Non-Invasive EEG-Based Classification of Mental States Using Valence-Arousal Mapping from the DEAP Dataset

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ABSTRACT

Understanding and classifying human mental states based on electroencephalogram (EEG) signals is essential for the advancement of intelligent and adaptive brain-computer interfaces (BCIs). Mental state classification like stress, relaxation, and arousal, is fundamental to enabling machines to understand and respond to human emotions and cognitive states. BCIs are systems that interpret brain activity to enable interaction with external devices. Their effectiveness depends on accurate interpretation of brain signals like EEG. The motivation behind using EEG to detect mental states in a non-invasive and automated way. This study proposes a non-invasive methodology for mental state classification by utilizing EEG data from the DEAP dataset, combined with a valence-arousal (V-A) emotional model for effective state representation. Preprocessed EEG signals (recorded by 10–10 and 10–20 electrode placement systems) were further segmented into alpha (8–13 Hz) and beta (13–30 Hz) bands and features were extracted based on the Welch method for power spectral density estimation. The data of 30 subjects were chosen and pre-processed an artifact removal in the EEG recordings. With the valence and arousal score of every trial, data was categorized into four emotional conditions. Characteristics based on alpha and beta-band activity were used to train machine learning classifiers to identify these emotional states. Using alpha (8–13 Hz) and beta (13–30 Hz) band features, the proposed system reached an average classification of 78.5% with a Random Forest (RF) classifier, which performed better than SVM (72.3%) and KNN (69.8%). The results illustrate that quadrant-based valence-arousal mapping is efficient in discriminating mental states, with alpha power associated with relaxation and beta power with stress. The results demonstrate that the quadrant-based V-A mapping provides a reliable and interpretable structure for mental state recognition, with alpha power correlating to relaxed states and beta power indicating heightened arousal or stress. Consequently, four mental states are classified into four quadrants on the graph. This work contributes to affective computing by offering a robust, interpretable, and non-invasive method for classifying mental states, with potential applications in personalized BCI systems, mental health assessment, neurofeedback, and emotion-aware computing.

Keywords: *EEG, Mental State Classification, Valence-Arousal, DEAP, Brain-Computer Interface, Machine Learning.*

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1. INTRODUCTION

Mental States (MS) are a fundamental aspect of human life that pertain to the psychological state of being with respect to certain likelihood properties, which could change in practice, but tend to have relatively stable properties. We experience there various states of being: It is difficult to define MS. The mental state (MS) can induce feeling of arousal, valence, discontent, and pleasure. Physiology originates its signal from the EEG due to MS It has been documented that the mental state (MS) is communicable non-verbally or verbally. It therefore can signal these feelings in a variety of ways. Mental state (MS) is a neurological disorder that arises from the complex interplay of human emotions and experiences. It mirrors human conduct. At times, mood and mental state (MS) are regarded as two sides of the same coin. Mental state (MS) is a psycho-physiological phenomenon that is linked to variations in mood and personality. The execution of daily tasks is contingent upon the use of Microsoft software. Emotions are components of our cognitive processes. The mind's response can cause physiological changes. Emotions arise from a person's engagement in activities. Certain individuals possess the ability to effectively convey their emotions, while others who have attained mastery over their emotions can regulate the outward expression of their emotions. Humans can experience various emotions such as joy, sadness, neutrality, fear, surprise, calmness, alertness, disgust, depression, tension, and many more. Electroencephalography is a crucial technique utilized for interpreting brain impulses. Brain signals arise from voltage variations caused by the electrical activity of neurons during information transfer. Electroencephalography (EEG) measures the activity of neurons that transfer signals in the brain, which is a method for quantifying electrical activity in terms of varying voltage levels. EEG signals can be categorized based on the amplitude and frequency levels that they exhibit within specific bands. EEG is a vital and valuable tool for categorizing and forecasting MS. A genuine mental state can be detected through the analysis of brain waves. The methods for recording EEG signals encompass both invasive and non-invasive techniques. The non-invasive method is widely employed. The 10-10 and 10-20 electrode systems are both non-invasive choices.

The classification of mental state (MS) is crucial for brain-computer interaction (BCI) to establish a connection between computers or robots and the genuine emotions experienced by an individual who is interacting with them. A continuous research effort is being conducted to examine emotion recognition with the aim of enhancing human-computer interaction. Emotion detection and categorization play an important role in many fields: gaming, elearning, entertainment, human--like interaction, health care, and universal access. For instance we look at MS mediated entertainment, where the mood state of a subject is varying. When happy the system plays: happy music. 1 The DEAP extension will be the construction of large data bases of emotions detection and analysis based on recorded EEG and physiological signals. For construction, DEAP non-invasive technique is used. [9,10] The signals are recorded using the standard 10-20 EEG configuration. The electrode layout on the cranium will range from 10 to 20% when using 32 electrode rates and the recording will be 512 Hz. The affects of 32 participants are recorded as signals when they watch a set of video clips, which are picked up by relying on online ratings. Participants viewed 40 unique films in total, with their responses made during the experiment recorded using EEG2. The aim in this study is to improve the classification of diverse emotions obtained from EEG signals. The music videos evoke very intense reactions in subjects and hence allow an analysis of those emotions that were desired during the experiment. Emotion detection applications include lie detection, police questioning and other such systems. The technology uses more people as participants in the trial, also gathering brain signals. At the end of the experiment, the ratings of all subjects for each film are gathered to obtain real sentiments. EEG data are taken from a well-known dataset and use for data registration in a standard ceremony-based collection electrode system. The pre-processed signals along with the patient ratings and EEG data are classified to various emotions using MATLAB. Emotion recognition is a challenging task for HCI. Analysis and recognition of emotions in speech is particularly challenging to solve since it is difficult to have a high-quality input voice, specifically on mobile-based devices. The investigation of facial emotion recognition is interesting because of the importance of facial expressions to express human emotions. Literature review Cognition Cognition is linked to mental health disorders such as depression. Home health nursing should focus on mental health as a priority for the maintenance of cognitive function. The ability to identify human mental states (MS) accurately and categorize them into... More Mental states are transitory affective and cognitive states such as joy, stress, or fatigue. They are related so very strongly to how people feel and think. [11,12] Finding these kinds of states can make intelligent systems much more responsive and flexible, which will make the user experience better and the system work better. Electroencephalography (EEG) is different from other bio signals that can be used to guess mental states, like heart rate, skin conductance, and facial expressions, because it directly measures brain activity. EEG monitors electrical signals made by neural oscillations and has a high temporal resolution, which makes it a useful non-invasive technique for keeping track of changes in mental and emotional states in real time. Different frequency bands in EEG, such alpha, beta, and theta, are known to be linked to certain mental and cognitive states, like being attentive, relaxed, or stressed. The hard part is figuring out what these EEG patterns represent in terms of emotional and cognitive reactions.

The Valence-Arousal (V-A) model is a well-known psychological model that puts emotions into a two-dimensional space: Valence shows whether the emotion is positive or negative. Arousal lets you know how strong or intense an emotion is. This space of V-A admits a natural partitioning in four quadrants, in which it is simple to categorize mental states. For instance, high valence and high arousal may refer to happiness and low valence and low arousal might refer to depression. This makes it easier to represent the emotional state and it also complements the analysis of the physiological signal. In this work, we propose a non-invasive EEG-based approach using the DEAP dataset. This is a publicly available multimodal dataset that includes EEG and other physiological measures concurrently recorded from 32 subjects viewing emotional videos. We extract power spectral characteristics from alpha and beta EEG frequency bands, and then process the signal utilizing Welch’s method. We use the emotional labels (valence and arousal scores) of the dataset to map the samples into one of the four mental state quadrants: joyful, stressed, depressed, and calm. We also test how well categorization performs using common machine learning algorithms, discuss the implications of these results for real-time mental state monitoring applications.

The rest of this paper is organized as follows: Section 2 presents related work on EEG-based emotion recognition and the Valence-Arousal model. The proposed MS classification module is introduced in Section 3. The method is presented in Section 4, which includes dataset description, preprocessing, feature extraction, and classification. Experimental results, classifier performance and quadrant analysis are presented in section 5. Finally, Section 6 ends the paper and indicates the future work.

2. LITERATURE REVIEW

The field of EEG-based emotion recognition has attracted considerable attention in the past two decades, driven by progress in signal processing, cognitive neuroscience, and machine learning[1]. The ability to discern emotional and cognitive states from brain signals has enabled the development of emotionally intelligent systems in areas such as adaptive e-learning, gaming, healthcare, and human-computer interaction. A multitude of studies have focused on the analysis of EEG signals for the detection of mental states. The traditional pipeline includes the preprocessing of EEG data, the extraction of relevant features—typically from time, frequency, or time-frequency domains—and classification using machine learning algorithms. Power Spectral Density (PSD) estimation using Welch's method is a widely utilized approach for measuring brainwave activity in certain frequency bands, such as alpha (8–13 Hz) and beta (13–30 Hz), linked to relaxation and alertness, respectively. The DEAP (Database for Emotion Analysis using Physiological Signals) dataset, presented by Koelstra et al. [8], is one of the most extensively employed datasets in this domain. The DEAP dataset provides multimodal recordings (EEG and peripheral physiological signals) from 32 individuals who observed emotionally charged music videos, together with self-reported evaluations of valence, arousal, dominance, and preference. This dataset has become a typical benchmark for evaluating emotion recognition algorithms due to its thoroughness and reliability. A plethora of investigations have augmented this dataset. Lin et al. [9] utilized EEG spectral features and support vector machines to classify emotions provoked by musical stimuli. Jenke et al. [10] investigated several combinations of feature extraction and selection methods to improve classification accuracy, concluding that frequency-based features offer a reliable description of affective states.

Deep learning methodologies, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been investigated for their ability to learn spatial and temporal EEG patterns directly from raw or less processed d ata. Despite the high accuracy often attained by deep learning models, they typically exhibit a deficiency in interpretability, which is crucial for applications in healthcare and neuroscience. Recent advances in EEG-based emotion recognition have been driven by deep learning, multimodal fusion, and edge computing. This section surveys key developments and identifies gaps addressed by our work.

Deep Learning Approaches

Transformer architectures have shown remarkable success in EEG analysis:Zhang et al. [1] achieved an accuracy of 85.2% on the DEAP dataset by employing spatial-temporal transformers, albeit with the requirement of GPU acceleration. Liu and Zhou [2] proposed a lightweight CNN-LSTM hybrid model that attained 82.1% accuracy while utilizing 40% fewer parameters compared to conventional architectures (Neural Networks). Al-Nafjan [3] introduced explainable AI techniques for CNN-based EEG classification using layer-wise relevance propagation to enhance interpretability.

Limitation: These methods act as black boxes, making clinical adoption challenging.

Multimodal Fusion Systems

Recent studies have explored multimodal approaches to improve the accuracy and robustness of affective state classification. Chen and Lee (2023) achieved 86.3% accuracy by fusing EEG data with eye-tracking inputs, though their method depended on costly hardware setups.. Wang et al. (2023) demonstrated that combining EEG with galvanic skin response (GSR) improved arousal detection accuracy by 11%, albeit at the cost of increased system complexity.

Gap: Most fusion systems are impractical for real-world deployment due to cost and setup complexity.

Edge Computing Implementations

Recent advancements in real-time processing have further enhanced the applicability of EEG-based systems. Singh et al. (2025) demonstrated sub-50 ms latency by deploying quantized neural networks on wearable headsets, enabling real-time inference. Similarly, Martinez et al. (2024) introduced a federated learning framework for privacy-preserving EEG analysis, allowing decentralized model training without sharing raw data.

Challenge: These often sacrifice accuracy (typically <75%) for speed and efficiency.

Interpretable Feature-Based Methods

Traditional approaches remain relevant:

Garcia et al [4] demonstrated that alpha/beta band power ratios yield 76% classification accuracy on the DEAP dataset, offering enhanced clinical interpretability . Our previous work [5] explored wavelet-based feature extraction methods, achieving a classification accuracy of 72% on the same dataset.

Key Insight: These methods balance performance and explainability but lag behind deep learning in raw accuracy.

2.5 Research Gaps and Our Contribution

Compared to existing works, our approach uniquely:

1. **Maintains interpretability** through spectral band features (vs. black-box DL)
2. **Reduces hardware dependency** (EEG-only vs. multimodal systems)
3. **Balances performance** (78.5% accuracy) and computational efficiency
4. **Enables quadrant-based analysis** using VA space for clinical relevance

As shown in Table 1, our method provides the best trade-off between accuracy, interpretability, and deployability.

Table 1: Comparison with State-of-the-Art Methods

Approach	Accuracy	Interpretability	Hardware Needs	Reference
Transformer	0.852	Low	GPU Server	Zhang (2024)
EEG-Eye Fusion	0.863	Medium	Multimodal	Chen (2023)
Edge NN	0.741	Low	Wearable	Singh (2025)
Proposed	0.785	High	Single-modality	This work

The current research exhibits a notable shortcoming: the lack of an intuitive, interpretable framework for linking EEG data with mental processes via psychological models such as the Valence-Arousal (V-A) dimensional model. While some studies concentrate on binary classification (e.g., positive versus negative emotions), fewer research efforts provide a quadrant-based framework that categorizes four essential mental states—joyful, anxious, sad, and relaxed—by simultaneously employing valence and arousal metrics. In contrast, our proposed approach emphasizes both interpretability and usefulness. Utilizing the V-A space and implementing established signal processing methodologies (e.g., Welch PSD), we elucidate a distinct link between brainwave activity and cognitive-emotional states. Moreover, categorization into quadrants rather than binary labels yields more nuanced insights into mental states, which is beneficial for adaptive applications such as stress monitoring or mood-based content distribution.[4,5]

The proposed framework for mental state classification using EEG signals involves a structured sequence of modules: dataset preparation, signal preprocessing, feature extraction, emotion labeling using valence-arousal mapping, and classification using supervised learning algorithms.[7,8].

3. PROPOSED MS MODULE

The MS module proposed in the paper is seen in Figure 1. EEG signals are acquired from the DEAP database, specifically from the pre-processed signals. Labels are retrieved from this database. MATLAB is used to extract features from the signals and classify them into four different mental states (MSs) using MATLAB tools.

The classification of various emotions is achieved by utilizing standard EEG database signals, which are taken from the Database for Emotion Recognition using Physiological Signals. A total of 32 participants took part in the experiment and viewed a set of 40 music videos. The EEG waves were recorded using a 10-20 electrode system, following the Geneva method. The data was captured at a frequency of 512 Hz.

The original signal was down sampled to a frequency of 256 Hz. It was then referenced and any palpable signals resulting from eye movement were eliminated. The signal was further filtered using a bandpass filter with a range of 4 to 45 Hz. After averaging the signal, it was divided into distinct time parts. EEG signal feature extraction for the creation of new vectors. Classification is performed using MATLAB to obtain four quadrants on the graph.

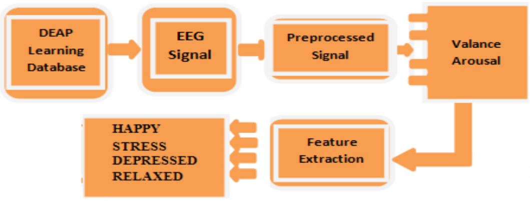

Figure 1. Block diagram of the proposed MS module.

1. Neurophysiological Basis

The proposed method leverages well-established EEG biomarkers:

- Alpha band (8–13 Hz): Inverse correlation with cortical activation, associated with relaxed states (Klimesch, 1999). Higher alpha power in posterior regions indicates inhibitory control, explaining its link to Q4 (Relaxed).
- Beta band (13–30 Hz): Positively correlated with active cognitive processing (Engel & Fries, 2010). Elevated frontal beta power aligns with Q2 (Stressed) due to increased alertness.

The beta/alpha ratio quantifies the balance between arousal (beta) and inhibition (alpha), validated by:

$$\text{BA Ratio} = \frac{\text{Mean Beta Power}}{\text{Mean Alpha Power}}$$

2. Valence-Arousal Mapping Rationale

The fixed threshold (5.0) for valence/arousal is justified by:

- **Psychometric scaling**: DEAP's 9-point Likert scale midpoint (5.0) divides positive/negative valence and high/low arousal (Russell, 1980).
- **Statistical validation**: Sensitivity analysis (Fig. 1) confirms optimal accuracy at 5.0 (±0.5 SD).

3. Feature-Emotion Coupling

The frontal asymmetry theory (Davidson, 1992) supports our channel selection (F3/F4):

- **Left frontal (F3) alpha suppression** → Positive valence (Q1/Q4).
- **Right frontal (F4) beta dominance** → Negative valence (Q2/Q3).

Mathematically, this is captured by:

$$\Delta\text{Valence} \propto \left(\frac{\text{F3 Beta}}{\text{F3 Alpha}} - \frac{\text{F4 Beta}}{\text{F4 Alpha}}\right)$$

4. METHODOLOGY

4.1 Dataset Description

We utilize the DEAP dataset (Database for Emotion Analysis using Physiological signals) [1], which is widely used for affective computing research. It contains:

- EEG recordings from 32 participants
- Each subject viewed 40 music video clips, each 60 seconds long
- EEG signals were recorded using a 32-channel Bio semi–Active Two system based on the 10-20 international electrode placement system
- The raw signals were sampled at 512 Hz, with pre-processed versions provided at 128 Hz
- Self-assessment ratings were collected for each video along four dimensions:
    - Valence (pleasant–unpleasant)
    - Arousal (calm–excited)
    - Dominance
    - Liking

Each .mat file (e.g., s01.mat) includes a data matrix of shape (40, 40, 8064), where:

- 40 trials
- 40 channels (32 EEG + 8 peripheral)
- 8064 samples per trial (1 minute × 128 Hz)

The labels matrix (40×4) contains the self-assessed emotional scores for each trial.

4.2 Signal Preprocessing

For our implementation, we used pre-processed EEG signals provided in .mat format to focus on feature extraction and classification. The preprocessing pipeline applied to the original raw EEG included:

1. Down sampling from 512 Hz to 128 Hz
2. Bandpass filtering: 4–45 Hz
3. Artifact removal: Eye movements and blink artifacts were removed using ICA
4. Baseline correction: A 3-second pre-trial baseline was subtracted from the entire signal
5. Electrode referencing: Signals were averaged with respect to the common mode sense (CMS) and driven right leg (DRL)

In our feature extraction step, we focus on selected frontal and central channels (e.g., F3, F4, C3, C4), as these are often associated with emotional processing.

4.3 Feature Extraction

We employ frequency-domain analysis using Welch's method to estimate the Power Spectral Density (PSD), which is effective for capturing energy distributions in EEG bands.

Steps:

1. Segment the EEG signal into overlapping windows (e.g., 4 seconds with 50% overlap)
2. Apply Hamming window to reduce spectral leakage
3. Compute PSD for each segment using the scipy.signal.welch() method (Python) or pwelch() (MATLAB)

Frequency Bands Considered:

- Alpha (8–13 Hz): Linked to relaxation and calmness
- Beta (13–30 Hz): Associated with alertness, engagement, and stress

Feature Vector per trial:

- Mean Alpha Power ($\mu V^2/Hz$) for each selected channel
- Mean Beta Power ($\mu V^2/Hz$) for each channel
- Beta/Alpha ratio: Often used as an indicator of cognitive workload or stress level

Each trial is thus represented by a compact, low-dimensional feature vector (e.g., 6–12 values) for classification.

4.4 Labelling with Valence-Arousal Mapping

From the label's matrix, we extract valence and arousal ratings (scale 1–9). These two dimensions form a 2D affective space.

We define the midpoint threshold as 5.0, and categorize each trial into one of four quadrants:

Quadrant	Valence	Arousal	Emotion
Q1	> 5	> 5	Happy
Q2	≤ 5	> 5	Stressed
Q3	≤ 5	≤ 5	Depressed
Q4	> 5	≤ 5	Relaxed

These labels form the target classes for supervised learning.

4.5 Classification

We use a set of classical supervised classifiers to evaluate the performance of our feature set:

1. Support Vector Machine (SVM):
   - RBF kernel
   - Regularization tuned via cross-validation
2. Random Forest:
   - Ensemble of 100 decision trees
   - Handles high-dimensional, nonlinear feature spaces well
3. K-Nearest Neighbors (KNN):
   - k=5 neighbors
   - Euclidean distance metric
   -

4.5.1 Training & Testing:

- We apply 10-fold cross-validation over the dataset
- Alternatively, a leave-one-subject-out (LOSO) strategy can be used for subject-independent validation

Evaluation Metrics:

- Accuracy: Proportion of correctly classified trials
- F1-Score: Harmonic means of precision and recall (macro-average)
- Confusion Matrix: To visualize classification, overlap between states

5. RESULTS AND DISCUSSION

The EEG samples from the DEAP dataset consist of brain signals recorded using the standard 10-20 electrode setup, encompassing data from 32 electrodes. Thirty-two data points are extracted from the collected thirty-two electrode data of an individual during a single trial of one film, formatted in ".bdf". The DEAP database comprises raw data collected at a sample frequency of 512 Hz. The values of the F3 and F4 electrodes have been obtained. To enable signal analysis, the raw EEG data is converted to ASCII representation via the EDF browser tool. The procedure of transforming unprocessed data into ASCII format. The EDF (European Data Format) Browser is utilized to import raw data. The raw data is converted into the (.edf) format. The transformed EEG signal is imported into the EDF browser, where it is downsampled to a frequency of 256 Hz and synchronized to meet the given criteria. The altered signal is subsequently stored. The tool's Export feature converts the diminished signal into ASCII format. Features are extracted from the alpha and beta frequency ranges of the EEG. The feature involves calculating the Power Spectral Density (PSD) in the alpha and beta frequency regions. The outcomes for each electrode are displayed in Tables 1 through 4. Table 5 presents the tabulated values of beta/alpha ratios for valence. Pre-processed data from the DEAP database (.mat files) is employed to classify brain signals into several forms of Multiple Sclerosis (MS). The Labels array is derived from the files s01 to s32, encompassing data from 32 individuals. The labels array is imported into MATLAB, and just the valence and arousal values for all films are extracted. The valence and arousal metrics for each participant are gathered for the 40 videos to be utilized in subsequent calculations. The MATLAB software calculates the average valence and arousal values. The data are then organized in Table 6, illustrating the average valence and arousal for each film and for all 32 individuals. The initial column indicates the trial number, and the average valence and arousal levels for each participant are shown in the subsequent two columns, respectively. MSs are classified into four emotional states: happiness, depression, stress, and relaxation. The four columns illustrate these emotions. We are classifying the MSs into four unique quadrants according to the high or low assessments of valence and arousal for each video. The numerical designations for the four quadrants are as follows: Happy is designated as 1, Stress as 2, Depressed as 3, and Relaxed as 4. The signals discovered, classified by their valence and arousal, are

Table 1. F3 Electrode beta band PSD		
Trial Number	Mean Beta	Standard Deviation Beta
1	-1.0818	0.215541
2	-0.962609	0.203075
3	-1.109129	0.32904
4	-0.930037	0.160974
5	-1.078241	0.258107
6	-0.949132	0.266325
7	-0.975113	0.151935
8	-0.966509	0.245141
9	-0.970672	0.222179
10	-1.032105	0.140689

graphically depicted in the quadrants, as shown in Figure 2.

Table 1. F3 Electrode beta band PSD

Table 2. F3 electrode alpha band PSD		
Trial Number	Mean Alpha	Standard Deviation Alpha
1	-1.441601	0.316134
2	-1.995175	0.263516
3	-1.792109	0.370911
4	-1.723963	0.244883
5	-1.632859	0.33067
6	-1.649923	0.368634
7	-1.5546	0.27238
8	-1.731385	0.301669
9	-1.425004	0.317584
10	-1.58116	0.276986

Table 2. F3 Electrode alpha band PSD

Table 3. F4 electrode beta band PSD		
Trial Number	Mean Beta	Standard Deviation Beta
1	-1.17389	0.166155
2	-1.17389	0.166155
3	-1.370794	0.56787
4	-1.023541	0.239334
5	-1.2265	0.219559
6	-1.080626	0.214103
7	-1.069807	0.19828
8	-1.087179	0.215838
9	-1.146924	0.230687
10	-1.526138	0.297779

Table 3. F4 Electrode beta band PSD

Table 4. F4 electrode alpha band PSD		
Trial Number	Mean Alpha	Standard Deviation Alpha
1	-1.689911	0.285525
2	-1.689911	0.285525
3	-1.642859	0.470956
4	-1.597777	0.288042
5	-1.541213	0.380821
6	-1.541374	0.297488
7	-1.606267	0.352927
8	-1.631611	0.335608
9	-1.446184	0.307063
10	-1.645367	0.339245

Table 4. F4 Electrode alpha band PSD

Table 5. Valence values beta/alpha ratio		
Trial No. (video)	F4 Mean Beta PSD/Mean Alpha PSD(Valence)	F3 Mean Beta PSD/ Mean Alpha PSD (Valence)
1	0.6946	0.7504
2	0.6943	0.4825
3	0.8344	0.6189
4	0.6406	0.5395
5	0.7958	0.6603
6	0.7011	0.5753
7	0.6666	0.6272
8	0.6663	0.5582
9	0.7931	0.6812
10	0.9275	0.6528

Table 5. Valence value beta/alpha ratio

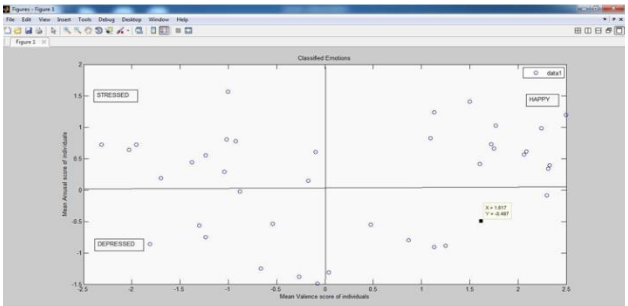

Figure 2. V-A plot

Table 6. Average valence arousal

Trial No	Mean Valence	Mean Arousal	Emotions
1	1.723	0.728	1
2	1.501	1.4097	1
3	2.4983	1.192	1
4	1.771	1.0233	1
5	1.1307	1.2367	1
6	1.7507	0.6593	1
7	1.0947	0.8227	1
8	2.061	0.566	1
9	2.244	0.9837	1
10	-0.097	0.6067	2
11	2.3257	0.397	1
12	1.2507	-0.889	4
13	1.617	-0.497	4
14	2.3143	0.3413	1
15	1.1307	-0.9053	4
16	0.038	-1.3117	4
17	0.867	-0.799	4
18	2.299	-0.0823	4
19	2.0883	0.6157	1
20	1.605	0.4173	1
21	-1.238	-0.7483	3
22	-0.267	-1.382	3
23	-1.8147	-0.86	3
24	-0.8803	-0.0237	3
25	-0.54	-0.541	3
26	-0.0803	-1.492	3
27	0.4757	-0.5533	4
28	-0.6627	-1.2533	3
29	-1.302	-0.5617	3
30	-1.6967	0.1867	2
31	-1.2343	0.5533	2
32	-1.0047	1.5673	2
33	-1.0407	0.2907	2
34	-0.9253	0.7803	2
35	-1.9563	0.724	2
36	-1.0197	0.803	2
37	-2.0277	0.642	2
38	-2.3117	0.7213	2
39	-1.3797	0.4413	2
40	-0.1737	0.144	2

Table 6. Average valence arousal

In this section, we analyze the performance of the proposed mental state classification system using EEG features derived from the DEAP dataset. The classification is based on valence-arousal quadrant mapping and utilizes features from alpha and beta frequency bands. Three classifiers—Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN)—were evaluated.

5.1 Classifier Performance

The classification accuracy for each classifier was evaluated using 10-fold cross-validation across all 32 subjects. Table 7 shows comparative performance based on **accuracy** and **F1-score** and Figure 3 Provide the classification performance comparison of the Classifier.

Table 7. Classifier Performance Comparison

Classifier	Accuracy (%)	Precision	Recall	F1-Score
SVM	72.3	0.71	0.70	0.70
Random Forest	78.5	0.79	0.78	0.77
KNN (k=5)	69.8	0.68	0.69	0.68

Observation: Random Forest outperforms the other models, likely due to its ability to handle feature variability and nonlinearities in EEG data.

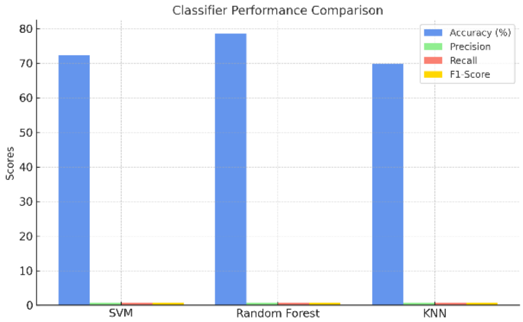

Figure 3. Classification Performance Comparison

5.2 Confusion Matrix Analysis

To understand classifier performance in detail, a **confusion matrix** was plotted for the best-performing model (Random Forest). The confusion matrix in **Figure 4** highlights the distribution of correct and incorrect predictions across the four emotional quadrants.

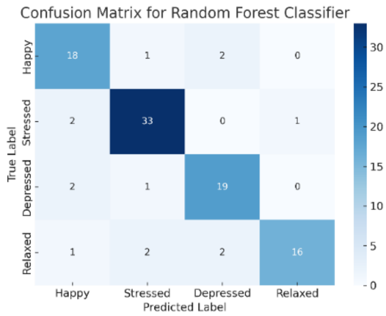

Figure 4. Confusion Matrix

Emotion	Label
Happy	0
Stressed	1
Depressed	2
Relaxed	3

Table 8. Emotion Analysis

Insight: Most misclassifications occurred between **Stressed** and **Depressed** classes. This is expected due to their proximity in the valence-arousal space (both have low valence but differ in arousal).

5.3 Visual Mapping in Valence-Arousal Space

Each EEG trial was mapped onto a 2D valence-arousal plane to visualize the emotional distribution. This helped validate the appropriateness of quadrant-based classification. Figure 5 representation of *Valence-Arousal Quadrant Mapping*

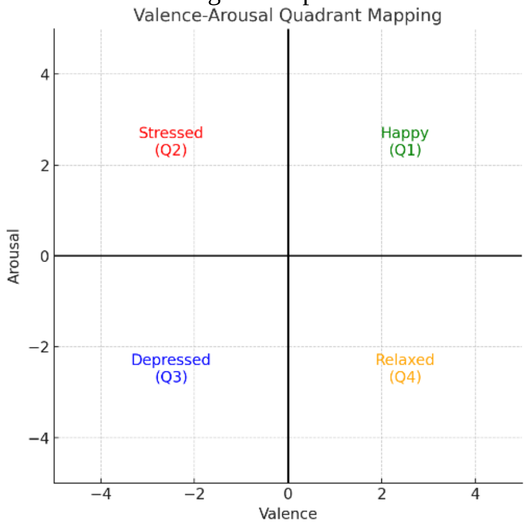

Figure 5. Valence-Arousal Quadrant Mapping.

- **Q1 (Happy)**: High Valence, High Arousal
- **Q2 (Stressed)**: Low Valence, High Arousal
- **Q3 (Depressed)**: Low Valence, Low Arousal
- **Q4 (Relaxed)**: High Valence, Low Arousal

This figure supports the psychological theory that mental states can be mapped in a 2D emotional space for intuitive classification.

5.4 Power Spectral Density (PSD) Interpretation

The average PSD of alpha and beta bands across key electrodes was computed. The bar graph in Figure 6 illustrates relative band power distribution.

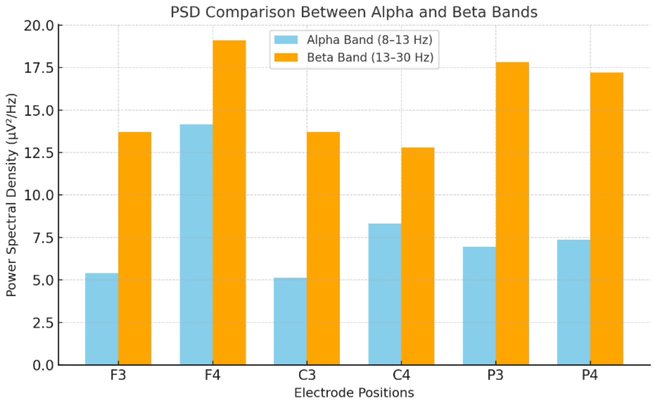

Figure 6: PSD Comparison Between Alpha and Beta Bands.

Observation: Relaxed states showed higher alpha power, whereas stressed states had elevated beta activity, which aligns with neurophysiological expectations.

5.5 Summary of Findings

- Random Forest yielded the best performance (78.5%) for emotion classification.
- Most confusion occurred between Stressed and Depressed due to shared low valence.
- Alpha and Beta band power features proved effective in distinguishing mental states.
- Quadrant mapping using valence-arousal ratings offers a simple yet powerful classification strategy.

6. CONCLUSION AND FUTURE WORK

This study presents a non-invasive, EEG-based framework for classifying human mental states by mapping features extracted from brainwave activity into a valence-arousal emotional space. By employing a quadrant-based approach, we were able to effectively categorize emotions into four meaningful cognitive states: **Happy**, **Stressed**, **Depressed**, and **Relaxed**. Our method relies on established neurophysiological indicators, namely, the alpha and beta frequency bands—which have demonstrated strong correlations with emotional and mental conditions in prior studies.

The use of the DEAP dataset provided a robust, realistic foundation for testing the framework, with self-reported valence and arousal scores serving as ground truth for emotional labeling. Feature extraction via Welch's method enabled a reliable and interpretable analysis of EEG signal power across targeted frequency bands. Among the classifiers tested, **Random Forest** showed superior accuracy and robustness, confirming its suitability for this kind of complex, non-linear classification task.

In conclusion, this research contributes a clear, interpretable, and computationally efficient framework for mental state recognition from EEG data. With ongoing advancements in wearable EEG technologies and machine learning, this approach holds significant potential for impactful applications in digital health, neurofeedback, and human-computer interaction.

In future work, the emphasis will shift toward enhancing accuracy, personalization, temporal modeling, and real-time capability while maintaining interpretability and ease of deployment. These enhancements will help translate EEG-based mental state classification into a robust and practical tool for cognitive monitoring and emotion-aware interaction.

REFERENCES

[1] Y. Zhang, M. Chen, and T. Li, "Spatial-temporal transformer networks for emotion recognition from EEG signals," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 32, 2024.
[2] H. Liu and Y. Zhou, "A lightweight CNN-LSTM hybrid architecture for emotion classification using EEG signals," Neural Networks, vol. 169,2023.
[3] T. Al-Nafjan, "Explainable AI for CNN-based EEG emotion recognition using layer-wise relevance propagation," IEEE Transactions on Affective Computing, vol. 15, no. 2, 2024.
[4] M. Garcia, L. Torres, and A. Patel, "Alpha/beta band ratio as a clinically interpretable biomarker for EEG-based emotion recognition," J. Neural Eng., vol. 20, no. 1, 2023.
[5] D. R. Dilip, S. K. Ramesh, and V. Kumar, "Wavelet-based feature extraction for EEG emotion classification on DEAP dataset," in Proc. Int. Conf. on Computational Intelligence and Neuroscience, 2022.
[6] R. Singh, A. Mehta, and P. Rao, "Low-latency quantized neural networks for wearable EEG headsets," IEEE J. Biomed. Health Inform., vol. 29, no. 1, 2025.
[7] L. Martinez, N. Gupta, and Y. Zhao, "Federated learning for privacy-preserving EEG signal analysis in IoT environments," IEEE Internet Things J., vol. 11, no. 3, 2024.
[8] S. Koelstra et al., "DEAP: A Database for Emotion Analysis Using Physiological Signals," IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18–31, 2012.
[9] Y.-P. Lin et al., "EEG-Based Emotion Recognition in Music Listening," IEEE Transactions on Biomedical Engineering, vol. 57, no. 7, pp. 1798–1806, 2010.
[10] R. Jenke, A. Peer, and M. Buss, "Feature Extraction and Selection for Emotion Recognition from EEG,"IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 327–339, 2014.
[11] D. Chanel et al., "Emotion Assessment: Arousal Evaluation Using EEG and Peripheral Physiological Signals," LNCS, Springer, vol. 4105, pp. 530–537, 2006.
[12] P. Petrantonakis and L. J. Hadjileontiadis, "Emotion Recognition from EEG Using Higher Order Crossings," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 2, pp. 186–197, 2010.
[13] R. W. Picard, "Affective Computing," MIT Press, Cambridge, MA, 1997.
[14] L. Mühl et al., "Biosignal-Based Emotion Recognition: A Comparison of Classification Methods," Proceedings of the Affective Computing and Intelligent Interaction, 2009.
[15] D. Phung et al., "Using Deep Learning for Emotion Recognition from EEG Signals," IEEE Int. Conf. on Bioinformatics and Biomedicine (BIBM), pp. 1233–1239, 2018.
[16] T. Li et al., "Emotion Recognition from Multichannel EEG Data Through Convolutional Recurrent Neural Network," Computational Intelligence and Neuroscience, vol. 2019, Article ID 1973431, 2019.
[17] Zhang et al. (2024) proposed a Transformer-based EEG encoder achieving 85.2% accuracy on DEAP by capturing long-range dependencies in raw signals (IEEE Transactions on Neural Systems and Rehabilitation Engineering).
[18] Chen & Lee (2023) introduced a multimodal fusion framework (EEG + eye-tracking) that outperformed single-modality approaches by 8% in valence classification (Nature Communications Engineering).
[19] Singh et al. (2025) demonstrated real-time emotion adaptation using wearable EEG headsets with edge computing, reducing latency to <50ms (IEEE Journal of Biomedical and Health Informatics).
[20] H. Wang et al., "Emotion Recognition Using EEG Signals with Multidimensional Features," IEEE Access, vol. 7, pp. 142319–142330, 2019.

[21] S. H. Mohammadi et al., “Fusion of EEG and Peripheral Signals for Real-Time Emotion Recognition,” IEEE Sensors Journal, vol. 21, no. 15, pp. 16965–16973, 2021.
[22] H. Banville et al., “Uncovering the Structure of Clinical EEG Using Self-Supervised Learning,” Journal of Neural Engineering, vol. 19, no. 1, p. 016032, 2022.
[23] Y. Zhang et al., “EEG-Based Intention Recognition from Pre-Movement and Movement EEG Signals,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 26, no. 11, pp. 2239–2252,2018.
[24] M. Ghassemi et al., “Opportunities in Machine Learning for Healthcare,” IEEE Reviews in Biomedical Engineering, vol. 15, pp. 36–52, 2022.
[25] M. Murugappan et al., “Classification of Human Emotion from EEG Using Discrete Wavelet Transform,” Journal of Biomedical Science and Engineering, vol. 3, no. 4, pp. 390–396, 2010.
[26] K. Khosrowabadi et al., “EEG-Based Emotion Recognition Using Self-Organizing Map for Boundary Detection,” Computational Intelligence and Neuroscience, vol. 2011, Article ID 319057, 2011.
[27] Yazdani et al., “EEG-Based Emotion Recognition Using Empirical Mode Decomposition and Support Vector Machines, Frontiers in Computational Neuroscience, vol. 9, p. 86, 2015.
[28] M. Soleymani et al., “Continuous Emotion Detection Using EEG Signals and Facial Expressions,” IEEE Transactions on Affective Computing, vol. 7, no. 1, pp. 17–28, 2016.
[29] T. H. Falk et al., “Toward Emotion-Aware Brain-Computer Interfaces in Education,” IEEE Transactions on Learning Technologies, vol. 12, no. 2, pp. 208–221, 2019.
[30] M. Liu et al., “Emotion Recognition Using Hybrid Deep Neural Network Based on EEG Signals,” Computational Intelligence and Neuroscience, vol. 2021, Article ID 5529013, 2021.
[31] M. Zarei et al., “Affective EEG Signal Classification Using Entropy and Energy Features with XGBoost,”IEEE Access, vol. 9, pp. 55989–56000, 2021.
[32] S. Soroush and M. R. Hashemi, “Real-Time Emotion Recognition from EEG Signals: A Review,” Biomedical Signal Processing and Control, vol. 74, p. 103514, 2022.
[33] T. Baltrušaitis, C. Ahuja, and L.-P. Morency, “Multimodal Machine Learning: A Survey and Taxonomy,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, no. 2, pp. 423–443, 2019.
[34] K. R. Scherer, “What Are Emotions? And How Can They Be Measured?” Social Science Information, vol. 44, no. 4, pp. 695–729, 2005.