JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Neuromarketing using Electroencephalography (EEG) signals and Machine Learning

Jonas Ninan Mathew
Department of Electronics and Telecommunication
MCT Rajiv Gandhi Institute of Technology
Mumbai, India

Harsh Kamble
Department of Electronics and Telecommunication
MCT Rajiv Gandhi Institute of Technology
Mumbai, India
harshkamble834@gmail.com

Mohit Patel
Department of Electronics and Telecommunication
MCT Rajiv Gandhi Institute of Technology
Mumbai, India

Sneha Burnase
Department of Electronics and Telecommunication
MCT Rajiv Gandhi Institute of Technology
Mumbai, India

Dr.Poonam Sonar
Department of Electronics and Telecommunication
MCT Rajiv Gandhi Institute of Technology
Mumbai, India

Abstract—In our research, we propose a practical methodology for product development by integrating electroencephalography (EEG) data with machine learning techniques. EEG signals provide a rich source of neurological data, offering insights into consumer behavior, preferences, and emotional responses to marketing stimuli.Utilizing advanced machine learning algorithms, including support vector machine (SVM), random forest classifier, k-nearest neighbors (KNN), convolutional neural network (CNN), and other classifiers, we aim to process and analyze EEG data to uncover hidden patterns, correlations, and predictive features. Notably, our SVM classifier achieved an accuracy of 98%, the random forest classifier attained 99%, the KNN classifier yielded 98%, and the CNN achieved 99% accuracy, demonstrating improved performance over prior research.This methodology facilitates a deeper understanding of consumer behavior compared to conventional marketing research methods. Practical applications include refining marketing strategies, product development, and advertising campaigns. By deciphering real-time neural responses, businesses can tailor their marketing efforts more effectively, resulting in increased customer engagement and satisfaction.Moreover, we address ethical considerations and privacy concerns associated with EEGbased neuromarketing, emphasizing the importance of upholding ethical principles and safeguarding data privacy in this evolving field.In summary, our study presents a practical and ethically sound approach to neuromarketing, leveraging EEG signal analysis and machine learning to transform how businesses comprehend and influence consumer behavior, while achieving superior accuracy rates compared to previous approaches.

Index Terms—neuromarketing, electroencephalography, electroencephalogram, machine-learning

I. Introduction

Neuromarketing, at its core, represents a groundbreaking fusion of neuroscience and marketing research methodologies. This innovative approach delves deep into the intricate workings of the human brain to decode consumer behavior and decision-making processes. By leveraging advanced technologies such as eye-tracking, facial coding, functional magnetic resonance imaging (fMRI), and electroencephalography (EEG), researchers can meticulously dissect how individuals respond to various marketing stimuli. Through these tools, they analyze sensory-motor actions, cognitive functions, and emotional reactions, providing unprecedented insights into consumer psychology. By deciphering the neural mechanisms underlying consumer preferences and purchasing behavior, companies can tailor their marketing strategies with unparalleled precision. Neuromarketing not only offers a glimpse into the subconscious motivations that drive consumer choices but also holds immense promise for revolutionizing the future of marketing research and strategy formulation. [1].

Neuromarketing, a burgeoning field at the intersection of neuroscience and marketing, employs sophisticated techniques such as Electroencephalography (EEG) to delve into the subconscious responses of consumers to marketing stimuli. By monitoring brainwave activity, researchers can decipher the intricate neural processes underlying consumer behavior, revealing invaluable insights into emotional and cognitive reactions triggered by marketing materials. Through meticulous analysis of EEG data, patterns emerge elucidating which aspects of marketing campaigns resonate most profoundly with individuals. These insights empower businesses to refine their advertisements, tailor product designs, and fine-tune overall marketing strategies to align more effectively with consumers' neuro-logical predispositions. Consequently, by tapping into the neural under-pinnings of consumer decisionmaking, neuro-marketing facilitates the creation of more compelling and resonant marketing experiences, ultimately fostering deeper connections between brands and their target audiences. Thus, the integration of neuroscientific methodologies in marketing holds immense significance, revolutionizing the traditional approaches to understanding and influencing consumer behavior in the competitive land-scape of contemporary business.

Neuromarketing offers a revolutionary approach to understanding consumer behavior and preferences, unlocking invaluable insights by delving into the intricate workings of neural responses. By deciphering the subconscious cues and emotional triggers that influence decision-making, businesses gain a profound understanding of their target audience, enabling data-driven marketing decisions. This deeper comprehension empowers the creation of highly effective strategies that resonate on a profound level, fostering stronger connections and engagement with consumers. Moreover, neuromarketing extends its impact beyond just advertising; it informs product development, allowing companies to tailor offerings precisely to consumer desires. By aligning products with neurological preferences, businesses can create more appealing and marketable products. Additionally, neuromarketing plays a pivotal role in branding and positioning, as it facilitates the crafting of strategies that leverage emotional and subconscious associations, thus building strong and memorable brands. Practical applications of neuromarketing insights lead to improved return on investment (ROI) by optimizing marketing efforts based on neuro-scientific data, resulting in more efficient and costeffective campaigns that ultimately benefit the bottom line. In essence, neuromarketing revolutionizes the way businesses understand, connect with, and cater to their target audience, driving success across various facets of marketing and product development. [2]

II. Literature Survey

The study introduces an innovative model merging data mining and machine learning algorithms to delve into consumer behavior using EEG signals. By extracting features related to time-frequency distribution from these signals, the research aims to understand how consumers respond to marketing strategies and make purchasing decisions. EEG data from 25 individuals spanning different ages and genders are gathered to provide comprehensive insights into consumer behavior across demographics. Through meticulous analysis, the study elucidates the factors driving individuals' preferences for specific marketing policies. Notably, the proposed model surpasses existing techniques, boasting a remarkable 95 percent accuracy rate compared to the prior 70 percent. Furthermore, the research delves into whether neuro-psychological measures can discern variations in consumer actions triggered by diverse marketing stimuli. Experimental results suggest promising prospects for advancing this field, potentially revolutionizing marketing strategies to the benefit of both producers and consumers. This interdisciplinary approach underscores the profound potential of integrating neuroscience with marketing, offering a deeper understanding of consumer behavior and paving the way for more effective marketing tactics in the future. [1].

Since the emergence of the Covid-19 pandemic, also known as Coronavirus, there has been a notable surge in the utilization of eCommerce platforms as consumers increasingly turn to online channels for purchasing goods and services. In response to this trend, researchers have delved into innovative methodologies to delve into the intricacies of consumer behavior, particularly focusing on capturing the underlying emotions during these digital transactions. Among the arsenal of techniques in neuro-marketing, two prominent approaches have emerged: neuroimaging and nonneuroimaging methods. Neuro-imaging methodologies, such as electroencephalogram (EEG), have garnered significant attention from researchers due to their ability to offer unbiased insights into consumers' brain activities, circumventing the limitations of conventional methods like surveys or interviews. This review critically examines prior studies that have employed neuroimaging techniques, with a particular emphasis on EEG, to unravel the complexities of neuro-marketing phenomena in the context of online transactions. Through an exploration of these studies, a deeper understanding of the neural mechanisms underlying consumer behavior in the digital landscape can be gleaned, offering valuable insights for marketers and businesses striving to optimize their online strategies in an ever-evolving market environment shaped by the Covid-19 pandemic. [3].

A groundbreaking study has introduced a novel technique for assessing consumers' reactions to advertisements and products by utilizing EEG signals. Volunteers, predominantly aged between 18 and 22, participated in the study, wearing a low-cost headset to record these neurological signals. The research employed both subject-dependent (SD) and subjectindependent (SI) analyses, employing various machine learning method-ologies including Naive Bayes (NB), Support Vector Machine (SVM), k-nearest neighbor, Decision Tree, and a newly proposed deep learning (DL) model. In the subject-dependent analysis, SVM and NB exhibited an accuracy of 0.63. Remarkably, SVM outperformed other techniques in the subject-independent analysis, particularly excelling in discerning responses to advertisements, products, and genderbased differences. Moreover, the DL model demonstrated comparable efficacy to SVM, notably in the analysis of products and advertisements. This pioneering approach holds significant promise in understanding consumer behavior, offering insights that can potentially revolutionize marketing strategies and product development. [4].

In the realm of neuromarketing, researchers delve into the intricacies of consumer behavior by leveraging physiological and neural signals to uncover underlying motivations and interests. This multidimensional approach offers insights crucial for the development of innovative marketing strategies, products, and pricing models. Through techniques such as brain scanning, which scrutinizes neural activity, and physiological tracking, which encompasses observations of eye movement, heart rate, and skin conductivity, researchers gain a holistic view of consumer responses. In a recent study cited by Kao et al., electroencephalogram (EEG) and functional near-infrared spectroscopy (fNIRS) are combined with galvanic skin response (GSR) and heart rate variability (HRV) [5] measurements to investigate the influence of different product colors on consumer preferences. This integration of diverse data streams enables a comprehensive analysis of consumer behavior. To distill meaningful insights from this rich dataset, sophisticated machine learning algorithms like k-nearest neighbor (kNN) and support vector machine (SVM) are deployed. These algorithms facilitate a deeper understanding of consumer choices by discerning patterns and relationships within the data, ultimately empowering marketers to tailor their strategies more effectively to consumer preferences and tendencies. [6].

Neuromarketing is a growing field of study, largely driven by the substantial amount of money spent annually on advertising and promotion, totaling around 400 billion US dollars. Even small improvements in marketing effectiveness can have significant financial impacts due to the size of this market. Traditional marketing methods typically rely on postpurchase feedback such as surveys or product reviews, but these don't fully capture the real-time decision-making process of consumers. To address this gap, researchers have turned to physiological measurement techniques, including brain imaging (such as fMRI, EEG, and SST) and biometric sensors. EEG, in particular, shows promise in neuromarketing as it can detect changes in brain activity quickly and accurately, providing insights into both unconscious and sensory reactions of consumers. Various EEG devices are accessible, each with distinct advantages and drawbacks, and researchers have conducted experiments across diverse demographics and product categories. Nevertheless, ethical considerations are pivotal, and both consumer and research protection groups vigilantly oversee neuromarketing studies to safeguard participant wellbeing. This article delves into several facets of EEG-based neuromarketing strategies, encompassing data types gathered, stimulus presentation techniques, impacts on consumer appeal and memory, machine learning utilities, and hurdles like ethical concerns. [7].

This paper intends to explore the functions, mechanisms, and generation process of different brainwaves in humans, as well as the utilization of non-invasive EEGs for detecting the electrical activity within the brain. The goal is to understand how this information can be applied in real-time neuro marketing applications through EEG signal classification. The paper will compare the effectiveness of different algorithms used for signal classification, utilizing the EEGLAB tool implemented in MATLAB. [8].

III. Objective

Neuromarketing projects aim to utilize neuroscience techniques to understand consumer behavior, emotions, and decision-making processes. The objectives outlined focus on leveraging neuroscientific insights to enhance various aspects of marketing strategies, consumer experience, and overall business performance. Let's delve deeper into each objective:

A. Consumer Insight

By gaining a deeper understanding of consumer preferences, motivations, and responses to marketing stimuli, businesses can tailor their offerings more effectively. Through techniques like EEG data analysis, marketers can uncover subconscious desires and motivations that traditional market research methods might overlook. This deeper under-standing enables companies to develop products and services that better meet consumer needs and desires, ultimately leading to increased customer satisfaction and loyalty.

B. Optimizing Marketing Strategies

Tailoring marketing campaigns, products, and services to resonate with consumers' sub-conscious desires and emotions is key to optimizing marketing strategies. Neuromarketing techniques allow businesses to identify which elements of their marketing efforts elicit positive neuro-logical responses in consumers. By optimizing these elements, such as visual cues, messaging, and branding, companies can create more compelling and persuasive marketing materials that drive engagement and conversion.

C. Enhancing User Experience

Improving the design, presentation, and overall experience of products or services to align with consumers' neurological responses is crucial for enhancing user experience. By utilizing insights from brain imaging or biometric measurements, businesses can identify areas where the user experience can be optimized to better meet consumer needs and preferences. This could involve refining product features, streamlining user interfaces, or personalizing interactions to create more enjoyable and satisfying experiences for consumers.

D. Measuring Emotional Responses

Utilizing brain imaging or biometric measurements to gauge emotional reactions to marketing stimuli provides valuable insights into how consumers engage with brands and products on an emotional level. By understanding the emotional impact of marketing materials, businesses can create more emotionally resonant campaigns that forge stronger connections with consumers. This can lead to increased brand affinity, customer loyalty, and ultimately, higher sales and revenue.

E. Improving Engagement and Sales

Using insights from neuroscientific research to increase customer engagement and drive sales involves leveraging the findings to create more compelling and effective marketing tactics. By understanding how consumers' brains respond to different stimuli, businesses can tailor their marketing efforts to capture attention, evoke positive emotions, and ultimately influence purchasing decisions. This can lead to higher levels of engagement with marketing materials, increased conversion rates, and ultimately, improved sales performance.

F. Predicting Consumer Behavior

Forecasting consumer behavior by understanding neural processes allows businesses to develop more accurate predictions and strategies. By analyzing brain responses to marketing stimuli, companies can gain insights into consumers' preferences, attitudes, and decision-making processes. This enables businesses to anticipate trends, identify emerging opportunities, and adapt their marketing strategies accordingly to stay ahead of the competition.

Overall, these objectives highlight the transformative potential of neuromarketing in informing strategic decision-making, enhancing customer experiences, and driving business growth in today's increasingly competitive marketplace.

IV. Problem Statement

Traditional marketing methods are not always effective, as people can lie or act accordingly which can alter the genuine preferences of the consumers. Neuromarketing can be used to understand the brain's response to marketing strategies, so that more effective marketing campaigns can be created. EEG can be used to measure brain waves in response to different marketing stimuli, such as images, videos, and text. This information can be used to identify which stimuli are most effective in eliciting positive emotions and influencing purchase decisions.

V. Methodology

The project embarks on a journey through the intricate realm of human emotions using state-of-the-art EEG technology. By employing a commercially available MUSE EEG headband equipped with four dry extra-cranial electrodes, it delves deep into the dynamics of brainwave activity underlying emotional responses. With meticulous recordings gathered from subjects experiencing a spectrum of emotions including positive, negative, and neutral states, the project meticulously captures the essence of 36 minutes of raw brain activity. Through sophisticated signal processing techniques such as Fast Fourier Transform (FFT), Min-Max method, etc it seeks to unveil the hidden patterns within the EEG signals' frequency-domain characteristics. Ultimately, this endeavor aims to shed light on the intricate neural mechanisms governing human emotions, offering profound insights into the complexities of the human mind.

VI. Block Diagram

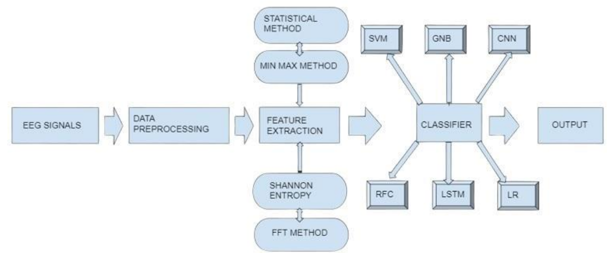

Fig. 1. Block Diagram

VII. Selection of headset

The decision to opt for EEG headbands over traditional EEG devices was driven by a holistic consideration of various factors. Primarily, the limitations posed by traditional EEG setups, characterized by their intricate wiring, bulky equipment, and discomfort during outdoor use, prompted the exploration of more user-friendly alternatives. Unlike their cumbersome counterparts, EEG headbands offer a sleek and portable solution, boasting a minimalist design equipped with just a few dry electrodes. This streamlined approach eliminates the need for cumbersome caps, cables, and conductive gels, significantly enhancing user comfort and overall usability.

In our research endeavors, we selected the Muse headband, crafted by InteraXon, as our EEG headband of choice. Notably, the Muse headband adheres to the internationally recognized 10-20 electrode placement standard, ensuring consistent and reliable positioning of electrodes for accurate brain activity measurement. Moreover, its deliberate design prioritizes userfriendliness and accessibility, making it an ideal candidate for widespread adoption among both researchers and the general public. The Muse headband's affordability and non-intrusive nature further underscore its suitability for our research objectives.

To collect EEG data, we strategically positioned four dry electrodes outside the skull, aligning them with the electrode

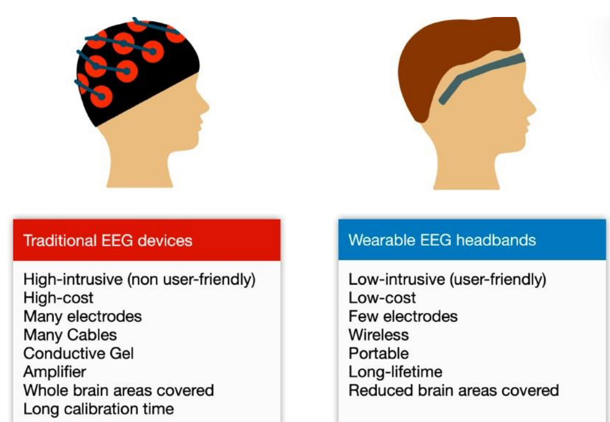

Fig. 2. Types of EEG headsets

positions of the Muse headband (TP9, AF7, AF8, and TP10). This configuration facilitated seamless data collection without the need for invasive procedures or extensive setup preparations. The collected data, resampled to a frequency of 150Hz, provided rich insights into brainwave activity, allowing us to capture intricate patterns associated with motor imagery tasks with exceptional precision.

Overall, the adoption of EEG headbands, particularly the Muse headband, represents a significant advancement in neuroimaging technology, offering a practical and accessible solution for investigating motor imagery tasks. By leveraging the convenience and portability of EEG headbands alongside advanced machine learning techniques, our research endeavors aim to revolutionize the classification of motor imagery within short timeframes. This innovative approach holds promise for real-time applications in healthcare and beyond, paving the way for enhanced patient care and personalized interventions.

VIII. About the Dataset

The study employed four dry electrodes positioned externally on the skull, employing a commercially procurable MUSE EEG headband. Voltage readings were obtained from designated electrode sites: TP9, AF7, AF8, and TP10. Data acquisition lasted for sixty seconds during each of the six video segments, culminating in a total of twelve minutes (720 seconds) of neural activity recordings per participant. Two individuals, one male and one female aged between 20 and 22, were recruited for the research. Additionally, six minutes of baseline brainwave data were gathered, resulting in a cumulative EEG dataset of 36 minutes per subject [9]. The dataset was resampled to a variable frequency of 150Hz, yielding 324,000 data points representing brainwave patterns. The stimuli utilized aimed to elicit emotional reactions classified as positive or negative, eschewing specific emotions. Neutral data were also collected to establish a baseline emotional state devoid of external stimuli, acquired prior to the emotional stimuli to prevent contamination. Each day, three minutes of data were collected to mitigate the impact of participants' underlying emotional states. [10]. The 'mean' columns likely represent mean values or statistical measures related to different aspects of the EEG brainwave data. The subscripts '0' to '4' and 'd0' to 'd4' might denote different frequency bands or other characteristics of the EEG signals. The "fft" columns may represent features obtained using Fast Fourier Transform (FFT) on the EEG data, likely capturing frequency-domain characteristics of the brainwave signals. label: This column represents the label or category associated with each data entry, indicating the emotional state or sentiment, such as "NEGATIVE," "NEUTRAL," or "POSITIVE." Each row in the dataset seems to represent a specific sample or recording of EEG brainwave data, with the corresponding mean and FFTbased features for different frequency bands, along with the associated emotional label. [11]

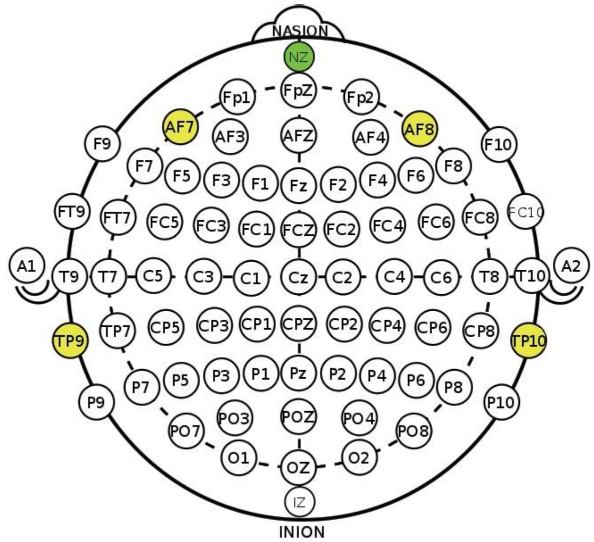

Fig. 3. The International 10-20 EEG Electrode Placement Standard is a widely recognized method for positioning electrodes on the scalp to measure brain activity. The Muse headband, which incorporates EEG sensors, follows this standard, with its sensors highlighted in yellow. The NZ placement serves as a reference point for calibration purposes, ensuring accurate measurements of brain signals. [10]

IX. Data Collection

In our data collection endeavors, we rely on electroencephalography (EEG) as the corner-stone for capturing the intricate dynamics of brain activity. By strategically situating electrodes on the scalp, we can detect and document the electrical signals generated by neural cells. This process provides us with a direct insight into the inner workings of the brain, affording us the opportunity to observe and analyze the nuanced responses evoked by various marketing stimuli.

Throughout the data collection phase, participants are immersed in a diverse array of marketing strategies, encompassing everything from advertisements and product imagery to packaging designs. As participants engage with these stimuli, we meticulously record their brain activity in real-time. This meticulous approach to data collection forms the bedrock of our research, furnishing us with invaluable insights into how the human brain reacts to different facets of marketing.

The importance of this data collection process cannot be overstated. It not only facilitates the exploration of the intricate relationship between marketing stimuli and neural activity but also deepens our comprehension of consumer behavior and decision-making mechanisms. By decoding the neural signatures associated with marketing engage-ment, we gain access to latent motivations, preferences, and cognitive processes that shape consumer responses.

Ultimately, the data garnered through EEG serves as a potent instrument for unraveling the multifaceted landscape of consumer psychology. It empowers us with the knowledge and understanding required to craft more impactful marketing strategies, tailor offerings to align with consumer desires, and drive organizational success in today's fiercely competitive market milieu. [12]

X. Feature Extraction

The preprocessing of raw EEG data is crucial for extracting pertinent features amidst its inherent complexity and noise. Techniques such as isolating frequency bands (alpha, beta, theta waves), detecting event-related potentials (ERPs), and analyzing coherence patterns across brain regions are vital steps. In the realm of brain-computer interface (BCI) applications, the extraction and classification of EEG signals pose significant challenges due to their nonlinear, non-stationary, and random nature. These signals exhibit stationarity only over short intervals, necessitating the use of short time windowing techniques, albeit with limitations during changes in mental states like alertness, wakefulness, and eye blinking.

This study focuses on delineating various mental states by employing a range of features computed using statistical techniques, Fast Fourier Transform (FFT)-based time-frequency analysis, min-max methods, and log-covariance. Features are calculated within 1-second temporal windows at a sampling rate of 250 Hz, with a 0.5 overlap between consecutive windows (e.g., w1, w2, w3). These windows encapsulate specific time intervals for feature computation, covering frequencies such as alpha, beta, gamma, delta, and theta obtained from the EEG signals. Consequently, a total of 2549 feature values are derived, contributing to the discrimination of distinct mental states.

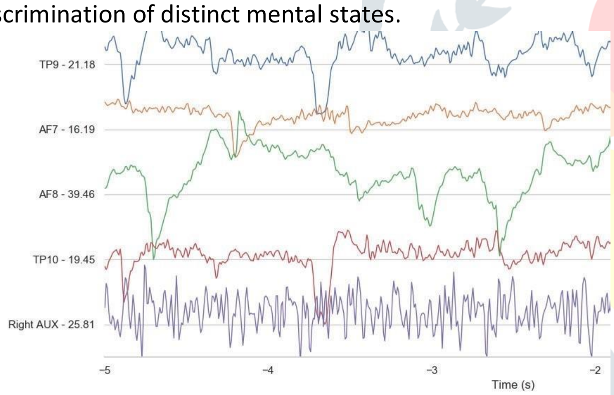

Fig. 4. The EEG data stream from the four Muse sensors is being displayed live. The Right AUX sensor was inactive and therefore excluded from the graph as it only produced noise. The Y-axis represents the measured microvolts at the initial time point for each sensor, while the X-axis shows the progression of time. [10]

A. Statistical method

To condense the raw sensor data within a specific timeframe, we employ a selection of traditional statistical characteristics. These metrics are known for their effectiveness in enhancing the analysis of time series data, alongside other diverse features, aiding in the identification of patterns. The statistical features are as follows:

- Given a dataset comprising values x1, x2, ..., xn obtained within a temporal window, the mean value of the sequence is calculated as follows. Here, denotes the population mean, M represents the total number of data points in the dataset, and xi denotes each individual data point. The summation symbol signifies the summing up of all data points (xi) from i = 1 to M.. [10]

$$\mu = \frac{1}{M}\sum_{k=i}^{M} x_i \tag{1}$$

- The standard deviation denoted as

$$\sqrt{\frac{1}{M}\sum_{i}^{M}(x_i-\mu)^2} \tag{2}$$

- Skewness and kurtosis, essential measures in analyzing data asymmetry and peakedness, are computed using the third and fourth order statistical moments. These moments are pivotal in assessing data characteristics and are represented as follows:

$$y = \frac{\mu^k}{\sigma^k} \tag{3}$$

$$\mu^k = \frac{1}{M}\sum_{i}^{M}(x_i-\mu)^k \tag{4}$$

B. Min-Max method

Each 1-second duration is subsequently split into two equal halves, leading to sequences of data sampled at roughly 125 Hz. This approach enables the distinction between the initial and latter halves of the original 1-second period. [12] A similar methodology is applied to derive the maximum and minimum features within sub-time windows:

$$uv = \frac{\mu^w - \mu^{w/2}}{2} \tag{5}$$

$$\max_t = \frac{\max^w - \max^{w/2}}{2} \tag{6}$$

$$\min_t = \frac{\min^w - \min^{w/2}}{2} \tag{7}$$

C. Log-covariance method

After analyzing the initial 150 temporal features, we decided to exclude the last 6 features. This brings the total down to 144 features, allowing us to construct a square matrix with dimensions of 12 by 12. We use this matrix to calculate the log-covariance. [13] $lcM = U(\log m(\text{cov}(M)))$ (8)

$mean_{0a}$	$mean_{1a}$	$mean_{2a}$	$mean_{3a}$	$mean_{4a}$
4.62	30.3	35	15.6	26.3
28.8	33.3	32	25.8	22.8
8.9	29.4	41	16.7	23.7
14.9	31.6	14	19.8	24.3
28.3	31.6	45	27.3	24.5
31	30.9	29.6	28.5	24
10.8	21	44.7	4.87	28.1
17.8	27.8	10.2	16.9	26.9
11.5	29.7	34.9	10.2	26.9

TABLE I
Feature extracted EEG dataset

D. Shannon Entropy Method

Non-linear analysis methods like Shannon entropy are widely used in signal processing and time series analysis because they effectively capture the randomness inherent in non-linear data. Entropy serves as a measure of uncertainty, and in applications such as brain-machine interfaces, it helps quantify the level of chaos within a system, reflecting the complexity of the data. Shannon entropy, a fundamental concept in information theory, is utilized in this context. Specifically, in the computation of entropy, denoted as 'h', each time window of 1 second is analyzed. The elements within each window, denoted as 'S', are normalized.The temporal window undergoes division into two segments for the computation of log-energy entropy. In this context, 'i' denotes the index for elements within the initial sub-window (0-0.5 seconds), whereas 'j' signifies the index for elements within the subsequent subwindow (0.5-1 seconds).. [14]

$$h=-\sum_{j} S_{j} \times \log \left(S_{j}\right) \tag{9}$$

$$\log e=\sum_{i} \log \left(S_{i}^{2}\right)+\sum_{j} \log \left(S_{j}^{2}\right) , \tag{10}$$

E. Fast Fourier Transform

The Fast Fourier Transform (FFT) is a useful technique for analyzing the frequency spectrum of a given set of data collected over time. It involves breaking down the data into its constituent frequencies within specified time intervals as follows. [14]

$$X_{k}=\sum_{n=0}^{M-1} S_{n}^{t} e^{-i 2 \pi k \frac{n}{M}}, k=0, \ldots, M-1 \tag{11}$$

The raw dataset consists of the readings captured from the muse electrode which is passed through the feature extraction algorithm like mean, standard deviation, log covariance, eigen vector and fast fourier transform. The raw data set is first sampled using the short windowing technique. The output is the feature extracted data which is then fed to the classifier model.

XI. Data Labelling

The process of data labeling in neuromarketing is fundamental for constructing predictive models aimed at understanding consumer behavior. Participants' responses to marketing stimuli, including emotional engagement, attention, and preference categorization (positive, negative, or neutral), are meticulously recorded and annotated. This labeling process captures the nuanced nuances of consumer reactions and lays the groundwork for subsequent model development.

Labeled data plays a crucial role in facilitating supervised learning algorithms to discern patterns between EEG-derived features and consumer responses. Each data point is annotated with the corresponding consumer reaction, enabling machine learning models to learn from examples and extract predictive insights. This iterative process imbues the models with the ability to anticipate consumer reactions based on underlying brain activity patterns, unlocking deeper understandings of consumer preferences and decision-making processes.

XII. Model Training

Following the meticulous labeling of EEG data, machine learning algorithms embark on a transformative journey of knowledge acquisition and pattern recognition during model training. Support Vector Machines (SVM), Random Forest, and Deep Learning architectures are enlisted to traverse the vast landscape of neuroscientific data in pursuit of predictive insights.

During training, these algorithms leverage the annotated EEG data to establish connections between features and consumer reactions, honing their predictive prowess through iterative optimization. The goal is to distill underlying patterns and correlations within EEG signals, culminating in the creation of robust predictive frameworks.

The ultimate objective of model training in neuromarketing is to craft predictive models capable of discerning nuances in consumer behavior based on neural activity patterns. By harnessing the predictive capabilities of machine learning, researchers aim to unlock actionable insights into consumer preferences, emotional responses, and decision-making processes, revolutionizing marketing strategies and driving sustainable growth.

A. Random Forest Classifier

In our project, the Random Forest classifier serves as a cornerstone in decoding consumer responses derived from EEG signals. By constructing multiple decision trees during the training phase, this classifier effectively captures the intricate relationships between various brainwave patterns and consumer preferences. The ensemble learning approach employed by Random Forest not only provides valuable insights into the importance of different EEG features but also ensures the model's robustness against overfitting. This robustness is particularly crucial in handling the inherent complexity and noise present in EEG data. Moreover, the scalability and efficiency of Random Forest enable us to analyze large-scale EEG datasets with ease, facilitating a comprehensive exploration of consumer behavior. By leveraging the predictions from multiple decision trees, we enhance the accuracy and flexibility of our model, thus enabling us to uncover nuanced insights that drive targeted marketing strategies tailored to individual consumer preferences.

B. Convolutional Neural Network

In our neuromarketing project, Convolutional Neural Network (CNN) classifiers play a pivotal role in efficiently decoding consumer responses derived from EEG signals. Unlike traditional machine learning approaches, CNNs are specifically designed to extract relevant features from spatial data, making them particularly well-suited for analyzing EEG signals that exhibit complex spatial patterns. By automatically learning hierarchical representations of brain activity patterns associated with consumer preferences, CNNs enable us to uncover subtle nuances in neural responses to marketing stimuli. Their robustness to variability in EEG data further enhances our ability to generalize findings across diverse consumer populations. Additionally, the interpretability of CNN outputs provides valuable insights into the neural underpinnings of consumer behavior, guiding the development of targeted marketing strategies tailored to individual preferences.

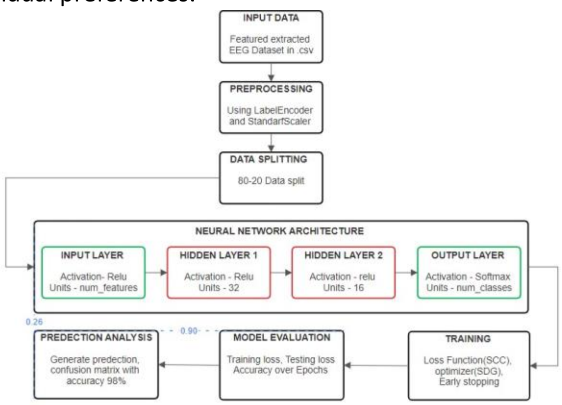

Fig. 5. Block diagram of CNN classifier

The block diagram described outlines a neural network project designed to analyze neuro-marketing data derived from EEG signals. The process begins by sourcing raw EEG data from a CSV file. This data undergoes a series of preprocessing steps including handling missing values, encoding categorical labels using a LabelEncoder, and standardizing the features with a StandardScaler to ensure the data is suitable for effective machine learning processing. The dataset is divided into training and testing sets, with 80% allocated to training and 20% to testing. This partitioning facilitates model training on a substantial portion of the data while ensuring separate data for evaluating model performance. The neural network architecture comprises multiple layers: an input layer matching the dataset's feature count, followed by a dense layer with ReLU activation and neurons equal to the features. Subsequently, two additional dense layers with 32 and 16 neurons, respectively, also utilize ReLU activation. The output layer consists of neurons corresponding to the dataset's classes and employs a softmax activation function to yield class probabilities. During training, the Sparse Categorical Crossentropy function serves as the loss function, and Stochastic Gradient Descent (SGD) functions as the optimizer, with accuracy tracked as a performance metric. Early stopping is implemented based on validation loss to prevent overfitting. Model evaluation includes monitoring training and testing loss and accuracy, complemented by visualizations illustrating these metrics' behavior across epochs. Finally, predictions are generated from the test data, and model performance is assessed using a confusion matrix and classification report to evaluate the neural network's accuracy in categorizing EEGbased neuromarketing data.

C. Gaussian Naive Bayes

Within our neuromarketing project, Gaussian Naive Bayes serves as a foundational classification algorithm for predicting consumer responses based on EEG signals. Despite its simplicity, Gaussian Naive Bayes offers computational efficiency and generalization capabilities that make it well-suited for analyzing large-scale EEG datasets. By assuming feature independence, Gaussian Naive Bayes simplifies the calculation of posterior probabilities, enabling us to efficiently classify consumer preferences based on brainwave activity. Its ability to perform well across various tasks, including text classification and EEG signal prediction, underscores its versatility and applicability in our project. Moreover, Gaussian Naive Bayes provides valuable insights into the probabilistic relationships between EEG features and consumer behavior, guiding the development of targeted marketing strategies tailored to individual preferences.

D. Support Vector Machine

In our neuromarketing project, we leverage Support Vector Machine (SVM) classifiers to delve into the intricate connections between EEG signals and consumer preferences. SVMs possess a remarkable ability to decipher patterns within highdimensional data, making them invaluable for dissecting EEG signals characterized by complex spatial and temporal patterns. By identifying optimal decision boundaries that maximize the margin between distinct classes, SVMs enable us to discern nuanced consumer response patterns to marketing stimuli. Furthermore, their adeptness at handling noise and intricate relation-ships within EEG data enhances our capacity to unveil subtle nuances in neural responses that underlie consumer behavior. Leveraging SVM outputs empowers us to glean valuable insights into the neural mechanisms driving consumer preferences, thereby informing the development of precisely targeted marketing strategies tailored to individual preferences. In our implementation, we employ a Support Vector Machine (SVM) classifier to analyze EEG data gathered during consumer response experiments. The code initiates by loading the dataset from a CSV file and segregating it into input features and target labels. Subsequently, the data undergoes partitioning into training and testing sets, utilizing a predefined test size ratio. To ensure uniform contribution of all features during model training, standardization is applied to the input features. We proceed to define a parameter grid for the SVM model, encompassing parameters such as the regularization parameter (C), options for the loss function ('hinge' or 'squared hinge'), and the kernel type (e.g., linear or radial basis function (RBF)). Following this, an SVM instance is instantiated with the specified kernel type, along with an increased maximum number of iterations to accommodate convergence. Randomized search coupled with cross-validation is then employed to explore and identify the optimal hyperparameters for the model, considering various combinations within the defined parameter distributions. Finally, the best-performing SVM model derived from the randomized search undergoes evaluation on the test set, wherein performance metrics including accuracy and confusion matrix are computed and presented.

E. Logistic Regression

Logistic regression classifiers serve as a cornerstone in our neuromarketing project utilizing EEG signals to decode consumer responses. With its ability to model the likelihood of binary outcomes based on brainwave activity, logistic regression provides valuable insights into the probabilistic relationships between EEG features and consumer preferences. Unlike linear regression, which assumes a linear relationship between predictors and outcomes, logistic regression accommodates nonlinear relationships through the logistic function. This enables us to accurately model the probability of consumer preferences based on complex neural responses to marketing stimuli. By leveraging logistic regression outputs, we gain actionable insights into the neural processes underlying consumer behavior, guiding the development of targeted marketing strategies tailored to individual preferences.

F. K Nearest Neighbour

The k value in the k-NN (k-Nearest Neighbors) algorithm determines the number of neighboring data points considered when classifying a new data point.In our implementation, we've constructed a pipeline that incorporates standard scaling followed by a KNeighborsClassifier. To optimize the model, we've defined a hyperparameter grid, encompassing parameters like the number of neighbors (n-neighbors) and the distance metric (metric). Employing cross-validation coupled with grid search, we've identified the most effective combination of hyperparameters. Subsequently, we've assessed the performance of the top-performing KNN model on the test set, generating and presenting key performance metrics such as the classification report, accuracy, Cohen's Kappa coefficient, and confusion matrix. The selection of the appropriate k value is critical as it influences the trade-off between underfitting and overfitting. A smaller k value, such as 1, can lead to flexible decision boundaries with high variance but low bias. Conversely, a larger k value may yield smoother decision boundaries with low variance but high bias. The choice of k should be guided by dataset characteristics; for instance, data with noise or outliers might benefit from larger k values.

It is advisable to use an odd k value to avoid ties in classification. Employing cross-validation techniques can assist in determining the optimal k value for a given dataset. [15]

G. Decision Tree

The decision tree, a supervised learning technique for classification and regression tasks, functions without preconceptions about the underlying data distribution. It constructs a hierarchical tree structure comprising root, branch, internal, and leaf nodes. Employing a divide-and-conquer strategy, it seeks optimal split points in the data through an iterative search to maximize data separation based on class labels or regression errors. The recursive splitting process traverses from the root to leaf nodes until predefined stopping criteria are met. Each leaf node denotes a class label or regression value, enabling classification or regression for most records.In our implementation, we leverage the DecisionTreeClassifier from the scikit-learn library. We delineate a parameter grid to fine-tune hyperparameters such as maximum depth, minimum samples split, minimum samples leaf, and maximum features. Grid search with cross-validation identifies the optimal hyperparameter combination. Subsequently, we assess the best Decision Tree model from the grid search on the test set, yielding performance metrics like the classification report, accuracy, Cohen's Kappa coefficient, and confusion matrix for evaluation. [16]

XIII. Model Evaluation

The trained model's accuracy, robustness, and performance need evaluation. Various metrics are employed to assess how well the model predicts consumer responses. Cross-validation techniques and testing on new data ensure the model's generalizability. The assessment of our model's efficacy involves rigorous examination of its accuracy, resilience, and performance across diverse metrics. Employing cross-validation techniques and testing against new data sets, we ensure the model's capacity to generalize findings. Through meticulous evaluation, we gauge the model's proficiency in predicting consumer responses based on EEG signals, paving the way for enhanced insights into the intricate dynamics of human emotions in response to marketing stimuli.

XIV. Application and Interpretation

Once the model is established and validated, it can be used to predict consumer reactions to new marketing strategies, products, or advertisements. The results are interpreted to understand which aspects of the marketing stimuli drive positive or negative responses in the target audience.

XV. Results

Accuracy serves as a crucial measure for assessing classification models. It quantifies the proportion of accurate predictions relative to all predictions made. In our specific model context, a higher Accuracy indicates the model's effectiveness in correctly predicting whether a test subject's review will be categorized as positive, negative, or neutral. The A can be calculated by equation.

$$A = \frac{TN + TP}{TN + TP + FN + FP} \tag{12}$$

We also utilize the Kappa coefficient in our neuromarketing project using eeg signals to assess agreement between classifiers. This measure goes beyond simple Accuracy, considering agreement beyond chance. The formula for Cohen's Kappa is:

$$K = \frac{po - pe}{1 - pe} \tag{13}$$

Incorporating the Kappa coefficient enhances the model evaluation's robustness, providing a more nuanced understanding of its performance. Our project utilized a variety of machine learning algorithms to address the classification task effectively. The inclusion of Random Forest [17], Support Vector Machines (SVM), Gaussian Naive Bayes, and Convolutional Neural Network (CNN) algorithms formed a comprehensive and resilient framework for predictive modeling.

A. Random Forest Classifier

The Random Forest classifier, known for its ensemble learning technique, offered excellent accuracy and resilience to overfitting. By constructing multiple decision trees during the training phase, this classifier effectively captures the intricate relationships between various brainwave patterns and consumer preferences.Employing the ensemble learning strategy of Random Forest not only provides valuable insights into the importance of different EEG features but also ensures the model's resilience against overfitting. When the model underwent testing with the random forest classifier, it achieved an accuracy rate of 99

No. of Decision Tree: 95

	precision	recall	f1-score	support
NEGATIVE	0.99	0.99	0.99	143
NEUTRAL	1.00	0.99	1.00	137
POSITIVE	0.98	0.99	0.99	147
accuracy			0.99	427
macro avg	0.99	0.99	0.99	427
weighted avg	0.99	0.99	0.99	427

```
[[141   0   2]
 [  0 136   1]
 [  1   0 146]]
Cohen's Kappa: 0.9859409982878967
```

Fig. 6. Confusion Matrix of RFC

B. Support Vector Machine

SVM, a powerful algorithm for both classification and regression, provided efficient decision boundaries in higherdimensional spaces.SVMs excel in discerning patterns within high-dimensional data, making them well-suited for analyzing EEG signals characterized by intricate spatial and temporal patterns. By identifying optimal decision boundaries that maximize the margin between different classes, SVMs facilitate the delineation of distinct consumer response patterns to marketing stimuli. When the model was tested with SVM, the accuracy received is 98 percent.

	precision	recall	f1-score	support
NEGATIVE	0.97	0.99	0.98	143
NEUTRAL	0.99	0.99	0.99	137
POSITIVE	0.98	0.95	0.97	147
accuracy			0.98	427
macro avg	0.98	0.98	0.98	427
weighted avg	0.98	0.98	0.98	427

```
[[142   0   1]
 [  0 135   2]
 [  5   2 140]]
Cohen's Kappa: 0.9648611728303625
```

Fig. 7. Confusion Matrix of SVM

C. Gaussian Naive Bayes

Gaussian Naive Bayes, a probabilistic classifier, demonstrated its strength in handling large feature spaces with relatively simple assumptions. Gaussian Naive Bayes offers computational efficiency and generalization capabilities that make it well-suited for analyzing large-scale EEG datasets. By assuming feature independence, Gaussian Naive Bayes simplifies the calculation of posterior probabilities, enabling us to efficiently classify consumer preferences based on brainwave activity. Its ability to perform well across various tasks, including text classification and EEG signal prediction, underscores its versatility and applicability in our project. When the model was tested with Gaussian Naive Bayes, the accuracy received is 68 percent.

	precision	recall	f1-score	support
NEGATIVE	0.88	0.74	0.80	143
NEUTRAL	0.61	0.99	0.76	137
POSITIVE	0.54	0.31	0.39	147
accuracy			0.67	427
macro avg	0.68	0.68	0.65	427
weighted avg	0.68	0.67	0.65	427

```
[[106   0  37]
 [  0 136   1]
 [ 15  87  45]]
Cohen's Kappa: 0.5110980257454569
```

Fig. 8. Confusion Matrix of GNB

D. Computational neural network

The CNN algorithm, renowned for its prowess in pattern recognition in image data, was adept at identifying complex temporal patterns within the EEG signals. CNNs are specifically designed to extract relevant features from spatial data, making them particularly well-suited for analyzing EEG signals that exhibit complex spatial patterns. By automatically learning hierarchical representations of brain activity patterns associated with consumer preferences, CNNs enable us to uncover subtle nuances in neural responses to marketing stimuli. Their robustness to variability in EEG data further enhances our ability to generalize findings across diverse consumer populations. When the model was tested with Gaussian Naive Bayes, the accuracy received is 99 percent.

	precision	recall	f1-score	support
0	0.97	1.00	0.99	142
1	0.99	1.00	0.99	143
2	1.00	0.96	0.98	142
accuracy			0.99	427
macro avg	0.99	0.99	0.99	427
weighted avg	0.99	0.99	0.99	427

```
[[142   0   0]
 [  0 143   0]
 [  4   2 136]]
```

Fig. 9. Confusion Matrix of CNN

E. Logistic Regression

Logistic regression, a statistical method commonly applied in neuromarketing projects utilizing EEG signals, categorizes data into two distinct groups. It evaluates the probability of cognitive or emotional states based on EEG features, offering insights into consumer responses to marketing stimuli. By employing a logistic function, it analyzes neural activity's influence on consumer behavior, aiding in the development of targeted marketing strategies. Unlike linear regression, logistic regression can handle nonlinear relationships via the logistic function, accurately modeling the likelihood of consumer preferences based on intricate neural responses to marketing stimuli. It boasts an impressive accuracy rate of 98 percent.

```
              precision    recall  f1-score   support

    NEGATIVE       0.96      1.00      0.98       143
     NEUTRAL       0.99      0.99      0.99       137
    POSITIVE       0.99      0.95      0.97       147

    accuracy                           0.98       427
   macro avg       0.98      0.98      0.98       427
weighted avg       0.98      0.98      0.98       427

[[143   0   0]
 [  0 136   1]
 [  6   2 139]]
Cohen's Kappa: 0.9683797393364929
```

Fig. 10. Confusion Matrix of Logistic Regression

F. Decision Tree

The decision tree functions as a supervised learning technique employed in classification and regression tasks, devoid of assumptions regarding the underlying data distribution. It constructs a hierarchical tree structure, comprising root nodes, branches, internal nodes, and leaf nodes. Decision tree learning adopts a divide-and-conquer strategy, initiating by identifying optimal split points in the dataset through a greedy search.

	50-50	70-30	80-20
LR	A=96%	A=99%	A=98%
SVM	A=96%	A=98%	A=98%
GNB	A=71%	A=68%	A=67%
RFC	A=96%	A=99%	A=99%
DT	A=95%	A=94%	A=93%
KNN	A=96%	A=98%	A=98%
CNN	A=97%	A=97%	A=99%

TABLE II

COMPARISON OF CLASSIFIERS BY SPLITTING DATA ON THE BASIS OF OVERALL ACCURACY DENOTED BY A

These splits aim to maximize the segregation of data points with distinct class labels or minimize regression errors. This recursive splitting process progresses from the root node to the leaf nodes until predefined stopping criteria are met. The achieved accuracy stands at 92.97

```
Classification Report:
              precision    recall  f1-score   support

    NEGATIVE       0.92      0.94      0.93       143
     NEUTRAL       0.94      0.99      0.96       137
    POSITIVE       0.93      0.86      0.89       147

    accuracy                           0.93       427
   macro avg       0.93      0.93      0.93       427
weighted avg       0.93      0.93      0.93       427

Confusion Matrix:
[[135   0   8]
 [  0 135   2]
 [ 11   9 127]]
Best Decision Tree Model Parameters: {'max_depth': None, 'max_features': 'auto',
Accuracy: 0.9297423887587822
Cohen's Kappa Coefficient: 0.8946407422029214
```

Fig. 11. Confusion Matrix of Decision Tree

G. K Nearest Neighbour

The k value in the k-NN (k-Nearest Neighbors) algorithm determines how many neighboring data points are considered when classifying a new data point. Selecting the appropriate k value is crucial as it impacts the balance between underfitting and overfitting. By considering the nearest neighbors in feature space, k-NN enables us to identify patterns in EEG data and discern distinct consumer response profiles. The choice of the k value plays a crucial role in balancing the trade-off between model flexibility and bias, ensuring optimal classification performance. The accuracy found is 97.65 percent.

```
Classification Report:
              precision    recall  f1-score   support

    NEGATIVE       0.96      0.99      0.97       143
     NEUTRAL       0.99      1.00      0.99       137
    POSITIVE       0.99      0.95      0.97       147

    accuracy                           0.98       427
   macro avg       0.98      0.98      0.98       427
weighted avg       0.98      0.98      0.98       427

Best KNN Model Parameters: {'knn__metric': 'manhattan', 'knn__n_neighbors': 3}
Accuracy: 0.9765807962529274
Cohen's Kappa: 0.9648669551909691
Confusion Matrix:
[[141   0   2]
 [  0 137   0]
 [  6   2 139]]
```

Fig. 12. Confusion Matrix of K Nearest Neighbour

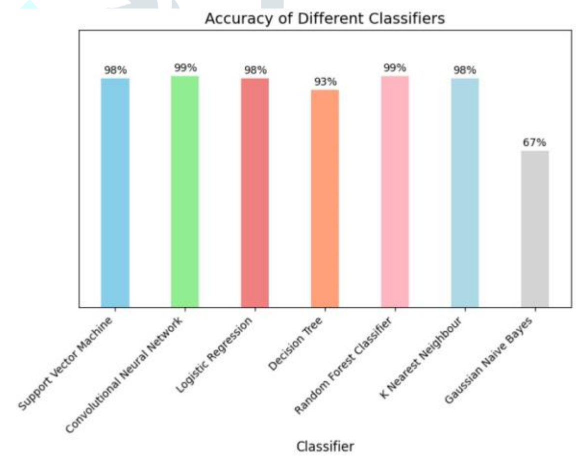

Fig. 13. Graphical representation of accuracy of classifiers

XVI. CONCLUSION

In conclusion, our project marks a pioneering venture amalgamating neuro-marketing, EEG signal analysis, and machine intelligence, with far-reaching implications for reshaping shopping research paradigms. Through meticulous investigation and analysis, we've unearthed the profound potential of this interdisciplinary fusion, achieving commendable accuracy across diverse classifiers.

The Gaussian Naive Bayes classifier exhibited respectable performance, registering an accuracy of 68 percent. While not the frontrunner, its contribution underscores the adaptability of probabilistic models in capturing nuanced patterns within consumer datasets.

The Support Vector Machine (SVM) emerged as a formidable contender, boasting a noteworthy accuracy of 98 percent. This underscores the robustness of SVMs in discerning intricate relationships within high-dimensional data, particularly in EEG signal analysis.

Logistic Regression, a stalwart in classification algorithms, showcased commendable accuracy, matching SVM with a solid 98 percent. Its simplicity and interpretability render it invaluable for unraveling the factors influencing consumer behavior.

The Decision Tree classifier demonstrated a strong performance, achieving an accuracy of 93 percent. Its hierarchical structure facilitates intuitive decision-making, making it adept at identifying pivotal features driving consumer preferences.

K-Nearest Neighbors (KNN) showcased remarkable accuracy, aligning with SVM and Logistic Regression at a solid 98 percent. Its simplicity and reliance on local neighborhood information make it versatile for consumer data analysis.

The Random Forest Classifier emerged as the standout performer, delivering outstanding accuracy of 99 percent. Harnessing ensemble learning and decision trees, Random Forests excel in capturing complex interactions within consumer datasets, anchoring predictive modeling for marketing research.

Additionally, our exploration extended to Convolutional Neural Networks (CNN), which mirrored Random Forests with an accuracy of 99 percent. CNNs' prowess in extracting hierarchical features from EEG signals underscores their efficacy in capturing intricate spatial and temporal patterns, offering invaluable insights into consumer behavior.

As we navigate forward, addressing challenges and refining methodologies becomes imperative. Exploring emerging techniques like Extreme Gradient Boosting (XGBoost), renowned for superior performance in classification tasks, holds promise for unlocking deeper insights into consumer preferences and behaviors. Embracing innovation in machine learning heralds a new era of enriched shopping experiences tailored to individual preferences.

XVII. Future Scope

Neuromarketing initiatives leveraging EEG (Electroencephalography) represent an innovative approach to understanding consumer behavior. EEG technology provides marketers with a direct insight into the human mind, enabling a comprehensive exploration of consumer responses to various stimuli. From advertisements to products and experiences, EEG allows marketers to decode neural signals, revealing invaluable insights into subconscious reactions. This personalized data empowers marketers to customize their strategies, products, and advertisements based on individual neural responses, maximizing engagement and resonance with target audiences. Through EEG analysis, marketers gain deeper insights into consumer preferences and behaviors, driving innovation and fostering brand loyalty in an ever-evolving market landscape.

Analyzing brain responses during product testing offers invaluable insights into consumers' subconscious desires, allowing companies to refine and innovate their products effectively. EEG data not only aids in designing more engaging advertisements but also enables marketers to discern which elements trigger positive neural responses, thus optimizing future campaigns for maximum impact. Real-time analysis of brain activity further enhances customer experience by identifying elements that positively influence satisfaction and engagement, enabling businesses to tailor their offerings accordingly. However, the ethical implications of neuromarketing involving EEG data collection necessitate careful consideration, emphasizing the importance of consumer consent, privacy protection, and responsible data usage. Looking ahead, advancements in EEG technology hold promising prospects for widespread market research applications. The potential for miniaturization, improved wearability, and higher resolution could make EEG devices more practical and affordable. Integration with AI and Big Data analytics could provide marketers with comprehensive insights and predictive capabilities, empowering them to forecast trends and consumer behavior with greater accuracy, ultimately driving the success of their products and campaigns.

Apart from marketing, EEG technology could also expand into healthcare and wellness sectors, allowing for applications in cognitive health monitoring, mental state analysis, and personalized wellness strategies. With the rapid evolution of technology, there will be a need for updated regulations to address data privacy, consent, and ethical use of neuro data in marketing, requiring collaboration between industries and regulatory bodies. The future of neuro marketing utilizing EEG holds immense potential, yet its realization will depend on technological advancements, ethical considerations, and the fusion of neuroscience, marketing, and data science.

References

[1] C. R. Amin, M. F. Hasin, T. S. Leon, A. B. Aurko, T. Tamanna, M. A. Rahman, and M. Z. Parvez, "Consumer behavior analysis using eeg signals for neuromarketing application," in *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 2061–2066, 2020.

[2] N. Lee, A. J. Broderick, and L. Chamberlain, "What is 'neuromarketing'? a discussion and agenda for future research," *International Journal of Psychophysiology*, vol. 63, no. 2, pp. 199–204, 2007. Cognitive Neuroscience: Contributions from Psychophysiology.

[3] N. Phutela, P. Abhilash, K. Sreevathsan, and B. N. Krupa, "Intelligent analysis of eeg signals to assess consumer decisions: A study on neuromarketing," in *2022 3rd International Conference for Emerging Technology (INCET)*, pp. 1–7, 2022.

[4] V. Khurana, M. Gahalawat, P. Kumar, P. P. Roy, D. P. Dogra, E. Scheme, and M. Soleymani, "A survey on neuromarketing using eeg signals," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 13, no. 4, pp. 732–749, 2021.

[5] P.-C. Kao and P. Craigie, "Evaluating student interpreters' stress and coping strategies," *Social Behavior and Personality: an international journal*, vol. 41, 07 2013.

[6] M. Ramirez, S. Kaheh, and K. George, "Neuromarketing study using machine learning for predicting purchase decision," pp. 0560–0564, 12 2021.

[7] N. N. A. M. Nizam, Y. H. Yahaya, M. F. M. Amran, S. R. Ahmad, N. M. M. Yusop, and N. A. M. Razali, "Benefits and limitations of neuromarketing techniques in enhancing marketing strategies," in *2022 International Visualization, Informatics and Technology Conference (IVIT)*, pp. 231–238, 2022.

[8] A. Jain, T. Choudhury, R. Singh, and P. Kumar, "Eeg signal classification for real- time neuro marketing applications," in *2018 International Conference on Advances in Computing and Communication Engineering (ICACCE)*, pp. 434–438, 2018.

[9] K. S. Bano, P. Bhuyan, and A. Ray, "Eeg-based brain computer interface for emotion recognition," in *2022 5th International Conference on Computational Intelligence and Networks (CINE)*, pp. 1–6, 2022.

[10] J. J. Bird, L. J. Manso, E. P. Ribeiro, A. Ekart, and D. R. Faria, "A study´ on mental state classification using eeg-based brain-machine interface," in *2018 International Conference on Intelligent Systems (IS)*, pp. 795– 800, 2018.

[11] "Eeg brainwave dataset: Feeling emotions," https://www.kaggle.com/datasets/birdy654/eeg-brainwave-datasetfeeling-emotions.

[12] J. J. Bird and D. R. Faria, "Mental emotional sentiment classification with an eeg-based brain-machine interface," 2018.

[13] J. Bird, D. Faria, L. Manso, A. Ekart, and C. Buckingham, "A deep´ evolutionary approach to bioinspired classifier optimisation for brainmachine interaction," 08 2019.

[14] E. H. Houssein, A. Hammad, and A. A. Ali, "Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review," *Neural computing applications*, vol. 34, pp. 12527–12557, 5 2022.

[15] "What is the k-nearest neighbors (knn) algorithm?," https://www.ibm.com/topics/knn.

[16] "What is a decision tree?," https://www.ibm.com/topics/decision-trees.

[17] "Introduction to gradient boost - classifiers random forest," https://academic-accelerator.com/Manuscript-Generator/GradientBoost/classifiers-random-forest.