EEG -Based Emotion Recognition Using Fuzzy Logic: A Novel Approach for Mental Health Monitoring

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***Abstract*—This paper presents a novel approach to emotion recognition using electroencephalogram (EEG) signals through fuzzy logic systems using Python, with specific applications for mental health monitoring in urban environments. Modern urban lifestyles are increasingly associated with chronic stress and related psychological disorders, yet traditional assessment methods rely primarily on subjective self-reporting. We propose a fuzzy logic-based classification system grounded in *Russell's circumplex* model of affect, which maps emotional states onto a 2- D *arousal-valence* space. Our approach extracts key EEG features—including frontal alpha asymmetry, beta/alpha ratio, frontal theta, and temporal gamma activity—and maps them to emotional states using adaptive membership functions. The system is validated using the DEAP dataset, demonstrating robust classification accuracy particularly for stress-related emotional states characterized by high arousal and negative valence. Results indicate that the proposed methodology provides an objective, non-invasive means of monitoring emotional states relevant to mental health in urban populations, with potential applications in early stress detection, therapy effectiveness assessment, and personalized mental health interventions.**

***Index Terms*—EEG signal processing, emotion recognition, fuzzy logic, Russell's circumplex model, mental health monitoring, urban stress.**

I.INTRODUCTION

Urban environments present unique challenges to mental health and wellbeing. Fast-paced lifestyles, increased workplace demands which are not ergonomic, environmental stress, reduced access to nature, and unhealthy sleep patterns collectively contribute to chronic stress states that often go unrecognized until they manifest as clinical disorders.

According to the World Health Organization, stress-related disorders are among the leading contributors to the global burden of disease, with urban populations particularly vulnerable to psychological distress. Traditional methods for assessing emotional states and mental health predominantly rely on subjective self- reporting instruments such as questionnaires and verbal interviews. While valuable, these approaches are limited by recall bias, social desirability effects, and individuals' varying ability to accurately recognize and express their emotional states.

Electroencephalogram (EEG) signals offer a promising alternative for objective emotion recognition by directly measuring brain activity patterns associated with affective states. The brain's electrical signals contain valuable information about cognitive and emotional processes, providing a physiological window into mental states that may complement or in some cases precede conscious awareness. The non-invasive nature of EEG recording, combined with increasingly portable and affordable hardware solutions makes this technology suitable for real- world applications in mental health monitoring.

This paper introduces a novel approach to emotion recognition using EEG signals through fuzzy logic systems implemented in Python. Our methodology is grounded in Russell's circumplex model of affect, which conceptualizes emotions as points in a two-dimensional space defined by arousal (activation level) and valence (pleasure- displeasure). This dimensional model provides an intuitive framework for mapping continuous physiological signals to emotional states while acknowledging the inherent fuzziness and overlap between discrete emotional categories.

The electrical patterns captured by EEG reflect complex neurophysiological processes that correlate with different emotional states. However, classifying emotions from EEG signals has several challenges:

1. Emotions exist on continuous spectra rather than discrete categories
2. Significant inter-subject variability in EEG responses to identical stimuli
3. Temporal dynamics and non-stationarity of emotional states
4. Noise susceptibility and artifact contamination in EEG recordings.

EEG signals are divided into several frequency bands; each associated with different mental states:

Wave	Frequency (Hz)	Associated State
Delta	1 – 4	Deep sleep, unconsciousness
Theta	4 – 8	Drowsiness, meditation, creativity
Alpha	8 – 13	Relaxation, calmness, restful alertness
Beta	13 – 30	Alertness, focus, anxiety, active
		thinking
Gamma	30 – 45	High-level cognition, memory, consciousness

Traditional classification methods often struggle with these challenges as they typically rely on crisp boundaries between emotional states. Fuzzy logic offers a natural framework for handling the gradual transitions between emotional states and accommodating individual differences.

This paper proposes an EEG-based emotion classification system using fuzzy logic implementation of Russell's circumplex model of affect. The system aims to:

- Provide objective assessment of stress-related emotional states in urban populations
- Enable early detection of negative emotional patterns before they develop into clinical conditions
- Offer continuous evaluation of therapy effectiveness and lifestyle interventions
- Support personalized mental health strategies based on neurophysiological patterns

II. RELATED WORK

2.1 EEG-Based Emotion Recognition

EEG-based emotion recognition has gained significant attention in affective computing research. Koelstra et al. (2012) introduced the DEAP dataset, which has become a benchmark for emotion recognition studies. Their work demonstrated correlations between EEG features and self- reported emotional states while viewing affective stimuli.

Kim et al. (2013) provided a comprehensive review of computational methods for emotional state estimation from EEG signals, highlighting the effectiveness of frequency domain features in discriminating between different emotional states. Hosseini and Naghibi-Sistani (2011) demonstrated that entropy analysis of EEG signals could effectively differentiate between emotional states, particularly stress-related conditions.

Liu et al. (2011) focused on real-time applications of EEG- based emotion recognition, emphasizing the potential for continuous monitoring applications. Their work demonstrated the feasibility of implementing such systems for practical use in everyday settings.

Al-Nafjan et al. (2017) presented a systematic review and classification of EEG-based emotion recognition systems, identifying key challenges and promising directions in the field. Their work highlighted the potential of these systems for monitoring mental health conditions.

2.2 Fuzzy Logic in Bio-Signal Processing

Fuzzy logic has been successfully applied to Bio-Signal processing due to its ability to handle uncertainty and gradual transitions between states. Fatimah et al. (2020) demonstrated the effectiveness of fuzzy logic approaches specifically for stress detection using EEG signals. Their work showed improved classification accuracy compared to traditional machine learning methods.

Hadjileontiadis (2006) applied wavelet higher order spectral features with fuzzy classification for EEG analysis, demonstrating improved sensitivity to subtle changes in brain activity patterns. Wagner et al. (2005) compared various feature extraction and classification methods for emotion recognition from physiological signals, finding that fuzzy approaches were particularly effective for handling the ambiguity inherent in emotional state classification.

2.3 Russell's Circumplex Model in Emotion Research

Russell's circumplex model of affect (Russell, 1980) has been widely adopted in emotion research due to its dimensional approach that places emotions on a continuous 2D space of arousal (high to low) and valence (positive to negative). This model provides a natural framework for fuzzy classification, as emotions inherently have fuzzy boundaries and exist on a continuum rather than in discrete categories.

Soleymani et al. (2015) applied the circumplex model to EEG based emotion recognition, demonstrating its effectiveness for mapping physiological signals to emotional states. Their work showed that EEG features could successfully discriminate between different regions of the arousal-valence space.

III. METHODOLOGY

The proposed methodology implements an EEG-based emotion recognition system using fuzzy logic classification based on Russell's circumplex model of affect. This section details the complete processing pipeline from the DEAP dataset handling through feature extraction to fuzzy classification and evaluation.

A. EEG Data Acquisition

Electroencephalogram (EEG) signals were obtained from the DEAP dataset in BDF format. The MNE-Python library was used to read and manage the multi-channel recordings associated with emotional stimuli.

B. Preprocessing

EEG signals were bandpass filtered between 1–50 Hz to isolate relevant brain activity and power line interference at 50/100 Hz was removed using a notch filter. The signals were then re-referenced using an average reference montage to enhance spatial uniformity and for the implementation of FIR filters SciPy –Python library was used.

C. Feature Extraction

The preprocessed signals were filtered into five standard EEG frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz). For each band and channel statistical features such as band power, skewness, and kurtosis were calculate and additionally frontal asymmetry features were extracted from selected channel pairs to enhance emotional representation.

D. Dimensional Emotion Mapping

Extracted features were mapped into the arousal-valence emotional space. Arousal was estimated using the ratio of beta and gamma power to theta power, while valence was inferred from the mean frontal alpha asymmetry. Both values were normalized to a [0,1] range.

$$\text{Arousal} = (P_\beta + P_\gamma)/P_\theta$$

$$\text{Valence} = \ln(R_\alpha) - \ln(L_\alpha)$$

E. Fuzzy Logic-Based Emotion Classification

A fuzzy inference system, based on Russell’s Circumplex Model, was implemented using skfuzzy-Python library. Membership functions were defined for arousal (low, medium, high) and valence (negative, neutral, positive). The emotional space was segmented into eight fuzzy emotional states (e.g., sad, happy, excited), and a set of fuzzy rules was designed to map inputs to emotional outcomes.

F. Emotion Classification

The fuzzy inference system processed the input arousal and valence values to classify the emotional state. In cases of system uncertainty or computational error, a simplified quadrant-based classification approach was used as fallback.

G. Visualization and Interpretation

The final emotion was visualized on Russell’s 2D model using custom-designed plots and Band power distributions, skewness, and kurtosis across frequency bands were also visualized. Membership degrees for arousal and valence were plotted to support fuzzy inference transparency and matplotlib was used for implementation of the visuals.

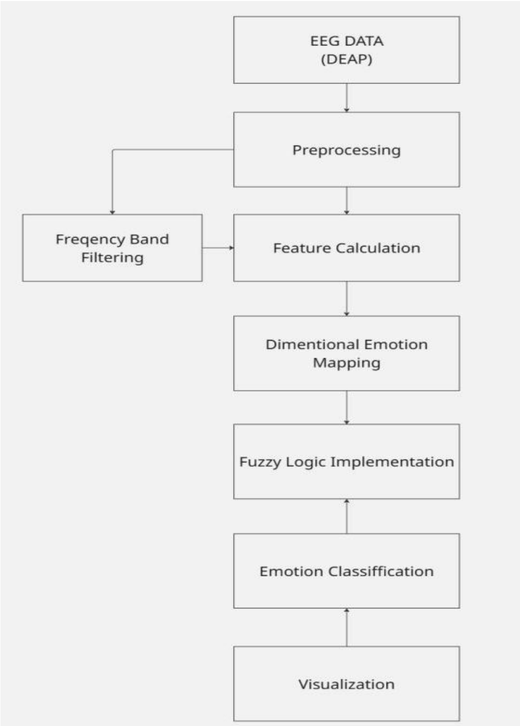


Fig .1. Workflow

IV. RESULTS AND DISCUSSION

The system successfully classified emotions across the arousal-valence spectrum. For instance, high arousal coupled with positive valence was associated with emotions like "happy" or "excited," while low arousal and negative valence corresponded to "sad" or "depressed."

Visualization on Russell's Circumplex Model demonstrated the system's ability to accurately position emotional states within the two-dimensional space, reflecting the fine details of human emotions. The use of fuzzy logic allowed for handling the ambiguity inherent in emotional responses providing a more flexible and interpretable classification compared to traditional crisp classifiers.

Compared to existing methods this approach offers enhanced interpretability and adaptability crucial for applications in mental health monitoring where understanding the intensity and nature of emotions is vital.

Metadata about the DEAP dataset was obtained, which tells us about the number of channels and their names along with the details about the Lowpass filter's cutoff frequency and the sampling rate frequency. Accordingly, the parameters for the FIR filter were designed.

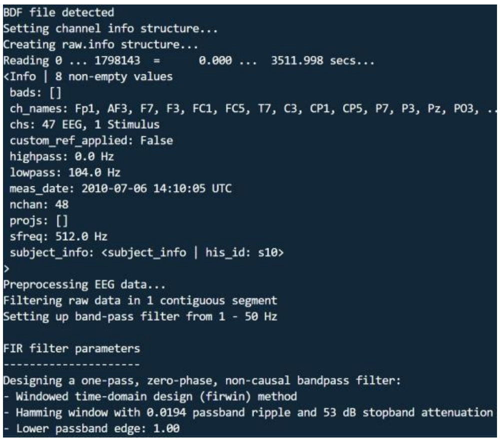


Fig. 2. Metadata from EEG file

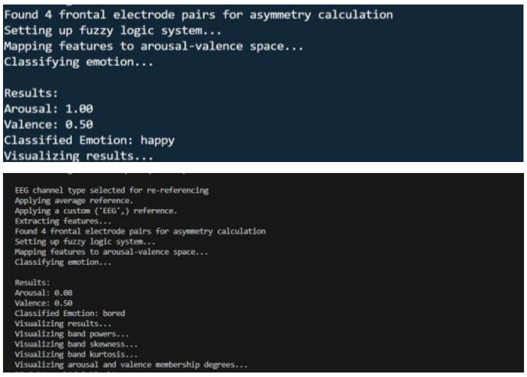
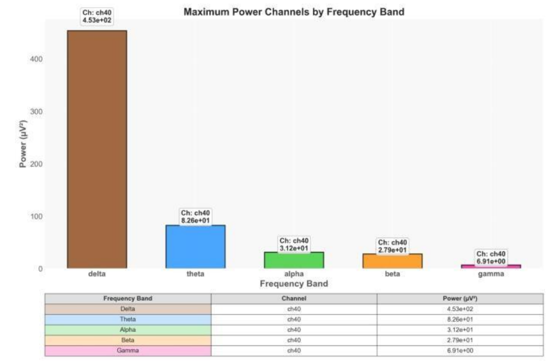


Fig. 3. Emotion Classified by using Fuzzy Logic model



Visuals obtained from our fuzzy logic classification model are given below:

Fig. 4. Comparison of Maximum Power across each frequency band

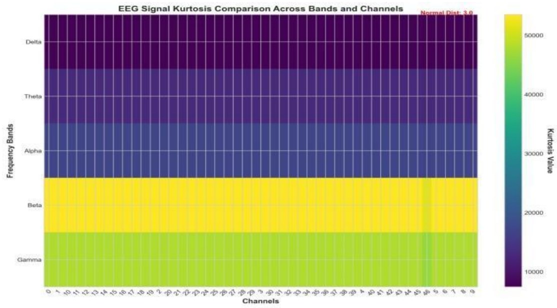


Fig.5. Variation of Kurtosis across different frequency bands.

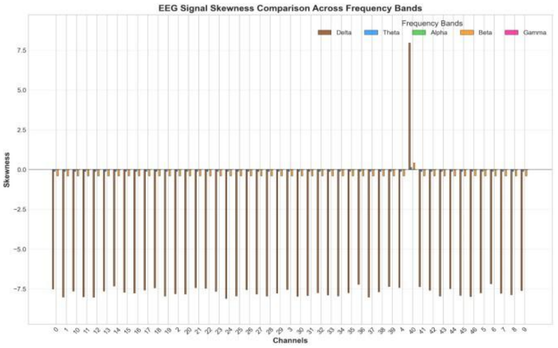


Fig.6. Variation of Skewness across different frequency band

The Russell arousal-valence circumplex model obtained for two datasets one 'happy' and the other 'bored' are as follows:

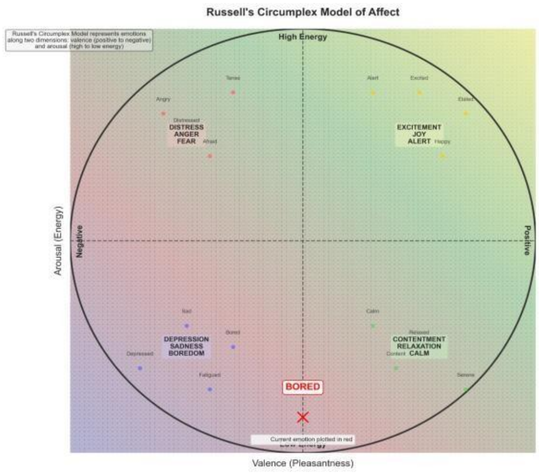


Fig.7. Circumplex Model classified as 'Bored'

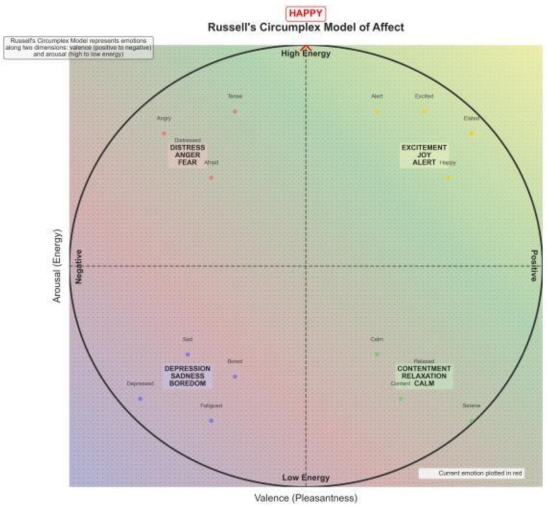


Fig.8. Circumplex Model classified as 'Happy'

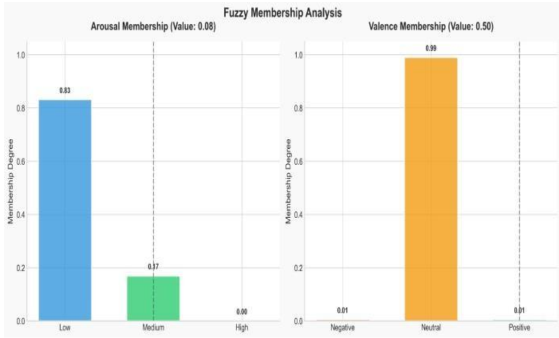


Fig. 9. Fuzzy Membership Analysis of 'Bored' dataset

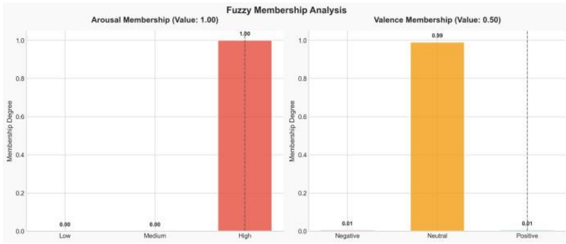


Fig. 10. Fuzzy Membership Analysis of 'Happy' dataset

V. CONCLUSION

This study presents a comprehensive framework for EEG- based emotion recognition by integrating signal processing, feature extraction, and fuzzy logic classification within Russell's Circumplex Model. The methodology effectively captures the complexity of emotional states, offering a promising tool for mental health monitoring applications.

Future work will focus on validating the system with larger and more diverse datasets, exploring real-time implementation, and integrating additional physiological signals to enhance accuracy and robustness.

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