BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
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2025, Volume 16, Issue 3, pages: 153-168
Submitted: April 9th, 2025 | *Accepted for publication:* August 18th, 2025

Electroencephalography (EEG) - Based Neuromarketing: Predicting Favourable and Unfavourable Consumer Reactions Using ML Techniques

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Abstract: *Neuromarketing is an emerging field that combines neuroscience with marketing to gain insights into unconscious consumer behaviour. Traditional methods like surveys often fail to capture real-time emotional and cognitive responses. To address this gap, this study employs EEG signal analysis to predict favourable and unfavourable consumer reactions to advertisements and products. The theoretical foundation is based on the dual-process theory, which distinguishes between fast, emotional decision-making (System 1), and slow, rational thinking (System 2). EEG markers such as alpha, beta, and theta bands are used to assess attention, engagement, and decision conflict. EEG data was collected using a single-channel Neurosky Mindwave headset from 14 participants aged 18–22. A total of 80 ads were shown, categorised by product and design type. Subject-dependent and subject-independent analyses were conducted. In the SD study, Naïve Bayes and SVM classifiers achieved a maximum accuracy of 0.62. In the SI analysis, SVM showed strong performance across product and gender-based classification. A deep learning model also produced comparable accuracy. These findings demonstrate the potential of EEG-based neuromarketing to provide deeper insights into consumer behaviour, with possible implications for both commercial and clinical applications.*

Keywords: *deep learning; neuro marketing; advertising analysis; EEG signal analysis; consumer response; support vector machine (SVM).*

How to cite: Velammal, R. S., Leo, A., Abraham, J. M., Fortuna, C. M., & Kumar, V. (2025). Electroencephalography (EEG) - based neuromarketing: Predicting favourable and unfavourable consumer reactions using ML techniques. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, *16*(3), 153-168. https://doi.org/10.70594/brain/16.3/12

1. Introduction

Due to technological developments in the field of human-computer interaction, the Brain-Computer Interface (BCI) has gained prominence, allowing users to control computers using brain signals instead of physical input. This technology is particularly beneficial for individuals with paralysis or motor impairments (Vaid, Singh, & Kaur, 2015). Neuroelectrical signals (EEG) are widely used in brain activity research due to their high temporal resolution, affordability, and ease of use. Neuromarketing has become more popular as a result of a better knowledge of brain activity, which combines neuroscience and marketing to analyse consumer preferences. Traditional methods, like surveys, are often unreliable, whereas EEG-based analysis provides deeper insights into decision-making (Fisher, Chin, & Klitzman, 2010; Lee, Broderick, & Chamberlain, 2007).

It is based on the Cognitive Dual-process Theory of decision-making, which differentiates between two types of thinking: system 1 and system 2. System 1 is quick, automatic, and intuitive, while system 2 is slow, deliberate, and rational. In neuromarketing terms, EEG signals provide the capability of knowing when the subliminal customer jumps to system 1 versus system 2, an impulsive response. For example, emotional or attention-getting ads may activate system 1, whereas ads containing product comparisons may induce system 2. This model enables a more detailed understanding of EEG bands while evaluating ads (Kahneman, 2011). This study uses the Neurosky Mindwave Monitoring EEG device, which records EEG signals while participants watch product advertisements. Participants evaluated advertisements using a scale of Approve, Reject, Purchase, and Indifferent, which was later streamlined into Favourable (Approve/Purchase) and Dismissive (Reject/Indifferent) reactions. The performance measures of various advanced soft computing techniques are compared, offering insights into qualitative and quantitative responses.

The structure of the human brain includes four primary lobes – the frontal, parietal, temporal, and occipital — with distinct cognitive and sensory functions that are critical to decoding consumer responses. The frontal lobe is involved in decision-making, executive functions, and regulating emotions. It is even more important in the context of neuromarketing, where individuals are judging and responding to advertisements via conscious (i.e., rational) and affective (i.e., emotional) ways (Song & McCarthy, 2014). The parietal lobe is involved in the processing of somatosensation and spatial sense (e.g., our perception of product placement or tactility-related visuals) (Purves et al., 2001). Auditory processing and memory consolidation occur in the temporal lobe. It allows the consumer to remember information associated with the brand, such as jingles, voiceovers, or product claims (Yadava et al., 2017). The occipital lobe, which processes visual information, is also very active during exposure to promotional videos or product images from consumers (Purves et al., 2001).

Being able to elucidate the different functions of these brain regions will help researchers in developing even richer interpretations of EEG signals, connecting neurological processes to consumer behaviours. This is conducive to the more rigorous and scientific neuromarketing research (Plassmann, Ramsøy, & Milosavljevic, 2012).

Vaid, Singh, & Kaur (2015) discuss the application of Deep Learning (DL) in Multiple Input Multiple Output (MIMO) detection, highlighting its ability to balance computational complexity and Bit Error Rate (BER). The study focuses on DetNet, a DL-based MIMO receiver, and enhances its performance using Bayesian Optimisation (BODetNet). Unlike traditional methods, DL-based detectors, such as Deep Neural Networks (DNNs), act as function approximators, reducing complexity while maintaining optimal detection accuracy. In Fisher, Chin, & Klitzman's (2010) work, the effectiveness of the K-Nearest Neighbours (KNN) algorithm for short-term wind energy forecasting is analysed. The study evaluates different input variable configurations, including historical wind energy data and meteorological parameters. Cross-validation is used to determine the optimal number of neighbours (k) for various distance metrics. The findings highlight the impact of input selection on the forecast accuracy and emphasise KNN's strengths.

In Lee, Broderick, & Chamberlain's (2007) study, advances in machine learning-based image reconstruction are discussed, including CNNs, GANs, and transfer learning. Techniques like feature extraction and pattern superposition are improving the recognition accuracy. The use of ML in occluded face recognition is explored in security and medical imaging. Challenges include high computational cost and accuracy loss in heavily occluded images. Lahane et al. (2019) investigated the effectiveness of machine learning and deep learning algorithms in analysing EEG signals for epileptic seizure detection. The study evaluates six ML and eight DL models, using EEG data from the Guinea-Bissau and Nigeria epilepsy datasets. Among machine learning models, the SVM classifier achieves the highest accuracy (83.2% and 77%), with minimal impact from single-channel exclusion. Deep learning models, including CNN-LSTM (92.5%) and IC-RNN (91.8%), demonstrate superior performance, highlighting the importance of precise electrode placement in the frontal and parietal zones for accurate diagnosis.

The study by Song & McCarthy (2014) reviews EEG-based signal processing advances, including adaptive filters, Common Average Reference (CAR), Independent Components Analysis (ICA), and various classification methods, like Adaptive Classifiers and Deep Learning (DL) techniques. It highlights Brain Computer Interface (BCI) applications in medicine and home automation, while addressing challenges such as signal non-linearity, high error rates, and weak signals. A consumer's decision-making process is the emphasis of the theoretical side of neuromarketing, which is described by Purves et al. (2001), Bočková, Škrabánková, & Hanák (2021), Yadava et al. (2017), and Jain et al. (2018), along with survey results that indicate interest in the services provided by neuromarketing. The study describes how neuromarketing is used in practice, while also examining the ethical concerns surrounding it. The various classifiers for understanding consumer preferences are discussed by Purves et al. (2001). Studies conducted by Plassmann, Ramsøy, & Milosavljevic (2012), Bočková, Škrabánková, & Hanák (2021) propose a modelling framework using EEG signals to classify "likes" and "dislikes," comparing Support Vector Machine (SVM), Random Forest, and Hidden Markov model (HMM), with HMM performing best but lacking a neutral option (Plassmann, Ramsøy, & Milosavljevic, 2012). A comparative analysis in Bočková, Škrabánková, & Hanák's (2021) work shows that Artificial Neural Network (ANN) outperformed K Nearest Neighbours (KNN), SVM, and linear classifiers. The study conducted by Yadava et al. (2017) explores brain responses to visual stimuli using affordable EEG equipment.

The outcome of the ANN with a specific hidden layer is better than the decision tree (DT) method. A thorough study was carried out to look into consumer preferences for several product categories, including smartphones, cars, fast food, and beverages. The study finds that selecting a product results in high Detrended Fluctuation Analysis DFA values for alpha waves, and low DFA values for beta waves (Morillo et al., 2015). The research conducted by Oon, Saidatul, & Ibrahim (2018) explores the EEG spectral power for predicting consumer preferences and interpreting shifts in buying behaviour based on ad content. Increased theta power in the left frontal region is linked to an "Approve" preference, while higher theta power in the right frontal region corresponds to a "Reject" choice.

2. Methodology

The proposed methodology involves machine learning techniques to analyse EEG data collected during advertisement viewing. The overall process is illustrated in Figure 1 below.

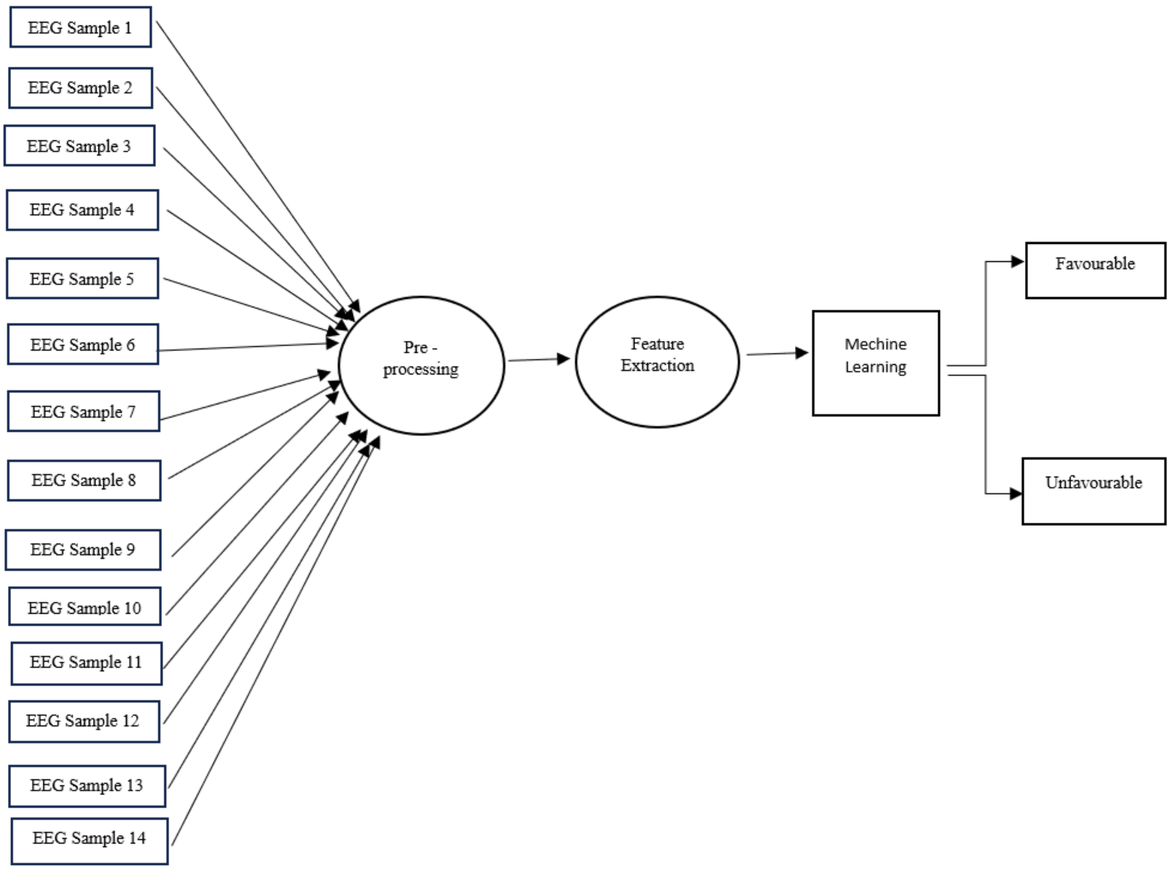

Figure 1: Proposed Methodology – Machine Learning

The proposed methodology involves Deep Learning techniques to analyse EEG data collected during advertisement viewing. The overall process is illustrated in Figure 2 below.

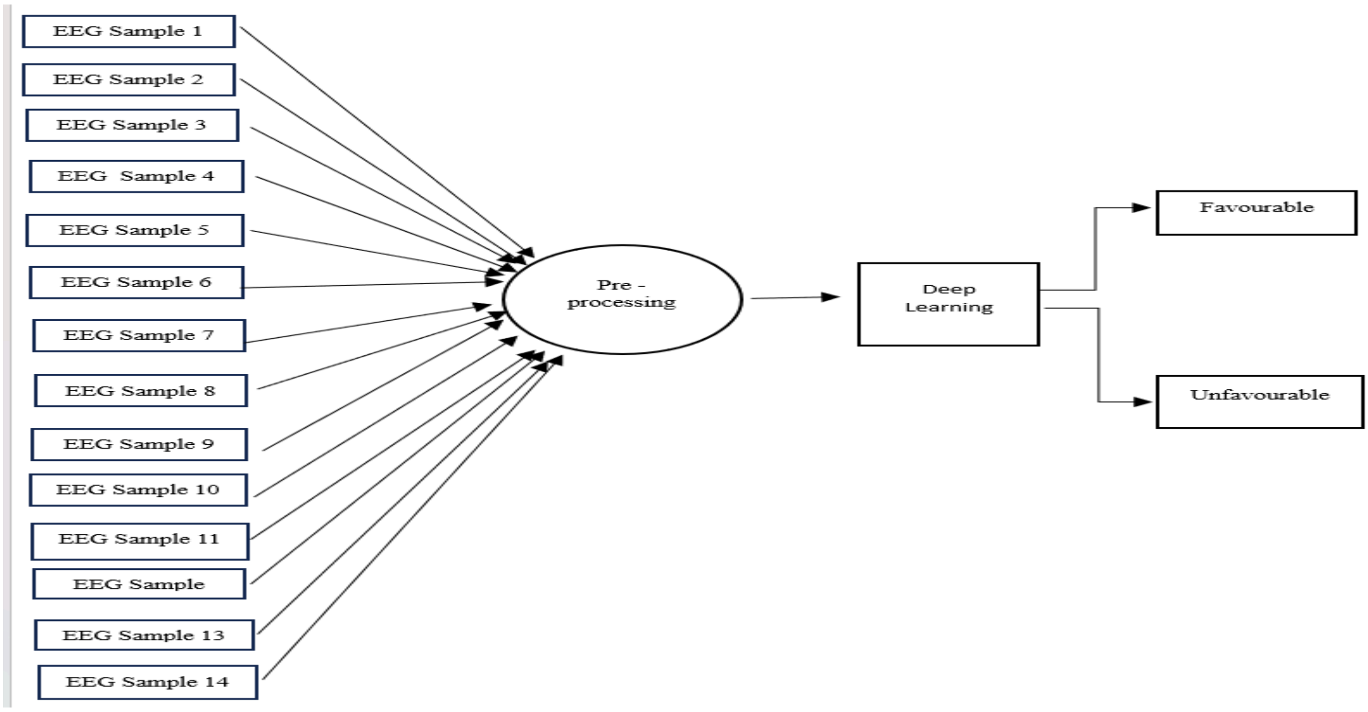

Figure 2: Proposed Methodology – Deep Learning

At 513 Hz, data is captured from the Neurosky EEG Monitoring Device. The study includes 14 participants: 6 males and 8 females. There are 80 advertisements per subject. Each ad recording lasts 7 seconds, resulting in 3584 samples per subject. Electrode values, time log, focus level, and meditative state indicators are retrieved using the Neurosky EEG Monitoring Device and saved in CSV files. 1140 recordings in all were gathered. The labels from the datasheet were taken out and placed in different CSV files. As participants view the commercial on a laptop positioned at an appropriate distance, the Neurosky Mindwave Monitoring EEG device records their EEG data. Their preferences are recorded and used as the classifier's ground truth. Following pre-processing and feature extraction, the EEG signals are trained using ML and DL models, as shown in Figure 1a and Figure 2a.

3. Input Dataset and Experimental Setup

This standardised EEG electrode placement technique covers all areas of the brain, using 10–20 electrodes. Raw EEG data is acquired by electrodes, a headset with an ear clip and a sensor arm. A single dry electrode minimises noise and enables real-time signal replication. The left upper-side region of the frontal lobe plays a role in perceptual judgments, while the ventromedial section contributes to value-based choices. Overall, the frontal lobe is essential for decision-making processes (Jain et al., 2018). EEG signals were sampled at 512 Hz, capturing alpha, beta, gamma, theta, and delta waves. OpenViBE software facilitated data recording for analysis. Figure 3 illustrates electrode placement.

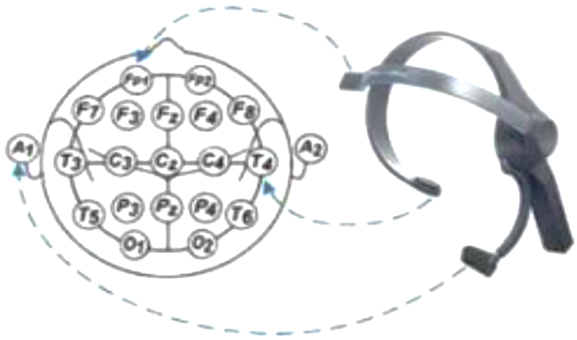

Figure 3. Neurosky mind wave electrode system (Lahane et al., 2019)

Four product categories - headphones, laptop bags, sunglasses, and smartphones were selected, so that there is no gender bias among them. Four distinct product brands are chosen from a catalogue for each category. For instance, there are several brands of Ray-Ban, Wildcraft, Samsung, and Boat. According to the data gathering protocol, there are four distinct advertisements for every product.

- **Ad 1:** Figure 4(a) displays the product against a plain white background without any offers.
- **Ad 2:** Figure 4(b) illustrates the product with a vibrant yellow background and a rating.
- **Ad 3:** Figure 4(c) presents the product on a dark background without any offers.
- **Ad 4:** Figure 4(d) features the product with animated GIFs and promotional offers.

Consequently, there are a total of 80 ads. Five categories, four products, and four ads:

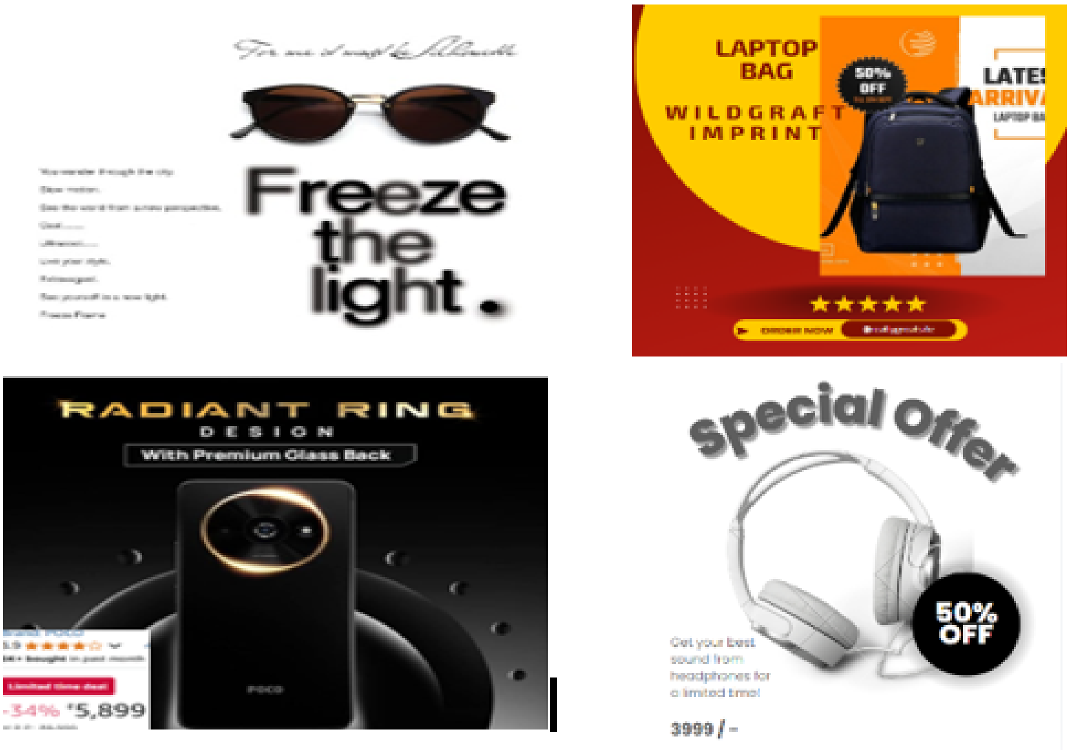

Figure 4. Sample product advertisements used in the experiment
(a) plain backround, (b) yellow backround with rating
(c) dark backround, (d) animated with promotional offers

The study includes 14 participants – six males and nine females aged 18 to 22. Prior to the experiment, participants signed a consent form expressing their desire to participate. The study procedure and purpose were explained in detail. The Neurosky Mindwave EEG device was put on the person's head, after they were told to sit. A laptop with a presentation of the adverts was put at a suitable distance. Participants were instructed to maintain minimal muscle movement, while viewing the advertisement. Four brands were chosen, each with five products and four distinct advertisements (as detailed in the previous parts), totalling 80 ads. The 80 advertisements were divided into eight presentations, with 10 ads each. To avoid the learning bias, the adverts were given in a random order. The experiment was conducted in the following order:

- Initially, a 12-second rest period;
- A seven-second ad display;
- A four-second delay between the advertisements, to capture the user's preferences and act as ground truth.
- A one-minute gap between presentations, to avoid mental weariness.

Participants filled out a datasheet with their preferences categorised as 'Purchase', 'Approve', 'Reject', or 'Indifferent'. The study lasted about 40 minutes per person. The Neurosky Mind wave provided the data, which was then saved in CSV files. Each participant obtained 90 CSV files per advertisement, each containing four columns: 'Timestamp,' 'Sensor,' 'Focus Level,' and 'Meditation Score.'

A datasheet and a corresponding CSV file were prepared for each participant. The classifier labels used were: 'P' for Purchase, 'A' for Approve, 'R' for Reject, and 'I' for Indifferent. To structure this as a binary classification task, the "Purchase" and "Approve" responses were categorised under "Favourable Reaction," whereas the "Reject" and "Indifferent" responses were grouped as "Unfavourable Reaction". These classifications represent the participants' feedback on the advertisement.

EEG data was collected experimentally using the Neurosky Mindwave single-channel device from 14 participants, aged 18–22, under controlled conditions. Each participant was exposed to a sequence of advertisements, while the device recorded their brainwave activity. The data collection process was conducted in a distraction-free environment. All participants provided informed consent and were informed about the research purpose, privacy, and their right to withdraw. This confirms that the dataset used in this study is primary in nature and specifically acquired for the purpose of neuromarketing analysis.

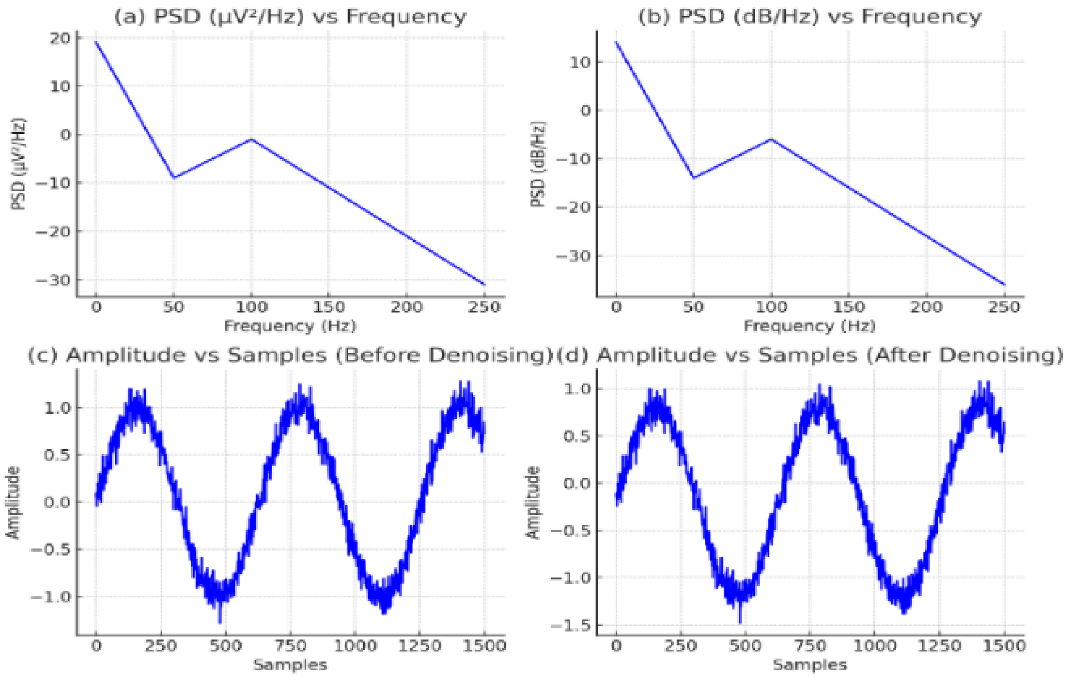

Figure 5. The EEG signal (a) prior to filtering, (b) following filtering, (c) prior to denoising, and (d) following denoising

4. Pre – processing and Future Extraction

The Fast Fourier Transform (FFT) is applied to the signal to mask out lower amplitude components, while producing a powerful pulse at 0 Hz due to the DC offset. To remove the DC offset, we needed to subtract the signal's mean from the original. A Recursive Butterworth passband filter with low and high cutoff frequencies of 0.6 H_z and 45H_z is used to reduce the high-frequency noise and the low-frequency breathing. To minimise the electrical line interference, a 45 Hz operating frequency is used for the design of the IIR batch filter. Figures 5(a) and 5(b) illustrate the signal frequency distribution, before and after filtering. Analysis of EEG signals in both temporal and frequency domains is recommended due to their non-stationarity. According to (AI-Qazzaz & Ali, 2015) EEG signal denoising was achieved using a 6-level decomposition, utilising the 'db7' wavelet. Wavelet denoising employs the wavelet transformation to condense signal and feature information into a small number of significant coefficients. Figures 5(c) and 5(d) show the signal prior to and after denoising.

4.1. Wavelet Signal Coefficients

The EEG signal was divided into four levels using the Daubechies 4(dB4) wavelet. Five group wavelet coefficients are provided by this decomposition: D1, D2, D3, D4, and A4. The data relating to the five distinct frequency bands are represented by each group. The four coefficients of (D1, D2, D3, and D4) with A4 approximation represent the γ, β, α, θ, and δ frequency bands. The energy band of individual coefficients of wavelet signals was calculated by Purves et al. (2001).

4.2. Welch's Power Spectral Density (PSD) Estimation

The *Welch's Power Spectral Density (PSD)* provides an estimate of the signal's power at different frequencies; however, there is a trade-off, because the frequency precision is decreased at the expense of less noise in the power spectra (Yadava et al., 2017).

4.3. Hijorth Activity Parameters

Hijorth Activity Parameters denote specific statistical characteristics, applied to signal processing in the time domain. Mobility and complexity are among the parameters, as seen in images (1) and (2):

$$mobility = \frac{\sqrt{Variance\ (y'(t))}}{variance(y(t))}\ mobility = \frac{\sqrt{Variance\ (y'(t))}}{variance(y(t))} \tag{1}$$

$$Complexity = \frac{Mobilit(y'(t))}{mobilityy(t))}\ Complexity = \frac{Mobilit(y'(t))}{mobilityy(t))} \tag{2}$$

4.4. DFA

The EEG signal based on the DFA model can be analysed i.e., the degree of statistical similarity model in long term memory processes. This method is suitable for EEG signals because of their non-stationary characteristics (Yadava et al., 2017).

4.5. Attention Parameter

The Neurosky EEG Monitoring Device extracts the attention parameter. It shows the extent to which the person is paying attention. The range of the value is 0-100. When a user concentrates his attention on a single idea, the value rises; when he is distracted, the value falls. To provide information about the user's level of attention - it might be affected by the type of advertisement they are seeing. This feature has been removed. As seen in Table I, ten characteristics are recovered overall, for each signal.

Table 1. Vector of Features

Index	Signal Characteristics	
1	Wavelet Power	(D1) γ Band
		(D2) β Band
		(D3) α Band
		(D4) θ Band
		(A5) δ Band
Spectral Power Distribution		
2	Hjorth Metrics	Motion
		Complexness
3	DFA	-
4	The parameter of attention	-

4.6. Interpretation of EEG Frequency Bands

EEG signals are composed of multiple frequency bands, each associated with distinct mental states and cognitive functions. Alpha waves (8-13H_Z) are typically linked to a relaxed but alert state; a drop in alpha power can indicate increased emotional engagement or visual attention. Beta waves (13-30H_Z) are generally related to deep internal focus or fatigue. Gamma activity (>30H_Z) reflects high-level information integration and memory processing. Interpreting these changes helps connect consumer reactions to psychological responses.

Table 2. EEG frequency bands and psychological interpretation

EEG Band	Frequency	Psychological meaning	Related state
Alpha	8-13 H_z	Attention, relaxed alertness	Engagement
Beta	13-30 H_z	Active throughout focus	Cognitive load
Theta	4-8 H_z	Working memory, emotion	Decision conflict
Delta	0.5-4 H_z	Deep focus, fatigue	Low awareness
Gamma	>30 H_z	Integration, memory encoding	High-level processing

5. Classification

In this study, the "Favourable Response" category combines the "Approve" and "Purchase" classes, whereas the "Indifferent" and "Reject" classifications are grouped under a "Dismissive Response". These updated class names indicate whether the advertisement was received positively or negatively by the participants. This decreases the classification task to a binary classification problem. After being scaled with a MinMax scaler, the feature vector is fed into the classifier. For the classification model, the study used ML and DL techniques.

We used 10-fold cross validation to evaluate model performances and minimise biases. Before each fold, the dataset was randomised, and stratified sampling ensured balanced class distributions across training and testing sets. To address non-stationarity in EEG signals and to simulate variability, data augmentation was applied, using Gaussian noise injection. Both subject-dependent and subject-independent models were employed to examine a different generalisation behaviour. Subject-dependent models focused on capturing individualised EEG patterns, which led to higher accuracy, being less generalisable. In contrast, subject-independent models experimented with the ability to generalise across different individuals, a more realistic application scenario for neuromarketing.

This dual-model approach allowed us to compare personalisation with generalisation performance, and reduced the risk of overfitting to a single participant's signal patterns. By combining cross-validation, randomisation, data augmentation, and diverse modelling strategies, we ensured a more robust and generalisable evaluation framework.

5.1. Machine Learning Algorithms

This study utilises four machine learning models: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes (NB) classifier. Each of these algorithms follows a unique approach to perform classification, based on the characteristics of the dataset.

5.1.1. K-Nearest Neighbors (KNN)

The KNN algorithm is a distance-based classifier. It works by identifying the 'k' closest training samples to a new data point, and classifying that point based on the majority class among its neighbors. The closeness is usually calculated using a distance metric such as the Euclidean distance. KNN does not require a training phase, as it stores the entire dataset, making predictions at the time of testing by comparing the new data point to the existing data.

5.1.2. Support Vector Machine (SVM)

The classifier operates by mapping the input data into a higher-dimensional feature space where it seeks to find an optimal hyperplane that clearly separates different classes. It aims to maximise the margin between the closest data points of each class, providing better generalisation during the classification. Once trained, the SVM classifies a test sample based on its position relative to the hyperplane.

5.1.3. Decision Tree (DT)

The DT model builds a tree-like structure where internal nodes represent decisions based on input features, branches represent possible outcomes, and leaf nodes represent the final class labels. The model uses a set of observations about the data to make inferences about its target or class value. It is easy to interpret and useful for both categorical and numerical data, as the tree visually maps out the path leading to a classification decision.

5.1.4. Naive Bayes (NB)

A NB classifier is a probabilistic model based on Bayes' Theorem. It assumes that the features are conditionally independent of each other, given the class label, which is often not true in practice, but still results in accurate performance. It calculates the probability of each class for a given input and predicts the one with the highest probability. Naive Bayes is known for its efficiency and scalability, as it can train very quickly even on large datasets.

In KNN classification, the sample's class is determined by the majority class among its k-nearest neighbors. The main metric used to calculate KNN classification is distance. In SVM classifiers, the training samples are mapped into a space that maximises the distance between the classes. The classification is determined by analysing the position of the test samples within the mapped space, and identifying on which part of the boundary they fall on. The decision tree model DT, the model makes inferences about the samples' goal value based on the observations obtained about them. The classes are represented by the leaves in the classification paradigm, while the combinations of the attributes that result in the classification are represented by the branches. NB classifiers are probabilistic classifiers that emphasise independent assumptions (naive) between features, and are constructed using the Bayes Theorem. In contrast to the more costly iterative method used by the other classifiers, this model is quite scalable and trains in linear time. Hyperparameter adjustment optimises the classifiers. These models' effectiveness has been demonstrated by Purves et al. (2001), Plassmann, Ramsøy, & Milosavljevic (2012), Bočková, Škrabánková, & Hanák (2021), and Yadava et al. (2017).

5.2. DL Algorithms

The deep learning model is implemented using Keras. The input features are processed through an Artificial Neural Network (ANN) with three densely connected layers, containing 30, 20, and 10 neurons. At the same time, the raw EEG signal is processed through a 1D Convolutional Neural Network (CNN), which comprises two convolutional layers with 128 and 32 filters, each having a kernel size of five. This is followed by Batch Normalisation, Dropout, and MaxPooling layers for further processing. These outputs are combined and passed through ten densely connected layers. Finally, a softmax layer is used for binary classification. The Conv1D layer captures the spatial characteristics of the EEG data, while the ANN identifies patterns within the extracted features. The overall architecture of the model is illustrated in Figure 6.

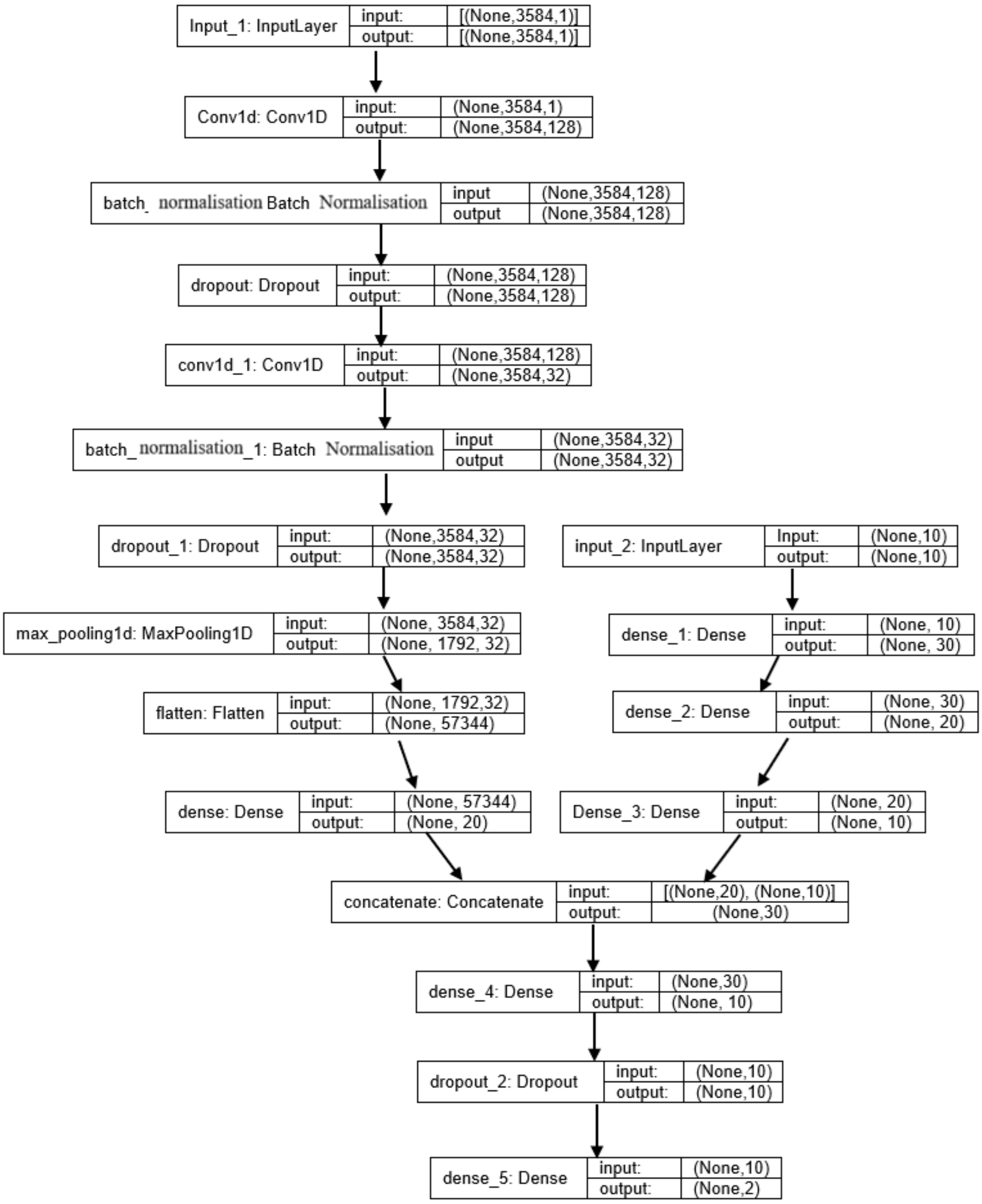

Figure 6. DL Model Architecture

6. Experimental Results and Discussions

The augmented data from 14 subjects were used for this analysis.

Subject-independent analysis: A variety of analyses have been conducted, including product-, ad-, and gender-based analyses.

- **Gender-based analysis:** The recorded data are divided into groups depending on gender, in order to conduct the analysis. The study involves eight ladies and five guys. After the data has been enhanced, ML models are used to extract features for categorisation.
- **Ad-based analysis:** For this analysis, the recorded signals corresponding to the four different advertisement categories are segmented. Here, the data is not enhanced. There are 260 data recordings in each advertising, for a total of 1040 recordings. The extracted

features are taken from these recordings and they categorise the different classes, using ML and DL models.

6.1. Psychological Interpretation of EEG Markers

EEG waveforms can be meaningfully interpreted by connecting their variations to cognitive and emotional states. For example, increased frontal theta activity may signal higher working memory load or emotional decision conflict. Increased beta activity suggests greater cognitive engagement and evaluation effort, while reduced alpha indicates focused visual attention or emotional arousal. This interpretation helps bridge the observed EEG signals with underlying consumer behaviour, during the advertisement exposure.

6.2. Product - Specific Analysis

The five distinct product types are represented by the recorded signals, which are then separated for analysis. Here, the data is not enhanced. There are 208 data recordings for every product, for a total of 1130 recordings. Features are extracted from these recordings and sent to the Machine Learning and Deep Learning models or product – type classification.

The results are presented in two subject-dependent sections: subject-independent analysis and dependent analysis.

6.3. Analysis based on Subject Dependence

Data augmentation is used to expand dataset size and improve model correctness (Acc.). EEG signals cannot be rotated or shifted due to their continuous and non-stationary nature, which would modify the time domain properties. To compensate for non - stationarity, the Gaussian noise is applied to the signal. To prevent amplitude and standard deviation fluctuations, Gaussian noise with zero mean is used. New samples are generated by adding this noise to the original signal (Golnar-Nik, Farashi, & Safari, 2019). Since each individual has only a limited number of recordings, data augmentation is applied in subject-dependent analysis to enhance the dataset. The testing set includes no enhanced data. Each individual has 75 recordings, 15 of which are randomly assigned to the testing set. The remaining 50 recordings are sent to the training set, after being enhanced six times, giving the ML and DL models 300 samples in total. 5 trials are conducted on each model, producing a distinct training and testing set. Along with the F1 measure, specificity, and sensitivity, the average accuracy over ten trials is presented. The results are summarised in Table 3. With a mean accuracy of 0.62 across 8 participants, the Naive Bayes and Support Vector Machine models exhibit a superior performance in subject-dependent analysis, with the Naive Bayes model achieving the best results, reporting specificity and sensitivity values of 0.53 and 0.54, respectively.

Table 3. Performance measures of different classified model of 8 Subjects

Classification Model	**K-NN** (Approach)	**SVM** (Technique)	**DT** (Method)	**NB** (Algorithm)	**DL** (Model)
Accuracy	0.53	0.62	0.51	0.62	0.51
F1- score	0.4	0.37	0.48	0.47	0.42
Precision	0.4	0.32	0.51	0.53	0.42
Recall	0.51	0.4	0.48	0.54	0.50

6.4. Analysis based on Subject Independence

The study included nine female participants and six male participants. The average accuracy by gender for each classifier is displayed in Tables 4 and 5. While the SVM and NB classifiers both get the greatest Acc. of 0.65 for female respondents, the NB model yields the highest Acc. of 0.56 for male participants. According to the NB model, the greatest P for male individuals is 0.58, and the highest P for female subjects is 0.86. For both males and females, the NB model produces the greatest R, at 0.55 and 0.53 respectively.

Table 4. Mean outcomes of 6 male participants

Classification Model	**K-NN** (Approach)	**SVM** (Technique)	**DT** (Method)	**NB** (Algorithm)	**DL** (Model)
Accuracy	0.51	0.57	0.51	0.56	0.53
F1- score	0.45	0.33	0.44	0.47	0.47
Precision	0.42	0.26	0.45	0.58	0.47
Recall	0.51	0.47	0.47	0.55	0.54

Table 5. Mean outcomes of 9 female participants

Classification Model	**K-NN** (Approach)	**SVM** (Technique)	**DT** (Method)	**NB** (Algorithm)	**DL** (Model)
Accuracy	0.54	0.65	0.53	0.65	0.50
F1- score	0.82	0.68	0.49	0.47	0.32
Precision	0.86	0.36	0.53	0.41	0.37
Recall	0.52	0.49	0.4	0.53	0.48

6.5. Advertisement Performance Analysis

In this case, a custom DL model, which was covered in the earlier parts, is employed in addition to the ML model. There are 250 samples in each advertisement, 50 of which are used in the training set and the other 50 in the testing set. The data is not augmented here. Over five trials, the DL and ML models' average accuracy (Acc.), precision (P), recall (R), and F1-score are determined. The outcomes, which are shown in Table 6, show both user reactions to different ad kinds and model accuracy. The Decision Tree (DT) algorithm achieves the top recall (sensitivity) of 0.52 across multiple advertisements, while the Support Vector Machine (SVM) classifier attains the best mean accuracy of 0.55 among the models. Additionally, throughout the advertisement set, the Deep Learning (DL) approach obtains the greatest sensitivity of 0.55.

Table 6. Summary of average outcomes for 4 advertisements

Classification Model	**K-NN** (Approach)	**SVM** (Technique)	**DT** (Method)	**NB** (Algorithm)	**DL** (Model)
Accuracy	0.49	0.55	0.51	0.48	0.54
F1- score	0.50	0.42	0.51	0.17	0.4
Precision	0.51	0.43	0.52	0.49	0.51
Recall	0.49	0.50	0.52	0.11	0.55

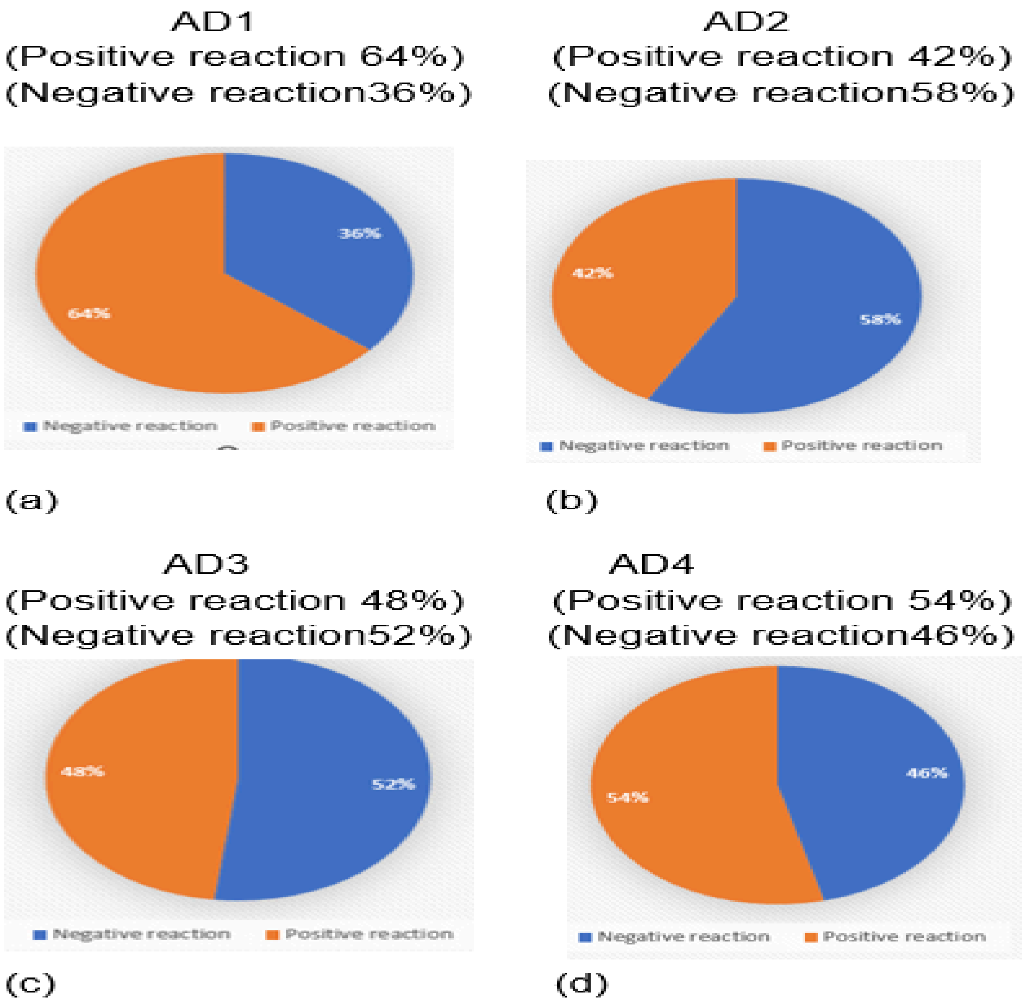

Figure 7. Type of ads. (a) Ad type 1- Plain back round without discount, (b) Ad type 2 - Appealing design with customer ratings, (c) Ad type 3 - Dark-themed with ratings, (d) Ad Type 4 - Animated visuals with promotional offers

The subjects react more unfavourably to Ad types 2 (0.57) and 3 (0.52), as shown in Figures 7(b) and 7(c), but more favourably to Ad types 1 (0.63) and 4 (0.53), as shown in Figures 7(a) and 7(d).

6.6. Product Wise Analysis

The study includes four products: bags, phones, sunglasses, and headphones. There are 208 samples altogether for each product, 60 of which are utilised for testing, and the remaining samples are used for training. Here, data is not enhanced. The average accuracy, F1- Score, Precision, and Recall for the Deep Learning and Machine Learning models over five trials are displayed in Table 7. The SVM model shows the highest average accuracy of 0.57. The Naive Bayes model achieves the best precision value of 0.61, while both the SVM and Deep Learning models record the highest recall score of 0.55.

Table 7. Average results of 5 products

Classification Model	K-NN (Approach)	SVM (Technique)	DT (Method)	NB (Algorithm)	DL (Model)
F1 Score	0.50	0.47	0.53	0.30	0.48
Accuracy	0.49	0.57	0.50	0.50	0.55
Precision	0.52	0.56	0.53	0.61	0.51
Recall	0.49	0.55	0.52	0.35	0.55

Since both individual-based analysis and product-based analysis were not mentioned, as carried out in this research, the result cannot be compared to those of other similar papers in this field. When a larger dataset is available, the Deep Learning model utilised in this paper can perform better. Furthermore, the most recent articles have not indicated any study based on advertisements or products. However, as shown by Purves et al. (2001), Cleveland Clinic (2022), Plassmann, Ramsøy, & Milosavljevic (2012), Bočková, Škrabánková, & Hanák (2021), Yadava et al. (2017), and Jain et al. (2018), we find that the results are comparable (60–70%) when compared to other studies that do not mention the various modes of analysis.

7. Conclusion

The study presents recent research on electrophysiological insights into consumer decision-making based on EEG signals related to buyer behaviour. EEG raw data from fifteen individuals was collected using the acquisition device, and analysis of both quantitative and qualitative metrics were evaluated. The subject-dependent analysis showed that the NB classifier has the highest accuracy (0.60). Independent assessments depending on product, ad, and gender were also carried out. Using SVM and KNN, males demonstrated marginally greater accuracy than females. SVM achieved the highest accuracy (0.56), with ad types two and three receiving negative answers, and ad types one and four receiving positive responses. The accuracy of SVM and DL models was the highest in product-based analysis (0.55). A direct comparison is challenging because there is no comparable research. The EEG artifact removal, multiclass classification, and larger datasets for Deep Learning analysis may be investigated in future research.

In summary, the study demonstrates that EEG signals can effectively predict favourable and dismissive consumer responses. Among the various classifiers, SVM and DL models delivered a high performance, particularly in the product and gender-based evaluations. These results highlight the potential of EEG-driven neuromarketing analytics.

Additionally, the frontal EEG patterns may have implications for clinical populations. For example, individuals with ADHD, depression, or impulse control disorders often show abnormal frontal lobe asymmetry or beta activity. Understanding how these patterns emerge in healthy individuals during a product evaluation can provide a baseline for interpreting the clinical EEG responses, supporting future translational research in neuromarketing and clinical diagnostics.

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