BEHAVIOURAL INSIGHTS MARKETING BASED ON PHYSIOLOGICAL SIGNALS

Table of Contents

List of Figures

List of Tables

CHAPTER1

INTRODUCTION

Neuromarketing is a growing field that combines the disciplines of neuroscience, psychology, and marketing to gain a deeper understanding of consumer behavior and decision-making processes. It uses advanced technologies such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and biometrics to measure and analyze brain activity, physiological responses and emotional reactions in real time. Tapping into the subconscious, neuromarketers seek to understand how people perceive, interact with, and respond to marketing stimuli such as advertisements, product packaging, pricing strategies, and brand communications. The Neuromarketing market size is estimated at USD 1.44 billion in 2023 and is expected to reach USD 2.21 billion by 2028, growing at a CAGR of 8.89% during the forecast period (2023-2028).

The concept of neuromarketing arose from the recognition that traditional market research methods such as surveys, focus groups and self-reporting have limitations. These methods are often based on conscious responses and may be influenced by social desirability or cognitive bias, resulting in inaccurate or incomplete data. Neuromarketing addresses these challenges by exploiting implicit, nonverbal, and often involuntary responses that occur on a neurological or physiological level, providing a more objective and holistic understanding of consumer preferences and motivations. First, it provides a deeper understanding of consumer behavior by revealing unconscious factors, emotional responses and cognitive processes that influence decision making. While traditional market research methods often focus on conscious preferences and rational explanations, neuromarketing reveals the implicit motives, biases and preferences that shape consumer choices. This deeper understanding allows marketers to create more targeted and effective strategies that influence consumers on a subconscious level. Second, neuromarketing improves marketing effectiveness by using neuroscientific insights to create more effective and efficient advertising campaigns, product design, and brand experiences.

Understanding how certain stimuli activate neural pathways associated with pleasure, reward or attention can help optimize marketing messages to elicit desired emotional responses and increase engagement. By combining marketing strategies with brain-based insights, companies can capture consumer attention, increase brand loyalty and guide purchasing decisions.

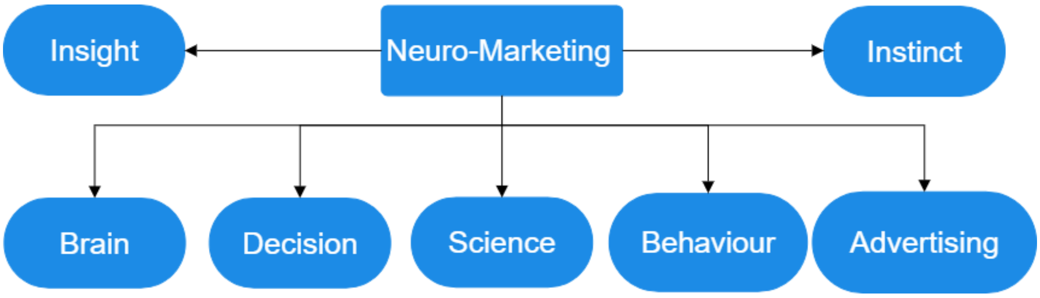


Fig 1.1. Steps in Neuro-marketing

It drives product development and innovation by identifying consumer preferences, pain points and unmet needs at an unconscious level. Neuromarketers can gauge consumer reactions to product features, package design, pricing strategies, and sensory experiences, resulting in product improvements that resonate with target audiences. This iterative feedback loop between neuromarketing insights and product development leads to continuous improvement and innovation in organizations. The stages of neuromarketing are described in Figure 1.1.

In addition, neuromarketing plays a vital role in optimizing the customer experience across various touch points, from digital platforms to retail environments. By analyzing neurophysiological responses and biometric data, companies can tailor communications, content delivery and user interfaces to create seamless, engaging and emotionally resonant experiences that increase customer satisfaction and loyalty. A personalized and empathetic customer experience builds trust, improves brand visibility and nurtures long-term relationships with consumers. It fosters cross-disciplinary collaboration between neuroscientists, psychologists, marketers and data scientists and bridges the gap between research and industrial applications. This collaborative approach leads to innovative solutions, evidence-based marketing strategies and continuous progress in understanding people's consumer behavior. By integrating diverse perspectives and expertise, neuromarketing can use cutting-edge technology and methods to solve complex challenges and drive business growth. The importance of neuromarketing extends to pricing strategies and consumer decision making.

By studying neural responses to price cues such as discounts, price increases, and valuations, neuromarketing can optimize pricing strategies for maximum profitability and consumer satisfaction. Understanding how the brain processes price information can help companies set competitive prices, create compelling value propositions and influence purchasing decisions without compromising perceived quality or product image. In addition, neuromarketing contributes to brand management and positioning by uncovering unconscious associations, feelings and memories associated with brands. Neuroimaging techniques allow marketers to assess brand resonance, brand loyalty and brand equity based on patterns of neural activation.

This deep understanding of brand perception enables companies to refine brand communication, storytelling and visual identity to engage with audiences on an emotional level, creating strong brand connections and impact. In the digital age, neuromarketing plays a key role in optimizing online user experience, digital advertising and e-commerce platforms. By analyzing neurocognitive processes during digital interactions, companies can design intuitive user interfaces, personalized content recommendations and powerful call-to-action strategies that increase user engagement and results. Neuromarketing insights also inform digital advertising tactics such as ad placement, creative elements and targeting parameters to maximize advertising effectiveness and ROI for digital marketing campaigns. In addition, neuromarketing improves retail environments and physical spaces by optimizing store appearance, product presentations and sensory experiences.

By measuring the brain's responses to store atmosphere, product placement and in-store promotions, retailers can create engaging and memorable shopping experiences that engage consumers, encourage discovery and increase purchase intent. Neuromarketing also talks about package design strategies using neuroscience principles to improve product visibility, appeal and brand recognition on retail shelves. In the context of consumer engagement and customer relationship management (CRM), neuromarketing offers insights into building emotional connections, trust and loyalty with customers. By understanding the neural correlates of empathy, social connection, and trust communication, companies can develop empathic communication strategies, personalized customer experiences, and relationship-building initiatives that respond to customers' emotional needs and preferences.

Neuromarketing also provides insight into customer feedback mechanisms, enabling companies to gather actionable insights and address customer concerns proactively. Cortical and subcortical regions of the brain that light up when watching pleasant or unpleasant videos have already been used in many neuroimaging techniques. EEG signals provide insight into the neural correlates of advertising effectiveness and help develop targeted and effective advertising strategies based on objective neuroscientific data. EEG signals are said to be able to interpret a client's unconscious responses, interpret behavioral and cognitive indicators, and provide real-time functional information. The use of EEG signals in this experiment provides a targeted approach to directly measure the neural activity associated with cognitive responses and emotional responses to advertising stimuli.

EEG provides real-time information on brain wave patterns that allow analysis of attention, engagement and emotional valence while viewing an ad. These neurophysiological data, combined with behavioral measures such as participant feedback and ratings of multimedia content, provide a comprehensive view of how viewers subliminally process and respond to advertisements. Electroencephalogram technology (EEG) has emerged as a cost-effective, versatile, portable, and easy-to-use tool for measuring cognitive workload and assessing neural activity associated with emotional responses. It is an ideal choice for experiments that focus on cognitive responses to stimuli such as advertisements. Its ease of use, wireless connectivity and low maintenance requirements make it a viable option for integrating neurophysiological data into classification prediction frameworks. EEG headphones are preferred over other sensors in neuroscience and cognitive research because they can directly measure brain activity non-invasively and offer high temporal resolution for analyzing rapid changes in cognitive processes and responses to stimuli. The field of emotional AI, which can be defined as the application of artificial intelligence to understand the implicit and unspoken feelings of a customer, is still largely unexplored.

With the explosion of digital media and the growth of multimedia content, there is a growing need for advanced classification models to effectively assess and predict the popularity, appeal and success of various media materials. This is particularly important in the marketing industry, where advertisements play a key role in attracting and engaging audiences. Rating prediction systems have traditionally relied on metrics such as viewer comments, interviews, or social media engagement indicators such as likes and dislikes. Although these methods provide valuable information, they often fail to accurately predict the overall reception and impact of multimedia content. Using big data analytics, machine learning algorithms and predictive modeling techniques, neuromarketing with EEG signals can identify actionable trends, segment consumer profiles and accurately predict market trends. This strategic approach enables companies to effectively allocate resources, prioritize marketing initiatives and drive sustainable growth and profitability.

CHAPTER 2
LITERATURE REVIEW

Advertising plays a huge role in today's world as it acts as an important bridge between businesses and consumers, promoting brand awareness, product visibility and market share. With intense competition and choices, advertising plays a key role in attracting public attention, shaping perceptions and influencing purchasing decisions. It enables companies to effectively communicate their value propositions, unique selling points and brand stories that foster brand loyalty, customer trust and long-term relationships. In addition, advertising promotes economic growth, innovation and supports industries by stimulating demand, supporting income generation and creating jobs in advertising agencies, media platforms and creative industries.

This reference link [1] emphasized that neuromarketing solutions have become key tools for understanding consumer behavior through the use of neuroscientific techniques. Companies such as PepsiCo, The Weather Channel, eBay and Daimler have adopted neuromarketing research to analyze the market, target groups and create effective marketing campaigns. These technologies study customer preferences, and big brands like Campbell's and Frito-Lay are using neuroimaging to refine packaging strategies based on how color, text and images influence purchasing decisions. However, data security issues arise when technologies such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and eye tracking are used, highlighting the need for strict data security measures.

The COVID-19 pandemic has had a significant impact on the neuromarketing market in the short term. Blocking limits the collection of data from physical locations, which disrupts normal consumer behavior data. In addition, the production of neuromarketing systems has been hampered by disruptions in the global supply chain and production stoppages. These challenges underscore the importance of adapting neuromarketing strategies to changing market conditions while addressing privacy and security concerns to sustain long-term growth in the field.

In this paper [3], the author examines consumer preferences through the lens of neuroscience and focuses primarily on car choices, one of which is an electric car. Using consumer neuroscience, researchers aim to deepen our understanding of how individuals process information and make decisions when choosing products. The study uses EEG-based experiments where participants are exposed to images and specifications of different cars. Signal processing techniques, statistical analysis, and brain mapping tools are used to separate emotional and attentional responses and correlate them with participants' decisions. The study also examines long-term temporal correlations (LRTCs) to determine whether product preferences affect neuronal dynamics over time.Analyzing the results, the study reveals significant differences in brain activity and coherence patterns, especially in the alpha frequency range, between the participants who chose the electric car.

These differences point to specific memory and long-term attentional demands associated with choosing an electric vehicle. In addition, the study uses machine learning (ML) models such as K-Nearest Neighbors (KNN) to group participants based on EEG measurements that discriminate them. Results show correlations between these neural measures and self-reported data, indicating that internally distributed measures can influence consumer purchasing behavior. Overall, this study sheds light on the role of neuroscientific insights in understanding and predicting consumer preferences, especially in the context of innovative product options such as electric cars.

In this paper [4], the author discusses convolutional neural networks (CNN) and their applications to image recognition and other tasks. CNNs are deep learning algorithms designed for image processing that use co-weighted models, such as Fourier transforms, to detect spatially invariant features. They are widely used for tasks such as image and video recognition, decision support, text analysis and more.

This also applies to regularization techniques in CNNs that help avoid overtuning by adjusting weights and trimming joints. Unlike traditional multilayer perceptrons, CNNs use a structured form of regularization, dividing data into smaller patterns that are printed on filters to effectively remove complex features.Basically, CNNs are powerful tools for visual data analysis with special regularization methods and feature extraction capabilities that make them effective in various applications.

In this paper [5], resting frontal electroencephalographic (EEG) alpha asymmetry was investigated in a study with 16 participants to predict emotional responses to different musical stimuli. Three types of music expressing neutral, positive and negative moods were played, and participants rated these stimuli in terms of "expressed mood" and "level of enjoyment". The results showed that subjects with higher alpha power at the right frontal electrode site evaluated all stimuli more positively than subjects with higher alpha power at the left frontal electrode site. However, the valence of the musical stimuli on the "expressed mood" scale did not influence this difference between left- and right-handed individuals.In contrast, when evaluating the "enjoyment" scale, the most significant difference was observed in the ratings of left-handed and right-handed people during the negative condition.

This suggests that resting alpha asymmetry, particularly in the alpha frequency range, may indicate a person's tendency to respond emotionally, as people have higher alpha power at certain alpha electrode sites and have different affective responses to music. These findings are consistent with previous studies and highlight the potential of EEG alpha asymmetry as a predictor of affective responses.

In this paper [6], the author reviews the progress of the last 25 years in the study of affect-related EEG frontal asymmetry. It acknowledges important advances but notes a critical gap in linking this research with neuroscientific studies of primate prefrontal cortex (PFC) structure and function. The commentary emphasizes the importance of bridging this gap to gain a deeper understanding of the role of the PFC in affective processing, as understanding the different domains of the PFC can improve our understanding of affective mechanisms. In addition, the commentary presents information from the neuroscience literature and emphasizes the heterogeneity of different areas of the PFC. It offers more specific hypotheses about the functions of different sectors of the PFC in affective processing. In addition, methodological issues related to EEG measurement of functional prefrontal asymmetry are discussed, emphasizing the need for rigorous methods to accurately measure and interpret EEG data in the context of affective neuroscience research.

In this paper [7], the author focuses on the emotional detection of EEG signals, which is an important part of human-machine communication, because it allows a direct assessment of the internal emotional state of the user. The review states that although various feature extraction methods have been investigated for this purpose, the selection of appropriate features and electrode locations is usually based on neuroscientific findings.

However, the applicability of these features to emotion recognition has often been tested with limited features and small datasets lacking systematic feature comparisons.To address this shortcoming, the review analyzes 33 studies on extraction methods for EEG-based emotion recognition. The experiment is performed using machine learning techniques to compare these features on a self-recorded dataset, focusing on the performance of different feature selection methods, the types of features selected, and the choice of electrode locations. The results show that features selected by multivariate methods are slightly better than features selected by univariate methods. In addition, advanced feature extraction methods have advantages over conventionally used spectral power bands, and electrode locations over the parietal and centroparietal lobes are preferred for better emotion recognition. They also emphasized the use of the Isolation Forest ML model to interpret the results.

This paper [8] presents a new approach for continuous detection of valence, an important emotional component, from electroencephalogram (EEG) signals and facial expressions in response to videos. Multiple annotators ensured a constant level of valence by observing videos of participants' faces as they watched emotionally charged videos. The study uses power spectral features of EEG signals and facial reference points as features that continuously detect valence levels in each frame.

In particular, the work investigates the relationship between EEG properties and expressive facial expressions with a constant valence level, helping to understand how emotional states are expressed in these facial expressions.The researchers used a Random Forest machine learning model to analyze the collected EEG and facial expression data for emotion detection and valence detection. They confirmed the performance of the model in detecting emotional highlights and demonstrated the potential of such multimodal fusion techniques to capture subtle and spontaneous affective responses over time. By integrating EEG signals and facial expressions, this work lays the foundation for more accurate video highlight detection and implicit recognition, improving our ability to understand and respond to emotional signals in multimedia content.

This paper[17] proposes a predictive modeling technique to identify consumer product preferences "likes" and "dislikes" for electronic commerce (e-commerce) products. The EEG signals and product preferences of volunteers of different ages were recorded after they were exposed to different consumer products. Product- and subject-specific classification was performed using user-independent testing technology using artificial neural networks and other classifiers such as logistic regression, decision tree classifier, K-nearest neighbors and support vector machine. However, the topic-based classification results showed that k-Nearest Neighbors achieved 60.89 percent and Artificial Neural Networks (ANN) achieved 50.40 percent.

In addition, the percentage of products using artificial neural networks (81.23%) and support vector machines (80.38%) is ranked. %) was higher.This paper[18] presents emotion recognition using a combined analysis of electroencephalogram (EEG) and galvanic skin response (GSR) data. 27 people participated in the trial. The presentation of the collection of twenty-one films created emotions. Fast Fourier transform (FFT) analysis of the EEG signal was performed in the frequency domain to extract features. Support vector machine (SVM) and k-nearest neighbors (k-NN) were two classifiers used to classify emotions based on valence and arousal. In user-dependent classification, the classification accuracy was 0.88, while in group classification it was 0.72.

CHAPTER 3
METHODOLOGY

In the proposed study, the advertisements are segregated into many categories. The video advertisements belong to categories namely, animation, dialogues, animals, jingle and celebrity. This categorization helps us understand how different types of advertisements impact viewers' brain responses and subsequent behavior. Our approach involves recording EEG signals from 22 subjects both in their relaxed state and while they watch the advertisements. This dual recording setup allows us to capture the brain's real-time reactions to the stimuli presented in the advertisements, providing valuable insights into cognitive and emotional processing.

One of our main objectives is to identify which specific band of EEG signals the brain utilizes when responding to the stimuli in advertisements. EEG signals are divided into different frequency bands, each associated with distinct brain activities such as attention, relaxation, or emotional arousal. By knowing the relevant EEG band used during advertisement viewing, we gain a deeper understanding of how advertisements influence neural responses and perception. This knowledge forms the basis for our subsequent analysis processing of EEG data and classification of advertisements as likes and dislikes.

3.1. PARTICIPANTS SUMMARY

This research aimed to explore the neural responses and cognitive reactions elicited during exposure to various advertisement stimuli. The study adhered to ethical guidelines and employed rigorous methodologies to ensure accurate data collection and analysis. Twenty two participants (20 males and 2 females) aged 18 to 22 years old were involved in the study. The participants volunteered to partake in EEG recordings as they engaged with advertising content. All participants were the students of SASTRA University. We made the subjects who came forward to take part in the experiment feel safe and assured them that any sort of their data will not be misused by any means. It was instructed to the participants to maintain composure throughout the commercial video. The participant’s metadata have been given in Table 3.1. The experiments adhered to the guidelines set forth by the Institutional Ethics Committee for Human Volunteer Research at SASTRA Deemed University. Prior to participation, subjects had to read and sign an informed consent form that outlined the purpose, procedures, potential risks, and benefits of the study, as well as their rights as participants. By obtaining their signed consent, we aimed to establish a transparent and ethical framework that prioritized participant understanding and autonomy, thereby minimizing the likelihood of any post-experiment confusion or concerns. The experiments were conducted at the Measurements and Transducers Lab in the School of Electrical and Electronics at SASTRA Deemed University, Thanjavur. Table 3.1 displays the meta data of participants.

Table 3.1. Participant's metadata

NAME	AGE	HEIGHT (cms)	WEIGHT (kgs)
Subject1	22	166	63
Subject2	18	170	72
Subject3	21	162	68
Subject4	21	172	65
Subject5	21	166	64
Subject6	21	168	70
Subject7	21	170	69
Subject8	21	165	61
Subject9	21	167	64
Subject10	21	163	62
Subject11	21	166	68
Subject12	21	172	67
Subject13	21	164	65
Subject14	21	170	66
Subject15	21	167	69
Subject16	22	164	59
Subject17	18	165	69
Subject18	17	164	68
Subject19	21	170	64
Subject20	21	168	61
Subject21	21	175	65
Subject22	21	177	62

3.2. MINI-MENTAL STATE EXAMINATION (MMSE)

A rigorous pre-testing protocol has been employed by administering the Mini-Mental State Examination (MMSE) to evaluate the cognitive functioning and responsiveness of the subjects before initiating the advertisement sessions. The MMSE included standard questions assessing various cognitive domains such as orientation to time and place, attention and calculation, memory recall, language abilities, and visuospatial skills. Sample questions from the MMSE included inquiries about the current date and location, serial subtraction of numbers, recalling three unrelated words after a delay, naming common objects, and copying a complex figure. This comprehensive pre-testing procedure was crucial in ensuring the participants' mental readiness and engagement levels, thereby enhancing the reliability and validity of the EEG data collected during the experimental sessions.

In addition to administering the Mini-Mental State Examination (MMSE) to assess cognitive function, we implemented a thorough screening process before the EEG recordings. This screening involved gathering demographic information, assessing overall health status, and evaluating any potential factors that could influence EEG readings, such as medication use or previous neurological or depression conditions. We also conducted a brief interview to gauge the participants' familiarity with advertising content and their ability to concentrate during the experimental tasks. The Mini-mental state examination is scored on a scale of 0-30 with scores > 25 interpreted as normal cognitive status, scores between 18-23 as mild and 0-17 as severe cognitive status. This comprehensive approach aimed to ensure that the subjects were not only cognitively capable but also suitable for the specific demands of the EEG recording session, thereby enhancing the accuracy and relevance of the collected data for our study on neural responses to advertisements.

3.3. SELECTION OF ADVERTISEMENTS

The selection of advertisements for the study was methodically structured around five distinct categories: ads featuring actors, ads showcasing animals (2 ads), ads characterized by dialogues, jingle ads, and animation ads. These categories were chosen to represent varied stimuli that could elicit different cognitive and emotional responses from viewers providing a comprehensive spectrum of stimuli for analysis. The ads were curated based on an extensive analysis of feedback and engagement metrics gathered from reputable platforms such as YouTube and Google Search. This data-driven approach ensured the inclusion of ads that had demonstrated widespread appeal and effectiveness in capturing audience attention and interest, thereby enriching the diversity and relevance of stimuli used in our study on neural responses to advertising content. In this study, six videos of advertisements were chosen. The selection criteria for the advertisement videos were based on the marketing of several product categories, such as beverages, cars, paints, smartphones and personal care product. The lengths of the videos vary. These videos also vary widely in terms of resolution. Table3.2 displays a summary of the video properties.

Category	**Advertisement Link**	**Duration (mins)**	**Views and Comments**	**Resolution**
Celebrity	https://youtu.be/n-YiJq4Xj_c?si=1uGZHepE19oWpOMo	1.25	32M & Comments turned off	1080p
Jingle	https://youtu.be/BybZXC7FubA?si=115FCH1sbbt6EF7W	1.20	2.1M & Comments turned off	1080p
Dialogue	https://youtu.be/eKCA5cYx7EM?si=qGLkDgmP4bJ0-Ty-	0.35	1.4M & 125	480p
Animal	https://www.youtube.com/watch?v=0K8lrVjT6fM	1.29	804K & 311	360p
Paint	https://www.youtube.com/watch?v=pWU-JWMtrfU	0.30	417K & 7	1080p
Animal'	https://www.youtube.com/watch?v=qyumyb6hQvo	0.51	402K & 73	240p

Table 3.2. Video attributes obtained from Youtube

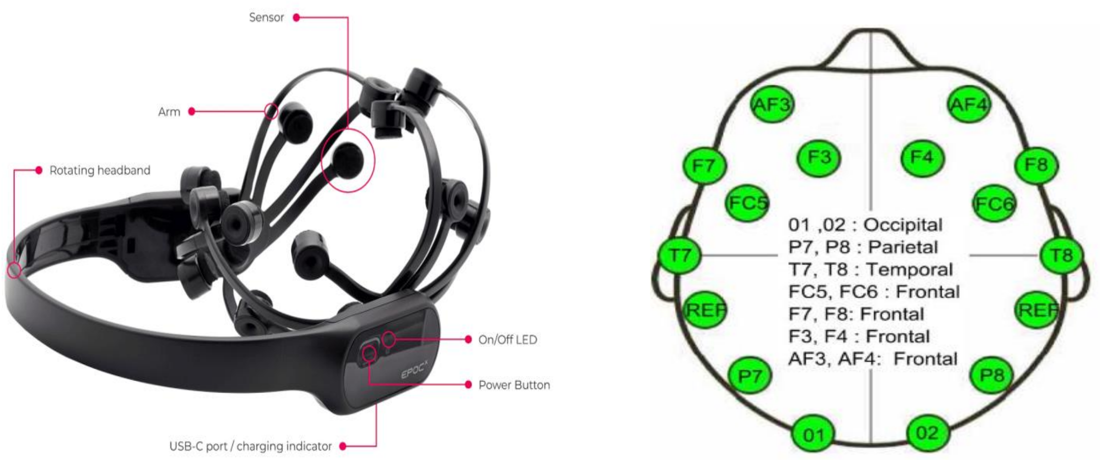
3.4. SELF ASSESMENT QUESTIONNAIRE

Following the presentation of advertisements, the participants are asked to answer the structured questionnaire to gather their feedback and ratings of the ads .Questionnariei is prepared by inpsiring from [19],[20] references .The questionnaire included a list of the ads shown during the session, and participants were asked to provide the score ratings on a scale of one to five stars, based on various criteria such as brand appeal, relevance, appeal, visual aesthetics, clarity of message, emotional impact, and overall effectiveness. Each ad was individually rated according to the subjects' perceptions and preferences, allowing for a comprehensive evaluation of audience responses. This data collection method enabled us to obtain valuable qualitative feedback and insights into how the ads were perceived and received by the participants, contributing to a nuanced analysis of advertising effectiveness in our study. By gathering both quantitative ratings and qualitative comments, we aimed to obtain a comprehensive understanding of the audience's perceptions and preferences, enriching our analysis of advertising efficacy and audience engagement strategies.

3.5. EXPERIMENTAL PROTOCOL

3.5.1 EMOTIV EPOC X BRAINWEAR ELECTRODE LOCATIONS

The EPOC X headset is designed for research and professional applications, offering 14 channels for comprehensive EEG recordings to track and analyze brain activity in real time. It is sleek design aids neuroscientists, researchers, and professionals to record high-quality EEG data for advanced brain research and analysis. The electrodes arranged in a certain pattern on this wearable headset record electrical impulses that are sent from the brain through the scalp.



(a) (b)

Fig. 3.1. a) Emotiv EPOC X headset b) Emotiv electrode placement

The EPOC X allows thorough data gathering across multiple brain areas using the electrode array consisting of 16 electrodes, in which 14 electrodes covers important scalp regions such the frontal (AF3, AF4, F4, F8, FC6, F3, F7, FC5), temporal (T7, T8), parietal (P7, P8), and occipital lobes (O1, O2) and two reference electrodes (CMS-Common mode sense and DRL-Driven right leg) for maintaining a stable electrical reference point. Moreover, it allows for smooth interaction with suitable software platforms due to its wireless connectivity and sophisticated signal processing capabilities, which enable in-depth EEG research and experimentation. Figure 3.1 a and b displays the Emotiv headset and electrode positions. The colors of the electrode reveal the electrodes' level of contact. The green color on the head map in EMOTIV application interface ensures the contact quality and impedance are good enough to take recordings.

3.6. EXPERIMENTAL DETAILS

Following the completion of cognitive assessments, participants were fitted with Emotiv headsets to meticulously record brain signals during the subsequent phases of the study as shown in Figure 3.2. This meticulous process ensured the accurate capture of neural activity and responses, enhancing the precision and reliability of the EEG data collected. The Emotiv headsets were securely positioned on the subjects' heads by trained personnel, adhering to standardized procedures to minimize interference, optimize signal quality and obtain robust neurophysiological insights in our investigation of cognitive responses to advertising stimuli.

Fig 3.2. Placement of Headset

Before placement on the subjects' heads, the electrodes of the Emotiv headsets were carefully moistened with saline solution to optimize the capture of EEG signals. This preparatory step was essential for ensuring optimal conductivity and signal quality during the recording process. Subsequently, the headsets were securely fitted onto the subjects' heads. The connection between the Emotiv headset and the laptop was established through a provided USB receiver dongle, enabling real-time data transmission and monitoring of EEG signals throughout the experimental Emotiv application sessions. This meticulous setup procedure and connectivity protocol were implemented to uphold the standards of

EEG recording and data acquisition, thereby facilitating accurate and reliable neurophysiological insights in our study.

In the first phase of our study, we conducted continuous ad exposure sessions lasting 19 minutes without any breaks. Participants were asked to sit and watch the ads continuously during this period. This approach was designed to simulate real-world scenarios where ads are often presented in a continuous stream. However, our analysis did not reveal any significant differences between various features of neural responses, suggesting a possible state of boredom or fatigue among the subjects. This finding highlights the potential limitations of prolonged ad exposure without breaks and underscores the importance of considering viewer engagement and attention span in designing effective advertising strategies.

In the second study, a standardized relaxation protocol was implemented. Participants were instructed to sit with their eyes open for 15 seconds, followed by 15 seconds with their eyes closed, to establish a relaxed baseline state. This pre-advertisement relaxation period aimed to minimize potential confounding factors and promote a consistent neural state among subjects during the subsequent ad-viewing sessions. Throughout the experiment, a total of 6 ads were presented to the participants, with structured breaks incorporated into the viewing schedule. In first session 3 ads were presented and next session another 3 ads.

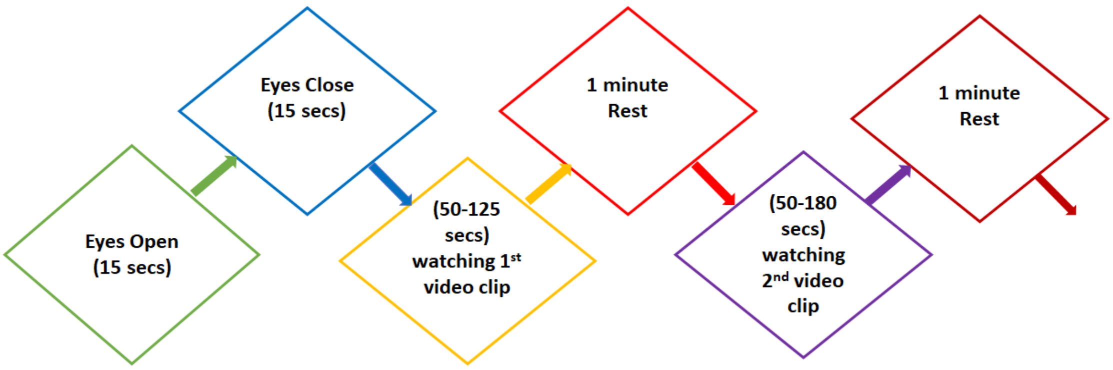


Fig. 3.3 The experimental protocol

Specifically, subjects were given a 1-minute rest between each ad, and after completing the viewing of 3 ads, they were provided with a 4-minute rest period before visualizing another set of 3 ads. The order of presentation of ads for each participant was randomized. These strategic breaks and randomness have been utilized to prevent fatigue, maintain participant engagement, and optimize the quality of EEG data collected during the experiment. These findings suggest that incorporating strategic breaks during ad viewing sessions can optimize viewer engagement and potentially improve the effectiveness of advertising campaigns. Figure 3.3 displays the experimental protocol. Figure 3.4 displays Images of participants watching the advertisements.

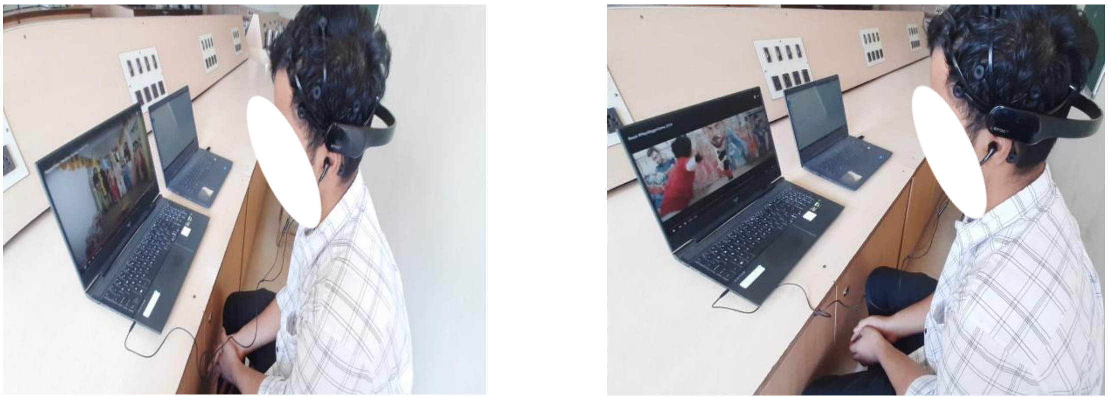


Fig. 3.4 Images of participants watching the advertisements

3.7. SIGNAL PROCESSING AND FEATURE EXTRACTION

The process starts by filtering raw EEG data to reduce noise and isolate the relevant frequency ranges. This involves using bandpass filters to remove frequencies outside the targeted range and notch filters to eliminate specific interference, such as power line noise and artefacts. The filter's parameters were set at 64 Hz and 0.16 Hz as the cut off frequencies, respectively. A sampling frequency of 256 Hz was selected for data processing. Once cleaned, the data is segmented into epochs based on user-defined start and endpoints.

Wavelet decomposition is then applied to these segments using the Daubechies 8 (db8) wavelet function, breaking the EEG signals into distinct frequency bands like delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ). It breaks down a signal into its constituent parts, referred to as wavelet coefficients, by convolving the signal with wavelet functions. Higher coefficients capture finer details, whereas lower coefficients capture wider patterns. These coefficients describe the energy of the signal at different levels of detail. This decomposition allows for a more detailed analysis of brain activity across different time windows. Following decomposition, the detail coefficients (D1 to D5) indicate signal features at delta, theta, alpha, beta, and gamma brainwave frequencies, respectively, and correspond to distinct frequency bands. Next, particular wavelet coefficients for analysis are reconstructed using the 'wrcoef' function. The average energy or power inside each frequency band can be found by taking the mean of these coefficients (A1 to A5, and D1 to D5). Thus, the wavelet decomposition essentially makes it possible to analyze EEG data across a range of frequency bands, which in turn makes it possible to characterize the patterns of brain activity connected to various cognitive states or tasks. With the use of this technique, it is easier to extract features from the EEG signal, such as delta, theta, alpha, gamma, and beta band powers. These features can then be further examined or categorized for a variety of uses in cognitive science and neuroscience.

Figure 3.5 displays the proposed methodology Different brain frequency bands, such as beta, gamma, theta, alpha, and delta, are associated with distinct mental and physical states. While beta waves are associated with increased attentiveness and engaged thinking, alpha waves signify a relaxed yet alert state. Advanced cognitive functions are frequently accompanied by gamma waves. While theta waves are prevalent during a relaxed state during sleep, delta waves are associated with profound sleep and unconscious activity. Various parameters can be derived from these frequency bands. These include indices like arousal index, task load index, CNS arousal, brain perfusion, vigilance index, neuronal activity, synchronization, heart rate index, synchronization, desynchronization, LF/HF ratio, executive load index, performance enhancement index, alpha gamma ratio, and cognitive performance index. Each of these metrics provides insights into the underlying brain activity and cognitive states that is being stated in Table 3.3.

S.NO	EEG Feature	Formula	Physiological indication
1	Beta	β	Increased mental activity
2	Alpha	α	Relaxation, calmness, alertness
3	Theta	θ	Meditation, memory, learning and emotional regulation
4	Delta	δ	Restless sleep
5	Gamma	γ	Physiological and cognitive functions
6	Synchronisation (Sync)	δ / θ	Degree of coherence of brain activity in various regions
7	Brain Perfusion (BP)	α / δ	Veritas flow and nerve activity in the brain
8	CNS Arousal (CNSA)	θ / β	n Level of excitation and reactivity of the central nervous system
9	Desynchronisation (Dsync)	α / β	Lack of uniformity of brain activity in different regions
10	Cognitive Performance Index (CPI)	$\beta / \alpha + \theta$	General cognitive activity and efficiency in processing advertising content
11	Executive Load Index (ELI)	δ+θ/ α	Level of cognitive load and distribution of executive resources
12	Performance Enhancement Index (PEI)	θ / α	Improvement in cognitive performance and task performance
13	LF to HF Ratio (LF)	θ+δ/ α+β	Proportion of low- and high-frequency heart rate variability
14	Task Load Index (LTI)	α / θ	Level of cognitive workload and task complexity
15	Vigilance Index (VI)	θ+α / β	Level of sustained attention and vigilance
16	Heart Rate Index (HRI)	θ / α	Mirrors heart rate while watching an ad.
17	Arousal Index (AI)	β / α	Indicates the level of emotional arousal.
18	Neuronal Activity (NA)	β / θ	Represents the level of neural activity in the brain.
19	Alpha Gamma Ratio	α/ γ	relative balance between two different frequency bands

Table 3.3 Physiological Indications of EEG Features

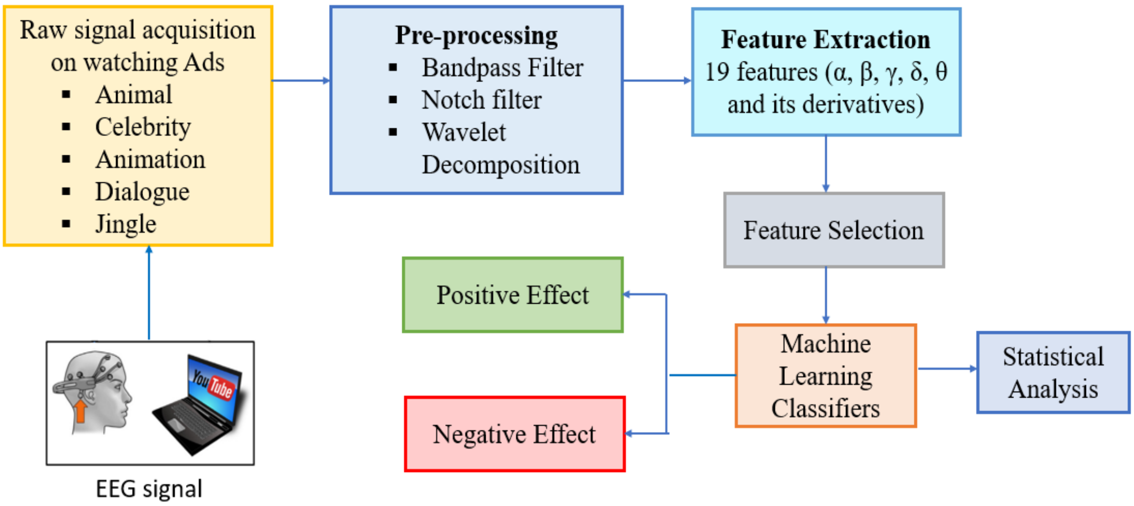


Fig. 3.5 The proposed methodology

3.8. MACHINE LEARNING

In the machine learning segment of the test, features were extracted. Various machine learning (ML) models were then applied to these features to evaluate accuracy and other performance metrics. By capturing EEG signals both in a relaxed state and during exposure to advertisements, we can compare baseline brain activity with stimulus-induced responses. This comparison helps us identify specific neural signatures associated with ad perception and emotional attachment. By correlating neural activity with opinion analysis results, we can explain the neural basis of consumers' perceptions, preferences and decision-making processes in relation to advertising stimuli. This approach allows us to bridge the gap between neurophysiology and consumer behavior by providing a nuanced understanding of how the human brain responds to external stimuli such as advertising. By integrating processed EEG signals into emotion analysis using machine learning models, we gain a multidimensional perspective of consumer responses to advertisements. This holistic approach allows us to unravel the complex interplay of cognitive processes, emotional states and decision-making tendencies triggered by advertising stimuli. Using a neuroscientific lens, we can unravel the underlying mechanisms that drive consumer engagement, brand perception and ultimately purchase behavior

CHAPTER 4

RESULTS

4.1 MINI MENTAL TEST RESULT:

Before the experiment, we evaluated the mental capacity of the subjects through a brief mental assessment. As previously indicated, individuals with a score below 25 were ineligible to participate. All participants met this minimum requirement, ensuring they exhibited no signs of cognitive impairment and were deemed suitable for the research. Additionally, the test outcomes are depicted in Figure 4.1 as indicated.

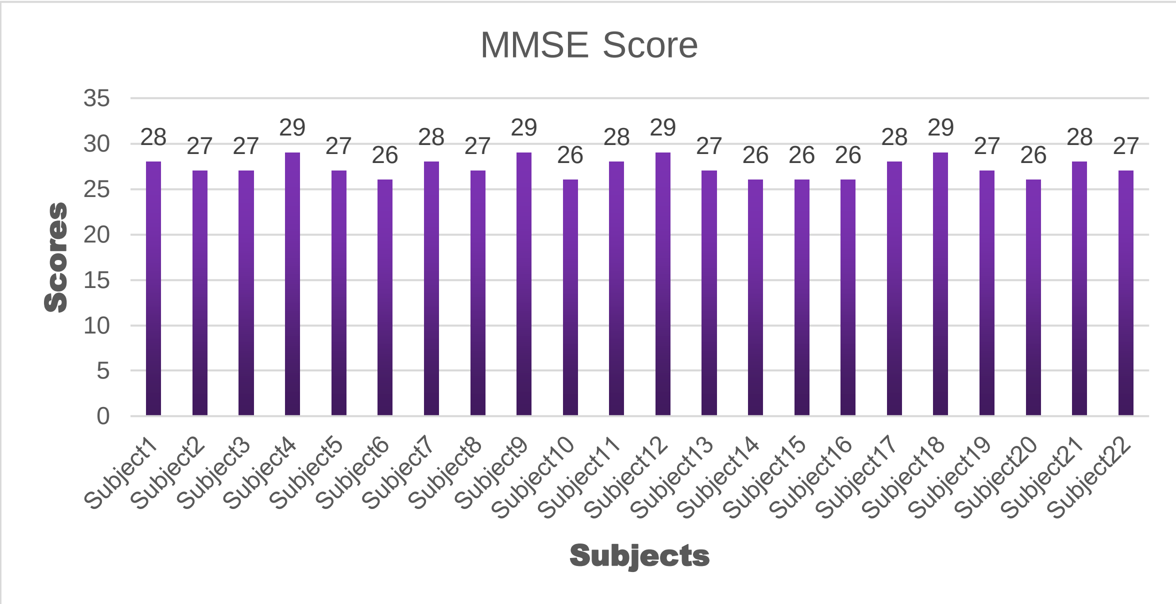


Fig.4.1 Mini Mental test scores of subjects

4.2 RESULTS OF QUESTIONNARIE:

After the participants completed seeing the ads, we recorded their feedback using a questionnaire comprising fifteen question per advertisement. We utilized a Google Form to collect their responses, employing a 5-point rating system where participants assessed their performance during gameplay as "Excellent," "Good," "Neutral," "Bad", "Worst." Through their responses, we gained a clear understanding of the participants' expectations regarding advertisements.

This classification method enabled us to categorize the advertisements into two distinct labels: "Good" and "Bad." By adopting this methodological approach, we ensured a clear understanding of participants' preferences regarding the advertisements presented during the study. Table 4.2 displays the ratings of ads.Figure 4.2 displays the bargraph of ratings given by each subject.

Name	Celebrity	Jingle	Dialogue	Animal	Paint	Animal’
Subject1	4	4	2	5	2	3
Subject2	4	4	2	5	1	2
Subject3	4	4	2	5	1	1
Subject4	5	4	2	4	2	1
Subject5	4	4	2	5	1	2
Subject6	5	5	2	4	2	1
Subject7	5	5	1	4	2	2
Subject8	4	3	3	5	5	3
Subject9	5	4	3	5	3	3
Subject10	5	5	1	2	3	3
Subject11	5	4	2	5	3	1
Subject12	5	4	5	5	2	5
Subject13	5	3	1	5	2	1
Subject14	3	4	4	3	3	4
Subject15	5	4	4	3	4	4
Subject16	5	3	2	5	2	1
Subject17	3	2	2	4	4	4
Subject18	4	5	5	5	5	5
Subject19	4	5	3	5	4	1
Subject20	5	4	2	5	3	1
Subject21	4	5	3	5	4	1
Subject22	4	4	3	5	4	1
Result	4.409	4.045	2.545	4.5	2.818	2.273

Table.4.2. Ratings of advertisements from each subject

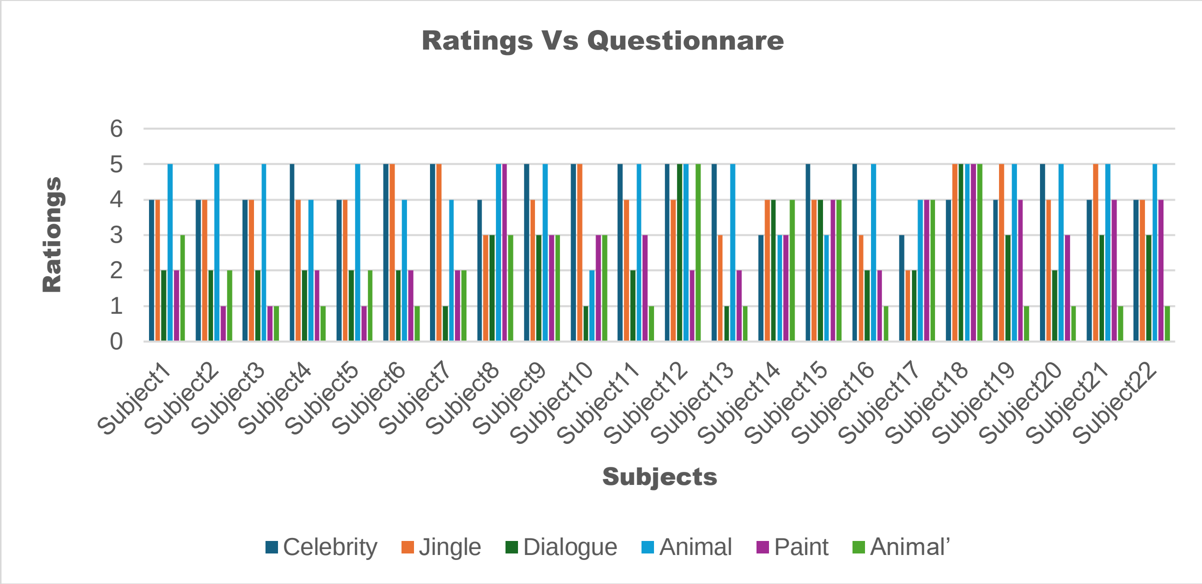
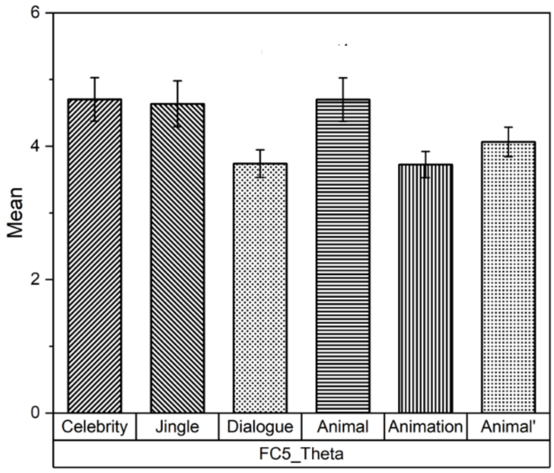


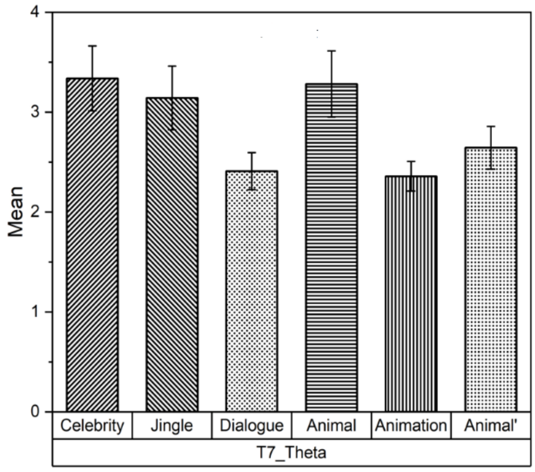
Fig.4.2 Bargraph of results of questionnare

4.3 STATISTICAL ANALYSIS OF EEG FEATURES:

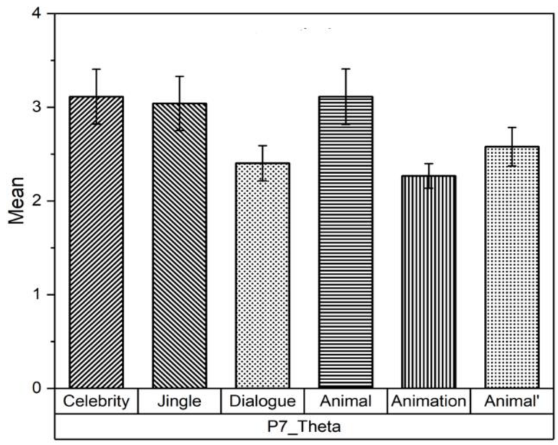
The statistical analysis is done for six situations, because there are six advertisements, of which two belong to animals and the others to celebrities, dialogues, jingles and animations. The most significant characteristics of the different channel electrodes are identified using the p-value ($p < 0.05$). In addition, graphs of important salient features are displayed to visualize the differences between the ads that users experience when they see them. All 14 electrodes showed importance for the frequency band characteristics of the EEG signal in the visualization of advertisements. In addition, the important properties of the various electrodes are tabulated.



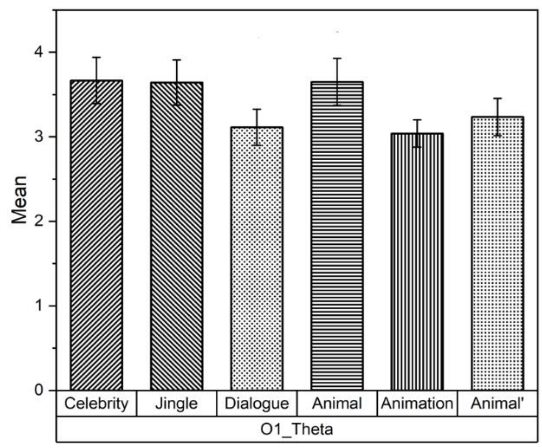
(a)



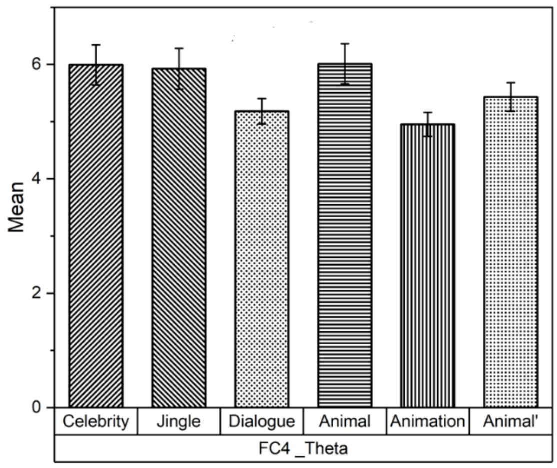
(b)



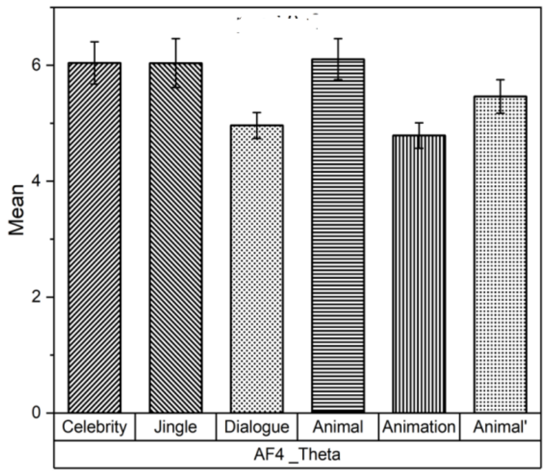
(c)



(d)



(e)



(f)

Fig 4.3.1: Graph of significant features - mean and standard error of theta energy of (a) FC5, b) T7, c) P7, d) O1, e) FC4, h) AF4 electrode positions

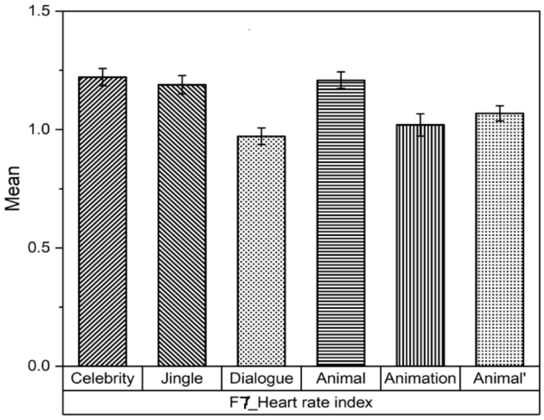
Figure 4.3.1 displays the graphs of theta energy of five different electrodes.High theta activity in ads indicates that viewers find the ads emotionally or engaging because they show active engagement in cognitive processing, attention management, and emotional responses. Efforts to effectively process advertising content are reflected in this increased brain activity. Low theta activity, on the other hand, could indicate reduced engagement, negative opinions, indifference, or disengagement from ads. Optimizing the effectiveness of ads helps understand viewers' emotional and cognitive reactions to advertising through Theta activity analysis.

High theta activity in advertisements can be a sign of heightened attention and cognitive processing. Theta brain waves are associated with deep focus, concentration and memory formation. Thus, when viewers show high theta activity when interacting with ads, it suggests that they are actively processing and encoding the information presented in the ads. This can be a positive sign for advertisers because it shows that the ads are engaging and likely to be remembered by viewers.

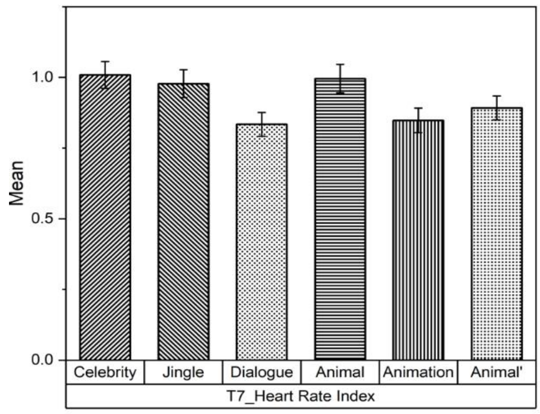
Table.4.3.1 Significant value of Theta energy

Electrodes	Condition	Mean	Standard Error of Mean	Significant value (p)
AF3	Celebrity	5.501	0.277	0.005
	Animal’	4.913	0.205	
	Jingle	5.43	0.302	0.001
	Animation	4.574	0.264	
	Dialogue	4.565	0.189	0
	Animal	5.46	0.267	
FC5	Celebrity	4.704	0.325	0.015
	Dialogue	3.74	0.206	
	Jingle	4.636	0.345	0.022
	Animation	3.736	0.198	
	Animal	4.698	0.326	0.109
	Animal’	4.065	0.221	
T7	Animation	2.3578	0.1477	0.038
	Jingle	3.1412	0.31933	
	Dialogue	2.4089	0.18462	0.014
	Celebrity	3.3375	0.32419	
	Animal’	2.6432	0.21456	0.09
	Animal	3.2807	0.33106	
P7	Animation	2.2662	0.13148	0.025
	Jingle	3.0402	0.28911	
	Dialogue	2.4025	0.18803	0.04
	Celebrity	3.1134	0.29229	
	Animal’	2.579	0.20601	0.121
	Animal	3.1128	0.2958	
O1	Animation	3.0391	0.16136	0.025
	Jingle	3.6414	0.26715	
	Dialogue	3.1116	0.2136	0.04
	Celebrity	3.6649	0.27371	
	Animal’	3.2335	0.21935	0.121
	Animal	3.6493	0.27632	
FC6	Animation	4.6034	0.18513	0.004
	Jingle	5.7394	0.34777	
	Dialogue	4.7813	0.1792	0.012
	Celebrity	5.7681	0.33257	
	Animal’	5.0928	0.20517	0.081
	Animal	5.7704	0.32295	
FC4	Animation	4.9517	0.20853	0.022
	Jingle	5.9241	0.35802	
	Dialogue	5.1808	0.22238	0.055
	Celebrity	5.9931	0.35051	
	Animal’	5.4323	0.24954	0.171

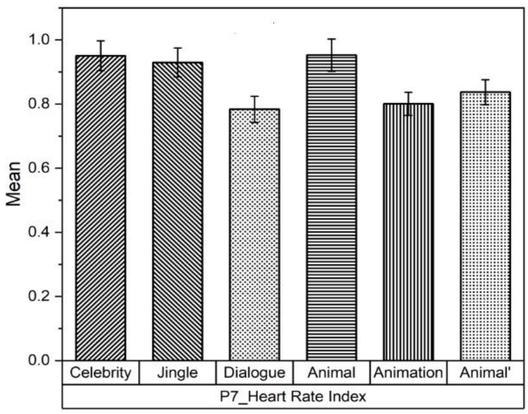
	Animal	6.0108	0.34978	
F8	Animation	5.0603	0.26565	0.002
	Jingle	6.5988	0.40242	
	Dialogue	5.3248	0.27107	0.005
	Celebrity	6.6839	0.37115	
	Animal’	5.8893	0.3108	0.092
	Animal	6.6988	0.37903	
AF4	Animation	4.788	0.22024	0.007
	Jingle	6.0382	0.42171	
	Dialogue	4.9632	0.22347	0.019
	Celebrity	6.0412	0.36477	
	Animal’	5.4632	0.28841	0.16
	Animal	6.1055	0.35337	



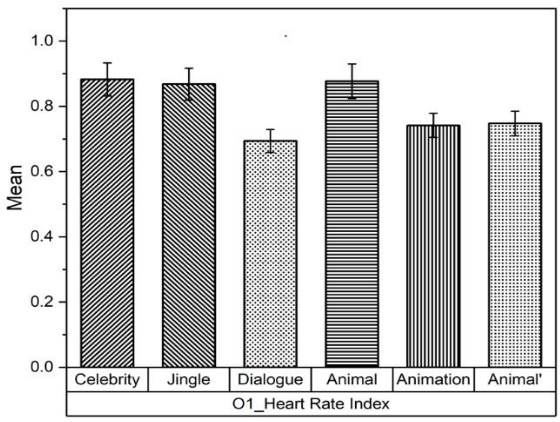
(a)



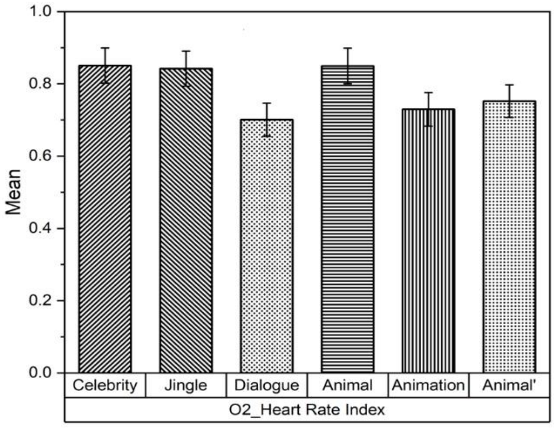
(b)



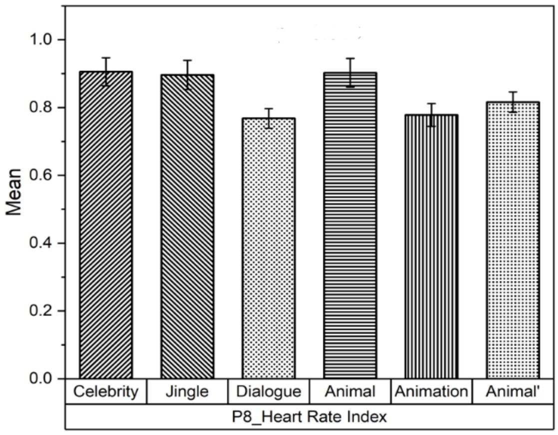
(c)



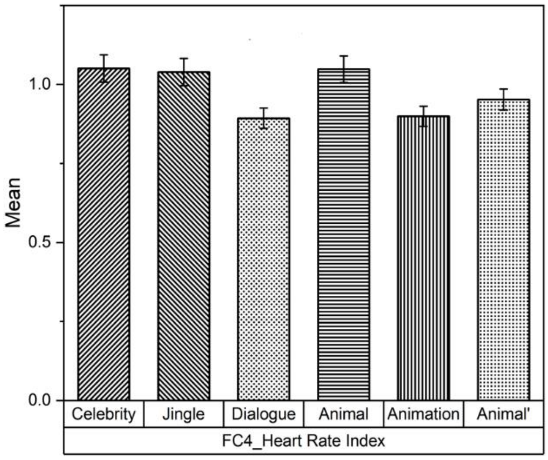
(d)



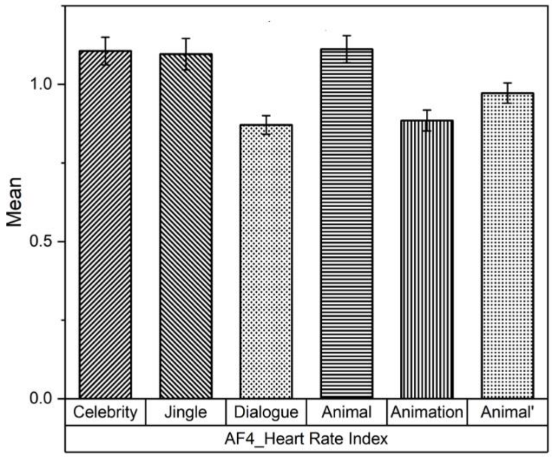
(e)



(f)



(g)



(h)

Fig 4.3.2: Graph of significant features - mean and standard error of heart rate index of (a) F7, b) T7, c) P7, d) O1, e) O2, f) P8, g) FC4, h) AF4 electrode positions

Figure 4.3.2 displays the graphs of Heart Rate Index energy of five different electrodes Variations in heart rate index (HRI) power indicate that viewers exposed to different advertisements show varying degrees of physiological arousal and emotional stimulation. Elevated arousal and emotional response indicate positive engagement, as indicated by a higher HRI for celebrity, jingle, and animal advertisements. On the other hand, a lower HRI means potential detachment and reduced physiological arousal. A comprehensive understanding of viewers' cognitive and emotional engagement with advertisements requires the analysis of various variables in addition to heart rate.

If an advertisement has a high HR index, it indicates that viewers are emotionally and physiologically engaged, which can indicate a positive response. To fully understand the cognitive and emotional engagement of viewers, it is necessary to consider several variables other than heart rate. On the other hand, a low heart rate index indicates a decrease in emotional and cognitive engagement and may indicate a detrimental effect. In order to fully understand how viewers react and perceive advertisements, it is necessary to analyze other physiological and psychological factors besides heart rate. For PEI and TLI graphs are similar to heart rate index of F7, T7, P7, O1, O2, P8, FC4, AF4 electrode positions. A low Performance Improvement Index (PEI) for ads suggests that viewers may not experience significant cognitive or behavioral improvements when interacting with them. Regardless of potential enjoyment or pleasantness, other metrics must be considered to measure overall cognitive and emotional engagement. On the other hand, a high PEI indicates that viewers may experience significant cognitive or behavioral improvement despite their negative perception of the ads. Considering other metrics in addition to PEI is crucial for a comprehensive understanding of viewers' cognitive and emotional responses to advertisements. The effective augmentation index of advertisements indicates that viewers experience enhanced cognitive functions and emotional responses to advertisements. This index typically combines several dimensions such as attention, emotional involvement, memory encoding, and persuasion. If this index is high, it indicates that advertisements are effective in improving the cognitive processing, emotional responses and general engagement of viewers, which can lead to a more positive perception of the advertised brand or product. It is important for advertisers to track this index along with other related metrics to measure the effectiveness of their advertising campaigns and make informed decisions about future marketing strategies.

The high workload index (TLI) for ads indicates that viewers find these ads mentally engaging and demanding and require significant cognitive resources to process them. While this can attract attention and activate, it is important to ensure that the cognitive demand matches the processing capacity of the viewers. On the other hand, a low TLI indicates that advertisements are perceived as easy to use and require little cognitive effort. Despite the potential negative effects, considering metrics other than TLI helps to understand viewers' overall cognitive and emotional response to ads. A high task load index for ads indicates that viewers find ads mentally challenging or difficult to process. This index measures the cognitive workload of individuals when dealing with advertisements. A high task load index indicates that viewers experience a greater cognitive effort to understand or process the content of the advertisements. This may be due to factors such as complex information, fast images or a dense message in advertisements. While a high workload index may indicate that viewers are deeply engaged with content, it is important for advertisers to strike a balance between capturing attention and overwhelming the audience with excessive cognitive demands.

High gamma power in good cues indicates increased neural activity associated with cognitive processing, attention, and memory encoding. This increased gamma oscillation may reflect viewers' active engagement and processing of ad content, which may indicate positive cognitive responses and improved memory retention. Analyzing gamma activity provides insight into the cognitive processing and emotional reactions of viewers, which helps to understand the effectiveness and impact of advertisements.

4.4 MACHINE LEARNING RESULTS:

In the machine learning phase of the project, data containing 19 features were processed to create reliable models. ANOVA feature selection was used to identify and retain the most significant features to improve model performance. This step helped to reduce dimensionality and improve computational efficiency by ensuring that the models focused on the most important features.

Because there was class imbalance in the dataset, SMOTE (Synthetic Minority Over-Sampling Technique) was used to create a balanced dataset. This method synthetically generates samples that match the minority class, which helps models learn from a balanced perspective, reducing the risk of overfitting the majority class. A random search was performed to identify the best model parameters, exploring many possible hyperparameters. This approach offered wider configuration options, allowing for a more flexible and efficient search process. After determining the appropriate parameter range, grid search was used to fine-tune the model hyperparameters for four different algorithms: ensemble learning, extreme gradient boosting (XGBoost), neural networks (NN), and k-nearest neighbors (KNN). The best grid search parameters were then fitted to each model. Training and testing accuracies were calculated to evaluate the performance of the models. A confusion matrix was used to evaluate the classification performance of each model, which provides insight into precision, recall and the balance between true positives, false positives, true negatives and false negatives. In addition, a receiver operating characteristic (ROC) curve was constructed for each model. This graph illustrates the ratio of true positives to false positives. It provides a visual representation of model performance and allows comparison of models based on their area under the curve (AUC). Figures 4.4.1 ,4.4.2,4.4.3, 4.4.4 displays the onfusion matirx and Roc curve of ensemble model of channel 4,6,8 and all channel together.

Using these combined techniques, the project achieved a deep understanding of data characteristics, effectively addressed imbalances, and gained insight into the accuracy and effectiveness of various machine learning models in predicting desired outcomes. This approach facilitated the selection of the best performing model for future applications. Table 4.4.1 and 4.4.2 shows the training and testing accuracies.

Channel	ENSEMBLE		XGBOOST		NEURAL NETWORK		KNN	
	TRAINING	TESTING	TRAINING	TESTING	TRAINING	TESTING	TRAINING	TESTING
1	83%	65%	92%	68%	68%	62%	97%	65%
2	83%	68%	83%	63%	68%	53%	95%	71%
3	85%	70%	88%	55%	67%	58%	94%	60%
4	79%	73%	89%	66%	68%	52%	94%	67%
5	84%	70%	87%	61%	70%	50%	92%	68%
6	87%	71%	80%	63%	69%	54%	90%	64%
7	89%	68%	92%	60%	70%	57%	95%	63%
8	85%	69%	90%	62%	71%	54%	92%	68%
9	84%	71%	86%	63%	65%	56%	96%	66%
10	85%	72%	80%	62%	67%	58%	97%	64%
11	87%	72%	82%	66%	64%	58%	96%	65%
12	83%	72%	86%	69%	69%	57%	95%	66%
13	88%	70%	83%	68%	64%	60%	94%	64%
14	83%	71%	85%	67%	68%	63%	96%	65%
All Channel	84%	73%	88%	70%	63%	62%	92%	69%

Table 4.4.1 Training and testing accuracy of four models without feature selection

Table4.4.2 Training and testing accuracy of four models with feature selection

Channel	ENSEMBLE		XGBOOST		NEURAL NETWORK		KNN	
	TRAINING	TESTING	TRAINING	TESTING	TRAINING	TESTING	TRAINING	TESTING
1	89%	66%	93%	72%	70%	63%	95%	72%
2	88%	72%	76%	64%	65%	55%	85%	72%
3	86%	73%	88%	63%	63%	60%	96%	61%
4	85%	74%	81%	67%	64%	55%	94%	71%
5	89%	72%	85%	66%	70%	53%	90%	69%
6	88%	74%	89%	71%	62%	58%	98%	67%
7	85%	70%	89%	64%	769%	59%	89%	70%
8	88%	71%	77%	65%	71%	56%	85%	70%
9	87%	73%	82%	68%	65%	58%	93%	71%
10	82%	74%	83%	67%	63%	60%	94%	69%
11	86%	73%	84%	69%	66%	59%	96%	72%
12	82%	74%	83%	72%	65%	58%	94%	70%
13	84%	72%	84%	71%	63%	61%	97%	68%
14	84%	73%	83%	69%	64%	65%	96%	72%
All Channel	81%	76%	85%	73%	67%	64%	92%	74%

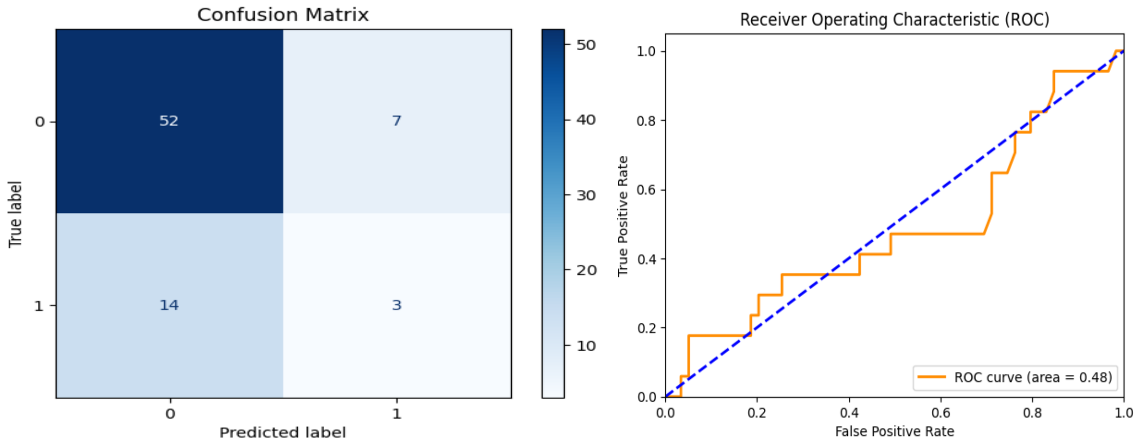


Fig 4.4.1 Confusion Matrix and Roc Curve for the Ensemble model of channel 4

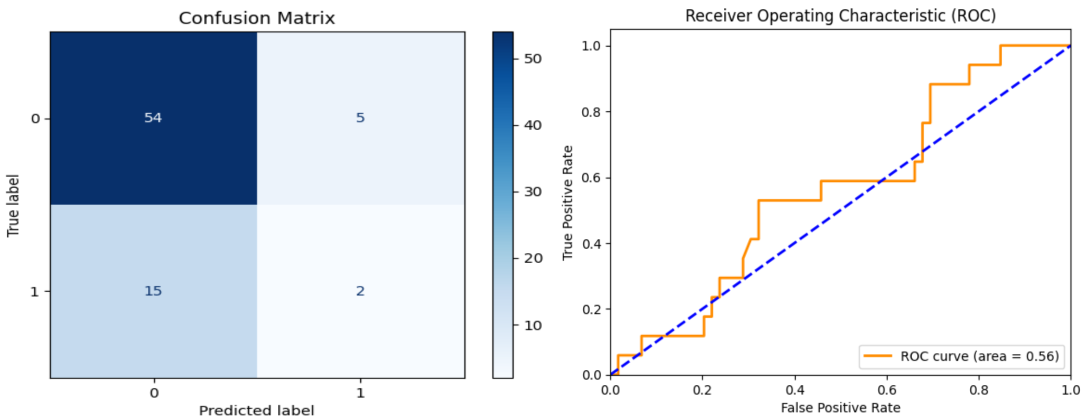


Fig 4.4.2 Confusion Matrix and Roc Curve for the Ensemble model of channel 6

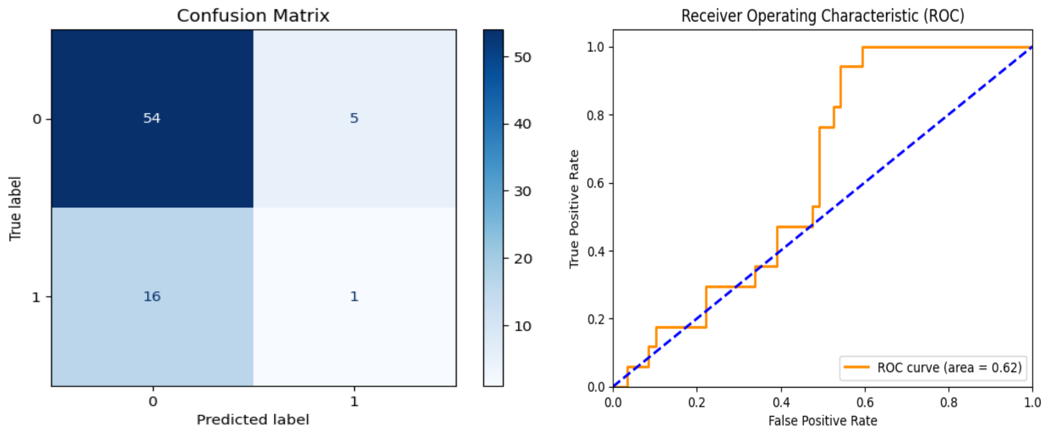


Fig 4.4.3 Confusion Matrix and Roc Curve for the Ensemble model of channel 8

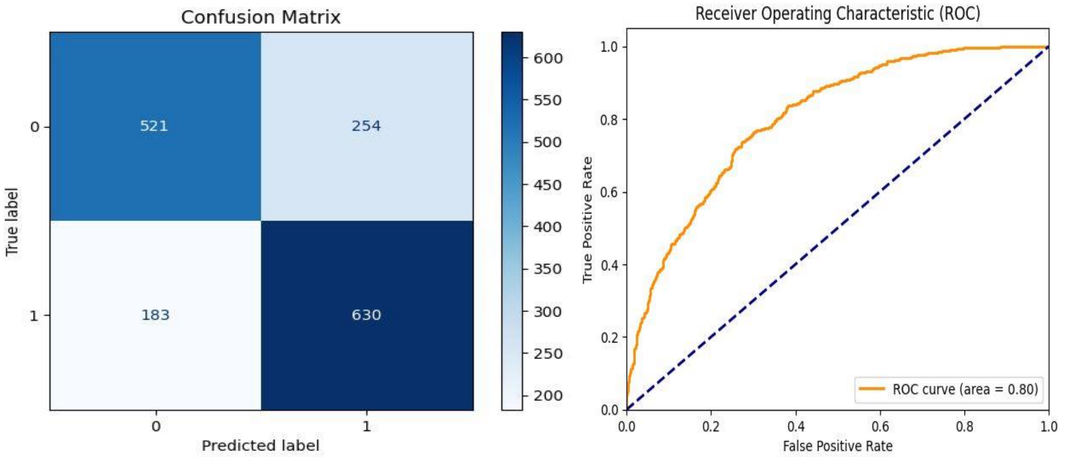


Fig 4.4.4 Confusion Matrix and Roc Curve for the Ensemble model of all channel combined together

CHAPTER 5

DISCUSSIONS AND CONCLUSION

The findings of this project highlight the importance of understanding neural responses to different advertising stimuli, as evidenced by the careful selection of actors and animals in commercials and the lack of dialogue. The integration of EEG recordings and in-depth participant feedback provided valuable information about the cognitive engagement and emotional responses elicited by different types of advertisements. Moving forward, a future scope of the project is to further analyze the EEG data to determine the neural correlates of advertising effectiveness, which may reveal neuro cognitive markers of advertising success. This research sets a precedent for using neuroscientific methods to inform advertising strategies, paving the way for more targeted and effective marketing methods in the future. The culmination of this project highlights the importance of disentangling neural responses to different advertising stimuli, as demonstrated by careful categorization of advertisements.

By analyzing EEG recordings and detailed participant feedback, comprehensive insights into the cognitive engagement and emotional responses elicited by different types of advertisements were gained. The future trajectory of the project will include an in-depth analysis of EEG data to determine the neural correlates of advertising effectiveness, which may reveal neurocognitive markers important to advertising success. This research not only sets a benchmark for using neuroscience methods to inform advertising strategies, but also opens up opportunities to develop more targeted and effective marketing campaigns in an ever-evolving consumer engagement landscape.

REFERENCES:

1. https://www.globenewswire.com/news-release/2023/08/16/2726680/0/en/Neuromarketing-Market-Size-Share-Analysis-Growth-Trends-Forecasts-2023-2028.html
2. https://economictimes.indiatimes.com/small-biz/startups/features/using-human-emotions-in-marketing-with-the-help-of-ai-entropik/articleshow/70547834.cms?from=mdr
3. Raiesdana, S.; Mousakhani, M. An EEG-Based Neuromarketing Approach for Analyzing the Preference of an Electric Car. Comput.Intell. Neurosci. 2022, 2022, 9002101. [CrossRef] [PubMed]

4. Chakravarthi, B.; Ng, S.C.; Ezilarasan, M.; Leung, M.F. EEG-based emotion recognition using hybrid CNN and LSTM classification.Front. Comput. Neurosci. 2022.

5. Schmidt, B., Hanslmayr, S. Resting frontal EEG alpha-asymmetry predicts the evaluation of affective musical stimuli. Neurosci Lett. 460 (3),237-240, (2009).

6. Davidson, R.J. What does the prefrontal cortex 'do' in effect: perspectives on frontal EEG asymmetry research. Biol Psychol. 67 (1-2),219-234 (2004).

7. R. Jenke, A. Peer, and M. Buss, “Feature Extraction and Selection for Emotion Recognition from EEG,” IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 327–339, Jul. 2014.

8. M. Soleymani, S. Asghari-Esfeden, M. Pantic, and Y. Fu, “Continuous emotion detection using EEG signals and facial expressions,” in 2014 IEEE International Conference on Multimedia and Expo (ICME), 2014, pp. 1–6.

9. Iigaya K., O’Doherty J.P., Starr G.G. Progress and Promise in Neuroaesthetics. Neuron. 2020;108:594–596. doi: 10.1016/j.neuron.2020.10.022.

10. Conway B.R., Rehding A. Neuroaesthetics and the Trouble with Beauty. PLoS Biol. 2013;11:e1001504. doi: 10.1371/journal.pbio.1001504.

11. Sanchez-Nunez P., Cobo M.J., Las Heras-Pedrosa C.D., Pelaez J.I., Herrera-Viedma E., de las Heras-Pedrosa C., Pelaez J.I., Herrera-Viedma E. Opinion Mining, Sentiment Analysis and Emotion Understanding in Advertising: A Bibliometric Analysis. IEEE Access. 2020;8:134563–134576.

12. Lee N., Broderick A.J., Chamberlain L. What is ‘neuromarketing’? A discussion and agenda for future research. Int. J. Psychophysiol. 2007;63:199–204. doi: 10.1016/j.ijpsycho.2006.03.007.

13. Pearce M.T., Zaidel D.W., Vartanian O., Skov M., Leder H., Chatterjee A., Nadal M. Neuroaesthetics: The Cognitive Neuroscience of Aesthetic Experience. Perspect. Psychol. Sci. 2016;11:265–279. doi: 10.1177/1745691615621274.

14. Fortunato V.C.R., Giraldi J.D.M.E., De Oliveira J.H.C. A Review of Studies on Neuromarketing: Practical Results, Techniques, Contributions and Limitations. J. Manag. Res. 2014;6:201. doi: 10.5296/jmr.v6i2.5446.

15. Ferrer G.G. Encyclopedia of Information Science and Technology. 4th ed. IGI Global; Hershey, PA, USA: 2018. A Neuroaesthetic Approach to the Search of Beauty From the Consumer’s Perspective; pp. 5767–5774.

16. Wang Y.J., Cruthirds K.W., Axinn C.N., Guo C. In search of aesthetics in consumer marketing: An examination of aesthetic stimuli from the philosophy of art and the psychology of art. Acad. Mark. Stud. J. 2013;17:37–56.

17. Asad Ullah, Gulsher Baloch, Ahmed Ali, Abdul Baseer Buriro, Junaid Ahmed.Neuromarketing Solutions based on EEG Signal Analysis using Machine Learning. Vol. 13, No. 1, 2022.International Journal of Advanced Computer Science andApplications.DOI:10.14569/IJACSA.2022.0130137

18. Paweł Tarnowski, Marcin Kołodziej, Andrzej Majkowski, Remigiusz Jan Rak.Combined analysis of GSR and EEG signals for emotion recognition . 978-1-5386-6143-7/18 .2018 IEEE

19. https://www.123formbuilder.com/free-form-templates/Advertising-Effectiveness-Survey-3554335/\

20. https://www.questionpro.com/survey-templates/advertising-effectiveness/