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Research Article

EEG-BASED ASSESSMENT OF EMOTIONS AND STRESS USING AROUSAL VALENCE CLASSIFICATION

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ABSTRACT

Emotions and stress significantly influence human cognition, behavior, and overall well-being. Electroencephalography (EEG) provides a non-invasive method to monitor brain activity and classify emotional states. This study employs the arousal-valence model to analyze EEG signals recorded from participants performing mental and physical tasks. EEG data were acquired using the RMS Maximums 24-channel EEG system, and analysis software was used for artifact removal, feature extraction, and emotional state classification. The emotional states were visualized using a color-coded tomography map, allowing easy interpretation of different emotions. This approach offers potential applications in monitoring mental health and improving cognitive function.

Keywords: EEG, Emotions, Stress, Arousal-Valence Model, RMS EEG, Tomography Map.

INTRODUCTION

Emotions and stress are complex psychological phenomena that affect human motivation, attention, learning, decision-making, and overall quality of life. Accurate assessment of emotional states can provide valuable insights into cognitive and mental health. Among the available neuroimaging techniques, including functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and positron emission tomography (PET), EEG remains a widely used tool due to its low cost, high temporal resolution, and ease of use for patients. The human brain comprises the forebrain, midbrain, and hindbrain, containing millions of neurons responsible for transmitting electrical signals via action potentials. EEG captures these electrical activities through electrodes placed on the scalp, reflecting brain waves such as alpha, beta, theta, and delta, with frequencies typically up to 50 Hz. The cerebral cortex, the largest brain region, consists of four lobes frontal, parietal, temporal, and occipital each associated with different cognitive and emotional processes.

EEG-based emotion classification relies on mapping brain activity to emotional states. The arousal-valence model is commonly used, where valence represents the positivity or negativity of an emotion, arousal measures the intensity or excitement, and dominance reflects the strength of the emotion. Changes in alpha and beta wave activity across frontal and parietal regions are indicative of these emotional dimensions. By analyzing EEG signals using this model, emotional states can be effectively classified, providing insights into human affective responses. Emotion and stress recognition has become a central research focus in neuroscience and affective computing due to its growing relevance in mental health assessment, adaptive human–computer interaction, and intelligent assistive technologies. EEG is widely used for this purpose because it captures rapid neural fluctuations linked to emotional states, making it suitable for real-time monitoring. Foundational work in affective neurophysiology demonstrated that distinct

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cortical regions regulate emotional processing and stress responses, particularly the frontal and parietal regions involved in cognitive emotional integration (Davidson & Irwin, 1999). Subsequent studies highlighted the importance of understanding individual differences in EEG patterns, leading to the development of personalized and context-aware emotion recognition systems (Begum *et al*., 2009). Traditional EEG-based research initially relied on handcrafted features, where multivariate and entropy-based analyses were used to characterize stress-related neural dynamics and improve classification reliability (Ahmed & Mandic, 2012). Similarly, early biomedical engineering studies applied multichannel EEG analysis to explore sleep, cognition, and affective variability, providing foundational insights into EEG interpretation (Ilan and Inna, 2009). In recent years, machine learning approaches for EEG emotion analysis have matured significantly. Comprehensive reviews have demonstrated the effectiveness of supervised classifiers using spectral, statistical, and asymmetry features, which remain highly discriminative for identifying emotional and stress states (Ahmad & Kim, 2022). Additional studies have shown that accurate feature extraction combined with robust preprocessing improves system generalization, especially in cross-subject scenarios where EEG variability poses a major challenge. Benchmark databases such as DEAP have played a key role in standardizing emotional labeling and enabling reproducible evaluation across studies (Koelstra *et al*., 2012). Deep learning further advanced the field by enabling automated representation learning directly from raw EEG signals. For example, sparse autoencoder–based architectures demonstrated significant improvements in modeling latent affective characteristics, enabling more robust classification under noisy conditions (Liu *et al*., 2020). Practical applications of EEG-based affective computing have also expanded with the emergence of embedded and wearable platforms. Lightweight CNN models deployed on portable EEG devices showed that real-time emotion classification is feasible even with limited computational resources, marking a major step toward mobile stress-monitoring solutions (Embedded EEG-based Emotion Recognition System, 2023). These developments support the broader movement toward intelligent brain–computer interfaces capable of adapting to user emotions in naturalistic environments. Additionally, interdisciplinary studies from biomedical engineering and cognitive science have helped refine preprocessing pipelines and artifact removal strategies, drawing from related domains such as biosignal processing and neuroergonomics (Devasena *et al*., 2005; Hosseini and Naghibi-Sistani, 2012). The continued evolution of these techniques reflects an increasing effort to integrate emotion-aware systems into healthcare, education, and personalized human technology interaction. Overall, the field of EEG-based emotion and stress recognition has progressed from early exploratory analyses to sophisticated deep learning and embedded frameworks. Research continues to emphasize interpretability, individual variability, and real-time performance, encouraging the development of resilient affective computing systems capable of operating across diverse real-world settings. As machine learning, neuroscience, and wearable sensor technologies converge, EEG-based emotion recognition is poised to provide transformative solutions for mental health monitoring, personalized computing, and adaptive user experience design.

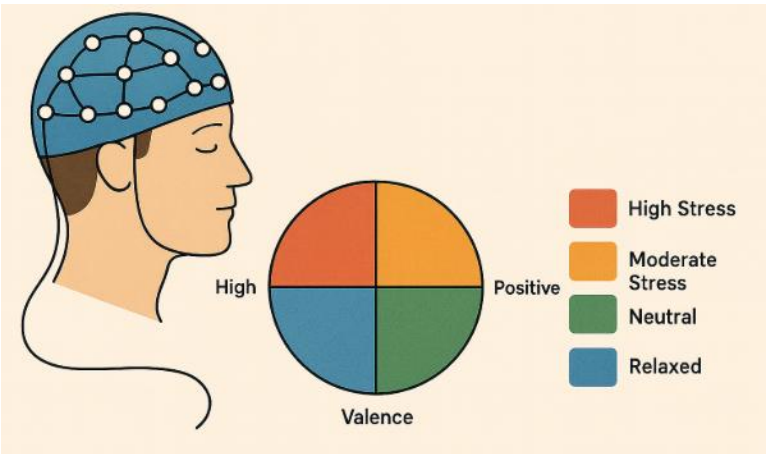

Figure 1. Arousal valence model for EEG emotion assessment.

MATERIALS AND METHODS

Ten healthy volunteers (5 males and 5 females) aged 18-25 years were recruited from the university campus, consistent with standard participant selection practices used in EEG emotion-recognition studies (Ryu and Park, 2024). Shown in Figure 1 All participants had normal or corrected-to-normal vision, no history of neurological or psychiatric disorders, and provided informed consent prior to participation. The study protocol followed ethical guidelines for human research, similar to recent wearable and portable EEG-based affective computing research (Liu *et al*., 2022). EEG signals were recorded using an RMS Maximums 24-channel EEG system. Electrodes were positioned according to the 10-20 international system at frontal (Fz), central (C3, C4, Cz), parietal (Pz), and temporal (T7, T8) locations, following recommended electrode placement standards for emotion recognition (Sreeshakthy *et al*., 2016). Two reference electrodes (M1, M2) were placed on the mastoids, and impedance was maintained below 5 kΩ to ensure high-quality acquisition, as emphasized in stress-feature EEG studies (Sulaiman *et al*., 2010). Participants were seated in a comfortable chair in a dimly lit room, instructed to minimize movement during recording, aligning with best practices in multichannel EEG-based affective analysis (Wu *et al*., 2020). Participants were exposed to emotion-eliciting stimuli, including images and short videos selected from the DEAP dataset, which is widely used in EEG emotion research due to its validated valence-arousal labeling (Koelstra *et al*., 2012). Each stimulus lasted 30 seconds, followed by a 10-second rest period. EEG signals were sampled at 256 Hz and band-pass filtered between 0.5–50 Hz, consistent with preprocessing guidelines adopted in portable and real-time EEG emotion detection studies (Real-time EEG Emotion Detection, 2025).

Recorded EEG signals were preprocessed using independent component analysis (ICA) and visual inspection to remove artifacts, a strategy also reported in wearable EEG emotion-recognition systems (Liu *et al*., 2022). Eye-blink, muscle, and movement artifacts were eliminated, and data were segmented into stimulus-specific epochs. Feature extraction included time-domain, frequency-domain, and nonlinear features such as PSD in alpha, beta, theta, and delta bands, frontal asymmetry indices, beta/alpha ratios, and entropy and Hjorth parameters methods frequently emphasized in earlier stress and emotional-state EEG analyses (Hosseini and Naghibi-Sistani, 2012). A 2D arousal-valence model was employed to map emotional states, in alignment with widely used affective modeling frameworks in BCI literature (Ryu & Park, 2024). Extracted features were input into an SVM classifier with an RBF kernel for baseline classification. Additionally, deep-learning models such as CNN-LSTM were evaluated to capture spatio-temporal EEG dynamics, supported by recent hybrid-model emotion recognition research (Zheng *et al*., 2022; Real-time EEG Emotion Detection, 2025). Classification performance was assessed using validation metrics appropriate for EEG-based emotion studies, building on precedent from prior comprehensive analyses of EEG feature extraction techniques (Zheng, and Lu, (2018).

RESULTS AND DISCUSSION

The EEG recordings revealed distinct patterns associated with different emotional states. High-valence states exhibited increased alpha power in frontal regions, consistent with approach-related positive affect, while low-valence states showed increased beta power in right parietal regions (Davidson & Irwin, 1999; Thayer & Lane, 2000). High-arousal stimuli were associated with enhanced beta activity across frontal and parietal lobes, whereas low-arousal stimuli showed dominant alpha activity (Zheng, & Lu,. (2018). SVM Classifier**:** Achieved accuracy of 78% for valence classification and 75% for arousal classification. CNN-LSTM Model**:** Achieved accuracy of 88% for valence and b for arousal, demonstrating the advantage of deep learning in capturing spatio-temporal dependencies in EEG data. Frontal asymmetry was highly correlated with valence ratings, confirming prior research (Koelstra *et al*., 2012). Beta/alpha ratios in frontal and parietal regions effectively reflected arousal levels. Nonlinear measures such as entropy improved classification by capturing subtle EEG dynamics, particularly for low-arousal states. The results indicate that EEG-based arousal-valence classification provides reliable markers for emotional states. Deep learning models outperform traditional machine learning due to their ability to learn complex temporal relationships. The study also highlights individual variability, as some participants showed atypical responses to stimuli, suggesting the need for personalized models in real-world applications. These findings are consistent with prior literature emphasizing the importance of spatial, spectral, and temporal EEG features for emotion recognition (Li *et al*., 2021; Xu *et al*., 2022; Thapa and Rai, 2025).

CONCLUSION

This study demonstrates that EEG signals can be effectively used for emotion and stress assessment using the arousal-valence classification model. Both traditional machine learning and deep learning approaches were explored, with CNN-LSTM models providing the highest classification accuracy. EEG features such as frontal asymmetry, beta/alpha ratios, and nonlinear dynamics are crucial for distinguishing emotional states. The findings support applications in mental health monitoring, adaptive human-computer interfaces, and affective computing**.** Future work should involve larger and more diverse participant groups, incorporate multimodal physiological signals (e.g., ECG, GSR), and explore real-time wearable EEG systems to enhance practicality and robustness of emotion recognition frameworks.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest

ETHICS APPROVAL

Not applicable

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AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

DATA AVAILABILITY

Data will be available on request

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