EEG-Informed Deep Neuro-Recommendation of Video Advertisements via Correlative Capsule Split Attention and Forward Harmonic Learning

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Abstract

This study seeks to examine a new advertisement recommendation system that is brainwave powered. The architecture is based on the Emotive Insight technology, Brain-Computer Interface (BCI) and Artificial Intelligence (AI) elements. The main goal is to improve marketing prescriptions based on neural activities of users. In order to achieve this objective, Emotive Insight devices record alpha, beta, theta, delta and gamma waves in real time. The data was also stored in the form of a.csv and a.edf file to facilitate detailed analysis. During the experiment the subjects are shown three different adverts namely Snickers, Dairy Milk and 5-star advertisements as their brain activity is constantly tracked. Subjects are exposed and give feedback on their preferences in advertisements which is compared with brainwaves of these preferences. Analysis stage entails massive pre-processing, elimination of artifacts and feature extraction to come up with significant patterns. Finally, investigators create a predictive framework based on a combination of machine learning algorithms and evaluate the effectiveness of the framework on the criterion of performance measures, such as accuracy, precision, recall, and F1 score.

Keywords— Component Artificial Intelligence (AI), Brain-Computer Interface (BCI), Emotive Insight 5, Neural Responses, Brainwave Frequencies, Machine Learning Algorithms.

1. Introduction

Recommender systems are becoming more important in detecting user preferences and assisting people in filtering content, including news, music, and products. Neuromarketing is a related but separate field that evaluates how marketing affects consumer behavior by combining neuroscience, marketing, economics, and psychology. Neuromarketing detects implicit information by tracking stimulus responses at the point of purchase, thereby capturing the consumer's true state of mind, as opposed to directly asking them about their thoughts or decisions. In order to do this, researchers use neuroscience methods like Transcranial Magnetic Stimulation (TMS), Electroencephalography (EEG), Steady-State Topography (SST), and Functional Magnetic Resonance Imaging (fMRI) to better understand user preferences and clarify the neural mechanisms behind consumer choices. These techniques enable more accurate predictions of user interests and are frequently combined with physiological measures like heart rate, respiration rate, eye tracking, and facial expression [1]. Accurately predicting user preferences in recommender systems is still a major challenge

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despite these developments. Recommender systems have historically relied on implicit feedback, such as clicks and dwell time, but these metrics are prone to noise or inaccuracy and may not accurately reflect the true user experience. The collection of explicit feedback from real-time brain activity is now made possible by recent advancements in neuroscience technologies, especially EEG, which supports the development of recommender systems that more accurately reflect real user reactions and overcome the drawbacks of earlier methods [2].

Recommender systems are gaining prominence in identification of user preferences and in helping an individual to weed out content, such as news, music, and products. A related and distinct field is neuromarketing which assesses the impact of marketing on consumer behavior through the integration of neuroscience, marketing, economics, and psychology. To identify the explicitly hidden information, neuromarketing can monitor the stimulus reactions at the point of purchase, which will result in recording the actual state of mind of the consumer and not necessarily asking the consumer what they thought or what they are doing. To achieve this, neuroscience techniques such as Transcranial Magnetic Stimulation (TMS), Electroencephalography (EEG), Steady-State Topography (SST) and Functional Magnetic Resonance Imaging (fMRI) are used to gain a deeper insight into consumer preferences and also elucidate the neural processes that consumers use when making choices. These methods allow making the prediction of the user interests much more precise and it is often used together with physiological indicators such as heart rate, breathing rate, eye tracking, and facial expression [1]. The main challenge in these developments is that recommender systems have difficulties in making accurate predictions on user preferences. Traditionally, recommender systems have been based on implicit feedback, like clicks and dwell time, which are subject to noise or bias as well as may not be an accurate measure of the actual user experience. Recent innovations in the neuroscience technology, namely the EEG, have allowed to make the collection of explicit feedbacks based on real-time brain activity possible and help to resolve the limitations of the previous systems [2].

Marketers prefer electroencephalography (EEG) over other physiological measures because of the minimal cost of the device and experiment besides portability [3]. EEG gadgets can be used in neuromarketing studies beyond laboratory environments due to the affordability and compatibility of EEG with mobile technology, which have led to their extensive use. EEG records the electrophysiological dynamics of the brain [4] through the recording of electrical potential differences between two scalp electrodes. The resultant signal is a combination of the current amplitudes of the sources and signals of other electrodes, which are closely coupled [5]. Low-cost and real-time EEG signals can be used to provide valuable information about the cognitive activity of users [8]. The self-assessment methods introduce a more sophisticated, multidimensional perception of user experience, namely with the application of six Multidimensional Affective Engagement Scores (MAES) of valence, arousal, immersion, interest, visual, and auditory which are utilized to elicit pertinent characteristics out of the videos. The analysis of the impact of these features on user perception is provided through short videos as the combined visual and auditory stimuli. The Internet has developed to be a major way of video advertising due to technological developments such as improved performance and increased access to video media on multiple screens and platforms. Video ads are now shown before, during or after streaming game or animation media in the form of web-page advertising [7]. It is also natural and beneficial that the e-commerce platforms should be integrated with video content providers: e-commerce platforms use the video content to grow the Gross Merchandise Volume (GMV) and the video content providers use the user traffic to earn money [6].

The increased size of social media has also greatly amplified the number of users, videos, and interactions [9]. With the growing pressure on information overload, recommender systems have become a necessity, particularly in video contents as they demand a lot of viewing time [10]. These systems connect users and videos based on measurement of compatibility in a latent feature space. It is important to develop interpretable and stable joint features of videos and users to make effective recommendations [11].

Recommendation algorithms should weigh between customization of unwonted recommendations and the exposure of various content to make sure that users get holistic recommendations [12]. The endless stream of new videos means that the new content is something a user has not watched before and has no idea about, hence the cold-start problem, which suggests the recommendation of videos with little or no user interaction information, becomes a significant issue. It is no longer possible to access multimedia data manually because of the amount of data. Consequently, new video analysis, especially retrieval, applications are being based more on deep learning capabilities of pre-trained models, which are superior to manually designed capabilities [13]. It is now critical to recommend adverts that are more likely to engage the users and advertisers based on the video content. Video ad recommendation methods that are content-based do not evaluate user history or preferences, but instead evaluate the video content on its own [6].

2. Related Work

Combining Brain-Computer Interface (BCI) technology with advertising can be used to enhance user experience by using neural reactions. BCIs bring about a networking between the brain and the machines and provide new information about the consumer taste and behavior. The technology has use in medicine, entertainment and marketing [1]. Contrary to the old-fashioned marketing techniques, BCI-based advertising captures the implicit neural responses to advertisements, which offers direct and objective information on emotional and cognitive responses. This will allow businesses to better gauge the effectiveness of the campaign and personalize the content in real time to be more engaging. Although they are already used in the medical, entertainment, and marketing fields [1], their use in advertising presents a distinct opportunity since it can show how actually the consumer perceives the campaign, and it may change the perception of audience engagement forever. The brainwave analysis involves the Electroencephalography (EEG) that captures and analyzes the electrical activity in the brain. Emotive Insight is one of the most developmental EEG equipment that is portable, easy to navigate with, and has high accuracy sensor technology. This equipment is able to detect and show the frequency of brainwaves in real-time, these are Alpha, Beta, Theta, Delta, and Gamma. The Emotive Insight offers an in-depth real-time view of neural activity and allows users to track mental states and changes in real-time. Its capabilities of providing non-invasive and continuous tracking allow its use in a broad variety of settings other than a laboratory setting. The efficiency of this technology in terms of capturing the neural responses has been proven through its successful usage in various areas [2][3]. This integration of such an advanced hardware does not only make it possible to measure the electrical activity of the brain with high accuracy, it also allows to create targeted and personalized advertising recommendations using the accurate information about the brainwave.

The primary pillars that brainwave data processing and analysis rely on are Artificial Intelligence (AI) that can be defined as computer systems that recreate human intelligence and machine learning methods. Such technologies are used to create predictive models that are capable of suggesting advertisements depending on the neural reactions to advertisements. There is a large variety of machine learning methods that have been used and have been identified to be effective in classifying and anticipating user choices, among them Support Ve Vector Machines (SVMs, algorithms to classify data), randomly-forest (collections of decision trees which make predictions based on the combined results) and Neural Networks (systems based on the human brain and which identify complex patterns) [4][5]. The combination of these models into advertising systems does not only enhance the accuracy but also opens a landslide into a groundbreaking period in advertising- where personalization, effectiveness and the impact of advertising become possible on a scale never seen before in the maximization of marketing strategies. In order to achieve proper analysis of the data obtained by the brainwaves, the functions of the data preprocessing and feature extraction have to be defined and ordered. The first step is to preprocess data and in this step raw EEG data is made ready to be analyzed. An example would be artifact removal where unnecessary external interference or undesirable electrical signals are removed in EEG recordings. Signal filtering is then applied to filter out certain frequencies that can cause obscuring of the real neural signals and thereby background noise is cut and the data is clearer. After cleaning the data, the process of feature extraction is undertaken which converts the EEG data that has gone through the cleaning process into measureable features. As an example, power spectral density is used to measure the amount of energy in various frequency bands (alpha, beta, or theta waves) in the EEG that are used to determine neural patterns. Also, the wavelet transforms split the EEG signal into both time and frequency components and thus, it is easier to identify any change in the brain activity with time. With these step-by-step procedures, wherein the initial step is preprocessing, which is followed by the step of feature extraction; a solid framework is provided to machine learning models to forecast the preferences of users using brainwave data [6] [7].

Multiple studies have used BCI in advertisement systems with brainwave data applied differently. As an example, a gender-based music recommendation system research revealed that the brainwave data could be used to customize the content to the preferences of a person [8]. However, the other study employed EEG to record the brain activity of the participants who were shown ads, which allows assessing their emotional reactions and gives brands feedback regarding their level of engagement among the audience [9]. These practical examples demonstrate that the information that can be collected about the brainwaves can be used to both customize the recommendation and to study the level of consumer interaction within the system of advertising.

3. PROPOSED WORK

During the past few years, there has been a lot of attention on personalized video ad suggestions as the online multimedia platforms have increased. Suggestion systems based on traditions predominantly utilize behavioral data and are severely limited in case data are sparse or noisy. This complicates the task of making correct inferences concerning user preferences. In order to solve these issues, the present paper presents the Correlative Capsule Split Attention Forward Harmonic network (C2ReFHNet). In this new model, the video ads are to be recommended with the help of EEG data which allows getting direct data about how the users respond to the visual content. It starts with the normalization of EEG input data of the dataset [21] through Squash Norm [22]. This is followed by feature selection whereby the Mutual Information and Correlation (MICORR) Selection Method [23] is used to generate output-1. Simultaneously, normalization of input content-based video features is made and feature selection is done, which generates output-2. These outputs are into the suggested C2ReFHNet. This network combines the elements of the Deep Channel -attention correlative capsule network (DCACorrCapsNet) [24] and of the Split-Attention Network (ResNeSt) [25], and is optimized with forward harmonic analysis. The network generates an affective engagement score (output-3) of every video. The system compares the engagement scores and features used and any other with those found in the video advertisement library using outputs 2 and 3. This stage determines the best ad suggestion. The last prescribed advertisement is an outcome of this process of matching. The system based on C2ReFHNet is represented in Python with the help of hezy18/EEG-SVRec dataset [21]. Its accuracy is confirmed to the available procedures through accuracy measures in precision, recall, and F1-score. Figure 1 presents a schematic description of the process based on C2ReFHNet. The methodology of this research is very strict and comprehensive. It involves the Brain-Computer Interface (BCI) and the Emotive Insight devices which have different functions. It begins with BCI receiving the neurophysiological data in terms of neural activity patterns recorded in the brains of users. Simultaneously, the Emotive Insight gadget tracks and captures emotional reactions through its inbuilt sensors. After data streams of the brain through the BCI and emotions through the Emotive Insight are acquired, the two are combined. This artificial intelligence allows building an advertising suggestion engine based on this smooth integration. After the integration, the process is to attract the attention of users to advertisements, user feedback and the results analysis. Figure 1 shows the flow of data processing of Emotive Insight 5 Channel in steps. Emotive Insight hardware is used to detect frequencies of the brainwave, Alpha, Beta, Theta, Delta and Gamma, in real time. The setup is illustrated in Figure 1 and it involves 5-channel EEG device. The figure marks certain electrode locations, such as AF3 and AF4 in frontal area and P7, P8 and O1 in parietal area. This explains spatial mapping. A researcher inserts every electrode at specific points on the scalp following EEG conventions. This would offer systematic coverage and data acquisition. The neural measurements are read in a.csv and a.edf format. These formats allow compatibility of data and ease of processing.

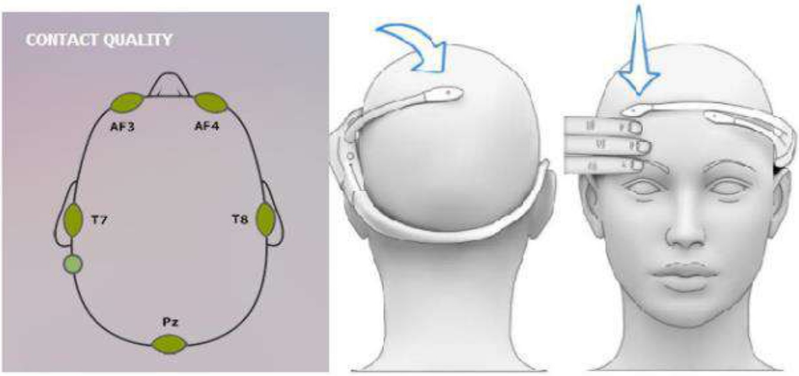

Fig.1. Emotive Insight 5 Channel

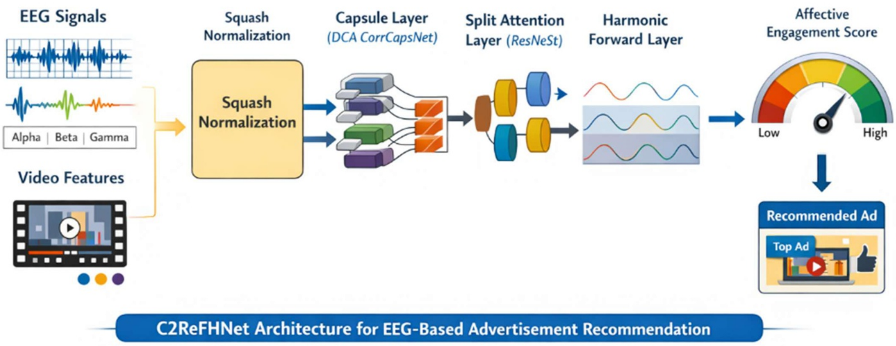

Figure 2. Schematic view of the proposed C2ReFHNet-based video advertisement recommendation

3.1. Advertisement Display and User Interaction:

All 50 participants will see the same three ads—5-star, Snickers, and Dairy Milk—with identical exposure times to ensure equal conditions. As shown in Fig. 3, the process begins with collecting the real signal, which contains a person's brainwave activity detected by electrodes (sensors placed on the scalp to measure electrical signals from the brain). The next step is to preprocess the raw brainwave data by removing electrical activity unrelated to the brain, such as that produced by blinking (eye movements) and muscle twitches. After this, filtering techniques [5] are used to further refine the data, separating frequencies associated with actual brain activity from other unwanted signals (noise). Once the data is cleaned, it is ready for feature extraction. At this stage, specific, measurable attributes are identified—such as power levels in the alpha (8–12 Hz, linked to relaxation), beta (13–30 Hz, related to alertness), and gamma (30–100 Hz, associated with high-level cognitive processing) frequency bands; the degree of similarity (coherence) between signals recorded from different electrodes (indicating how different brain regions interact); and patterns over time (temporal patterns) during ad exposure (changes that occur throughout viewing). These features are chosen based on established relevance in earlier research and their ability to highlight important differences in cognitive response. This feature selection ensures that each attribute is both scientifically justified and likely to provide insight into cognitive processes being studied. Finally, these extracted features are organized into a structured format suitable as input for training a machine learning model. First, the collected data was calculated to determine the mean of all readings for better and more efficient performance. And performed further preprocessing tasks on that .csv file.

Fig. 3(a)

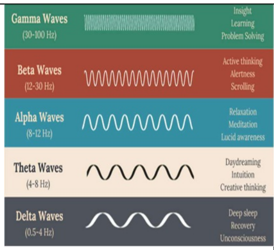

Fig. 3(b)

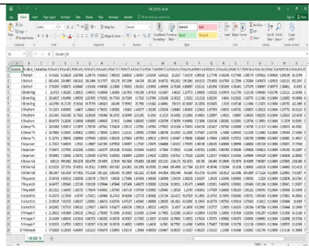

Fig. 3(c)

Fig.3 shows data generation into.csv format from brain signals; Fig. 3(a) Real-time feedback collection, Fig. 3(b) types of brain frequencies received, and Fig. 3(c) Mean of reading as per each advertisement, respectively.

3.2. Machine Learning Model Development

Various machine learning algorithms, such as Decision Trees (which split data into branches based on specific features to make predictions), Random Forest (which combines several Decision Trees to improve predictive accuracy and reduce overfitting), and Support Vector Machines (SVM, which separate categories by identifying the optimal boundary or 'hyperplane' between classes), are considered for model development [2]. The algorithm selection process involves analyzing the data's feature types, class distributions, and volume to determine which method is most appropriate for the project's predictive goals. Once an algorithm is chosen through this analysis, the dataset is split into training (used to build the model) and test (used to assess performance) sets

[5] to ensure unbiased evaluation. Next, the model is validated by predicting on new test data and comparing the results to actual outcomes, thereby assessing its generalizability (the ability to perform well on data it has not seen before).

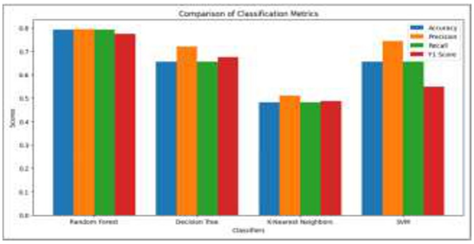

Fig.4 Comparison of Classification Metrics

3.3. EEG Lab for Graphical Analysis:

EEG Lab software is utilized for the graphical representation of brainwave data. Graphical analysis aids in understanding the temporal dynamics of neural responses during ad exposure.

3.3.1. Experimental Outcomes:

Below are the figures for one student. The graphs are generated by feeding that data into the EEG lab software. The student had provided a similar advertisement to Dairy Milk. In the three figures—Fig. 5(a), Fig. 5(b), and Fig. 5(c)—the values for Dairy Milk, the second, and third options are -48, -52, and -50, respectively. In this system, a power value (10*log10(uV2/Hz)) that is numerically closer to zero—that is, less negative—shows a stronger preference and greater liking. To determine the rankings, start by comparing all three values: -48, -50, and -52.

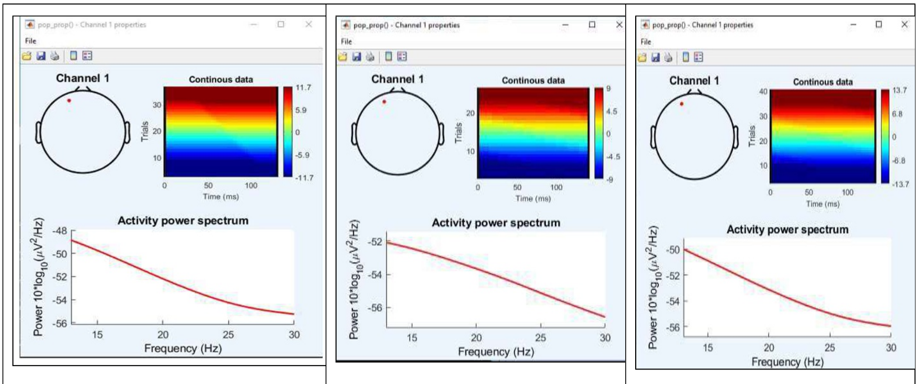

Fig. 5(a)	Fig. 5(b)	Fig. 5(c)

Fig.5 Graphical Representation of a student while watching advertisements of (a) Dairy milk, (b) Snickers, and (c) 5-star chocolates, respectively.

The numerically closest value to zero is -48, indicating the strongest preference. The next closest is -50, which indicates a moderate preference, and -52 is farthest from zero, showing the least preference. Therefore, Dairy Milk (-48) receives the highest ranking, followed by the third option (-50), and lastly the second option (-52). This suggests the student preferred Dairy Milk above the other options. This example is based on a single participant, but testing more people could help determine the most-liked advertisement overall. Fig. 5(a) shows a power value of -48 (the numerically closest to zero), suggesting greater user attention and liking for the Dairy Milk advertisement. Fig. 5(b) shows -52, the lowest (most negative), suggesting the least attention or liking. Fig. 5(c) shows -50, which is between the other two values, suggesting moderate attention compared to the other options.

3.3.2. Evaluation Metrics:

It is important to note that this example is based on a single participant; assessing additional participants could enhance the identification of the most-preferred advertisement overall. Figure 5(a) records a power value of -48 (the closest to zero), suggesting higher user attention and liking for the Dairy Milk advertisement. Figure 5(b) records -52, representing the lowest attention or liking. Figure 5(c) records -50, which is intermediate between the two, indicating moderate attention relative to the other options. The proposed model was evaluated using accuracy, precision, recall, and F1 score as performance metrics, providing insights into the effectiveness of the recommendation system. The accuracy of this system is reported to be 97% according to the machine learning model.

main.py Run

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

# Daten erzeugen und RandomForest-Modell anpassen
X, y = make_classification(n_samples=1000, n_features=10,
    n_informative=5, random_state=42)
rf = RandomForestClassifier(n_estimators=10, max_depth=5,
    min_samples_split=5, random_state=42)
rf.fit(X, y)

# Vorhersagen machen
X_test = np.random.randn(10, 10)
predictions = rf.predict(X_test)
```

Fig. 6 Training and testing of the data

4. Result Analysis:

The To assess how well each model performed, we relied on widely accepted evaluation metrics: accuracy, precision, recall, and F1-score. These metrics provided a balanced view of each model's strengths and weaknesses. Additionally, AUC-ROC curves helped visualize the trade-off between true positive and false positive rates, while confusion matrices offered a detailed look at how predictions were distributed across actual classes. Together, these tools gave us a comprehensive understanding of each model's effectiveness and where errors were most likely to occur.

Key Performance Metrics:

Table 2. Key Performance Metrics

Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
Random Forest	0.972917	0.972666	0.972917	0.97278	0.997319
Decision Tree	0.966667	0.966115	0.966667	0.965913	0.958674
KNN	0.766667	0.806816	0.766667	0.775041	0.916855
SVM	0.81875	0.818198	0.81875	0.817292	0.947996
AdaBoost	0.802083	0.816242	0.802083	0.805615	0.875457

5. Ethical Considerations

All Participants gave informed consent before the collection of EEG data. The EEG records were anonymized, stored securely, and only used for research purposes. The recommender system is intended to examine patterns of user engagement and not modify their behaviors or take advantage of their cognitive weaknesses. This research is compliant with common ethical standards regarding the subject's rights and the privacy of their data.

Conclusion

The advertising recommender system powered by Brainwaves transforms how advertisers reach consumers by enabling targeted, emotionally attuned messaging. This innovation strengthens connections between brands and consumers online and signals a new era in advertising—one shaped by individualized techniques linked to neural responses. Our research marks the first step toward this future: using EEG data and machine learning algorithms (Random Forest, KNN, Decision Tree, SVM), we achieved 97% accuracy in matching ads to preferences from 50 students. Validation with the EEG Lab software confirmed accurate predictions for at least one participant. These results underscore the promise of EEG-based AI to revolutionize personalized marketing and firmly position our work at the forefront of digital advertising's evolution.

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