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A Spiking Neural Network Approach to Electroencephalography based Consumer Preference Modeling

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Abstract

Neuromarketing is an emerging interdisciplinary field that applies neuropsychology in marketing to study consumer sensory-motor actions such as cognitive and affective responses to marketing stimuli through Brain Computer Interface (BCI) technology. While marketers spend over 750 billion dollars annually on traditional marketing procedures such as surveys, interviews, and consumer's feedback, these methods are often criticized for their inability to capture genuine consumer preferences. Neuromarketing promises to overcome such issues by analyzing neural responses directly. This paper presents a novel framework for predicting consumer preferences by analyzing Electroencephalography (EEG) signals. EEG signals are acquired from 25 volunteers while administering 14 products with three different variations. The EEG signals are preprocessed using Modified Wavelet Thresholding (MWT) to remove noise while preserving neural activity patterns. A third-generation network, Spiking Neural Network (SNN) is designed to recognize consumer preferences based on EEG frequency bands. Unlike conventional models, SNN captures temporal dynamics through spike timing, which is crucial for EEG signals. The efficacy of the model is tested across individual EEG bands to identify the most influential frequency band in decision-making. Simulation outcomes demonstrate that the proposed model can effectively predict consumer preferences. The model achieved an accuracy of 90.91%, recall of 90.7%, a precision of 91.14%, a specificity of 91.12%, and an F1-score of 90.92%. The outcomes highlight the potential of EEG based neuromarketing systems to decode subconscious consumer responses, enabling brands and businesses to design more targeted marketing strategies based on objective neural data.

Keywords: BCI, EEG, Consumer Preference, Neuromarketing, Spiking Neural Network, Wavelet Transform.

1. Introduction

In today's highly competitive marketplace, companies offering similar products invest heavily in marketing to capture and retain consumer attention. Advertising is a key tool in this effort. However, identifying which advertisement design best influences consumer responses. poses a significant challenge [1]. Conventional approaches such as interviews, surveys, and feedback forms are widely used to evaluate the effectiveness of advertisements. These self-reliant methods are full of bias and misrepresentation, limiting their reliability [2]. To overcome

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these obstacles, researchers are turning to automatic and data -based techniques that can objectively measure customer answers. The goal of these technologies is not only to identify the most influential aspects of marketing stimuli, but also to predict consumer preferences with minimal human error [3].

An increasing area of focus within this domain is neuromarkating, which seeks to better understand neuroscience and marketing influence consumer decisions in response to marketing signals [4].

Human behavior is shaped by unconscious mental processes. Neuromarketing addresses this by moving beyond traditional surveys and discovering hidden layers of consumer thinking. Instead of asking direct questions, it taps into the brain's subconscious to reveal real choices and decisions. This approach is non-invasive and helps achieve more accurate insights than traditional methods [5]. As a result, it enables marketers to understand customer behavior at the subconscious level. This insight supports the construction of a more effective and targeted marketing strategy, which can lead to higher sales and better customer engagement.

Neuromarketing methods use biometric tools to monitor physical and neural signals that reflect emotional engagement. Techniques such as facial expression analysis, eye tracking, functional Magnetic Resonance Imaging (FMRI) [6], and Electroencephalography (EEG) [7] have been applied to analyse customer behavior in real time. Among these, EEG has attracted significant interest due to its high temporal resolution and the ability to capture the activity of micro -brains associated with attention and decision-making.

Deep Learning (DL) models have been successfully implemented in many areas to solve complex problems due to the ability to learn from high-dimensional data [8].

However, the use of DL models in neuromarketing is relatively low. Spiking Neural Networks (SNN) are a form of DL models that closely mimic actual brain methods, making them suitable for Brain-Computer Interfaces (BCI) and EEG applications.b This paper proposes a new model to decode consumer preferences using SNN trained on EEG signals. Unlike prior EEG and DL models, the proposed model integrates wavelet-based preprocessing with SNNs to jointly exploit spectral and temporal information.

This combination enhances robustness and accuracy. The key contributions of this paper are as follows:

- A new framework is designed to predict consumer preferences using DL techniques.
- A Modified Wavelet Transform (MWT) is proposed to eliminate noise while preserving critical neural patterns.
- A SNN is implemented to predict consumer preferences effectively.
- The scalability of the developed model is tested using EEG signals collected from individuals exposed market stimuli.

The rest of the paper is outlined as follows: Section 2 discusses related works. Proposed methodology is explained in Section 3. Simulation results are given in section 4. Section 5 concludes the paper.

2. Literature Review

Consumers often hesitate to fully share their opinions and preferences during product evaluations, making it difficult to understand the nuances of their decision-making process. The advancement of neuroimaging technologies offers a faster and more efficient way to observe brain activity while individuals assess and select products. In recent years, several approaches have been introduced to classify customer responses, especially the differences between selected and disliked items in terms of neuromarketing.

Quzir et al. [1] discovered how brain reactions affect consumer decisions, focusing on EEG signals to understand preferences for e-commerce products. The authors investigated the role of various brain areas. Four classifiers such as KNN, Random Forest (RF), Neural Network (NN), and Grade -Grade Boosting (GB) were applied to classify liked and disliked products.

Chandra et al. [2] Proposed a model to identify consumer preferences by processing EEG signals. The signals were disintegrated and features were extracted using a wavelet transform. These features were then classified into "Like" or "Dislike" using K-nearest neighbor (KNN), multilayer perceptron (MLP), and support vector machine (SVM) classifiers.

Usman et al. [3] presented a multimodal approach to predict customer preferences by combining EEG and eye-tracking data. EEG signals were filtered using a band pass filter. SMOTE was applied to remove class imbalance. Statistical, wavelet and automatic features were extracted and merged to create a comprehensive feature presentation. Two classifiers, like RF and GB, were used to discriminate between liked and disliked products.

Wei et al. [9] applied SVM to predict customer preferences. EEG signals were collected from participants while they were watching ads. The signals were divided into different frequency bands and used as inputs for validation. In the end, SVM was used to recognize customer preferences.

Golnar-Nik et al. [10] examined how decision-making affects brain responses by analyzing EEG data while participants viewed different brands. Power Spectral Density (PSD) was calculated and used as input for classification. Both SVM and Linear Discriminant Analysis (LDA) were employed to predict consumer preferences.

Oon et al. [11] designed a model to predict consumer choices using machine learning models. EEG signals were collected and then filtered to isolate different frequency bands. Two classifiers such as NN and KNN were used to predict consumer choices.

Sourov et al. [12] explored EEG data collected from individuals exposed to image-based advertisements. Several features were computed, and NN was used to recognize consumer preferences. In another study, Y

adav et al. [13] used EEG signals to predict consumer choices. EEG signals were preprocessed with a Savitzky-Golay (S-G) filter and then decomposed into different frequency bands using wavelet transform. Finally, a Hidden Markov Model (HMM) was employed to predict consumer choices.

Shah et al. [14] compared the performance of the SVM, RN, and DL models in recognizing consumer choices.

Nafjan et al. [15] introduced a model to recognize consumer preferences based on ML. EEG signals were collected and preprocessed. These signals were divided into multiple frequency bands. Different classifiers including SVM, RF, LDA, and KNN were used to predict consumer choices. While earlier methods have achieved moderate success, they ignore spike based temporal coding and lack robustness across frequency bands. This highlights the need for an SNN-based approach. Kharel et al. [20] suggested an end-to-end mobile system that integrates computer vision and augmented reality to improve consumer experiences. The model addressed three major challenges in e- commerce: low user engagement, product uncertainty, and product customer misfit.

3. Materials and Method

3.1 Details of Data

EEG data employed in this study are sourced from a dataset compiled by Yadava et al. [13]. The recordings were collected from 25 participants using an Emotiv EPOC headset as they viewed 42 different product images on screen. These images represented 14 distinct products, each presented in three variations. In total, 1050 EEG recordings were obtained. Signals were captured from 14 electrodes, AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4, as depicted in Figure 1. The data were downsampled to a frequency of 128Hz. During the experiment, each image was displayed for 4 seconds. Sample recordings along with participants; preference labels are shown in Figure 2. Additional details regarding the product categories and their variations are summarized in Tables 1 and 2.

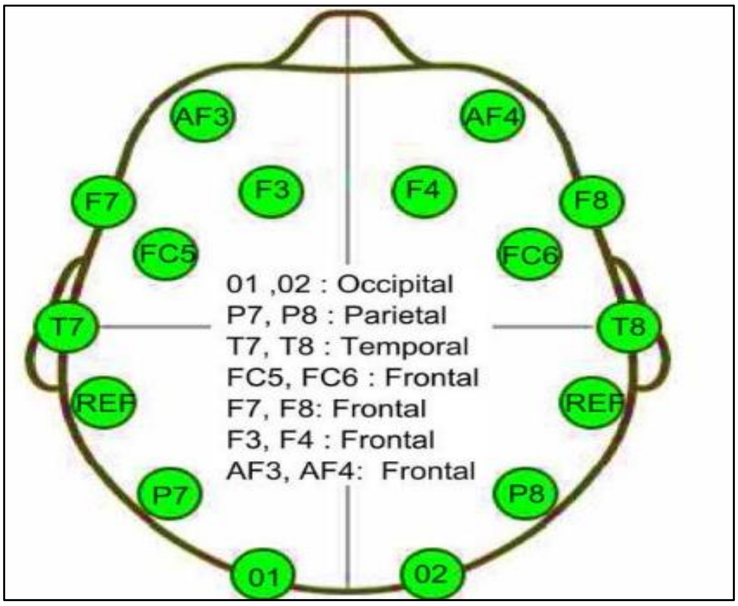


Figure 1. Electrode Placement Map of the Emotive EPOC Headset [19]

Table 1. Data Source Information

1	Number of participants	25
2	Participants age	18 to 38 years
3	Gender	Male
4	Number of products	14
5	Number of images	42
6	Total samples	1050
7	Device	Emotiv EPOC
8	Recording time	4 Seconds
9	Stimuli	Visual
10	Number of channels	14
11	Sampling frequency	128 Hz
12	Number of choices	2(like and dislike)

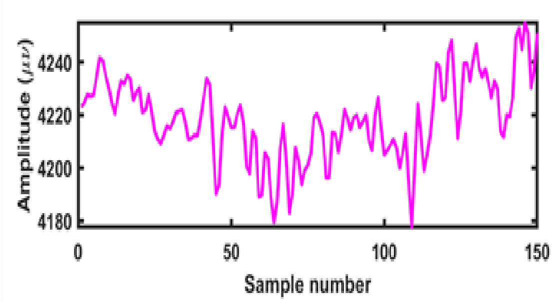
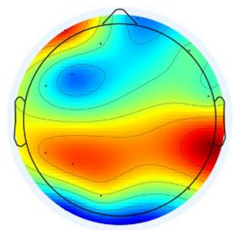
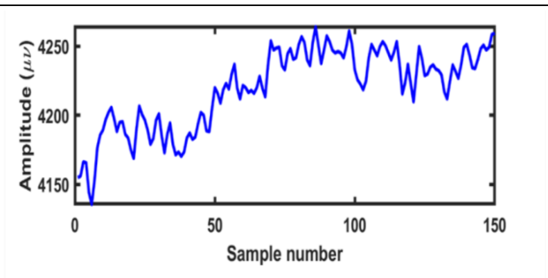
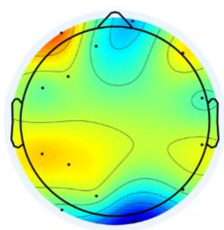
EEG signal	Topographic plot	Choice
		Like
		Dislike

Figure 2. Sample EEG Signals

Table 2. Sample Products and Their Variations

Products	Variation 1	Variation 2	Variation 3
Sun glass			
Bracelet			
Sweeter			

3.2 Proposed Method

The workflow of the proposed consumer preference recognition system is shown in Figure 3. The system consists of several phases: data collection, preprocessing, encoding, SNN training, and testing. Initially EEG signals are collected and then preprocessed using MWT. Different frequency bands such as gamma, alpha, beta, theta, and delta are extracted from the denoised signals. The chosen frequency bands are well established in cognitive neuroscience. Each band is linked to distinct brain activities relevant to consumer decision-making. Including all major bands ensures a comprehensive capture of neural dynamics influencing consumer preferences. These bands are transformed using an encoding technique, and the encoded features are fed into the SNN to recognize consumer preferences. The efficacy of the model is validated using test data.

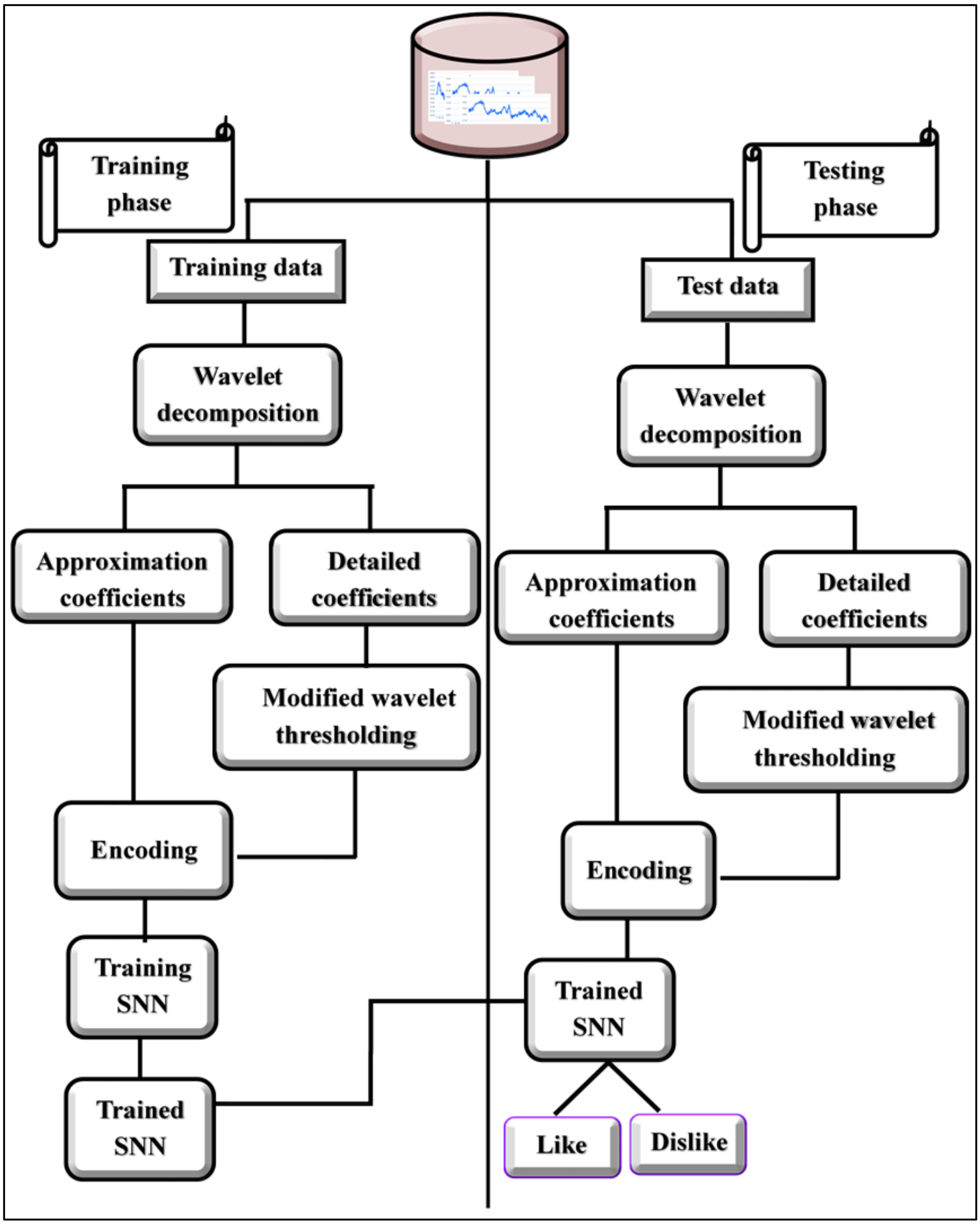


Figure 3. Proposed Consumer Preference Recognition Model

In this investigation, MWT is employed to denoise EEG signals. MWT enhances denoising by adaptively selecting thresholds based on signal statistics, leading to better preservation of EEG features. Compared to standard wavelet thresholding, MWT reduces distortion in critical frequency components, thereby improving the recognition rate when utilized with SNN. The EEG signal is decomposed into four levels utilizing the Daubechies (Db4) wavelet, yielding five subcomponents: including approximation (A) and four detailed coefficients (D1, D2, D3, D4). Since noise primarily affects the detailed coefficients, a thresholding method is applied to these coefficients to diminish unwanted noise. The MWT based denoising approach performs noise reduction at each level, which can be represented as,

$$\widehat{w_{j,k}} = \begin{cases} (1-\beta^2) + sgn(w_{j,k}) - \frac{T^{2\alpha+1}}{1+e^{|w_{j,k}|}} & |w_{j,k}| \geq T \\ \frac{|w_{j,k}|^{2\alpha+1}}{(2\alpha)T^{2\alpha+1}} & otherwise \end{cases} \tag{1}$$

$$T = \left(\frac{median(|d_j - median(d_j)|)}{0.6745}\right)\frac{\sqrt{2log(N)}}{log(j+1)} \tag{2}$$

Wavelet transform is employed to decompose EEG signals into their frequency components while preserving time-frequency information. This improves noise reduction and enhances feature extraction from non-stationary signals. The preprocessing pipeline significantly influences accuracy, as cleaner and more discriminative features lead to better spike encoding and improved classification outcomes.

After denoising, different frequency bands are extracted. These frequency bands are converted into spikes using the population encoding method [16]. In this population coding, each input feature is projected onto multiple receptive field neurons, where each neuron generates a single presynaptic spike based on the input value. This approach enables the input features to be represented as distributed patterns of neural activity, preserving important information through temporal coding. The resulting spike patterns are used to train the SNN [17], allowing the network to learn the underlying relationships between input features and corresponding output classes.

4. Experimental Results

4.1 Metrics

The proposed model was implemented on MATLAB2022a. Effectiveness of the model is assessed using some commonly used metrics, which are given below:

$$\text{Accuracy (ACC)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{3}$$

$$\text{Recall(R)} = \frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{Specificity ((SPE)} = \frac{\text{TN}}{\text{TN+FP}} \tag{5}$$

$$\text{Preicion (P)} = \frac{\text{TP}}{\text{TP+FP}} \tag{6}$$

$$\text{F1 score} = 2\ \text{X}\ \frac{\text{P X R}}{\text{P+R}} \tag{7}$$

$$\text{Balanced Classification Rate (BCR)} = \sqrt{\text{SPE X R}} \tag{8}$$

4.2 Performance Analysis

In this work, an SNN is designed to recognize consumer preferences based on extracted frequency bands. Parameters of the SNN are tabulated in Table 3. Spiking neuron parameters were initialized based on biologically inspired models such as the Leaky Integrate-and-Fire (LIF) framework. Synaptic weights were initialized randomly within a small range and adapted through training to capture temporal firing patterns. These parameters were chosen because they yielded the best results after conducting a series of tests using the same initial population.

Table 3. Parameters used for the SNN

Number of receptive field neuron	6
Encoding scheme	Population encoding
Overlap constant	0.7
Presynaptic spike interval	[0 3] ms
Postsynaptic spike interval	[0 4] ms
Time constant	2.5 ms
Learning rate	0.001
Efficacy update range	0.05ms
Plasticity window for STDP learning	0.5 ms
Firing threshold	0.69
Epoch	100
Number of input neurons	6X35
Number of output neurons	1

The encoded spike patterns represent the presynaptic firing times of the input neurons. The resulting postsynaptic potentials, generated in response to the test input patterns along with the corresponding presynaptic and postsynaptic spikes for both the "like" and "dislike" classes are illustrated in Figure 4 and Figure 5, respectively. For the "like" class, the postsynaptic potential reaches the firing threshold at 0.685 ms, triggering a postsynaptic spike at that moment. In contrast, for the "dislike" class, the postsynaptic potential v(t) fails to reach the threshold level within the simulation window. As a result, no postsynaptic spike is generated, and it is assumed to occur at the end of the simulation interval.

The performance of the model is reflected in Figure 6. The gamma band outperformed all other bands across all metrics, achieving the highest accuracy of 95.48%. This indicates strong overall correctness in recognition. Both recall and precision values of 95.26% and 95.71%, respectively, reflect that the model successfully identifies true positives (TPs) and minimizes false positives (FPs). With an F1 score of 95.49% and a balanced classification rate (BCR) of 95.48%, the gamma band proves to be the most reliable indicator of consumer preferences, highlighting its critical role in consumer preference recognition.

The beta band showed the second-best performance with an accuracy of 91.9% and balanced values across other metrics, with a recall of 91.51% and precision of 92.38%. These results demonstrate that the beta band carries useful information for decoding user intention. The alpha band followed closely, yielding 90.95% accuracy and an F1 score of 91%. While slightly lower than the beta band, it still contributes meaningfully to preference recognition. On the other hand, the theta and delta bands demonstrated reduced recognition performance. Theta attained 89.05% accuracy, while delta lagged with the lowest accuracy of 87.14%. These outcomes suggest that lower frequency bands contain less discriminative information for consumer choice detection.

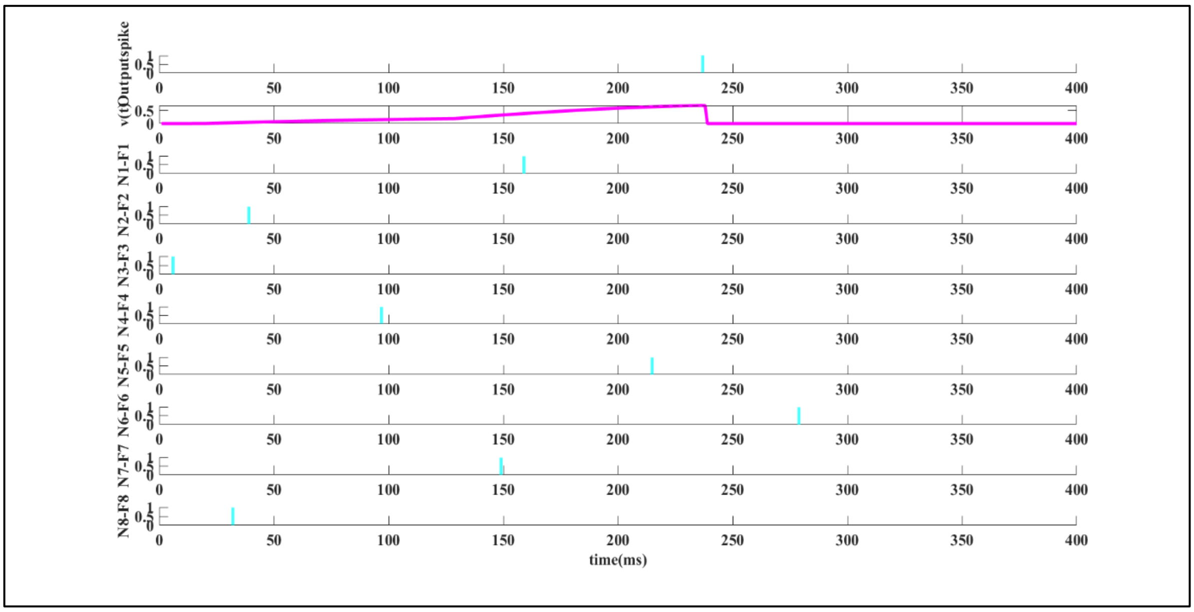


Figure 4. Postsynaptic Potential and Corresponding Presynaptic Spike Pattern for a Like Class Sample

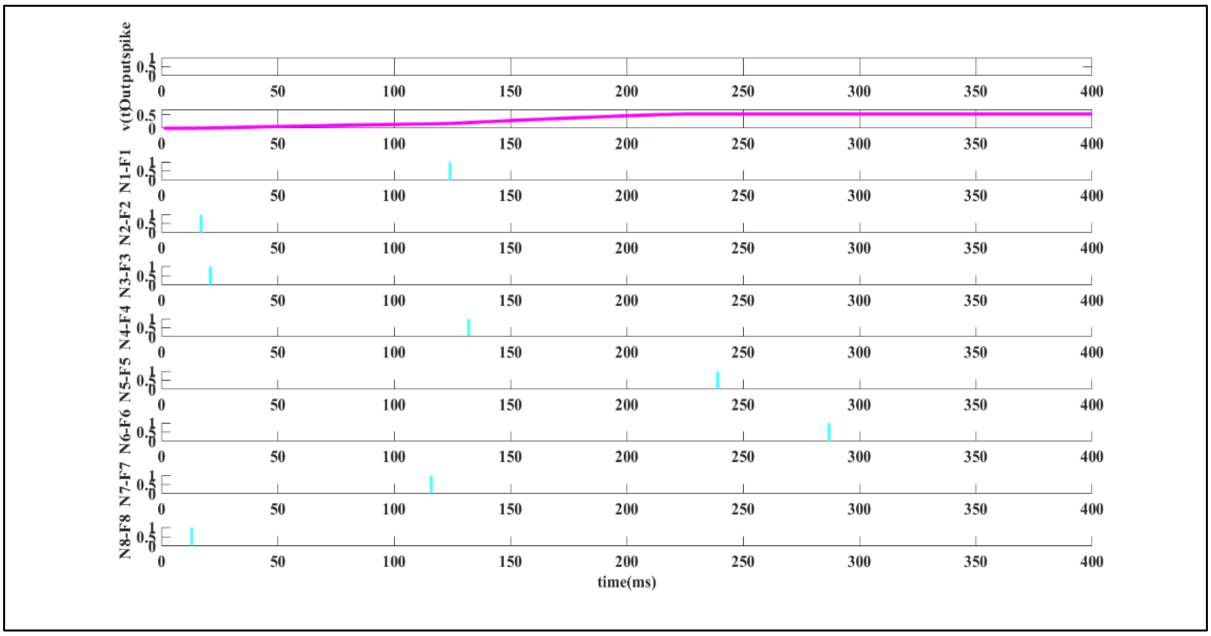
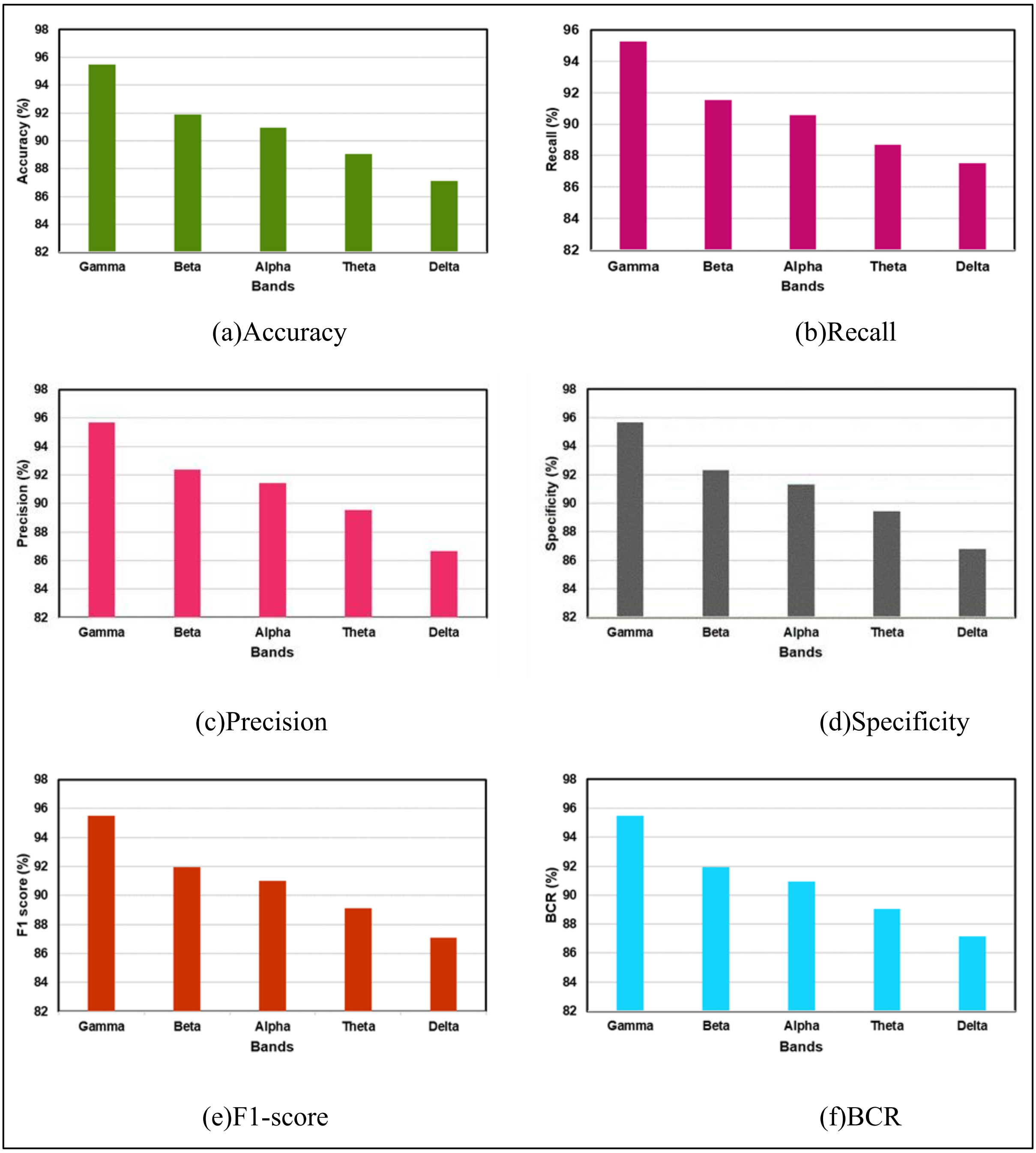


Figure 5. Postsynaptic Potential and Corresponding Presynaptic Spike Pattern for a Dislike Class Sample

Spike-timing parameters directly affect how temporal information is encoded. Lower thresholds may increase sensitivity but risk capturing noise, while higher thresholds may reduce sensitivity to weak signals. Adjusting periods influences the network's ability to capture rapid changes in neural activity. Proper tuning of these parameters can improve robustness.



(a)Accuracy (b)Recall

(c)Precision (d)Specificity

(e)F1-score (f)BCR

Figure 6. Performance of the Proposed Model

4.3 Comparison with Benchmarks

Table 4 presents a comparative analysis of earlier methods including BPF-statistical-SVM [12], SG-DWT-PSD-EC [14], BPF-PSD-RF [15], and BPF-DWT-LSTM [18] and the proposed approach for neuromarketing applications. The BPF-statistical-SVM model attained the lowest performance with an accuracy of 74.2%. Although recall was relatively high, the specificity was 69.57%. This indicates poor discrimination between like and dislike classes. The SG-DWT-PSD-EC demonstrated a considerable improvement, achieving an accuracy of 88.9%. Its recall and specificity were well balanced. Similarly, the BPF-PSD-RF yielded a comparable accuracy of 88.89%. The BPF-DWT-LSTM showed further improvement with an accuracy of 89.5%. It maintains high recall and uniqueness. The proposed model outperformed all the other models in terms of all metrics. It achieved the highest accuracy of 90.91%, a recall of 90.7%and a specialty of 91.12%. These results illuminate SNN's strength to model temporal mobility and recognize neural signals. Improvement in all metrics indicates enhanced strength and reliability. Traditional classifiers depend on stable features and often ignore temporal coding. In contrast, SNN naturally encodes temporal mobility through spike timing and neuronal firing patterns. This allows the model to capture a fine-grained temporal dependence in EEG signals that is important for distinguishing customer preferences.

Table 4. Comparative Performance Analysis of Different Methods

Methods	Accuracy (%)	Recall (%)	Specificity (%)
BPF-Statistical-SVM	74.2	89.19	69.57
SG-DWT-PSD-EC	88.9	87.9	88.5
BPF-PSD-RF	88.89	84.68	86.76
BPF-DWT-LSTM	89.5	87.12	89.56
Proposed	90.91	90.7	91.12

5. Conclusion

This study introduces an effective structure to predict consumer preferences using EEG signals processed by MWT and SNN. The model was tested on data collected from 25 participants in which 14 product stimuli were presented with a variety. The analysis of individual EEG frequency bands reveals that the gamma band offers the highest forecast accuracy, highlighting its importance in the decision-making process. The proposed system demonstrates strong potential for real-time neuromarketing applications, offering an objective and non-invasive method to decode consumer intent. In future work, the model can be extended to multimodal data by incorporating eye tracking or facial expression inputs. Additionally, testing on larger and more diverse populations will enhance model generalizability. Real-time implementation and feedback-driven adaptive marketing systems are also promising directions for further research.

References

[1] Ouzir, Mounir, Houda Chakir Lamrani, Rachel L. Bradley, and Ismail El Moudden. "Neuromarketing and decision-making: Classification of consumer preferences based on changes analysis in the EEG signal of brain regions." Biomedical signal processing and control 87 (2024): 105469.

[2] Chandar, S. Kumar, J. Vijayadurai, and M. Palanivel Rajan. "Consumer Decision Recognition Based on EEG Signals for Neuromarketing Applications." International Journal of Information Technology & Decision Making (IJITDM) 24, no. 06 (2025): 1825-1847.

[3] Usman, Syed Muhammad, Shehzad Khalid, Aimen Tanveer, Ali Shariq Imran, and Muhammad Zubair. "Multimodal consumer choice prediction using EEG signals and eye tracking." Frontiers in Computational Neuroscience 18 (2025): 1516440.

[4] Goto, Nobuhiko, Xue Li Lim, Dexter Shee, Aya Hatano, Kok Wei Khong, Luciano Grüdtner Buratto, Motoki Watabe, and Alexandre Schaefer. "Can brain waves really tell if a product will be purchased? Inferring consumer preferences from single-item brain potentials." Frontiers in integrative neuroscience 13 (2019): 19.

[5] Zeng, Li, Mengsi Lin, Keyang Xiao, Jigan Wang, and Hui Zhou. "Like/dislike prediction for sport shoes with electroencephalography: An application of neuromarketing." Frontiers in human neuroscience 15 (2022): 793952.

[6] Hsu, Melissa Yi-Ting, and Julian Ming-Sung Cheng. "fMRI neuromarketing and consumer learning theory: Word-of-mouth effectiveness after product harm crisis." European journal of marketing 52, no. 1/2 (2018): 199-223.

[7] Kaya, Ümran, Diyar Akay, and Sevgi Şengül Ayan. "EEG-based emotion recognition in neuromarketing using fuzzy linguistic summarization." IEEE Transactions on Fuzzy Systems 32, no. 8 (2024): 4248-4259.

[8] Alimardani, Maryam, and Mory Kaba. "Deep learning for neuromarketing; classification of user preference using EEG signals." In 12th Augmented human international conference, 2021, 1-7.

[9] Wei, Zhen, Chao Wu, Xiaoyi Wang, Akara Supratak, Pan Wang, and Yike Guo. "Using support vector machine on EEG for advertisement impact assessment." Frontiers in neuroscience 12 (2018): 76.

[10] Golnar-Nik, Parnaz, Sajjad Farashi, and Mir-Shahram Safari. "The application of EEG power for the prediction and interpretation of consumer decision-making: A neuromarketing study." Physiology & behavior 207 (2019): 90-98.

[11] Oon, Hooi Nee, A. Saidatul, and Zunaidi Ibrahim. "Analysis on Non-linear features of electroencephalogram (EEG) signal for neuromarketing application." In 2018 international conference on computational approach in smart systems design and applications (ICASSDA), IEEE, 2018, 1-8.

[12] Sourov, Injamamul Haque, Faiyaz Alvi Ahmed, Md Tawhid Islam Opu, Aunnoy K. Mutasim, M. Raihanul Bashar, Rayhan Sardar Tipu, Md Ashraful Amin, and Md Kafiul Islam. "EEG-Based Preference Classification for Neuromarketing Application." Computational Intelligence and Neuroscience 2023, no. 1 (2023): 4994751.

[13] Yadava, Mahendra, Pradeep Kumar, Rajkumar Saini, Partha Pratim Roy, and Debi Prosad Dogra. "Analysis of EEG signals and its application to neuromarketing." Multimedia Tools and Applications 76, no. 18 (2017): 19087-19111.

[14] Shah, Syed Mohsin Ali, Syed Muhammad Usman, Shehzad Khalid, Ikram Ur Rehman, Aamir Anwar, Saddam Hussain, Syed Sajid Ullah, Hela Elmannai, Abeer D. Algarni, and Waleed Manzoor. "An ensemble model for consumer emotion prediction using EEG signals for neuromarketing applications." Sensors 22, no. 24 (2022): 9744.

[15] Al-Nafjan, Abeer. "Feature selection of EEG signals in neuromarketing." PeerJ Computer Science 8 (2022): e944.

[16] Bohte, Sander M., Joost N. Kok, and Han La Poutre. "Error-backpropagation in temporally encoded networks of spiking neurons." Neurocomputing 48, no. 1-4 (2002): 17-37.

[17] Jeyasothy, Abeegithan, Suresh Sundaram, and Narasimhan Sundararajan. "SEFRON: A new spiking neuron model with time-varying synaptic efficacy function for pattern classification." IEEE transactions on neural networks and learning systems 30, no. 4 (2018): 1231-1240.

[18] Gill, Rupali, and Jaiteg Singh. "A Proposed LSTM-based neuromarketing model for consumer emotional state evaluation using EEG." Advanced Analytics and Deep Learning Models (2022): 181-206.

[19] Sadhukhan, Mrinal Kanti, Mitul Kumar Ahirwal, and S. K. Saritha. "An Online Learning and Problem Solving (OLPS) EEG Database for Mental Workload Assessment and Its Initial Benchmark Classification Performance." In International Conference on Computational Intelligence, Singapore: Springer Nature Singapore, 2023, 251-264.

[20] Kharel, Anisha, Alija Bhujel, and Smita Adhikari. &Transforming E-commerce Experiences with Augmented Reality and Computer Vision: A Framework for Virtual Try-Ons and Home Decor Visualization & Journal of Soft Computing Paradigm 7, no. 3 (2025): 187-211.