# The Influence of Neuromarketing: Machine Learning Based Empirical Analysis

by

MD. Abdullah Al Muktadir
18301168
Shamsul Malek
18301235
Zakia Hossain
20201141

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
September 2023

# Declaration

It is hereby declared that

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

**Student's Full Name & Signature:**

Muktadir

MD. Abdullah Al Muktadir
18301168

Sayem

Shamsul Malek
18301235

Zakia Hossain

Zakia Hossain
20201141

# Approval

The thesis/project titled "The Influence of Neuromarketing: Machine Learning Based Empirical Analysis" submitted by

1. MD. Abdullah Al Muktadir (18301168)
2. Shamsul Malek (18301235)
3. Zakia Hossain (20201141)

Of Fall, 2023 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on January 08, 2024.

**Examining Committee:**

Supervisor:
(Member)

Tanzim

Md Tanzim Reza
Lecturer
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi, PhD
Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Thesis Coordinator:
(Member)

Md. Golam Rabiul Alam, PhD
Professor
Department of Computer Science and Engineering
Brac University

#### Abstract

This study attempts to investigate the topic of neuromarketing and how it has become an emerging topic that might be used as a tool for market research. Both academic writing and real-world marketing are embracing neuromarketing. Additionally, it applies brain science to a management setting. It looks after the theoretical contribution of neuromarketing which comprehends modern consumer response to marketing stimuli. Again, the research in the field of neuromarketing looks at how people's brains respond to marketing strategies. Researchers use methods like FMRI, EEG and eye tracking to study why consumers may claim to desire one thing but ultimately make choices depending on their feelings. In order to understand how customers' bodies, thoughts, emotions and inner selves are engaged in decision making, the research will use neuromarketing strategies. Additionally, it covers the expanding use of neuromarketing across sectors and lists the top neuromarketing firms in each. Also, it analyzes the expanding use of neuromarketing across a range of sectors and lists the top neuromarketing firms currently operating. The study examines the equipment and methods used in neuromarketing, such as eye tracking, galvanic skin reaction, EEG analysis and cognitive analysis. These approaches can be combined to create a comprehensive understanding. That can allow the customers to respond to marketing stimuli. Overall, this study adds to the expanding body of information on neuromarketing that leads to creating interest in this particular area. Besides, it's potential for use in brand management, advertising, and marketing. Explores the potential of EEG technology in neuromarketing which is emphasizing the ethical considerations. It highlights the role of machine learning algorithms. In terms of analyzing consumer responses to marketing stimuli through EEG signals.Through, suggesting the field is on the verge of significant breakthroughs. It focuses on the empirical approaches in neuromarketing applied to food choices. Therefore, it presents a comprehensive approach to predict consumer emotions. Through EEG signal analysis, it can achieve a remarkable accuracy of approximately 96.89% in predicting consumer preferences.

**Keywords:** Neuromarketing; stimuli; FMRI; EEG; Cognitive analysis; advertising; EEG; Ethics; Algorithms; Empiricism; Food Real-time; Emotions.

# Table of Contents

# Chapter 1

# Introduction

## 1.1 Introduction

Marketing and neuroscience are two intriguing topics of research that are combined. Although strategies like eye tracking have been employed in marketing for some time, the term ”neuromarketing” rose to prominence after an Atlanta advertising agency named BrightHouse announced in a press release back in June 2002 that they were starting a business division using fMRI (functional magnetic resonance imaging) for marketing research. More explanations of neuromarketing have now developed. Recently, new Artificial Intelligence based systems have been developed for the extraction of emotions from facial expression. That can help to demonstrate effectively [1]. Simply said, neuromarketing is the application of quantitative and qualitative techniques to comprehend and forecast customer behavior. It explores customers' underlying motives and emotions, offering insightful data that goes beyond the scope of conventional marketing research techniques. Neuromarketing seeks to learn factual facts about how customers' brains function rather than depending primarily on subjective reports. Besides, Neuromarketing applies neuroscience to understand marketing's impact on consumer behavior, offering valuable insights through neural processes, validating researchers, and inspiring actionable research [26].

Traditional marketing and advertising techniques frequently fall short in attracting consumers attention, Also, it measures the performance of campaigns. Accurate self-evaluation is made more difficult by consumers' limited capacity to articulate their views regarding commercials. Moreover, directly examining minds without conscious involvement, neuromarketing provides a solution. It discloses confidential information and alters purchasing behavior. Neuromarketing applies neuroscience and EEG technology to understand consumer behavior. It also offers data-driven strategies grounded in scientific analysis. This evolving field promises to reshape marketing strategies. Therefore, it gives focus on food choices and navigating ethical dilemmas.While it keeps exploring consumer emotional responses. [20] [6] [25]

The application of EEG technology and machine learning has revolutionized neuromarketing. Despite facing challenges such as noise interference. The field necessitates ethical discussions. Additionally, it balances its benefits and potential overpowering of consumers' free will [20] [16].

Neuromarketing is poised to guide the evolution of marketing strategies. For example, adapting to the digital age and promising a holistic understanding of consumer decisions. Especially in real-time environments. [20] [6] It gets through the drawbacks of self-reporting and offers beneficial insights that conventional tools can't match. Marketers may revolutionize how they engage with and influence audiences by adopting neuromarketing. It allows them to delve into customers' subconscious minds to produce powerful campaigns.

## 1.2 Problem Statement

The traditional methods used by marketers have gone through considerable alterations since the introduction of neuromarketing in the 1990s. This essay aims to examine the changes and the future potential of neuromarketing. The authors seek to address several questions regarding the functioning and influence of Neuromarketing on consumer habits, particularly in relation to the biological aspects of the brain that are analyzed. They also aim to determine if Neuromarketing appeals to the subconscious of consumers, and whether neuroscience can provide a comprehensive understanding of consumer behavior. Furthermore, the paper explores the potential of Neuromarketing in developing predictive buying models that explain consumer choices and investigates the awareness and acceptance of this intrusive technique within the wider population. Ultimately, the authors aim to assess the effectiveness of Neuromarketing in providing efficient results to marketers. The evolutionary nature of marketing over the past century, undergoing paradigm shifts that reflect the changing social and economic relations. In addition, it prioritizes consumer needs and sustainable development in organizational marketing activities [4]. As a result, it is opening avenues for further research in the field [25].

The use of conventional market research techniques has its limits when it comes to properly predicting customer behavior customers frequently act incongruously saying one thing while doing another marketers have been baffled by this disparity between what they really do and say for years by offering a direct measurement of customers subconscious reactions and avoiding the biases and constraints of self-reporting neuromarketing offers a potential answer to this issue. In this study, it intends to answer the research issue. Neuromarketing is a useful instrument for market research and how it operates. The goal of the study is to better understand consumer behavior and decision-making processes. To obtain this it switches to examining how neuromarketing could close the gap between what they really do and what customers say. Again, this study intends to identify the fundamental elements that affect customers' preferences. In addition, it tends to purchase decisions by investigating the conceptual role of neuromarketing in market research. It aims to shed light on how well neuroscientific methods can record customers' subconscious and emotional reactions to marketing cues. The study also attempts to examine how neuromarketing affects the four aspects of consumers: their physical

bodies, minds, hearts, and spirits. Marketing professionals may better understand their target market and create more successful marketing strategies by grasping the holistic nature of customer behavior. The conventional methods used by marketers have undergone considerable alterations since the advent of neuromarketing in the 1990s. This essay seeks to examine these alterations and the future
possibilities of neuromarketing. The authors seek to address several questions regarding the functioning and influence of Neuromarketing on consumer habits, particularly in relation to the biological aspects of the brain that are analyzed. They also aim to determine if Neuromarketing appeals to the subconscious of consumers, and whether neuroscience can provide a comprehensive understanding of consumer behavior. Furthermore, the paper explores the potential of Neuromarketing in developing predictive buying models that explain consumer choices and investigates the awareness and acceptance of this intrusive technique within the wider population. Ultimately, the authors aim to assess the effectiveness of Neuromarketing in providing efficient results to marketers. Ahmed H. Alsharif acknowledges the limitations of the study in his writing, such as the focus on recent publications from the Scopus database, and empirical papers in the English language only. These limitations highlight potential areas for future research that the current study may not be completely free from bias [18]. Traditional marketing research tools have limitations when it comes to testing human subjects and assessing consumers' motivations, which has led to a need for more effective and accurate methods of understanding consumer behavior and preferences.As a potential remedy, neuromarketing techniques have evolved, offering quick and precise input on customer preferences and behavior. The additional benefit of neuromarketing tools in the many stages of the marketing process, such as fully knowing the market, creating customer-driven marketing strategies, and creating value propositions, needs to be explored and understood more. [19] There are other restrictions to take into mind, such as the necessity of taking cultural and environmental aspects into account when making decisions based on neuroimaging data. To overcome these issues and establish the genuine potential and application of neuromarketing methods in marketing research, more study is needed.

## 1.3 Research Objectives

Based on the study's theme, the following are its primary objectives:

- To look at how neuromarketing might theoretically improve market research and what it means for a deeper understanding of customer behavior.
- To look into and evaluate the effectiveness of different neuromarketing tools, such as neuroimaging, EEG, FMRI, and eye tracking, in recording customers' emotional and subconscious responses.
- To examine the utilization of consumer perceptions of their actual bodies, brains, souls, and spirits to guide marketing strategies. Utilizing neuromarketing strategies is accomplished.
- To investigate the expanding usage of neuromarketing across numerous economic sectors and to pinpoint the top companies in the field.
- To be aware of the techniques and tools used in neuromarketing, such as eye tracking, galvanic skin response, EEG analysis, and cognitive analysis, and to assess how well they contribute to a full knowledge of consumer behavior and decision-making.
- Loading and extracting the EEG dataset: Initiating the process with the collection.And after that initial analysis of the EEG data.
- Data and label preparation using Python: Organizing the EEG data and labels for efficient analysis.
- EEG data preprocessing: Implementing normalization and feature engineering.So that to define the raw EEG data.
- Feature engineering from raw EEG data: Transforming raw data to extract meaningful information for model training.
- Machine learning model training with EEG data: Utilizing LSTM networks.And also logistic regression to train models using the processed data.
- Performance evaluation using a separate test set: Ensuring unbiased.And also reliable model evaluation through separate test sets.

- Model assessment through various metrics: Utilizing metrics such as accuracy, precision and recall for a comprehensive performance evaluation.
- Results visualization: Graphically representing the analysis results so that it can produce clear and effective presentation.

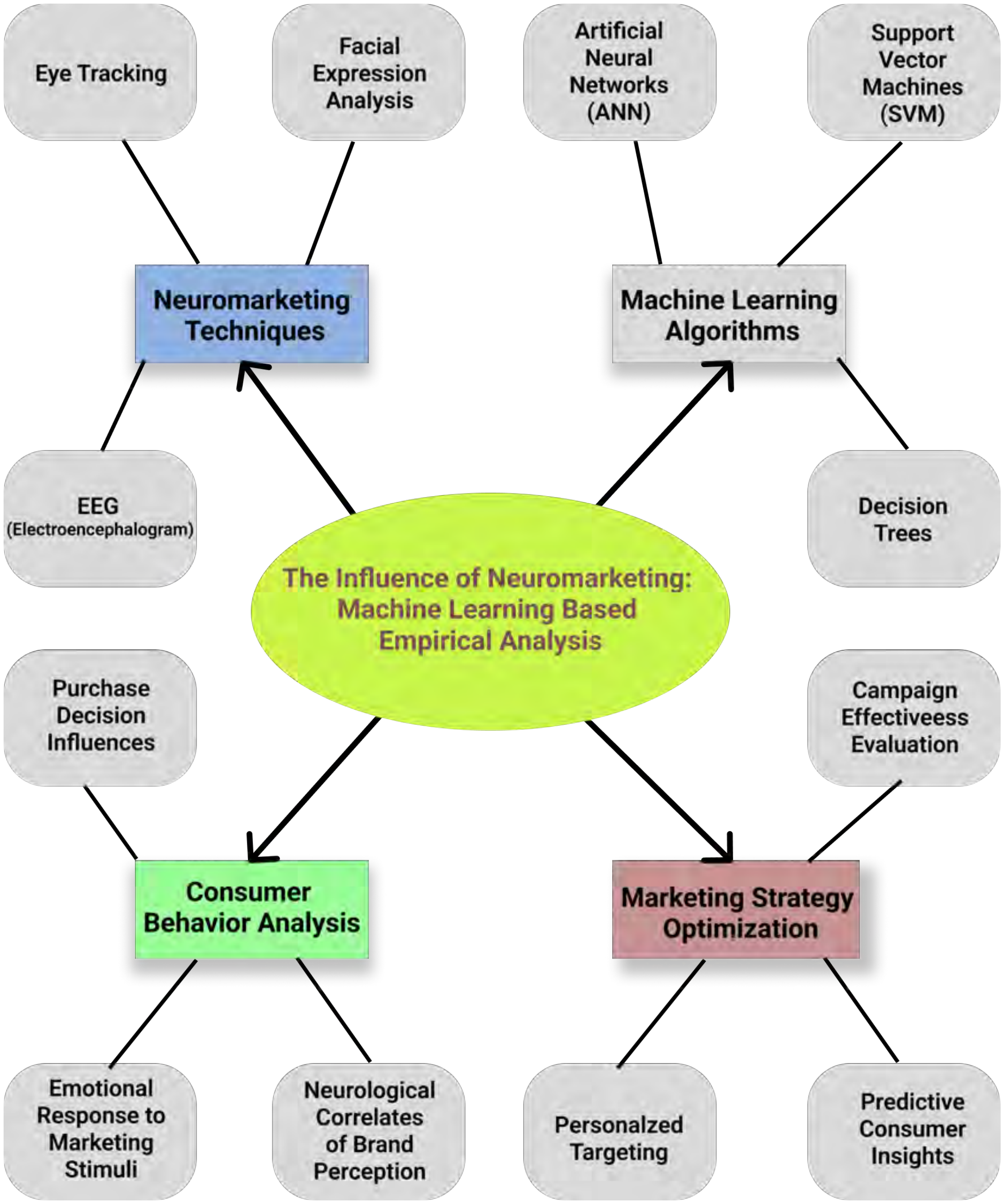


Figure 1.1: Conceptual Framework: Integration of Machine Learning and Neuromarketing

# Chapter 2

# Literature Review

This comprehensive study, written by Eben Harrell, gives a summary of the most current developments in neuromarketing research. Harrell examines the methods and instruments used in the industry. Also, their study emphasizes their capacity to comprehend and affect customer behavior. Again, the report highlights ground-breaking research showing how neuromarketing is useful for forecasting and influencing consumer decision-making. This paper is a priceless tool for marketers, researchers and anybody else interested in learning more about the state of neuromarketing today thanks to Eben Harrell's experience and insights. Harrell adds to the investigation of the uses and consequences of neuromarketing in the rapidly changing market environment of today by providing a thorough examination [8]. Also, Narendra P. Parchure delivers an informative analysis of the transformative impact of digital marketing and the relevance of neuromarketing in understanding consumer behavior in their research paper [15].

Edmundas Kazimieras Zavadskas focusing on the integration of emotional and physiological factors in assessing the hedonic value of one-to-one marketing. In addition, the findings highlight the importance of analyzing potential buyers' emotional states, valence and arousal, and affective attitudes to enhance the effectiveness of personalized marketing strategies [11]. The article by Ferdousi provides a thorough analysis of technological developments in neuromarketing. The review includes 57 pertinent literature sources and emphasizes how frequently consumer items are used as marketing tools. In research based on video advertisements, EEG is preferred over fMRI. In addition to brain recordings, various physiological response measurement techniques are employed. Consumer reaction prediction using machine learning algorithms like ANN, SVM, and LDA show great accuracy. Future researchers in the field of neuromarketing will benefit from the review's insightful recommendations [16]. Besides, Natalia Abuín Vences emphasizing the relevance of neuromarketing in enhancing emotional connections between organizations and users in social networks, while highlighting the impact of social influence on communicative effectiveness [17].

David Juárez-Varón's research addresses the relevance of package design in consumer preferences for educational toys. The study utilizes neuromarketing techniques and proposes a methodology to predict the attention-grabbing aspects for potential customers [13]. The aim is to optimize the communication design of educational toy packaging. By applying machine learning techniques to experimental data. In addition, the study identifies the primary areas of focus and those that do not capture customers' attention. The results highlight the significance of graphics details in packaging. The methodology also analyzes and segments these areas based on social circumstances and consumer types. Mainly, the research offers valuable insights into the key elements of packaging design for educational toys [13].

The article by Rupali Gill highlights how neuromarketing has revolutionized the area of marketing and improved our understanding of customer behavior. For businesses to grow sustainably and to build strong brands, neuromarketing strategies must now be integrated. However, current methods lack a comprehensive framework for understanding geometric data, making it difficult to sustain performance levels without incurring significant costs. The analysis of the available literature reveals a dearth of studies that made use of an integrated approach. By putting out a financially sensible approach that takes into account advertisers' viewpoints, the study seeks to close this gap. This research intends to provide beneficial insights and solutions for optimizing neuromarketing strategies by integrating performance and cost consideration [24].

Contrary to past ideas that the heart was the source of all strength, Hippocrates promoted the idea that the intellect and the brain are independent of one another. Descartes proposed that the body and mind can interact. Thomas Willis studied how various brain regions affect behavior by combining the concepts of neurology and psychology. In Plato's philosophy, the mind was represented by a chariot drawn by two horses, which stood for reason and feeling. Despite making up only 2% of our body, the brain needs 20% of our energy for functions, many of which take place without our awareness. [19] Surprisingly, we barely utilize 20% of the wholecapability of our brains. The neurons that make up the brain communicate with one another by passing signals through the little spaces between them [27].

According to Hafez, the activities of the brain, and nerve systems are connected to neuromarketing like advertisements. Besides, different marketing tools like fMRI, EEG, MEG, Eye tracking and so on show how they can do the work in the field of advertising. Moreover, the author wanted to show how effective they are. Moreover, it can deepen the capacity and efficiency of neuromarketing strategies. Hence, the advertising camp can create a brand new model and a model named "Black Box" which presents the reasons for customers' behavior differently, it can make a good side of the product in the customer's mind so that the product can be sold numerous [7].

Kenechi John Onyeke states in his article its historical dimension and revolutionary potential in understanding consumer behavior. While limited empirical studies have been conducted, he emphasizes the need for further research in the field to address reliability, validity, and generalizability challenges and advance the field of neuromarketing [12]. Accordingly, Prinka Singh says in her article that neuromarketing as an effective tool for understanding consumer behavior in today's intelligent buyer-driven market, focusing on its conceptual role and the utilization of neuroimaging techniques in marketing research [3].

In ”A Survey on Neuromarketing using EEG Signals,” the investigation of neuromarketing is focused on the using of EEG signals to track brain activity in a effort to better understanding the complex mechanisms that influence customer choices.The technology facilitates the monitoring of electrical activity in the brain which offers insights into the internal thought processes a consumer undergoes when choosing between different products. The paper highlights the roadmap it offers companies to refine their marketing strategies based on objective data derived from consumers' brain activities/functionalities [20]. EEG technology in neuromarketing which emphasizes the ethical considerations and the necessity for a deeper understanding of consumer preferences to shape future marketing strategies [20]

In, ”Technological advancements and opportunities in Neuromarketing: a systematic review” paper it mentions that in neuromarketing. In addition, it focuses on machine learning applications. In recent years in this sector, it also focuses on the outcome and also the methodologies. It discusses various classification algorithms employed in neuromarketing studies. Besides, it includes Support Vector Machine (SVM) and Artificial Neural Network (ANN), and their computational advantages and accuracy levels in distinguishing between 'like' and 'dislike' EEG signal patterns [6].

Despite the promising prospects outlined in ”A Survey on Neuromarketing using EEG Signals,” neuromarketing faces a series of challenges, predominantly stemming from the limitations inherent to EEG technology. The paper discusses the noise interference in EEG-based systems and the difficulty in removing unrelated marketing stimuli as significant hurdles in the field [16]. In another research A. Stasi said that the study is proposing an integrated methodology for a holistic understanding of consumer decision-making processes in real time environments [6]. Furthermore, K. M. Rahman says in their study that promises deeper insights into consumer behavior [16].

On the other hand, ”Technological advancements and opportunities in Neuromarketing: a systematic review” stands at the point of a revolution with machine learning algorithms. Therefore, It plays a vital role in advancing research. The paper suggests a preference for linear classifiers. It is practical neuromarketing applications, given the limitations in data availability and emphasizes the need for researchers [16]. It selects appropriate EEG devices and classifiers meticulously. Various classification algorithms have been employed in neuromarketing studies. Additionally, those algorithms over the past half-decade, including Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), Naïve Bayes, k-Nearest Neighbor (KNN) and Hidden Markov Model (HMM). Above these, SVM has been praised for its computational simplicity. It has a high accuracy level, functioning as a discriminative classifier. So that It separates different classes through a hyperplane created based on training data.

Patricia Nuñez-Gomez's study delves into the perception of advertising among individuals with Asperger syndrome compared to a neurotypical population [14]. They developed the study using neuromarketing techniques to measure attention and emotion through physiological and biometric variables. It reveals significant differences in the perception of commercial and social-themed advertisements between these groups. On the other hand, Margherita Zito's research, titled "Assessing the Emotional Response in Social Communication: The Role of Neuromarketing," focuses on the impact of social advertising on behavior where they specifically analyze Unicef's bequest campaign [23]. Additionally, utilizing tools like EEG, skin conductance,and eye-tracking, the study demonstrates substantial differences in emotional and cognitive responses. Besides, it reflects particularly among those without children which leads to a notable 35% increase in donations. This highlights the effectiveness of neuromarketing in enhancing communication strategies for non-profit organizations.

Furthermore, Nicolae Alexandru Pop, Dan-Cristian Dabija and Ana Iorga's study, "Ethical Responsibility of Neuromarketing Companies in Harnessing the Market Research – a Global Exploratory Approach," tackles the ethical challenges in neuromarketing [2]. They focus on how to satisfy consumer needs while ensuring corporate profitability. Again, this study delves into the evolution of research methods and the ethical implications for companies performing neuromarketing research. This study is underpinned by the Neuromarketing Science and Business Association's ethical code. It includes exploratory research on 67 global neuromarketing companies which provide crucial insights for the field. Complementing this, Micu Adrian and Alex Capatina's "A New Challenge In Digital Economy: Neuromarketing Applied To Social Media" investigates neuromarketing's role in social media where it aiming to correlate neuroscience behavioral data with social media users' cognitive processes [21]. The study highlights the importance of neuromarketing in optimizing social media content and offers managerial recommendations. Additionally this study in based on a systematic literature review and analysis of neuroscience research methods in digital commerce. Again, it underlines its significance in enhancing the effectiveness of social media strategies in the digital economy.

Weiwei Deng and Xiaoliang Ling's research, "Ad Click Prediction in Sequence with Long Short-Term Memory Networks: an Externality-aware Model," introduces a novel approach to ad click-through rate (CTR) prediction using Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) cells, a first in literature [5]. This method considers user browsing behavior and the impact of top ads on the current ad's quality. However, this method demonstrates superior performance over Deep Neural Network (DNN) models in terms of accuracy and relevance. Later, they validated their model on a real dataset. In this part they showcased its effectiveness and also proposed a simplified version to balance gains with serving costs. Complementing this, Sudhanshu Kumar and Mahendra Yadava's study, "Fusion of EEG Response and Sentiment Analysis of Products Review to Predict Customer Satisfaction," proposes a multimodal framework for predicting product ratings [10]. This framework combines physiological signals (EEG data) and sentiment analysis of global product reviews using Natural Language Processing (NLP). Consequently, the innovative use of Random Forest regression and Artificial Bee Colony optimization fuses global and local ratings which results in a more accurate prediction model. Their approach, tested with EEG data from 40 participants viewing 42 products. Also, it shows significantly lower Root Mean Square Error (RMSE) compared to traditional unimodal schemes. Concurrently, their research offers new insights into consumer behavior modeling and product satisfaction prediction. It highlights the practical applications of EEG signals and sentiment analysis in market research.

Debadrita Panda and Debashis Das Chakladar's study, "Prediction of Consumer Preference for the Bottom of the Pyramid using EEG-Based Deep Model," focuses on the use of EEG-based emotion detection to understand consumer preferences among the Bottom of the Pyramid (BoP) segment [22]. This study demonstrates its advantages over traditional rating-based methods. Meanwhile, Sabih Ahmad Khan's research, "Comparative Analysis on Facebook Post Interaction using DNN, ELM, and LSTM," investigates user interactions on Facebook posts [9]. This research uses machine learning algorithms like DNN, ELM, and LSTM. This study analyzes post attributes and word embeddings generated by Word2Vec and Doc2Vec models which offer insights into the effectiveness of these methods in predicting social media user interactions. Next, they emphasize the efficiency of Word2Vec in syntactic tasks. Both studies contribute valuable insights into consumer behavior and social media interaction prediction by using advanced data processing and machine learning techniques.

ANN, a collection of artificial neurons producing non-linear decision boundaries. Though, it has emerged as a popular tool for neuromarketing data interpretation, despite requiring a large dataset and numerous features for optimal functionality. Remarkably, ANN-based models have achieved up to 80% average accuracy in advertisement. For example, recognition, outperforming other classifiers like C4.5. The rapid advancements in neuromarketing bring forth a range of ethical concerns. As it highlighted in "A Survey on Neuromarketing using EEG Signals." The paper emphasizes the need for standard rules. To ensure that neuromarketing enhances the shopping experience without manipulating consumers into programmed buying patterns [20].

Looking forward, "Facial Expression Decoding and Emotional Responses" anticipates that neuromarketing tools will evolve to offer faster and more affordable applications. It provides insights that traditional marketing methods cannot. The paper sees the integration of various neuromarketing techniques [28]. For example, including EEG measures and automatic emotional facial expression analyses. As a result, it is a promising avenue for future research in food neuromarketing.

"An Ensemble Model for Consumer Emotion Prediction Using EEG Signals for Neuromarketing Applications" discusses the meticulous preprocessing of EEG signals to enhance the signal-to-noise ratio (SNR). The paper highlights various strategies adopted including bandpass filtering and fast Fourier transform (FFT). Again, the strategy is the use of Savitzky–Golay filters among others. It underscores the potential avenues for future research. Furthermore, it is aiming for even more refined and accurate consumer emotion prediction systems. These experiments have underscored the vital role of preprocessing in enhancing accuracy. Those techniques like bandpass and Savitzky–Golay filters show pronounced efficacy. Additionally, it has been discovered that combining manually created and automatically created features extracted using DWT, PSD and LSTM. As a result, it significantly increases sensitivity and specificity [25].

As neuromarketing continues to evolve, it focuses on adapting to shifts from traditional to internet-based advertising. The importance of understanding consumer behavior through neuroscience becomes increasingly significant as outlined in "A Survey on Neuromarketing using EEG Signals." Meanwhile, "An Ensemble Model for Consumer Emotion Prediction Using EEG Signals for Neuromarketing Applications" sees the field ripe for further exploration with potential focus areas. It includes the incorporation of more robust features and classifier combinations to enhance prediction outcomes further.

# Chapter 3

# Work Plan

Our research work plan describes a structured pathway to conduct a careful investigation into the realm of machine learning-based neuromarketing. Besides, we incorporated the leveraging EEG data to gain deeper insights into consumer behavior. The workflow is systematic and iterative which allows for adjustments and improvements as necessary. Below, we outline the key stages of our research:

**Defining Research Objectives**
We initiate our research by clearly defining the objectives. Which will guide the subsequent stages of the study.

**Literature Review**
A comprehensive literature review will be undertaken to gather insights from previous studies and to understand the current landscape of neuromarketing research.

**Data Collection**
We collected the data from our supervisor.

**Data Loading and Inspection**
The collected data we loaded and inspected to understand its structure and contents. This stage involves preparing data and label files for easy manipulation.And it is analysis using Python data structures.

**Data Preprocessing and Feature Engineering**
Following the inspection, the data undergo preprocessing steps to clean and transform it while ensuring its readiness for model training. We have employed normalization techniques and feature engineering to extract meaningful information from the raw EEG data.

**Model Selection and Training**
We have explored various machine learning algorithms that have been used for different tasks. Neural networks including Simple Neural Network are utilized to capture complex patterns in the data. Special attention has been given to LSTM networks and logistic regression for training with a subset of the data.

**Model Evaluation**
The performance of the models has been evaluated using a separate test set to ensure a fair evaluation. Metrics such as accuracy, precision and recall are used to assess the performance.

As the results were visualized through various graphs to provide a clear depiction of the model's efficacy.

**Analysis and Strategy**

Formulation Based on the model outputs, we derived valuable insights into consumer behavior. Which guided decision-making processes and aided in the formulation of strategies such as personalized marketing campaigns and targeted product recommendations.

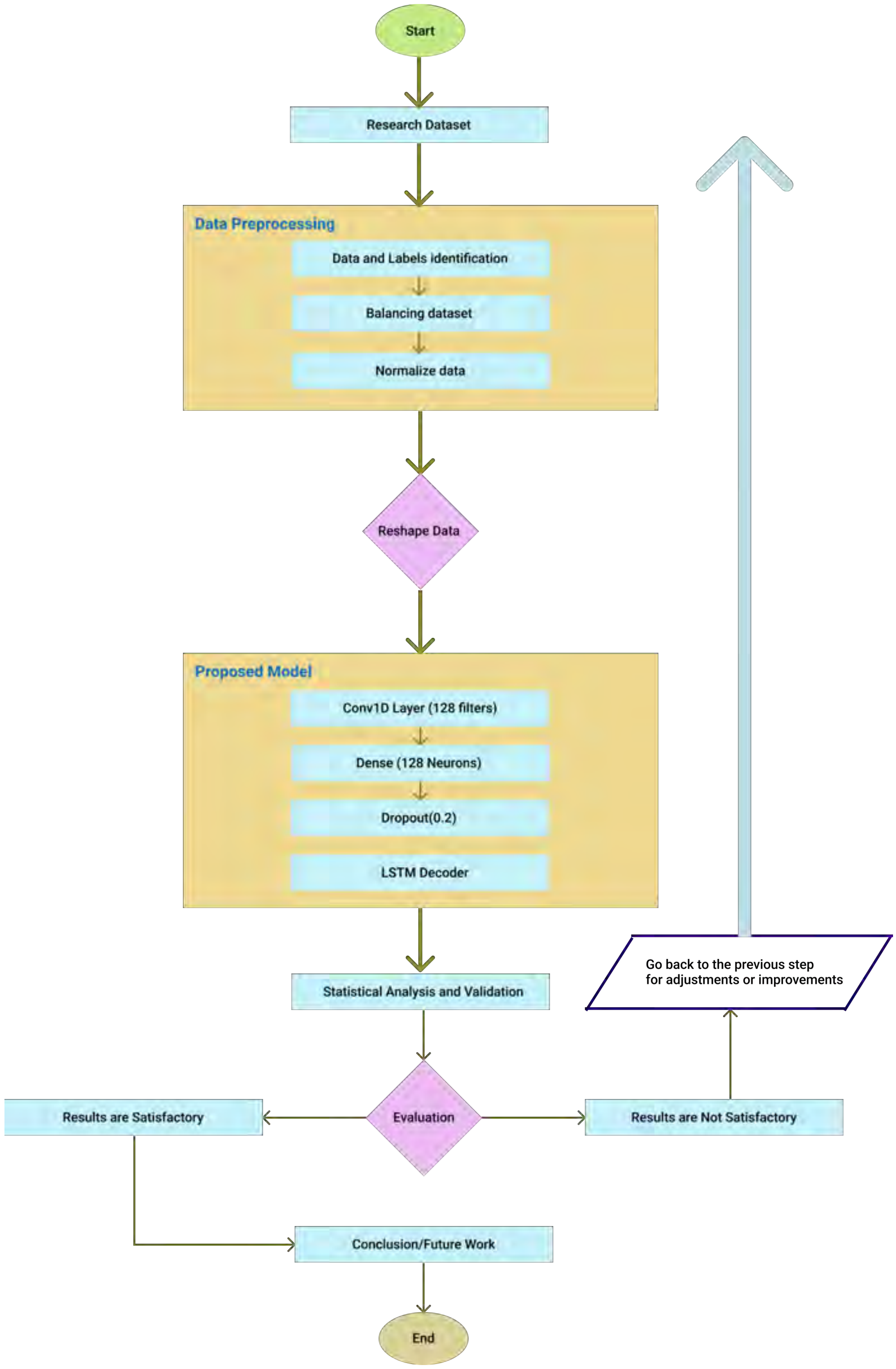


Figure 3.1: A diagram illustrating our planned approach with the proposed model.

# Chapter 4

# Dataset Description

The dataset utilized in this study is a rich collection of EEG data gathered from 25 different users. The data is a representation of the neurological responses of these individuals. Again, it was captured while they were engaged in a neuromarketing study. Additionally, each individual's data is stored in separate files with corresponding labels indicating their preferences as 'Like' or 'Dislike'. The labels are binary and provide a clear demarcation for classification tasks.

## 4.1 Dataset Details

The dataset is structured in a way that each user has two distinct files: one containing the EEG data and the other containing the respective labels. The EEG data files are text files containing rows of numerical values representing the EEG signals recorded during the study. These files are named after the individual participants. Also, it is facilitating easy identification and retrieval of data. Each row in the EEG data files represents a snapshot of the EEG signals at a particular time point. That includes each column representing a different electrode's reading. The data is raw and requires preprocessing to be utilized effectively for machine learning models. When we see the label files, on the other hand, those are simple text files containing the word 'Like' or 'Dislike', representing the individual's preference. These labels are the ground truth values that we aim to predict through our machine learning models. The dataset is quite substantial. Additionally, it is providing a robust ground for training machine learning models. Besides, the large number of data points ensures that the models have a sufficient amount of data to learn the underlying patterns and nuances in the EEG signals which are indicative of the users preferences.

If we look at some random EEG signals to visually inspect the data-

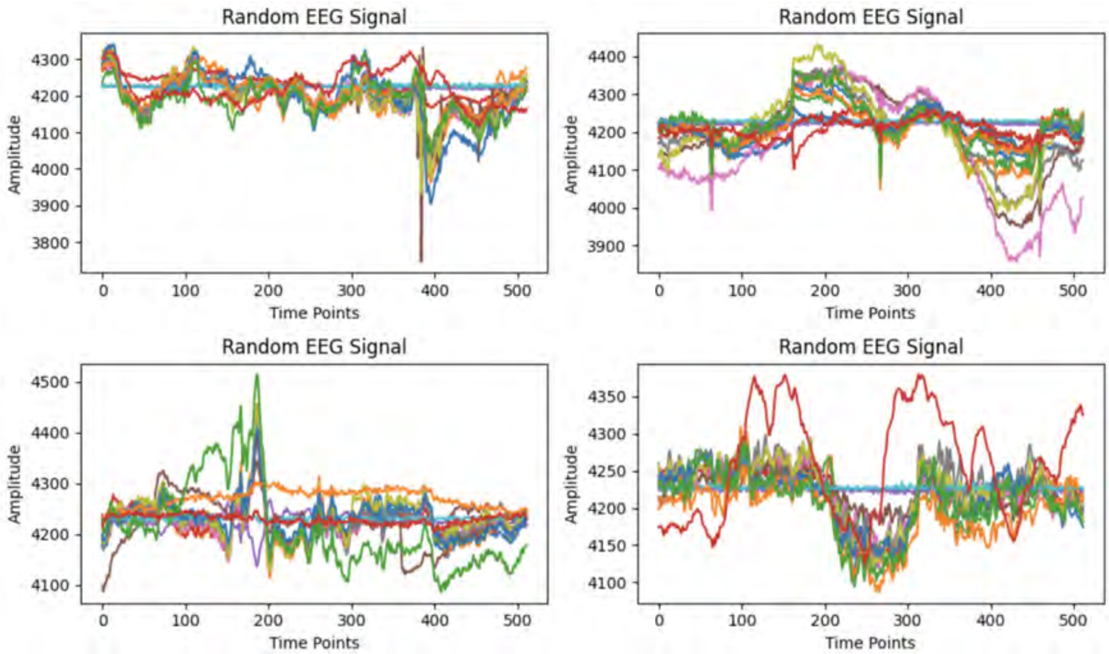


Figure 4.1: EEG Signal with times which indicate noisy channels

For gaining deeper insight about the dta we have derived the Standard Deviation of Each Channel Across All Samples. If we look at this-

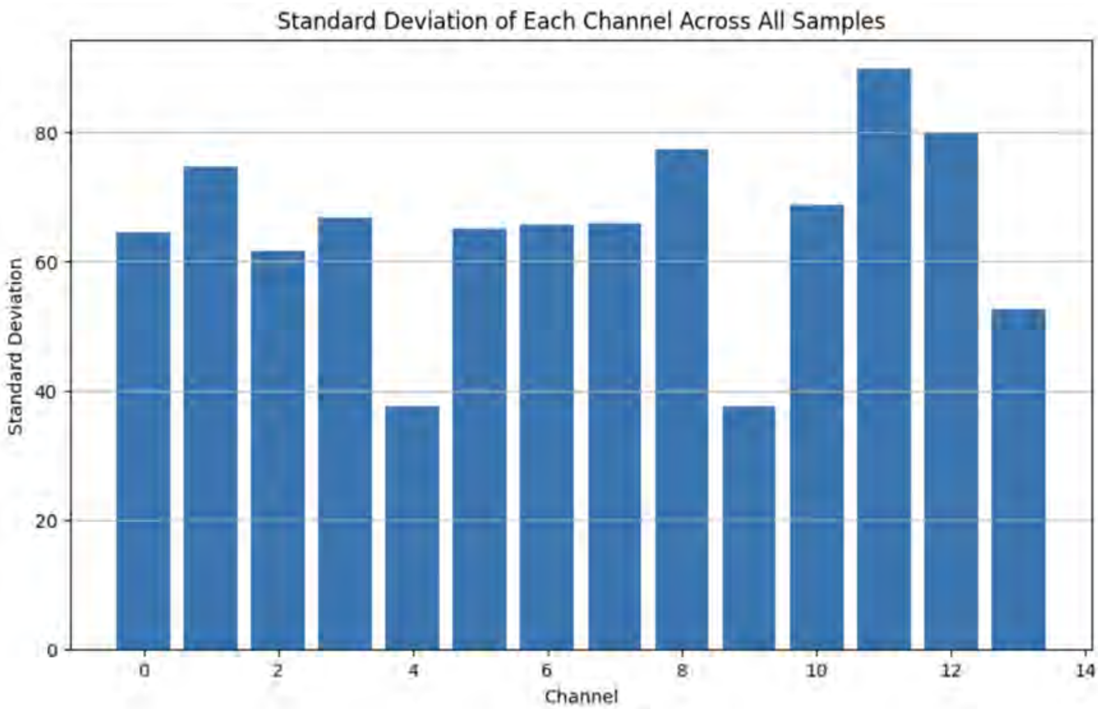


Figure 4.2: EEG Signal Standard Deviation of Each Channel Across All Samples

# Chapter 5

# Methodology

The initial step in the workflow involves loading and extracting the dataset. The loading and extracting the dataset is followed by a meticulous inspection to understand its structure and contents. In addition, this is succeeded by data preparation where the data files and label files are loaded into Python data structures for easy manipulation and analysis. After that, the data undergoes several preprocessing steps including normalization and feature engineering to prepare it for model training. Moreover, the features are engineered to extract meaningful information from the raw EEG data. After that we made those data in a way which is used to train various machine learning models including LSTM networks and logistic regression. The models are trained using a subset of the data. Also, training was performed by their performance which was evaluated using a separate test set to ensure a fair evaluation. Besides, various metrics including accuracy, precision and recall are used to evaluate the performance of the models. As a result, the results are visualized using different types of graphs to provide a clear picture of the model's performance.

## 5.1 Data Acquisition and Loading

The initial step in our research involved acquiring a rich dataset comprising EEG readings from 25 users. The data was meticulously sourced and loaded into our environment by setting the stage for the subsequent phases of our research. This dataset, which is a cornerstone of our research. It also facilitated a deep dive into the nuances of neuromarketing. Additionally, it offers a fertile ground for analysis and interpretation.

## 5.2 Data Inspection and Preparation

Following the acquisition of the data, we embarked on a journey of data inspection and preparation. In addition, this phase involved a random selection of files for inspection. Also, that offers a preliminary glimpse into the data's structure and content. The data files and their corresponding labels were loaded and examined to ensure a smooth transition to the data processing stage.

## 5.3 Data Exploration and Preprocessing

Data exploration and preprocessing formed the crux of our methodology. This stage saw a meticulous exploration of the data. Additionally, this step was inspected with a keen eye on the distribution of EEG signal values across different files. The data underwent a series of transformations. Also, the data includes normalization and feature engineering to extract meaningful attributes that would serve as the input for our machine learning models. After that we made changes to the imbalanced data. If we take a look-

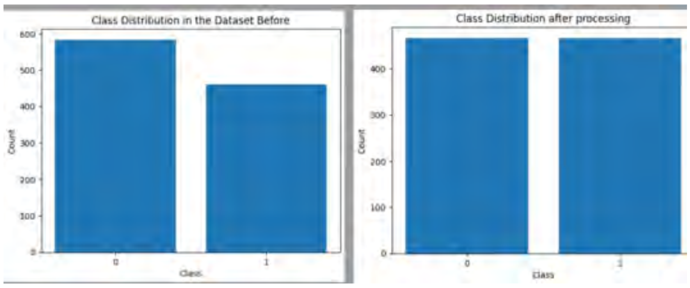


Figure 5.1: Processing imbalanced data to Balanced data

## 5.4 Model Development

Our research focused on the development of a machine learning model optimized for EEG data analysis. In addition, we initially considered various algorithms including LSTM, logistic regression and simple neural networks. After implementing those models we eventually honed in on LSTM due to its superior performance with our dataset.

We dedicated our efforts to extensively modifying and refining the LSTM model. Besides, we created what we now refer to as the ”Proposed Hybrid LSTM Model.” This adaptation was specifically tailored to our dataset’s characteristics by integrating with CNN Conv1D and the max-pooling layer. Again, it involves strategic enhancements and algorithmic adjustments. The details of these modifications will be elaborated on in a later section.

This phase of our study was pivotal in evolving a standard LSTM into a model uniquely suited for our research needs. Moreover, it demonstrates the effectiveness of specialized algorithm adaptation in machine learning.

## 5.5 Proposed Hybride LSTM model Architecture

Our model architecture is a sophisticated integration of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) layers. Specifically, it is crafted for effective sequential data processing. The architecture is systematically designed to excel in feature extraction and sequential learning.

1. **Input Layer:**
   This layer is responsible for identifying input data and labels. It includes steps for balancing the dataset to ensure equal representation of all classes and normalizing the data to standardize feature scales.

2. **Convolutional Layers:**

   - The first Conv1D layer, equipped with 256 filters and a kernel size of 12, uses ReLU activation for non-linear transformations.
   - A MaxPooling layer follows with a 2x2 pool size to reduce spatial dimensions.
   - The second Conv1D layer features 128 filters and a kernel size of 6. It is also followed by ReLU activation and a 2x2 MaxPooling layer.
   - The third Conv1D layer with 64 filters and a kernel size of 3. This third layer leads into another 2x2 MaxPooling layer. Each of these layers progressively refines the feature maps for the subsequent LSTM layers.

3. **Sequential Learning Layer:**
   An LSTM layer with 128 units is employed to capture the temporal dependencies and dynamics inherent in the sequential data.

4. **Regularization:**
   A Dropout layer with a rate of 0.2 is integrated to mitigate overfitting. Sometimes, we regulate this to 0.2 - 0.3 so that it ensures the model's generalizability.

5. **Output Layer:**
   The final layer is a Dense layer tailored to the number of output classes. Also, the final layer includes a softmax activation function for multi-class classification.

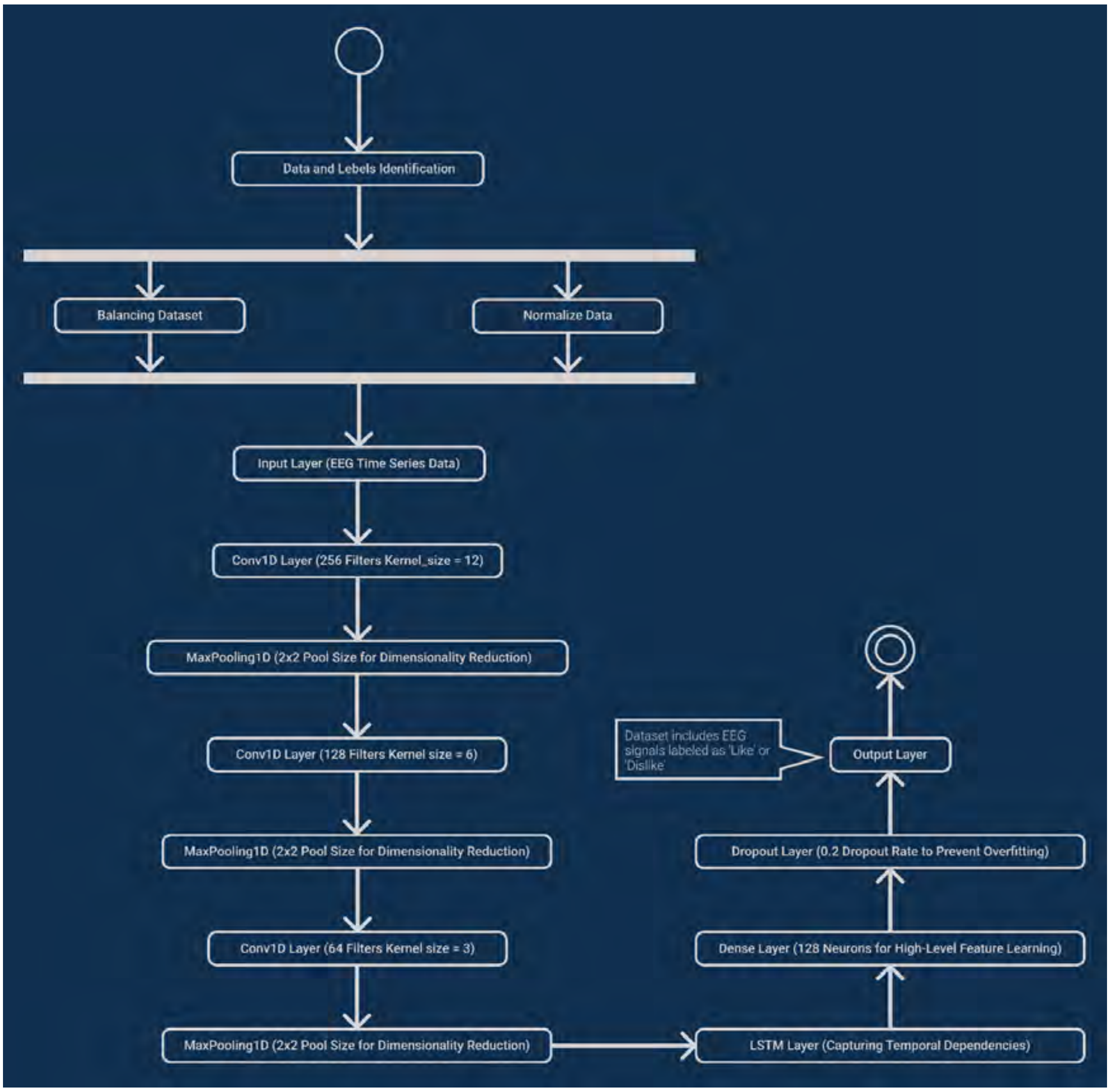


Figure 5.2: Proposed LSTM model Architecture

This architectural fusion harnesses the spatial feature extraction capabilities of CNNs and the sequential pattern recognition strengths of LSTMs. Again, this architecture is optimized using the Adam optimizer and categorical cross entropy as the loss function. As a result, our model is not only robust but also adaptable to a variety of sequential data scenarios.

## 5.6 Model Evaluation and Optimization

The evaluation and optimization of our proposed LSTM model constituted a crucial phase in our research. This process was not only methodical but also multidimensional. Besides, it encompasses a comprehensive assessment of the model's performance.

1. **Performance Metrics:**
   Our primary focus was on evaluating the model using key metrics such as accuracy, precision and recall. These metrics provided a quantitative measure of the model's effectiveness in handling EEG data.

2. **Optimization Techniques:**
   The model contains various aspects of fine tuning in the optimization process. Layer configuration , rates of learning and other hyper parameters are included in the layer configuration. This increases the accuracy and efficiency of this model.

3. **Graphical Analysis:**
   Graphical representations are used to show a clear and accurate understanding of the performance of the model. The benefits of visualizations in understanding model accuracy. The use of these aids helped. It helps quickly and tangibly perceive how well the model was functioning. It also represents the graph of the error rates and learning curves.

4. **Iterative Refinement:**
   The evaluation and optimization were iterative. In addition, it allows us to progressively refine the model. Besides, each iteration brought us closer to an optimal balance of precision and recall. Again, it ensures the model's robustness and reliability in real-world applications.

This meticulous process of evaluation and optimization has been pivotal in elevating our LSTM model's performance. As a result, it ensures that it not only meets but exceeds the standards required for sophisticated EEG data analysis.

# Chapter 6

# Results of the Model

In this section, we delve into the results obtained from the machine learning models trained on the preprocessed EEG data. The results are presented through various graphical representations that vividly illustrate the performance of the models.

## 6.1 LSTM Model

The LSTM (Long Short-Term Memory) model was one of the primary models utilized in this study. The architecture of the LSTM involved layers of 100 units. Again, the architecture dropout layers to prevent overfitting and a dense layer with a sigmoid activation function to output the predicted labels.

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{6.1}$$

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \tag{6.2}$$

$$g_t = \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \tag{6.3}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot g_t \tag{6.4}$$

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \tag{6.5}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{6.6}$$

The mathematical functions of a Long Short-Term Memory (LSTM) network are intended to aid in the learning and retention of knowledge over time. The LSTM manages the flow of information within its memory cell with input, output and forget gates. Further, it manages cell state updates. The input gate controls the storage of fresh information. Again, the forget gate regulates the retention of relevant prior knowledge. At the same time the output gate adjusts the output based on the cell state. These equations, which use sigmoid and hyperbolic tangent activations. Those equations allow LSTMs to capture and remember long-term dependencies while making them ideal for applications like sequential data analysis and time series prediction.

## 6.2 Logistic Regression Model

Apart from the LSTM model, a logistic regression model was also employed to classify the EEG data. The logistic regression model was optimized using a grid search approach to find the best hyperparameters.

### 6.2.1 Model Optimization

The optimization process involved tuning the regularization strength (C), penalty type, and solver. The best parameters obtained were C=0.001, penalty=l2, and solver=newton-cg. These parameters were used to train the final logistic regression model, which exhibited a good performance on the test data.

```
▾ LogisticRegression
LogisticRegression(C=0.001, solver='newton-cg')
```

## 6.3 Neural Network

A simple neural network with two hidden layers of 32 units each wehre a sigmoid activation function in the output layer was also explored. The model was trained using the Adam optimizer and binary crossentropy as the loss function.

## 6.4 Proposed Model

The performance of our Proposed LSTM Model was rigorously evaluated through a comprehensive training and validation process. This evaluation was pivotal in understanding the model's effectiveness and efficiency in handling sequential data particularly EEG data as we have worked with EEG data. Additionally, in our Proposed Model, it represents an advanced iteration of the LSTM architecture, specifically tailored for enhanced performance. In this model, we integrated a refined structure, featuring layers with adjusted unit counts. Additionally, we implemented strategic dropout layers for overfitting prevention. Lastly, we have added a dense layer with a tailored activation function to accurately output predicted labels.

### 6.4.1 Training and Validation Accuracy and Loss percentage

Throughout the training phase, we closely monitored the model's behavior using key metrics. The primary focus was on assessing accuracy and loss. It was a critical indicator of model performance. This process involved repeated iterations and adjustments. Also, this process is refined to optimize the model's learning capability. The model's efficacy was rigorously assessed during the training phase. We made some modifications with a keen focus on accuracy and loss metrics. The corresponding graphs, which will be included in this section. This graph delineates the training and validation accuracy and loss across epochs. These visual representations are crucial in illustrating the model's learning trajectory. Notably, our Proposed Model achieved a significant milestone in accuracy. It reached 81%, and maintained a loss of 19%. The graphs exhibit a consistent improvement in accuracy and a reduction in loss with underscoring a successful learning curve.

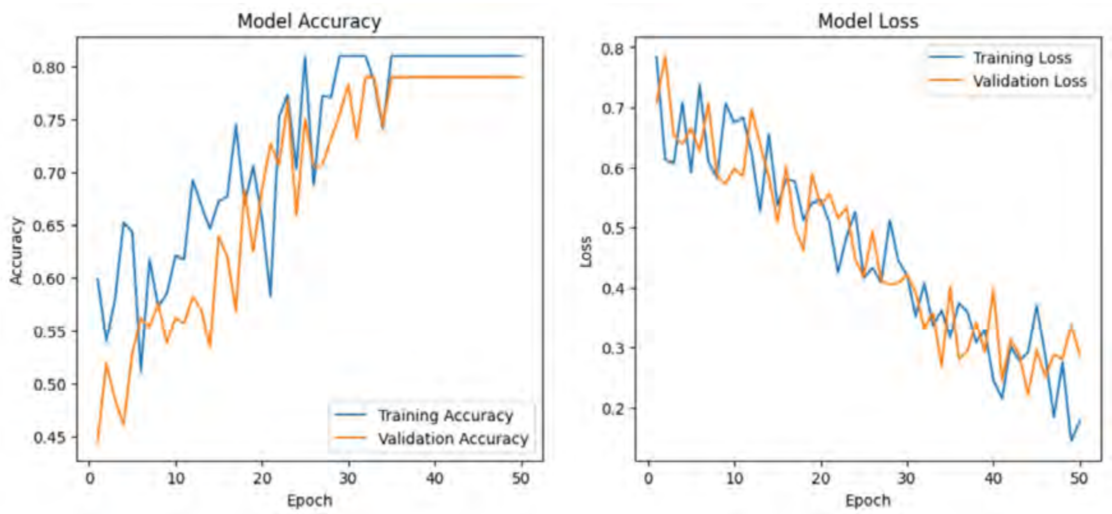


Figure 6.1: Proposed LSTM training and validation accuracy and loss

A significant milestone was reached with our proposed model. We achieved an accuracy rate of 81%. This high accuracy indicates the model's adeptness at correctly classifying EEG data. Concurrently, the model maintained a loss rate of 19%. The results indicate a successful adaptation of the LSTM model to our specific dataset. The steady improvement in key metrics over the epochs underscores the model's capability to learn and adapt effectively.

### 6.4.2 Mean Squared Error percentage

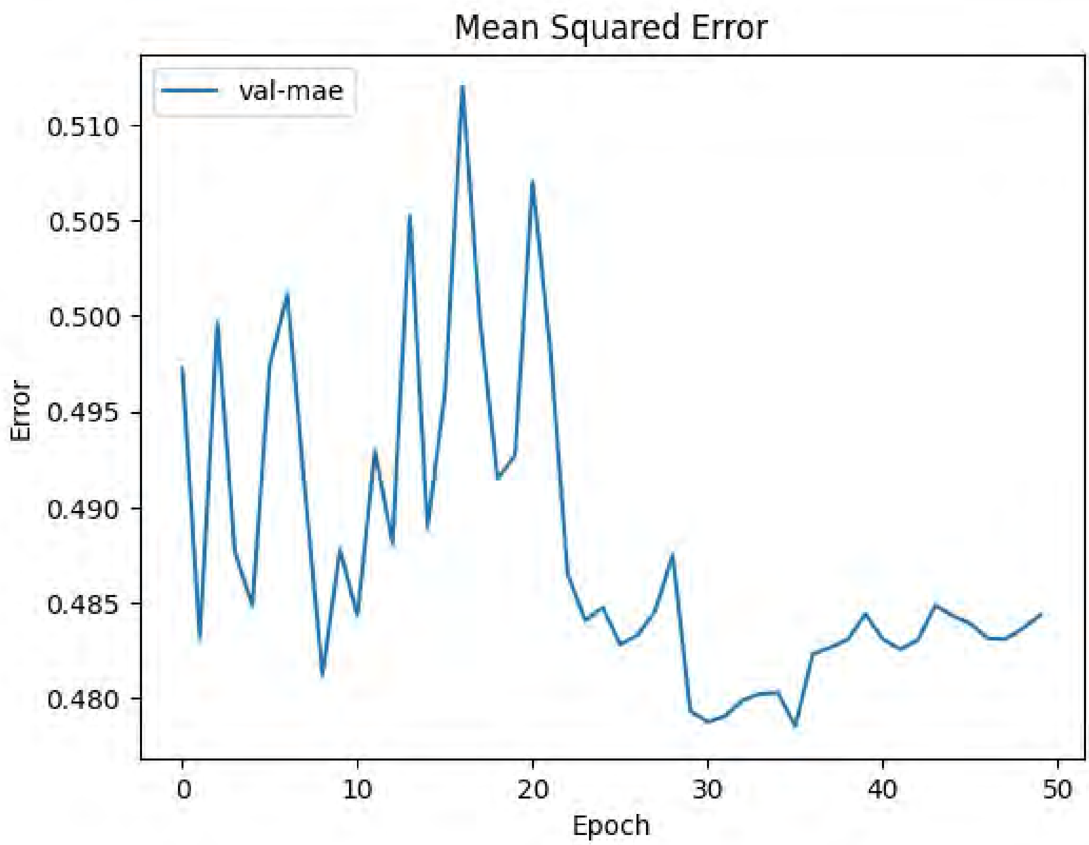


Figure 6.2: Mean Squared Error observation

Our proposed LSTM model works well for our task and the dataset we have selected where it achieved 81% accuracy. The model's loss is low at 0.19 which shows it learned effectively during training. Also, its Root Mean Squared Error (RMSE) is very low at 0.485. The low value of RMSE represents that it makes accurate predictions with few errors. Overall, these results show that the LSTM model is good at finding patterns and making accurate predictions for our dataset.

# Chapter 7

# Discussion

## 7.1 Model Performance and Graphical Analysis

In this section, we delve deep into the performance metrics of the models developed during our research. The LSTM, logistic regression and simple neural network models were subjected to rigorous testing to evaluate their performance. The LSTM model exhibited a promising performance. Also, the model was performed with the training and validation accuracy graphs. Concurrently, it showcases a steady increase in accuracy over the epochs. Besides, the loss graphs, on the other hand, depicted a consistent decrease. Again, it indicates the model's learning and adaptation capabilities. The graphical representations provided a vivid insight into the model's learning trajectory. Finally, it offers a visual testament to its performance.

## 7.2 Confusion Matrix Analysis

A critical aspect of our results section is the analysis of the confusion matrices generated during the model evaluations. The confusion matrix which is a vital tool in machine learning. In brief, it facilitated a detailed understanding of the true positive, true negative, false positive and false negative rates. The seaborn heatmaps offered a graphical representation of the confusion matrices. Further the heatmaps provide a clear visualization of the model's performance in classifying the 'like' and 'dislike' labels correctly.

**Confusion Matrix**
The confusion matrix is a pivotal tool in the realm of machine learning. Additionally, it offers a comprehensive visualization of a model's performance which is delineating both the correct and incorrect predictions made during the testing phase. In study of machine learning, confusion matrices were employed to evaluate the performance of the LSTM model, logistic regression model and the simple neural network.

**Understanding the Confusion Matrix**
Before delving into the individual matrices, it is pertinent to understand the components of a confusion matrix. Additionally, tt is a square matrix that consists of four values: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). These values represent the following:

- True Positive (TP): The instances correctly identified as positive by the model.
- True Negative (TN): The instances correctly identified as negative by the model.
- False Positive (FP): The instances incorrectly identified as positive by the model.
- False Negative (FN): The instances incorrectly identified as negative by the model.

The diagonal from the top left to the bottom right represents the correct predictions while the other diagonal represents the incorrect predictions.

**LSTM Model**

The LSTM model's confusion matrix vividly illustrates the number of correct and incorrect predictions made during the testing phase. The matrix provides a granular view of the model's ability to correctly identify the 'Like' and 'Dislike' labels from the EEG data.

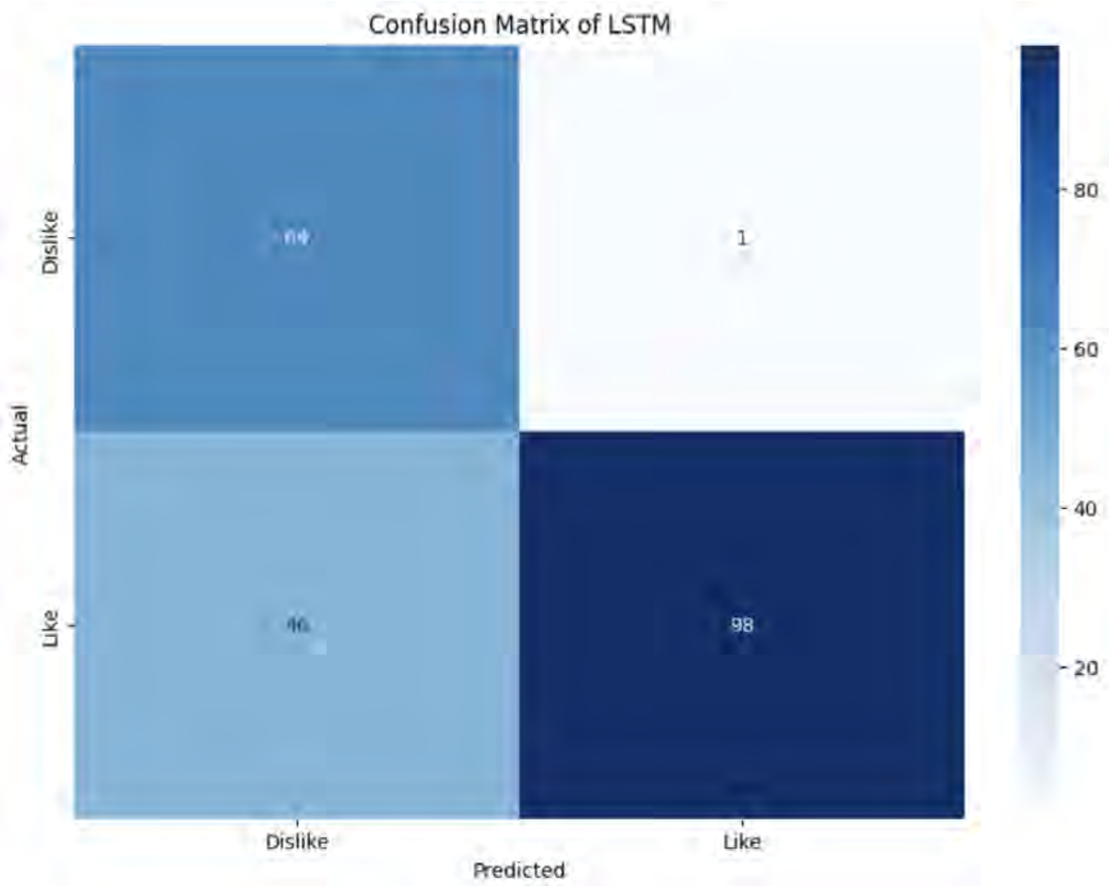


Figure 7.1: Confusion Matrix of LSTM Model

**Logistic Regression Model**

Similar to the LSTM model, the logistic regression model's confusion matrix delineates the true and false predictions for both classes. It serves as a testament to the model's classification prowess while offering insights into areas where the model excelled and where it faltered.

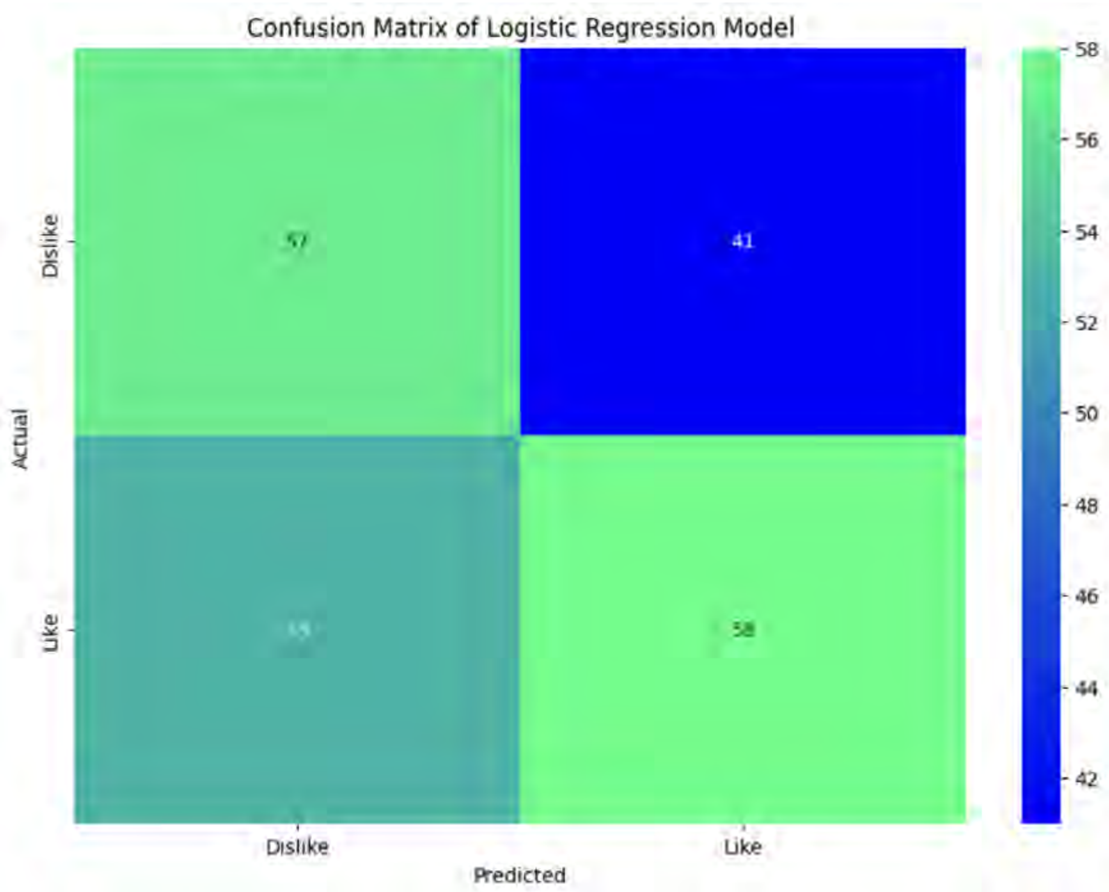


Figure 7.2: Logistic Regression confusion matrix

**Neural Network**
The confusion matrix for the simple neural network echoes the performance exhibited in the training and validation phases. Besides, it offers a detailed breakdown of the true and false predictions across both classes. This matrix aids in understanding the nuances of the network's classification capabilities.

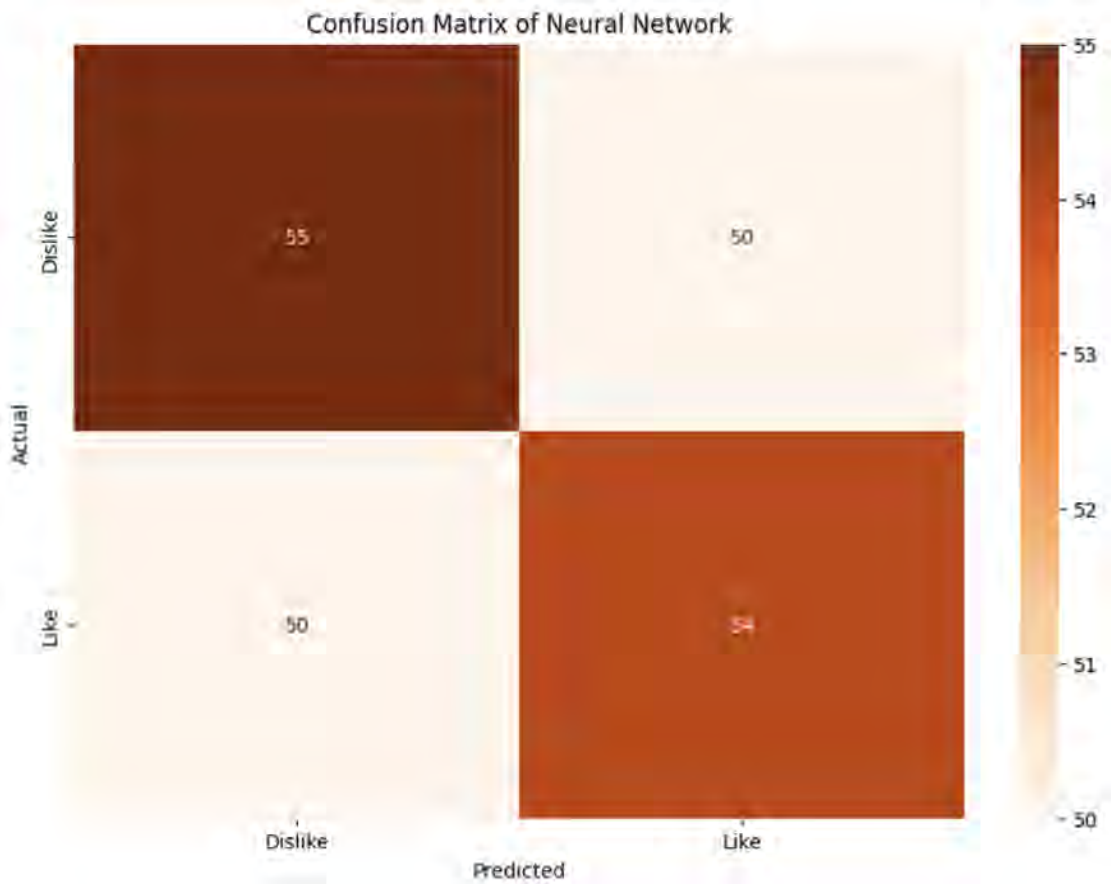


Figure 7.3: Simple Neural Network confusion matrix

**Proposed LSTM model**

The confusion matrix for our Proposed LSTM Model effectively highlights its predictive performance. This matrix showcases a detailed distribution of accurate and inaccurate predictions for each category. Also, it reflects the model's enhanced ability to interpret EEG data. It provides valuable insights into the model's precision. Again, it particularly distinguishes between different classes and illustrates the significant improvements achieved through our targeted modifications.

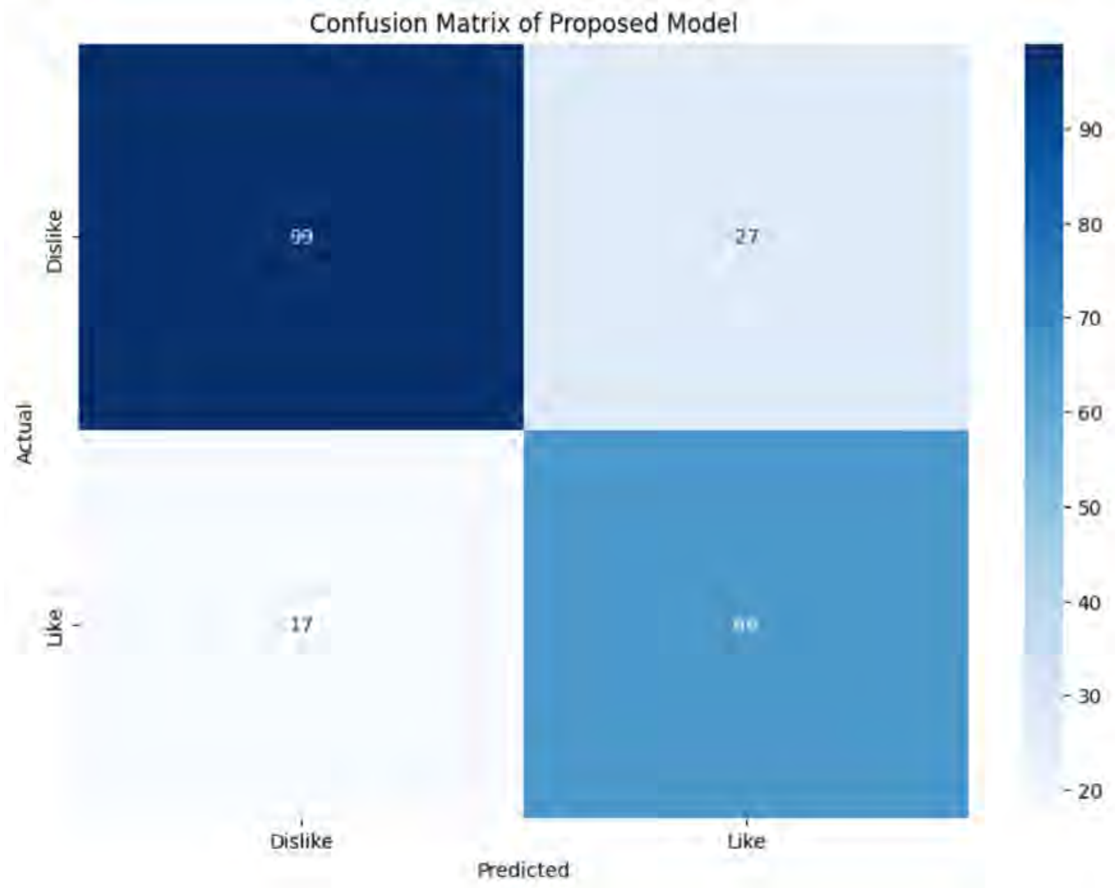


Figure 7.4: Proposed LSTM model confusion matrix

## 7.3 Accuracy Analysis

Our research ventured further to analyze the accuracy of the models in detail. This involved a meticulous examination of the accuracy metrics. It is also organized both in tabular and graphical formats. The bar charts and tables presented a clear depiction of the precision, recall, and F1 score metrics, offering a comprehensive view of the model's performance.

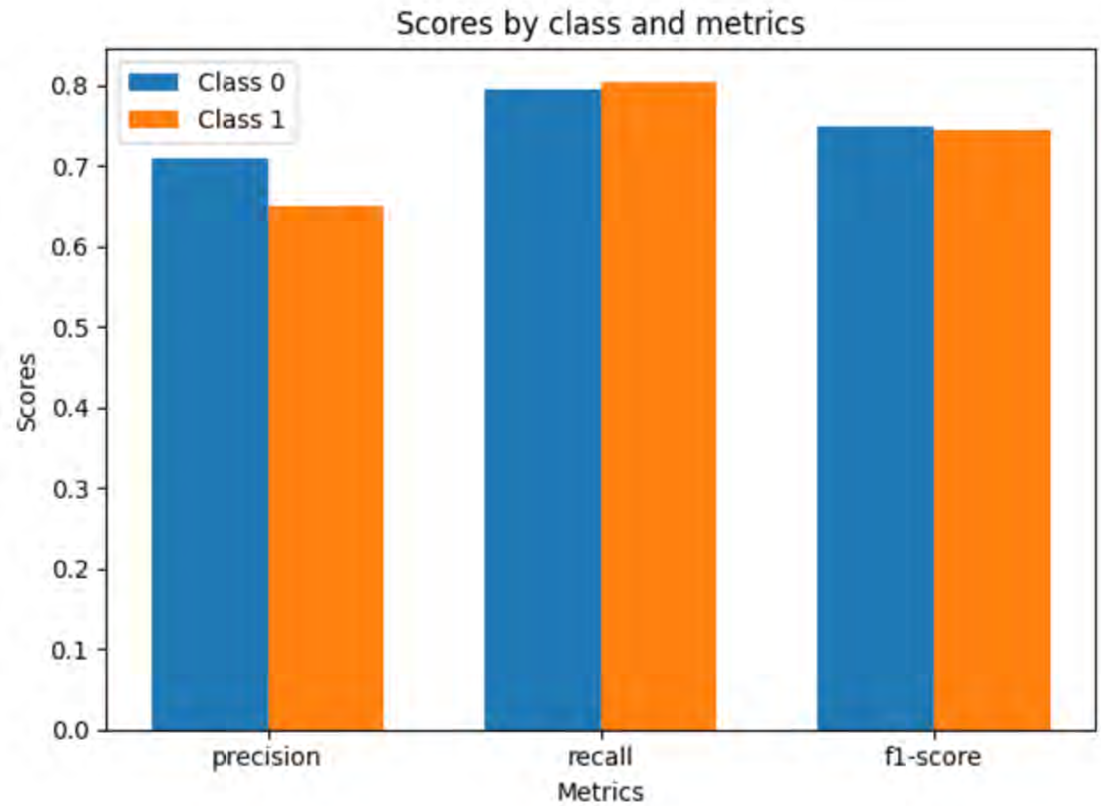


Figure 7.5: Accuracy Analysis: Scores by Class and Metrics

The accuracy analysis was further substantiated with classification reports. Moreover, it provided a detailed breakdown of the performance metrics for each class. The reports were visualized through bar charts which offered a graphical representation of the precision, recall and F1 scores for individual classes. As a result, it provides a detailed insight into the model's classification prowess.

## 7.4 Comparison with previous models

The properties of data which we have chosen and task requirements determine whether to use LSTM, linear regression or a basic neural network. LSTMs excel at capturing sequential dependencies. On the other hand, linear regression is appropriate for linear interactions. Also, the basic neural networks are adaptable across multiple domains while balancing complexity and interpretability.

| Models | Accuracy | Loss | RMSE |
|---|---|---|---|
| LSTM | 0.7815 | 0.2091 | 0.513 |
| Logistic Regression | 0.5561 | 0.4439 | 0.515 |
| Neural Network | 0.5284 | 0.4716 | 0.558 |
| **Proposed Model** | **0.8132** | **0.1868** | **0.481** |

Table 7.1: Comparison among LSTM, Logistic Regression, Simple Neural Network and our proposed model

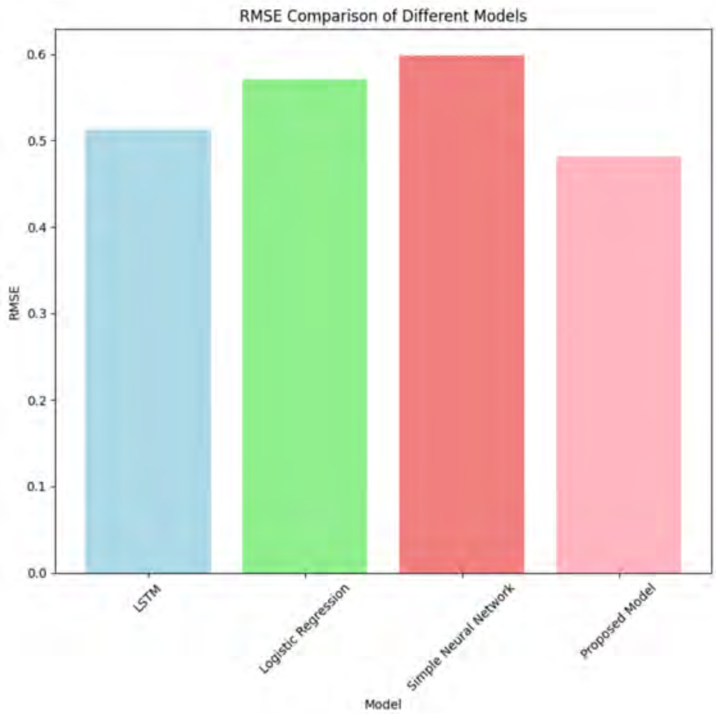


Figure 7.6: RMSE Analysis graph

The Proposed Model stands out as the top performer among all the models we've implemented. It achieved an impressive accuracy rate of 81.32% and coupled with the lowest loss at 18.68% . Also, the smallest RMSE (Root Mean Square Error) of 0.485. This performance indicates that our model is well-crafted and highly effective. Additionally, it delivers accurate predictions with minimal errors. As such, the Proposed Model surpasses all other models in every key metric which showcases its reliability and accuracy as a predictive tool for our specific task.

# Chapter 8

# Conclusion and Future Work

## 8.1 Conclusion

In this research, we embarked on an in-depth exploration of neuromarketing using EEG data to decode consumer behavior and preferences. Our study capitalized on a rich dataset derived from EEG readings of 25 participants. It provides a solid base for our comprehensive analysis.

Our journey encompassed meticulous data preparation, exploration, preprocessing and forming a strong foundation for the subsequent phases of our study. In addition, we initially considered a range of machine learning models. We include LSTM, logistic regression and simple neural networks. However, we found two models as the most effective tools for our specific dataset. One the modified LSTM model and another one is our "Proposed Model".

We tested various models but in the final phase of our research we identified our enhancement to the original LSTM architecture which gave us an outstanding accuracy of 81.32%, a low loss of 18.68%, and a minimal RMSE of 0.481. These results show the model's ability of accurate prediction and superiority of consumer preference based on EEG data

In this thesis, we can see the advanced usage of modified LSTM models in neuromarketing research. Our study contributions show that specific modification to machine learning models and significantly improve the performance in a complex dataset like EEG readings

In conclusion, our research represents the importance of model selection and optimization in neuromarketing to get more accurate, efficient and reliable consumer preference predictions using EEG data.

## 8.2 Future Work

As we stand on the threshold of a new era in neuromarketing. Moreover, the findings of this study pave the way for further exploration and development in this field. The following are some avenues that hold promise for future research:

- Data Augmentation: Expanding the dataset by including indicators from a larger population. As a result, it has the potential to improve models and provide a more general understanding of consumer preferences.
- Feature Engineering: We dig deeper into feature engineering. That will help us to discover more sophisticated attributes and can have a significant impact on a model's predictive accuracy.
- Hybrid Models: It explores the partnership between different machine learning algorithms. It helps to develop hybrid models that supports the strengths of individual algorithms to improve performance.
- Real-time Analysis: Developing a framework for real time analysis of EEG data. It enables instant feedback and insights that can be transformative in the marketing field.
- Personalized Marketing Strategies: Utilizing the insights derived from this research to craft personalized marketing strategies that resonate with individual preferences, paving the way for more targeted and effective marketing campaigns.

# Bibliography


[1] E. Mircia, S. Imre, T. Balaci, V. Avrigeanu, and G. Hancu, "Formulation and study of some controlled release tablets with pentoxifylline based on hydroxypropylcellulose matrix obtained by wet granulation method with peg 6000," *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, pp. 178–193, 2010.

[2] N. A. Pop, D.-C. Dabija, and A. M. Iorga, "Ethical responsibility of neuromarketing companies in harnessing the market research–a global exploratory approach," *Amfiteatru economic*, vol. 16, no. 35, pp. 26–40, 2014.

[3] H. Kumar and P. Singh, "Neuromarketing: An emerging tool of market research," *International Journal of Engineering and Management Research (IJEMR)*, vol. 5, no. 6, pp. 530–535, 2015.

[4] S. Karpova, "Innovative marketing: A textbook for undergraduate and graduate programs [innovatsionnyiy marketing: Uchebnik dlya bakalavriata i magistraturyi]," *M.: Publishing House Yurayt [Izdatelstvo Yurayt]*, vol. 457, pp. 25–30, 2016.

[5] W. Deng, X. Ling, Y. Qi, T. Tan, E. Manavoglu, and Q. Zhang, "Ad click prediction in sequence with long short-term memory networks: An externality-aware model," in *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, 2018, pp. 1065–1068.

[6] A. Stasi, G. Songa, M. Mauri, *et al.*, "Neuromarketing empirical approaches and food choice: A systematic review," *Food research international*, vol. 108, pp. 650–664, 2018.

[7] M. Hafez, "Neuromarketing: A new avatar in branding and advertisement," *Pac. Bus. Rev. Int*, vol. 12, no. 4, pp. 58–64, 2019.

[8] E. Harrell, "Neuromarketing: What you need to know," *Harvard Business Review*, vol. 97, no. 4, pp. 64–70, 2019.

[9] S. A. Khan and H.-T. Chang, "Comparative analysis on facebook post interaction using dnn, elm and lstm," *PloS one*, vol. 14, no. 11, e0224452, 2019.

[10] S. Kumar, M. Yadava, and P. P. Roy, "Fusion of eeg response and sentiment analysis of products review to predict customer satisfaction," *Information Fusion*, vol. 52, pp. 41–52, 2019.

[11] E. K. Zavadskas, R. Bausys, A. Kaklauskas, and S. Raslanas, "Hedonic shopping rent valuation by one-to-one neuromarketing and neutrosophic promethee method," *Applied Soft Computing*, vol. 85, p. 105 832, 2019.

[12] B. C. Iloka and K. J. Onyeke, "Neuromarketing: A historical review," *Neuroscience Research Notes*, vol. 3, no. 3, pp. 27–35, 2020.

[13] D. Juárez-Varón, V. Tur-Viñes, A. Rabasa-Dolado, and K. Polotskaya, "An adaptive machine learning methodology applied to neuromarketing analysis: Prediction of consumer behaviour regarding the key elements of the packaging design of an educational toy," *Social Sciences*, vol. 9, no. 9, p. 162, 2020.

[14] P. Nuñez-Gomez, A. Alvarez-Ruiz, F. Ortega-Mohedano, and E. P. Alvarez-Flores, "Neuromarketing highlights in how asperger syndrome youth perceive advertising," *Frontiers in psychology*, vol. 11, p. 2103, 2020.

[15] N. P. Parchure, S. N. Parchure, and B. Bora, "Role of neuromarketing in enhancing consumer behaviour," in *AIP Conference Proceedings*, AIP Publishing, vol. 2273, 2020.

[16] F. S. Rawnaque, K. M. Rahman, S. F. Anwar, *et al.*, "Technological advancements and opportunities in neuromarketing: A systematic review," *Brain Informatics*, vol. 7, pp. 1–19, 2020.

[17] N. A. Vences, J. Díaz-Campo, and D. F. G. Rosales, "Neuromarketing as an emotional connection tool between organizations and audiences in social networks. a theoretical review," *Frontiers in psychology*, vol. 11, p. 1787, 2020.

[18] A. H. Alsharif, N. Z. Md Salleh, R. Baharun, and A. Rami Hashem E, "Neuromarketing research in the last five years: A bibliometric analysis," *Cogent Business & Management*, vol. 8, no. 1, p. 1 978 620, 2021.

[19] A. Hakim, S. Klorfeld, T. Sela, D. Friedman, M. Shabat-Simon, and D. J. Levy, "Machines learn neuromarketing: Improving preference prediction from self-reports using multiple eeg measures and machine learning," *International Journal of Research in Marketing*, vol. 38, no. 3, pp. 770–791, 2021.

[20] V. Khurana, M. Gahalawat, P. Kumar, *et al.*, "A survey on neuromarketing using eeg signals," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 13, no. 4, pp. 732–749, 2021.

[21] A. Micu, A. Capatina, A.-E. Micu, M. Geru, K. A. Aivaz, and M. C. Muntean, "A new challenge in digital economy: Neuromarketing applied to social media.," *Economic Computation & Economic Cybernetics Studies & Research*, vol. 55, no. 4, 2021.

[22] D. Panda, D. D. Chakladar, and T. Dasgupta, "Prediction of consumer preference for the bottom of the pyramid using eeg-based deep model," *International Journal of Computational Science and Engineering*, vol. 24, no. 5, pp. 439–449, 2021.

[23] M. Zito, A. Fici, M. Bilucaglia, F. S. Ambrogetti, and V. Russo, "Assessing the emotional response in social communication: The role of neuromarketing," *Frontiers in psychology*, vol. 12, p. 625 570, 2021.

[24] R. Gill and J. Singh, "A study of neuromarketing techniques for proposing cost effective information driven framework for decision making," *Materials Today: Proceedings*, vol. 49, pp. 2969–2981, 2022.

[25] S. M. A. Shah, S. M. Usman, S. Khalid, *et al.*, "An ensemble model for consumer emotion prediction using eeg signals for neuromarketing applications," *Sensors*, vol. 22, no. 24, p. 9744, 2022.

[26] P. Varghese, "Neuromarketing and artificial intelligence for effective future business," *IUJ Journal of Management*, vol. 1, no. 1, pp. 240–254, 2022.

[27] J. S. AH, “Neuromarketing: How neuroscience can inform marketing,”

[28] A. Almasoudi, S. Baowidan, and S. Sarhan, “Facial expressions decoded: A survey of facial emotion recognition,” *International Journal of Computer Applications*, vol. 975, p. 8887,