Neuromarketing Insights: A Comprehensive Review of EEG Signal Classification and ML Models for Unveiling User Preferences

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***Abstract*—Contemporary marketing strategies are deeply rooted in the effective promotion of consumer products through advertising campaigns, aiming to enhance sales and brand awareness. The reproducibility of products hinges on a multi-faceted evaluation, encompassing market consumption, reviewer feedback, and overall ratings. In contrast, Neuromarketing delves into the realm of unconscious processes to ascertain consumer preferences, enabling decision-making insights and behavior predictions.**

Electroencephalography (EEG) emerges as a pivotal tool in unraveling the complexities of consumer decision-making processes. The integration of machine learning and deep learning methodologies in the analysis of EEG signals offers a robust framework for predicting relevant consumer preferences. While traditional machine learning approaches necessitate extensive signal processing and feature engineering for classification, deep learning methods leverage raw brain signals, thereby circumventing time-consuming preprocessing.

This project presents a comprehensive exploration of EEG signals through the lens of different machine learning models. Leveraging a publicly available EEG neuromarketing dataset, the study systematically evaluates changes in EEG signals across diverse brain regions. The findings underscore the nuanced patterns of brain activity associated with the formation of consumer preferences, specifically distinguishing between preferences such as liking and disliking.

***Index Terms*—Neuromarketing, EEG, EPR, SVM, CNN, Extreme Gradient Boost**

I. Introduction

E-commerce is a growing field these days. People want to expand their businesses, so they spend money on marketing to learn about their customers' preferences[9]. Understanding consumer choices is essential for businesses to thrive in the market, deliver products that meet consumer needs, and contribute to overall economic growth. It allows for more efficient resource allocation, better-targeted marketing efforts, and improved customer satisfaction. The consumer commodity sector spends a huge amount of money on advertising the usability or success of the products. This is necessary during the pretesting of various alternative advertisement campaigns before launching and also during the in-market analysis of the campaign after launching [13].

Traditional medium for advertisement includes television, questionnaire, attitude, or verbal communication. However, such techniques may fail in predicting the consumer mindset towards the product as customers may provide wrong feedback during such communications. Other methods of advertisement include social networking sites such as Facebook, eBay, Amazon, Flipkart, Myntra, etc., where a customer can express his/her opinion in the form of a piece of text for the product. However, recently researchers have developed solutions where a manufacturer can take direct feedback on their products by analyzing brain signals. This technique is also known as 'Neuromarketing' [10].

Neuromarketing is a cutting-edge research field dedicated to uncovering the intricacies of decision-making, which involves the study of brain responses that explain the consumer's behavior toward products and services [12]. Electroencephalography (EEG) is a widely used technique in neuromarketing, allowing the capture of electrical brain surface activity by attaching electrodes [7]. EEG measures and physiological measures (e.g., ET, GSR) are most commonly used in neuromarketing research due to them being relatively inexpensive and easy to implement [2, 6]. EEG measurements are considered useful for their high temporal resolution and ability to adapt traditional experimental designs into neuroscience experiments and are highly compatible with machine-learning algorithms due to the richness of data collected[2, 5].

Historically, a multitude of algorithms, including Support Vector Machine (SVM) [3], Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), Naïve Bayes, k-Nearest Neighbor (kNN), and Hidden Markov Model (HMM) [11], have played pivotal roles in the landscape of Neuromarketing studies. Notably, kNN has showcased its prowess, achieving remarkable accuracies ranging from 74.6% to an impressive 97.99% when decoding EEG signals associated with aesthetic preferences [1].

In the [11], the authors have proposed a predictive modeling method based on EEG signals to understand customer preferences for E-commerce products in terms of ”likes” and ”dislikes”. EEG signals were recorded while volunteers of various ages and genders browsed through various consumer goods. The tests were performed on a dataset containing a variety of consumer goods. The accuracy of choice prediction was calculated using a user-independent testing approach and a hidden Markov Model (HMM) classifier.

In the [1] the authors implemented a machine learning model comprising an ensemble of algorithms that was compared to the performance of a convolutional neural network (CNN) on two independently collected EEG datasets, one concerning product choices and the other movie ratings. While both models showed poor performance in the prediction of product choices, the convolutional neural network proved more accurate in the prediction of movie ratings. This provides evidence for the superiority of deep learning algorithms in certain neuromarketing prediction tasks.

Furthermore, in [11], the authors analyzed the EEG data of 12 males and 12 females using a classifier (2-class preference). They obtained high classifier accuracies of 84.82% and 89.36% using KNN and SVM, respectively. However, neural networks such as DNN had a maximum accuracy of 79.76%.

II. Materials & Method

A. Datasets

1) Yadava et al: The dataset by Yadava et al [13] comprises EEG recordings obtained from a cohort of 25 participants, ranging in age from 18 to 25 years. EEG signals were captured using a 14-channel Emotiv Epoc+—a wireless device designed for neuro signal data acquisition, adhering to the international standard 10–20 system. The participants were engaged in viewing various e-commerce product images displayed on a computer screen for a duration of 4 seconds.

The stimuli encompassed 14 distinct product categories, namely shirts, shoes, ties, school bags, mufflers, belts, bracelets, gloves, sunglasses, sweaters, socks, wall clocks, pens, and wristwatches. Each category featured three different images, resulting in a total of 42 unique products (14 × 3). Subsequent to the presentation of each image, participants were required to express their preference or aversion towards the exhibited product. Consequently, a total of 1050 EEG data points were generated (42 × 25) across all participants. The sampling rate for recording the EEG signals was set at 128 Hz.

Furthermore, following the display of each image, the preferred choice of the participant was recorded for subsequent analysis. This dataset and experimental design provide a comprehensive basis for investigating neural responses and preferences in the context of e-commerce product perception.

Fig. 1. A collection of 14 different products where each product has three different varieties which create 42 (14×3) different product images.

2) NeuMa Dataset: The NeuMa dataset [4] offers a comprehensive exploration of consumer behavior through its multimodal approach, integrating EEG recordings, eye-tracking data, and behavioral responses. This dataset stands out for its realistic shopping scenario, where participants engage in browsing a simulated supermarket brochure and selecting products as they would in real-world decision-making processes. Notably, the dynamic data collection methodology captures EEG and eye-tracking data simultaneously, enabling researchers to analyze the temporal dynamics of brain activity and visual attention during product evaluation.

In terms of data components, the EEG data is recorded using a 64-channel EEG system with a sampling rate of 500 Hz. Pre-processing steps are implemented to eliminate artifacts and noise, ensuring the reliability of the neural signals. The eye-tracking data, obtained through a Tobii Pro X3-120 eye tracker, provides valuable insights into gaze patterns and fixations, contributing to a more nuanced understanding of visual attention. The dataset also includes behavioral data in the form of questionnaire responses, covering demographics and product preferences, as well as information on mouse clicks and product selections.

3) DEAP Dataset: The primary objective of this initiative is to furnish a multi-modal dataset [8] specifically designed for the analysis of emotions through physiological signals, with a particular emphasis on EEG data. The dataset encompasses EEG recordings obtained from 32 participants, evenly distributed between 16 female and 16 male subjects. These recordings were conducted utilizing a 32-channel Biosemi

ActiveTwo system, featuring a sampling rate of 512 Hz. Participants engaged with 40 one-minute music videos during the data collection process.

In addition to EEG data, the dataset includes other physiological signals such as Electrocardiography (ECG) and Galvanic Skin Response (GSR). Participants were also prompted to provide self-assessment ratings for each music video, evaluating them based on three emotional dimensions: Arousal (level of excitement), Valence (level of pleasantness), and Dominance (level of control). Facial video recordings are available for 22 of the participants, contributing an additional layer to the understanding of emotional responses.

Key features of this dataset include its multi-modal nature, incorporating EEG, ECG, GSR, and facial video data, thereby providing a more comprehensive insight into emotional responses. The EEG data is pre-processed for convenience, with artifacts and noise already removed. Furthermore, the dataset offers valuable emotional annotations in the form of self-assessment ratings for each video, facilitating the correlation of physiological signals with subjective emotional experiences. Importantly, this dataset is publicly available for research purposes, promoting openness, reproducibility, and collaborative exploration in the field of emotion analysis through physiological signals.

4) SINES EEG Dataset: In our EEG data collection at the SINES lab, we employ the NeuroSky Mind Wave EEG headset as our brain-computer interface (BCI) device. This headset allows us to monitor and measure brainwave activity using electroencephalography (EEG) technology, which detects and quantifies the electrical signals produced by the brain. The device focuses on capturing brainwave frequencies associated with various mental states, such as attention and meditation.

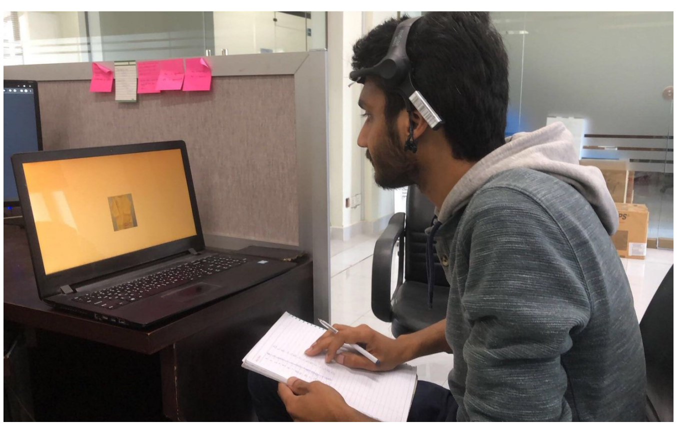

Fig. 2. An individual is utilizing the NeuroSky MindWave headset to acquire EEG data. The recorded instances are displayed on a laptop screen, and the person is actively engaged in manually labeling the data

For electrode placement, the Mind Wave typically employs a single electrode situated on the forehead, specifically at the FP1 position. FP1 corresponds to Frontal Pole 1 in the international 10-20 system, a standardized approach to electrode positioning in EEG. This positioning allows us to capture brainwave signals from the frontal lobe, providing insights into cognitive processes and mental states.The instances we used were 7 different objects images as shown in fig. 3 . Data was collected at 128Hz.

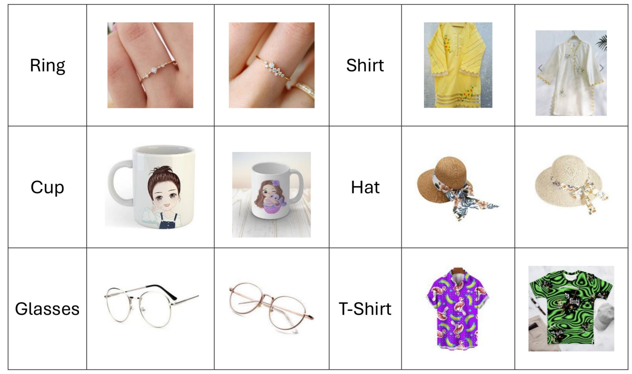

Fig. 3. Seven distinct objects, each categorized into two groups, were employed as instances

III. Data Processing and Integration for EEG Analysis

Processing EEG datasets involves a series of critical steps to prepare the raw data for analysis and machine learning applications. Initially collected through electrodes on the scalp, EEG data is subject to preprocessing steps to enhance its usability. These steps include setting the sampling rate and defining time windows for analysis, applying filters to isolate relevant frequency bands, and removing artifacts such as eye blinks and muscle activity. Referencing methods ensure a common baseline for the data, and segmentation into epochs facilitates event-related potential analysis. Normalization techniques may be employed to standardize the data, and feature extraction involves computing statistical measures or extracting frequency domain features. Notably, the flattening of multi-dimensional arrays into one-dimensional arrays is a common practice, simplifying the handling and processing of data, which is often organized into a 2D array combining both data and labels. Labels are normalized, and the dataset is typically split into training and testing sets for model evaluation. These preprocessing steps are crucial for ensuring the quality and suitability of EEG data for subsequent analyses or machine learning applications.

IV. Machine learning Models on Yadava et al Dataset

Our goal is to leverage a range of machine learning algorithms, including K-Nearest Neighbors, Support Vector Machine, Gradient Boosting, Random Forest, and Artificial Neural Networks. The overarching objective is to conduct a thorough analysis to discern the algorithm that produces optimal results for our specific use case. This entails evaluating the performance of each algorithm and comparing their outcomes systematically. The aim is to pinpoint the most effective solution among these algorithms for our intended application, ensuring a comprehensive understanding of their strengths and weaknesses in the context of our specific dataset and problem domain.

A. Implementation of KNN classifier

The selection of the K-Nearest Neighbors (KNN) algorithm is based on its merits of simplicity, effectiveness, and adeptness in handling non-linear relationships within the dataset. Integrating KNN with neuromarketing through EEG signals represents a promising avenue for comprehending and predicting consumer behavior.

Through the implementation of the KNN classifier, our analysis reveals a discernible trend: as the threshold increases, precision experiences an upward trajectory, while recall undergoes a decrease. This phenomenon is attributed to the model's propensity to predict fewer instances as positive when the threshold is elevated, resulting in a higher likelihood of correctness for those predictions.

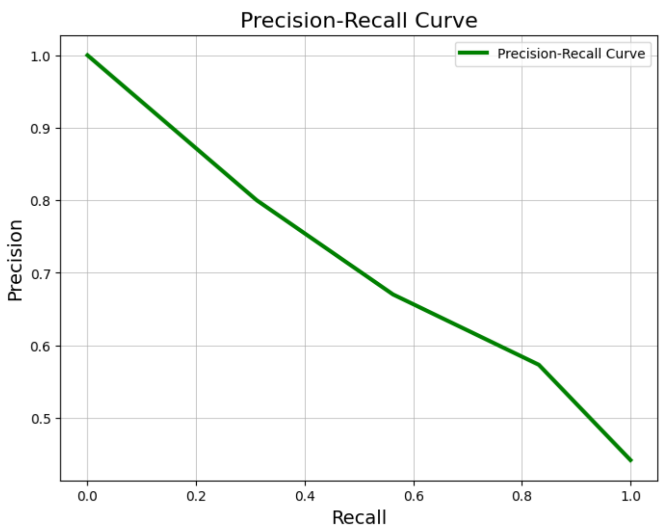

Fig. 4. Precion Recall Curve for KNN Classifier

TABLE I
CLASSIFICATION REPORT KNN BASED ON DATASET(1)

Class	precision	recall	f1-score	support
0.0	0.69	0.78	0.73	292
1.0	0.67	0.56	0.61	231
Accuracy	0.68			
Macro Avg.	0.68	0.67	0.67	523
Weighted Avg.	0.68	0.68	0.68	523

The EEG-based K-Nearest Neighbors (KNN) classifier demonstrated an overall accuracy of 68%, with balanced precision for class 0 (69%) and class 1 (67%). However, a notable difference in recall values was observed, with class 0 exhibiting a recall of 78% and class 1 at 56%. The F1 scores reflected this asymmetry, with class 0 (73%) outperforming class 1 (61%), indicating potential challenges in identifying instances of class 1.

To enhance the F1 score, we employed Hyperparameter Tuning and Feature Scaling. Post-tuning, the model exhibited high precision across all recall values, suggesting accurate identification of positive instances. However, there is room for improvement in recall at higher values, indicating a potential for the model to miss some positive instances. Overall, the model performs well, with ongoing opportunities for refinement.

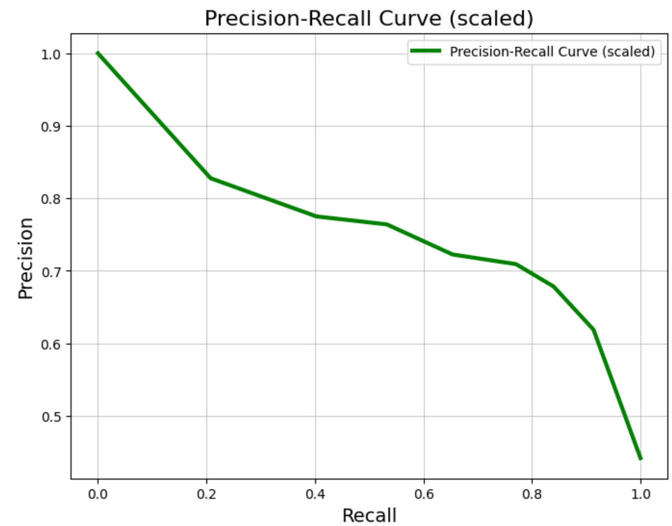

Fig. 5. Precision Recall Curve for Scaled KNN Classifier

TABLE II
CLASSIFICATION REPORT SCALED KNN CLASSIFIER

Class	precision	recall	f1-score	support
0.0	0.75	0.80	0.77	292
1.0	0.72	0.65	0.69	231
Accuracy	0.74			
Macro Avg.	0.73	0.73	0.73	523
Weighted Avg.	0.74	0.74	0.73	523

Following data scaling, the updated classification report demonstrates an enhanced overall accuracy, with increased precision for both classes. The F1 scores, indicative of a harmonized balance between precision and recall, show improvements for both classes. This indicates a positive impact of data scaling on the model's pattern recognition ability, with notable benefits observed in the classification performance for instances belonging to class 1.

B. Implementation of SVM classifier

Support Vector Machines (SVM) are powerful classifiers known for their effectiveness in discerning complex decision boundaries in both linear and non-linear datasets. The algorithm operates by identifying the optimal hyperplane that maximizes the margin between different classes, ensuring robust separation. This hyperplane becomes the key determinant for classifying new instances.

In SVM, the concept of the ”kernel trick” is integral for handling non-linear data. Kernels transform the input features into a higher-dimensional space, making it possible to find a linear hyperplane in this transformed space. Commonly used kernels include the linear kernel for linearly separable data, and non-linear kernels like the radial basis function (RBF) for more intricate decision boundaries.

Moreover, SVM incorporates the notion of support vectors, which are the data points critical for defining the decision boundary. These support vectors influence the model's learning process, and the algorithm is particularly resilient to outliers due to its focus on these crucial data points.

In the context of our analysis, while the precision-recall curve demonstrates the model's aptitude in identifying "like" signals with high precision, the observed dip in recall at elevated thresholds prompts consideration for potential adjustments in the model parameters or exploration of alternative kernel functions to enhance the capture of true positive instances. SVM's versatility and capacity to handle diverse datasets make it a valuable candidate for our comprehensive evaluation of machine learning algorithms.

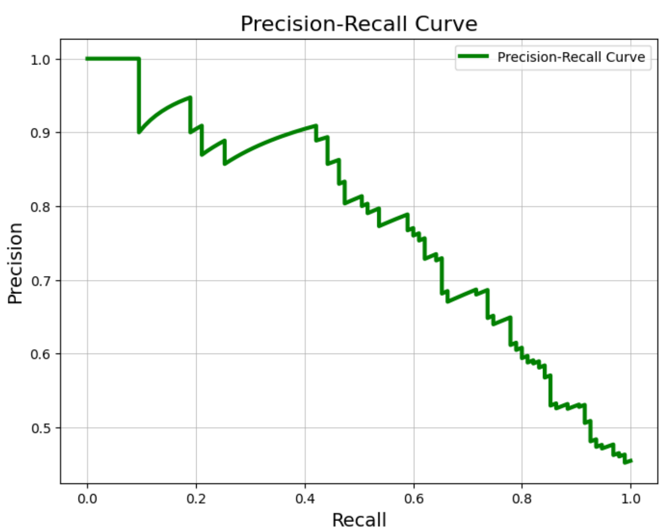

Fig. 6. Precision Recall Curve for SVM Classifier

TABLE III
CLASSIFICATION REPORT SVM CLASSIFIER

Class	precision	recall	f1-score	support
0.0	0.72	0.81	0.76	114
1.0	0.73	0.63	0.68	95
Accuracy	0.73			
Macro Avg.	0.73	0.72	0.72	209
Weighted Avg.	0.73	0.73	0.72	209

Optimizing F1 score for our SVM classifier yielded promising results. Scaling the model significantly improved its performance, demonstrated by a steeper precision-recall curve and higher precision at high recall values. This suggests the model effectively identifies true positives without sacrificing precision at higher recall thresholds.

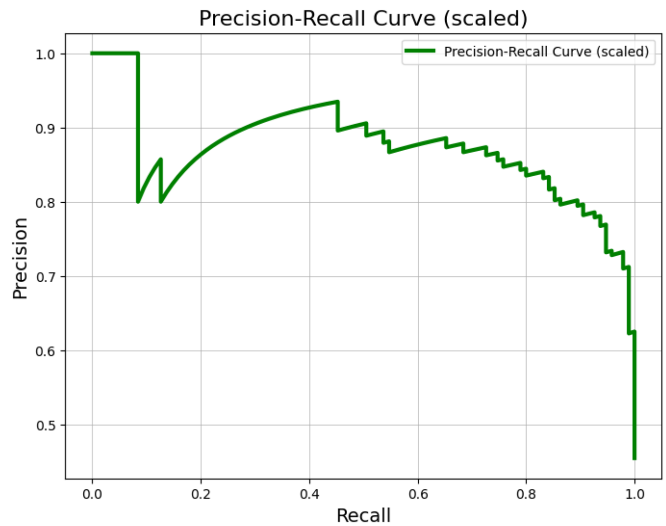

Fig. 7. Precision Recall Curve for Scaled SVM Classifier

TABLE IV
CLASSIFICATION REPORT SCALED SVM CLASSIFIER

Class	precision	recall	f1-score	support
0.0	0.88	0.82	0.85	114
1.0	0.80	0.86	0.83	95
Accuracy	0.84			
Macro Avg.	0.84	0.84	0.84	209
Weighted Avg.	0.84	0.84	0.84	209

C. *Random Forest*

Random Forest, an ensemble learning method, demonstrates its efficacy by aggregating predictions from a multitude of decision trees. Each tree is constructed using a subset of the training data and features, introducing diversity and mitigating the risk of overfitting—a common concern in the analysis of intricate EEG signals.

One notable strength of Random Forest lies in its adaptability to high-dimensional data, a characteristic well-suited for the complex nature of EEG datasets. The ensemble approach allows the model to capture intricate patterns and relationships within the data, enhancing its predictive capabilities.

The process of constructing decision trees involves selecting random subsets of features at each node, fostering decorrelated trees that collectively contribute to a more robust and generalizable model. Additionally, the incorporation of bootstrap sampling ensures variability in the training data for each tree, further enhancing the model's resilience to outliers and noise.

In our application focused on predicting user preferences from EEG data, the Random Forest model not only demonstrated an impressive overall accuracy of 84% but also showcased high precision and recall for both preference classes ([like/dislike]), indicating its proficiency in discerning subtle distinctions in user responses. The F1-score, indicative of the model's precision-recall balance, underscored its effectiveness in achieving a harmonious blend of accurate positive identifications and comprehensive class coverage. This ensemble learning approach, with its inherent versatility and ability to handle complexities, solidifies Random Forest as a robust choice for EEG signal analysis in scenarios where nuanced discrimination and generalization are paramount.

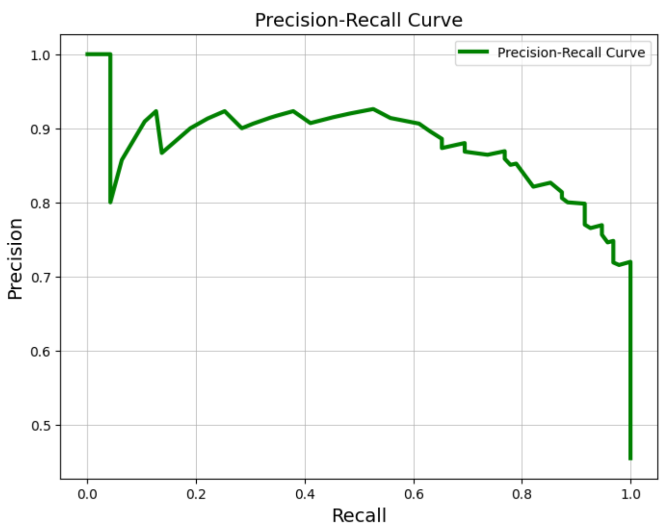

Fig. 8. Precision Recall Curve for Random Forest

TABLE V
CLASSIFICATION REPORT RANDOM FOREST

Class	precision	recall	f1-score	support
0.0	0.89	0.82	0.85	114
1.0	0.80	0.88	0.84	95
Accuracy	0.85			
Macro Avg.	0.85	0.85	0.85	209
Weighted Avg.	0.85	0.85	0.85	209

D. *Extreme Gradient Boosting*

Extreme Gradient Boosting (XGBoost) is a machine learning algorithm that has gained prominence for its exceptional predictive performance and versatility. Specifically tailored to handle complex interactions between features, XGBoost excels in scenarios where intricate relationships within the data need to be uncovered. This attribute makes it particularly well-suited for the analysis of EEG signals, which often contain rich and nuanced information.

One of the key strengths of XGBoost lies in its ensemble learning approach, which involves sequentially adding decision trees to correct errors made by the preceding ones. This iterative process enables the model to continuously refine its predictions, ultimately yielding a robust and accurate result. XGBoost's regularization techniques, such as shrinkage and pruning, contribute to its resistance against overfitting, ensuring that the model generalizes well to new, unseen data.

In our specific application focused on predicting user preferences from EEG signals, the XGBoost model demonstrated a notable predictive accuracy of 83%, aligning closely with the performance of the Random Forest model. Precision and recall values for both preference classes ([like/dislike]) consistently exceeded 80%, indicating the model's proficiency in making accurate distinctions between classes while minimizing false positives and negatives.

The sustained F1-score of 82% for both classes highlights the model's ability to strike a delicate balance between precision and recall, showcasing its effectiveness in achieving a well-rounded classification of user preferences. XGBoost's capability to navigate the complexities of EEG data, coupled with its impressive performance metrics, reinforces its standing as a powerful algorithm for uncovering subtle patterns and preferences within intricate neurophysiological signals.

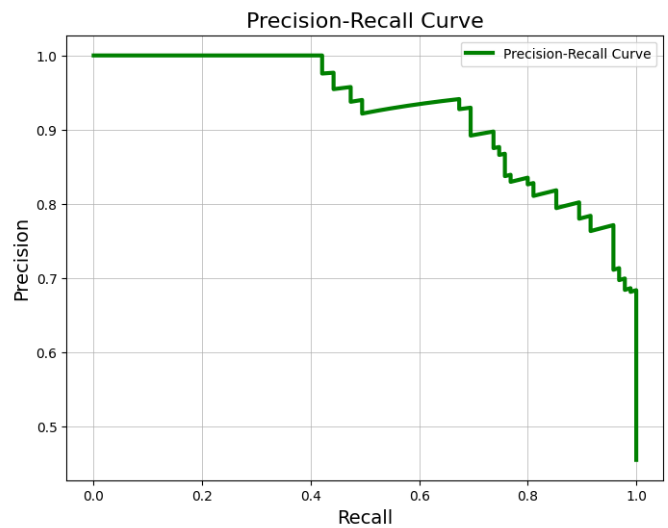

Fig. 9. Precision Recall Curve for Extreme Gradient Boost

TABLE VI
CLASSIFICATION REPORT EXTREME GRADIENT BOOST

Class	precision	recall	f1-score	support
0.0	0.87	0.82	0.84	114
1.0	0.79	0.85	0.82	95
Accuracy	0.83			
Macro Avg.	0.83	0.83	0.83	209
Weighted Avg.	0.84	0.83	0.83	209

E. *Artificial Neural Network*

Artificial Neural Networks (ANNs) represent a powerful class of machine learning models inspired by the structure and functioning of the human brain. Comprising interconnected nodes or neurons organized into layers, ANNs can effectively learn complex non-linear relationships within data. This capability makes them particularly well-suited for applications where the underlying patterns are intricate and not easily captured by linear models.

In the context of our analysis, ANNs were selected to explore whether they could offer improvements over previous models like Random Forest and Extreme Gradient Boosting.

TABLE VII
SUMMARY OF NEUROMARKETING STUDIES

Previous Work	Device/System	Dataset	Participants	Analysis Method	Accuracy/AUC	Results
Neuromarketing and decision-making: Classification of consumer preferences based on changes analysis in the EEG signal of brain regions	14-channel Emotiv Epoc+	14 different product categories, each containing three different images(14x3=42) images	25 participants (18-25 years)	k-NN, RF, NN, GB	KNN: (71.81%, 71.97%) RF: (69.76%, 69.69%) NN: (76.02%, 75.95%) GB: (73.74%, 73.59%)	The study reveals that Neural Network classifier outperforms Gradient Boosting in classification, with AUC scores being crucial in distinguishing between false positive and false negative classifications.
The application of EEG power for the prediction and interpretation of consumer decision-making: A neuromarketing study	32-channel electrode system	4 different mobile phone brands (Apple, Meizu, Samsung, Nokia)	16 participants (23 $\pm$ 3 years)	SVM, LDA	LDA: 63.95% ($\pm$5.19) SVM: 63.62% ($\pm$4.16)	The study found that non-linear SVM classifiers better separated ”Like” and ”Buy” conditions from neutral, while linear LDA classifiers identified ”Dislike” conditions from neutral.
Neuromarketing Solutions based on EEG Signal Analysis using Machine Learning	Muse 2 headset	10 different product categories and three different images	15 participants	ANN, SVM, Decision tree, and K-Nearest Neighbors.	ANN: 50.4% DT: 57.3% KNN: 60.89% Log. Reg: 51.34%	Product wise accuracy is higher product-wise. Highest Classification accuracy of up to 92.21% on the Delta band. K-nearest neighbors proved to be best algorithm for classification of the Delta band signals.
Analysis of EEG signals and its application to neuromarketing Cardinal analysis	Emotiv EPOC+ (14 channels)	42 images (14 categories)	40 participants (25M, 15F)	Bayesian Regression,	Bayesian: 68.2% Cardinal: 65% HMM: 70.33%	By using HMM classifier we can analyze the effectiveness of the proposed framework and provides a complementary solution to the traditional measures of predicting the product success in the market.
Deep Learning for Neuromarketing; Classification of User Preference using EEG Signals	14-channel Emotiv Epoc+	Dataset 1 (Product Choice) Dataset 2 (Movie Rating)	25 participants (18-25 years)	DL Model (CNN), ML Model (Ensemble)	CNN: 51.48% (1) 63.54% (2) Ensemble: 50.71% (1) 74.57% (2)	The convolutional neural network outperformed the ensemble classifier in movie rating prediction, demonstrating its potential as a superior neuromarketing framework with minimal preprocessing.
EEG-Based Preference Classification for Neuromarketing Application	14-channel EMOTIV EPOC+	Approximately 1400 feedback responses as likes/dislikes	49 subjects (24 males and 25 females)	PNN, DNN, KNN, SVM	PNN: 96.62% KNN: 84.82% SVM: 89.36% DNN: 79.76%	The convolutional neural network demonstrated its potential as an excellent neuromarketing framework with minimal preprocessing by outperforming the ensemble classifier in movie rating prediction.
Deep Learning for EEG-Based Preference Classification in Neuromarketing	A BCI System	DEAP Database	32 participants (19-37 years)	SVM, Log. Reg., HMM, KNN+TF, DNN	SVM: 75.44% Log. Reg.: 67.32% HMM: 70.33% KNN + TF: 83.34% DNN: 63.99%	When compared to KNN and SVM, the suggested DNN shows better accuracy, recall, and precision; on the same dataset, RF achieves results that are comparable to those of DNN.

The learning process in ANNs involves adjusting the weights between neurons during training to minimize the difference between predicted and actual outcomes. This adaptability allows ANNs to discern and model intricate patterns, making them especially valuable in scenarios where features interact in complex and non-linear ways, as often seen in EEG signal data.

The ANN model applied in our study demonstrated commendable accuracy, reaching 82% in predicting user preferences. While this slightly trailed behind the performance of previous models, the precision and recall metrics for both preference classes ([like/dislike]) consistently exceeded 70%. These metrics underscore the model's ability to accurately identify true positives while minimizing instances of false positives and negatives.

With an F1-score of 74% for both classes, the ANN showcased a reasonable equilibrium between precision and recall, indicating its proficiency in striking a balance between accurate positive identifications and comprehensive class coverage. Despite being slightly below the metrics achieved by simpler models, the ANN's notable performance suggests potential advantages, especially in its capability to capture and comprehend intricate non-linear relationships within EEG signal data. The exploration of ANN adds depth to our understanding of the trade-offs involved in choosing models for EEG signal analysis and highlights the importance of considering the complexity of underlying relationships in the data.

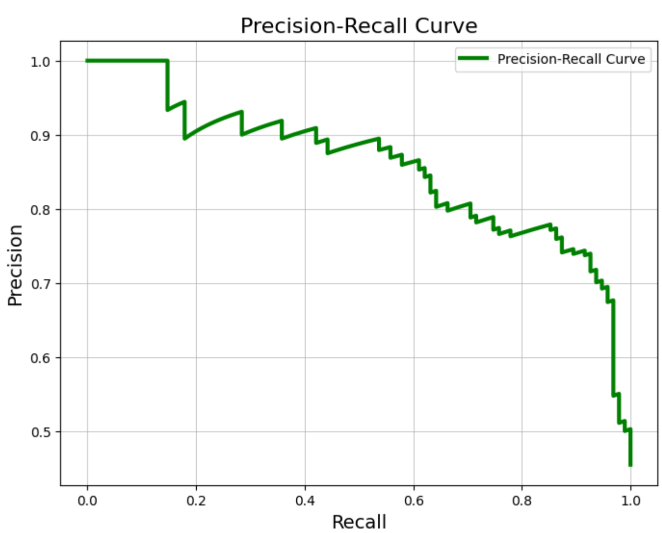

Fig. 10. Precision Recall Curve for Artificial Neural Network

V. Results

1) Yadava et al Dataset: In our comprehensive analysis of machine learning algorithms for EEG signal-based prediction of user preferences, several models were evaluated, each offering unique strengths and considerations. The K-Nearest Neighbors (KNN) algorithm, chosen for its simplicity and efficacy in handling non-linear relationships, achieved an overall accuracy of 68%. The precision-recall trade-off analysis

TABLE VIII
Classification Report Artificial Neural Network

Class	precision	recall	f1-score	support
0.0	0.78	0.85	0.81	114
1.0	0.80	0.71	0.75	95
Accuracy	0.78			
Macro Avg.	0.79	0.78	0.78	209
Weighted Avg.	0.79	0.78	0.78	209

indicated a nuanced behavior, with precision increasing as the threshold rose, albeit at the expense of decreased recall. Post-hyperparameter tuning and feature scaling, the model exhibited improved precision across recall values, highlighting its potential for accurate positive identifications, yet with room for enhancement in recall at higher thresholds.

Support Vector Machines (SVM) demonstrated a robust capability in discerning complex decision boundaries within EEG datasets, achieving high precision in identifying "like" signals. The precision-recall curve suggested a potential for adjustments to improve recall at elevated thresholds. Following optimization, SVM exhibited enhanced performance, particularly in precision-recall balance at higher thresholds, emphasizing its versatility in handling diverse datasets.

Random Forest, an ensemble learning method, showcased its adaptability to high-dimensional EEG data, achieving an impressive accuracy of 84%. This model excelled in discerning subtle distinctions in user responses, with high precision and recall values for both preference classes. The ensemble approach and bootstrap sampling contributed to its resilience against overfitting, solidifying Random Forest as a robust choice for nuanced EEG signal analysis.

Extreme Gradient Boosting (XGBoost) exhibited exceptional predictive performance, aligning closely with Random Forest with an accuracy of 83%. XGBoost's ensemble learning approach and regularization techniques contributed to its proficiency in handling intricate relationships within EEG data, achieving a harmonious balance between precision and recall.

Artificial Neural Networks (ANNs), chosen for their capacity to learn complex non-linear relationships, demonstrated a commendable accuracy of 82%. While slightly below the performance of simpler models, ANNs exhibited strong precision and recall metrics, suggesting potential advantages in capturing intricate non-linear patterns within EEG signal data.

In summary, each model presented distinct advantages and trade-offs. KNN showed promise with its simplicity, SVM excelled in discerning complex decision boundaries, Random Forest and XGBoost demonstrated robust ensemble learning capabilities, and ANNs exhibited proficiency in capturing complex non-linear relationships. The choice of the most suitable model depends on the specific goals and characteristics of the EEG dataset, with ongoing opportunities for refinement and optimization in pursuit of improved performance.

2) SINES Dataset: When we implemented our models on SINES dataset the accuracy shown is 46%. All models are mostly giving the same result.

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