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IMPACT OF NEUROMARKETING CUES ON CONSUMER DECISION-MAKING: AN EXPERIMENTAL STUDY USING EYE-TRACKING AND EEG

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ABSTRACT

There is a clear correlation between the effectiveness of marketing to generate engagement, brand recognition, and sales and the bottom line of a firm. Neuromarketing makes use of patterns of eye movement and brain activity to get significant insights into client behavior. These insights are then used to refine the process of marketing with the goal of developing more effective marketing strategies. In comparison to electroencephalogram (EEG), which has been widely used to examine consumer responses, eye tracking (ET) is currently undervalued when it comes to understanding decision-making processes. This is in contrast to EEG, which has been utilized extensively. The findings of this study address that requirement by proposing a multimodal experimental technique that includes EEG and ET data in order to investigate the ways in which neuromarketing signals influence the decision-making process of customers. The EEG data were preprocessed using ASR, Fast Orthogonal Regression for Classification and Estimation (FORCE), and band pass filtering in order to reduce the amount of noise that was present in the data. The class imbalance was addressed by the usage of SMOTE. Utilizing a CNN-LSTM framework, automatic features were created. In addition, statistical and wavelet methods were used in order to extract features from the electroencephalogram information. Following the completion of the interpolation, gaze plot analysis, and SMOTE processes on the ET data, the feature extraction process was carried out with the assistance of LeNet-5 and manually produced metrics such as fixations and saccades. Following the creation of a multimodal feature space via the feature-level fusion of EEG and ET, a meta-learner ensemble that included Random Forest, Gradient Boosting, and Extended Gradient Boosting was used for the purpose of classification. The model was able to achieve an accuracy of 84.01% in predicting consumer purchase selections and an accuracy of 83% in detecting positive customer preferences. This was accomplished by the integration of EEG and ET. It may be deduced from this that neuromarketing signals have a considerable influence on the method of decision-making.

Keywords: *Neuromarketing, Consumer Decision-Making, Electroencephalogram (EEG), Eye Tracking (ET), Multimodal Analysis, Consumer Behavior*

INTRODUCTION

When done well, marketing has the potential to boost a company's profitability, as well as the level of customer involvement and brand recognition [1]. Due to social desirability and memory issues, the data that is acquired via self-reporting in conventional marketing research techniques such as focus groups and questionnaires is very prone to bias and inaccuracy [2]. Neuromarketing offers a fresh perspective on consumer behavior analysis; it is an interdisciplinary discipline that combines marketing with neuroscience. This area of study examines the physiological and neurological responses of the brain to marketing stimuli [3]. It is possible that businesses may benefit from doing research on people's attention, brain waves, and emotional responses in order to develop advertisements that target consumers where it hurts: on a subconscious level.

Neuromarketing and Consumer Behavior

The objective of neuromarketing is to get an understanding of the mental and neurological processes that play a role in the choices that customers make. When compared to more traditional survey methods, neural responses are superior in terms of their ability to predict consumer preferences and behavior [4]. For example, studies have shown that some regions of the brain, including as the ventromedial prefrontal cortex and the prefrontal cortex, are strongly associated with value-based decision-making and emotional engagement, both of which have an effect on the intention to make a purchase [5]. The information may be used by marketers to fine-tune their efforts in order to achieve the highest possible level of engagement and conversions.

Role of EEG in Neuromarketing

A method that enables very precise temporal assessment of brain electrical activity is electroencephalography (EEG) [6].The study of both cognitive and emotional processes is made possible as a result of this. Research in the field of neuromarketing has made substantial use of electroencephalography (EEG) to assess the level of engagement, emotional arousal, memory recall, and attention that consumers have in connection to advertisements and product presentations. It is usually true that traditional techniques of self-reporting are not able to disclose the preferences of consumers who are not consciously aware of them; but, by monitoring these neurological signals, marketers may be able to get insights into these preferences.

Role of Eye Tracking in Consumer Analysis

It is possible to discover the visual attentional foci of consumers by analyzing their eye movements, gaze patterns, fixations, and saccades, all of which are recorded using Eye Tracking (ET) technology. The area in which ET truly excels is in the analysis of responses to product packaging, online interfaces, and advertisement design [7]. By assessing visual attention and refining the design and positioning of essential components, marketers have the ability to increase consumer engagement and have an influence on decision-making.

Integration of EEG and Eye Tracking

While recordings of electroencephalograms (EEG) may provide information on the functioning of the brain, eye tracking (ET) monitors attention in real time. Through the integration of EEG and ET, it is possible to construct a multimodal method that incorporates both visual and cognitive activity in order to get a deeper understanding of the decision-making process of consumers. Utilizing this combination, marketers have the potential to improve their ability to predict the behavior of customers by illuminating the relationship between cerebral processing and visual signals.

In the field of neuromarketing research, there have been a few studies that have used EEG and ET separately; however, very few studies have combined the two in order to investigate consumer decision-making in more detail. This is due to the fact that the majority of research only focus at particular metrics, such as brain activity or gaze patterns, which means that there is a dearth of understanding about the interaction between these physiological responses and their influence on judgments. By using a multimodal experimental design that combines EEG and ET, this study addresses the need that has been identified by investigating the influence that neuromarketing signals have on the choices that customers make.

OBJECTIVES

1. To use eye tracking and EEG to examine how neuromarketing signals affect consumer decision-making.

2. To use multimodal EEG and eye tracking data to create a prediction model for consumer purchasing decisions.

RESEARCH METHODOLOGY

Feature extraction, categorization, and preprocessing of EEG and Eye Tracking (ET) data are the three key components that make up the technique that has been recommended. This approach makes use of multimodal data in order to investigate the ways in which neuromarketing signals influence the decision-making processes of customers.

Preprocessing of EEG Signals

Initially, the EEG values were cleaned of any electrical interference, eye movements, and muscle activity that happened throughout the experiment. After a bandpass Butterworth filter was applied with a frequency range of 0.5-45 Hz, the data quality was maintained using fast orthogonal regression for classification and estimation (FORCE) and artifact subspace reconstruction (ASR). For the purpose of enhancing the reliability of the feature extraction process, the signals were divided into overlapping chunks of one second each. As a result, the data density and continuity were enhanced.

Preprocessing of Eye Tracking Data

A linear interpolation technique was used in the preprocessing of the ET data in order to address the issue of missing values brought about by blinks. When data was segmented using overlapping windows

(with a 50% overlap), the major objective was to guarantee that the temporal coherence was maintained. The creation of gaze plots, which were then grayscaled and saved in NumPy arrays, came before the feature extraction process could get underway [8].

Handling Class Imbalance

In order to rectify the dataset's imbalances between the "Buy" and "No Buy" classes, SMOTE—the Synthetic Minority Over-sampling Technique—was used [9]. As part of the training process for the model, SMOTE generates fictitious samples for the minority class in order to guarantee that the dataset is balanced.

Feature Extraction

EEG Features: The following characteristics were extracted: frequency-domain Power Spectral Density using Welch's technique [10] and statistical features mean, variance, skewness, and kurtosis. Features that use wavelet transforms were also included. For better categorization, a CNN-LSTM model also recorded automatic spatiotemporal characteristics [11].

ET Features: We computed statistical parameters such as saccade amplitude and fixation time. To extract spatial information, gaze plots were processed using LeNet-5 CNN [12].

The characteristics of both modalities were integrated at the feature level in order to present a comprehensive picture of the responses provided by customers.

Classification

Through the use of a stacked ensemble classifier, the samples were distinguished into the categories of "Buy" and "No Buy." In order to make this combined prediction, we used Random Forest as a meta-classifier [16]. The Gradient Boosting [14], XGBoost [15], and Random Forest [13] classifiers were the three fundamental ones that contributed to it. The model's performance was assessed using the F1-score, accuracy, precision, and recall. Optuna was used for hyperparameter tweaking [17].

Table 1. The NeuMa dataset

Characteristic	Details
The quantity of topics	42 (23 males, 19 females)
The quantity of goods	144
Page count Average choices	6 (24 products per page)
Data files for each topic	18 products per participant
EEG apparatus	2 (S01.xdf, S01.xls)

EEG frequency of sampling	Wearable Sensing DSI24
EEG sensors	300 Hz
ET sampling frequency for the ET device	21 dry sensors
Characteristic	Tobii Pro Fusion
The quantity of topics	120 Hz

Table 2. Previous work comparing EEG and ET data for customer choice prediction [19–24].

Author	Data	Year	Preprocessing	Feature Extraction	Classification	Results
Khushaba et al. (2013)	EEG, ET	2013	ICA	DWT, FFT, Mutual Information	Preference	—
Ohme et al. (2010)	EEG, ET	2010	Bandpass filter	FFT	Not specified	Improvement in Ads
McClure et al. (2004)	EEG, ET	2004	Bandpass filter	P300 ERP, N100, Pupil dilation	Statistics	ERP and ET results were inconsistent
Handy et al. (2010)	EEG, ET	2010	Downsampling, Notch filter	Attentional Asynchrony, Cognitive Congruency	Regression	R^2, 72% accuracy
Vecchiato et al. (2011)	EEG, ET	2011	Interpolation, Bandpass filter	PCA	Logistic regression	71.09% accuracy
Rossiter et al. (2001)	EEG, ET	2001	Not specified	Alpha-Band Oscillation, AOI	Not specified	Eye movements could predict packaging preference
Ariely et al. (2010)	EEG, ET	2010	ASR, Notch filter	TD, FD, TFD	SVM-RBF	96.97% accuracy

Table 4. CNN-LSTM model.

Layer	Output Shape	Parameters

Input layer	(None, 19, 300, 1)	0
Conv2D	(None, 17, 298, 32)	320
MaxPooling2D	(None, 8, 149, 32)	0
Conv2D	(None, 6, 147, 64)	18,496
MaxPooling2D	(None, 3, 73, 64)	0
Flatten layer	(None, 14,016)	0
Reshape layer	(None, 14,016, 1)	0
LSTM	(None, 64)	16,832
Dense	(None, 128)	8,320
Dense	(None, 64)	8,256

Table 5. The LeNet-5 model.

Layer	Output Shape	Parameters
Input layer	(None, 64, 64, 1)	0
Conv2D	(None, 60, 60, 6)	456
MaxPooling2D	(None, 30, 30, 6)	0
Conv2D	(None, 26, 26, 16)	2,416
MaxPooling2D	(None, 13, 13, 16)	0
Flatten layer	(None, 2,704)	0

RESULT AND DISCUSSION

Evaluation of the effectiveness of classification models is accomplished via the use of metrics that assess the machine learning algorithm's capacity to effectively classify the objects. When confronted with problems such as skewed classes or different costs associated with a mistake, it is essential to make use of the appropriate metrics in order to get an accurate and unbiased assessment and to monitor performance. Counting the percentage of data items that are properly assigned to a certain category is the most basic performance indicator, and precision is the measurement of this proportion. The positive predictive value, or accuracy, of a model may be expressed as the proportion of correct predictions relative to the total number of correct predictions produced by the model. It indicates the extent to

which the model accurately identifies positive instances. To evaluate a model's efficacy, one may look at its recall and sensitivity. One way to evaluate a model's performance is by looking at its recall and sensitivity, which both assess the model's ability to distinguish between positive and negative inputs. The results show how well the model matches the training examples with all the good instances.

The F1 score is the mean of the two metrics we've just covered; it also gives proportionate insights into accuracy and recall. Both false positives and false negatives have a substantial impact on the information's value. Both false positives and false negatives have a substantial impact on the information's value. Analyses of the approaches' relative merits are presented in Table 6. The F1 score, recall, accuracy, and precision rate are all part of these comparisons. With an accuracy of 0.84, the suggested method outperforms all of the competing approaches. It is possible to attribute the large improvement in accuracy to the stacking ensemble approach as well as the effective integration of machine learning and deep learning qualities. In terms of accuracy in detecting affirmative situations, the recommended technique beats rival alternatives, as shown by its precision of 0.83, which sets it apart from the competition. This is of the highest significance in trying to minimize the number of false positives that occur in situations when the cost of false positives is substantial.

Because it is able to identify the vast majority of actual positive occurrences (0.84), the approach that was recommended also performs well in terms of recall effectiveness. When there is an issue with false negatives, it is helpful to have a big recall component since it improves the possibility that the model will include more positive instances in the result set. However, it also raises the likelihood that it will include some negative cases. When it comes to fish identification, the technique that has been offered states that it is capable of achieving an F1 score of 0.83, which places equal importance on memory rates and accuracy. When the F1 score is high, it indicates that the suggested method is not only precise but also accurate, since it has been researched and tested on a wide variety of measurement standards and tables. This is so because the F1 score is a harmonic average of the two variables, recall and accuracy. Analyses of the approaches' relative merits are presented in Table 6. The F1 score, recall, accuracy, and precision rate are all part of these comparisons.

Table 6. Metrics of evaluation for the different approach

Method	Accuracy	Precision	Recall	F1 Score
1. EEG (ML features, SVM, unprocessed)	0.62	0.60	0.59	0.59
2. EEG (DL features, SVM + RF, preprocessed)	0.65	0.61	0.64	0.62
3. EEG (preprocessed, SVM + RF + DT, ML + DL features)	0.74	0.70	0.75	0.72

4. ET (ML features, RF, not preprocessed)	0.60	0.58	0.59	0.59
5. ET (DT, DL features, preprocessed)	0.62	0.55	0.56	0.55
6. ET (preprocessed, XGB + RF + DT, ML + DL characteristics)	0.65	0.64	0.61	0.62
7. EEG and ET (ML features, SVM, unprocessed)	0.72	0.71	0.67	0.68
8. EEG & ET (RF, DL features, preprocessed)	0.75	0.74	0.72	0.73
9. ET & EEG (preprocessed, SVM + RF + XGB, ML + DL features)	0.80	0.78	0.79	0.78
EEG and ET (preprocessed, ML + DL features, stacking ensemble) are suggested.	**0.84**	**0.83**	**0.84**	**0.83**

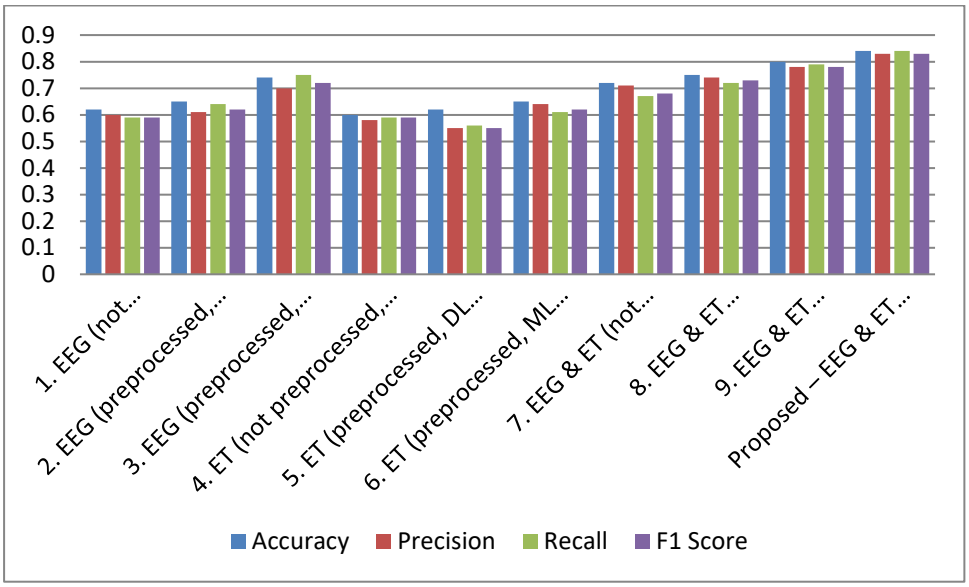


Figure 1. Comparing suggested technique results to existing methods

Figure 2 shows the area under the ROC curve and Figure 1 shows the assessment score for the strategy given during the chat. The ROC curve, or receiver operating characteristic curve, is a graphical way to show how well a model does at different classification hurdles. One side we have the True Positive Rate, often called Sensitivity, and the other side has the False Positive Rate, sometimes called Fall Out. The terms "sensitivity" and "fall out" describe these two rates, respectively. When the ROC curve's data points are concentrated in the upper left corner, it means the model did a good job of differentiating between the classes. The probability that the model assigns a higher ranking to a randomly selected negative instance compared to a positive instance can be calculated using the area under the curve (AUC), which is a representation of the overall performance of the receiver operating characteristic (ROC). A comparison of the two cases will do the trick.

The tester's ability to classify the data is proportional to the area under the curve (AUC). The larger AUC is evidence of this. An area under the receiver operating characteristic curve (AUCROC) of 0.89 was achieved, as shown in Figure 2, which displays the data. It is reasonable to claim that the targeted technique is effective in separating the two groups since this outcome is considered to be of a "good" quality. A comparison is shown in Figure 1 between the results produced from the suggested approach and the methods that are currently considered to be state-of-the-art. Table 6 provides a comprehensive breakdown of the evaluation standards for the different methodologies. The strategy that has been recommended is the one that is most effective in meeting all of the stated metrics. This technique makes use of the preprocessing that has been supplied for EEG and ET data and incorporates ML and DL features into a stacking ensemble.

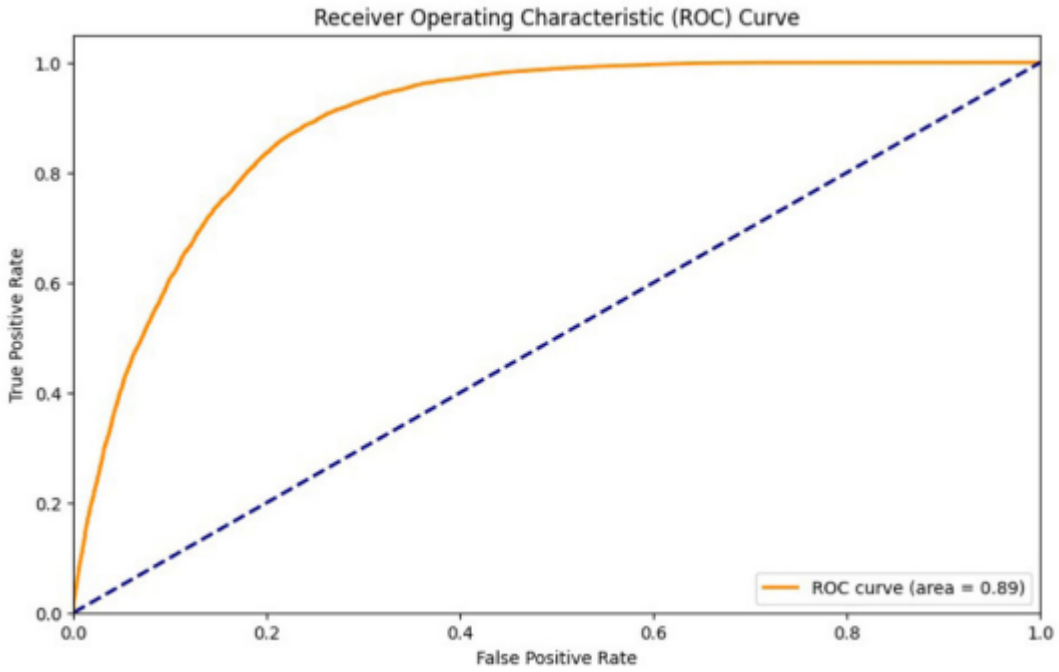


Figure 2. ROC curve.

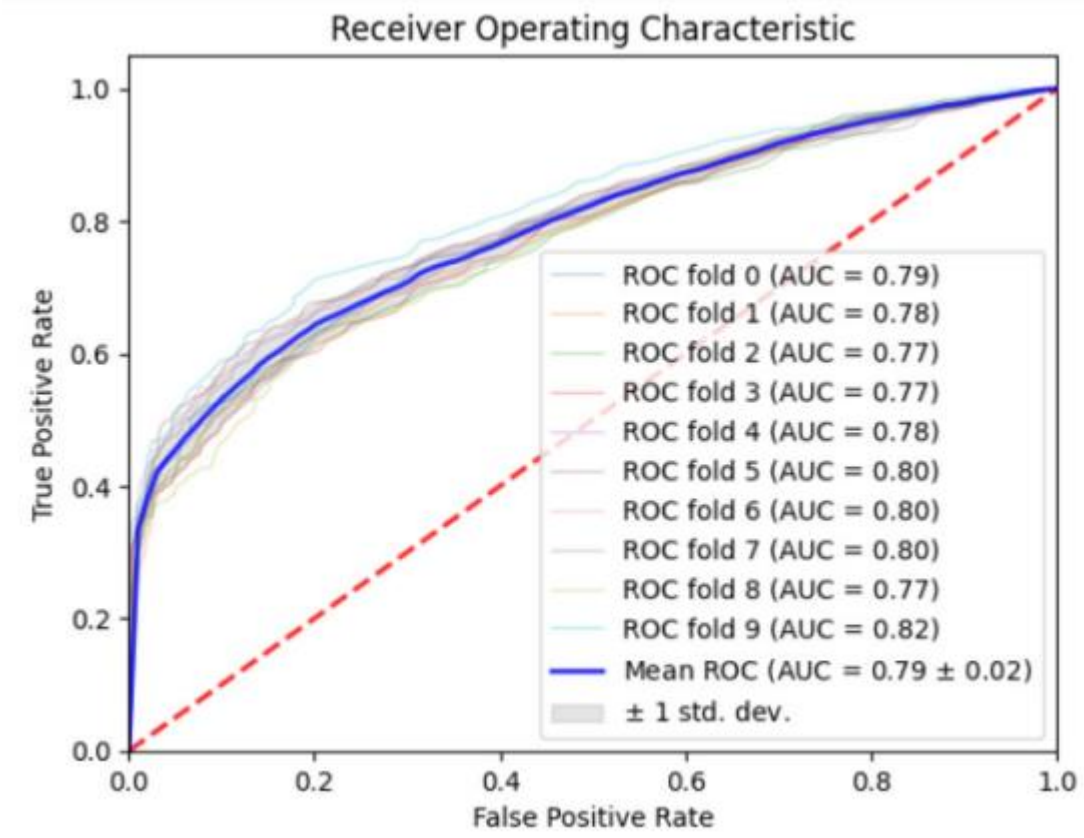


Figure 3. Proposed approach ROC curve (EEG).

Table 7. Alomari et al. (2013) Comparison

Aspect	Alomari et al. (2013)	Proposed Method (EEG only)
Dataset	BCI2000 PhysioNet (hand movement EEG)	NeuMa
Accuracy	0.898 (NN) / 0.971 (SVM)	0.74
Precision	Not mentioned	0.70
Recall	Not mentioned	0.75
F1-score	Not mentioned	0.72
AUC score	Not mentioned	0.79

A degree of accuracy of 0.62 was attained by Method 1, which used ML features and SVM on raw EEG data. This was the greatest level of accuracy that was achieved. While this is going on, the technique that was proposed is far more effective, with an accuracy of 0.84. In this universal improvement for accuracy, recall, and F1 score, the advantages of data preparation and the stacking ensemble method's endeavor to mix ML and DL features are more visible than they would be otherwise. Preprocessing was shown to increase performance in a number of different situations, as demonstrated by strategies that included preprocessing (for example, Method 1) and techniques that did not utilize preprocessing (for example, Method 2). Method 2's preprocessing of EEG data and use of DL features, for instance, results in higher rates of accuracy and recall compared to Method 1.

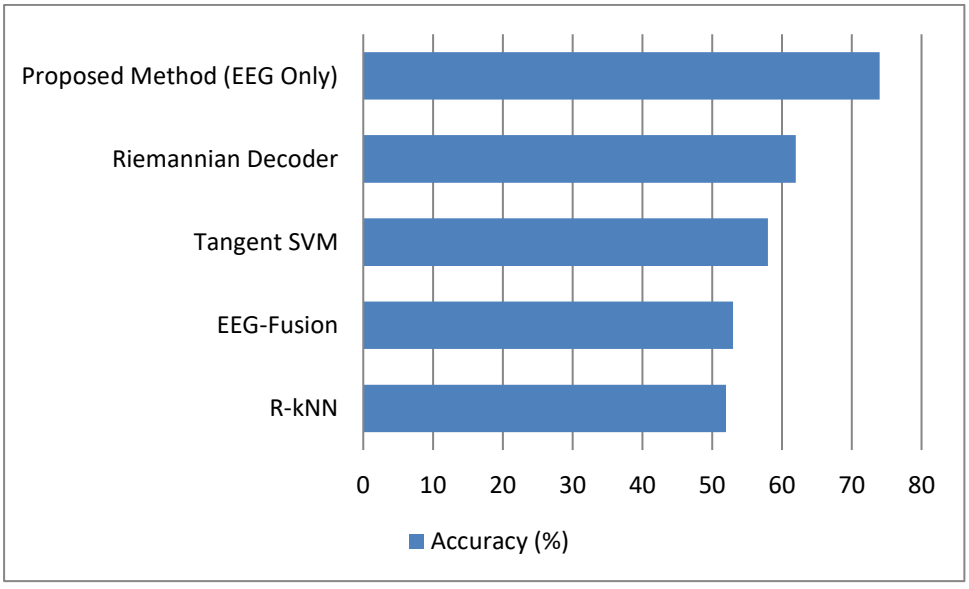


Figure 4. Compare accuracy with different approaches.

Users who integrate EEG and ET data at the same time outperform those that use either kind of data alone. As an example, consider Method 9's capability to integrate preprocessed EEG and ET data with conventional ML features and deep learning successes, leading to an accuracy of 0.80. Incorporating

EEG and ET data into the model demonstrates its ability to provide superior results. The suggested technique not only takes advantage of the features employed by this approach, but also employs stacking ensemble, which does double duty by enhancing classifier performance. As a consequence, all parameters are optimized to their maximum potential, which helps build a robust and efficient model. When EEG data was evaluated using ML and DL in conjunction with SVM, RF, and DT, the results were undeniably positive, indicating good classification findings. The method was successful in its aims as it received a 0.75% recall, a 0.70% accuracy, and an F1 score of 0.72%. Figure 3 shows that the constructed model had a consistent and discriminating ability for classifying consumer preferences based on EEG data, thanks to its relatively high area under the curve (AUC) with an average value of 0.79. All things considered, these metrics show that the suggested approach, which merges classic ML techniques with deep learning characteristics, works.

In contrast, the work published in the aforementioned publication introduced a novel deep learning decoder for Riemannian geometry and SPDNet structure [25] with the objective of evaluating the signals of the NeuMa EEG dataset. The average accuracy that the researchers found throughout their examination was 72 percent. We compare the most cutting-edge method already available, developed by Alomari et al. (2013), with our suggested method (EEG Only). Figure 4 displays the outcomes of our accuracy comparison. Incorporating regular classifiers into ML and DL, the study delves into the domain's Riemannian Geometry and SPDNet. This proves that these methods outperform more traditional EEG-based algorithms like Tangent Space SVM [26], EEGFusion [27] and R-kNN [28]. The results were statistically significant, especially when contrasted with the data provided by R-kNN (51.96%), EEG-Fusion (52.75%), and Tangent Space SVM (67.72%). But we failed to reach statistical significance.

It is important for everyone to know that the research contains many flaws. The first thing to keep in mind is that 42 people is probably not enough to draw any firm conclusions about the whole community. The results may not generalize to other product types, marketplaces, or cultural contexts as they are based on a specific dataset. While EEG and eye-tracking sensors are capable of collecting useful data, their sample rates and accuracy limitations may limit the overall data quality. Additionally, greater investigation into other methods or advanced deep learning architectures might enhance the performance of the models. And that's the case regardless of how well the feature extraction methods integrated the two sets of features (manually and automatically produced). Final thoughts: using EEG and ET data together makes the research more difficult than it otherwise would have been. It is plausible that synchronization issues greatly affected the model's overall accuracy.

CONCLUSION

According to the findings of this research, which analyzed data from eye-tracking and electroencephalography, neuromarketing signals have a significant influence on the decisions that consumers make. We were able to obtain highly accurate and exact consumer preference prediction by using a combination of machine learning and deep neural network methodologies. This was accomplished with the assistance of CNN-LSTM for extracting EEG signals and LeNet-5 for eye-tracking data. Important factors that contributed to the achievement of these results include the use of a robust stacking classifier, the extraction of features, and the accurate compilation of EEG and ET

data. In order to guarantee the accuracy of the findings, we used a number of methods, such as SMOTE-based class balancing, signal-to-noise ratio augmentation, and noise reduction. In spite of the fact that the proposed approach brings about consistent and good results, there is still space for development. It is possible that more advanced feature extraction methods, such as deep learning architectures that take into consideration the location of brain activity, may be used in order to improve the accuracy of predictions. Comparable to this, the investigation of individualized prediction strategies or the incorporation of subject-dependent models might potentially enhance categorization techniques. To ensure that the results can be generalized, it is essential to perform cross-validation on datasets that are both larger and more diverse. It would be beneficial for future research to compare this neuromarketing method to others, investigate ethical concerns such as data protection and user permission, and find ways to use it in contexts other than online shopping, such as in-store promotions, advertisements, and customer engagement initiatives. All of these things would be beneficial. In short, the theoretical results of the research and the practical implications for marketers show the prospect of merging eye-tracking and electroencephalogram (EEG) data in order to get a better knowledge of and capability to forecast the decision-making activities of customers.

REFERENCES

1. Kotler, P., & Keller, K. L. (2012). Marketing management (14th ed.). Pearson.

2. Fugate, D. L. (2007). Neuromarketing: A layman's look at neuroscience and its potential application to marketing practice. Journal of Consumer Marketing, 24(7), 385–394.

3. Plassmann, H., Venkatraman, V., Huettel, S., & Yoon, C. (2015). Consumer neuroscience: Applications, challenges, and possible solutions. Journal of Marketing Research, 52(4), 427–435.

4. Ariely, D., & Berns, G. S. (2010). Neuromarketing: The hope and hype of neuroimaging in business. Nature Reviews Neuroscience, 11(4), 284–292.

5. Plassmann, H., Ramsøy, T. Z., & Milosavljevic, M. (2012). Branding the brain: A critical review and outlook. Journal of Consumer Psychology, 22(1), 18–36. https://doi.org/10.1016/j.jcps.2011.11.010

6. Vecchiato, G., Astolfi, L., De Vico Fallani, F., Toppi, J., Aloise, F., Bez, F., & Babiloni, F. (2011). Spectral EEG frontal asymmetries correlate with the experienced pleasantness of TV commercial advertisements. Medical & Biological Engineering & Computing, 49(5), 579–583.

7. Wedel, M., & Pieters, R. (2008). A review of eye-tracking research in marketing. Review of Marketing Research, 4, 123–147

8. Khushaba, R. N., Wise, C., Kodagoda, S., Louviere, J., Kahn, B. E., Townsend, C., et al. (2013). Consumer neuroscience: assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking. Expert Syst. Appl. 40, 3803–3812. doi: 10.1016/j.eswa.2012.12.095

9. Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). Smote: synthetic minority over-sampling technique. J. Artif. Intell. Res. 16, 321–357. doi: 10.1613/jair.953

10. Welch, P. (1967). The use of Fast Fourier Transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. IEEE Trans. Audio Electroacoust. 15, 70–73. doi: 10.1109/TAU.196

11. Hochreiter, S., and Schmidhuber, J. (1997). Long short-term memory. Neural Comput. 9, 1735–1780. doi: 10.1162/neco.1997.9. 8.1735

12. LeCun, Y., Bottou, L., Bengio, Y., Haffner, P. (1998). Gradient-based learning applied to document recognition. Proc. IEEE 86, 2278–2324. doi: 10.1109/5.726791

13. Breiman, L. (2001). Random forests. Mach. Learn. 45, 5–32. doi: 10.1023/A:1010933404324

14. Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Ann. Stat. 29, 1189–1232. doi: 10.1214/aos/1013203451

15. Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20(3),* 273–297. https://doi.org/10.1007/BF00994018

16. Wolpert, D. H. (1992). Stacked generalization. Neural. Netw. 5, 241–259. doi: 10.1016/S0893-6080(05)80023-1

17. Bergstra, J., Bardenet, R., Bengio, Y., & Kégl, B. (2011). Algorithms for hyper-parameter optimization. Advances in Neural Information Processing Systems, 24, 2546–2554.

18. Kohavi, R. (1995). "A study of cross-validation and bootstrap for accuracy estimation and model selection," in Proceedings of the 14th international joint conference on Artificial intelligence, Volume 2 (Princeton, NJ: Citeseer), 1137–1143.

19. Ohme, R., Reykowska, D., Wiener, D., & Choromanska, A. (2010). Analysis of neurophysiological reactions to advertising stimuli by means of EEG and galvanic skin response measures. Journal of Neuroscience, Psychology, and Economics, 3(1), 21–31. https://doi.org/10.1037/a0018514

20. McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. Neuron, 44(2), 379–387

21. Handy, T. C., Smilek, D., Geiger, L., Liu, C., & Schooler, J. W. (2010). ERP evidence for rapid hedonic evaluation of logos. Journal of Cognitive Neuroscience, 22(1), 124–138. https://doi.org/10.1162/jocn.2008.21180

22. Rossiter, J. R., Silberstein, R. B., & Nield, G. E. (2001). *Brain-imaging detection of visual scene encoding in long-term memory for TV commercials*. Journal of Advertising Research, 41(2), 13–21

23. Vecchiato, G., Astolfi, L., Fallani, F. D. V., Cincotti, F., Mattia, D., Salinari, S., ... & Babiloni, F. (2011). On the use of EEG or MEG brain imaging tools in neuromarketing research. Computational Intelligence and Neuroscience, 2011, 643489. https://doi.org/10.1155/2011/643489

24. Ariely, D., & Berns, G. S. (2010). Neuromarketing: The hope and hype of neuroimaging in business. Nature Reviews Neuroscience, 11(4), 284–292. https://doi.org/10.1038/nrn2795

25. Alomari, M. H., Samaha, A., & AlKamha, K. (2013). Automated classification of left/right hand movement EEG signals using advanced feature extraction and machine learning. arXiv preprint arXiv:1312.2877

26. Barachant, A., Bonnet, S., Congedo, M., & Jutten, C. (2010). Common spatial pattern revisited by Riemannian geometry. IEEE Signal Processing Letters, 17(4), 433–436. https://doi.org/10.1109/LSP.2010.2044007

27. Vecchiato, G., Astolfi, L., De Vico Fallani, F., Cincotti, F., Mattia, D., Salinari, S., ... & Babiloni, F. (2010). Changes in brain activity during the observation of TV commercials by using EEG, GSR and HR measurements. Brain Topography, 23(2), 165–179. https://doi.org/10.1007/s10548-009-0127-0

28. Congedo, M., Lotte, F., & Lécuyer, A. (2006). Classification of movement intention by spatially filtered electromagnetic inverse solutions. Physics in Medicine & Biology, 51(8), 1971–1989. https://doi.org/10.1088/0031-9155/51/8/004