TIPTEKNO'24 MEDICAL TECHNOLOGIES CONGRESS
10-12 October 2024
Yasmin Bodrum Resort, Muğla, Türkiye

Decoding Olfactory EEG Signals Using Multi-Domain Features and Machine Learning

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***Abstract*—Accurate detection of human emotion is an important topic for affective computing. Especially with the rise of artificial intelligence in the marketing industry, the tools available are subjective and often heavily dependent on sample sizes and demographics. This study explores the neural responses to olfactory stimuli by analyzing EEG data collected from 57 participants exposed to a perfume scent in correlation with self-reported survey results. The electroencephalogram (EEG) signals were processed to extract time-domain, spectral-domain, and nonlinear features, which were subsequently classified using various machine learning algorithms. The classification outcomes were mapped onto a two-dimensional pleasure-arousal plane, with the Medium Gaussian support vector machine (SVM) achieving the highest performance, including 99.8 % validation accuracy and 100 % test accuracy. These results highlight the significant potential of EEG-based approaches in decoding the neural underpinnings of sensory experiences, with implications for applications in neuromarketing and therapeutic contexts.**

***Keywords*—olfactory EEG, EEG, machine learning, emotion recognition, arousal-valence plane, neuromarketing**

I. Introduction

Emotion which is the process by which persons try to manage their environment to keep up with their well-being [1] is integral to human interactions and exerts a profound influence on various aspects, including consumer behavior. In the subject of affective computing, effective emotion detection is a key difficulty since it requires computer systems to process, identify, and interpret the emotional states presented by humans precisely. This field integrates concepts from computer science, biology, and psychology, making it essentially multidisciplinary. Engineering-based research on emotions became popular over the last decade as a result of the significance of emotions in artificial intelligence and human-computer interface (HCI). Advances in emotion recognition technology contribute to progress in various fields such as forensics, neuroscience, and marketing [2].

Several physiological indicators can be employed to anticipate and comprehend emotional states. The brain serves as a principal organ in both emotional processes and decision-making. The orbitofrontal cortex has a significant impact on emotional reactions and is essential for estimating rewards. Particularly in the context of neuromarketing research, methods such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and functional near-infrared spectroscopy (fNIRS) have been used to investigate emotional brain activity. EEG has become a popular technique due to its non-invasive nature, ease of use, cost-effectiveness, and high temporal precision [3].

The field of consumer neuroscience has increasingly focused on olfactory stimuli recently, as scents can significantly influence emotions and affect purchasing decisions [4]. Recent scientific and technological advancements in brain science, computer science, and AI have enabled researchers to explore the connection between olfaction and mood using EEG. However, the complicated link between olfactory inputs and emotional responses is still only partially understood, with many intricacies to be discovered.

The human brain goes through a variety of cognitive and emotional processes in reaction to olfactory inputs, such as the aroma of perfume, which can elicit emotions ranging from pleasure to aversion. Understanding these brain reactions is crucial for applications in emotion identification, advertising, and medicine. Studies have demonstrated that the perception of odor pleasantness is reflected in EEG patterns [5]. For instance, Lanata et al. [6] achieved 75 % accuracy in classifying pleasant and unpleasant olfactory emotions using EEG. Saha et al. [7] improved classification accuracy by applying principal component analysis and a recurrent neural network model. Becerra et al. [8] achieved 99.9 % accuracy using support vector machines (SVM) with a linear kernel for odor classification. While these findings show the feasibility of EEG-based odor classification, developing a universal model remains challenging.

Kroupi et al. [9] demonstrated that EEG-based odor categorization could assess odor pleasantness using participant-specific models, but a universal model is difficult to achieve. In a follow-up study [10], they developed a three-class classification method using EEG signals from participants exposed to pleasant, unpleasant, and neutral odors. Pehlivan et al. [4] also investigated detecting olfactory stimuli with EEG signals. Their study, involving 33 volunteers exposed to unscented and scented products, found that brain responses to scents could

*This study was partially supported by Izmir University of Economics, Scientific Research Projects Coordination Unit. Project number: 2022-07.

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be distinguished, with the Random Forest classifier performing best and showing a significant increase in frontal brain activity in response to the scents.

Brain responses to a wide range of inputs, such as auditory, visual, and olfactory signals, have been widely studied using EEG. Nevertheless, data analysis and interpretation are complicated by the non-stationary and nonlinear character of EEG signals. The complete intricacy of EEG data is frequently not fully captured by conventional linear algorithms, especially when the data is being processed in response to faint sensory cues like smells.

In this study, a multimodal approach to classify emotions via machine learning algorithms is proposed. The goal of this study is to investigate the classification of electroencephalogram (EEG) signals combined with self-reported survey results which include questions that form an arousal-valence plane. From 57 volunteers who were exposed to a perfume aroma, with a special emphasis on the cerebral processing of various olfactory experiences. A combination of time and frequency domains, as well as nonlinear features extracted from EEG data are used, followed by machine learning classification.

II. Methodology

The methodology of the study can be broken down into four main steps which are data acquisition, preprocessing, feature extraction, and classification.

A. Experimental Setup and the Dataset

This study involved 57 participants, each exposed to two conditions: one with a scent stimulus and one without. In both cases, they were sitting in They were asked to rate their emotional states with a survey after each case. The survey was designed to asses pleasure and arousal with 12 questions in total and the measures were evaluated using a 5-point scale. EEG signals were recorded using Bitbrain Versatile-32. 23 of the 32 channels available were selected which are relevant to this study. Data was collected in a controlled environment where participants were seated comfortably in a quiet environment to minimize motion artifacts and noise. The study was carried out under the approval of X.

B. Data Preprocessing

Preprocessing the EEG signals is an important step in ensuring the quality and reliability of the data. This process included applying a band-pass filter with (0.5-45) Hz pass-band to remove noise, baseline correction to standardize the data, and independent component analysis (ICA) to detect and remove artifacts such as eye blinks [3]. Data was divided into 1 second segments and 5 segments were used in total for each participant.

C. Feature Extraction

In this study, time-domain, spectral, and nonlinear features were obtained to provide unique insights into the brain's response to olfactory stimuli [11].

Time-domain features are commonly used in EEG studies to analyze the amplitude characteristics of the brain's electrical activity. The time-domain features considered in this study include Variance, Mean Value, Skewness, Kurtosis, Hjorth Parameters (activity, complexity, mobility), Mean Absolute Deviation (MAD), Root Mean Square (RMS), and Peak-to-Peak Values (PTP) [12], [13].

As spectral features, Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-14 Hz), Beta (14-30 Hz), and Gamma (>30 Hz) powers were calculated using Power Spectral Density (PSD) which was obtained with Welch method [13].

To capture nonlinear and chaotic behavior, Katz Fractal Dimension (KFD), Higuchi's Fractal Dimension (HFD), Approximate Entropy (ApEn), and Spectral Entropy (SE) were extracted as nonlinear features [13], [14]. These features are critical for capturing the more subtle aspects of EEG signals, which are not easily discernible through time-domain or spectral analysis alone.

D. Machine Learning-Based Classification

In this phase of the study, the extracted features were used as input for various ML algorithms. The goal was to classify the EEG signals based on the participants' responses to the olfactory stimuli. For this purpose, survey scores were analyzed to obtain pleasure and arousal scores for both scented and unscented cases. The difference was calculated between pleasure scores and the average of the difference was obtained. Label "1" was given for the case where the difference was higher than the average and "0" was given for the otherwise. The same procedure was performed for the arousal case. The features of the participants who were labeled as "1" were used. Volunteers who had "0" as a label were eliminated since there was no difference in their pleasure or arousal states for scented and unscented cases. For the pleasure case, 29 volunteers, and for the arousal 31 volunteers were labelled as "1".

Several algorithms were evaluated, including Decision Trees, SVM, and K-nearest neighbors (KNN) with different kernels, and ensemble algorithms. The maximum number of splits was 100 for Fine Tree and Gini's diversity index was used as split criterion. Two different SVM algorithms were used with linear and Gaussian kernels. Fine KNN algorithm used 5 neighbors with Euclidean distance. Lastly, Subspace KNN Ensemble worked with 30 learners with 10 as the subspace dimension.

ML part was performed using MATLAB Classification Learner Toolbox with each classifier and its variants. 5-fold cross-validation was performed and 20% of the data was selected for the test phase. In total, 19 features were used to train and test the models. Later, the ANOVA test was applied to select the most relevant features from the feature set. Mean, kurtosis, MAD, RMS, and skewness features were selected for the pleasure case. In the arousal case mean, kurtosis, KFD, PTP, and Hjorth activity were used.

The performance of each classifier was assessed using standard metrics such as accuracy, sensitivity, and specificity. The results indicated that all of the classifiers successfully distinguished between responses to scented and unscented conditions.

III. Results and Discussion

This study's primary objective was to classify neural responses to olfactory stimuli using EEG features combined with survey data via ML classifiers. EEG data from 57 participants, who were exposed to both scented and unscented conditions, were analyzed. The classification focused on mapping these neural responses onto a two-dimensional Arousal-Valence plane.

Table I presents the classification results of various ML classifiers used to predict emotional states (Pleasure and Arousal) based on the extracted EEG features. The table provides key performance metrics for each classifier, including accuracy, sensitivity, and specificity values for validation and testing. The results are presented separately for Pleasure and Arousal, allowing for a clear comparison of how each classifier performs across these two emotional dimensions. Since the results were similar for all of the classifiers of the Classification Learner Toolbox, only 5 of them were represented in the Table.

In Table I, it can be seen that accuracy values ranged from 96.6% to 99.7% for validation and 96.7% to 99.6% for test in pleasure case. Similarly, accuracy for the validation ranged from 99% to 99.8%, while 100% test accuracy was reached for the arousal. The best classifier was SVM with a medium Gaussian kernel for both cases. Looking at the sensitivity for validation and test, it can be seen that a maximum of 99.9% and 100% was achieved for the pleasure case. Similarly, 99.7% and 100% validation and test sensitivity were obtained for the arousal case. Validation specificity was 99.4% and test specificity was 99.3% for the pleasure case. Finally, while perfect specificity was achieved for the test in the arousal case, validation specificity was significantly close to the perfect score of 99.9%.

In a closer look, at the pleasure case, it can be seen that validation and test sensitivities of Fine Tree were relatively high. However, its test specificity was slightly lower at 95.8%. This indicated that it was slightly less effective in distinguishing between negative and non-negative states. Fine SVM demonstrated good performance with a validation accuracy of 98.8% and a test accuracy of 99.0%. Medium Gaussian SVM outperformed others with a validation accuracy of 99.7% and a test accuracy of 99.6%. 100% sensitivity was achieved in the test phase and specificity was also very high at 99.3%, making it the most balanced and reliable model for pleasure classification.

In the arousal case, Fine KNN performed slightly less effectively compared to the SVM classifiers but still achieved a validation accuracy of 99.5% and a test accuracy of 99.6%. Subspace KNN Ensemble achieved a validation accuracy of 99.7% and a test accuracy of 99.9%. The classifier also maintained perfect sensitivity. Medium Gaussian SVM again demonstrated the highest performance, with a validation accuracy of 99.8% and a perfect test accuracy of 100%. It achieved 100% sensitivity and specificity during testing.

After feature selection, as seen in Fig. 1 and 2, for both cases accuracy values were lower than the scores obtained from the total feature set. However, this decrease was insignificant and can be ignored considering the computational cost of training 19 features versus 5 features. The mean and kurtosis features were significantly important for both pleasure and arousal. Theta power, delta power, gamma power, alpha power, HFD, and SE were considered least significant for the pleasure case while SE, MAD, skewness, alpha power, and Hjorth mobility were considered least significant for the arousal case. Using only the sub-band powers resulted in an average validation accuracy of 68.2% for the pleasure case and 73.5% for the arousal case. This indicated that sub-band powers were improper for this classification case. The most suitable features were found to be the time domain features, especially mean and kurtosis. However, it should be noted that although spectral features were unsuccessful, the relationship between them can be important such as alpha/beta ratio.

IV. Conclusion

In conclusion, this study was performed to understand how olfactory stimuli affect emotional states by utilizing EEG data analysis techniques. A strong framework for emotion

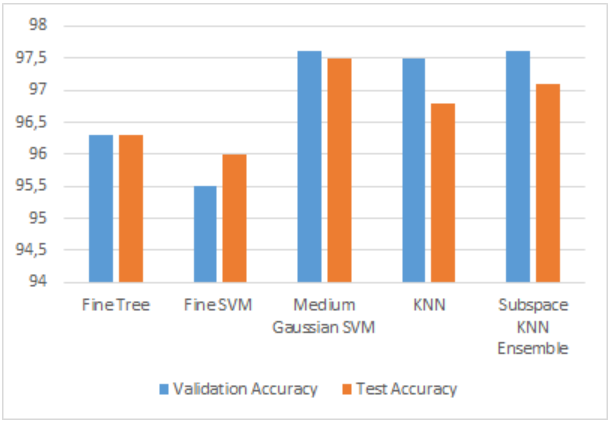


Fig. 1: Validation and test accuracy metrics for pleasure given as percentage

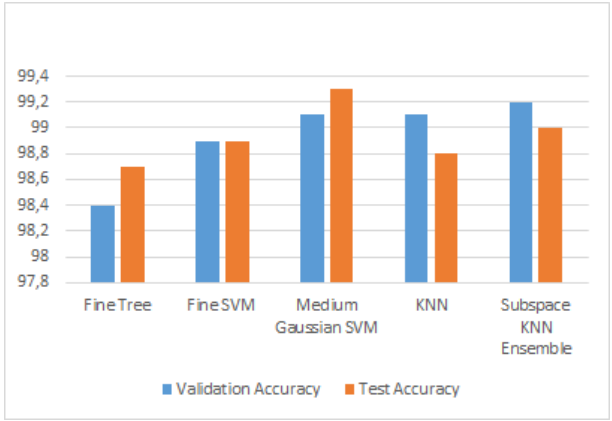


Fig. 2: Validation and test accuracy metrics for arousal given as percentage

TABLE I: Classification results for pleasure and arousal using the total feature set. "Val." indicates performance metrics related to validation. Best results are indicated in bold.

Pleasure						
Classifier	**Val. Accuracy(%)**	**Val. Sensitivity(%)**	**Val. Specificity(%)**	**Test Accuracy(%)**	**Test Sensitivity(%)**	**Test Specificity(%)**
Fine Tree	96.6	96.7	96.6	96.7	97.6	95.8
Fine SVM	98.8	99.3	98.2	99	99.7	98.2
Medium Gaussian SVM	**99.7**	**99.9**	**99.4**	**99.6**	**100**	**99.3**
Fine KNN	98.5	99.1	97.9	98.9	99.4	98.4
Subspace KNN Ensemble	99	99.4	98.5	99.3	99.9	98.7
Arousal						
Classifier	**Val. Accuracy(%)**	**Val. Sensitivity(%)**	**Val. Specificity(%)**	**Test Accuracy(%)**	**Test Sensitivity(%)**	**Test Specificity(%)**
Fine Tree	99	99	99	99	99.6	98.5
Fine SVM	99.7	99.5	99.9	99.5	99.3	99.7
Medium Gaussian SVM	**99.8**	**99.7**	**99.9**	**100**	**100**	**100**
Fine KNN	99.5	99.3	99.7	99.6	99.9	99.4
Subspace KNN Ensemble	99.7	99.7	99.7	99.9	100	99.7

recognition was created by combining feature extraction with ML-based classification. Results show that EEG has the ability to reveal the neural foundations of sensory experiences and establish a relationship between olfactory stimuli and emotions.

Although there are not many papers that correlate directly to this study that can be fairly compared, it is evident that the method proposed in this paper outperforms them. Study [16] focuses on food identification and pleasure analysis via odors and EEG analysis where they numerous features with selection algorithms and machine learning methods and reached relatively high classification metrics for a multi-class classification problem. Another interesting study [15] combines questionnaire data with EEG data to find optimal urban design patterns. As stated in the previous sections, there still is a research gap for odor perception and its physiological responses, which this study was focused on.

This study's findings can open up new areas for utilizing olfactory stimuli in various domains, including neuromarketing and therapy. Future research could explore different types of olfactory stimuli and their effects on a broader range of emotional states using 4 quadrants of the pleasure-arousal plane. Furthermore, mapping features onto a topographic map of the scalp and observing the local information with EEG Feature Maps (EEG-FMs). Finally, utilizing deep learning architectures such as those featured in our previous study [17] but not considered in this study due to time constraints may provide deeper insights into the emotion cognition systems.

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