

## ENT-DASM and ENT-RASM: Novel Energy-Entropy Asymmetry Features for Enhanced EEG-Based Emotion Classification

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**Abstract.** Electroencephalography (EEG) based emotion recognition is crucial for advancing brain-computer interfaces and affective computing. However, existing feature extraction methods often fail to capture the complex emotional information in EEG signals. This study introduces novel energy-entropy based features, ENT-DASM and ENT-RASM, which combine differential and rational asymmetry measures with energy and entropy calculations. We evaluate these features on the DEAP dataset using various machine learning classifiers across different brain regions and frequency bands. Our method achieves a maximum accuracy of 83.24% for the High Arousal Low Valence (HALV) emotional state using Support Vector Machines, outperforming existing approaches by 1-2%. The proposed features demonstrate consistent performance across all frequency bands, particularly excelling in beta and gamma ranges. This study contributes to the field by providing more robust and informative features for EEG-based emotion classification, potentially improving applications in mental health monitoring and adaptive user interfaces.

**Keywords:** Emotional Analysis, EEG, Machine Learning

## 1. Introduction

Emotion has a significant role in human communication, decision, and interaction. It is through emotions that a human expresses their internal and external behavior. Human psychology, education, and medicine have benefitted from brain-computer interaction (BCI) (Chang et al., 2022) and many societal applications. Therefore, emotional recognition is getting more attention and is becoming very important today. There are many ways to identify emotions, specifically from physiological signals such as ECG, EEG, EMG, GSR, and respiration rate. Researchers have paid attention to Electroencephalogram (EEG) (Casson, 2019) among these signals due to its low cost and portable characteristics. EEG signals from the brain have brought a great scope to the human-computer interaction field, and diverse applications, especially in the field of cognition and neuroscience, have played a vital role in understanding emotions. The meticulous examination of brain activity in neuroscience is contributing to understanding the complexities of emotional experiences. Electroencephalogram (EEG) has become an indispensable tool in neuroscience since it has the capability to provide real-time insights into diverse neural problems like mental disorders. The contributions of EEG in neuroscience, like cognitive processes, understanding brain development, assessing brain health, and diagnosing neurological disorders, are invaluable for elucidating. While EEG-based emotion recognition has shown promise, current feature extraction methods often struggle to capture the complex emotional information in EEG signals.

Different feature extractions are available based on the time, frequency, and spatial domains; however, researchers find identifying which features can benefit from emotional classification is challenging. A recent review by (Kim et al., 2022) found that applying a CNN-based deep learning method on EEG data for emotion recognition with the help of frequency bands of alpha, beta, and low and high gamma could attain the highest average accuracy at 75.4%. The feature fusion techniques for fully connected layers and SVM achieve excellent performance and average emotion recognition accuracies of 80.52% and 75.22% in the valence and arousal classification (Gao et al., 2022). Recent studies found that the existing method achieves an average accuracy of 70 – 80% in multi-class emotion classification, so there arises the need to identify the best feature extraction techniques. The main objective of the current study is to introduce the best feature extraction technique and to address the gap by proposing novel energy-entropy-based features that capture both the intensity and randomness of EEG signals across different brain regions. It can be represented as EDASM, ERASM, ENT-DASM, and ENT-RASM. With the help of this technique, the features are extracted and experimented on in the proposed brain region. The existing brain regions are frontal, parietal, occipital, and temporal (Casillo et al., 2020). This study used the proposed six brain regions for the experiment to identify which parts of the brain are more prone to emotional inclinations. The main outline of the paper is to extract the features from EEG signals with the help of a proposed formula and to experiment on different brain regions; so, to begin the process, the EEG signals are distributed to the leading four frequency bands: alpha, theta, beta, and gamma with specific frequency range. In the psychological field, emotions are being scaled with the help of arousal and valence parameters. The intensity of emotions is valued by arousal, and pleasantness is valued by valence. According to Russal's model Fig 1, there are two dimensions of emotions: arousal and valence.

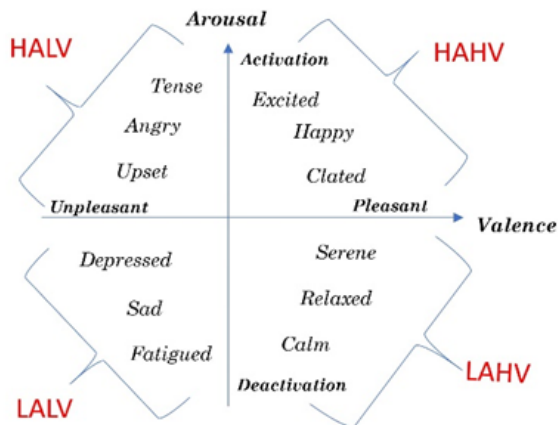


Fig 1. Russel's circumplex model

It is divided into categories like High Arousal and High Valence, High Arousal and Low Valence, High Valence and Low Arousal, and Low Arousal and Low Valence (Koelstra et al., n.d.). Different features are extracted from EEG signals like PSD (Power Spectral Density), Energy and Entropy of DASM, and RASM. The research focused on removing the features with the help of the newly formed formula, which is used for the different classification methods and on 14,28,32 channels.

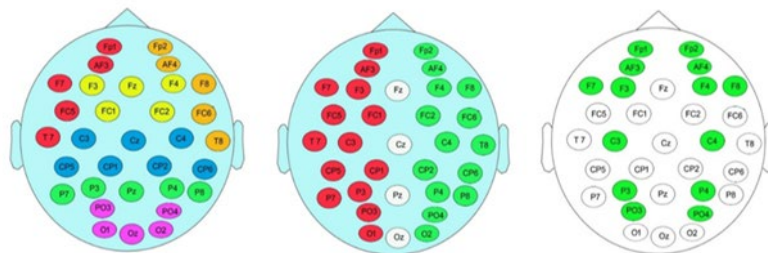


Fig 2. Distribution of channels: a)32 channels b)28 channels c)14 channels

Each phase's visual representation is vividly portrayed in Fig 2. elucidating the selected channels and their respective brain regions. The classification models used are SVM, KNN, MLP, Logistic Regression, Random Forest, and Decision Tree. The accuracy rate increased by 2% with the SVM classifier on the proposed feature extraction method in connection with the formulation of energy and entropy formulas to generate EDASM, ERASM, ENT-DASM, and ENT-RASM.

The key objectives of the paper are:

- 1)The newly formed formula from energy and entropy on DASM and RASM features has increased classification efficiency.
- 2)The features generated from the formula were well performed on the frontal-parietal combination of the brain region.
- 3)Among the three algorithms, SVM has gained the same accuracy on four frequency bands

The proposed ENT-DASM and ENT-RASM are significantly helpful for feature extraction to improve efficiency and accuracy simultaneously. Moreover, the proposed method does not require complicated calculations to get features. After learning the different channel combinations and the proposed brain regions, these features are fed into the emotional classification system. The proposed

method's evaluation and effectiveness are experimented on the benchmark DEAP dataset. The proposed method occasionally improved the accuracy of emotion recognition with the help of different combinations of channels. The main structure of this paper is as follows: Section 2 provides a brief overview of the existing literature of the current study; Section 3 describes the method and materials, and the subsections explain descriptions of data and pre-processing, feature extraction, and underlying methodology employed and experiment carried out, the results and discussion is presented in Section 4. Finally, the conclusion is subsequently followed in Section 5.

## 2. Related Works

EEG data and feature extractions have become real problems due to the low accuracy of emotion identification. So, many studies focused on feature extraction techniques from different domains like time, frequency, spatial and energy, entropy and power spectral density, and difference and division between two symmetric electrodes.

### 2.1 Time Domain

In the time domain, features are extracted based on the temporal patterns presented in the EEG signals and calculated based on the decomposed signals. There are many time domain features available, among them statistical features, event-related features, Hjorth features, and fractional features are main. (Tan et al., 2021) explained mainly on the time domain features, which are extracted from the spikes of the neural activity based on the times, reflecting the person's emotional states. It also uses spatiotemporal analysis in connection with the spatial distribution of signals over different brain regions. The basic statistical features like standard deviation, mean, and normalized first and 2nd differences are also used as the study's features. (Namazi et al., 2020) focused on the fraction pattern identified in the EEG signals and analyzed the variations of the brain with the help of fractional dynamics. The study aimed to focus on identifying epilepsy. The feature extracted in (Y. Wang et al., 2021) primarily focuses on the temporal dynamics of EEG signals to facilitate emotion recognition. The emphasis on spatial-temporal features and second-order statistics further supports this. The prototype-based learning mechanism is used to extract time domain features. It also focuses on how features change over time.

In a novel approach, EEG signals from 14 channels of 5 subjects aged 12 to 14 were collected, pre-processed, and subjected to feature extraction using Hjorth parameters (Mehmood & Lee, 2015). PCA is employed for feature reduction, with SVM achieving high accuracy for arousal, valence, dominance, and liking labels. Hybrid Adaptive Filtering applied Genetic Algorithms to Empirical Mode Decomposition, resulting in a new EEG signal representation, HAF-HOC, facilitating emotion classification for six emotions from 16 healthy participants (Petranonakis & Hadjileontiadis, 2010). Power features excelled, with DE RASM and DASM proving effective over frequency domain methods with relief and Bhattacharyya distance (Byun et al., 2017). The time domain features like statistical (Sohaib et al., 2013)(Matlovič, 2016) have been used mainly in the above papers where it could not perform well as compared to the proposed method.

(Frantzidis et al., 2010) identified ERPs related to emotions as challenging for online applications, and ERP amplitude and latency were utilized as features. (Kroupi et al., 2011) capture the self-similarities in EEG signals extracted from the normalized 1st difference in the normalized length density. Hjorth (Romand, 2004) used time-series features for EEG studies, including activity, mobility, complexity, and standard deviation. The activity is defined as the squared standard deviation, and the NSI is calculated by the standard deviation of all means, where higher values indicate less consistency of local averages. The measures of indexes are done by examining variations in the local average over time and the complexity, and the average is taken over each segment of the normalized signal, divided into small segments. The paper extracts statistical features like mean, SD, and first and second differences from real-time EEG signals. (Sharma & Bhattacharyya, 2021) features, specifically

Information Potential (IP) and Centered Correntropy (CEC), are derived from the reconstructed components (RCs) of the physiological signals (EEG and ECG) after applying the Sliding Mode Singular Spectrum Analysis (SM-SSA) method of time domain is designed to analyze nonstationary signals in different multi-resolution levels for emotional analysis approach. (Kamble & Sengupta, 2022) emphasizes frequency domain techniques, particularly through discrete wavelet transform (DWT) and empirical mode decomposition (EMD). It decomposed into different frequency bands: theta, alpha, beta, and gamma. Its separation allows for a more detailed analysis of the brain's oscillatory activity associated with different emotions. It highlights 31 statistical features extracted from the intrinsic mode functions (IMFs) of the band-separated EEG signals.

## 2.2 Frequency Domain

Among the power features, the most widely used feature is Power Spectral Density (PSD) (Jenke et al., 2014) which measures the power of a signal as a function of frequency. PSD is inherently a frequency domain feature on EEG signals across the common frequency bands such as delta, theta, alpha, beta, and gamma, and their ranges are 0-4, 4-8, 8-13, and 13-50, respectively. The power bands are extracted by the most common method of FFT (Murugappan, 2013). The alternative method to find the PSD is the Short Time Fourier Transform (STFT) (Zheng et al., 2019) which analyzes the signal in the frequency domain over short time intervals. This further emphasizes the focus on frequency domain analysis in the feature extraction process employed by bi-spectra and bi-coherence magnitudes within this category. To analyze these, spectrograms of EEG channels were plotted using FFT (Nie et al., 2011). (Y. J. Liu et al., 2018) proposed an event-related method to extract time-frequency features from EEG signals for which desynchronization (ERD) and synchronization (ERS) were performed. The power of certain frequency bands corresponds to event-related activity changes based on ERD/ERS theory.

Advanced computational models aid in understanding brain responses for emotion recognition, supported by studies correlating EEG signals with emotions. Gamma band features such as ASM, DE, DASM, and RASM show superior accuracy for emotion classification using SVM and KNN (Kimmatkar & Babu, 2018) Wavelet transform combined multichannel signals and CNN/RNN extracted features focusing on arousal and valence (Yang et al., 2018). The study collected EEG from 26 subjects, applying 5-fold cross-validation with KNN on eight channels, categorizing features based on subjects' responses to a questionnaire, including arousal and valence (Khosrowabadi et al., 2010). The EEG signals are converted into EEG rhythms by the pre-processing method of Continuous Wavelet Transform (CWT) and Wavelet Transform (WT) method and, with the help of CNN models, extracted the features. SVM acted as the classifier to classify arousal and valence (Demir et al., 2021). While frequency domain features like PSD have been widely used (Alsolamy & Fattouh, 2016) (S. Liu et al., 2016) (Stikic et al., 2014) they often fail to capture the temporal dynamics of emotional states. Our proposed ENT-DASM and ENT-RASM features aim to address this limitation by incorporating energy and entropy information across different brain regions.

## 2.3 Time and Frequency

For emotion recognition from EEG signals, power spectral density (PSD), spectral entropy, and statistical features are well-known features, whereas time-frequency features also hold another role in identifying emotions. To extract the time-frequency features is the method of segmenting signals into different time-frequency bands with the help of a wavelet transform, and it also examines the time-frequency space locally using a variable 'time-frequency' window. The original signal can be reconstructed from the decomposed wavelet transform (WT) coefficients. According to (Murugappan et al., 2010) the EEG signal decomposed into three frequency bands (alpha, beta, and gamma) and extracted statistical features based on energy features like absolute logarithmic recouring energy efficiency (ALREE). recouring energy efficiency (REE), and logarithmic recouring energy

efficiency (LREE). Recently, (Taran & Bajaj, 2019) examined the tunable-Q wavelet transform (TQWT) widely used for feature extraction in biomedical signal processing. The properties of the sub-bands decomposed by TQWT are activity, clearance factor, range, and mean based on time-frequency domain features.

## **2.4 Hybrid Features**

(Pane et al., 2019) uses various feature extraction techniques like the hybrid approach. EEG signals are analyzed based on their amplitude variations over time in the time domain. In the frequency domain, features are extracted by analyzing the frequency components of the EEG signals with the help of Fourier transform techniques. In connection with the Wavelet Domain, EEG signals at different frequency bands and time scales are being analyzed, providing a more detailed representation of the signal characteristics. Although many features extracted energy-entropy from the wavelet domain, it was highlighted as particularly important for EEG emotion recognition. This feature helps quantify the complexity and variability of the EEG signals, which can indicate different emotional states. (Yin et al., 2020) emphasizes the importance of evaluating the similarity of density functions between pairs of subjects. This evaluation helps in describing the inter-individual consistency of the EEG features, which is vital for selecting robust features across different individuals. The derived consistency from the probability density evaluations leads to identifying locally robust EEG features, which are considered important as they are examined based on the margin loss between different emotional states. (Zhou et al., 2021) study encompasses a variety of time-domain, frequency-domain, wavelet transform, statistical features, and the innovative application of transfer learning and echo state networks to enhance the recognition process. (Pandey & Seeja, 2022) contribute to the effectiveness of the emotion recognition system, by enabling it to operate independently of individual subject characteristics by extracting features combining both traditional statistical methods and deep learning approaches and these comprehensive feature set is crucial for accurately identifying emotions from EEG signals. (Liang et al., 2019) encompass a variety of features like time-domain, frequency-domain, wavelet, entropy, connectivity between different brain regions, and nonlinear dynamics measures that are being extracted and human emotions decoded from EEG data.

(Gao et al., 2020) utilizes features from the frequency domain, specifically through the power spectrum analysis. This method examines how the power of EEG signals is distributed across different frequency bands. It operates on a multi-resolution analysis that can be considered a hybrid approach, capturing both time and frequency information. However, it is primarily focused on the frequency characteristics of the EEG signals, making it more aligned with frequency domain analysis. This frequency domain approach allows researchers to identify specific patterns associated with emotions like happiness, sadness, and neutrality. (Garg et al., 2022) model's ability to effectively classify music mood and correlate it with human emotions. The combination of audio and physiological features includes musical, physiological, statistical, nonlinear, and audio and lyrical features. (R. Li et al., 2022) combined with diverse features like statistical, frequency, wavelet transform, entropy measures, nonlinear dynamics features, and temporal features, these are more effective for practical applications in human-computer interaction and mental health. The integration of these multiple feature types permits a comprehensive representation of the emotional state, enhancing the overall performance of the recognition system.

The survey concludes that integrating features from all domains—time, frequency, and spatiotemporal—yields the most notable results in emotion recognition. Our proposed combined features ENT-DASM and ENT-RASM features also aim to address this limitation by incorporating energy and entropy information across different brain regions and it effectively contributed to the

identify and enhance the emotional accuracy level.

### 3. Methods And Materials

This section provides a comprehensive overview of proposed brain regions and DEAP datasets, with procedures for pre-processing. Followed by a detailed introduction to the proposed formula for feature extraction techniques. Lastly, elucidates the results of different machine learning models and the highest result attained by the proposed brain region. Fig 3 illustrates the process of the proposed framework.

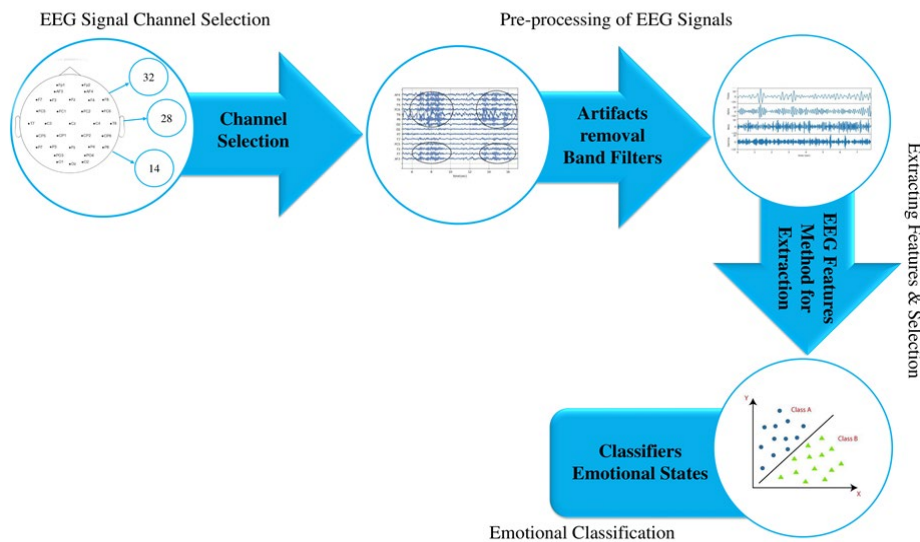


Fig 3: Diagram of proposed method

The methodology, including the brain's proposed intricate structure, is segmented into six distinct regions: left, right, occipital, frontal, parietal, and central. Within the left region, electrodes are strategically placed in the inner left sector of the brain, and one channel extends into the temporal lobe. The right region, encompassing four proper channels and one temporal signal, forms another segment. The frontal region comprises five channels, paralleled by an equivalent number in the parietal region. The central domain boasts seven channels strategically positioned at the core of the cerebral architecture.

Table 1. Different proposed brain regions

Brain Region	Channel name
Frontal	F3, FC1, Fz, F4, FC2
Occipital	O1, Oz, O2, PO3, PO4
Central	CP5, CP1, Cz, C4, C3, CP6, CP2
Parietal	P3, P7, Pz, P4, P8
Right	Fp2, AF4, F8, FC6, T8
Left	Fp1, AF3, F7, FC5, T7

The parietal lobe intricately manages sensory perceptions, while the temporal lobe, in turn, oversees instincts related to hunger, thirst, and facial recognition. The occipital lobe, responsible for processing visual information, oversees the recognition of colours, size, depth, shape, and distance. According to the suggested methodology, the brain's complex structure is divided into six separate areas. The proposed brain regions in Table 1 were selected based on previous neuroimaging studies (Jeong et al., 2023) identifying these areas as crucial for emotion processing.

### 3.1 Data Description and Pre-Processing

Emotion discernment, meticulously analyzed through the lens of DEAP datasets (Koelstra et al., n.d.) unveils a dynamic exploration into the realm of emotions. This multimodal dataset carefully combines EEG signals from a cohort of thirty-two individuals with peripheral physiological variables. The experimental setup involved subjects immersing themselves in a series of 40 music videos, with each individual subjected to 40 trials.

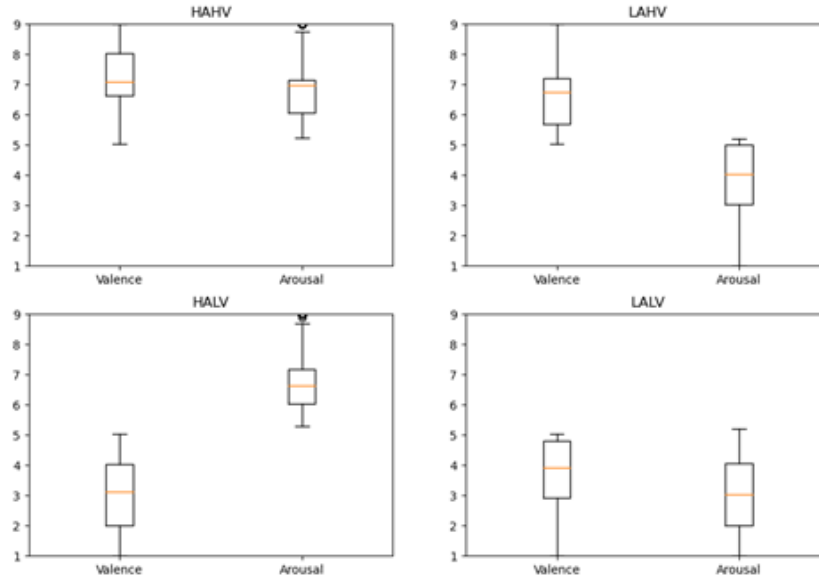


Fig 4. Box plot representation of 4 classes (HAHV, HALV, LAHV, LALV)

Participants, 16 men and 16 women with an average age of 26.9, meticulously rated the videos on a scale of 1 to 9, contributing to a rich metadata repository. Before signal collection, subjects underwent trial experiments to acclimate to electronic equipment and induce a relaxed state. EEG signals were recorded from 32 electrode caps. The metadata, a trove of user-specific information, underwent pre-processing and was divided into four distinct classes—HAHV, HALV, LAHV, and LALV.

Table 2. Data Description of Datasets

Subjects	No of Channels	The trial for each subject	Data/Labels
32	40	40	8064(data)
32	40	40	4(labels)

The box plot representation is vividly depicted in Fig 4. The database amalgamation also features online and physiological ratings, with subjects providing feedback across five dimensions: arousal, valence, dominance, liking, and familiarity. Utilizing Russel's 2D model (Russell, 1980) emotions were categorized into quadrants—HAHV (High Valence, High Arousal), LALV (Low Valence, Low Arousal), LAHV (Low Arousal, High Valence), HALV (High Arousal, Low Valence). Recordings took place in two different locations, Geneva and Twente, capturing EEG signals and facial expressions. The original .bdf file encompassed EEG and peripheral signals, with eight non-EEG signals utilized, including hEOG, vEOG, zEMG, tEMG, GSR, Respiration belt, Plethysmograph, and Temperature (Koelstra et al., n.d.) With each signal boasting 198,029 rows and 49 columns, the DEAP datasets provide researchers with pre-processed Python and MATLAB files, forming a foundational aspect elucidated in the subsequent section of this study. Table 2 describes information about the dataset of pre-processed Python files. The pre-processing steps involved separating the

EEG signals from non-EEG signals and making the dimensions of datasets (32,40,32,8064). The 32 is the participants, the 40 is the trial taken for each participant, the 32 is the EEG channels selected for the feature extraction, and the 8064 is the data collected. For better performance on the data, 32 subjects' trials are combined, and the dimensions of the datasets are (1280,32,8064). 32\*40 is 1280. These pre-processed data are used for feature extraction, which will be explained in consecutive subheadings.

### 3.2 Feature Extraction

The current study embarked upon in the investigation for feature extraction involves the meticulous decomposition of pre-processed EEG signals into distinct frequency bands using the potent Welch Method. This method intricately generates features such as Power Spectral Density (PSD) (X. W. Wang et al., 2014) and corresponding frequency values. The fundamental frequency bands employed for PSD computation encompass  $\alpha$ ,  $\beta$ ,  $\gamma$ , and  $\delta$ , delineated by specific frequency ranges of 4-8Hz, 9-13Hz, 14-30Hz, and 30-64Hz, respectively (Kumar & Bhuvanewari, 2012). Across each channel, PSD computation unfolds, furnishing invaluable insights into signal patterns, vividly portrayed in Fig 5. The X-axis unfurls the frequency band for each channel, while the Y-axis articulates the Power Spectral Density, measured in watts per hertz (W/Hz). Situated in the upper-right corner of the image, topographic maps elucidate the precise electrode positions of EEG signals across the brain. The dynamic color variations in Fig 5 encapsulate the nuanced analysis of each signal.

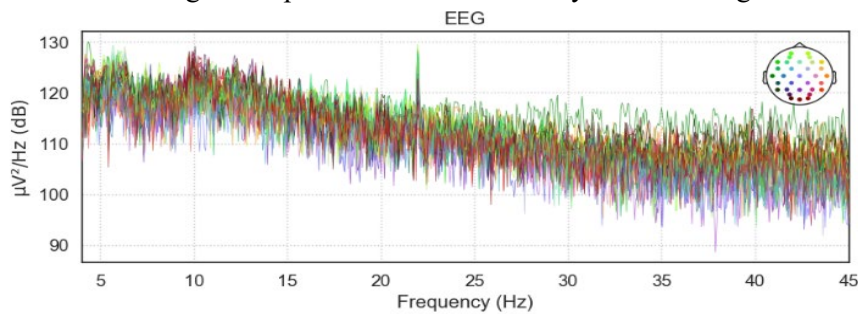


Fig 5. Power Spectral Density of EEG signal

The research aims to extract features beyond PSD, and diverse features extracted from signals encompass the pivotal domains of energy and entropy. Energy (Yang et al., 2018) is meticulously computed through the defined equation, and entropy (Wu et al., 2017) is quantified across distinct brain regions, as outlined in Table 1. The pioneering endeavor of this study extends to discerning distinct features, including E-DASM (Energy Difference Asymmetry), E-RASM (Energy Rational Asymmetry), ENT-DASM (Entropy Difference Asymmetry), and ENT-RASM (Entropy Rational Asymmetry).

Emotions are associated with the left and right hemispheres between lateralization and the asymmetry features. The asymmetry indexes calculated by difference and division are called asymmetry of 14 electrode pairs. The feature extraction is calculated where  $i \in [1, \text{no of channels}]$   $X_{\text{Left}}$ ,  $X_{\text{Right}}$ , and  $i$ th symmetric electrode pairs. The differential asymmetry (DASM) and rational asymmetry (RASM) are the differences and divisions between the energy and entropy features of 14 pairs of asymmetry electrodes. The concatenation of DASM and RASM features of asymmetry. The proposed brain regions of spectral difference are the frontal and occipital brain regions. The total electrodes used in the study are 32 (Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Fp2, AF4, F4, F8, FC6, FC2, C4, T8, CP6, CP2, P4, P8, PO4, O2) whereas the study focused on six brain regions in Phase I. The difference and division between the energy and entropy features of 28 channels are just divided into left and right hemispheres (Fp1- Fp2, AF3- Fp2, F3- F4, F7- F8, FC5- FC6, FC1- FC2, C3- C4, T7- T8, CP5 - CP6, CP1- CP2, P3 -P4, P7-P8, PO3-PO4, O1-O2) in Phase II. The third phase III has separate channels (Fp1- Fp2, AF3 - AF4, F3-F4, F7- F8, C3- C4, P3- P4, PO3- PO4). The

calculation of EDASM is the energy features of DASM of 32,28,14 channels. The energy is the power of the signals, whereas the entropy always finds a combination of two parts of the signals to predict. In our case, EEG signals have pairs of electrodes. The reason for using ENT-DASM is that DASM can obtain the index of asymmetry values, and the energy and entropy can be calculated based on the formula. The pair values are collected and used based on probability. Since feature extraction is based on asymmetry features, entropy and energy are used in the new formulation to extract the features. The equations are explained below.

$$Energy = \sum_{i=1}^n X[i, j]^2 \quad (1)$$

Equation(1) is calculated for all six brain regions by summing up all the squared magnitudes of the signal samples from  $i = 1$  to  $n$ .

$$Entropy = - \sum (X[i, j]^2 \log(X[i, j])^2) \quad (2)$$

The Entropy equation measures the randomness of the signal. It also measures the uncertainty or information content associated with a probability distribution

EDASM (Energy Difference Asymmetry)

$$E(DASM) = E(X_{left}) - E(X_{right}) \quad (3)$$

ERASM (Energy Rational Asymmetry)

$$E(RASM) = \frac{E(X_{left})}{E(X_{right})} \quad (4)$$

The application of Equations (3) and (4) unveils the computation of EDASM and ERASM, systematically applied to both left and right regions of the brain for 28 channels. These equations are further deployed across diverse brain regions, such as frontal & occipital and frontal & parietal of proposed brain regions. Additionally, Equation (2) orchestrates the calculation of entropy across channels, encompassing all proposed combinations of brain regions elucidated in this study. Features extracted from the central region of the brain encompass PSD, energy, and entropy, as empirical studies underscore the central region's paramount role in eliciting emotional responses. Our novel features, ENT-DASM and ENT-RASM, combine energy and entropy measures to capture the intensity and complexity of EEG signals in these regions.

## 4. Result And Discussion

The methodology's subtle features are divided into four main classes: HAHV, HALV, LAHV, and LALV. These classes outperform valence and arousal, demonstrating the strong performance of the suggested paradigm. Our proposed Ent-DASM and ENT-RASM features achieved a maximum accuracy of 83.24% for HALV emotional state using SVM, explained in Table 3, outperforming the existing methods by 1-2%. The frontal-occipital combination has taken the lead in identifying emotional states. Though KNN and MLP have shown commendable performance in different emotional states, SVM outperformed in all the emotional states. This improvement was consistent across all frequency bands, as shown in Table 4, suggesting the robustness of our approach. The study also follows evolutionary phases. Phase I includes all 32 channels, Phase II includes 28, and Phase III contains 14.

### Phase I:

Channels are carefully classified into six regions in the I Phase, and all models are evaluated thoroughly to ensure accuracy levels are reached. Among the 32 channels, experiments were carried out on six brain regions by experimenting with EDASM, ERASM, ENT-DASM, and ENTRASM

based on frontal, occipital, and frontal and parietal combinations. The features are the energy and entropy features of differential asymmetry differences and division based on left and right regions (Fp1- Fp2, AF3- AF4, F7- F8, FC5- FC6, T7- T8), frontal and parietal (F3- F4, FC1- FC2, Fz- Pz, P3- P4, P7- P8), and the frontal and occipital (F3 - F4, FC1- FC2, Fz- Oz, O1-O2, PO3-PO4) combinations. Among all the combination frontal occipital combinations, the highest accuracy of HALV was achieved, above 83.24% in the emotional state, based on different frequency bands with the help of SVM classifiers. MLP maintains an 81.01% accuracy level for all the emotional states. Among the frequency bands, beta and gamma performed well.

Table 3. Accuracy level of Frontal-Occipital combination

Emotional State	HAHV			HALV			LAHV			LALV		
	KNN	SVM	MLP	KNN	SVM	MLP	KNN	SVM	MLP	KNN	SVM	MLP
Theta	66.48	73.74	68.16	78.77	81.01	81.01	68.72	74.3	74.86	74.86	77.09	75.98
Alpha	64.25	70.39	65.92	74.86	82.68	81.01	69.27	75.42	74.86	75.42	77.09	75.98
Beta	65.36	64.8	65.92	80.45	83.24	81.01	72.63	75.98	74.86	74.86	77.07	74.3
Gamma	62.01	71.51	66.48	78.77	82.12	81.01	73.74	73.18	73.74	71.51	77.09	73.74

**Phase II**

The last third phase divides the brain area into left and right, leaving out the middle four channels. All three phases undergo rigorous performance evaluations across diverse classification methods and extracted features. The 28 channels eliminated the middle line channels like Fz, Cz, Oz, and Pz and experimented. The combination of asymmetry is like Fp1- Fp2, AF3- Fp2, F3- F4, F7- F8, FC5- FC6, FC1- FC2, C3- C4, T7- T8, CP5 - CP6, CP1- CP2, P3 -P4, P7-P8, PO3-PO4, O1-O2. In the case of 28 channels, the accuracy of the SVM model is maintained for all the frequency bands for all the features, so the average accuracy as shown in Table 4 and with all the features with 28 channels, shows an accuracy level of 81.01% for the SVM model. The LAHV and LALV emotional states also attained the accuracy between 70 to 80. specially the SVM sustained the accuracy level 77% for LALV.

Table 4. The average accuracy of Emotional state from 28 channels for all the frequency bands

Emotional State	HAHV			HALV			LAHV			LALV		
	KNN	SVM	MLP	KNN	SVM	MLP	KNN	SVM	MLP	KNN	SVM	MLP
Features												
EDASM	61.45	68.16	60.48	72.77	81.01	69.56	66.34	73.06	62.15	65.37	77.09	62.71
ERASM	62.57	68.12	61.17	71.09	81.01	69.27	63.97	73.74	61.73	68.16	77.04	64.95
ENTDASM	59.92	68.16	60.06	71.79	81.01	68.86	63.55	73.34	58.66	66.76	77.02	62.71
ENTRASM	60.76	68.06	58.10	70.11	81.15	68.02	62.71	73.74	60.90	66.90	77.09	66.06

**Phase III:**

It uses various classification techniques and carefully selects 14 channels from multiple brain regions to extract features. For 14 channels differential asymmetry combinations are as follows Fp1- Fp2, AF3 - AF4, F3-F4, F7- F8, C3- C4, P3- P4, PO3- PO4. The energy and entropy formula on difference and division is carried out on this combination to extract the features based on the new formulation. The result of these combinations of 14 channels could not perform well. The accuracy rate remains below 60%. Since the performance was not good, the table description is not mentioned here.

This tri-phasic approach seamlessly extends to new pre-processed datasets for exhaustive experimental scrutiny, validating the methodology's efficacy. In direct comparison with other machine learning paradigms, the novel approach spearheaded by KNN emerges triumphant. This pioneering model not only excels but significantly outperforms in emotional recognition tasks. While SVM and KNN classifiers exhibit commendable performance, specific brain regions prove challenging for these

models, a trend mirrored by the MLP classifier.

From Table 5, the classifier widely used SVM in emotion recognition as it separates the data points based on the features provided. Features are scaled and normalized with the help of normalization techniques like standardization to improve the SVM classifier 5-fold cross-validation performance. Since SVM performs on multi-dimensional feature space, it has been chosen where other prominent classifiers like KNN and MLP are also being used for the experiment. The performance of SVM outstands the other classifiers.

To conclude, the result of more than 28 channel combinations, the frontal-occipital combination, has gained a leading role in identifying the emotional state. Detailed results of each experiment across frontal-parietal combinations are meticulously presented in Table 4. The emotional state of HALV has produced higher accuracy on the SVM model for all frequency bands. Comparatively, SVM also performed in all the frequency bands between 80 and 85%, whereas MLP maintained at 81.01% for all bands.

Table 5. Comparison Result

Ref. No	Database	Features	Classifier	Accuracy
(Z. Li et al., 2018)	DEAP	RASM	LSTM	75%
(Vafaei et al., 2023)	DEAP	Wavelet entropy	SATEM CNN	81.73% 80.37%
(Candra et al., 2015)	DEAP	PSD	SVM	77.4% 69.1%
(Al-Galal et al., 2016)	IAPS	KDE	MLP	76.81%
(Duan et al., 2013)	DEAP	DASM RASM	SVM KNN	81.75% 67.08%
(Y. Liu & Sourina, 2012)	IADS	Statistical, Fractional Dimension	SVM	76.51%
(Lin et al., 2010)	DEAP	DASM	SVM	82.29%
(Naser & Saha, 2021)	DEAP	Dual-tree complex wavelet packet transform (DT-CWPT)	SVM	69.33 69.49
(Wei et al., 2020)	SEED	Mean absolute value, PSD, Dual-tree Complex Wavelet Transform	SRU	83.13
(Topic & Russo, 2021)	DEAP	Hjorth, peak-to-peak, Topographic Feature Map (TOPO-FM), Holographic Feature Map (HOLO-FM)	CNN+SVM	76.61 77.72
(Joshi & Ghongade, 2021)	DEAP SEED	Linear Formulation of Differential Entropy	BiLSTM	80.64
<b>Proposed method</b>	<b>DEAP</b>	<b>EDASM, ENTDASM, ERASM, ENTRASM</b>	<b>SVM</b>	<b>83.24%</b>

The findings of the proposed feature extraction technique in light of existing literature are shown in

Table 5. It also compares the different features used by the researchers in their study and the accuracy attained. It also showcases an appreciable increase in accuracy levels—nearly 1 to 2 percentage points. The dynamic performance of EDASM, ERASM, ENDASM, and ENRASM on 32 channels. The combinations of frontal-parietal and frontal-occipital features generated from DASM and RASM of energy and entropy significantly shine brighter in the SVM algorithm.

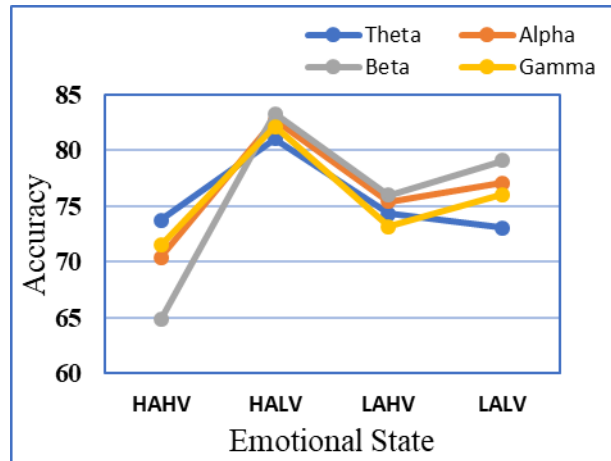


Fig 6. Graphical representation of emotional states SVM classifier with Accuracy

The emotional state of HALV contains different emotions like tension, anger, and upset, which are not expressed visibly; rather, the emotions one holds inside can be captured by EEG brain signals. The other emotional states like HAHV and LALV are extreme, and the subjects who were exposed to the experiments in the DEAP dataset not express visibly what we understood from their facial videos, due to which it was not able to identify with a higher accuracy rate like HALV.

The graphical representation of accuracy attained by SVM in all the emotional states is depicted in Fig 6. Among the frequency bands, beta and gamma bands have sustained an accuracy between 70 and 85. The current study has increased performance to 2% to classify the emotional state with the help of proposed feature extraction methods. It underscores their adaptability and enhanced efficacy, notably leveraging the requisite asymmetry channels.

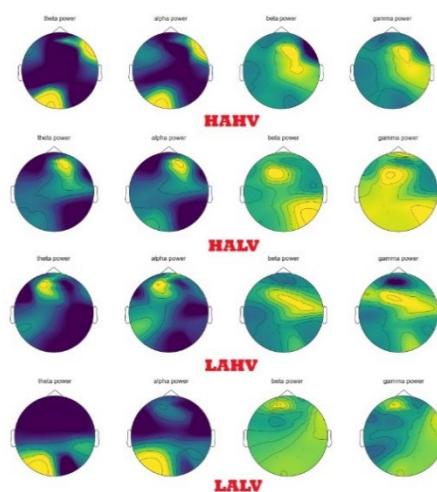


Fig 7. Topological representation of emotional states of 4 frequency bands

The topological representation of frontal-occipital combination with four classes of emotional states. The result showed that beta and gamma frequency bands are more active compared to alpha and theta

bands, in depicted in Fig 7. The alpha and theta band active channels are from the frontal and occipital lobes of the brain. The light color green shows the active channels, which acted as the best feature in identifying emotion. The superior performance of our ENT-DANSM and ENT-RASM features, particularly in the beta and gamma bands, aligns with the previous studies (Staffa et al., 2023) that have highlighted the importance of these frequency ranges in emotion processing. However, the variability in performance across different emotional states suggests that emotion-specific feature optimization may be necessary for future improvements.

## 5. Conclusion

This study introduces ENT-DASM and ENT-RASM, novel energy-entropy based features that significantly enhance the accuracy of EEG-based emotion classification. By combining differential and rational asymmetry measures with energy and entropy calculations, these features capture both the intensity and complexity of emotional states across different brain regions. Our experimental results, achieving a maximum accuracy of 83.24% for the HALV emotional state, demonstrate the superiority of this approach over existing methods.

The consistent performance of our features across all frequency bands, particularly in beta and gamma ranges, aligns with neuroscientific understanding of emotion processing in the brain. This robustness suggests that ENT-DASM and ENT-RASM could be valuable tools for a wide range of affective computing applications, from mental health monitoring to adaptive user interfaces in brain-computer interaction systems.

However, the variability in performance across different emotional states indicates that there is still room for improvement. Future research should explore the integration of these features with deep learning approaches, investigate their efficacy in real-time emotion recognition systems, and examine their performance on larger and more diverse datasets. Additionally, the potential of these features in distinguishing between finer-grained emotional states and their applicability to clinical populations warrant further investigation.

In conclusion, this study represents a significant step forward in EEG-based emotion recognition, providing a foundation for more accurate and reliable affective computing systems. As we continue to refine our understanding of the neural correlates of emotion, methods like ENT-DASM and ENT-RASM will play a crucial role in bridging the gap between neuroscientific theory and practical applications in human-computer interaction.

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