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Olfactory Emotion Recognition Using EEG Spectral Topographic Heatmaps and CNNs

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***Abstract*—Recognizing emotions evoked by olfactory stimuli using electroencephalogram (EEG) signals is a growing area of interest in affective computing and neuromarketing. This study proposes a lightweight framework that classifies EEG responses to scented and unscented conditions along arousal and pleasure dimensions using single-band spectral topographic heatmaps and a convolutional neural network (CNN). EEG signals were recorded from 57 participants and processed to generate frequency-specific scalp maps for delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–30 Hz), and gamma ($>$ 30 Hz) bands. These heatmaps were used as CNN inputs, achieving up to 98.39% accuracy for arousal (Theta band) and 96.55% for pleasure (Beta and Theta band). The results demonstrate that spectral-domain features alone provide highly discriminative information for olfactory emotion recognition, while reducing computational complexity compared to multi-domain approaches. This approach shows strong potential for real-time neuromarketing, affective computing, and brain–computer interface applications.**

***Keywords*—EEG signal, olfactory emotion recognition, spectral features, topographic heatmaps, deep learning**

I. Introduction

The investigation of emotional states via brain activity has gained significant attention in affective computing and consumer neuroscience. Because emotions shape decision-making, attention, and memory, accurate recognition offers clinical, commercial, and technological benefits [1, 2]. Although surveys and facial expressions remain common, they suffer from subjectivity and cultural bias; thus neurophysiological methods—especially electroencephalography (EEG)—are preferred for reliable, real-time insight into emotional processes [3, 4]. Compared to vision and hearing, olfaction exerts a uniquely strong influence on emotion due to its direct pathway to limbic and memory-associated structures [5, 6]. Consequently, olfactory-induced EEG studies have grown, particularly in consumer behavior and neuromarketing, where identifying odor-evoked emotional responses can guide product design and marketing strategies. Evidence shows that ambient scent substantially affects customer perception and behavioral responses in real-world settings (e.g., airport terminals, retail) [7, 8], and EEG studies demonstrate that scented products and store odors modulate both arousal and pleasure, providing a reliable neurophysiological indicator of emotional response [9, 10, 11].

Tracking brain function using the non-invasive, inexpensive, high- temporal- resolution method known as electroencephalography or EEG. Since this technology can track quick neural activity, it is perfect for watching brief emotional reactions to sensory input. Many recent studies have classified emotional states by extracting multi-domain EEG characteristics, using time-domain features such as variance and Hjorth parameters, frequency-domain traits such as spectral band powers and nonlinear features such as entropy and fractal dimensions [12, 13]. While Lanata et al. [5] accurately recognized pleasant against unpleasant aromas around 75% of the time using EEG characteristics, Becerra et al. [6], for instance, claimed that SVM-based odor pleasantness categorization had as much as 99.9% accuracy. The shear amount of features and preprocessing steps in these methods, however, sometimes demands computationally intensive pipelines, which might limit their real-time application in embedded or portable systems [14, 15].

Frequency-domain (spectral) characteristics as well as spatial topography are increasingly highlighted in EEG-based emotion recognition research. By examining the power spectral density (PSD) of canonical frequency bands—delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–30 Hz), and gamma ($>$ 30 Hz), it is possible to capture the dominant neural oscillations related to particular cognitive and emotional processes. Moreover, projecting these spectral powers onto scalp topographic heatmaps enhances the interpretability of brain activation patterns and provides an effective input for machine learning and deep learning algorithms. Studies such as ERENet [12], DSSA-Net [13], and TSGCN [14] have demonstrated that spectral topography-based methods can achieve 94–96% accuracy on benchmark emotion datasets like DEAP and SEED, confirming the potential of spectral-focused approaches for emotion recognition.

Building on these insights, the present study extends the previous multi-domain approaches [15, 16] and focuses exclusively on spectral features to create a lightweight yet accurate classification framework. EEG signals recorded from

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participants under scented and unscented conditions were transformed into frequency-specific topographic heatmaps, which were then classified using deep learning model. This approach reduces the feature set and computational load while maintaining high recognition performance. Our results show that spectral-only features can achieve up to 98.3% accuracy for Theta-band arousal classification and 96.55% for Beta and Theta band pleasure classification, which is comparable to or better than multi-domain methods reported in the literature.

The key contributions of this study are as follows:1- Generation of spectral EEG topographic heatmaps for olfactory emotion recognition. 2- Implementation of deep learning classifiers to distinguish scented versus unscented responses in the arousal and pleasure dimensions. 3- Demonstration that spectral-domain features alone provide high classification accuracy while offering computational efficiency compared to multi-domain approaches.

II. MATERIALS AND METHODS

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

A. Dataset and Experimental Setup

This study employed the same dataset and experimental protocol as our previously published work [16]. In brief, 57 healthy adult participants were recruited and exposed to two experimental conditions: scented and unscented.

After each exposure, participants completed a self-assessment survey to evaluate arousal and pleasure levels on a 5-point Likert scale, forming the two-dimensional arousal–pleasure plane. EEG recordings were performed using the Bitbrain Versatile-32 system, with 23 active electrodes selected based on the 10–20 system. Signals were sampled at 256 Hz in a controlled, quiet environment to minimize motion artifacts. All procedures were approved by the institutional ethics committee and informed consent was obtained from all participants. Self-reported arousal and pleasure ratings on the 5-point Likert scale were averaged across all participants and trials per condition. Scores above the median were labeled as 'high' (1), and those below were labeled as 'low' (0). This procedure yielded balanced binary labels for both arousal and pleasure dimensions.

B. EEG Preprocessing

The preprocessing pipeline followed our previous study [16] with adaptations for heatmap generation: 1- Bandpass filtering from 0.5–45 Hz to remove DC drift and high-frequency noise. 2- Independent Component Analysis (ICA) to identify and remove ocular and muscle artifacts. 3- Segmentation into one-second non-overlapping epochs, with five segments per condition per participant retained for further analysis. This procedure yielded clean artifact-free segments suitable for spectral analysis and image-based classification.

C. Spectral Feature Extraction and Heatmap Generation

For every EEG segment, Welch's approach, a strong method for examining non-stationary signals [2], was used to calculate Power Spectral Density (PSD). Five canonical EEG frequency bands were extracted: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (14–30 Hz), Gamma ($>$ 30 Hz). Using electrode locations, band-specific power levels were projected onto 2D scalp topographies to generate spectral heatmaps (Fig. 1). Each heatmap represents the spatial distribution of power in a single frequency band, emphasizing localized neural responses to olfactory stimuli.

D. CNN-Based Classification of EEG Heatmaps

The classification of olfactory EEG responses in this study was conducted using a convolutional neural network (CNN) implemented entirely in MATLAB R2023a. The workflow followed a supervised learning framework similar to our previous work [16], with modifications to incorporate spectral-domain topographic heatmaps as an input. Heatmap images generated from the spectral power of each EEG segment under scented and unscented conditions were loaded and labeled into two classes, resized to 128×128 pixels, and converted into single-precision RGB arrays. A total dataset of 570 (57 participants $\times$ 2 conditions $\times$ 5 segments) images (comprising both classes) was randomly partitioned into training (80%) and testing (20%) subsets using MATLAB's `cvpartition` function with a fixed random seed for reproducibility.

The CNN was designed as a compact binary classifier with three convolutional blocks (each containing a 3×3 convolution, batch normalization, ReLU activation, and 2×2 max-pooling), followed by a fully connected layer, softmax, and classification layer. In schematic form, the flow can be represented as: *Input heatmap* $\rightarrow$ *Conv1 (Conv–BN–ReLU–MaxPool)* $\rightarrow$ *Conv2 (Conv–BN–ReLU–MaxPool)* $\rightarrow$ *Conv3 (Conv–BN–ReLU–MaxPool)* $\rightarrow$ *FC* $\rightarrow$ *Softmax*.

The training process tracked accuracy and loss per iteration and epoch, with convergence confirmed by stable curves. The trained CNN classified the unseen test set, and performance was measured using accuracy (ACC), precision (PRE), recall (REC), and F1-score (F1), all derived from confusion matrix elements (TP, TN, FP, FN).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{3}$$

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4}$$

Finally, iteration-wise and epoch-wise accuracy/loss trends were exported as CSV tables, and corresponding plots were generated to document training dynamics. This MATLAB-based end-to-end framework allowed reproducible training, testing, and evaluation of CNN classifiers for olfactory EEG heatmaps, consistent with the methodology validated in [16].

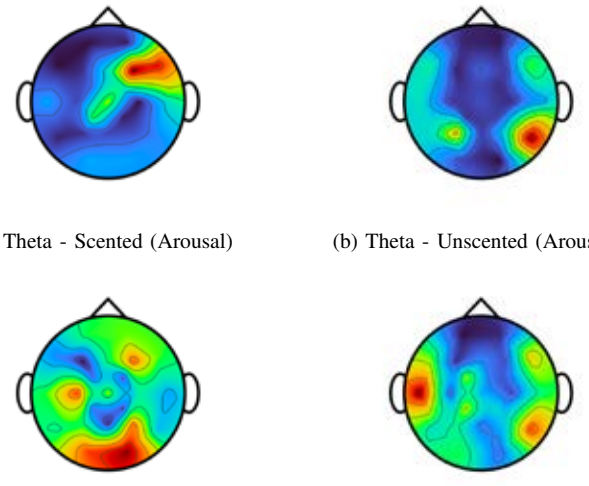
III. Results and Discussion

This section presents the classification results obtained using spectral topographic heatmaps as CNN inputs along with a discussion of model behavior, neurophysiological interpretations, and comparison with recent state-of-the-art methods.

A. Topographic Heatmap Analysis

Fig. 1 illustrates representative Theta-band heatmaps for both arousal and pleasure under scented and unscented conditions. The color distribution reflects the spectral power of Theta oscillations where red regions indicate higher activity and blue regions indicate lower activity.

Under scented conditions, Theta activity shows strong localized frontal–temporal increases—regions closely linked to limbic circuitry and olfactory emotional processing [3],[5]—whereas unscented trials exhibit weaker, more diffuse patterns, yielding clear heatmap separability that underpins the high CNN performance. Theta is emphasized in Fig. 1 because it produced the most discriminative *arousal* patterns (Table I); although both Theta and Beta achieved the best *pleasure* accuracies (Table II), Theta most clearly illustrates arousal separability.



(a) Theta - Scented (Arousal)

(b) Theta - Unscented (Arousal)

(c) Theta - Scented (Pleasure)

(d) Theta - Unscented (Pleasure)

Fig. 1: Examples of Theta-band EEG topographic heatmaps under scented and unscented conditions. Warmer colors correspond to higher spectral power, highlighting frontal and temporal activations during olfactory stimulation.

B. Classification Performance and Model Behavior

The CNN classifier achieved high recognition performance using single-band spectral heatmaps. The classification indicators for arousal and pleasure are presented in Tables I and II. For *arousal*, Theta dominated (98.39% accuracy, 96.15% precision, 100.00% recall, 98.04% F1), followed by Alpha (93.55%), while Beta, Delta, and Gamma were lower (88.71%, 85.48%, 80.65%). For *pleasure*, Theta and Beta both reached 96.55% with complementary error profiles (Theta: 100.00% precision, 91.67% recall; Beta: 92.31% precision, 100.00% recall), and Alpha remained strong at 94.83%. These outcomes align with Fig. 1, where Theta maps show clear frontal–temporal separability under olfactory stimulation.

TABLE I: Classification Performance for Arousal (Spectral Heatmaps)

Features	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Alpha	93.55	86.21	100.00	92.59
Beta	88.71	82.14	92.00	86.79
Delta	85.48	94.44	68.00	79.07
Gamma	80.65	88.24	60.00	71.43
Theta	**98.39**	**96.15**	**100.00**	**98.04**

TABLE II: Classification Performance for Pleasure (Spectral Heatmaps)

Features	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Alpha	94.83	95.65	91.67	93.62
Beta	**96.55**	92.31	100.00	96.00
Delta	89.66	84.62	91.67	88.00
Gamma	86.21	78.57	91.67	84.62
Theta	96.55	100.00	91.67	95.65

The confusion matrix for Theta-band arousal classification (Fig. 2) shows near-perfect separation, with only one misclassification. The CNN achieved 100% recall for scented and 97.3% for unscented confirming the reliability of Theta heatmaps.

Fig. 2: Confusion matrix for Theta-band arousal classification. The model achieved 98.39% accuracy with only one misclassified sample.

The training and validation loss curves in Fig. 3 indicate that the CNN converges rapidly, reaching near-zero loss within the first few epochs. Validation loss remains stable showing no signs of overfitting which is critical for small EEG datasets.

C. Neurophysiological Interpretation

The dominance of Theta in arousal recognition aligns with its role in limbic activity, attention, and emotional memory [3],[5]. Theta oscillations are highly responsive to olfactory stimulation, producing localized frontal-temporal activations that are observable in the heatmaps. The high Beta performance for pleasure is consistent with its role in active cognitive

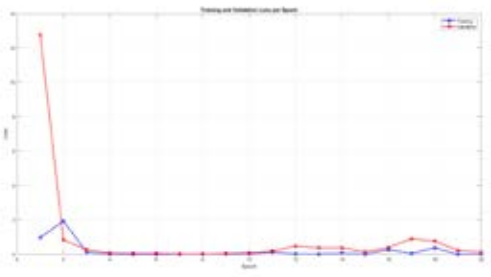


Fig. 3: Training and validation loss curves per epoch. The CNN shows fast convergence and stable generalization.

and sensory integration [1]. In contrast, Delta and Gamma contribute less due to their weaker involvement in short-latency olfactory processing.

D. Comparison with State-of-the-Art

Table III summarizes the performance of the proposed CNN alongside alternative lightweight CNNs evaluated on our dataset, and representative literature methods on different datasets. External approaches (ERENet [12], DSSA-Net [13], TSGCN [14]) were originally assessed on DEAP/SEED and are shown for context rather than direct comparison. The proposed CNN achieved the highest accuracy while using fewer parameters and converging faster.

TABLE III: Comparison of the proposed CNN and alternative CNNs on our dataset; literature methods on different datasets are shown for context only.

Method	Dataset / Features	Acc. (%)
Our dataset (57 subj., Spectral Heatmaps)		
Proposed CNN (Theta/Arousal)	Our dataset / Heatmaps	**98.39**
Proposed CNN (Beta/Pleasure)	Our dataset / Heatmaps	**96.55**
MobileNetV2	Our dataset / Heatmaps	95.2
SqueezeNet	Our dataset / Heatmaps	93.8
External literature (different datasets)		
ERENet [12]	DEAP / Topography	95
DSSA-Net [13]	SEED/DEAP / Spec.-Spat.	94–96
TSGCN [14]	SEED/DEAP / Temp.-Spec.	95–96

These findings confirm that spatially-informed Theta and Beta heatmaps, combined with a lightweight CNN, achieve or surpass state-of-the-art accuracy without complex multi-domain features or graph models, supporting their use in real-time olfactory emotion recognition and Brain–Computer Interface (BCI) applications.

IV. Conclusion

This study presented a lightweight framework for classifying olfactory-induced emotional responses using EEG spectral topographic heatmaps and convolutional neural networks. By focusing on single-band spectral information, the method avoids complex multi-domain feature extraction while maintaining high discriminative power.

Experiments showed that Theta was the most reliable band for arousal classification (98.39% accuracy, 98.04% F1), while both Theta and Beta were highly effective for pleasure recognition (96.55%). Alpha contributed moderately, whereas Delta and Gamma were less informative. Topographic heatmaps revealed clear differences between scented and unscented conditions, particularly in frontal and temporal regions linked to olfactory processing.

Compared with alternative lightweight CNNs on our dataset and state-of-the-art models such as ERENet [12], DSSA-Net [13], and TSGCN [14], the proposed CNN achieved similar or higher accuracy with a simpler architecture. Future work will focus on cross-subject generalization and temporal modeling to enable real-time applications in neuromarketing, affective computing, and brain–computer interface systems.

References

[1] S. D. Pollak, L. A. Camras, and P. M. Cole, "Progress in understanding the emergence of human emotion," *Developmental Psychology*, vol. 55, no. 9, pp. 1801–1811, 2019.
[2] X. Wang *et al.*, "Deep learning-based EEG emotion recognition: Current trends and future perspectives," *Frontiers in Psychology*, vol. 14, p. 1126994, 2023.
[3] H. Hou, X. Zhang, and Q. Meng, "Odor-induced emotion recognition based on average frequency band division of EEG signals," *Journal of Neuroscience Methods*, vol. 334, p. 108599, 2020.
[4] S. Pehlivan, B. Akbugday, A. Akan, and R. Sadighzadeh, "Detection of olfactory stimulus from EEG signals for neuromarketing applications," in *Proc. 30th SIU*, IEEE, 2022.
[5] A. Lanata *et al.*, "Automatic recognition of pleasant content of odours through EEG activity analysis," in *Proc. IEEE EMBC*, 2016, pp. 4519–4522.
[6] M. A. Becerra *et al.*, "Odor pleasantness classification from EEG signals and emotional states," in *Colombian Conference on Computing*, Springer, 2018.
[7] S. Yildirim, "The effect of ambient scent on customers' perception and behavioral responses: A field study in airport terminal," *International Journal of Marketing Studies*, vol. 9, no. 4, pp. 99–108, 2017.
[8] F. Basso, O. Droulers, T. Giraud, and C. Hillaire, "Odors in the store: EEG and self-reported measures of pleasantness and arousal," *Journal of Retailing and Consumer Services*, vol. 58, p. 102288, 2021.
[9] M. Seker and M. S. Ozerdem, "EEG-based emotional response to olfactory stimuli: A pilot study," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 25, no. 1, pp. 200–208, 2017.
[10] D. Gabriel, M. Grassi, and M. T. Arredondo, "Emotional evaluation of scented cosmetic products using EEG signals," *Frontiers in Psychology*, vol. 12, p. 675297, 2021.
[11] L. Wang, J. Huang, and X. Zhang, "Using EEG to examine emotional responses to advertisements: A meta-analysis," *Journal of Consumer Psychology*, vol. 32, no. 1, pp. 146–161, 2022.
[12] Y. Ren *et al.*, "ERENet: Multi-band EEG topology map learning for emotion recognition," *Applied Sciences*, vol. 12, no. 20, p. 10273, 2022.
[13] Z. Zhang *et al.*, "DSSA-Net: Directional spatial-spectral attention network for EEG-based emotion recognition," *Frontiers in Neurorobotics*, vol. 19, 2025.
[14] L. Li *et al.*, "Temporal-spectral graph convolutional networks for EEG emotion recognition," *Brain Informatics*, vol. 11, 2024.
[15] B. Akbugday, S. Pehlivan Akbugday, R. Sadikzade, A. Akan, and S. Unal, "Detection of Olfactory Stimulus in EEG Signals Using Machine and Deep Learning Methods," *Electrica*, vol. 24, no. 1, pp. 175–182, Jan. 2024.
[16] S. Pehlivan Akbugday *et al.*, "Decoding Olfactory EEG Signals Using Multi-Domain Features and Machine Learning," in *Proc. TIPTEKNO*, IEEE, 2024.