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An Intelligent EEG-based Advertisement Recommendation System using Correlative Capsule Networks and Similarity Matching

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ABSTRACT: This paper describes the design and implementation of a new Brainwave Driven Advertisement Recommendation System using state of the art Emotive Insight hardware, Brain Computer Interface (BCI) and Artificial Intelligence (AI). The technology is primarily aimed at improving the precision and personalization of ad recommendations by directly harnessing people's neural responses. The Emotive Insight headset can record brainwave frequencies including alpha, beta, theta, delta and gamma in real time. This rich data set is carefully preserved in both edf formats and is the basis for a thorough analysis. The participants saw three separate advertisements: Snickers, Dairy Milk and 5-star. To test the effect of each advertisement, they measure their brain responses simultaneously. Then the users comment on what ads they like best, tying subjective beliefs to brain wave patterns. Data Analysis: The data analysis stage involves meticulous preprocessing, artifact removal, and feature extraction to guaranty the extraction of meaningful insights. We build a strong predictive model using various machine learning approaches. The model is evaluated by the accuracy, precision, recall and F1 score metrics.

1. INTRODUCTION

Recommender systems play an increasingly important role in our daily life with their preference prediction ability. Neuromarketing aims to remodel and combine concepts and methods from neuroscience, marketing, economics, and psychology to assess the impact of marketing on the target consumers. It has gained massive attention due to accessing hidden information without asking consumers directly about their thoughts, feelings, memories, evaluations, decision-making, and so on. Neuromarketing captures the stimulus responses at the time of purchase. Hence, it represents the actual state of mind. Various techniques such as Functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG), Steady-State Topography (SST), and Transcranial Magnetic Stimulation (TMS) are used to capture brain activity signals. Various other techniques like respiratory rates, heart rate, eye tracking, and facial expression capture can also be integrated with the capture of EEG signals [1]. The most difficult part of a recommender system is accurately predicting users' preferences. However, existing methods mainly rely on users' implicit feedback such as click and dwell time, and attempt to connect them with users' subjective feelings. But this implicit feedback is usually inaccurate and noisy. It ignores the detailed user experience and may be different from the true feelings. Recently, with the development of neuroscience technology (e.g., EEG), access to users' explicit feedback to circumvent the problems mentioned above has become possible. Since EEG records the firing information of neuronal activity in the brain, it attracts great attention [2].

In comparison to other physiological measures, EEG is more preferable to the marketer due to its low device cost, experimental cost, and device portability [3]. Due to its low cost and being easily connected with mobile devices, EEG devices can be used from outside the laboratory, which has led to huge popularity for neuromarketing-based studies. The electrophysiological dynamics of the brain [4]. Moreover, EEG measures electrical potential differences between pairs of electrodes placed on the scalp. The recorded signal is a linear mixture of source current amplitudes and the signals in neighboring electrodes [5]. Moreover, the combination of e-commerce platforms and video content providers is inevitable and mutually beneficial, since e-commerce platforms expose their products to videos to increase Gross Merchandise Volume (GMV), and video content providers look forward to traffic monetizing [6]. Owing to advancements in technology in terms of performance capabilities and availability of video content across various screens and platforms, the Internet is increasingly being seen as an opportunity for video advertising. Video advertisements (ads) now appear before, during, or after streaming game or animation content as in-webpage video advertising [7]. The short videos serve as a combined visual and auditory medium, which is used for understanding the impact of visual and auditory features on user's perceptions. Accordingly, six Multidimensional Affective Engagement Scores (MAES) are used, which are valence, arousal, immersion, interest, visual, and extract the visual and auditory features of the videos. By employing self-assessment techniques, a more detailed and multidimensional perspective of user experience is obtained. Furthermore, real-time, low-cost EEG signals can be utilized to gain insights into users' cognitive activity [8].

The emergence of social media brought us a vast number of users, videos, and observable interaction behaviors between users and videos [9]. Recommender systems are becoming increasingly important because of the overload of information brought about by today's Internet. Video recommender systems are required, in particular, because of the high timing costs of watching videos [10]. These video recommender systems play the role of a bridge between users and videos, where a common representation of videos and users is required to measure the matching degree of user-video pairs. Developing an interpretable and stationary common representation method for both videos and users is of paramount significance for effective and efficient video recommendation [11]. In the development process of resource recommendation technology, it is needed to balance the relationship between personalized recommendation and information diversity to ensure that users can access comprehensive and diverse information resources [12]. With the tremendous increase in the number of new videos being continuously uploaded, some video streaming services have to deal with unrated, unaudited, and completely new content of which they do not know nothing. The new item cold-start problem has to be handled well in order for the uploaded content to be discovered by most of their users. In addition, because of the massive number of videos being produced, it is unfeasible to rely on manual processing of multimedia data to solve a wide variety of multimedia problems. As a result, recent studies on video content analysis and especially video retrieval tasks use various types of Deep Learning (DL) features extracted using pre-trained models due to their outstanding performance in different domains compared to hand-crafted features [13]. Hence, the recommendation of relevant advertisements aligned with video content has become crucial for maximizing user engagement and advertiser. Content-based advertisement video recommendation analyzes the actual content of a video without relying on user history or preferences [6].

2. RELATED WORK

The merging of Brain-Computer Interface (BCI) technology with advertisement systems is a groundbreaking method to use neural responses as a means of enhancing user experience. The BCIs have made the communication between the brain and machines possible, thus giving a new way of knowing the consumers' likes and dislikes and their behavior. The use of this technology has been witnessed in the medical field, entertainment, and marketing [1] among other areas.

Brainwave analysis entails the use of Electroencephalography (EEG) to record and interpret the brain's electrical activities. One of the most advanced EEG devices is Emotive Insight that has the capability of identifying and recording brainwave frequencies in real-time namely, Alpha, Beta, Theta, Delta, and Gamma waves. It can be found that the application of this technology in different fields has been quite successful, proving its effectiveness in neural response capturing [2][3]. The incorporation of such high-tech hardware makes it possible to accurately determine the brain's electrical activity which is a prerequisite for creating targeted and personalized advertisement recommendations.

Artificial Intelligence (AI) and machine learning techniques are the main pillars on which the processing of brainwave data and analysis is built. These technologies help in creating predictive models that can recommend advertisements based on the neural responses to the ads. A wide range of machine learning approaches like Support Vector Machines (SVM), Random Forest, and Neural Networks have been applied and recognized as efficient for the purpose of classifying and predicting user preferences

[4][5]. The use of these models in advertisement systems will not only increase the accuracy but also the personalization of the recommendations to a great extent.

To ensure correct analysis of brainwave data, effective data preprocessing and feature extraction are very important. Techniques like artifact removal, filtering of the signal, and extracting features (for example, power spectral density, and wavelet transform) are usually applied to determine the data's quality and reliability. These processes are really important in reducing noise and improving the signal-to-noise ratio in EEG recordings [6] [7]. Proper preprocessing and feature extraction are the pillars on which machine learning models stand in predicting user preferences from brainwave data.

BCI has been applied to advertisement systems in several studies. For example, a study on gender-based music recommendation systems showed the promise of brainwave data in content personalization [8]. EEG was another research theme that revealed the use of brain data for emotional response assessment to the ads, thus giving brands not only feedback but also [9] a way to increase their presence by analyzing whoever engages with their ads. Consequently, these real-world applications have confirmed that brainwave data is a powerful tool for the development of recommendation systems in advertising that are more personalized to the consumers' preferences

Table 1. Literature Review

Title of Reference Papers	**Year of Publication**	**Author**	**Method Used Techniques/Technology**	**Advantages**	**Disadvantages**
Machine learning-based viewers' preference prediction on social awareness advertisements using EEG	**2025**	Ishtiaque F. et al.[30]	14-channel EEG, EEG feature extraction, ML, engagement index, alpha activity	Very High – directly predicts preference for video advertisements using EEG	Only 20 participants and 8 advertisements; binary preference prediction rather than personalized recommendation; accuracy was 72%.
Predicting Consumer Ad Preferences: Leveraging a Machine Learning Approach for EDA and FEA Neurophysiological Metrics	**2025**	Marques et al.[31]	EDA, FEA, ML, XAI	High – focuses specifically on predicting consumer advertisement preferences and interpretable ML	Does not use EEG and therefore does not capture neural activity directly; no EEG-based recommendation mechanism.
Intelligent neuromarketing framework for consumers' preference prediction from electroencephalography signals and eye tracking	**2024**	Fazla Rabbi Mashrur et al.[34]	EEG, eye tracking, time/frequency/time-frequency features, SVM	Very High – real advertisements and consumer preference prediction	Uses SVM and handcrafted features; does not provide deep EEG representation or similarity-based video recommendation.
A systematic review on EEG-based neuromarketing: recent trends and analyzing techniques	**2024**	Recent review study[35]	Systematic review, clustering/text mining	Useful for establishing the research gap and state of the art in EEG neuromarketing	Review paper rather than a new recommendation model. It identifies ads/video commercials as a major research cluster.

Quantum Cognition-Inspired EEG-based Recommendation via Graph Neural Networks (QUARK)	**2025**	Jinkun Han et al.[36]	EEG + Graph Convolutional Network + quantum cognition	Extremely High for your recommendation component – directly investigates EEG-based recommendation	General item recommendation rather than video advertisements; architecture differs from your proposed capsule/attention/harmonic network.
MindMem: Multimodal for Predicting Advertisement Memorability Using LLMs and Deep Learning	**2025**	Sepehr Asgarian et al.[37]	Multimodal deep learning, visual/audio/text features, LLM	Relevant to video-advertisement modeling and advertisement effectiveness	Does not use EEG; focuses on memorability rather than neural preference and recommendation.
Machines learn neuromarketing: Improving preference prediction from self-reports using multiple EEG measures and machine learning	**2020**	Adam Hakim et al.[38]	Multiple EEG measures + ML; video commercials	Important foundation: demonstrates that EEG improves prediction of preferences for video commercials.	Older than your preferred period; conventional ML and no personalized recommendation engine.
A systematic review of the prediction of consumer preference using EEG measures and machine-learning in neuromarketing research	**2022**	Adam Byrne et al.[39]	Systematic review of 174 studies	Useful for supporting your choice of EEG features and ML; identifies frontal alpha asymmetry and LPP as important markers.	Review rather than a proposed recommendation system.

3. METHODOLOGY

In recent years, personalized video advertisement recommendations have gained considerable attention due to the exponential growth of online multimedia platforms. Existing recommendation systems primarily rely on behavioral data, which faces limitations when inferring user preferences due to issues such as data sparsity and noise. For tackling such issues, this paper develops a novel model named Correlative Capsule Split Attention Forward Harmonic network (C2ReFHNet) for video advertisement recommendation using EEEG. The EEG data plays a crucial role in video recommendation by offering direct insights into a user's response while watching visual content. Initially, the input EEG data collected from the dataset [21] will be normalized using Squash Norm normalization [22]. Afterward, the required features will be selected using the Mutual Information and Correlation (MICORR) Selection Method [23], and the selected feature will be considered as output-1. Likewise, input content-based video features will be normalized using Squash Norm normalization, and the features will be selected by the MICORR selection method. The selected features will be denoted as output-2. Following that, output-1 and output-2 will be applied to given to affective engagement score calculation, where the proposed C2ReFHNet will calculate the affective engagement score for each video. The merging of Deep Channel-attention correlative capsule network (DCACorrCapsNet) [24] and Split-Attention Network (ResNeSt) [25] will develop the C2ReFHNet, where the layers will be modified by forward harmonic analysis. The calculated score will be represented as output-3. Then, the advertisement video recommendation will be performed using similarity matching by considering selected content-based video features (output-2), calculated affective engagement score(output-3), and the video advertisement library. Finally, the advertisement video will be recommended. Moreover, the proposed C2ReFHNet-based video advertisement recommendation will be implemented in the Python tool using the hezy18/ EEG-SVRec dataset [21]. In addition, the effectiveness of the developed model will be validated by comparing it with existing methods using metrics, like precision, recall, and F1-score. Figure 1 shows the schematic view of C2ReFHNet-based video advertisement recommendation.

The research methodology described here portrays a very disciplined and thorough method for the application of the Brain-Computer Interface (BCI) and Emotive Insight devices in building an advertising recommendation system powered by Artificial Intelligence. The complete cycle includes obtaining data, engaging the users, gathering feedback, and analyzing the data afterward. Figure 1.showing step by step data Processing.

Brain-Computer Interface (BCI) Data Acquisition: Real-time brainwave frequency (Alpha, Beta, Theta, Delta, and Gamma) acquisition is being done through the Emotive Insight hardware. A 5-channel EEG device is depicted in Fig 2 along with the respective electrode positions. Participants are being subjected to neural response recording which is done at the same time in two formats, .csv and .edf, for further analysis. The dual-format recording assures data compatibility and ease of processing.

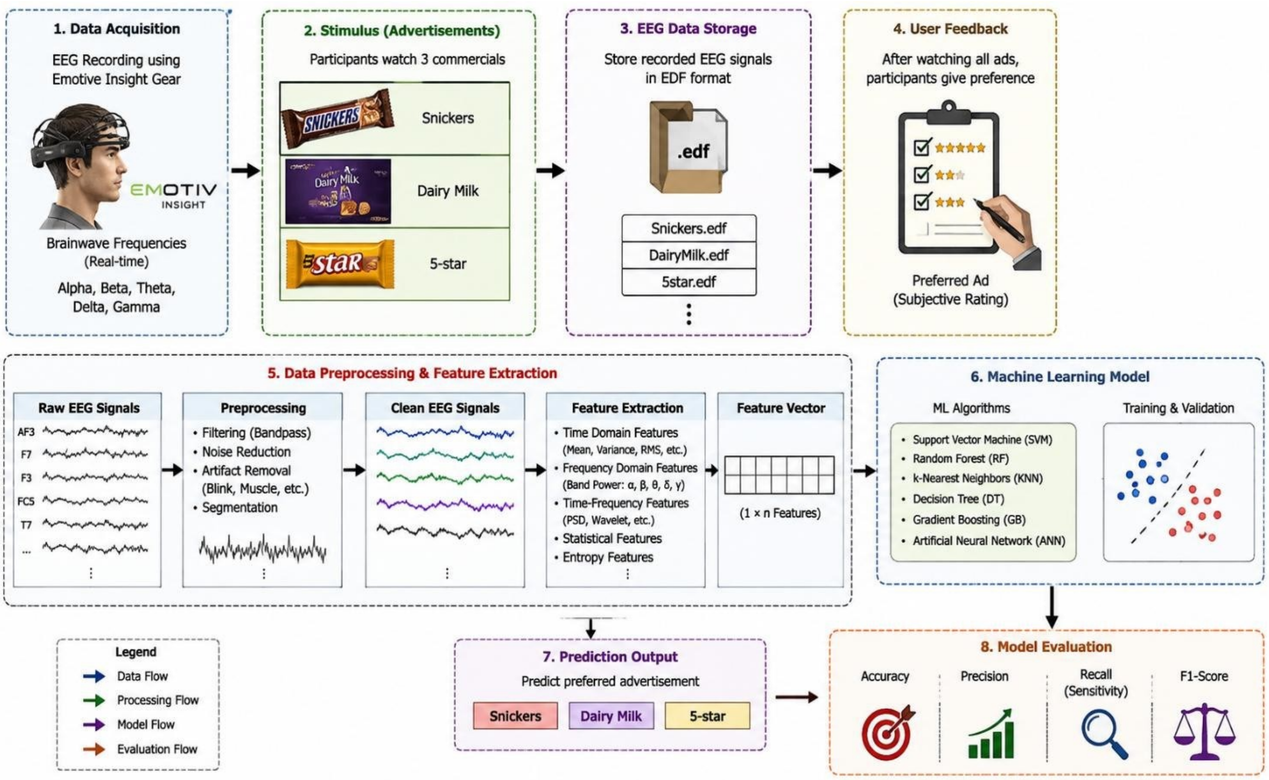

Figure 1. Architecture of the EEG-Based Video Advertisement Recommendation System

Advertisement Display and User Interaction:

All the participants will be shown the same three ads which are 5-star, snickers, and dairy milk. The time for exposure will be the same for all participants in order to keep the conditions equal. Fig 3 shows the real signal collection.

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Figure:2 Signal Collection

4. RESULTS AND DISCUSSION

4.1 Performance Metrics:

In this research, data model was used to calculate how accurately the model is predicting the accurate words (dairy milk, snicker, five star). All the parameters are taken into account for the correct word prediction. These parameters are used for checking the accuracy to predict the output from the data model. The following graph is the loss chart of accuracy of model.

I got below accuracy by using the Data model algorithm 4 times and averaging all the accuracies .

This whole process helps to understand which method might be better suited for the given task, by comparing the results of some machine learning classifiers on a particular dataset, over a range of evaluation criteria. The results can be further optimized and improved by changing the models or datasets.

The several classifiers under comparison (`Random Forest, `Decision Tree`, `K-Nearest Neighbors, `SVM) are plotted on x-axis. The scores (Accuracy, Precision, Recall, F1 Score) are presented on the y-axis.

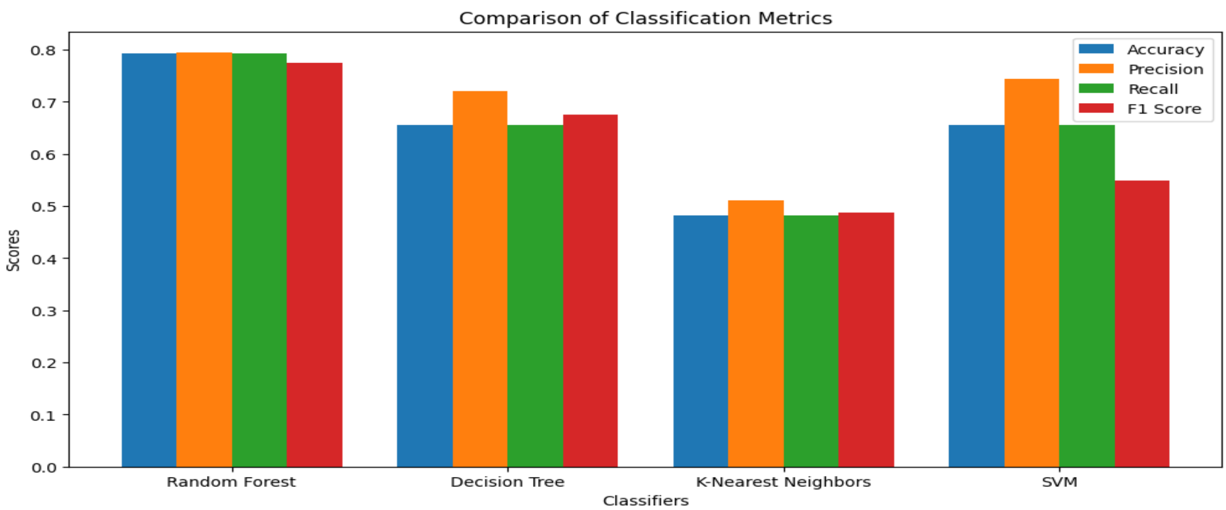


Figure 3: Model Accuracy, Precision, Recall and F1 Score Comparison

Table 2. Performance Comparison of Machine Learning Models for EEG-Based Advertisement Preference Prediction

Sr. No.	Model Title	Accuracy	Precision	Recall	F1 Score
1	Decision Tree	65.51	71.99	65.51	67.56
2	Random Forest	79.31	79.51	79.31	79.41
3	K-Nearest Neighbors	48.27	51.14	48.27	48.77
4	SVM	65.91	74.38	65.51	54.84

4.2 Plots of AUC/ROC:

The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) statistic were used to assess the categorization performance in more detail [8]. The trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various categorization thresholds is depicted by the ROC curve.

Plotting the ROC curve with FPR on the x-axis and TPR on the y-axis illustrates how the model differentiates across classes as the decision threshold varies. Next, the Area Under the ROC Curve, or AUC, is computed as [8]:

AUC values vary from 0 to 1, with AUC = 0.5 denoting no discriminative ability (equal to random guessing).Excellent separability between classes is indicated by an AUC near 1.0.Because it assesses the classifier's capacity to discriminate between positive and negative classes across all thresholds, the AUC–ROC analysis offers a crucial gage of model performance, especially when there is class imbalance. The AUC-ROC charts for each machine learning model before and after K-fold validation are displayed in Fig. 4.

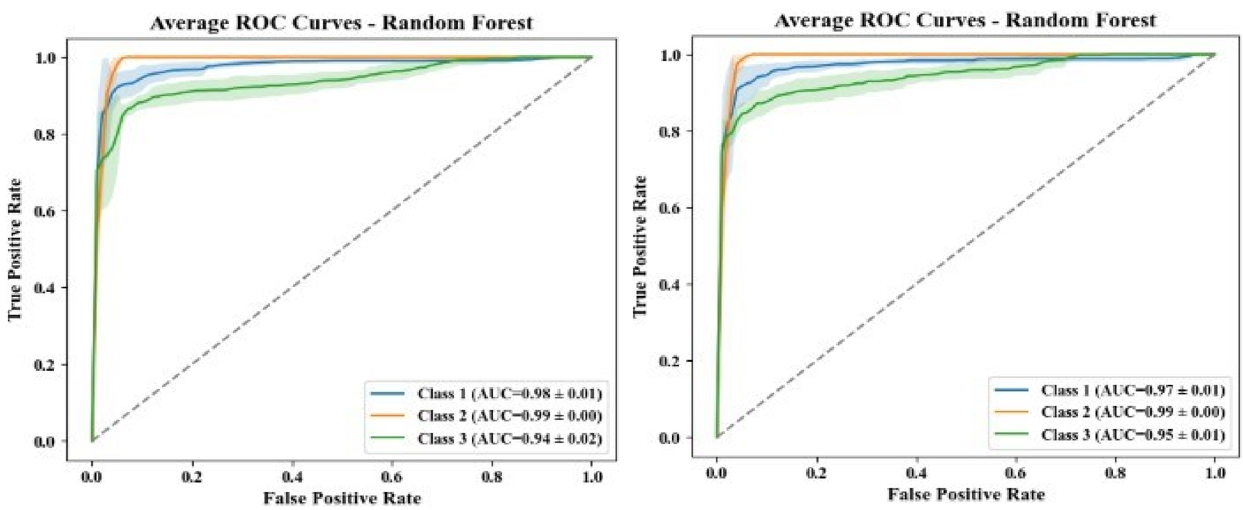
K-Fold Cross Validation (k=10) Train-Test Split (TTS)

a) The Random Forest

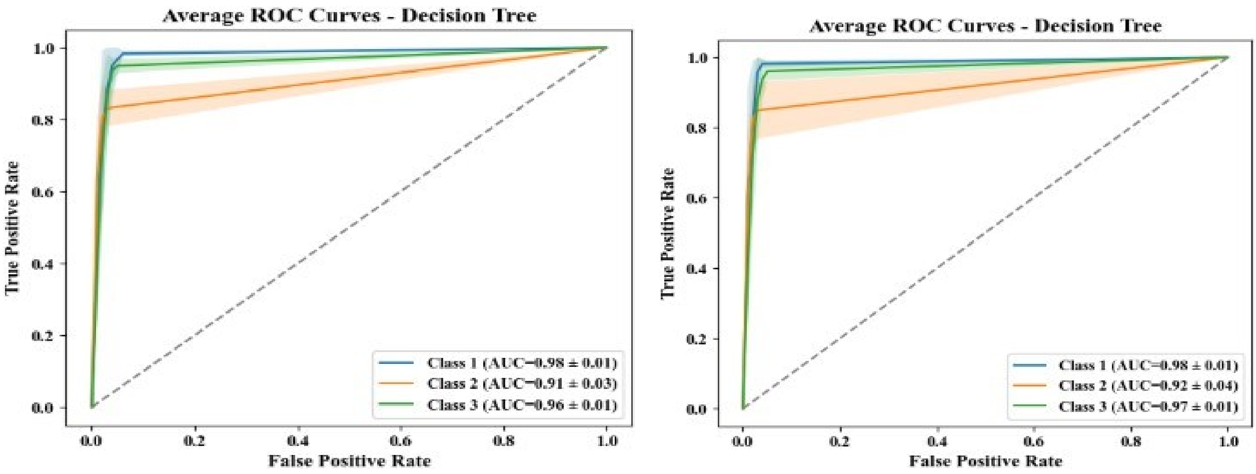
b) The Decision Tree

b) SVM, or Support Vector Machine

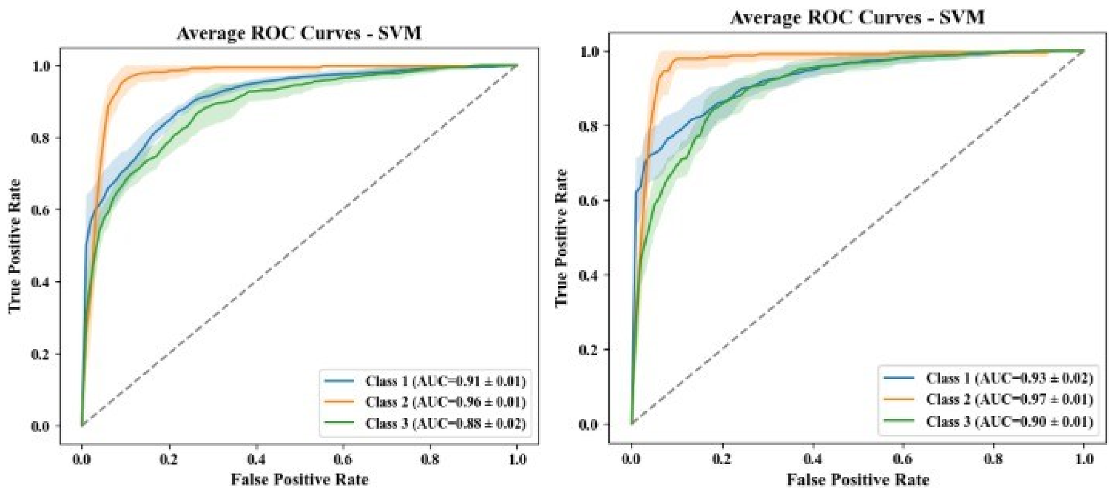
d) AdaBoost



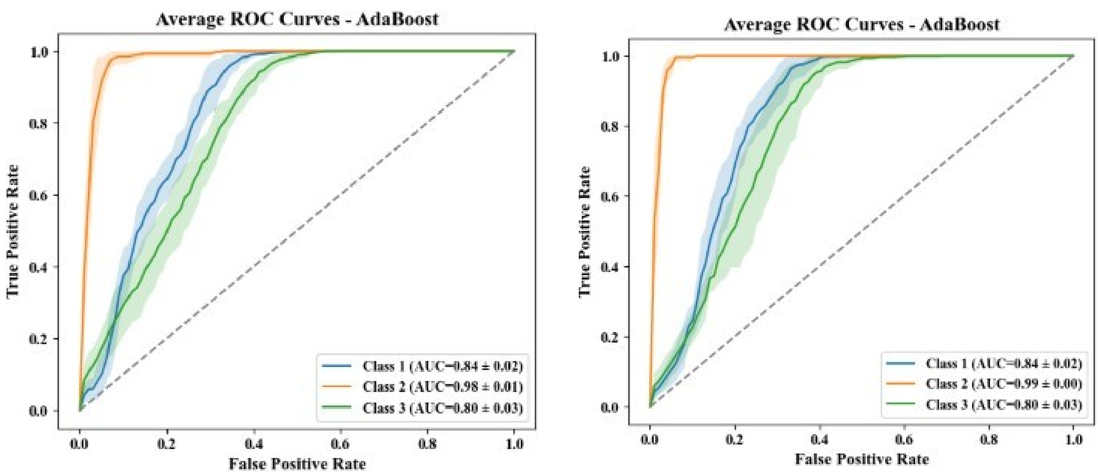
a) Random Forest



b) Decision Tree



c) Support Vector Machine (SVM)



d) AdaBoost

Figure 4: AUC/ROC Plots

Key performance indicators, including as Precision, Recall, F1-Score, and Accuracy, were used to evaluate the models under the Train–Test Split (80:20) and 10-Fold Cross Validation techniques. Along with these metrics, class-wise performance and misclassification patterns were examined using Confusion Matrix plots, and the AUC–ROC plots offered further information about the classifiers' capacity for discrimination across various thresholds. The findings show that tree-based models (Random Forest, AdaBoost, and Decision Tree) consistently performed better than other techniques. The Decision Tree (DT) had the best overall performance among them. Its capacity to capture non-linear correlations and interactions among features without the need for feature scaling is responsible for this better outcome. Additionally, the AUC–ROC analysis validated DT's high class separation abilities, and the confusion matrix demonstrated that it reduced false positives and false negatives more well than other models. The tree-based methodology proved more resilient than distance-based techniques like margin-based classifiers like SVM because it is less susceptible to data distribution and naturally handles both numerical and categorical data. The Decision Tree remained the most effective and comprehensible model, making it the best option for this dataset, even if ensemble models like Random Forest and AdaBoost increased robustness by lowering variance and concentrating on incorrectly classified samples.

4. CONCLUSION

The Brainwaves-powered advertising recommender system is model via BCI and ML. They recorded the brain waves of 50 students watching the three ads, then had the students choose which one they liked the best. The Data model predicts the text recognition of a student with 79% accuracy. There are three different types of chocolate advertisement and they show the advertisement to student and after they see the three advertized they choose the one they like most out of the three advertisement.(milk, snickers and five star).K-Nearest Neighbors is the worst performer.Random Forest and Decision Tree and SVM gives a moderate performance.The Data models especially the perform better in terms of accuracy, precision, recall and F1 score..

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AUTHOR CONTRIBUTIONS

Author One: Conceptualization, Literature Search, Formal Analysis, Writing, Original Draft, Visualization, Methodology, Literature Screening, Author two: — Review & Editing, Supervision. All authors have read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Informed consent was obtained from all participants before data collection. Participation was voluntary, and participants could withdraw at any time. EEG data were collected using a non-invasive device and were anonymized to protect privacy and confidentiality. The collected data were used solely for research purposes and securely stored. The study followed applicable institutional ethical guidelines for research involving human participants..

DATA AVAILABILITY STATEMENT

The EEG dataset used in this study was collected from participants during the experiment. Due to privacy and ethical considerations, the raw EEG data are not publicly available. The data may be made available from the corresponding author upon reasonable request, subject to appropriate ethical and privacy restrictions.

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