Analysis of Human Emotions for Different Taste Stimuli Using EEG Signals

Berkay Ilber Tunakan and Aydin Akan
Dept. of Electrical and Electronics Eng.
Izmir University of Economics
Izmir, Turkey
{berkay.tunakan, akan.aydin}@ieu.edu.tr

Yaren Taskin and Kamile Nazan Turhan
Department of Food Engineering
Izmir University of Economics
Izmir, Turkey
{yaren.taskin, nazan.turhan}@ieu.edu.tr

***Abstract*—This study investigates neurophysiological and subjective responses to beverages containing natural and artificial preservatives under blind and informed tasting conditions. EEG signals from 26 participants were categorized into positive and negative hedonic states based on post-trial subjective evaluations. Statistical analyses revealed significant task-related variations in the frontal gamma and parietal beta frequency bands. Behaviorally, explicit disclosure of the artificial preservative induced a strong cognitive bias, shifting acceptable baseline perceptions to highly negative evaluations. To classify these hedonic states, four models (Random Forest, XGBoost, SVM, and DNN) were trained on extracted time-frequency and time-domain EEG features. XGBoost achieved the highest accuracy (87.50%) and F1-Score (87.43%). Overall, tree-based ensembles outperformed deep learning approaches, demonstrating robust predictive capability for this neurophysiological dataset.**

***Index Terms*—Taste; Human emotion estimation; EEG; signal analysis; XGBoost; DNN; SVM; Neuromarketing**

I. INTRODUCTION

Modern food industry widely employs preservatives to extend shelf life and prevent microbial spoilage. These preservatives exist in both natural and synthetic forms, and although they serve similar technical purposes, they are perceived differently by consumers [1]. Previous studies have shown that labels such as “natural” and “artificial” significantly influence consumer preferences and purchasing behavior [2]. This suggests that sensory perception is not solely driven by physical stimuli but is also shaped by cognitive expectations.

Electroencephalography (EEG) has been extensively used to investigate neurophysiological responses to external stimuli and provides an objective framework for analyzing consumer behavior during food consumption [3], [4]. Taste perception is inherently a multisensory process, involving the integration of gustatory, olfactory, and cognitive components, and neural oscillations—particularly in higher frequency bands—have been associated with such integrative processing [5]. In recent years, machine learning and deep learning techniques have been increasingly applied to EEG signals, demonstrating strong performance in modeling cognitive and affective processes [6]. However, despite this progress, the application of these methods to EEG data collected during tasting experiments particularly in the context of differentiating natural and artificial preservatives under varying levels of prior knowledge remains limited.

The contribution of this study can be summarized under four main aspects. First, the study analyzes taste perception using EEG signals, thereby extending conventional sensory evaluation by incorporating neurophysiological evidence. Second, the blind and informed tasting protocol enables the investigation of how neural responses are affected not only by the sensory properties of the beverage but also by cognitive context and prior information. Third, the study considers preservative type, specifically natural and artificial preservatives, as a beverage-content factor in EEG-based taste perception analysis, representing a relatively unexplored variable in the existing literature. Fourth, the experimental results show that XGBoost provides the most effective classification performance among the evaluated models, indicating its suitability for extracting discriminative patterns from EEG-derived features in small-sample taste perception studies.

II. LITERATURE REVIEW

Product labeling strongly influences consumer behavior, with a marked preference for “natural” over artificial additives due to perceived health and safety benefits, even when actual compositions are comparable [2]. Consequently, sensory perception is not solely determined by physical properties, but is significantly modulated by cognitive expectations, which ultimately shape the overall evaluation of the tasting experience.

Electroencephalography (EEG) has been widely used as a non-invasive tool to investigate neural responses associated with sensory perception and emotional processing during food consumption. Prior research demonstrates that EEG signals can capture variations in affective states, attention, and cognitive evaluation when individuals are exposed to different food stimuli [3], [4]. In addition, studies focusing on food additives and sensory perception suggest that differences in ingredient composition can lead to measurable changes in neurophysiological responses, reflecting altered perception at the brain level [7]. These findings indicate that EEG provides a suitable framework for examining how both sensory input and contextual information influence the perception of food

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

products. Taste perception is inherently a multisensory process that involves the integration of gustatory, olfactory, and cognitive information. Previous studies have shown that neural oscillations, particularly in higher frequency bands, play a key role in coordinating such multisensory integration mechanisms in the brain [5].

Recent advances in machine learning and deep learning have significantly enhanced the analysis of EEG signals, enabling automated extraction of complex patterns related to emotional and cognitive states. Benchmark datasets such as DEAP have demonstrated the feasibility of classifying affective responses using data-driven approaches [6]. In the context of food perception, emerging studies have also begun to explore EEG-based differences in neural responses to varying ingredients and taste profiles [8]. Recent literature highlights the high efficacy of XGBoost in EEG-based emotion recognition. Notably, Khan et al. [9] proposed a hybrid CNN-XGBoost architecture that classifies EEG spectrogram features, achieving over 99.7% accuracy on the DREAMER dataset and significantly outperforming traditional SVMs. This robust capacity to process complex, high-dimensional neurophysiological data further justifies the selection of XGBoost for our classification framework.Furthermore, tree-based ensemble methods such as Random Forest have been successfully applied in recent EEG-based cognitive state detection studies utilizing standard preprocessing pipelines. For instance, Karthik et al. [10] applied a combination of notch and bandpass filtering, alongside Independent Component Analysis (ICA) and epoching, to classify stress states from EEG data. Operating on a restricted participant dataset, their Random Forest classifier achieved an accuracy of 83.33%. These findings demonstrate the reliable classification capabilities of Random Forest when coupled with standard frequency-filtering and artifact rejection techniques. In the domain of EEG-based emotion recognition, Support Vector Machines (SVM) are frequently utilized as a robust baseline for evaluating classification performance. For instance, Zheng and Lu [11] investigated multichannel EEG features for discriminating positive, neutral, and negative emotional states. In their comparative analysis of deep and shallow models, they demonstrated that a standard SVM classifier effectively processed extracted differential entropy features, achieving an average accuracy of 83.99%. This establishes the utility of maximum-margin classifiers as a reliable standard in neurophysiological data analysis. However, despite these developments, the application of machine learning methods to EEG data collected during tasting experiments remains limited. In particular, the combined effect of preservative type (natural vs. artificial) and prior knowledge (informed vs. blind tasting) has not been systematically investigated using data-driven models. This gap motivates the present study.

III. Methodology

A. Experimental Design

The experimental protocol was designed to investigate the effects of preservative type and prior knowledge on neurophysiological responses during food consumption across 26 participants. The study followed a 2×2 factorial structure, where the two factors were preservative type (natural vs. artificial) and information condition (blind vs. informed).

TABLE I
Experimental Conditions

Condition	Preservative	Information
Natural–Blind	Natural	Blind
Artificial–Blind	Artificial	Blind
Natural–Informed	Natural	Informed
Artificial–Informed	Artificial	Informed

EEG signals were acquired using a Bitbrain Versatile system configured with a dry electrode layout corresponding to the Bitbrain Diadem headset. Data were recorded from 12 active channels positioned according to the international 10-20 standard: AF7, FP1, FP2, AF8, F3, F4, P3, P4, P7, O1, O2, and P8.

Initially, a baseline recording phase was conducted. During this stage, participants were instructed to remain still with their eyes closed in order to minimize motion and visual artifacts. The recorded resting-state brain activity was later used as a reference for normalization and comparison with stimulus-driven responses.

Following the baseline phase, participants proceeded to the tasting stage. Two detox water samples were prepared such that they differed only in their preservative content. The first sample contained a natural preservative derived from olive extract, while the second sample contained an artificial preservative based on sodium benzoate. All samples were presented at room temperature in identical opaque containers to eliminate any visual or contextual bias.

To reduce motion artifacts during EEG acquisition, participants were instructed to consume the samples using a sterile straw without moving their head or upper body. A small amount of liquid was drawn into the mouth, and EEG recording was initiated one second after sip onset. The recording window lasted for five seconds, during which participants maintained a neutral posture. At the end of the recording period, participants were allowed either to swallow or to spit out the sample.

Each tasting trial was immediately followed by a short questionnaire designed to capture subjective evaluations, including hedonic perception and perceived attributes of the beverage. This step enabled the comparison of subjective responses with neurophysiological measurements.

The tasting procedure was conducted under two information conditions. In the blind condition, participants were not informed about the preservative type of the samples. In the informed condition, the preservative content was explicitly disclosed prior to tasting. The same experimental procedure was applied in both conditions, ensuring consistency across trials. This design allowed for the isolation of the effect of cognitive expectation from purely sensory-driven responses. The study was approved by the Science and Engineering Research Ethics Committee of Izmir University of Economics, with decision number E-97429853-050.04- 103637 dated 31.07.2025.

TABLE II
EEG RECORDING TIMELINE

Stage	Time (s)	Description
Baseline	–	Eyes closed resting state
Sip onset	0	Liquid enters mouth
Delay	0–1	Stabilization period
Recording	1–6	EEG acquisition window
Post-trial	–	Questionnaire response

B. Data Labeling

EEG recordings were segmented into fixed-length epochs corresponding to each tasting event. Each epoch was defined as a 5-second window starting one second after sip onset, ensuring that the analyzed signals primarily reflected post-ingestion neural responses.

To align the neurophysiological data with the subjective hedonic evaluations, the labeling strategy was established based on the participants' self-reported attitudes rather than the predefined experimental conditions. The responses from the post-trial questionnaires served as the ground truth to categorize the corresponding EEG epochs into two distinct classes. Epochs corresponding to trials where the participant reported a favorable or pleasant evaluation of the stimulus were labeled as Class 1 (Positive Attitude). Conversely, epochs corresponding to trials where the participant reported an unfavorable or aversive evaluation were designated as Class 2 (Negative Attitude).

This attitude-centric labeling framework shifts the classification objective from identifying the physical stimulus to predicting the consumer's cognitive and emotional response during the tasting event.

Baseline recordings were labeled separately and used for normalization purposes. Event markers were embedded into the EEG data stream to indicate baseline periods, sip onset, and recording windows, enabling precise segmentation and alignment of trials.

C. Preprocessing

Prior to feature extraction, the raw EEG signals underwent preprocessing to mitigate noise and enhance signal integrity. A band-pass filter with cutoff frequencies at 1 Hz and 50 Hz was applied to isolate the neurophysiological frequency bands of interest while attenuating low-frequency drifts and high-frequency artifacts. Additionally, a 50 Hz notch filter was implemented to eliminate power-line interference.

Following spectral filtering, Independent Component Analysis (ICA) was utilized to identify and remove artifactual components, predominantly those originating from ocular movements and minor muscular activity. Once the artifacts were rejected, the continuous EEG data were segmented into 5-second epochs aligned with the onset of the tasting events. To capture the dynamic temporal variations during the tasting process, each 5-second epoch was further subdivided into overlapping 1-second segments using a sliding window approach with 60% overlap (step size of 0.4 seconds). Feature extraction was subsequently performed independently on these 1-second segments.

D. Feature Extraction

EEG signals were processed to extract both frequency-domain and time-domain features representing neural responses during tasting.

1) Frequency-Domain Features: Spectral features were computed by estimating the power spectral density (PSD) of each EEG epoch using the Fast Fourier Transform (FFT). The power spectral density was then obtained as:

$$\mathrm{PSD}[k] = \frac{1}{N}|X[k]|^2 \tag{1}$$

where $\mathrm{PSD}[k]$ denotes the power spectral density at frequency bin k, $X[k]$ is the corresponding discrete Fourier transform coefficient, and N represents the total number of samples in the epoch. Band power features were calculated by integrating the PSD over standard EEG frequency bands Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–45 Hz). [6]

2) Time-Domain Features: Hjorth Parameters: To characterize the temporal dynamics of EEG signals, Hjorth parameters were extracted. Let $x(t)$ denote the EEG signal and $\dot{x}(t)$ its first derivative [14]. Activity, Mobility, and Complexity were used to describe the signal power, mean frequency content, and waveform irregularity, respectively.

3) Feature Set Summary: In total, seven features per channel were analyzed: Theta, Alpha, Beta, and Gamma band powers, alongside Hjorth Activity, Mobility, and Complexity. Integrating frequency and time-domain features is a validated approach to capture complex EEG dynamics; combining Power Spectral Density (PSD) with Hjorth parameters significantly improves classification accuracy across varying affective states [12], [13]. Additionally, the variability of these features across windows was computed alongside mean values to partially preserve temporal dynamics within each trial.

E. Validation and Hyperparameter Optimization

To systematically evaluate the implemented models (Random Forest, XGBoost, SVM, and DNN) and mitigate overfitting, a 5-fold Stratified K-Fold cross-validation strategy was employed during the training phase. Additionally, hyperparameter tuning for the tree-based and SVM classifiers was executed via GridSearchCV integrated within this cross-validation framework. This rigorous evaluation ensured the selection of optimal model configurations while preserving the representative class distribution across all experimental folds. The DNN was implemented in Keras as a sequential model with three fully connected layers (128, 64, and 32 units, ReLU), each followed by dropout (0.3, 0.3, and 0.2, respectively); batch normalization was applied after the first two layers. A single sigmoid unit performed the binary classification. The network was trained using the Adam optimizer (learning rate 0.001) and binary cross-entropy loss for up to 100 epochs, with early stopping (patience of 15 on validation

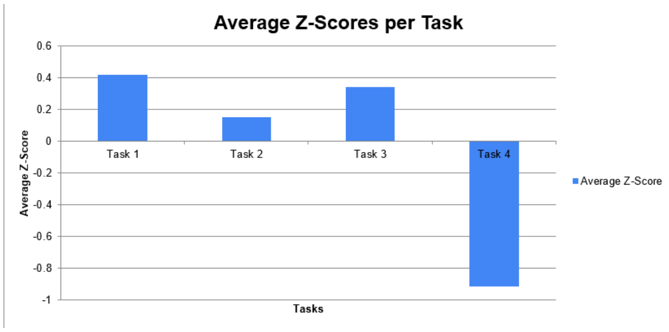


Fig. 1. Comparison of questionnaire responses across the four experimental conditions (Task 1: Natural-Blind, Task 2: Artificial-Blind, Task 3: Natural-Informed, Task 4: Artificial-Informed).

loss, restoring the best weights) and model checkpointing on the highest validation accuracy.

IV. Results

A. Subjective Evaluations

The subjective evaluations obtained from the post-trial questionnaires were normalized into Z-scores to analyze the hedonic attitudes across the four experimental conditions. As illustrated in Fig. 1, the blind tasting conditions yielded positive evaluations for both the natural (Task 1) and artificial (Task 2) preservatives, indicating that the baseline sensory profiles of both stimuli were generally acceptable to the participants.

In the informed conditions, the natural preservative (Task 3) maintained a positive rating consistent with its blind counterpart. Conversely, the explicit labeling of the artificial preservative (Task 4) resulted in a drastic shift to a strongly negative evaluation. This significant divergence indicates that the negative perception of the artificial stimulus in this experiment was primarily driven by the cognitive bias induced by the product label, rather than the physical gustatory input alone.

B. Statistical Analysis

Statistical analysis of the extracted EEG features identified the most significant variations ($p < 0.05$) between the positive- and negative-attitude classes in the frontal gamma and parietal beta bands. Variations in frontal gamma activity suggest distinct cognitive and emotional evaluations underlying the two hedonic states. Concurrently, shifts in parietal beta power indicate differences in somatosensory integration and attention allocation. The spectral and temporal dynamics of these features are detailed in Fig. 2.

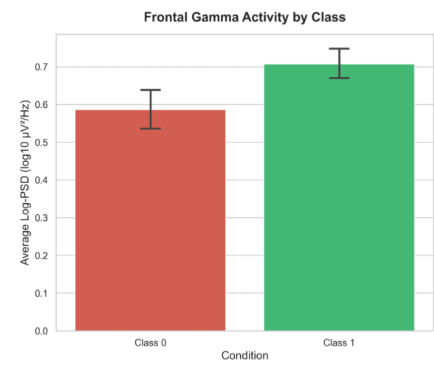
C. Classification Performance

To evaluate the effectiveness of distinguishing between the experimental conditions, four classification models were implemented: Random Forest, XGBoost, SVM, and DNN. A comprehensive performance comparison is presented in Table III. XGBoost achieved the highest performance across all metrics, with an accuracy of 87.50% and an F1-Score of 87.43%. Conversely, the DNN yielded the lowest classification performance at 73.72% accuracy.

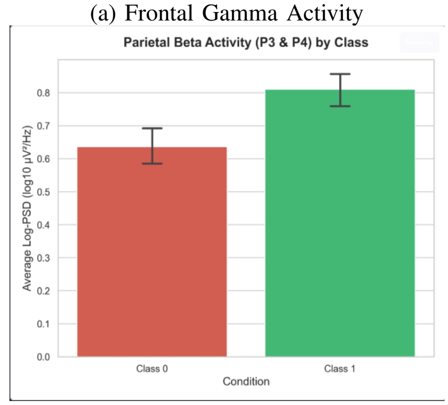
To further analyze the misclassification patterns, confusion matrices for each model were generated. The tree-based classifiers, Random Forest and XGBoost, are shown in Fig. 3. Both models demonstrate strong diagonal concentration, with XGBoost exhibiting fewer off-diagonal errors, consistent with its superior accuracy.

The corresponding confusion matrices for the SVM and DNN models are presented in Fig. 4.The SVM achieves competitive performance relative to the tree-based models, whereas the DNN exhibits more distributed misclassifications, reflecting the challenges of training deep networks on a limited dataset.

Furthermore, the learning dynamics of the DNN were analyzed to observe its convergence behavior. Fig. 5 displays



(a) Frontal Gamma Activity

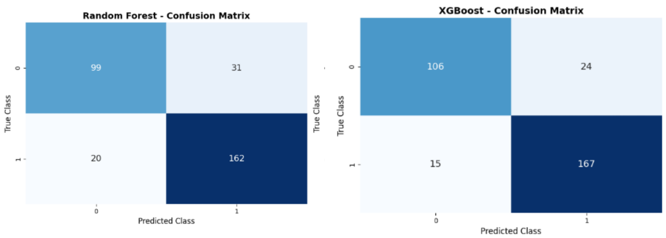


(b) Parietal Beta Activity

Fig. 2. EEG feature analysis graphs comparing Average Log-PSD variations for (a) frontal gamma and (b) parietal beta frequency bands between the positive- and negative-attitude classes.

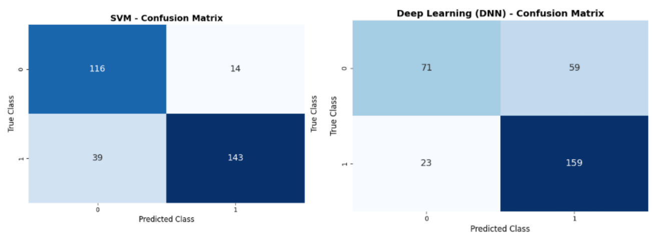
TABLE III
PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
Random Forest	83.65	83.63	83.65	83.53
XGBoost	**87.50**	**87.50**	**87.50**	**87.43**
SVM	83.01	84.31	83.01	83.13
DNN	73.72	74.02	73.72	72.79



(a) Random Forest (b) XGBoost

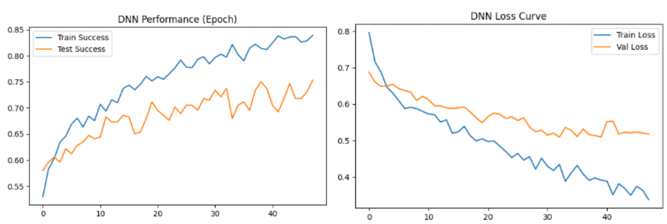
Fig. 3. Confusion matrices for tree-based classifiers.



(a) SVM (b) DNN

Fig. 4. Confusion matrices for SVM and DNN classifiers.

the accuracy and loss curves across training epochs for both the training and validation datasets.



(a) Accuracy (b) Loss

Fig. 5. DNN learning curves showing (a) training and validation accuracy as a function of epoch number and (b) training and validation loss as a function of epoch number. In both plots, the x-axis represents the number of epochs, while the y-axis represents accuracy in (a) and loss in (b).

V. Discussion

This study predicted consumer attitudes toward natural and artificial preservatives by correlating EEG signals with subjective evaluations. Statistical analysis revealed significant variations in frontal gamma and parietal beta bands. Frontal gamma oscillations [5] indicated that prior knowledge actively altered cognitive evaluations, aligning with reported hedonic responses. Simultaneously, parietal beta shifts reflected differences in the basic sensory processing of the chemical stimuli. These results demonstrate that both sensory input and cognitive expectations shape the final hedonic experience.

Classification validated the extracted time-frequency features, with tree-based ensembles outperforming deep learning models. Baseline performances of the SVM (83.01%) and Random Forest (83.65%) align closely with established EEG benchmarks, specifically corroborating the accuracies reported by Karthik et al. [10] and Zheng and Lu [11]. Building on these baselines, XGBoost achieved the highest accuracy (87.50%), confirming the efficacy of gradient boosting in mitigating overfitting within restricted neurophysiological datasets [9].

Conversely, the DNN yielded a lower accuracy (73.72%) due to insufficient data volume for optimal weight convergence. Future research should expand the dataset and implement advanced architectures, such as 1D-CNNs, to bypass manual feature extraction and achieve robust classification across varied hedonic states.

References

[1] J. Shi, J. Xu, X. Liu, et al., "Evaluation of Some Artificial Food Preservatives and Natural Plant Extracts as Antimicrobial Agents for Safety," *Discover Food*, vol. 4, p. 89, 2024.

[2] D. Lăzăroiu, A. Neguriță, C. Grecu, and I. Grecu, "Consumers' Decision-Making Process on Food Additives: Willingness to Buy Food with Natural versus Artificial Additives in Romania," *Sustainability*, vol. 11, no. 24, p. 6953, 2019.

[3] S. Bazzani, M. R. Battisti, and S. A. Santini, "Emotional Responses to Food Products: Physiological and Self-Reported Measures," *Foods*, vol. 14, no. 6, p. 1213, 2023.

[4] D. Perusquía-Hernández, Y. Hirokawa, T. Suzuki, and J. Suzuki, "Biosignal Measurements for Neurophysiological Tests Aimed to Determine New Beverage Responses," *Multimedia Tools and Applications*, vol. 79, pp. 30965–30991, 2020.

[5] J. Keil and D. Senkowski, "Neural Oscillations Orchestrate Multisensory Processing," *The Neuroscientist*, pp. 1–18, 2018.

[6] S. Koelstra, C. Mühl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A Database for Emotion Analysis Using Physiological Signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, 2012.

[7] M. Ciobanu, A. M. Grosu, A. D. Craciun, and D. O. Popa, "The Impact of Artificial and Natural Additives in Meat Products on Neurocognitive Food Perception: A Narrative Review," *Foods*, vol. 13, no. 18, p. 2842, 2024.

[8] Y. Wang, H. Chen, Z. Zhao, and L. Zhang, "EEG-Based Analysis of Neural Responses to Different Sweeteners," *Foods*, vol. 14, no. 14, p. 2460, 2025.

[9] M. S. Khan, N. Salsabil, M. G. R. Alam, M. A. A. Dewan, and M. Z. Uddin, "CNN-XGBoost Fusion-Based Affective State Recognition Using EEG Spectrogram Image Analysis," *Scientific Reports*, vol. 12, p. 14122, 2022.

[10] V. V. Karthik, N. Devarakonda, and P. Yasaswini, "EEG-Based Stress Detection Using Random Forest Algorithm," in *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)*, pp. 1–5, 2024.

[11] W.-L. Zheng and B.-L. Lu, "Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162–175, 2015.

[12] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal Feature Selection and Deep Learning Ensembles Method for Emotion Recognition From Human Brain EEG Sensors," *IEEE Access*, vol. 5, pp. 14797–14806, 2017.

[13] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks," *IEEE Transactions on Affective Computing*, vol. 11, no. 3, pp. 532–541, 2020.

[14] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalography and Clinical Neurophysiology*, vol. 29, no. 3, pp. 306–310, 1970.