Consumer Behaviour Analysis using EEG Signals for Neuromarketing Application

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

Department of Computer Science and Engineering
BRAC University
December 2019

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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Ethics Statement

We, hereby declare that this thesis is based on the results we obtained from our work. Due acknowledgement has been made in the text to all other material used. This thesis, neither in whole nor in part, has been previously submitted by anyone to any other university or institute for the award of any degree.

Abstract

Neuromarketing is applying neuropsychology in marketing research which studies consumer sensory-motor such as cognitive and affective response to marketing stimuli with the help of modern technologies. It is one of the most recent marketing research strategies and might be the future of marketing research. In our study, we demonstrated how marketing may benefit from Neuromarketing through analysing consumer behavior with the help of EEG signal. Consumer's responses toward marketing strategies and their behavior towards purchasing or selecting products or goods can be studied and analyzed for a better producer and consumer relationship. To do so we took a sample of our population for collecting EEG signals of different ages, groups and gender for a better understanding of consumer behavior towards a marketing policy. Through analyzing the data we tried to uncover how and why they like certain marketing policies and how different part of the human brain reacts while those marketing policies are applied to them.We used some machine learning approaches where Decision Tree achieved highest accuracy of 95%. We also tested whether neuropsychological measures can capture differences in consumer's actions in different marketing stimuli. And also if studies in this field can bring a change and improve marketing strategies for the betterment of both producer and consumer and result in the mutual benefit of both. We believe that neuropsychological measures soon will be widely acknowledged and used as a complimentary method in classical marketing research. We tried to contribute to this field by doing as much as we could with our work.

Keywords: Neuromarketing, EEG, Neuropsychology, Marketing Strategy, Consumer.

Firstly, this thesis is dedicated to our parents for their love, effort, endless support and encouragement which they always provided.

We are also thankful to our supervisor Dr. Mohammad Zavid Parvez. Without his guidance, support and motivation it would have been impossible for us to conduct the research.

Last but not the least, we want to share our gratitude towards the friends we found along the way, who shined the brightest in our darkest of days.

Acknowledgement

Firstly and foremost, we would like to thank our Almighty for enabling us to conduct our research, give our best efforts and complete it.

Secondly, we would like to thank our supervisor Dr. Mohammad Zavid Parvez for his feedback, support, guidance and contribution in conducting the research and preparation of the report. He encouraged us to conduct the research, gave guidance to us and always were present to offer any help we could ask for. We are grateful to him for his excellent supervision to successfully conduct our research.

We also would like to extend our gratitude to Mahendra Yadava, Pradeep Kumar, Rajkumar Saini, Partha Pratim Roy, Debi Prosad Dogra from Department of Computer Science and Engineering Indian Institute of Technology, Roorkee, India and School of Electrical Sciences, Indian Institute of Technology, Bhubaneswar, India for their article "Analysis of EEG signals and its application to Neuromarketing" which was published 18 March 2017. We used this article as our main role model article.

Last but not the least, we thank BRAC University for providing us the opportunity of conducting this research and for giving us the chance to complete our Bachelor degree.

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Nomenclature

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

AR Autoregressive

AUC Area Under Curve

$AUROC$ Area Under the Receiver Operating Characteristics

BCI Brain Computer Interface

DA Discriminant Analysis

$DLPFC$ Dorsolateral Prefrontal Cortex

DT Decision Tree

DWT Discrete Wavelet Transform

EEG Electroencephalography

ERP Event Related Potential

$fMRI$ Functional Magnetic Resonance Imaging

HMM Hidden Markov Model

KNN K-Nearest Neighbors

MEG Magnetoencephalography

NB Naive Bayes

PET Positron Emission Tomography

RF Random Forest

ROC Receiver Operating Characteristics

SST Steady Sstatetopography

SVM Support Vector Machine

TMS Transcranial Magnetic Stimulation

Chapter 1

Introduction

1.1 Thoughts behind working on Neuromarketing

Neuromarketing is the study of the brain's response using medical technologies to marketing stimuli [1]. It is a new strategy for marketing. Medical technologies such as eye-tracking, facial coding, fMRI and EEG are used by researchers to compute distinct types of brain activity in response to advertising messages. By analyzing the information collected corporations tries to find out the reasons behind consumer's decisions. They try to understand the reason behind consumer's purchasing commodities as well as try to understand which part of the brain influences them to do so.

Neuromarketing also have importance in recent marketing research because consumers may often lie or might be unable to organize and express their thought as they want to, however, statistics will not do so. Also, existing traditional marketing research methods are not able to decipher what goes inside consumers subconscious mind. The subconscious mind is the place where the majority of human thoughts takes place. Through Neuromarketing it is possible to know what a consumer is thinking willingly as well as subconsciously [2].

Neuromarketing is thought to be as some way to change consumers decision into purchasing a specific product. However, Neuromarketing actually is a way for corporations to find out and test marketing strategies if they are annoying consumers or is effectively reaching and helping consumer to select and buy the product of their need. In current marketing research Focus Groups are used to find out how effective marketing strategies are. However, as focus groups depends on self reporting also the report often can be clouded and biased by consumers own ideas. It is assumed by the Neuromarketing researchers that most consumer's decisions are made within a split second, most of these decision made by consumers are also made subconsciously. It is also believed that decisions and choices made by the consumers are often emotion driven rather than comparison of products depending on certain differentiator or criteria. Feelings or realizations from advertisement makes the consumer act accordingly in purchasing a certain product. Neuromarketing research is conducted by recording and analyzing certain bio-metrics features such as Electroencephalography (EEG), Facial Coding, Facial Expression Recognition, Gesture Pattern Recognition, Eye Tracking, Galvanic skin response and electrodermal activity. It is possible for marketers to create a more effective and engaging marketing strategy with the help of Neuromarketing. Understanding consumers viewpoints, behavior, action, emotion and non-conscious insights, feeling measurement and priming effects will help the marketers to plan and develop marketing strategies accordingly [3]. Not only the brand will be benefited by Neuromarketing, but also the general people who are exposed to hundreds maybe thousands of ads everyday. Through creating more informative, emotionally rewarding, and useful ads it is possible to create an enhancing customer's experience with products or brands long before consumer decides to purchase [4].

Neuromarketing can also benefit the device manufacturers. Researchers always wanted a mobile biosensor solution which is not intrusive nor intimidating but will provide accurate, clean data for research purpose [5]. Neuromarketing can be the solution to solve that problem and be the bridge between data and researchers.

Electroencephalography (EEG) and Functional Magnetic Resonance Imaging (fMRI) are two of those technologies which played a vital role in the field of Neuromarketing research acceleration. As subjects react to vision, taste, smell, sound and obvious signals brains bloodstream is followed and recorded by a ground-breaking magnet in fMRI. fMRI can detect a profound piece of the brain which is known as the "Pleasure center" which indicates how individuals react to the marketing strategy or advertisement. However, the price of fMRI is a thing to worry about as it is not that cheap. Therefore, it can sometimes be a burden for researchers and analysts. The equipment can cost from \$150,000 to \$300,000 or above [6]. However, on the other hand, EEG is far less expensive than fMRI. EEG signals can be derived by connecting a cap of electrodes to the sample's scalp where the electrodes can also be moved and placed freely. The electrodes can measure electrical waves that are created by the brain. Through analyzing the brain waves scientists can follow the subject's instinctual motions through their action variance. For instance, outrage, fervor, distress, and desire. However, EEG is unable to access the profound pieces of the brain like fMRI, which is known as the "Pleasure Centre" [7].

In Neuromarketing research EEG continues to be the most popular among many popular measurement technologies and there are many reasons behind it. EEG can measure and capture brainwave activity as the brain processes data. For example, EEG can measure brainwave signals as we perceive visual, auditory, smell, taste and tangible senses also as we process our thoughts. Through the subject's behavior and choices, EEG directly measures its brain activity, rather than indirectly. As technological advancement is occurring EEG equipment is becoming less expensive, portable, and wireless. The affordability and portability are creating new possibilities for studies such as mobile, in-store, and virtual reality. New machine-learning and statistical approaches are being used to understand and decipher the brainwave signals measured by the EEG signal. Analyzing these data and has brought up many groundbreaking discoveries that no one would have thought is possible a few years back [8].

1.2 Problem Statement

In the article of Bartels [9], it is mentioned that in the twentieth century the thought of development of marketing began. With time the concept of marketing evolved as well as the ideas behind it. Producers realized the importance and effect of marketing on consumers. To develop marketing strategies marketers started conducting research on market as well as on consumers.

Research conducted on market and consumer helped in understanding the buying behavior of consumers as well as developing advertise and marketing policies. However, traditional marketing method does not apply to every group of people. Manually conducted consumer research can be flooded with false and made-up information. Therefore, strategies developed based on consumer research might not always be effective.

People can lie or act accordingly. However, it is possible to know what the person is thinking through measuring the person's brain signals. Through measuring and analyzing the EEG signal it is possible to determine what someone is thinking. It is where neuropsychology comes handy. With the help of neuropsychology patterns in a person, action and behavior can be understood and thus, products and services can be developed according to their choice. Also, marketing strategies can be developed which will result in mutual benefit for all. Patterns recognized by analyzing neuropsychology can help in building Neuromarketing strategies.

1.3 Research objectives

It has been more or less 10 years Neuromarketing has been around and day by day it is becoming more and more popular. Many big organizations and corporations have adapted this method of marketing for planning, bundling and promoting their product though there are a lot who are skeptical about this approach of marketing. However, this process takes a lot of and is expensive than expected. Therefore, here through our approach, we are trying to find out how neuropsychology might help in the field of marketing with machine learning approach which can deliver more accurate and efficient results in a short span of time.

Our objective in this research covers various grounds. Starting from market research, to analyzing customer perception and lastly to create such a system to feel the void of a tool which could let the marketers peek into their customer's mind and predict possible future outcomes, a field that is yet to explode in the current business sector. Our objectives include but not limited to creating a framework that can extract consumers preferences based on their brain signal but also introduce a new method of market research that simultaneously gives information of a marketing strategy's current performance, its selling points, its issues and ways of renovating the strategy in future iterations. Information that the companies will be able to use in more than one way for their business development. Also, a system that can understand the recent market trends directly through measuring and analyzing consumer's perspectives and points of view.

Chapter 2

Literature review

2.1 Neuromarketing: the Next Big Thing

Neuromarketing is a recent uprising field which connects psychology and neuroscience with economics and marketing. Our brain is constantly being affected by advertising and marketing strategies. The goal of Neuromarketing is to study why and how is it being affected to understand and get the measure of the effectiveness of these strategies. Neuroimaging techniques like Electroencephalography (EEG) and Functional Magnetic Resonance Imaging (fMRI) are used to monitor and measure brain activity resulting from viewing an advertisement.

Preference between products can be measured on the basis of brand familiarity and other criteria with the help of Neuromarketing studies. With the traditional marketing study, it is hard to tell if a particular advertisement has any impact on consumer's product preference as the consumer might have a cognitive bias towards a product. A brand's familiarity with the consumer's choice of the product has a correlation with neural activity. According to a book by Christopher R Madan et al., Neuromarketing study and research is still a field that is viewed with caution by consumer protection groups as well as many academics as it is considered that it is possible to design such advertisements with the help of Neuromarketing that can intentionally cause specific neurological effects which might cause ethical implication [10].

2.2 Neuropsychology: The Science of Brain

For more than ten years neuroscience has played a vital role in the development of Neuromarketing research for measuring consumer behavior and market analysis. A few projects like the European Union's Human Brain Project [11], The Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative [12] shows the light of advancement in construction and development of neuroscience which will be able to help consumer neuroscientist to fulfill the gap between consumer neuroscience research.

Despite the fact that these research activities, right now, are not straightforwardly centered around Neuromarketing, the information on human brain anatomy and advanced understanding of the psychological capacities which will be accessible to scientists from other research areas including the consumer neuroscientists would assist them with generating further bits of knowledge into consumer behavior, which are right now impossible to be acquired through the available advancements. For instance, individual consumer's roles played by their senses in making their product choices and acquisition.

Consumer researchers surely need more depth of knowledge into how our brain helps us in making choices for products. For instance, what is the best fragrance to be sprayed in the retail location focused at senior customers or at a stature of 30,000 ft how an individual's brain reacts to the taste of food served in a plane flying? which frames a piece of purchaser involvement in the particular aircraft and thusly prompts the customers' satisfaction towards the airline brand.

The consumer neuroscientist has the same opinion that, consumer research will be improved with the advancement in neuroscience technology. Many reputed marketing and consumer research journals have either declared exceptional issues of consumer neuroscience or have just thought of such issues, for example, one of the most regarded showcasing journals, Journal of Marketing Research has quite recently thought of an extraordinary issue on neuroscience and marketing. In a book by Steven D Shaw et al. more and more neuroscience research is happening and consumer neuroscience will from now onwards, be more integrative in type to work beyond the traditional methods of EEG and fMRI [13].

2.3 What Future Neuromarketing Holds

Here authors discussed the rise of Neuromarketing and consumer neuroscience. Neuromarketing and consumer neuroscience examine uncover reality superior to customary strategies for inquiring about dependent on questionnaires and interviews [14]. It is likewise found to give data about consumer inclinations that are unreachable through traditional techniques [15]. The neural measures are better indicators of population-level information than self-report measures. The capacity of these neuroscience ways to deal with foresees decisions in genuine settings has huge consequences for advertisers [16]. Advertisers can apply these devices to pick up understanding into the buyer's goal towards their items and administrations and it can assist them with testing their marking and showcasing systems before really executing them in the objective market. Advertisers can pick the best techniques for advancing their items, for example, celebrity support or relationship with a social or natural reason. This would enable that specific brand to spare costs which may have generally been spent on a wasteful campaign or ineffective celebrity supports. Neuroscience can increase the value of consumer research from multiple points of view. It is noticed that there are a few zones where neuroscience is relied upon to give unmistakable advantages. Like giving chances and rules to encourage hypothetical advancement, encouraging new exact trial of standard hypothetical cases, clarifications for watched heterogeneity inside and crosswise over shopper gatherings and novel systems for thinking about the physiological setting and the job of various organic elements, including hormones and qualities, on buyer inclinations and choices [17]. Neuroscience has the mold that can shape future hypotheses and models in consumer basic leadership and propose manners by which these models can be utilized for decision-making research.

Consumer neuroscientists have a wide scope of appliances available to them for the methodological examination of their research issues. These appliances work by recording metabolic activities occurring inside the consumer's brain or recording the electrical/magnetic attributes of the neurons in the brain. Instruments taking a shot at the standard of recording the metabolic exercises incorporate Positron Emission Tomography (PET) and Functional Magnetic Resonance Imaging (fMRI). Electrical exercises recording apparatuses comprise of Electroencephalography (EEG) or Event Related Potential (ERP), Magnetoencephalography (MEG), Steady-State Topography (SST) and Transcranial Magnetic Stimulation (TMS). Instruments for estimating other physiological exercises incorporate galvanic skin response, eye tracking, facial electromyography and facial coding. Complete discourse on the utilization of these devices in showcasing is talked about somewhere else [18].

The consumer neuroscience scientists as of now concentrating on the consumer decision making-process in stages and currently there is no model of the mind which shows how sub-procedures, for example, consideration, memory and prize/repugnance preparing are coordinated and work simultaneously for basic leadership and decision making [19]. There is a need to construct an incorporated model that causes us to comprehend the customer basic leadership in an all-encompassing way. It is believed that further researches in this field will toss light upon the integrated model of information processing in the customer's brain [20].

2.4 Neuromarketing and Our Moral

As we are dealing with brain and it has very sensitive data stored in it so, we have to have some ethics. Neuroscientists decided to divide the ethics of neuroscience into two collections of problems: (1) the moral issues and contemplation that need to be referred to throughout outlining with and executing neuroscientific researches and (2) assessment of the moral and social influence that the results of these studies could have, or ought to have, on current social, ethical, and legal constructions. The authors also labeled these gatherings of study into as first one goes like, "ethics of practice," and the second the "ethical implications of neuroscience".

Basically, we have to follow our own standards of moral philosophy, as we are working on neuroscience. This assimilates some common place problems like optimal clinical inquiry composition, rules for the use of vertebrate tissues or undifferentiated organisms or biological study, privacy rights to consequences of testing for neurological disorder, etc. However, the ethics also incorporates some unusual questions to neuroethics.

The second subdivision of the ethics of neuroscience, the "ethical implications of neuroscience" within the field of neuroethics this is truly novel, and perhaps the foremost prepared for progression. The purpose is to explore the ramifications of unthinking comprehension of brain work for society, and it'll need integration neuroscientific info with the moral and social plan. Advances in neuroscience will presumably build, and to cure real social disparities. however we tend to utilize our insight can form our society.

Neuroethics will in all likelihood be associate expertise base field with wide-ranging impacts. Even so, seeing that it subsequently encroaches on the prosperity of the person and our widespread public, this is something however associate investigation that might also or want to be embraced in the cognitive state. It's very important that neuroethicists take part in a very discourse with fashionable society. To create this conceivable, in any case, it's critical within the moment to create progress toward "neuroliteracy" of the last population and therefore the media. We should always enterprise to create the nuances of neuroscientific consult regarding out there to the lay open via the media and forgo the contemporary act of bolstering it sound bites. For its truly with a nuanced comprehension of the science, and stuck up trust in the objectives of neuroscientists, that real advancement are created on these tough problems. Over the foremost current few months, we've detected quite recently the essential clamors of this kind of discourse. Francis Harper official executive of Dana Foundation said at NMTF, "You can call it what you need but, the neuroethics teach has left the station." [21]

2.5 Consumer Behavior and Marketing Strategies

Customer behavior answers why and how a purchaser buys a product or a service. Whereas marketing technique is the mix of product, price, distribution, and promotion which is appropriate for a batch of consumers. Understanding the purchaser's behavior and building up an advertising system appropriately can help in creating products and ventures with the best benefit making potential. So as to do so first customer conduct must be understood back to front. Steps of the purchaser's decision-making process should be seen completely. The purchaser decision-making process, for the most part, comprises of need acknowledgment, data search, assessment, buying choice and post buying behavior [22].

In view of buyer need and their acquiring procedure criteria, the market is divided into various gatherings. Extraordinary and distinctive advertising methodologies are created for each fragment. There are numerous components behind the purchaser's basic leadership. Among those impacts is a key factor. A customer can be impacted internally just as can be remotely affected. Circumstance likewise influences a consumer's decision-making process. Marketing techniques are created and suggested to invite shoppers to purchase specific items or merchandise [23].

2.6 How Brain Takes Decision

In a study Heekeren et al. examined and demonstrated activity of different brain parts. Like, prefrontal area has general basic decision making, free of stimulus and response modalities. Their outcomes are additionally steady with reports that sores in the back DLPFC hinder contingent segregation undertakings in both monkeys and people. Others have proposed that the capacity of the prefrontal cortex is to manage movement along task-applicable pathways from lower-level tactile locales to zones that arrangement and execute reactions. They also exhibited a system for how perceptual basic leadership procedures may be started up in the human mind, utilizing a moderately straightforward subtraction instrument. What stays to be indicated is the means by which this model can represent extra factors that influence the basic leadership process, for example, the normal estimation of various choices, the earlier likelihood of the presence of various alternatives and their interior valuation. In a perfect world, this model and the systems portrayed in their study will likewise clarify the substantially more entangled choices we face in regular day to day existence [24].

2.7 Neurons and Neuromarketing

The present discoveries furnish us with important bits of knowledge into the transient and spatial procedures supporting human worth based decision making for parallel choices. We show that worth sign identified with the outcome of the choice develop inside 200 ms after the beginning of the choice preliminary, most dominatingly in back areas in the region of the LIP just as in back transient projection cortex, yet in addition less noticeably in a front cortical locus. These discoveries propose a significant job for back mind areas remembering the LIP for the age of the choice itself, maybe through cortical collaborations with progressively front districts, for example, vmPFC. Besides, while dmPFC was found to report the distinction in esteem among unchosen and picked alternatives as in various past investigations, this sign didn't develop until some other time in the preliminary, roughly 1050 ms after the underlying upgrade introduction, and 850 ms after the primary rise of the worth sign mirroring the result of the choice (picked esteem signals). These discoveries propose that dmPFC may not assume a weighty job in the underlying development of the choice itself, yet rather may contribute at a later stage during the procedure of execution of activity choice.

One significant proviso of our discoveries is that the fMRI obliged limitation results we report here depend on the supposition that fMRI information and EEG information are created by the equivalent fundamental neural sources, a suspicion that may not generally remain constant [25]. In any case, the mind districts distinguished in our source confinement have been recently recognized as having neural action that is unequivocally embroiled in esteem related taking in utilizing direct neural chronicles from those territories [26, 27, 28]. In this manner, it is impossible that the outcomes we watch are a curio of the supposition basic fMRI-informed EEG localization [29].

2.8 EEG Based Communication

A definitive point of this exploration is to build up a computer interface based on EEG for the purpose of using by individuals with serious physical limitations. Which would encourage communication with a package of word-processor or authority of different natural controls. In this paper, they directed two distinctive methodologies. (1) Offline studies and (2) Online System.

In the event of offline studies William Penny and Stephen Roberts et al. discovered this research was helpful in solidly building up that motor imagery signals which could be found by complexity and spectral features. On a fundamental level, for driving cursor movements they could be utilized. It likewise recognized the optimal positions to put electrodes in.

For motor imagery tasks, subjects were asked to open and shut their hand depending on their handedness, and for the maths tasks, subjects were sequentially asked to subtract seven from a huge number. They also completed cursor trials in which the cursor is stationary [30]. Cursor movements were produced by drawing out auto-regressive (AR) highlights from the EEG and characterizing them utilizing a Bayesian logistic regression model. Movements of cursor were produced by characterizing auto-regressive (AR) highlights from EEG using Bayesian Logistic Regression model.

As their research demonstrated 75% precision in moving cursor trials so they finished up by saying this incredibly upgrades vigor of their framework/system [31].

2.9 EEG Signal Application in Neuromarketing

In a research by Mahendra et al. they suggested a prescient modeling structure to comprehend customer decisions towards E-commerce items as far as different preferences by dissecting EEG signals. They utilized the Emotiv EPOC+ tool to catch EEG signals. The EEG signals were recorded from volunteers of different age and sex while they were going through different customer items. In the first place, they introduced a Neuromarketing structure for anticipating shopper inclinations while they see E-commerce items by breaking down EEG signals.

The authors have demonstrated that characterization of items utilizing EEG signals was superior to anything the rating based order which was accounted for as 80% and 60%, separately when 30 pairs of shoes were arranged into two classes. The EEG signal data were recorded while the members watching virtual 3D items. The authors likewise suggested a customer decision inclination displaying structure for film trailers utilizing EEG signals. Where they have demonstrated diverse decision sets to 18 clients to research the distinctive mind exercises during basic leadership utilizing the EEG flag and eye tracker tool. The sign experiences certain signal preprocessing and feature extraction steps.

Preprocessing and feature extraction being done to the signals, where they displayed the subtleties of the signal smoothing system that is utilized to preprocess the signal for feature extraction. A Raw EEG signal being smoothed. Discrete wavelet change based highlights DWT is generally utilized in biomedical sign preparing in light of the fact that it speaks to a sign in time-recurrence area. The EEG signals utilizing every one of the 14 channels have been recorded from 25 members while seeing shopping items on the computer screen. A variety of items with various shading and surfaces shows the variety in the EEG signals of three unique members for a similar item according to their decisions for the item. EEG signal reaction against channel 'AF4' Product saw by three unique clients' brain action map while viewing the items the decision inclination for the item Figure. Customer choice classification where they displayed the decision inclination results utilizing the sequential HMM classifier [32].

2.10 Classifying with Classifiers

In a paper Fabien et al. talked about classifiers. Classifiers refers to the algorithms that learns from training data and can predict classes for test data. Classes are also known as labels/targets. Classification is the process of building a mapping function from non-target variables to target variables. For example, a music recommendation system can be a classification problem where users are recommended songs based on the songs they often listen to.

In this problem, the characteristics of the songs they listen to can be non-target variable or input variables and the song recommendations can be target/output variables. When there are two possible outcomes of a class for a given dataset the classification task is known as binary classification and multi-class classification otherwise.

There are many kinds of classification models based on the method of classification. The most popular ones include Support Vector Machines, K-Nearest Neighbors, Trees, Neural Networks, Ensembles, etc.

Which classification model will produce the best results depends on the kind of data and its applications. Some classifiers do some specific tasks better than other classifiers. For example, SVM manages outliers better than others. So, choice of a proper classification algorithm needs proper analysis of dataset and the application. There are various ways to calculate the effectiveness of a classifiers. For example, holdout method, cross-validation method, roc curve, etc. In holdout method, data is divided into test and training data. The model is trained with training data and then test data is used to compute its accuracy of predicting the correct output. The cross validation method divides the dataset into k equal sized partitions. One partition is used as testing data while others are used for training. This process is iterated k times and average accuracy is computed. This method produces the best results against overfitting. ROC or Receiver Operating Characteristic curve represents the trade-off between true positive rate and false positive rate. When the area under the ROC curve is close to 1 the models accuracy is high.[33].

2.11 Signal Processing

Signal processing refers to the analysis of signals such as sound, image and biological measurements. The technologies that drives our day to day life is powered by signal processing. Remarkable improvement of clinical analysis and detection of diseases and abnormalities was possible thanks to brain signal processing.

In the book by Saeid et al. the writers discussed the latest head ways in signal handling and mechanized strategies that are required to support the key parts of future advancement in biomedical research and innovation, especially on the new estimations and appraisal of signals and pictures from the human body.

There are various categories of signal processing depending on the application. For example, analog, continuous time, discrete time, digital, non-linear, statistical, etc. Analog signal processing is for non-digitized like television, radio signals. Continuous time signal processing is for signals that vary for the change of a continuous domain. Discrete time signal processing is for discretely sampled signals. Digital signal processing is for processing discretely sampled digitized signals. Non-linear signal processing is for processing signals produced from non-linear systems. Statistical signal processing is for processing signals using their statistical properties.

The application of signal processing is countless. In advancement of science, contribution of signal processing is enormous. In biomedical field, signal processing is turning into a key step towards future. Detection of various diseases, analysis of human behavior, these are all possible because of signal processing. Researchers believe the possibilities with signal processing in the medical research are boundless. [34].

2.12 Neuromarketing: A Bridge Between Producer and Consumer

Neuromarketing is the area of research where consumer sensory-motor, psychological and change in brain signals are studied for a better feedback of advertisements. Soumala et al. proposes to use to method and suggested that it can be used to discover brain enactment during consumer interaction. The researchers have developed a virtual simulation of a consumer's walkthrough to study consumer's response to specific advertisements. The consultative selling consists of five stages and they are: (1) Creating customer connection, (2) Understanding customer needs, (3) Addressing customer needs, (4) Closing the sell, (5) Establishing a sustainable relationship.

Neuromarketing is far superior than traditional market surveys and researches. Even though it can't make purchasers come to a conclusion regarding their choice of purchase, it can certainly help them get to that stage, since chance varies from individual to individual. Regarding this, researchers couldn't clear up remarking variance and saw chance in their analysis.

The authors have used fMRI throughout this virtual shopper journey to record the brain signals of consumers. The data at that point being pre-handled, a style framework was sketched out that was utilized as an arrangement for expected mind action and furthermore the applied measurable test investigate was performed on the non-heritable data. Authors have also mentioned that gathering electroencephalography (EEG) with functional magnetic resonance imaging (fMRI) can be a non-invasive method for the study of human brain. Even though it has been practiced a lot, the method still is very complicated and a traditional technique for knowledge analysis is to be built. During this study, we had to overview many challenges regarding every step of the information analysis pipeline in EEG-informed fMRI and given a descriptive explanation and representation of the over plus of ways out there to manage all the challenges. The inspiration fundamental the correspondent, multi-modular procurement of graphical record and fMRI was first featured, together with a speedy depiction of 11 the essentials of each neuroimaging methodology. Graphical record and magnetic resonance imaging(MRI) knowledge quality were given special focus since they are the most important factors, through classifying the artifacts iatrogenic by every modality on the opposite, moreover because the most significant modality-specific artifacts and explaining the individual whole reduction methods.

At long last, we will in general be focused on multi-modular information coordination inside the setting of the EEG- informed fMRI approach, measure each univariate and variable ways acclimated extricate graphical record choices that will anticipate brave sign changes. This very review could encourage the distinguishing proof of the procedure pipeline that most intently fits each study, in order to streamline information quality moreover in light of the fact that the affectability and particularity of the cerebrum systems got by EEG-educated fMRI investigation. The ideal system for the blend of information from the 2 modalities remains partner open inquiry, primarily because of a more profound comprehension of the substrates of each methodology and furthermore the degree to that these substrates cover remains required. In addition, a ton of inside and out, basic and independent approval ponders are required to manage the understanding of the discoveries acquired exploitation the ways outline over. [35]. As science moving forward with the pace of light we can surely hope for a bridge of steel and trust between producer and consumer.

Chapter 3

Background Study

3.1 Human Brain

The human brain is the most important and complex organ of the human body. The brain is the main part of our nervous system. It is connected by more than billion neurons and the neurons have more than trillion connections to communicate with each other thus, controlling all our activities. 2% of our total body weight is made up of the brain. The brain is situated inside the head near all the other neural organs [36]. The main functions of the brain are motor control, sensory, cognition lateralization, emotion, language, and regulation. The brain is mostly composed of 3 major segments that are Brain Stem, Cerebrum and Cerebellum.

3.1.1 Brain Stem

The position of the brain stem is just below the cerebrum. The brain stem connects the spinal cord with the brain. It acts like a rely center by connecting the cerebellum and the cerebrum with the spinal cord. The brain stem consists of three parts which are medulla oblongata, midbrain, pons. This part of the brain is made out of a blend of white and grey matter. Brain's wake and sleep cycles are controlled by this part of the brain and also muscle tone of the body is controlled by the brain stem. Body functions such as blood pressure, oxygen levels, puking, wheezing, coughing, swelling reflexes, homeostasis is overseen by this part of the brain.

3.1.2 Cerebellum

The Cerebellum is situated behind the Brain Stem and below the Cerebrum. The posterior and anterior lobes of the cerebellum are linked in the middle by the vermis. It looks like hemispheric and is wrinkly. Main tasks of the cerebellum to control the motor functions like posture, balancing and aligning muscle actions. It also manages the synchrony and tactfulness of human motor activities like walking, writing and speech.

3.1.3 Cerebrum

The cerebrum is the biggest part of the brain. It has both left hemisphere and right hemisphere. Both of these hemispheres are connected by fibers called corpus callosum. The left hemisphere of the cerebrum controls all the activities of the right half of the body and vice versa. The cerebral cortex covers the internal white matter which itself is the outer layer of grey matter. corpus callosum sends data from one side to the other side of the cerebrum. However, each side of the brain has a few functions assigned to them independently. For example, writing, calculations, cognitions, speech is assigned to the left part of the brain while the right side controls spatial capacity, imagination, creativity, musical aptitude, etc. For almost 92% of people, the left hemisphere is dominant for and responsible for language and writing which explains why most people use the right hand for writing.

3.2 Cerebrum: Brain Part that is Responsible for Judgement and Decision Making

The cerebrum is the large, outer part of the brain. Thinking, judgement and decision making is mainly controlled by this part of the brain [37]. The cerebrum controls reading, thinking, decision making, learning, speech, emotions, personality, reasoning, planned muscle movements like walking, vision, hearing and other senses[38]. The cerebrum consists of 4 lobes: (1) Frontal lobe, (2) parietal lobe, (3) occipital lobe, (4) temporal lobe.

3.2.1 Frontal Lobe

The frontal lobe as the name suggests is located in the front part of the brain. It is involved in motor abilities, self-awareness, writing and speech, intelligence, judgment, planning, problem-solving, and emotions [39, 40].

3.2.2 Parietal Lobe

The parietal lobe is situated just behind the frontal lobe. It is named so being close to the parietal bone. It has a somatosensory cortex and deals with processing sensory information to determine touch, sense of pain and temperature [37, 40, 41].

3.2.3 Occipital Lobe

The occipital lobe is situated at the back of the brain. It has a visual cortex that, receives visual information from the eye. this information is processed in this lobe to make decisions of color, perception and vision [40].

3.2.4 Temporal Lobe

The temporal lobe is located on the side of the brain and is involved with learning, memory, emotion and language. it contains the auditory cortex which processes auditory information [40].

3.3 Traveling of Brainwaves In Neurons

More than almost a billion neurons are connected to each other inside our brain. These neurons communicate and transfer information with each other through electrochemical pulses. Pathways of these pulses are made of nerve cells (neurons), brain cells and glial cells.

Neurons primarily comprises of 3 sections. They are a cell body, dendrites and axons. Dendrites is liable for moving messages from neurons. Axons are found toward the finish of the cell, neuro transmission happens among axon and a dendrite. The glial cells then again encourage neurons by guaranteeing neurotransmitters are transmitted appropriately. It is likewise liable for fixing nerves. In this manner, mind messages of engine activities or different reactions to upgrades make a trip through the nerves to the goal muscle, organ or cell. If there should be an occurrence of feeling, mind sends signal right to explicit muscle to direct reaction. For instance the tearing of eyes due to encountering a specific feeling.

3.4 Brainwaves

The repetitive Electrical pulses in our central nervous system is called "Brain Waves" [42]. These neural oscillations responsible for neural transmission are measured in Hertz (cycles per second). Pulses generated from either a neuron or due to interaction between two neurons. Information is passed onto the target muscle or destination through the nervous system in order to perform motor action, send sensory information or just virtual information. Therefore brainwaves differ based on what information or instruction they are communicating. High frequency brainwaves can be observed when a human is ecstatic, on the other hand low frequency brain waves can be observed when humans feel lazy or bored. The different brainwaves of varying frequency range can be observed through an EEG. They can be classified according to their frequency range into five types.

3.5 Types Of BrainWaves

As already mention earlier, brainwave frequency can be classified into five types. which are: (1) alpha, (2) beta, (3) gamma, (4) delta, (5) theta [43].

3.5.1 Alpha

Alpha waves range between frequencies 8 Hz and 13 Hz. This low frequency range is due to the fact that they are generated when the brain is calm and in a relaxed state. It is also generated in thoughtful or meditative state of mind [43]. Alpha waves extracted from EEG signal data of one of the subjects is shown in figure 3.1.

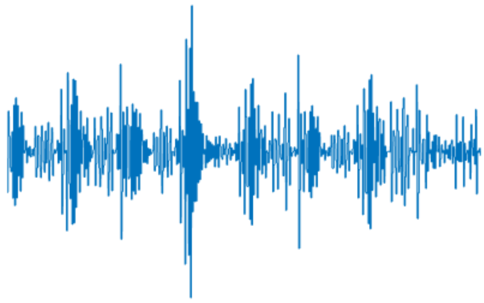

Figure 3.1: Alpha Wave

3.5.2 Beta

Beta waves range between frequencies 13 Hz to 38 Hz. Since it is mostly generated in the frontal lobe, this means it is produced during cognitive tasks, problem solving, planning, self awareness. When humans are actively participating or doing tasks that require attention, brainwaves in this frequency range can be observed [43]. Beta waves extracted from EEG signal data of one of the subjects is shown in figure 3.2.

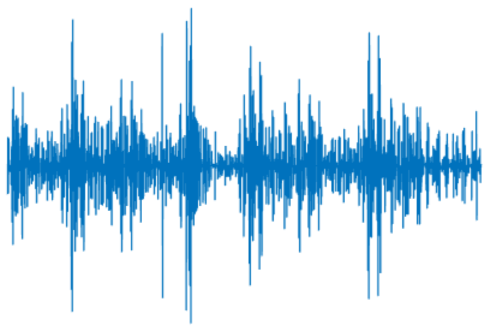

Figure 3.2: Beta Wave

3.5.3 Delta

Delta waves range between 0.5 Hz and 3 Hz. It has a frequency range lower than that of Alpha waves. Hence it is only generated while experiencing deep sleep, and there is no awareness of surroundings whatsoever. During this phase human body recovers and regenerates [43]. Delta waves extracted from EEG signal data of one of the subjects is shown in figure 3.3.

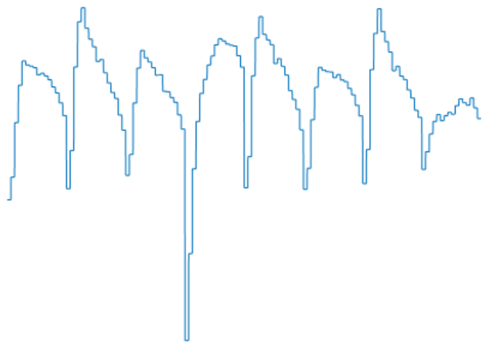

Figure 3.3: Delta Wave

3.5.4 Gamma

Gamma waves have frequencies higher than beta waves, they range from 38 Hz to 42 Hz. Being above neuron firing frequency, it is often related to broader consciousness. Initially it was considered as noise and discarded, till later on it was found out that it is active in the states of 'high virtue' [43]. Gamma waves extracted from EEG signal data of one of the subjects is shown in figure 3.4.

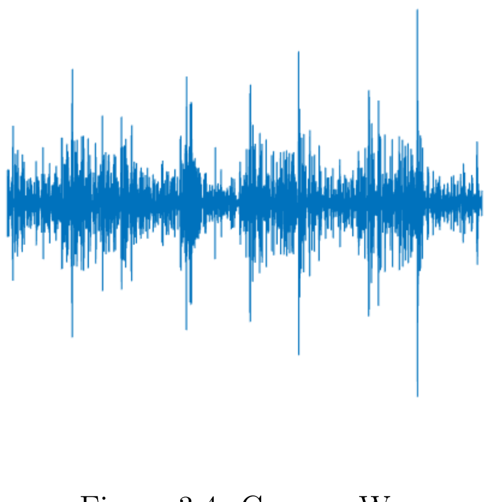

Figure 3.4: Gamma Wave

3.5.5 Theta

Theta waves range between 3 Hz to 8 Hz. It lies between alpha and delta waves and can be observed during meditation or while dreaming. while in this range humans tap into their subconscious mind [43]. Theta waves extracted from EEG signal data of one of the subjects is shown in figure 3.5.

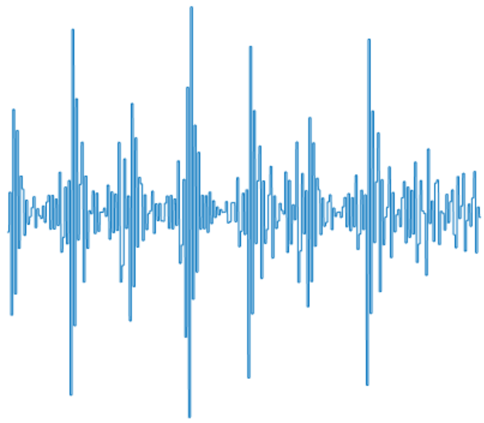

Figure 3.5: Theta Wave

3.6 EEG Analysis with Various Algorithms

EEG was invented by a German psychiatrist named Hans Berger [44]. In 1929 He proposed that brainwaves can be measured and recorded by placing electrodes on the human skull. He received a lot of criticism for this method of his. However, the criticism could not stop researchers from researching in this field. since then till now more and more researchers are conducting research in this field [45].

EEG device is called non-invasive because it does not impact or manipulate the brain in any situation. EEG allows electrodes to be mounted on the human skull which capture brain waves from electrochemical stimuli in the brain's neurons. To order to make them visible on a paper or screen, electrical chemical signals are generated by the EEG system and passed on to an amplifier. The EEG has become the best method for detection of brain waves, a simple mechanism and a noninvasive system [46].

Information from the electrodes of the EEG cap can be transferred in different methods such as Bio-Semi, B-Alert and Bioradio 150. while recording brainwaves the EEG machine picks up various noises due to eye blinking, muscle movement and also instrument noise. To avoid inconsistencies the noise is removed by using band pass filters. noise can be reduced further by making sure that there is proper conductivity at the contact points of the scalp.

The most common step of applying machine learning algorithms is feature extraction. This is done so to reduce huge data-set and to develop different combinations of variables in order to achieve good accuracy.

3.6.1 Support Vector Machine (SVM)

SVM is a machine learning classification algorithm. It separates points of two classes using a line that is farthest from both the points. This line is called a hyper-plane and draws the decision boundary between the two points. the hyper-plane ensure highest possible distance between the points to ensure high classification accuracy.

3.6.2 Discriminant Analysis (DA)

Discriminant Analysis searches for a set of equations using input variables, which are used to classify the data into classes. The main objective of this algorithm is to understand the relationship between the input variables and the output variables. Discriminant Analysis is very closely related to Regression Analysis. The main difference in these two algorithms is that Regression Analysis deals with continuous input variables and Discriminant Analysis deals with discrete input variables. In both algorithms the input variables are plotted against the output variables. Discriminant Analysis is also very closely related to one-way MANOVA. The main difference is that the roles of the variables are reversed in MANOVA.

3.6.3 Decision Tree (DT)

Decision Tree classifies data by continuously splitting them based on different conditions. Each node of the tree asks a different question. Depending on the boolean answer the next node is decided and last node outputs the predicted class for the data. The longer the tree, more complex and fitter the model. The sequence of the nodes is decided by information gain attribute of each condition.

3.6.4 Naive Bayes (NB)

Naive Bayes is a very popular classifier that works really well even with a small dataset. Many real world problems including spam filtering is solved by this simple machine learning algorithm. Naive Bayes is an extremely fast learner compared to other more complex machine learning classifiers. The key assumptions in this algorithm include, the independence of the features and their equal contribution to the output.

3.6.5 K-Nearest Neighbors (KNN)

KNN is a kind of lazy learning algorithm, where the key computations are done while classification rather than while training. As a result, the training time can be quite fast for KNN algorithms. However, the testing time is really slow. 'k' in KNN represents the maximum distance between neighbor that should be considered. In this algorithm, the neighbors that are close, contribute more towards the average than the ones that are farther. For example, the weight of each neighbor is calculated by $1/d$, where d denotes distance.

3.6.6 Random Forest (RF)

Random Forest is another very popular machine learning classification algorithm that as the name suggests, classifies data by averaging output variables from a large number of decision trees. Although, Decision Trees are proven to be very probable in classification problem solving, they are not very effective for non-linear regression. However, using large number of them together definitely improves accuracy at the cost of interpretation capability of the output.

3.7 EEG

The term Electroencephalography can be divided into 3 parts. Electro is short for electrotype or electroplate, encephalo means the brain and gram stands for the study or report of something. Therefore, it can be said that the electrical impulses of the brain can be understood with the help of EEG. In order to do so, first electrodes are needed to be placed at strategic points on the head so that the electrodes can detect and measure EEG signals. These signals are then engraved on the paper in wave structure [47].

It can be said that the singular unit of the brain are neurons. Though there are many other cells in the brain other than neurons, however, conveyance of impulses happens in only neurons. The transportation of impulse happens in form of electrical activity. Mostly all other body cells correspond to each other with chemicals. For instance, they communicate with each other through dopamine. However, neurons use electrical impulses to transfer information between them [48].

To understand what electrical activity means we need to get used to a few terminologies. Terminologies such as 'cycles per second' or 'voltage' can be several times when working with EEG signals. These terminologies are really important to understand the electrical connection and communication inside the brain.

While communicating with each other, neurons transfer electrical impulses between them. To generate that impulse a small amount of electricity is generated inside our brain. By 'voltage' we understand the magnitude of electrical activity. Meaning, the strength of the electricity firing. On the other hand, 'Cycles per second' represents the frequency of the firing. Number of times a neuron sending information to other neurons in a second [47].

Synchronicity means two simultaneous things working or being in the same state. If two or more neurons fire in the same direction at the same time then it can be said that the neurons synchronous. The voltage or amount of electrical impulse is not considered in this case. Only their direction and timing matter. These neurons are said to be in synchronicity if they send electric impulses at the same time. However, if the direction is opposite or different then the neurons are not in sync, they are then called asynchronous or non-synchronous. We can add up the electric impulse signal of the neurons that are in sync. Adding them up will give the final result of total electric impulse. In the case of asynchronous impulses if it is in the exact opposite direction in case of polarities of a signal then they will cancel out each other.

3.8 Neuropsychology

In the article by Sivakumar[47] Neuropsychology is addressed as a branch of psychology and neurology that aims to understand how the structure and function of the brain relate to specific psychological processes and how the brain and the rest of the nervous system influence a person's cognition and behaviors. Professionals in this branch of psychology mainly focuses on how injuries or illnesses of the brain affect cognitive functions and behaviors of a human being. This is a scientific approach which shares the information about processing view of one's mind with cognitive psychology and science. This specific one among the additional eclectic of the psychological methods, overlapping every now and then with areas like neurobiology, philosophy, neurology, medical specialty and applied science. That truly creating artificial neural networks.

The study of psychology generally know as the study of the mind and neurology refers as the study of brain specializes Neuropsychology. A neuropsychologist works to understand the structure and function of the brain and its association between thoughts and behaviors. This special branch of understanding helps us to learn how the brain and behavior are connected.

Chapter 4

Proposed Methodology

4.1 Workflow

In our short span of research work we found out the most precious part of a research is the workflow. A guideline of our working process is shown in Figure 4.1. To work in a constructed way or to make the best of the result we followed this process. The first step in our workflow was to collect EEG data-set. Then to pre-process the data before extracting features from it. Next, we extracted features from the processed EEG signals. Feature such as alpha power, beta power and etc. We then divided data for training and predicting purpose. Major part of the data was used to train our model. Through classification model was trained to predict future result. Once training was done our model was ready to predict. For any given test signal our model now will be able to predict future result.

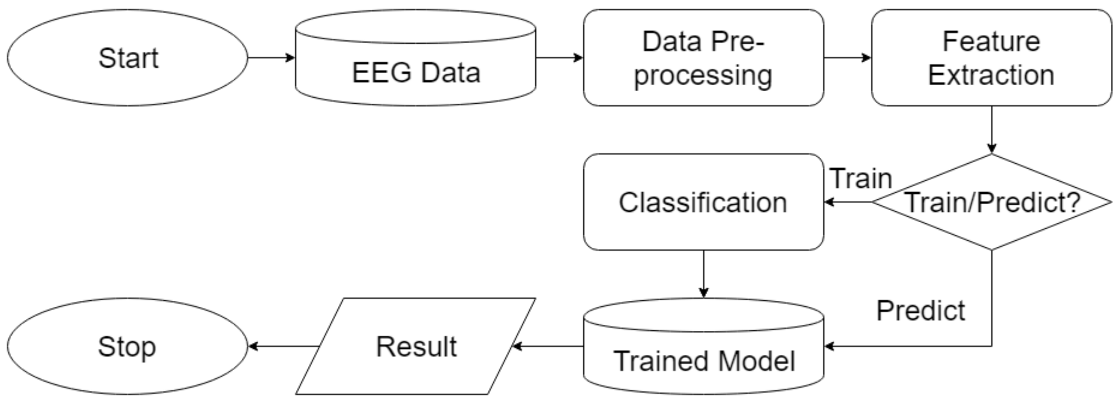

Figure 4.1: Workflow of the proposed method for consumer behaviour analysis.

4.2 Data-set Collection

As brain performs it's basic functions brain generates continuous electric impulses. These impulses are influenced by stimuli that surrounds us. It is possible to recognize pattern of a person's behavior, choice, mood feeling through analyzing these impulses can. For our framework to work well we required an EEG data-set for choice detection. However, it was quite difficult to find or collect standard EEG data-set.

In a research by Yadava et al.[32] they recorded EEG signals from 25 participants. Where the participants were shown 42 product images of 14 categories for 4 seconds each. As, 42 product images were shown to 25 participants therefore total 1050 (i.e. 42 x 25) EEG signals were recorded by them. Then they were asked to label the products with either like or dislike and their responses were recorded. The EEG data were recorded through 14 channels which are located at areas as per the International 10 - 20 system[49].

The data-set were made public for future prospective research in related field. For our research purpose we are using the data-set that were recorded by Yadava et al.

4.3 Data-set Pre-Processing

EEG recording is highly sensitive to different source and form of noise. The noise makes it difficult to intercept as well as analyze the EEG data. There are many existing methods to deal with the noise effectively. The noise can be dealt with while recording EEG signals. Also it is possible to pre-process the recorded EEG signals to reduce the noise. Data smoothing is a method which is used to remove noise from a data set. Using data smoothing helps pattern in signal to stand out. In figure 4.2 a raw EEG signal is shown. The signal consists of noise. Therefore it is difficult to extract feature from this signal. Also, if feature is extracted from this signal then the extracted feature will not be accurate.

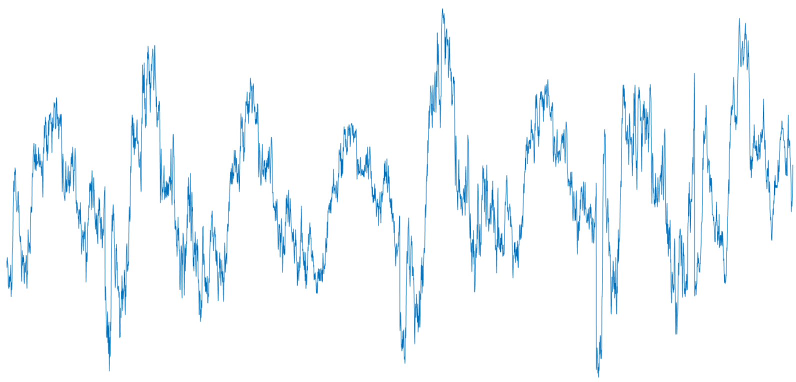

Figure 4.2: Raw EEG Sample Data before Running Smoothing Algorithm

To remove noise from the recorded EEG data in the data-set we used running average. Running average creates different subsets of the whole data set by calculating to interpret data points. If a fixed subset size and series of numbers are given then the first element of the running average is occupied by averaging initial fixed subset of the number series. Then the first value of the series is excluded and the next value in the subset is included to modify by "shifting forward". Running average was applied on the raw EEG signal shown in figure 4.2. After applying the data was smoothed. Figure 4.3 shows pre-processed EEG sample data which was smoothed.

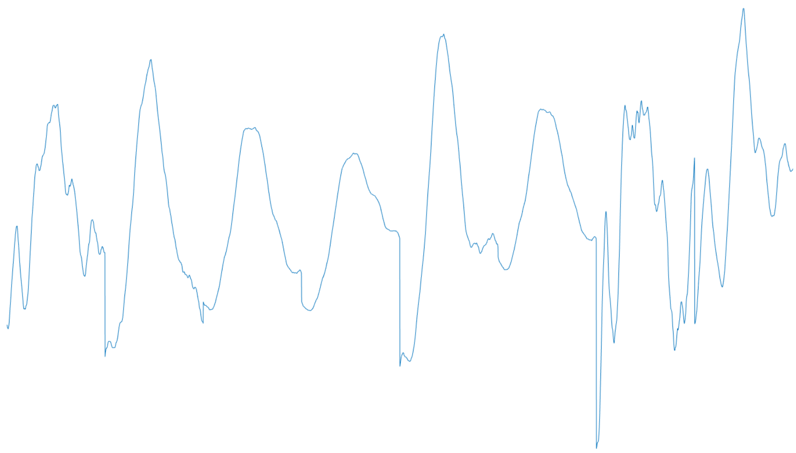

Figure 4.3: Pre-processed EEG Sample Data after Smoothing using Running Average

A running average is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The threshold between short-term and long-term depends on the application, and the parameters of the running average will be set accordingly.

4.4 Feature Extraction

Feature extraction is a process of extracting relevant information from raw data and reduction of dimensionality. There are different methods for feature extraction for different kind of data. For EEG signal processing the most popular and suitable method is Wavelet Transform (WT) method. It takes both time and frequency domain into account while extracting features. For high or low frequency resolution short-time and long-time windows are used respectively. In this method, EEG signals are represented using wavelets. There is a mother wavelet, which gives rise to these wavelets. There are two kinds of Wavelet Transform method. They are Continuous Wavelet Transform (CWT) Method and Discrete Wavelet Transform (WT) Method. We chose to use Discrete Wavelet Transform (DWT) in our feature extraction due to its superiority in fast non-redundant transforms.

4.4.1 Continuous Wavelet Transform Method

Continuous Wavelet Transform (CWT) is a Wavelet Transform (WT) method, in which the wavelets are sampled continuously using varying size of scaling and translation parameters. For real valued signal, CWT is a real valued function of scale and translation. For complex valued signal, CWT is a complex valued function of scale and translation. For scale parameter a, translational parameter b and mother wavelet function $\psi(t)$, CWT of a function $f(t)$ can be represented using equation (4.a).

$$CWT(a,b) = \int_{-\infty}^{\infty} f(t)\frac{1}{a}\psi^{*}(\frac{t-b}{a})dt \tag{4.a}$$

In equation (4.a) * denotes the operation of complex conjugate. The purpose of the mother wavelet is to generate daughter wavelets, which are just the scaled and translated versions of the mother wavelet. Continuous variation of the values of scale and translation yields CWT coefficients. Multiplying each coefficient by properly scaled and translated wavelet yields the original signal. Different admissible wavelets are used in the CWT depending on the features being extracted [50, 51, 52].

4.4.2 Discrete Wavelet Transform Method

The Discrete Wavelet Transform (DWT) is a form of wavelet transform (WT), in which the wavelets are sampled discretely using scaling and translation parameters. The signals are decomposed into an orthogonal wavelets vector. DWT is used for multilevel feature representation of signal data. In this method, both time and frequency domains are considered.

The DWT of a signal x is calculated by passing it through a series of filters. At first, it's passed through a low pass filter g and then a high pass filter h as shown equation (4.b) and equation (4.c) respectively.

$$y_a = x(t) \times g \tag{4.b}$$

$$y_d = x(t) \times h \tag{4.c}$$

From the high pass filter detail coefficients and from low pass filter approximation coefficients are obtained. Then, the filter output of the low pass filter is subsampled by 2 for further processing through new low pass filter g and high pass filter h. The detail coefficients from each level of processing are wavelet coefficients. We decomposed our signal data into five details coefficients also known as gamma, beta, alpha, theta, and delta.

We calculated power of each frequency band to use as features for our machine learning classifier using the equation (4.d).

$$Power(x) = \frac{1}{n}\sum_{i=1}^{n} x_i^2 \tag{4.d}$$

$$\text{Where, } x = \alpha, \beta, \theta, \gamma, \delta$$

For each electrode we calculated alpha power, beta power, gamma power, delta power and theta power. Total number of features per instance was number of electrodes multiplied by 5. Total number of instances were 1045. After feature extraction we classified them using different machine learning classifiers.

4.5 Classification

When we use the training data-set to get better performing or more accurate structural result which could be used to determine each target class and as soon as the boundary conditions are determined, the next task is to predict the target class. This structured process is known as classification. After extracting features from electrodes of different parts of cerebral cortex we then classified the data using different machine learning algorithms.

4.5.1 Discriminant Analysis

Discriminant Analysis is another popular yet simple classification algorithm. This algorithm is based upon finding a combination of predictors that separate two classes the best. The discriminant types used in this algorithm are linear, quadratic, diagonal-linear, diagonal-quadratic, pseudo-linear and pseudo- quadratic [53]. We used linear discriminant in our classification. In Linear Discriminant Analysis all classes have the same covariance matrix. Covariance matrix can be calculated using equation (4.e).

$$c_\gamma = (1 - \gamma)c + \gamma diag(c) \tag{4.e}$$

Where, c = empirical, pooled covariance matrix
γ = number of regularizations

Graphical plot of ROC curves of different brain areas for Linear Discriminant Analysis classification for our data-set is represented in figure 4.4.

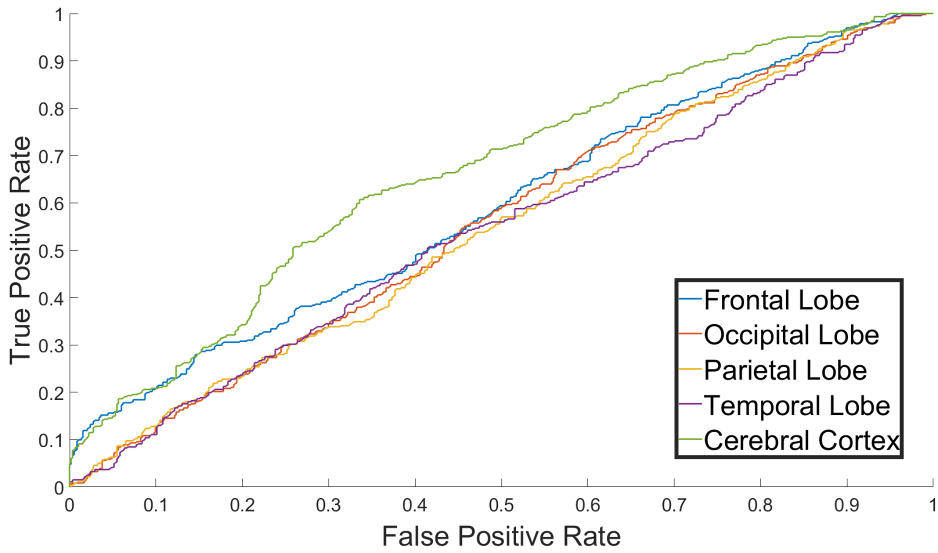

Figure 4.4: Five ROC Curves of Different Brain Areas for Discriminant Analysis Classification on Consumer Behavior Analysis Using EEG Signals.

In figure 4.4 we showed a receiver operating characteristic(ROC) curve of different brain areas for Discriminant Analysis classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

4.5.2 Decision Tree

Decision Tree is a supervised machine learning classification algorithm. In this algorithm data-set is constantly split into subsets according to certain parameters. Entropy and Information Gain are used to construct a decision tree [54], which can be calculated using the equations (4.f) and (4.g).

$$Entropy(S) = \sum_{i=1}^{k} -p_i \log_2 p_i \tag{4.f}$$

$$InformationGain, IG(T, X) = E(T) - E(T, X) \tag{4.g}$$

Where, E(T—X) = conditional entropy of T given variable X

Graphical plot of ROC curves of different brain areas for Decision Tree classification for our data-set is represented in figure 4.5.
In figure 4.5 we showed a receiver operating characteristic(ROC) curve of different brain areas for Decision Tree classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

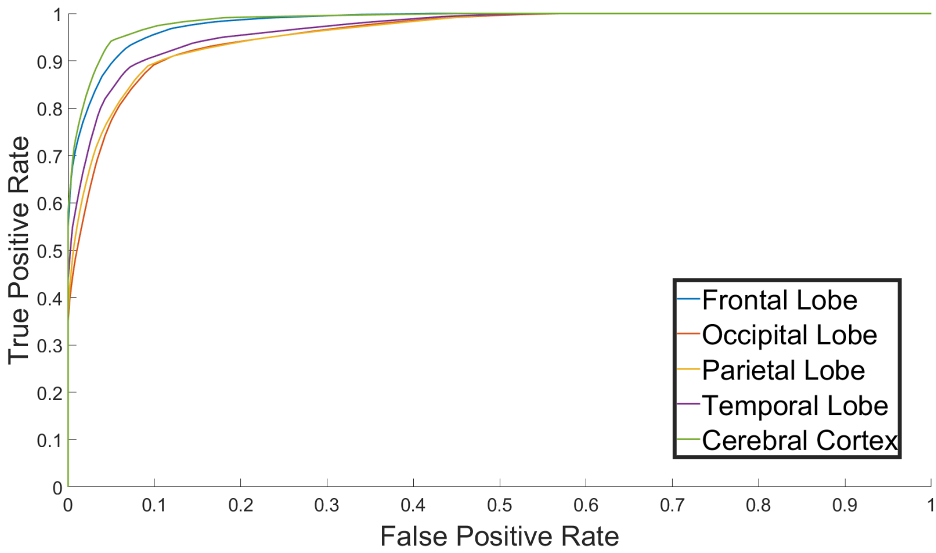

Figure 4.5: Five ROC Curves of Different Brain Areas for Decision Tree Classification on Consumer Behavior Analysis Using EEG Signals.

4.5.3 Naive Bayes

A Naïve Bayes classifier is a probabilistic machine learning model for classification. It is based upon Bayes theorem. Its fundamental assumptions are that each predictor makes an independent and equal contribution to the outcome. Its simplicity makes it useful for classification of large data-sets. Equation(4.h) finds the probability of an event given probability of another event that has already occurred.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4.h}$$

Where, A is the event we are finding the probability of and B is the event that has already occurred [55, 56]. In our model, we used Kernel Density Estimation, which is a way to estimate probability density function of a random variable.

Graphical plot of ROC curves of different brain areas for Naïve Bayes classification of our data-set is represented in Figure 4.6.

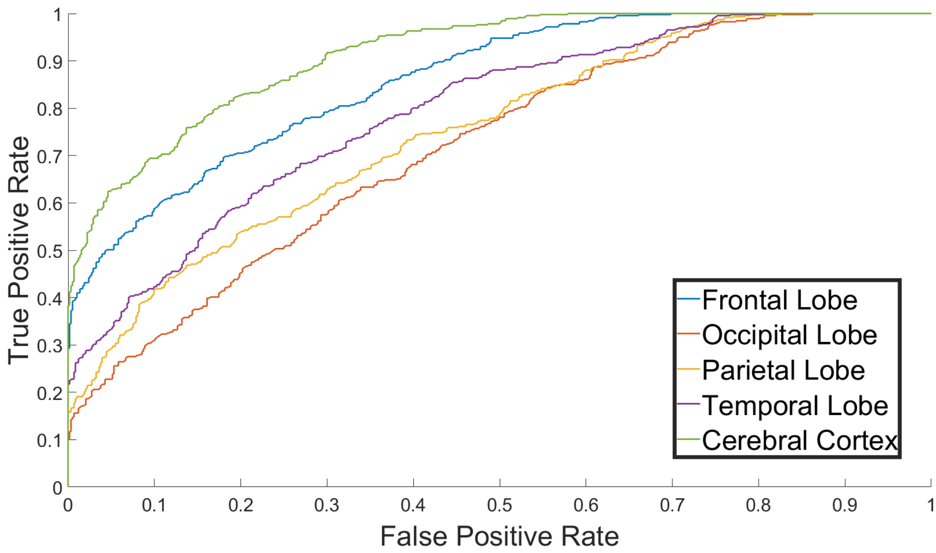

Figure 4.6: Five ROC Curves of Different Brain Areas for Naive Bayes Classification on Consumer Behavior Analysis Using EEG Signals.

In figure 4.6 we showed a receiver operating characteristic(ROC) curve of different brain areas for Naive Bayes classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

4.5.4 K Nearest Neighbors

K-Nearest Neighbors is one of the most popular machine learning algorithms due to its speed and predictive power. We used KNN for classification of our features. K in KNN specifies the maximum distance between neighbors we wish to include in our case. The optimal value for K is between 3-10 for most data-sets, which produces much better results than any other value of K [57]. We used K=3 for our classification. Distance is calculated using different distance functions. Euclidean Distance and Manhattan Distance functions are defined in Equation(4.i) and equation(4.j) respectively.

$$EuclideanDistance, D_E = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{4.i}$$

$$ManhattanDistance, D_{Ma} = \sum_{i=1}^{k}|x_i - y_i| \tag{4.j}$$

We used Euclidean Distance function to calculate distance. From the trained model we plotted Receiver 0perating Characteristic curve, which is one of the most important evaluation metrics for checking any classification model's performance.

Graphical plot for ROC curves of different areas of brain for KNN classification of our data-set is shown in Figure 4.7.

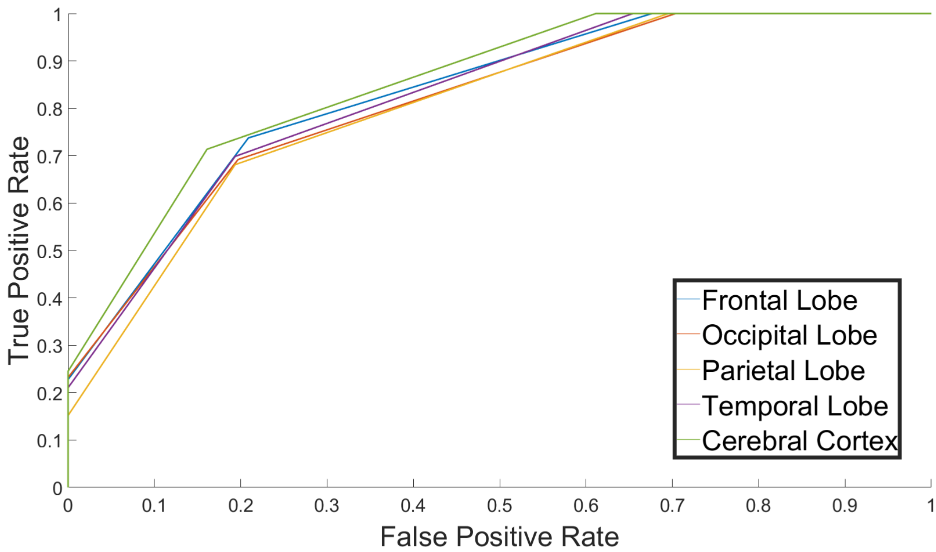

Figure 4.7: Five ROC Curves of Different Brain Areas for K-Nearest Neighbor Classification on Consumer Behavior Analysis Using EEG Signals.

In figure 4.7 we showed a receiver operating characteristic(ROC) curve of different brain areas for K-Nearest Neighbour classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

4.5.5 Random Forest

As the name implies Random Forest classification algorithm is consists of a large number of individual decision trees. The decision trees each vote for a class prediction and the class with highest votes becomes the model's prediction [58]. In our model, we have used 50 trees for training the model.

Graphical plot of ROC curves of different brain areas for Random Forest classification o our data-set is is shown in Figure 4.8.

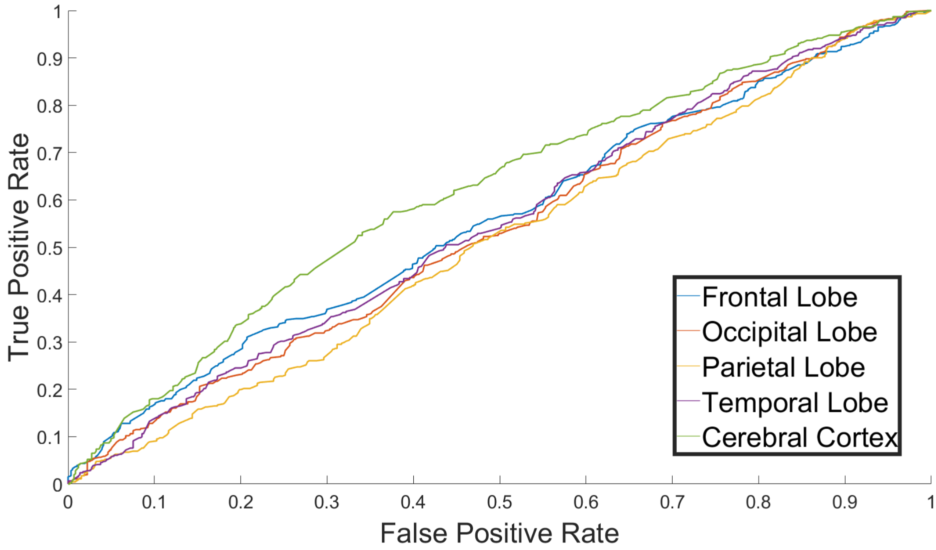

Figure 4.8: Five ROC Curves of Different Brain Areas for Random Forest Classification on Consumer Behavior Analysis Using EEG Signals.

In figure 4.8 we showed a receiver operating characteristic(ROC) curve of different brain areas for Random Forest classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

4.5.6 Support Vector Machine

If we consider all the classification algorithms of recent days Support Vector Machine will blindly stand out as one of the most popular supervised machine learning classification algorithms. This algorithm finds an optimal hyperplane given labeled training data. The hyperplane divides the two classes. Various parameters can be used to tune the classifier [59]. We used Radial Basis Function as Kernel to train our model for higher accuracy.

Graphical plot of ROC curves of different brain areas for Support Vector Machine classification of our data-set is shown in Figure 4.9.

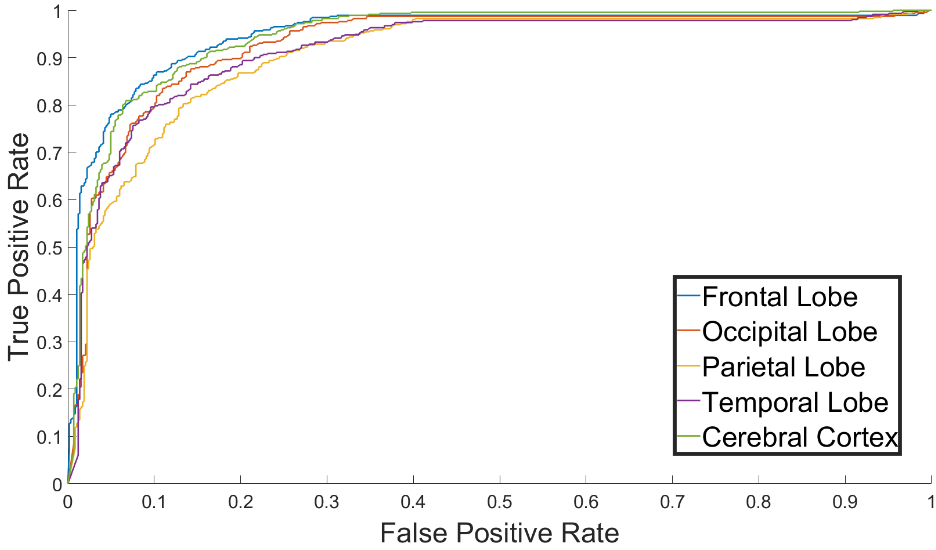

Figure 4.9: Five ROC Curves of Different Brain Areas for Support Vector Machine Classification on Consumer Behavior Analysis Using EEG Signals.

In figure 4.9 we showed a receiver operating characteristic(ROC) curve of different brain areas for Support Vector Machine(SVM) classification on consumer behaviour analysis using EEG signals. Where we labeled frontal lobe with blue color, occipital with red, parietal with yellow, temporal with violet and cerebral cortex with color green.

Chapter 5

Result Analysis

5.1 Comparative Analysis

A confusion matrix describes the performance or accuracy of the classification model or classifier through a table where the true values of a set of test data are known. Though the confusion matrix itself is really easy to understand, however, the terminologies related to it is a bit tough to get a hold of. Below is an example through which the terminologies of confusion matrix can be understood easily for a binary classifier:

	Prediction: Negative	Prediction: Positive
Actual: Negative	TN	FP
Actual: Positive	FN	TP

Table 5.1: Confusion Matrix

From this matrix we can see that there are four possible outcome. Which are,

1. true positives (TP): These are cases in which the consumer liked the product and our prediction is correct.
2. true negatives (TN): The consumer did not like the product and yet we predicted right.
3. false positives (FP): Here the consumer did not like the product and our prediction was wrong.

4. false negatives (FN): Here the consumer did not like the product and our prediction was right.

We used confusion matrix on our classifier algorithms to determine which algorithm is better by finding out area under curve, accuracy, sensitivity and specificity of the algorithms.

5.1.1 Area Under Curve

Performance measurement is really important in machine learning. Through AUC - ROC curve it is possible to measure the performance of classifier algorithms. AUC - ROC curve is used to check or visually represent the performance of multi-class classifiers. ROC curve is best among many evaluation techniques. It is also known as AUROC (Area Under the Receiver Operating Characteristics). In different threshold settings AUC - ROC curve can measure performance of classification problems. Separability of measurement is represented by AUC and Probability is determined by ROC curve. If the AUC is high then it means that the model is really good a at predicting right answer. When plotting ROC curve the x-axis is denoted as false positive rate and the y-axis is denoted as the true positive rate .

The terms that define AUC and ROC Curve are sensitivity, specificity, accuracy. When a model of AUC has result near to the 1 that means that the model will stand out and it also means it has good measure of separability. Whereas a poor model has AUC near the 0 which means it has unfavorable measure of separability. In fact it means it is reciprocating the result. It is predicting 0s as 1s and 1s as 0s. And when AUC is 0.5, it means model has no class separation capacity whatsoever [60].

Table 5.2 is of Area Under Curve for different classification algorithm we used on different brain parts. Brain parts we studied and implied our methodology are frontal lobe, occipetal lobe, parietal lobe, temporal lobe and cerebral cortex. The classification algorithms we used are KNN, DA, NB, DT, SVM, RF.

Classification Algorithms / Brain Area	KNN	DA	NB	DT	SVM	RF
Frontal Lobe	83%	59%	86%	98%	95%	56%
Occipital Lobe	82%	56%	72%	96%	93%	54%
Parietal Lobe	81%	55%	75%	96%	91%	51%
Temporal Lobe	83%	54%	79%	97%	92%	55%
Cerebral Cortex	85%	66%	91%	99%	95%	62%

Table 5.2: Area Under Curve for Different Classification Algorithm.

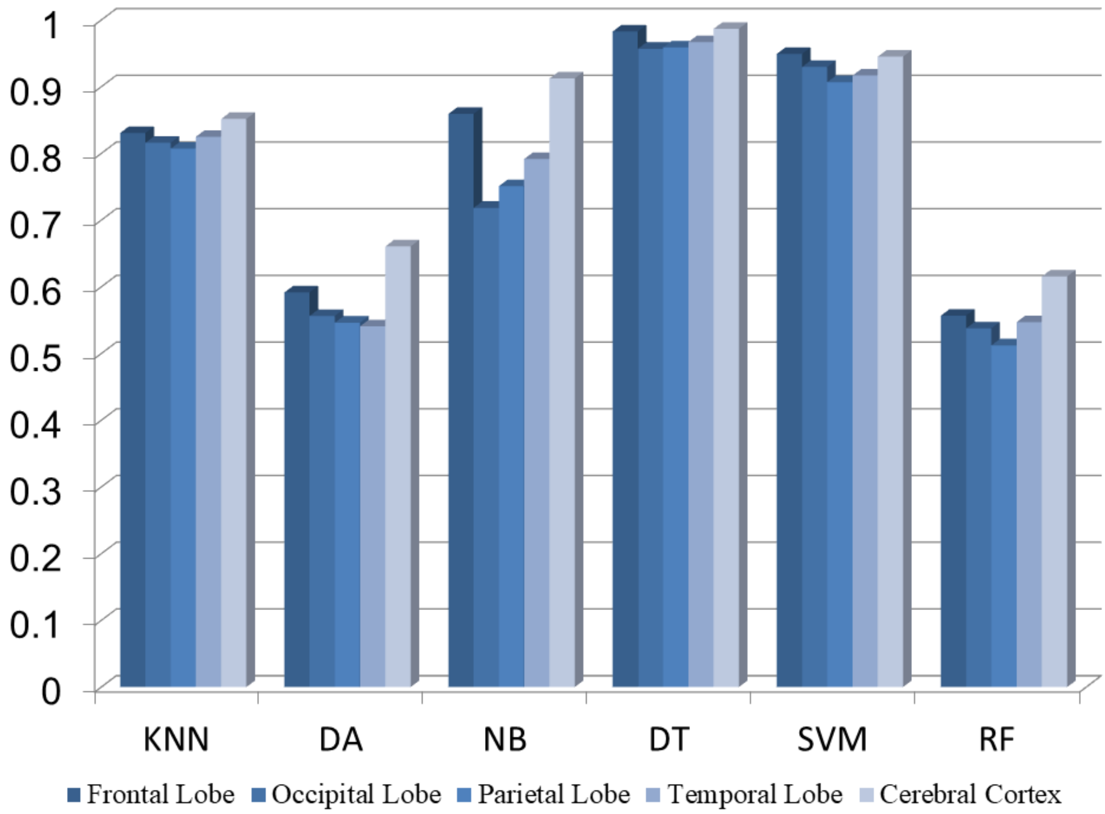

Figure 5.1: Bar Chart Showing AUC of Six Different Classifiers for Consumer Behaviour Analysis Using EEG Signal of Five Areas of Brain

5.1.2 Accuracy

Accuracy is one of the most useful metric for evaluating classification models. It is the fraction of correct predictions out of all predictions. In our model, higher accuracy implies models strength to correctly predict if the consumer will like the product or not. From a confusion matrix accuracy can be calculated by equation (5.a).

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{5.a}$$

Table 5.3 is of Accuracy for different classification algorithm we used on different brain parts. Brain parts we studied and implied our methodology are frontal lobe, occipetal lobe, parietal lobe, temporal lobe and cerebral cortex. The classification algorithms we used are KNN, DA, NB, DT, SVM, RF. Where Decision Tree(DT) shows highest accuracy of 95% in Cerebral Cortex.

Brain Area \ Classification Algorithms	KNN	DA	NB	DT	SVM	RF
Frontal Lobe	77%	60%	76%	93%	87%	54%
Occipital Lobe	75%	56%	63%	90%	85%	52%
Parietal Lobe	75%	56%	66%	90%	82%	52%
Temporal Lobe	76%	56%	71%	91%	85%	54%
Cerebral Cortex	78%	60%	81%	95%	87%	60%

Table 5.3: Accuracy for Different Classification Algorithm.

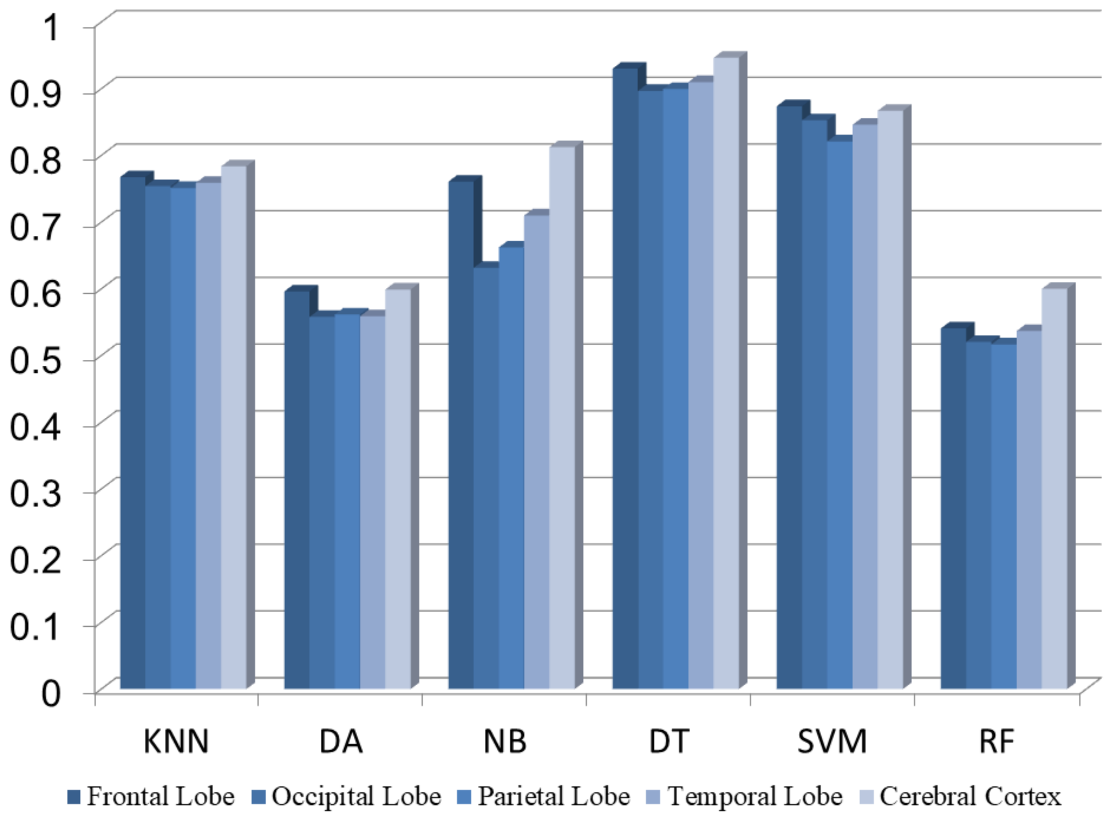

Figure 5.2: Bar Chart Showing Accuracy of Six Different Classifiers for Consumer Behaviour Analysis Using EEG Signal of Five Areas of Brain

5.1.3 Sensitivity

Sensitivity measures the proportion of positive predictions that are correct. In our model, higher sensitivity implies model's strength to correctly predict that consumer will like the product. Sensitivity can be calculated from a confusion matrix using equation (5.b).

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.b}$$

Table 5.3 is of Sensitivity for different classification algorithm we used on different brain parts. Brain parts we studied and implied our methodology are frontal lobe, occipetal lobe, parietal lobe, temporal lobe and cerebral cortex. The classification algorithms we used are KNN, DA, NB, DT, SVM, RF. Where Decision Tree(DT) shows highest result of 94% in Cerebral Cortex.

Brain Area \ Classification Algorithms	KNN	DA	NB	DT	SVM	RF
Frontal Lobe	74%	20%	67%	93%	79%	40%
Occipital Lobe	69%	5%	73%	89%	77%	38%
Parietal Lobe	68%	4%	73%	89%	72%	37%
Temporal Lobe	70%	3%	61%	89%	75%	38%
Cerebral Cortex	71%	31%	81%	94%	77%	46%

Table 5.4: Sensitivity for Different Classification Algorithm.

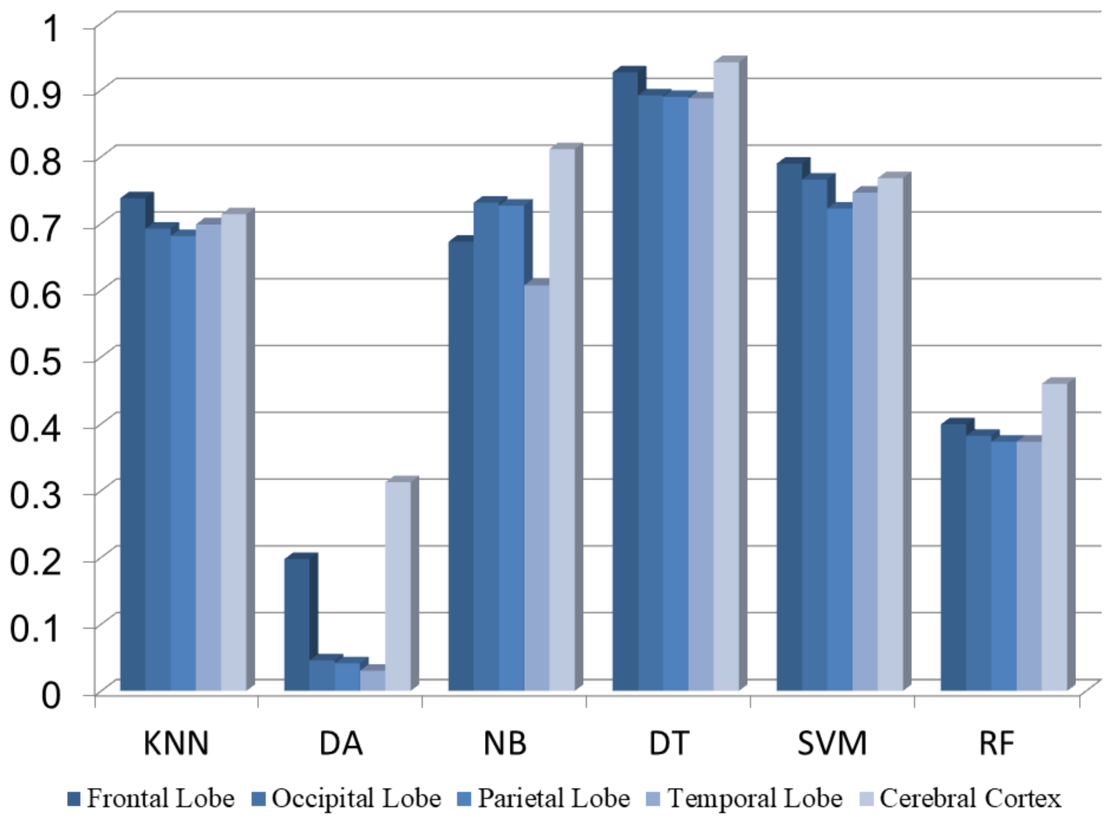

Figure 5.3: Bar Chart Showing Sensitivity of Six Different Classifiers for Consumer Behaviour Analysis Using EEG Signal of Five Areas of Brain

5.1.4 Specificity

Specificity measures the proportion of negative predictions that are correct. In our model, higher specificity implies model's strength to correctly predict that consumer will not like the product. Sensitivity can be calculated from a confusion matrix using equation (5.c).

$$Specificity = \frac{TN}{TN + FP} \tag{5.c}$$

Table 5.4 is of Specificity for different classification algorithm we used on different brain parts. Brain parts we studied and implied our methodology are frontal lobe, occipetal lobe, parietal lobe, temporal lobe and cerebral cortex. The classification algorithms we used are KNN, DA, NB, DT, SVM, RF. Where Decision Tree(DT) and Support vector Machine(SVM) both shows highest result of 95% in Cerebral Cortex.

Classification Algorithms / Brain Area	KNN	DA	NB	DT	SVM	RF
Frontal Lobe	79%	91%	83%	93%	94%	65%
Occipital Lobe	80%	96%	55%	90%	92%	63%
Parietal Lobe	81%	97%	61%	91%	90%	63%
Temporal Lobe	81%	98%	79%	93%	92%	67%
Cerebral Cortex	84%	83%	81%	95%	95%	71%

Table 5.5: Specificity for Different Classification Algorithm.

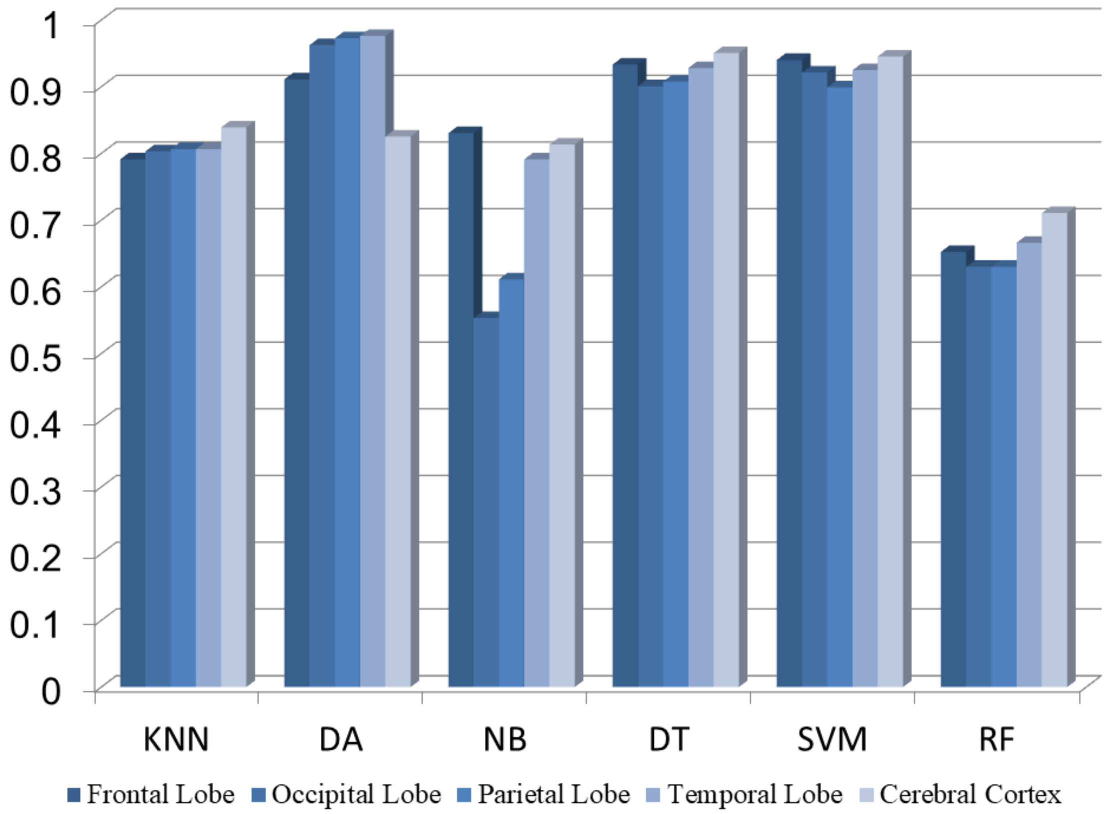

Figure 5.4: Bar Chart Showing Specificity of Six Different Classifiers for Consumer Behaviour Analysis Using EEG Signal of Five Areas of Brain

5.2 Comparison with Previous Works

Previously there has been many research works in the field of consumer choice and preferences. In table 5.6 we showed the comparison between our proposed model and the existing user preference based research work where they worked on the same data-set.

Author	Analysis Method	Prediction Rate	Imaging Tool
Mahendra et al [32] (2017)	HMM	70%	EEG
Proposed Model	Decision Tree	95%	EEG

Table 5.6: Comparison with Previous Works on Consumer Preference Prediction

Chapter 6

Concluding Remarks

Imagine a world where, when someone tries to buy something they do not have to spend hours looking for the specific product. Whenever someone decides to buy something a lot of time and effort is lost on product research that meet their needs, but if neuromarketing reaches its highest potential both consumer and advertiser will be benefited. Customers will not have to search for products that meets their requirements. Their utmost desires will be met instantly. This is when you realize how successful Neuromarketing has been.

In this research work we analyzed EEG signals to get better understandings of consumer behaviour, choice, preference. We tried to build a tool which can successfully predict consumer's choice. We applied different machine learning approaches and proposed a methodology where we acquired accuracy of 95%.

Neuromarketing is next big thing, that is something we have already assumed. There are a lot of scopes for improvement in this sector. Functional Magnetic Resonance Imaging(fMRI) is also one imaging tool that measures brain activity. We are inclined to work with "EEG informed fMRI". Also, in future we are planning to extract facial features of consumer to be more accurate about predicting consumer preference. Image processing can also contribute in the field of our research. If we can integrate image processing in the same time domain of EEG signals then it is possible to extract consumer visual preference features. For example, What object or which color is influencing them.

This methodology will help advertisers to realize which of their advertisement is effective and how they should plan their advertising strategy. Also, Neuromarketing will beneficial for consumer because once Neuromarketing reaches its full extent, it will be able to filter the products which meet the preference of specific consumers.

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