Preference Detection Harnessing Low-Cost Portable Electroencephalography and Facial Behavior Markers

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Abstract—**Delivering personalized recommendations can improve the effectiveness of user satisfaction. To do this, understanding user preference is critical to developing such recommender systems, however, existing studies mainly utilize high-cost devices and high computation in detecting preference. In this work, we propose a multimodal framework in which facial expressions and neural signals are captured by low-cost portable electroencephalography (EEG) devices in identifying a user's preference. We found that EEG combined with facial behavior features improves the preference detection, specifically whether a user likes or dislikes the given face images in controlled experiments. Further, we introduce a richer set of objective markers leveraging EEG-based neural features and facial behavior markers that contribute to preference detection. We demonstrate the multimodal-based preference detection using the commercialized portable EEG which can provide an efficient way to approach a user's preference detection in designing personalized recommendation systems in real-world settings.**

Index Terms—**Preference detection, Multimodality, EEG-based Neural Signals, Facial Behavior Markers, Facial Expression, Machine Learning**

I. Introduction

Preference detection provides insight into a person's inherent opinions, which may not be apparent to an external observer. It has been and can be applied to various contexts, including advertising, marketing, product development, and recommendation systems [1]. Knowing and understanding an individual's preference can help improve the quality of recommendation to the user by suggesting the most preferred product.

The specific type of data used to train preference models depends on the study, but electroencephalogram (EEG) data or facial behavioral signals are commonly used. Previous studies have attempted to detect customer preference to see whether they liked or disliked the given products to understand a user's product interest and choice directly from brain signals using electroencephalogram (EEG). The use of EEG specifically is a common approach for the creation of preference detection models. However, there is a general lack of information surrounding the previously developed models. Existing research that describes preference detection models that are trained with EEG data rarely report both a measure of accuracy and a measure of error. Although some studies report a considerably high accuracy measurement, most of those found do not report an error measurement [1]. And those who do report either both measurements or an error measurement [2] have the potential for moderate improvements. Furthermore, the majority of these works have achieved their performances by using EEG devices with 14 or more channels in an experimental setting.

Preference is an inclination towards one choice over an alternative. Studies that explore an individual's preference usually choose items from a specific category, including products, advertisements or commercials, music, videos, etc. This study specifically uses artificially generated faces as stimuli to elicit preference. This section explores the methods used in existing preference detection studies as well as other traditional methods used in other detection-based studies.

II. A Multimodal Approach

In total, 35 participants from our university were recruited and completed the experiment.

Study Setting EEG signals were collected using the Emotive Insight which consists of 5 sensors - 2 reference signals; CMS (Common Mode Sense) active electrode and DRL (Driven Right Leg) passive electrode; both of which are placed on the mastoid bone which is behind the left ear. The device has a sampling rate of 128Hz for each channel, which include the AF3, AF4, T7, T8, and Pz channels. The AF3 and AF4 channels are located in the forehead area, detecting signal from frontal lobe of the brain which is associated with planning, decision making, and problem solving. The T7 and T8 channels are located in the temporal lobe, which is associated with the processing of memories. The Pz channel is located in the parietal lobe, which is associated with the recognition and perception of stimuli [3].

The layout of the electrodes, highlighted on a 10-20 system with 32 channels, as well as an example channel amplitude graph can be seen in Figure 1 along with a visualization of the EEG signal collection setup. This device was chosen in large part due to its ease of implementation and adaptability. Devices traditionally used to detect EEG signals in preference detection studies most always have 14 or more electrodes. Although those devices provide more data, we found it difficult to achieve a good signal across all participants without taking an excess amount of setup time when implementing a device with 14+ channels. The Insight device both took a substantially less amount of time to implement and achieve a signal and had a substantially lower price compared to alternatives. We believe that the use of this device expands our study's adaptability and applications to settings outside of a formal lab.

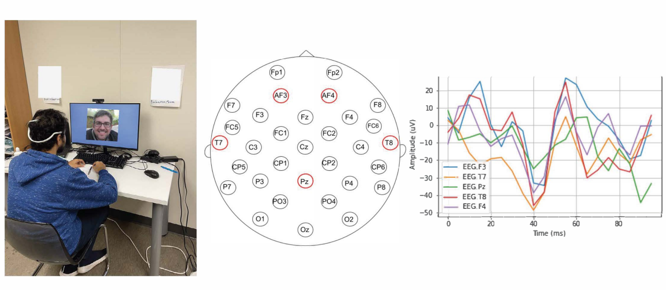

Fig. 1. Experiment setup and Example of EEG Device Recording

Facial Features: After the FacePsy framework ceased its facial feature extraction process, the extracted data was stored in a SQLite file. The SQLite file for each participant's data was then converted into a CSV file, and all CSV files were combined. As FacePsy does not generate markers that indicate the onset of a stimulus like Emotiv, we used the timestamps from the EEG recordings to append the preference reported by participants at the moment the stimulus was offered. We then ran this CSV through a filter that removed any extra data that did not occur when stimuli were being presented. **EEG Features**: From the raw EEG and the power spectral density (PSD), we calculated statistical summaries (mean, median, max, min, sum) for the data corresponding to each participant. This generated data was used to train multiple models for comparison. Once a dataset for training the models was prepared, we split it into 3 separate files for comparison. One containing features relating only to EEG signals, the other to FacePsy, and one with both.

III. Results and Analysis

1) Correlation and T-Test Analysis: To understand objective features patterns and relationships with the self-reported preference, we conducted a correlation analysis between the statistical summaries of each feature (EEG and facial expression) and the participants' self-reported preference. 104 features out of a total of 185 had a statistically significant correlation ($p<0.05$) with preference. A visualization of the specific correlations for 20 of these 104 features can be seen in Figure 2. We then split the combined dataset into two separate datasets based on the preference ground truth - one only contained data corresponding with 'liked' images and one contained data corresponding with 'disliked' images. To validate our feature selection, we conducted a t-test between the like and dislike subsets for each feature.

As seen in Figure 2, the majority of EEG channel summaries as well as a positive facial expression, happiness, are positively correlated with preference. However, the majority of the facial features, especially the facial action units are negatively associated with preference. Using an alpha level of .05, we can see that each t-test conducted with these significantly correlated features has a statistically significant result. Although Table I only shows 20 features, we a significant difference between like and dislike for each of the significantly correlated features.

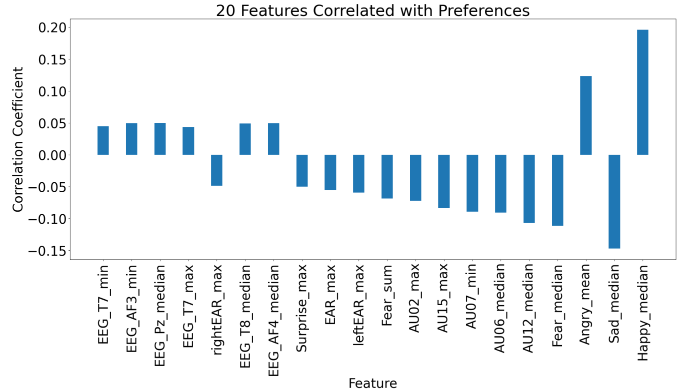

Fig. 2. 20 of the 104 Features Significantly Correlated with Preference

TABLE I
T-Test Results for 20 Features (*** refers to a p-value is smaller than 0.001)

Features	Like		Dislike		t	p
	Mean	SD	Mean	SD		
Happy Med	0.076	0.089	0.044	0.066	9.6	***
Sad Median	0.258	0.133	0.300	0.138	-7.8	***
Angry Mean	0.207	0.100	0.182	0.098	6.5	***
Fear Med	0.157	0.073	0.174	0.069	-5.8	***
AU12 Med	0.584	0.410	0.672	0.384	-5.5	***
AU06 Med	0.446	0.373	0.516	0.375	-4.7	***
AU07 Min	0.705	0.361	0.768	0.326	-4.5	***
AU02 Max	0.043	0.087	0.059	0.116	-4.1	***
AU15 Max	0.054	0.111	0.075	0.128	-4.6	***
Fear Sum	10.28	8.052	11.441	8.109	-3.6	***
LEAR Max	0.259	0.051	0.265	0.052	-3.1	0.002
EAR Max	0.255	0.049	0.261	0.051	-2.9	0.003
Surprise Max	0.031	0.047	0.037	0.066	-2.8	0.004
EEGAF4 Med	3474.8	1589.3	3300.2	1715.9	2.6	0.008
EEGT8 Med	3427.5	1565.3	3258.3	1692.2	2.6	0.008
REAR Max	0.255	0.049	0.261	0.051	-2.5	0.010
EEGT7 Max	3669.6	1676.5	3507.7	1819.5	2.3	0.019
EEGPz Med	3430.1	1565.4	3258.6	1691.7	2.6	0.007
EEGAF3 Min	3435.4	1583.5	3262.4	1715.6	2.6	0.007
EEGT7 Min	3559.874	1646.8	3397.3	1790.6	2.4	0.016

A. Feature Importance

There are numerous feature selection methods, which can be generally categorized into three groups: filter methods, wrapper methods, and embedded method [4]. Popular methods include ℓ_1-based feature selection [5], Minimum redundancy maximum relevance (mRMR) [6], sequential search algorithm based on regression or information entropy criteria [4]. In this paper, we use *mean decrease in impurity* to rank the feature importance implemented in the Random Forest classifier in scikit-learn Python package [7]. We computed feature importance of facial behavior markers streams for detecting flow state and mental states. Here we measure the importance of each feature for each of our target classes;

B. Machine Learning Models

: Seven classical machine learning algorithms were used and evaluated in our study, including decision tree (DT), random forest (RF), k-nearest neighbors (KNN), gradient boosting tree (GBT), logistic regression (LR), support vector machine

(SVM), and Naive Bayes (NB). The performance table is as follows:

TABLE II
ACCURACY TABLE FOR **MULTIMODAL MODEL**

	DT	**RF**	GB	KNN	LR	NB	SVM
AUC	0.548	**0.616**	0.581	0.576	0.559	0.557	0.578
Accuracy	0.578	**0.677**	0.652	0.631	0.659	0.498	0.628
Precision	0.406	**0.550**	0.503	0.466	0.528	0.387	0.463
Recall	0.452	**0.414**	0.345	0.397	0.228	0.752	0.410
F1	0.427	**0.472**	0.409	0.428	0.318	0.511	0.435
RMSE	0.367	**0.338**	0.349	0.369	0.341	0.407	0.348

IV. DISCUSSION

Our most accurate preference detection model trained with EEG was achieved using a random forest classifier, which gave an accuracy measurement of 65.2%, and AUC of 56.7%, a precision of 50.3%, a recall of 28.6%, an F1 score of 36.5 %, and an RMSE of 34.5%. Although these results are not as impressive as those achieved by models that used EEG devices with 14+ channels to record their data, they are similar to those achieved by Hakim et al.'s model. Hakim et al. used an 8 channel EEG device to collect their data and achieved an accuracy of 66.27%, a marginal increase from our value of 65.2%. Notably, our model achieves an almost identical RMSE measure as the one in the Davis et al. study, who reported an RMSE of 35% using an EEG device that included 32 channels. The similarities in this error measure highlight the potential for the use of this 5 channel device.

Similar to the phenomenon seen in multimodal emotion detection models [8], our multimodal preference detection method produced moderately better results than both of its unimodal alternatives. Using a random forest classifier, our model achieved an accuracy of 67.7%, with an AUC of 61.6%, a precision of 55.0%, a recall of 41.4%, an F1 score of 47.2%, and an RMSE of 33.8%. These measurements are all improvements on the best performing unimodal preference detection models, with the EEG only model achieving an accuracy of 56.7% using a random forest classifier and the facial feature only model achieving an accuracy of 59.1% with a gradient boosting classifier.

Although the performance of our multimodal model has room for improvement, it is on par with some existing research, specifically the model created in Gauba et al. [9]. Gauba et al.'s multimodal preference detection model also used a random forrest classifier on their combination of EEG and comment data to achieve an R^2 of 68& and an RMSE of 71.4%. Our model achieves and RMSE of 33.8%, a significant improvement.

Limitation: During the data collection process, we observed that the majority of male participants preferred a majority if not only female faces, while the female participants tended to prefer both male and female faces. Thus, our data had a disproportionate amount of 'liked' and 'disliked' faces, which impacted the balance of the dataset. Conducting a similar study with a different category of stimuli may lead to better results. Furthermore, our final dataset only included data from 25 participants. Expanding the study to include more participants may increase the accuracy of our model.

V. CONCLUSION

We found that EEG-brain signals combined with facial behavior markers achieved the best results, with an accuracy of 67.7% (AUC = 61.6%, precision = 55.0%, recall = 41.4%, F1 = 47.2%, RMSE = 33.8%) for detecting a user's preference, in comparison to uni-modal, EEG only and facial behavior features, only models. These results were achieved using a more accessible 5-channel EEG device. Although the accuracy measurements can be improved, the RMSE achieved rivals similar studies that use more expensive devices with more channels. Both the device used and the multimodal model developed have the potential for applications in designing recommender systems.

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