stays healthy tends to have confidence.

Some techniques of unsupervised learning include:

k-means for clustering problems:

K-means clustering is an unsupervised machine learning algorithm. It is used when the data available is unlabeled [59]. By unlabeled, it implies that the data are without specified groups.The algorithm works attractively to assign every data point according to the features given to one of the K groups [33]. The purpose of this algorithm is to find groups in the data, with variable K representing the number of groups. It classifies the data according to the likeness of features. [28].

ANN:

ANN stands for Artificial Neural Network. It is used for classification and regression.ANN uses models that are built upon the structure of biological neural network.Neural network learns from their input and output.Neural network learns by adjusting themselves by trying to find the right answer by their own, this increases the accuracy of their prediction [47].

After studying different brain signals and machine learning algorithms, this can be concluded that SVM is by far the most effective way to classify EEG signals. The next chapter discusses about the model of the work that has been conducted in this study.

Chapter 4

Proposed Model

This chapter discusses about the work flow of the study. It has been described how the study was conducted and feature and classification algorithms that has been used in order to achieve the result.

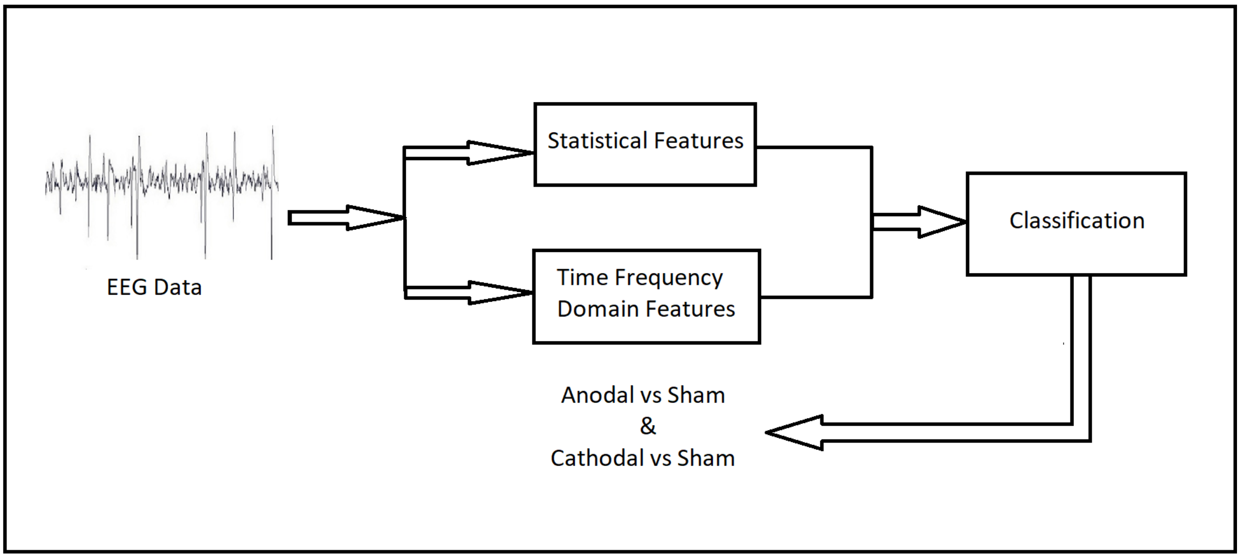

Figure 4.1: Workflow of our proposed method.

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The figure 4.1 shows the different stages of the proposed model and the specific sequence by which that has to be carried out.

4.1 EEG Dataset

The dataset used in the research is a EEG based neurofeedbaack dataset where twenty healthy participants were selected to take part in the study, with their age varying from twenty one years to thirty two years [42]. Ten of the participants were allocated to cathodal stimulation and the other ten of the participants were allocated to anodal versus sham stimulation [30]. Stimulation was added across the dominant (left) hemisphere and the Event-Related Desynchronization (ERD) and spectral power over the non-dominant (right hemisphere) is evaluated [30].

First, the EEG data obtained from the twenty healthy volunteers involved in the

research are categorized according to the sort of stimulation they received. Data are categorized according to the subject within each stimulation folder (S01, S02, S03, SO4.... to S10). For each subject, data are grouped according to the experimental day (day 1 and day 2) where One day corresponds to real stimulation and the other day corresponds to sham stimulation. Fifteen BCI operation with neurofeedback were run each day (neurofeedback01, neurofeedback02, neurofeedback03, neurofeedback04, neurofeedback05, neurofeedback06....neurofeedback15). Runs from one to five resembles 'before' tDCS stimulation , runs from six to ten resembles 'during' tDCS stimulation and runs from eleven to fifteen resembles 'after' the tDCS stimulation.
Data are obtained at a sample rate of Frequency=128Hz and are stored as arrays in the .txt files, where columns resemble channels and the rows resemble samples. It has twelve EEG channels in the order as follows: [Fcz Fc2 Fc4 Fc6 Cz C2 C4 C6 Cpz Cp2 Cp4 Cp6] [30]. Twelve column corresponds to these twelve channels. The thirteenth column contains the right ear lobe reference signal. For each feature extraction each of these channels were used in the research. And the fourteenth column contains the state of the trial. (0 means 'rest' , 1 means 'ready' , 2 means 'motor imagery', 3 means 'rest'). The neurofeedback was applied during the motor imagery period and we have only used motor imagery period in our research.

Table 4.1: Experimental day-stimulaion condition.

Anodal Group			**Cathodal Group**		
Subject	**Day1**	**Day2**	**Subject**	**Day1**	**Day2**
S_{01}	Sham	Anodal	S_{01}	Cathodal	Sham
S_{02}	Sham	Anodal	S_{02}	Sham	Cathodal
S_{03}	Anodal	Sham	S_{03}	Sham	Cathodal
S_{04}	Anodal	Sham	S_{04}	Sham	Cathodal
S_{05}	Sham	Anodal	S_{05}	Cathodal	Sham
S_{06}	Anodal	Sham	S_{06}	Cathodal	Sham
S_{07}	Anodal	Sham	S_{07}	Sham	Cathodal
S_{08}	Sham	Anodal	S_{08}	Cathodal	Sham
S_{09}	Sham	Anodal	S_{09}	Sham	Cathodal
S_{10}	Anodal	Sham	S_{10}	Cathodal	Sham

4.2 Feature Extraction

The procedure of dimensional reduction by which an underlying arrangement of fresh data is diminished to increasingly sensible groups to deal with is known as feature extraction. A property of these enormous data-sets is countless factors that require a great deal of computational staff or resources to process. Feature extraction is the name for procedure that select and/or consolidate factors into features, adequately diminishing the number of information that must be handled, while still precisely and totally depicting the original data-set. In this two types of features have been extracted from the data (1) Statistical Features and (2) Time-Frequency Domain Features which have been further discussed in the later sections.

4.2.1 Statistical Features

Statistical features are the components of the data set which can be characterized and determined by statistical calculations and analysis. By the help of statistical analysis, we can achieve deeper and more arranged knowledge of how precisely our data is organized, and depending on that structure how we can ideally apply other data science methods to get considerably more data. The following mentioned methods are some of the statistical features that we are using in our research.

Skewness

Skewness represents a degree of change from the mean of a distribution of data.It finds out the absence of symmetry in a data distribution. A normally distributed data has a perfectly symmetrical curve [23]. A symmetrical distribution has a skewness of zero. There are two types of skewness, (1) Positive and (2) Negative.The data are said to be almost symmetrical if the skewness is between -0.5 and 0.5.

Positive skewness is when most of the data restults are larger. A positively skewed data has a longer tail on the right side of the distribution. The mode(peak) will be lower than both mean and median.The data are said to be positively skewed if the value of skewness is between 0.5 and 1.0.

The opposite of postive skewness is negative skewness. A data distribution is negatively skewed when most of the data results are smaller. It has a longer tail on the left side of the distribution. The mode(peak) will be greater than both mean and median.The data are said to be negatively skewed if the value of skewness is between -1.0 and 0.5.
The coefficient of skewness is,

$$g_1 = m_3/m_2^{3/2} \tag{4.1}$$

$$m_3 = \sum (x - \bar{x})^3/n \tag{4.2}$$

and

$$m_2 = \sum (x - \bar{x})^2/n \tag{4.3}$$

where $\bar{x}$ is the mean and n is the sample size [51]. m_3 is the third moment of the data set and m_2 calculates the variance [51], which is the standard deviation squared [51] [1].

Kurtosis

Similar to Skewness, Kurtosis is also used to describe the type of distribution of data. Kurtosis tests extreme values in both tails. Kurtosis measures the degree to which the height and sharpness of the peak relative to the rest of the data [51].

The mode is the highest part of the distribution and both tails are the ends of the distribution. Larger values show a bigger and sharper peak; smaller values show a shorter and unclearer peak [23].

The calculation of the moment of coefficient of kurtosis of a distribution is roughly similar to the way coefficient of skewness is calculated.
The coefficient of kurtosis is,

$$a_4 = m_4/v^2 \tag{4.4}$$

and excess kurtosis is,

$$g_2 = a_4 - 3 \tag{4.5}$$

where,

$$m_4 = \sum(x - \bar{x})^4/n \tag{4.6}$$

and

$$v = \sum(x - \bar{x})^2/n \tag{4.7}$$

where $\bar{x}$ is the mean and n is the sample size and v calculates the variance [51], which is the square of standard deviation and m_4 calculates the fourth moment of the data distribution [51] [3] [24].

Mean

Mean refers to the average between multiple data [40]. The general formula for mean calculation is

$$Mean, M = \sum(f_i)/z \tag{4.8}$$

where f_i is the i-th variable and z is the number of variables in the dataset.

4.2.2 Time-Frequency Domain Features

Time-frequency analysis (TFA) is of significant intrigue when the signal models are not available. In these cases, only the time or only the frequency domain portrayals of a certain signal cannot give the overall data for feature extraction and categorization alone. The frequency portrayal of the signal cannot be deduced from the time area.

The signal's Fourier transform cannot delineate the variation of spectral information of the signal with time, which can be evaluated in numerous non-stationary signals practically. Henceforth, the time variable is presented in the Fourier-based investigation so as to give a legitimate portrayal of the spectral content varies as an element of time. Thus, the fundamental objective of the TFA is to decide the energy concentration along the frequency axis at a given time moment, i.e., to scan for joint time-frequency portrayal of the signal [14]. In a perfect case,the time-frequency change would give direct data about the recurrence segments occurring at any given time by joining the nearby data of a "prompt recurrence spectrum"with the global data of the fleeting conduct of the signal [14].

The figure 4.2 [38] displays the separate portrayals of the time domain and the frequency domain for a particular signal.

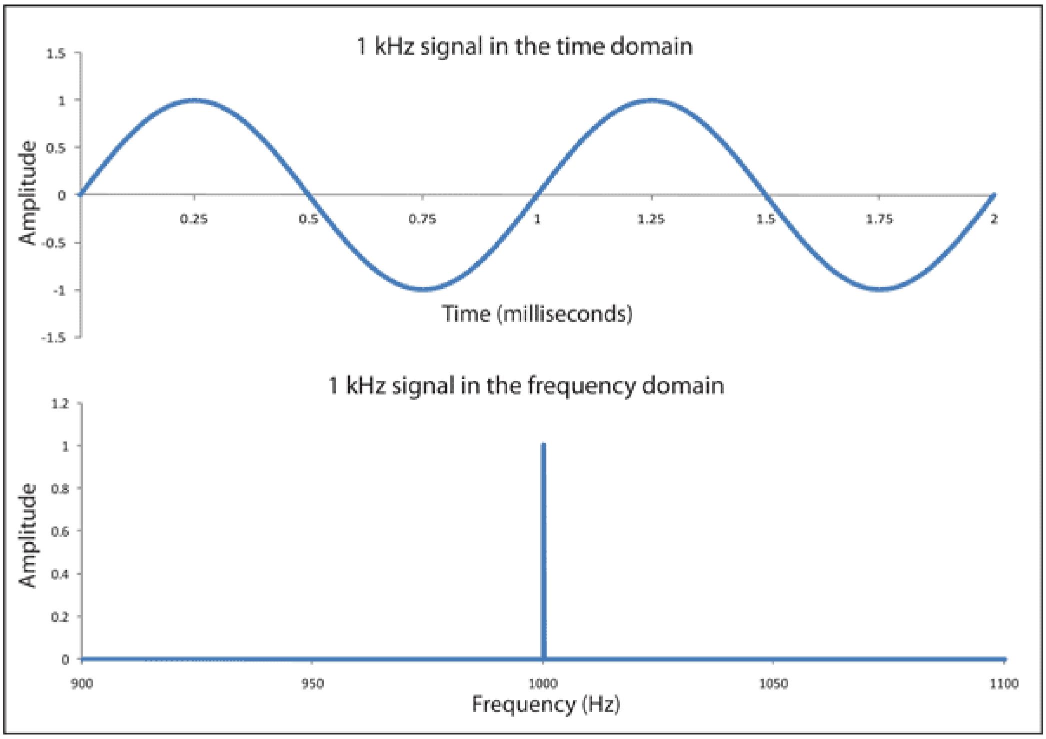

Figure 4.2: Time Domain and Frequency Domain.

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The two different types of time-frequency domain features which were used are: (1) Wavelet packet decomposition (wpdec) (2) Wave decomposition (wavedec).

Wavelet packet decomposition (wpdec)

wpdec is a one-dimensional wavelet packet analysis function.

$$T = wpdec(X, N, wname, E, P) \tag{4.9}$$

This function gives a wavelet packet tree T relating to the wavelet packet decomposition of X, which is the vector, at level N, and *wname* refers to the wavelet used [60].

The wavelet packet technique is an abstraction of wavelet decay that offers a more extravagant signal analysis. Wavelet packet atoms are wave-forms listed by three normally translated parameters: position and scale as in wavelet disintegration, and frequency [60].

For a particular symmetrical wavelet function, a wavelet bundles bases library is created. Each of the bases provides a specific method for coding signals, recreating accurate features. After that the wavelet packets would be able to be utilized for various extensions of a specific signal.

For any one of wavelet packets decomposition and ideal decomposition, straightforward and proficient algorithms exist. Versatile sifting calculations with direct applications in ideal signal coding and information pressure would then be able to be delivered [21].

In the symmetrical wavelet decomposition methodology, the common step slices the estimate coefficients into a pair of sections. After that we acquire a vector of estimate coefficients and a vector of detail coefficients, both at a coarser scale [22]. The data that was lost between the two progressive approximations is caught in the detail coefficients. The next stage comprises in parting the new estimate coefficient vector; progressive subtleties are never re-broken down [22].

Wave decomposition (wavedec)

wavedec is a function which is used for executing multilevel one-dimensional wavelet analysis.

$$[C, L] = wavedec(X, N, wname) \tag{4.10}$$

$$[C, L] = wavedec(X, N, Lo_D, Hi_D) \tag{4.11}$$

This can be done by either the use of a certain wavelet, named *wname* or certain wavelet decomposition filters, specified as Lo_D and Hi_D [36].

This function gives back the wavelet decomposition of the signal named X at level N (where N must always be a positive integer) of the specific wavelet *wname* [36].

Fast Fourier Transform

Fourier analysis implemented on a periodic function gives the extraction of the sines and cosine series which upon superimposing will again produce the function. This can be derived as Fourier series. Fast Fourier Transform (FFT) is a mathematical technique using which a time function can be transformed into a frequency function. It is also derived as transformation of a function to frequency domain from time domain and is very effective for the investigation of circumstances which are dependent on time [2]. FFT, *F(n)*, can be defined by the following,

$$F(n) = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \tag{4.12}$$

where t = *0,...,N-1*, x_0 to $x_N - 1$ are the complex numbers and $e^{-i2\pi kn/N}$ is a primitive Nth root of 1 [5].
We have extracted energy features from different time-frequency domain signals. The equation of energy is given as,

$$E = \int_{-\infty}^{\infty} x(t)^2 dt \tag{4.13}$$

where *x(t)* refers to signal energy, which also include signals that take complex values.

4.3 Classification

The dataset contained both anodal and cathodal data recorded from he subjects. On the first day(Day1) anodal vs sham and second day(Day 2) cathodal vs sham datas were recorded accordingly for all subjects. Sham is an inactive form of stimulation.

After feature extraction, anodal vs sham and cathodal vs sham were classified using SVM to measure the effect of the tDCS based neurofeedback.

The propose model thus describes the total workflow of the study and the methodologies that has been used in order to achieve the result.The next chapter will discuss about result and analysis that has been obtained from the study.

Chapter 5

Results and Discussions

Sensitivity and Specificity both are indicator for performance analysis. The ratio of the samples with a positive index test among all the samples that are genuinely positive is known as sensitivity and the ratio of samples with a negative index test among all the samples that are genuinely negative is known as specificity [52]. In other words, sensitivity is the ratio of the assessments that are true positive between all positive assessments and specificity is the ratio of the assessments that are true negative between all negative assessments [25]. True positive outcomes are the results that are actually positive and true negative outcomes are the results that are actually negative. All the positive assessments are the addition of false positive and true positive samples. Moreover, all the negative assessments are the addition of false negative and true negative samples. Accuracy of a test is the proportion of all the assessments that are correct between all the assessments. Accuracy can be assessed from sensitivity and specificity with the presence of commonness [15].

Equation of sensitivity:

$$SEN = TP/(TP + FN) \tag{5.1}$$

where SEN represents the sensitivity of the test, TP represents true positive and FN represents false negative.

Equation of Specificity:

$$SPE = TN/(TN + FP) \tag{5.2}$$

where SPE is the specificity of the test, TN represents true negative and FP represents false positive.

Equation of Accuracy:

$$ACC = (TN + TP)/(TN + TP + FN + FP) \tag{5.3}$$

where ACC represents the accuracy of the test, TN represents true negative FN represents false negative, TP represents true positive and FP represents false positive.

The Table 5.1 shows the classification results of anodal vs sham and cathodal vs sham tDCS group based on analysis of EEG signals using signal processing and machine learning approaches.

Table 5.1: Classification Results for Anodal and Cathodal tDCS group.

tDCS	SEN (%)	SPE (%)	ACC (%)
Anodal	96.55	100	98.67
Cathodal	100	97.50	98.67

From anodal vs sham tDCS group, we found an accuracy of 98.67%. The value of sensitivity is 96.55% and the value of specificity is 100%. From cathodal vs sham tDCS group, the accuracy is also 98.67%. The value of sensitivity is 100% and the value of specificity is 97.50%.

Receiver operating characteristic(ROC) curves typically feature true positive rate on the Y axis, and false positive rate on the X axis [35]. This means that the upper left corner of the plot is the “ideal” point - a false positive rate of zero, and a true positive rate of one [35]. This is not very realistic, but it does mean that a larger area under the curve (AUC) is usually better [35].

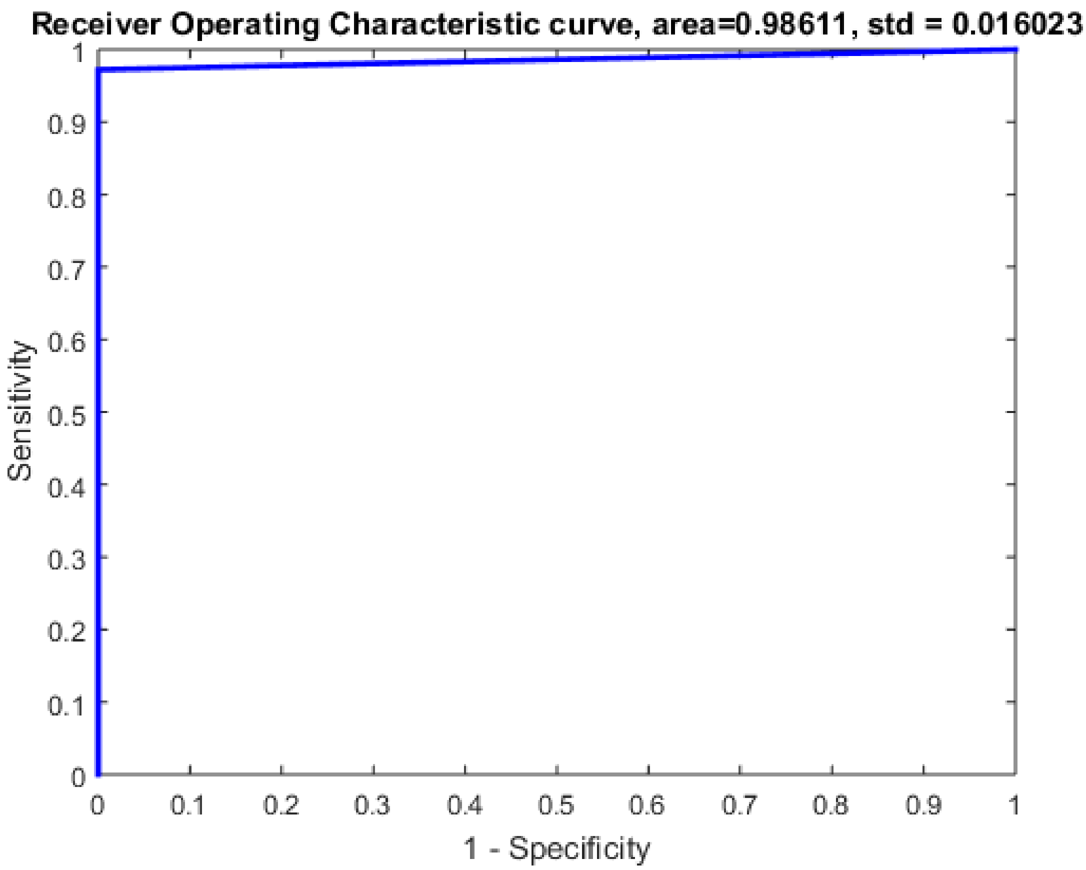

Figure 5.1: ROC Curve for anodal vs sham tDCS experiment.

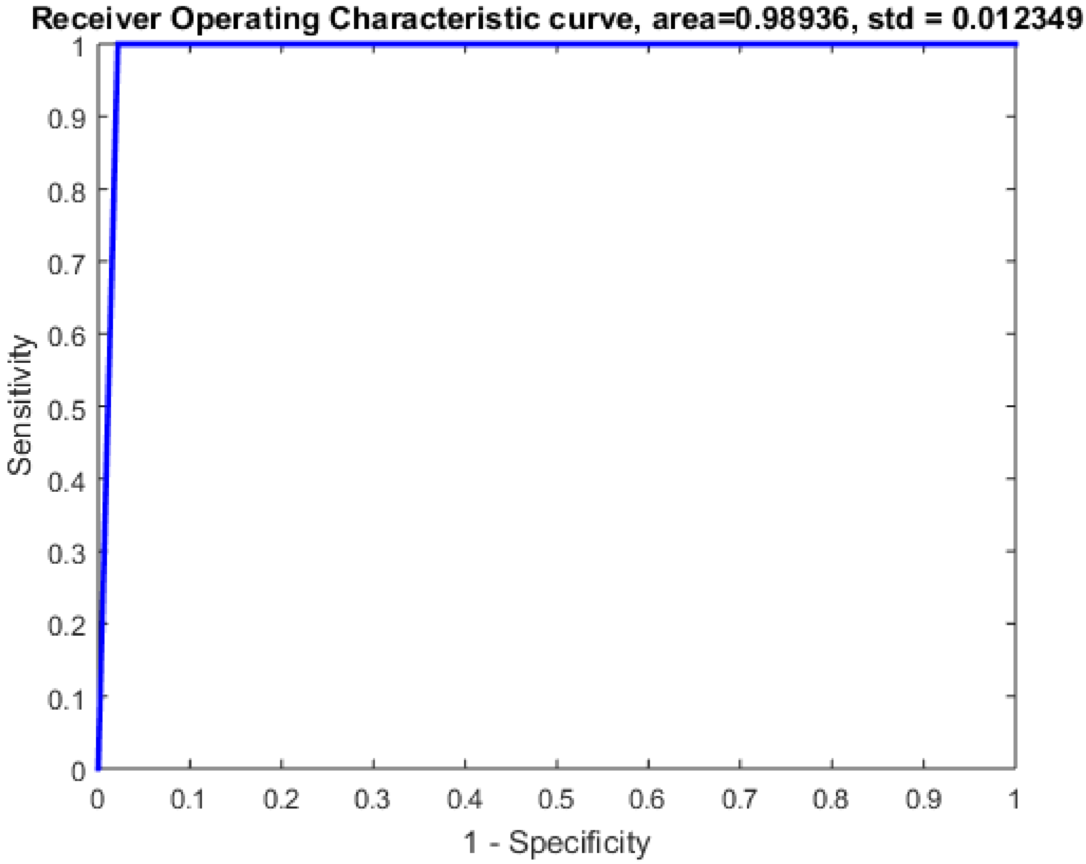

Figure 5.2: ROC Curve for cathodal vs sham tDCS experiment.

The figures of 5.1 and 5.2 from our experiments shows that neurofeedback based on tDCS has provided a better sensitivity and specificity in order to get accuracy that can be useful for further psychological experiments.

Chapter 6

Conclusion

For exploring the interrelation between the brain activity and human behaviour, tDCS is a progressively established method which can be utilized to incidentally and reversibly regulate cognitive states and activities. The objective of this paper is to characterize the anodal and cathodal based modulated motor cortex using tDCS stimulation, and to feature some significant components to consider while designing the experimentation. The outcomes propose that both anodal and cathodal incitement can instigate continuing consequences on the contralateral motor cortex. All in all, the outcomes bolster a number of ongoing findings, such as, showing the probability of tDCS regulation being transferred between practically correlated cortical zones. The main issue that has been faced as a constraint was the adversity in finding a relevant dataset. And since it was difficult to practically implement the study, it is challenging to conclude about how effective and radical the consequences of the study will be in improving the lifestyle of the people suffering from motor cortex related limitations.

The results of this study can be subsequently implemented for the intervention for a number of brain-related medical conditions. In conclusion, it can be recommended that the advancement of designs to translate the tDCS-prompted regulations on cortical pattern or flow would be valuable to better the comprehension of the technique's impacts of neuromodulation and to direct its implementation.

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