Deep Learning for Neuromarketing; Classification of User Preference using EEG Signals

Maryam Alimardani
Department of Cognitive Science and Artificial Intelligence, Tilburg University
m.alimardani@tilburguniversity.edu

Mory Kaba
Department of Cognitive Science and Artificial Intelligence, Tilburg University
m.leon.kaba@gmail.com

ABSTRACT

The present study investigates the applicability of deep learning methods in EEG neuromarketing prediction tasks, compared to traditional machine learning approaches. Neuroscientific methods have expanded research capabilities in marketing and created new insights into consumer behavior and decision making processes. Both machine learning and deep learning approaches can be employed to predict relevant consumer preference from brain activity. The former requires extensive signal processing and feature engineering for classification whereas the later relies on raw brain signals and thus avoids time-consuming preprocessing. In this paper, the performance of a machine learning model comprising an ensemble of algorithms 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 for 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. We discuss the limitations and future application opportunities.

CCS CONCEPTS

• **Applied computing** → Operations research; Marketing; • **Human-centered computing**;

KEYWORDS

Neuromarketing, EEG, User preference, Deep Learning, Machine Learning

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1 INTRODUCTION

The last decade has seen a rise in lean development practices, a term coined in the manufacturing industry, in which fast product development, waste reduction, and constant consumer feedback are integrated into the production cycle to ensure consumer satisfaction and market success of a product [1]. Companies and organizations have an increased need to understand and predict consumer preferences in order to be able to compete in an increasingly interconnected global economy. Traditional forms of gathering customer feedback include conducting surveys or interviews, mostly with focus groups that fit a particular target market. These explicit research schemes have been shown to introduce various biases that can distort the gathered information's quality and reliability [2, 3].

Neuromarketing research offers an extension to the traditional marketing research and aims at offering new ways of gaining insights into consumer behavior while improving the quality and reliability of this information [3]. A large amount of research from the neuromarketing literature uses data from EEG recordings, since compared to other research tools, it is often much cheaper and easier to collect, while still being able to distill relevant temporal and frequency patterns of brain signals related to marketing stimuli [4]. Some argue that neuromarketing augments our understanding of human perception and decision making by allowing researchers to access and assess information beyond the level of human consciousness [5].

Plassmann et al. laid out five key contributions of neuroscience to the field of marketing [6]. These include 1) identifying cognitive mechanisms, 2) measuring implicit responses, 3) distinguishing psychological processes, 4) understanding individual differences, and 5) making predictions about human behavior. Past neuromarketing research has mostly contributed to the first four principles by investigating neural mechanisms and psychological theories that underlie users' opinions and behavior in the market [6-9]. This reflects a scarcity of literature in the realm of neuromarketing prediction research.

The recent rise of artificial intelligence (AI) and machine learning (ML) has enabled researchers to effectively mine the patterns in EEG signals and make predictions about human preferences. For instance, Golnar-Nik et al. [10] showed that EEG spectral power could serve as a useful feature for predicting consumer choices. They conducted a study in which participants were shown different mobile phone advertisements while EEG signals were recorded. Using EEG band powers and a SVM classifier, they could achieve a peak accuracy of 87% in prediction of consumers' intention to buy the phones. In another study, Yadava et al. [11] collected EEG signals while subjects watched images of different products and then indicated whether they liked the presented product or not. Authors used wavelet decomposition coefficients as input for several machine learning algorithms and reported a peak accuracy of 70% achieved by a Hidden Markov model.

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Although machine learning models have shown favorable outcomes in prediction of EEG responses, they require tedious and time-consuming preprocessing and hand-crafted feature extraction steps. Deep learning (DL) models, on the other hand, can handle large amount of data and can directly learn complex features from raw signals. Craik et al. [13] conducted an extensive review of deep learning techniques used in a wide range of EEG classification tasks, including motor imagery, seizure detection, sleep stage scoring and Alzheimer's detection. The authors found that of all reviewed deep learning EEG classification papers, only 39% used raw signals as input into the neural networks and the rest still relied on extracted features or images created from the signals (e.g. spectrograms) to increase model performance.

Additionally, Craik et al. [13] found that convolutional neural networks (CNN) were the most popular architecture, having been implemented in 43% of all reviewed papers. CNNs are a subset of architectures used in deep learning and have been shown successful in various image classification problems, including radiology, MRI images and tomography images [14]. Moreover, they have been shown effective in signal processing applications, including EEG classification tasks, as they can handle raw data, facilitate end-to-end learning and require less parameters than other deep neural networks [15].

Even though deep learning approaches have been demonstrated to be successful in many EEG classification tasks [13, 15], the scientific literature on their employment in the field of neuromarketing remains scarce and reflects a need for more investigation [12]. Therefore, in this paper we examined the suitability of deep learning for neuromarketing applications by comparing two different frameworks; one relying on traditional EEG feature extraction and classic machine learning algorithms and the other exploiting the self-learning capabilities of a convolutional neural network. Moreover, to examine the validity of our proposed methodology, we applied both frameworks to two independently collected neuromarketing EEG datasets; one concerning product choices and the other movie ratings. We trained the ML and DL models on each EEG dataset separately and evaluated the obtained performances.

2 METHODS

2.1 Datasets

Two datasets were employed in this study to compare the performance of ML and DL approaches in neuromarketing tasks. A summary of both datasets is given in Table 1.

The first dataset, made available by Yadava et al. [11], included EEG recordings from 25 participants, aged between 18-25. EEG signals were recorded with a 14-channel Emotiv Epoc+ while participants watched different product images for 4 seconds. The stimuli consisted of 14 different product categories (e.g. shirts, shoes, ties, etc.), each containing three different images, resulting in 42 different products. After each image, participants had to indicate their liking or disliking for the presented product. This resulted in 1050 epochs of EEG signals, out of which 1045 were made public. The recording sampling rate was 128 Hz.

The second dataset was made available by Unravel[1], which is a neuromarketing company based in Utrecht, the Netherlands. The data was recorded as part of a research project conducted by the company. A total of 32 participants, aged between 21-71, were shown 6 movie trailers randomly selected out of 16, while their EEG was recorded. All movie trailers were from Hollywood production movies and included different genres, including action, comedy, thrillers, etc. The EEG signals were recorded using a 9-channel B-Alert X-Series. The sampling frequency rate was 256 Hz. After each presented trailer, participants had to answer three different questions: "Have you seen the movie?" (Yes/No), "How would you rate the movie?" (Likert Scale 1-10) and "Would you like to see the movie?" (Yes/No). In this work, only the question about movie rating was used. For comparison purposes, the ratings were transformed into a binary variable; scores ranging from 1 to 5 were interpreted as a dislike for the movie and scores ranging from 6 to 10 indicated participant's liking of the movie.

[1]https://www.unravelresearch.com/

2.2 Machine Learning Model

Figure 1a presents a schematic diagram of the ML classification algorithm.

2.2.1 EEG Preprocessing and Feature Extraction. For both datasets, first a bandpass filter between 0.5 Hz and 40 Hz was applied to the raw EEG signals to reduce the effect of noise. Next, all prominent frequency bands, i.e. delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (above 30 Hz) were extracted and the spectral energy associated with each band was calculated. Subsequently, all spectral energies from all channels were concatenated to form the signal's final feature vector.

2.2.2 Algorithm Architecture. In real-world machine learning applications, a common way to improve the prediction performance for a classification or regression task is to use an ensemble of models. Research shows that on average, an ensemble of predictors perform better than a single predictor on its own [16]. In this work, the ensemble combined three heterogenous predictors from different model classes. The ensemble comprised a support vector machine (SVM), random forest (RF) and logistic regression (LogReg), each using a unique approach for classification. These models were chosen based on their different decision functions to induce model diversity and help the ensemble deal with uncertainty for classifying new cases. A further argument for choosing a diverse set of predictors for the ensemble is that each predictor's distinct decision function inherently leads to disagreement between the predictors, which is an essential attribute for a well-performing ensemble [17]. In general, each predictor is trained individually on the training data and their predictions are averaged. As a result of this, the output of an ensemble consists of the integrated model's average output $f_i(x)$ and is defined as:

$$f(x) = argmax\left(\sum_{i=1}^{k} w_i f_i(x)\right) \quad (1)$$

where k refers to the number of classifiers used in the ensemble, and $w_i f_i(x)$ corresponds to the predicted probability for instance x of classifier i. A soft voting approach was used, where each predictor outputted the predicted probability of the instance's class label and the final output of the predicted class corresponded to the argmax of the sums of predicted probabilities for each class.

Table 1: Description of both EEG datasets employed in this study.

	Dataset 1 (Product Choice)	Dataset 2 (Movie Rating)
Participants	N = 25, Age 18-39	N = 32, Age 21-71
Task	Watched 14 product categories each having 3 images Rated the products (Like/Dislike)	Watched 6 movie trailers randomly selected Rated the movies on a 10-point Likert scale
EEG system	Emotiv Epoc+	B-Alert X-Series
Electrodes	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)	9 channels (POz, Fz, Cz, C3, C4, F3, F4, P3, P4)
Electrode positions		
Epoch duration	4-sec recording while viewing product images	Recorded while watching movie trailers

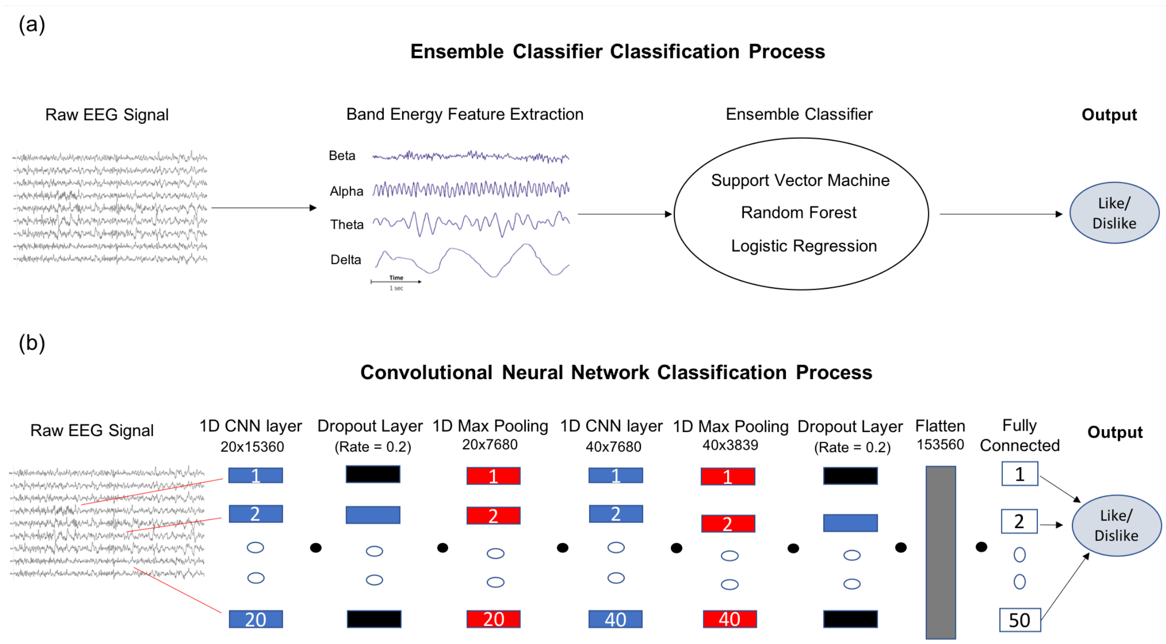

Figure 1: Schematic representations of the machine learning and deep learning algorithms employed in the classification of neuromarketing EEG datasets.

2.3 Deep Learning Model

Figure 1b presents a schematic diagram of the deep learning classification approach.

2.3.1 Neural Network Structure. In this study, a deep convolutional neural network (CNN) was employed. A CNN typically consists of three elementary units: convolution, pooling and fully connected layers. While the convolution and pooling units perform automatic feature extraction, the fully connected layers map these features onto the final output layer to produce the final prediction. Similar to a regular multi-layer perceptron, the output value is based on the connection weights and biases of the previous layers in the network structure. The weights and biases of the network with respect to the training instances are updated by using backpropagation. Hyperparameters that can be tweaked to influence model performance include the learning rate, momentum, and type of optimizer. The learning rate influences how fast the network learns, while the momentum aids with convergence by adjusting the rate of gradient descent based on the steepness of the loss function. Optimizers use the learning rate and momentum to update the weight parameters that minimize the loss function. In this research, the learning rate was initialized at 1.0×10^{-4}, with momentum of 0 and Stochastic Gradient Descent (SGD) was used as the optimizer. These hyperparameters were chosen based on trial and error.

2.3.2 Convolutional 1D Layer. This layer applied a convolution operation that automatically extracted features from the fixed-length EEG signals. In this process, a filter slid over the input signal and applied a matrix multiplication, which was then added to the feature map. This process was repeated numerous times with various filters that resulted in very different feature maps. At the end of this procedure, the feature maps were combined and merged into the layer's final output.

2.3.3 Dropout Layer. In this study, dropout layers were implemented in order to avoid overfitting the training data. Dropout refers to the random dropping out of units or neurons in a neural network during each training phase. Adding dropout layers to a neural network prevents co-dependency among neurons and often leads to better generalization performance.

2.3.4 Max-pooling 1D Layer. This layer reduced the dimensionality of the output neurons from the previous layer and thus reduced computational complexity and prevented overfitting. The max-pooling operation only chooses the maximum values from each patch of the final feature map from the previous convolutional layer. This resulted in a downsampled (i.e. pooled) feature map that emphasized the patch's most apparent feature.

2.3.5 Flatten Layer. In this layer, the feature matrix was transformed into a flat vector, which was then fed to the fully connected dense layers.

2.3.6 Fully Connected Dense Layer. This layer received the output from the convolutional layer and was fully connected to the output neurons of the flatten layer. In our network architecture, two different activation functions were used in the fully connected layers; 1) a rectified linear activation unit (ReLU), which is a non-linear activation function that outputs the following values based on input x:

$$f(x) = max(0, \ x) \tag{2}$$

And 2) a simple sigmoid activation function, which is applied to one neuron for the output layer and outputs the class label for an instance z, based on Equation 3.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

If the output of the sigmoid function is above 0.5, it will predict the positive class, otherwise the negative class.

2.3.7 Training and Evaluation. Both models were trained and tested separately on both datasets to draw reliable conclusions regarding the general performance and applicability of the two frameworks. While the ensemble classifier was trained on the extracted band energy features, the convolutional neural network was trained on the raw EEG signals (after bandpass filtering), skipping the manual feature extraction step. The convolutional neural network was trained using a batch size of 60, referring to the number of instances that were fed through the network at each training step. The number of epochs in this work was set to 100, which means that the algorithm iterated over the training set a hundred times while adjusting the network weights in this process. These numbers were chosen based on trial and error, leading to the algorithm's highest efficiency and performance.

The first dataset (product choice) was relatively balanced with a 45% Like to 55% Dislike ratio. The second dataset (movie choice) was skewed with a 68% Like to 32% Dislike ratio. Therefore we integrated class weights into the algorithms, so that they took the data distribution into account. This penalized misclassifications made by the minority class by setting a higher class weight and at the same time reducing weight of the majority class.

The two frameworks were evaluated on two evaluation metrics, accuracy and the F1 score. Accuracy is a standard measure of how accurate the algorithm predicts, however, in the case of a highly imbalanced dataset, this metric can be misleading since a majority class predictor would have a very high accuracy score. Therefore, F-score is also reported, which is defined as the harmonic mean of precision (the proportion of relevant instances among all predicted instances) and recall (the fraction of correctly classified instances among all relevant instances). F-score gives a more reliable measure of a model's performance since it considers how the data is distributed.

3 RESULTS

Classification results from both models are summarized in Table 2. As can be seen in this table, both frameworks performed poorly on the first dataset with an accuracy level that is not significantly above chance level and an even worse F1-score.

On the other hand, the performance results of the classification models on Dataset 2 were notably different. Here, machine learning approach achieved a reasonable accuracy of 63.54% and a F1 score of 76.83%. However, the CNN model outperformed the first approach with an accuracy of 74.57% and an F1-score of 84.13 %.

Given that the models yielded different outcomes on the two datasets, and that they both failed in reaching favorable results in Dataset 1, we further explored whether the issue was due to algorithm implementation or poor data quality. To examine this, we confirmed if the convolutional neural network was able to overfit the training data. Overfitting is observed when the training accuracy keeps increasing while the validation/test accuracy remains steady or decreases. This would suggest that the algorithm is able to memorize the data and its accompanying noise but it is not able to classify the data.

Figure 2 displays training accuracy against the validation accuracy of a simple train-test partition over one hundred epochs in Dataset 1. Here, the training accuracy rises steadily with the number of epochs and eventually reaches a point where the algorithm has memorized the dataset, thus overfitting it. In contrast, the validation accuracy shows no progression and stagnates around the chance level. This supports the notion that the algorithm was correctly implemented and that the quality of the dataset 1 should be blamed for the poor performance.

4 DISCUSSION

The goal of this study was to examine whether deep learning methods such as convolutional neural networks would prove a more suitable framework for neuromarketing prediction tasks compared to traditional machine learning approaches. Hereby, a convolutional neural network and an ensemble classifier composed of an SVM, RF and LogReg were trained and compared on two separately collected EEG datasets; one concerning product choices and the other movie ratings. It was shown that both approaches yielded sub-optimal performance in the first dataset (product choice prediction task).

Table 2: Classification performance of both machine learning and deep learning models on two EEG datasets.

	Dataset 1 (Product Choice)		Dataset 2 (Movie Rating)	
	Accuracy	F-score	Accuracy	F-score
ML Model (Ensemble)	50.71%	39.47%	63.54%	76.83%
DL Model (CNN)	51.48%	47.39%	74.57%	84.13%

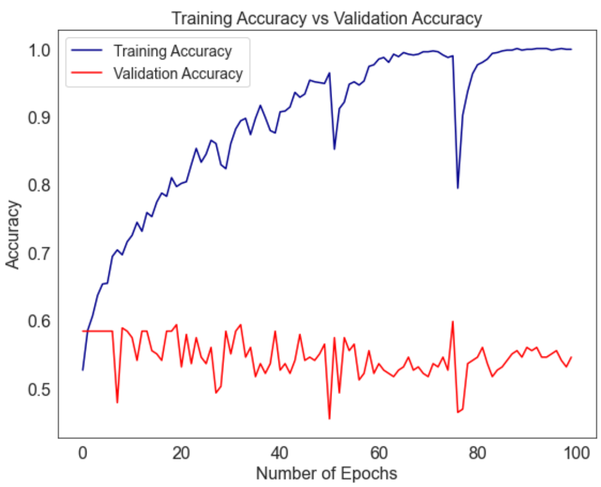

Figure 2: Training and validation accuracy in the CNN model on product choice dataset (Dataset 1)

However, the convolutional neural network significantly outperformed the ensemble classifier in the second dataset (movie rating prediction task).

The novelty of this study lies in the implementation of a deep convolutional neural network without EEG feature extraction and thus conducting an end-to-end learning with a neuromarketing dataset. This supports the assertion that deep learning methods are applicable in specific neuromarketing prediction tasks if certain conditions regarding the data are met. Plausible conditions that might increase the predictive power concerning deep learning applications in neuromarketing research will be further explored in this section.

Regarding Dataset 1, three probable reasons can be given as to why both ML and DL frameworks performed poorly in predicting product choices. First, the EEG signals were recorded using an Emotiv Epoc+ headset [11], which is a low-cost alternative to more expensive EEG recorders. These low-cost alternatives offer great opportunities for conducting inexpensive experiments. However, this cost reduction comes at the expense of an inability to capture accurate information in error-prone contexts [18]. Duvinage et al. [19] conducted a quantitative comparison between the Emotiv Epoc+ headset and a medical EEG device and demonstrated that even though the Emotiv headset was able to record some task-relevant EEG signals, it performed significantly worse than a medical EEG device in terms of the signal-to-noise ratio. The low spatial resolution of EEG recordings and the often inadequate measures of neural activity below the surface layers of the brain, compounded with a low signal-to-noise ratio of cost-efficient EEG devices, makes it arguably difficult to predict complex behavior like product preferences in the case of neuromarketing [20]. Second, the EEG signals were only recorded for four seconds while participants were looking at the products. This inevitably leads to small amounts of data and notably impedes the neural network from learning relevant patterns from the data. Neural networks offer much flexibility and can model a wide range of functions but rely on large amounts of usable training data to be able to do so [21]. Finally, upon closer inspection of the product stimuli [11], it became evident that the product pictures employed for data collection were neither visually appealing nor engaging as they usually are in a regular e-shopping experience. Since customers cannot wholesomely perceive the product through touch, online retailers typically try to approximate a real-world shopping experience by providing high-quality photos, short video snippets and a 3d interactive mode of the product, to provide the customer with a more realistic view of the product [22]. The detailed and vivid presentation of products is becoming increasingly important in shaping consumers' attitudes and behaviors towards the products [23]. Therefore, the quality of the EEG signals in Dataset 1 can be blamed for the poor learning of the models and further research is needed to examine if EEG can capture relevant predictive information in the context of a more realistic experimental setup.

In contrast to the product choice prediction task, both frameworks performed quite well on the movie rating prediction task, with the convolutional neural network performing significantly better than the ensemble classifier. Even though fewer EEG channels were recorded in Dataset 2, the EEG epochs were 30 seconds long, thus providing more samples for the algorithm to learn the task. Furthermore, stimuli consisted of movie trailers, which were processed visually and through auditory perception channels, thus potentially being more engaging and stimulating than simple static images of products. Past research has demonstrated that brain responses to movie trailers captured with EEG are able to predict individuals' preference and population-wide commercial success of the movies [24], thus supporting the notion that richer experimental stimuli can elicit more meaningful brain responses for neuromarketing prediction applications.

The obtained difference between the prediction outcomes on the two employed datasets shows the importance of the stimulus salience in neuromarketing research. Salience is defined as a product's perceptual influence on the consumer and its ability to stand out from other products and reach a higher level of awareness [25, 26]. Bordalo et al. [27] presented a predictive framework on how consumers' buying decisions are influenced by the salience of products. They posit that a consumer attaches disproportionately high weight to salient attributes, when it stands out among the good's attributes relative to that attribute's average level in the choice set. The more salient a product or stimulus is, the higher the likelihood that it will be regarded as having greater utility and thus elicit stronger brain responses that could be captured by EEG [28]. Therefore, future neuromarketing research should take salience into account as an important characteristic of experimental stimuli and employ a choice set that is salient enough to capture participants' attention.

Even though the proposed deep learning approach outperformed traditional machine learning framework in the case of movie rating prediction, it was not able to outperform state-of-the-art classification performance in EEG neuromarketing reports that have reached a preference prediction accuracy of 80-95% [29–31]. The main difference between our study and these papers is that they have used various feature extraction methods, including non-linear features from Detrended Fluctuation Analysis (DFA) or a combination of power spectral density (PSD), spectral energy (SE) and spectral centroid (SC) features. Additionally, the extracted features in these studies were used to train traditional machine learning algorithms, such as a K-Nearest Neighbors (KNN) or Multilayer Perceptron (MLP) algorithm, which demonstrate efficacy in neuromarketing research only when useful features and information are extracted from the signals. Our approach, on the contrary, employs an end-to-end learning without any dependency on data cleaning and feature engineering, which are usually the most time-consuming and error prone processes of a classification problem. This is particularly critical in the context of real-time EEG classification and further use of the model in real-world neuromarketing applications [32]. Preprocessing of EEG signals is often a complicated task that can introduce delay and unnecessary bias to the prediction process, which could then degrade the performance and efficiency of the application [32, 33]. Therefore, despite the lower performance that was obtained in this study compared to past reports, our proposed deep learning framework remains promising and useful for future developments, as it was able to achieve reasonable prediction accuracy despite the presence of noise in the EEG signals. Future studies should focus on integration of fast and automatic artifact rejection methods with deep learning models to reduce the cost and bias in the preprocessing step and thus ensure a more stable prediction for real-time applications.

Finally, recent research suggests the advantage of new media and computer-generated environments such as immersive virtual reality on the study of user behavior and brain responses [34, 36, 37]. Such technological advances offer great opportunities for a more engaging customer journey and multisensory interactive experience with the product [38], which can influence users on an affective, cognitive and behavioral level [35]. The field of neuromarketing should aim to keep up with these developments and integrate them as new research tools in order to be able to capture relevant and useful information with regards to consumer behavior [34]. This can lead to more informative data sources that AI methods such as neural networks could use to make more accurate and useful predictions in the realm of marketing research.

5 CONCLUSION

In this research, the applicability of a deep learning method (convolutional neural network) in neuromarketing was assessed by comparison with traditional machine learning methods (feature extraction and ensemble classification). These two frameworks were evaluated on a product choice and movie rating prediction task. Our results showed different performance of the models depending on the employed dataset. None of the frameworks performed well on predicting product choices, while the convolutional neural network significantly outperformed the ensemble classifier on the movie rating prediction task. It was shown that the deep learning method with minimal preprocessing could serve as a superior prediction framework for neuromarketing, if sufficient and high-quality data was made available. This framework could aid in developing product strategies or predicting product success by extending the existing methodologies and data sources. Additionally, we discussed the role of experimental stimuli in the context of neuromarketing and algorithmic performance. Future research in neuromarketing should consider the salience of the stimuli and investigate how new technologies such as virtual and augmented reality can be used to construct a more immersive and stimulating experimental environment to capture more promising brain data. Deep learning methods should then be assessed on their predictive performance by being trained on this new type of data.

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