



Classification of Emotions Under Multiple Olfactory Stimuli Using EEG Signals and Machine Learning

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Abstract—Accurately predicting emotional states is crucial in various fields, including cognitive sciences, artificial intelligence, human-computer interaction, and neuromarketing. In particular, the development of emotion-focused technologies requires the analysis of emotional responses with objective biological data. In this study, the emotional responses of individuals to different odor stimuli were examined using electroencephalogram (EEG) signals and classified using machine learning methods. A total of 46 participants were exposed to an odorless condition and four different odor stimuli (cinnamon, citrus, green tea, and lavender). After each exposure, participants filled out self-report questionnaires based on the valence-arousal model. Emotional states were predicted using time-domain features obtained from EEG signals, and various machine learning algorithms were applied for classification. The results show that EEG-based approaches can classify emotional responses with high accuracy, with lavender being the odor that created the most potent effect, achieving an accuracy rate of 80.14%. This study demonstrates that emotion analysis using EEG signals combined with subjective assessment has significant potential in areas such as neuromarketing and therapeutic applications.

Index Terms—Emotion Estimation, Olfactory stimulus, Electroencephalogram (EEG), Machine learning, Valence-Arousal Model

I. INTRODUCTION

Emotions are essential components of human cognition and physiology, playing a crucial role in decision-making, perception, social interaction, and intelligence [1]. Accurate recognition and analysis of emotions have become increasingly important in various domains, including artificial intelligence, neuroscience, human-computer interaction (HCI), education, mental health, entertainment, and neuromarketing [2]. Emotion recognition involves determining an individual's affective state by analyzing their physiological and neurological responses. Commonly used biosignals include electrocardiography (ECG), galvanic skin response (GSR), respiration, and electroencephalography (EEG) [3]. Among these, EEG has attracted significant attention due to its high temporal resolution and its ability to reflect cortical activity associated with affective processing directly. EEG enables the extraction of features related to emotional states in both time and frequency

domains, making it particularly suitable for real-time and fine-grained emotion analysis [4].

Machine learning-based techniques have been relatively successful in identifying emotions using EEG. Using data taken from EEG signals, algorithms including Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and k-nearest Neighbors (k-NN) accurately characterize emotional states [5]. Dai et al. showed that integrating multichannel feature extraction and machine learning methods effectively improves accuracy rates when predicting emotion from EEG signals [6]. Advances in artificial intelligence and neuroscience have enabled the study of the relationship between olfactory stimuli and emotional responses using EEG. Studies such as [7] and [8] analyzed the non-linear nature of EEG signals and demonstrated the effectiveness of the Multivariate Empirical Mode Decomposition (MEMD) method in identifying emotional states.

These studies reveal significant findings in classifying emotional responses to olfactory stimuli using EEG signals. In particular, multi-modal machine learning approaches have the potential to improve the classification of EEG signals. Recent studies have further validated the effectiveness of integrating multiple EEG domains for emotion recognition, especially in wearable and real-time contexts [9]. By focusing on the cerebral processing of olfactory experiences, the studies provide new insights into how the human brain processes different olfactory experiences. However, these studies lack consideration of emotion in all dimensions, namely, arousal and valence, in tandem with feedback from the participants. Consideration of feedback received from participants, alongside the EEG signals, allows for gaining further and more robust insight into the emotions of individuals.

This study proposes a method to classify emotional responses to four different odor stimuli using machine learning techniques and features derived from EEG signals. Unlike many prior works, which often rely on conventional stimuli (e.g., visual or auditory) or limited sensor/channel sets, this approach leverages olfactory stimuli. It incorporates personalized labeling via subject-specific thresholds derived from valence-arousal questionnaires. Time-domain features extracted from multi-segment EEG recordings are used in conjunction with various machine learning classifiers to model emotional

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responses. By combining EEG features with subjective reports within the valence–arousal framework, this study provides a richer and more individualized understanding of emotion, offering novel insights into EEG-based olfactory emotion recognition.

II. MATERIAL AND METHOD

A. Experimental Setup and the Dataset

The dataset consists of EEG recordings from 46 right-handed participants. Each participant was exposed to four odor stimuli (cinnamon, citrus, lavender, and green tea) as well as an unscented control condition. The stimuli were presented in randomized order using opaque boxes containing odor-saturated absorbent papers. To avoid olfactory habituation, coffee beans were provided between trials as a neutralizer. During each trial, participants were instructed to close their eyes and remain still for 1 minute, during which EEG signals were recorded using a Bitbrain Versatile-32 system. All experimental procedures were approved by the Izmir Katip Çelebi University Non-Interventional Clinical Research Ethics Committee (Decision No: 14, Date: 08.02.2024).

Each participant completed a single trial for each of the four olfactory conditions and an additional trial for the odorless baseline, resulting in a total of five trials. After each trial, participants completed a self-report questionnaire assessing their emotional responses across two core affective dimensions: valence and arousal. The questionnaire consisted of two tables with six bipolar adjective pairs (e.g., Happy–Unhappy, Calm–Tense), each rated on a scale from -2 to +2. Individual valence and arousal scores were calculated by averaging the corresponding item ratings. Emotional labeling was performed by comparing these scores with each participant's baseline values obtained under the odorless condition. EEG segments recorded during odor exposure that showed higher valence and/or arousal than the baseline were labeled as 1, indicating a positive emotional shift in Fig. 1. Segments from the odorless condition were labeled as 0, representing a neutral reference. This participant-specific, data-driven labeling strategy enabled the robust modeling of EEG-based emotional changes induced by olfactory stimuli, as shown in Fig. 2.

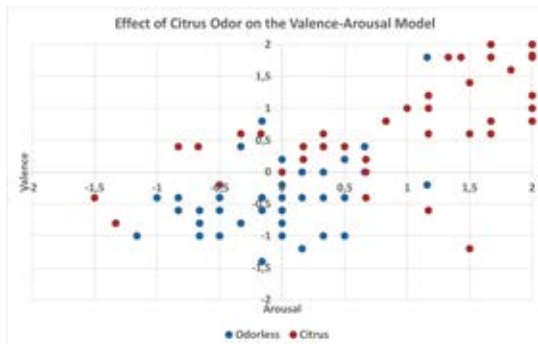


Fig. 1: Distribution of valence and arousal scores for citrus odor and odorless Conditions.

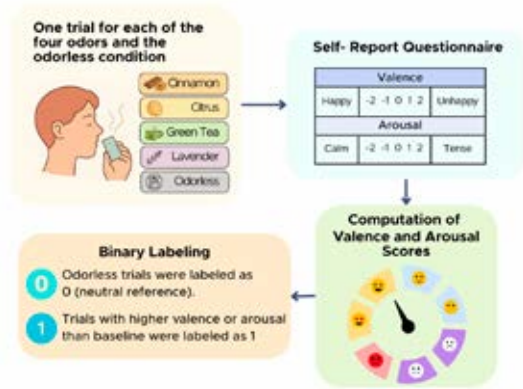


Fig. 2: Experimental setup and labeling before classification

B. EEG Preprocessing

Raw EEG signals were filtered using a 5th-order Butterworth band-pass filter with a passband of 0.5-45 Hz to remove low-frequency drifts, high-frequency muscle artifacts, and other physiological interferences unrelated to cortical activity. Segmentation was then performed by extracting five consecutive 1-second epochs immediately following the onset of each olfactory stimulus. Accordingly, five segments per odor condition were obtained from each participant, resulting in a balanced dataset structure suitable for feature extraction and classification.

C. Feature Extraction and Labeling

From each 1-second EEG segment, nine time-domain features were extracted to characterize both the statistical and dynamic properties of the signal. These included the mean, energy, skewness, and kurtosis to capture distributional aspects; root mean square (RMS) and mean absolute deviation (MAD) to reflect signal magnitude and variability; and the Hjorth parameters—activity, mobility, and complexity—which describe the amplitude variance, dominant frequency content, and frequency variation over time, respectively. These features are widely used in EEG-based emotion and neural signal analysis due to their computational efficiency and interpretability.

Two EEG channel configurations were used: the complete 23-channel set and a reduced 10-channel subset (F3–F4, F7–F8, FC1–FC2, FC5–FC6, FP1–FP2) based on prior affective EEG research [10].

Outliers were detected using z-score analysis, where a feature value x was considered an outlier if its absolute z-score exceeded 3; $z = \frac{x - \mu}{\sigma}$ where μ is the mean and σ is the standard deviation.

Detected outliers were replaced via mean imputation within the same feature vector. Each feature vector was labeled according to participants' questionnaire scores. Valence and arousal scores were binarized using subject-specific medians as thresholds to account for inter-individual variability. Separate classifiers were trained for each emotional dimension and odor type.

III. EMOTION ESTIMATION BY USING EEG FEATURES

To investigate the relationship between olfactory stimuli and emotional states, EEG-based classification models were developed within the valence-arousal framework. For model input, EEG features were extracted from two spatial configurations:

- 1) Complete 23-channel configuration: EEG features were extracted from all available channels to capture a comprehensive representation of brain activity across the scalp.
- 2) Reduced 10-channel configuration: A subset of frontal and central channels (F3–F4, F7–F8, FC1–FC2, FC5–FC6, FP1–FP2) was selected based on their known relevance to affective state processing, as supported by frontal asymmetry literature [11]. This approach aimed to reduce dimensionality while preserving emotion-relevant information.

Classification was performed separately for each odor condition and each emotional axis. A total of 17 machine learning classifiers, which offer competitive emotion classification performance with relatively low computation costs, were evaluated [12]. These are various types of SVM (Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM), k-NN (Fine k-NN, Medium k-NN, Coarse k-NN, Cosine k-NN, Cubic k-NN, Weighted k-NN), DT (Fine Tree, Medium Tree, Coarse Tree), and Kernel Approximation Methods (SVM Kernel and Logistic Regression Kernel). The performance of the trained model was evaluated using 5-fold cross-validation, as well as standard metrics such as accuracy, sensitivity, and specificity. An 80% to 20% train-test split was used on the whole dataset to ensure reliable performance estimation across different emotional states.

III. RESULTS AND DISCUSSION

This study utilizes EEG time-domain features to evaluate the performance of machine learning models that analyze the effect of four different odors on individuals' valence and arousal levels. The accuracy rates of models trained using all EEG channels and those trained using selected EEG channels are compared, and the performances of different machine learning classifiers are analyzed.

The results in Tables I and IV show that SVM-based models provide the highest accuracy rates and are the most successful in classifying odor-induced emotional responses. According to the classification results, lavender odor achieved the highest accuracy rates in predicting both arousal and valence levels (see 3 and 4). In contrast, the cinnamon odor had a less pronounced effect on EEG signals than the other odors, resulting in relatively lower accuracy rates. This difference may be attributed to the more consistent emotional response lavender elicits across participants, which supports clearer EEG patterns for machine learning models to capture.

These findings align with earlier research demonstrating the effectiveness of traditional classifiers such as SVM, DT, and k-NN in EEG-based emotion recognition tasks [13], [14]. In contrast to prior studies that predominantly utilize visual

or auditory stimuli, this work uniquely centers on olfactory triggers, which interact more directly with the limbic system and are thus well-suited for eliciting emotional responses. Additionally, subject-specific valence–arousal labels, derived from individualized self-assessment scores, were used to enhance model sensitivity and account for personal variation in emotional perception.

The comparison between 23-channel and 10-channel EEG configurations further revealed that the selected 10-channel setup targeting frontal and fronto-central regions (F3–F4, F7–F8, FC1–FC2, FC5–FC6, FP1–FP2) achieved superior classification performance. This selection was informed by prior findings indicating that these regions are critically involved in affective processing. Reducing the number of electrodes not only improved accuracy but also supports the development of more efficient and deployable emotion recognition systems.

Among the tested odors, lavender produced the highest classification accuracy in both emotional dimensions, reaching 80.14% for valence and 79.19% for arousal. These outcomes suggest that lavender elicits more consistent and distinguishable EEG patterns, thereby improving model reliability. Taken together, the results confirm the value of combining olfactory stimulation with personalized EEG analysis and contribute to expanding the scope of emotion recognition beyond conventional stimulus modalities.

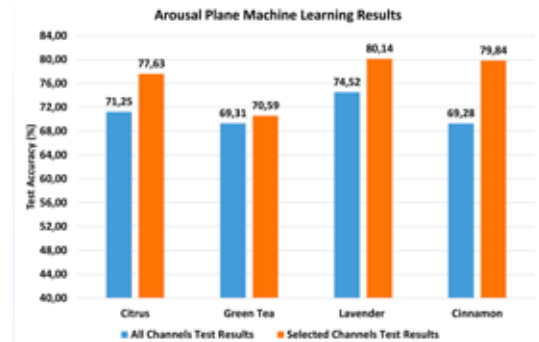


Fig. 3: Arousal estimation results using different classifiers

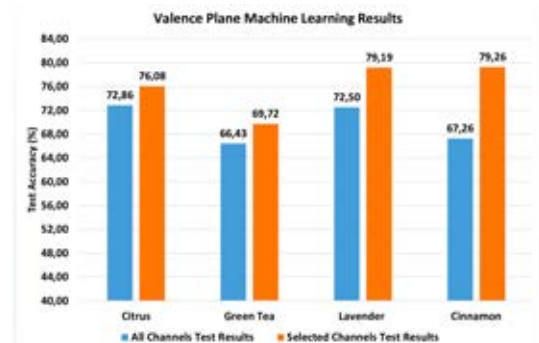


Fig. 4: Valence estimation results using different classifiers



TABLE I: Classification Results of Valence and Arousal for Citrus

Parameter	All 23 EEG Channels			Selected 10 EEG Channels		
	Model	Accuracy % (Validation)	Accuracy % (Test)	Model	Accuracy % (Validation)	Accuracy % (Test)
Arousal	Medium Gaussian SVM	71,22	71,25	Cubic SVM	75,66	77,63
	Fine Tree	66,17	66,36	Medium Tree	68,00	71,38
	Weighted k-NN	64,59	65,16	Coarse k-NN	64,66	67,25
	SVM Kernel	57,98	61,20	SVM Kernel	60,25	59,63
Valence	Medium Gaussian SVM	71,12	72,86	Cubic SVM	76,82	76,08
	Weighted k-NN	64,12	66,63	Fine Tree	71,52	67,3
	Fine Tree	66,07	66,45	Medium k-NN	66,26	66,22
	Logistic Regression Kernel	58,52	58,75	Logistic Regression Kernel	62,40	61,08

TABLE II: Classification Results of Valence and Arousal for Green Tea

Parameter	All 23 EEG Channels			Selected 10 EEG Channels		
	Model	Accuracy % (Validation)	Accuracy % (Test)	Model	Accuracy % (Validation)	Accuracy % (Test)
Arousal	Medium Gaussian SVM	65,62	69,31	Cubic SVM	69,45	70,59
	Cosine k-NN	61,13	65,03	Fine Tree	60,55	64,12
	Fine Tree	61,60	63,24	Weighted k-NN	62,65	63,09
	SVM Kernel	57,78	62,72	Logistic Regression Kernel	57,76	57,35
Valence	Fine Gaussian SVM	64,79	66,43	Cubic SVM	69,86	69,72
	Medium k-NN	60,49	63,95	Fine Tree	62,36	63,47
	Fine Tree	62,30	63,22	Coarse k-NN	60,24	62,92
	SVM Kernel	58,38	58,88	Logistic Regression Kernel	57,29	59,58

TABLE III: Classification Results of Valence and Arousal for Lavender

Parameter	All 23 EEG Channels			Selected 10 EEG Channels		
	Model	Accuracy % (Validation)	Accuracy % (Test)	Model	Accuracy % (Validation)	Accuracy % (Test)
Arousal	Medium Gaussian SVM	71,83	74,52	Cubic SVM	79,31	80,14
	Fine Tree	69,64	72,64	Fine Tree	71,88	72,08
	Coarse k-NN	65,37	68,36	Cosine k-NN	64,97	68,89
	Logistic Regression Kernel	58,95	62,32	Logistic Regression Kernel	62,36	64,31
Valence	Medium Gaussian SVM	72,50	72,50	Cubic SVM	77,94	79,19
	Weighted k-NN	67,63	68,63	Fine Tree	73,38	73,11
	Fine Tree	69,45	66,63	Weighted k-NN	66,89	67,03
	Logistic Regression Kernel	59,72	61,87	SVM Kernel	60,95	65,54

TABLE IV: Classification Results of Valence and Arousal for Cinnamon

Parameter	All 23 EEG Channels			Selected 10 EEG Channels		
	Model	Accuracy % (Validation)	Accuracy % (Test)	Model	Accuracy % (Validation)	Accuracy % (Test)
Arousal	Cubic SVM	67,95	69,28	Cubic SVM	77,18	79,84
	Weighted k-NN	63,38	66,90	Medium k-NN	62,14	65,32
	Fine Tree	61,48	62,90	Medium Tree	61,69	63,06
	SVM Kernel	57,31	60,80	Logistic Regression Kernel	57,26	60,00
Valence	Medium Gaussian SVM	66,50	67,26	Cubic SVM	76,62	79,26
	Weighted k-NN	63,99	65,66	Weighted k-NN	62,72	65,29
	Fine Tree	60,85	61,96	Medium Tree	62,54	62,35
	SVM Kernel	57,24	57,29	Logistic Regression Kernel	58,13	61,32

IV. CONCLUSIONS AND FUTURE ASPECTS

The experimental findings of this study demonstrate that both single and ensemble machine learning models can effectively classify emotional states elicited by olfactory stimuli, using time-domain EEG features. When benchmarked against recent research such as [15] and [16], the proposed methodology yields comparable accuracy levels, reaffirming the role of EEG as a viable modality in emotion recognition under sensory stimulation. In contrast to conventional approaches that rely on visual or auditory stimuli, this study solely focuses on olfaction. It enriches the existing literature by validating performance through valence–arousal–based classification.

Building upon earlier work [17], [18], [19], the integration of personalized labels and channel-specific modeling provided new insights into the emotional implications of odor stimuli on EEG dynamics. These results are also supported by recent efforts highlighting the efficacy of channel selection and feature domain hybridization for real-time and wearable emotion recognition systems [20], [21]. However, there is still room for improvement as the classification results are relatively low, especially for green tea. Moreover, due to time and scope constraints, this study only utilizes ML methods, whereas DL methods offer more accurate and robust classifiers, overall.

Looking forward, several enhancements are envisioned to improve model robustness and expand applicability. In particular, applying mode decomposition techniques and feature map representations [22] alongside DL methods will allow for generating augmented training data by decomposing the EEG into intrinsic mode functions, which could enhance classification accuracy and generalization. Furthermore, other feature sets, such as non-linear and entropy features, will enable a better representation of data, leading to more generalized classifiers. Clinically, the study contributes to a better representation for emotion modeling, the establishment of a baseline for the development of lightweight, high-accuracy models, as well as improved techniques for neuromarketing [17], affective computing [23], and cognitive interface [24] systems.

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