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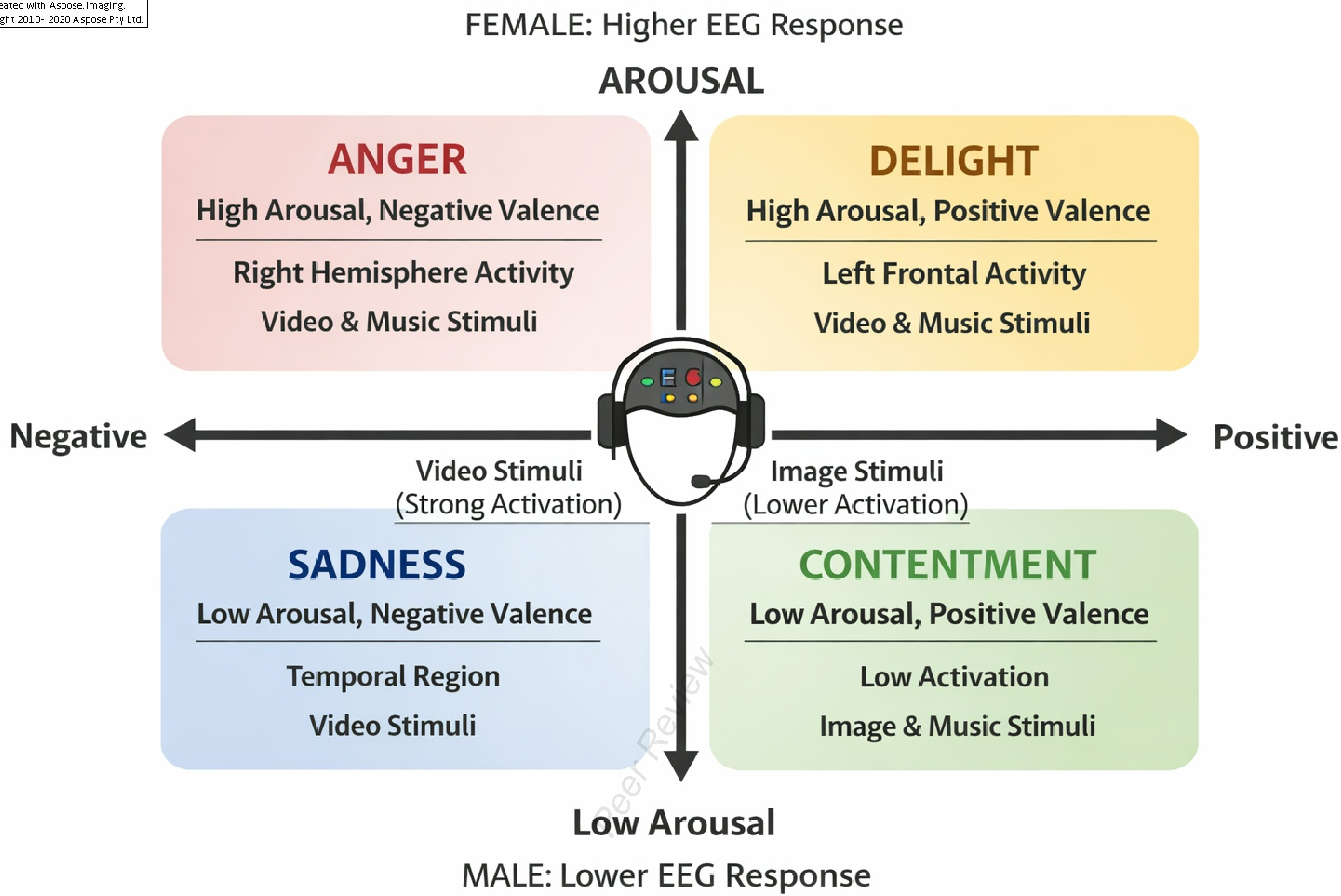
Abstract: Introduction: Emotion recognition using electroencephalography (EEG) has gained significant attention in the fields of affective computing and human–computer interaction due to its ability to capture real-time neural responses. This study aims to analyze EEG signal variations associated with emotional states using a wavelet-based signal processing approach within the arousal–valence framework.
Methods: A prospective observational study was conducted on 48 healthy participants. Emotional states were induced using image, video, and music stimuli categorized under the arousal–valence model. EEG signals were recorded using the standard 10–20 electrode placement system. The acquired signals were pre-processed and analysed using Discrete Wavelet Transform (DWT) to extract time–frequency features, including energy and entropy. Statistical analysis was performed to evaluate hemispheric differences and gender-based variations.
Results: Significant differences in EEG activity were observed between the left and right hemispheres across multiple emotional states ($p < 0.05$), confirming hemispheric asymmetry in emotional processing. Video and music stimuli produced stronger and more distinguishable EEG responses compared to image-based stimuli. Negative emotions demonstrated higher discriminative patterns than positive emotions. Gender-based variations were also observed in EEG responses.
Conclusion: The study demonstrates that wavelet-based EEG feature analysis provides meaningful and discriminative information for emotion recognition. The findings highlight the potential of EEG signals in developing automated emotion recognition systems and contribute to advancements in brain–computer interface (BCI) and affective computing applications.


FEMALE: Higher EEG Response
AROUSAL
ANGER
High Arousal, Negative Valence
Right Hemisphere Activity
Video & Music Stimuli
DELIGHT
High Arousal, Positive Valence
Left Frontal Activity
Video & Music Stimuli
Negative
Positive
Video Stimuli
(Strong Activation)
Image Stimuli
(Lower Activation)
SADNESS
Low Arousal, Negative Valence
Temporal Region
Video Stimuli
CONTENTMENT
Low Arousal, Positive Valence
Low Activation
Image & Music Stimuli
Low Arousal
MALE: Lower EEG Response

ELECTROENCEPHALOGRAPHY CHANGES IN EMOTIONAL RECOGNITION: A SIGNAL PROCESSING APPROACH USING WAVELET FEATURES

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ABSTRACT:

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Keywords: Electroencephalography (EEG), Emotion Recognition, Wavelet Transform, Arousal–Valence Model, Signal Processing, Affective Computing, Brain–Computer Interface (BCI)

INTRODUCTION:

BACKGROUND:

While all animals exhibit certain behaviours, only a subset experiences what we define as emotions. Emotions are instinctive states arising from complex cognitive functions. Despite their importance in daily life, our scientific understanding of human emotions is still limited [1]. Emotions are complex states involving physiological, psychological, and behavioural responses to external stimuli. The basic emotions—happiness, sadness, fear, anger, surprise, and disgust—play a crucial role in daily life, making accurate recognition essential in various fields.

Emotions are regulated by the limbic system, which includes the amygdala, hippocampus, thalamus, and hypothalamus. When triggered, these brain structures activate and initiate an emotional response. EEG-based emotion recognition has potential applications in human–computer interaction, affective computing, and intelligent systems[1,2].

ELECTROENCEPHALOGRAPHY SIGNAL

With emotions crucial in daily life, the demand for automatic emotion recognition has increased alongside human-computer interface growth. Recent research has increasingly focused on using EEG for detecting emotions [2,7]. We aim to enhance EEG-based emotion recognition by pinpointing key brain regions and frequency bands associated with emotions. This research promises significant societal benefits and practical applications.

Originally used in medicine, EEG is now explored for emotion recognition due to advances in digital media [2]. This paper explores recognizing "inner" emotions from EEG signals, which are spontaneous and less camouflaged, as emotional changes produce detectable variations despite controlled expressions. Incorporating EEG-based emotion recognition into intelligent systems can support real-time assessment of emotional states, enabling advancements in human–computer interaction and affective computing applications.
We use the Arousal-Valence model [6] (Figure 1) to map emotions onto a coordinate system, detecting brain activity patterns through EEG.
This provides valuable insights into the link between brain activity and emotions.

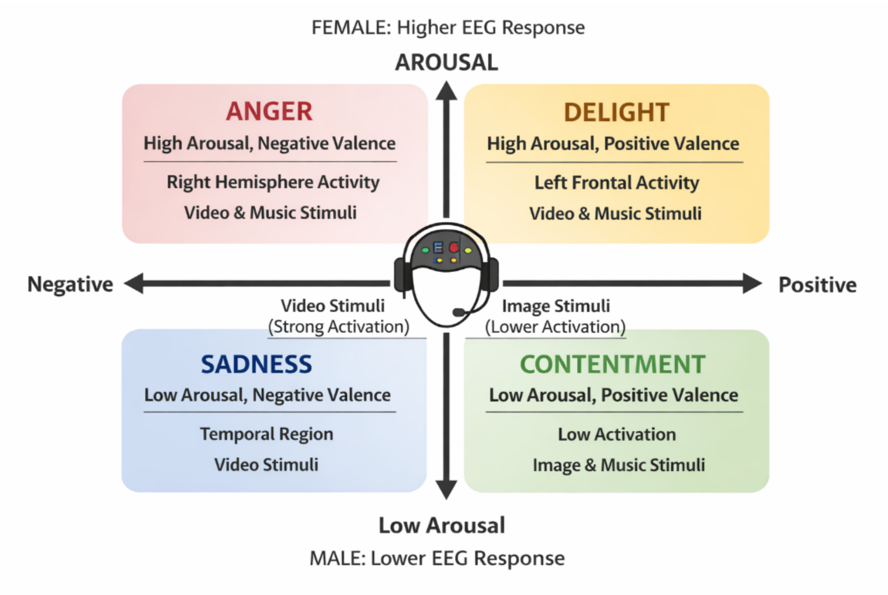

Figure 1: Modified arousal–valence model incorporating stimulus type and gender-based EEG variations

MATERIALS AND METHODS:

1. Study Design and Data Acquisition

This study was conducted as a **prospective observational study** at the EEG laboratory, Department of Neurology, SRIHER, Chennai, between April 2024 and July 2024. A total of **48 healthy participants** (29 males and 19 females), aged above 18 years, were included.
EEG signals were recorded using the **standard 10–20 international electrode placement system**, ensuring uniform spatial coverage of cortical activity. All participants were screened to exclude neurological, psychiatric, or systemic conditions that could influence EEG recordings.

2. Emotional Stimulus Induction

To elicit distinct emotional states, three categories of stimuli were used:

- **Image-based induction:** Standardized images from the IAPS dataset
- **Video-based induction:** Self-designed and DEAP dataset-based video clips
- **Music-based induction:** Emotion-specific auditory stimuli

Each stimulus type was designed to evoke emotions classified under the **arousal–valence model**, namely:

- High arousal–positive valence (delight)

- High arousal–negative valence (anger)
- Low arousal–negative valence (sadness)
- Low arousal–positive valence (content)

3. EEG Signal Acquisition and Preprocessing

EEG signals were recorded across multiple channels and organized using three montage configurations:

- AP bipolar montage
- RL transverse montage
- Average reference montage

Preprocessing steps included:

- Removal of noise and baseline drift
- Elimination of motion and ocular artifacts (as per standard EEG recording protocol)
- Segmentation of EEG signals based on stimulus duration

4. Feature Extraction Using Wavelet Transform

To analyze the non-stationary nature of EEG signals, Discrete Wavelet Transform (DWT) was employed[8].

- A Daubechies wavelet (db4) was used for signal decomposition
- EEG signals were decomposed into multiple frequency bands corresponding to[8,9]:
    - Delta (δ)
    - Theta (θ)
    - Alpha (α)
    - Beta (β)
    - Gamma (γ)

Extracted Features:

From each decomposed signal, the following features were obtained:

- Wavelet Energy – representing signal power distribution
- Entropy – indicating signal complexity
- Statistical measures (mean and variance of coefficients)

These features were used to identify variations in EEG activity corresponding to different emotional states.

5. Statistical and Comparative Analysis

Statistical analysis was performed to evaluate differences in EEG features:

- Descriptive statistics: Mean and standard deviation
- Paired t-test: To compare left and right hemispheric activity
- Independent sample t-test: To compare gender-based differences

Statistical significance was considered at $p < 0.05$.

6. Analytical Framework for Emotion Recognition

The overall analytical workflow of the study can be summarized as:
EEG Signal Acquisition → Preprocessing → Wavelet Feature Extraction → Statistical Analysis → Emotion Classification (Arousal–Valence Model)

This framework highlights the potential of EEG signals as a feature-driven input for automated emotion recognition systems.

RESULTS:

The descriptive statistical analysis demonstrated notable gender-based differences in EEG activity across emotional states. Female participants exhibited comparatively higher mean EEG values across both hemispheres for emotions such as delight, anger, and sadness, indicating enhanced emotional responsiveness. Male participants showed relatively lower variability, suggesting more stable neural responses. Statistically significant differences ($p < 0.05$) were observed for most emotional categories, except for contentment, where no significant variation was noted. These findings indicate that emotional processing may differ between genders, with females demonstrating greater neural activation in response to emotional stimuli.

Table 1: Gender-wise EEG Activity (VIDEO Stimuli – Sadness & Content

Electrode	Female (Mean ± SD)	Male (Mean ± SD)
Sadness – Fp1	16.86 ± 10.82	5.25 ± 5.09
Sadness – Fp2	23.01 ± 16.93	7.43 ± 4.50
Sadness – F3	12.86 ± 10.31	5.36 ± 6.74
Sadness – F4	16.50 ± 11.66	7.28 ± 6.50
Sadness – T6	19.96 ± 9.94	9.77 ± 6.64
Content – Fp1	23.85 ± 13.97	7.97 ± 4.77
Content – F3	18.80 ± 12.82	6.66 ± 5.50
Content – T3	21.08 ± 11.71	7.91 ± 5.15
Content – T5	22.24 ± 19.35	9.43 ± 5.72

Table 2: Gender-wise EEG Activity (IMAGE Stimuli – Delight & Anger)

Electrode	Female (Mean ± SD)	Male (Mean ± SD)
Delight – Fp1	25.96 ± 23.30	6.24 ± 4.30
Delight – F3	22.39 ± 16.40	6.48 ± 5.44
Delight – F7	29.15 ± 22.08	6.80 ± 4.60
Delight – T3	21.21 ± 17.40	7.79 ± 6.40
Anger – Fp1	25.08 ± 16.33	2.83 ± 2.50
Anger – F3	21.30 ± 15.84	2.56 ± 1.94
Anger – F7	26.94 ± 22.13	3.18 ± 2.68
Anger – T6	24.23 ± 26.35	9.74 ± 10.65

Table 3: Gender-wise EEG Activity (MUSIC Stimuli – Content & Sadness)

Electrode	Female (Mean ± SD)	Male (Mean ± SD)
Content – Fp1	29.68 ± 24.52	9.21 ± 9.86
Content – F3	22.52 ± 16.90	9.48 ± 10.00
Content – T3	17.48 ± 15.35	14.11 ± 19.37
Sadness – Fp1	13.97 ± 7.23	3.13 ± 2.03
Sadness – F3	12.28 ± 8.14	3.89 ± 3.89
Sadness – T4	15.80 ± 8.72	8.29 ± 6.09

Table 4: OVERALL SUMMARY

Emotion	Female EEG Activity	Male EEG Activity	Interpretation
Delight	High	Moderate	Strong emotional activation in females
Anger	Very High	Low	Marked gender difference
Sadness	Moderate–High	Low	Higher emotional sensitivity in females
Content	Moderate	Low	Stable but lower male response

Summary of Key Findings

The analysis of EEG signals demonstrated consistently higher mean values in female participants across all emotional stimuli, including video, image, and music. The differences were particularly pronounced in high-arousal emotions such as anger and delight. Male participants exhibited comparatively lower and more stable EEG responses. These findings suggest enhanced emotional reactivity and neural activation in females, especially in frontal and temporal regions.

DISCUSSION:

In the present study, EEG signal variations were analyzed to understand emotional recognition across different stimuli. EEG-based emotion recognition has been widely explored as a reliable method for assessing neural responses associated with emotional states [1,3] . The findings of this study demonstrate that video and music stimuli produced stronger EEG responses compared to image-based stimuli. This aligns with previous research in affective computing and human–computer interaction, where dynamic stimuli have been shown to elicit higher emotional engagement [2,11] .

Additionally, significant gender differences were observed, with female participants showing higher EEG activity across multiple emotional states. This may be attributed to differences in neural processing and emotional sensitivity between genders.

From a neurophysiological perspective, emotional processing involves complex interactions between cortical and subcortical brain regions, including mechanisms related to emotional appraisal and response generation[10].The proposed modified arousal–valence model further enhances the understanding of emotional mapping by incorporating stimulus-specific and gender-based EEG variations. This provides a more comprehensive framework for emotion recognition using EEG signals. The findings of this study have potential applications in brain–computer interfaces, affective computing, and intelligent systems, where real-time emotion recognition can improve human–machine interaction.

1. EEG as a Reliable Signal for Emotion Recognition

The findings indicate that variations in EEG activity across hemispheres are strongly associated with emotional states. Significant differences observed between the left and right hemispheres confirm that **EEG signals can effectively capture neural correlates of emotional processing**.

From a signal processing perspective, the extracted wavelet features successfully represented the **time–frequency characteristics** of EEG signals, which are essential for analyzing non-stationary brain activity. This highlights the suitability of **wavelet transform-based methods** for EEG-driven affective computing applications.

2. Hemispheric Asymmetry and Feature Discrimination

The observed dominance of the **left hemisphere for positive emotions** and the **right hemisphere for negative emotions** aligns with established neurophysiological theories of emotional lateralization. More importantly, from an engineering standpoint, this asymmetry provides a **useful feature space for classification**, where lateralized EEG activity can serve as a key input variable for emotion detection algorithms.
The strong statistical significance across multiple emotional states suggests that these features have **high discriminative potential**, which is critical for designing robust classification models.

3. Effectiveness of Stimulus Modalities

Among the different stimulus types, **video and music-based stimuli** elicited stronger and more consistent EEG responses compared to image-based stimuli. This indicates that **dynamic and multimodal stimuli enhance emotional activation**, resulting in more distinguishable EEG patterns.
This observation has direct implications for system design, suggesting that **emotion recognition systems incorporating multimodal inputs** may achieve higher accuracy compared to those relying solely on static visual stimuli.

4. Gender-Based Variations in EEG Signals

The study identified statistically significant differences in EEG responses between male and female participants for most emotional states. These findings suggest that **individual variability, including gender differences**, plays a role in emotional processing.
From a computational perspective, this highlights the importance of incorporating **personalized or adaptive models** in EEG-based emotion recognition systems to improve classification performance and generalizability.

5. Implications for Affective Computing and BCI Systems

The results of this study contribute to the growing field of **affective computing**, where physiological signals are used to detect and interpret human emotions.

The ability to extract meaningful features from EEG signals and associate them with emotional states demonstrates the feasibility of developing:

- **Real-time emotion recognition systems**
- **Brain–computer interface (BCI) applications**
- **Human–computer interaction (HCI) systems with emotional awareness**

The proposed analytical framework can serve as a foundation for integrating EEG-based emotion detection into applications such as **adaptive user interfaces, mental state monitoring systems, and intelligent assistive technologies**.

6. Comparison with Existing Studies

The findings of this study are consistent with previous research demonstrating the effectiveness of EEG signals in emotion recognition and the presence of hemispheric asymmetry. Additionally, the use of wavelet-based feature extraction aligns with current trends in EEG signal processing, where time–frequency analysis plays a crucial role in improving feature representation. Unlike studies that rely heavily on complex machine learning models, this study emphasizes the **importance of feature-level analysis**, demonstrating that even statistical approaches can reveal meaningful patterns in EEG data. This provides a **computationally efficient foundation** for future model development.

7. Limitations and Future Scope

Despite promising results, this study has certain limitations. The sample size is relatively small, and the analysis is primarily based on statistical comparisons rather than full-scale classification models.

Future work can focus on:

- Implementing **machine learning algorithms** (e.g., SVM, KNN, deep learning) for automated classification
- Expanding datasets to include **diverse populations**
- Integrating **multimodal physiological signals** (e.g., ECG, GSR)
- Developing **real-time emotion recognition systems**

Such advancements can significantly enhance the performance and applicability of EEG-based emotion recognition technologies.

CONCLUSION:

The present study demonstrates significant gender differences in EEG responses to emotional stimuli, with females showing higher neural activation across multiple emotional states. These findings contribute to the understanding of emotional processing and may have implications in neuroscience research, mental health assessment, and human-computer interaction systems.

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