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EEG Signals Based Emotion Prediction to Implement AI Therapeutic Bot

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Abstract
Emotion recognition using Electroencephalogram (EEG) signals has become an essential tool in mental health monitoring, human-computer interaction, and affective computing. EEG provides a non-invasive method for capturing electrical activity in the brain with high temporal resolution, making it highly suitable for real-time emotion analysis. Traditional emotion recognition methods relying on facial expressions or voice can be biased or manipulated, whereas EEG-based analysis offers a more objective and direct understanding of emotional states. Existing systems typically implement EEG-based emotion classification pipelines used Multi-Scale Principal Component Analysis (MSPCA) for denoising. Feature extraction methods like Second-Order Difference Plot (SODP) and Summation of Distance to Coordinate (SDC) are commonly used, followed by spatial transformations like Equidistant Azimuthal Projection (EAP). Advanced models integrate Convolutional Block Attention Module (CBAM) and Generative Adversarial Networks (GANs) for refinement and data augmentation, respectively. This system, often limited by fixed emotion categories, insufficient temporal modelling, and lack of real-time interaction. To overcome these limitations, the proposed system introduces an advanced end-to-end EEG-based emotion recognition framework. It enhances preprocessing using MSPCA and performs Welch's Power Spectral Density (PSD) estimation and Differential Entropy (DE) calculation across five EEG bands. A Linear Dynamic System (DE_LDS) with Kalman filtering effectively models temporal feature dynamics. The system integrates GANs for data augmentation and utilizes a Bi-Directional Long Short-Term Memory (Bi-LSTM) network for capturing complex temporal dependencies in EEG signals. The model is further integrated to a Flask-based AI therapeutic chatbot, which receives real-time emotion predictions via an external API and uses win32com.client for speech synthesis, enabling empathetic, voice-enabled interactions.

Keywords: Multi-Scale Principal Component Analysis, Generative Adversarial Networks, Welch's Power Spectral Density, Differential Entropy, Kalman filtering, therapeutic chatbot.

1. INTRODUCTION

1.1 Overview

Emotional well-being is an essential aspect of overall mental health, yet it remains one of the most complex and under-addressed challenges in modern healthcare and daily life. Factors such as stress, anxiety, and emotional instability can significantly impact productivity, social interaction, and quality of life. Traditional methods for emotional assessment—such as surveys, self-reporting, and clinical interviews—are often subjective, infrequent, and lack real-time feedback mechanisms. As a result, there is a growing need for intelligent systems that can continuously monitor emotional states and provide timely, personalized support. EEG stands out as a powerful tool due to its non-invasive, cost-effective nature and high temporal resolution, ideal for capturing real-time emotional dynamics. However, EEG signals are often noisy and non-stationary, requiring advanced preprocessing to extract useful features. Limited dataset size and subject variability further challenge model generalization. The overlapping and multidimensional nature of emotions complicates recognition tasks. To address these, this project combines sophisticated preprocessing, data augmentation, and deep learning models. It aims to capture spatial-temporal EEG patterns across frequency bands and improve robustness for therapeutic applications.

1.2 Objective of the study

The overall objective is to create a robust, accurate, and emotionally intelligent system that offers real-time support and enhances emotional well-being through intelligent interaction. The main objective of this project is to develop a comprehensive system capable of accurately recognizing human emotions from EEG signals and providing real-time, personalized therapeutic support through a voice-enabled chatbot. To achieve this, the project focuses on preprocessing raw EEG data using advanced filtering techniques such as Kalman filtering (Zhang et al., 2024) and Multi-Scale Principal Component Analysis (MSPCA) (Qiao et al., 2024) to remove noise and artifacts. Generative Adversarial Networks (GANs) (Qiao et al., 2024) is employed to classify seven distinct emotions while addressing data scarcity through GAN-based synthetic data generation. Differential Entropy (DE) (Fernandes et al., 2024) features are typically extracted using the Welch method (Zhang, Zhou, Chen et al., 2024) for estimating the Power Spectral Density (PSD) of EEG signals. A hybrid deep learning model combining Bi-Directional Long Short-Term Memory (Bi-LSTM) (Fan et al., 2024) , These emotion predictions are seamlessly integrated with a Flask-based therapeutic chatbot that uses speech recognition, text-to-speech synthesis, and a locally hosted language model to engage users in empathetic dialogue.

1.3 Motivation for the study

The increasing prevalence of mental health issues, coupled with limited access to timely and personalized psychological support, highlights the urgent need for intelligent, scalable emotional support systems. Traditional methods of emotion assessment, such as self-reports and behavioral observation, are subjective and often fail to capture real-time emotional fluctuations. EEG-based emotion recognition offers a more objective and dynamic alternative by directly analyzing brain activity. However, harnessing EEG for practical applications requires overcoming challenges like signal noise, data scarcity, and emotional complexity. This project is motivated by the potential to bridge the gap between neuroscience and therapeutic support using advanced deep learning techniques. By combining robust EEG signal processing with emotion-aware conversational AI, the study aims to create an accessible, voice-enabled mental health companion that can respond empathetically to users' emotional states. This not only supports early intervention and self-awareness but also opens up possibilities for continuous, real-time affective monitoring in everyday environments.

2. LITERATURE SURVEY:

2.1 Utilization of GAN and MSPCA in EEG Data Processing for Emotion Recognition

In EEG data processing for emotion recognition, Generative Adversarial Networks (GAN) and Multi-scale Principal Component Analysis (MSPCA) are employed to tackle the challenges of noise interference and limited data availability. GANs augment the dataset by generating synthetic EEG signals that closely resemble real recordings, addressing the issue of insufficient data for effective model training (Qiao et al., 2024). This adversarial training enhances the model's robustness and generalization capabilities. Meanwhile, MSPCA is utilized to remove noise from EEG signals, effectively filtering out interferences from muscle activity and eye movements while preserving essential features (Qiao et al., 2024). The combination of GAN for data augmentation and MSPCA for noise reduction significantly improves the accuracy and reliability of emotion recognition systems.

2.2 Power Spectral Density Estimation in EEG Data Processing for Emotion Recognition

In EEG data processing for emotion recognition, estimating the power spectral density (PSD) of the signals is a critical step that significantly impacts the accuracy of classification models. Accurate PSD estimation allows for the identification of specific frequency bands associated with different emotional states, which is essential for feature extraction. Various methods can be employed for PSD estimation, including the Welch method, which is known for its effectiveness in reducing noise and variance in the spectral estimates.This method is particularly advantageous due to its ability to provide a more accurate and reliable estimate of the signal's power distribution across different frequency bands. The Welch method works by dividing the EEG signal into overlapping segments, applying a windowing function to each segment, and then averaging the periodograms of these segments. This approach reduces the variance of the PSD estimate, making it less sensitive to noise and artifacts commonly present in EEG recordings (Zhang, Zhou, Chen et al., 2024).

2.3 Utilization of BiLSTM in EEG Data Processing for Emotion Recognition

In the context of EEG data processing for emotion recognition, the Bi-directional Long Short-Term Memory (BiLSTM) model is employed to effectively capture the temporal dependencies inherent in EEG signals. BiLSTM (Fan et al., 2024) enhances the model's ability to learn from sequential data by processing inputs in both forward and backward directions, allowing it to utilize context from both past and future time steps. This is particularly crucial for EEG data, which is sequential and can exhibit complex patterns over time. The architecture's capability to maintain long-term dependencies makes it well-suited for recognizing emotional states based on EEG patterns, as it can better interpret the nuances in the data that are indicative of different emotions. By leveraging the strengths of BiLSTM, the emotion recognition system can achieve improved accuracy and robustness in classifying emotional states from EEG signals (Fan et al., 2024).

3. Proposed System

3.1 Objective

The objective of this proposed work is to enhance EEG-based emotion recognition by improving both feature extraction and model performance. To achieve this, the proposed system employs Differential Entropy with Linear Dynamic System (DE_LDS) as the feature extraction technique. DE_LDS effectively captures the dynamic and complex variations in brain signals, providing more informative features for emotion classification. By leveraging this method, the system aims to increase the accuracy of emotional state recognition, enabling more reliable and real-time emotion-aware applications.

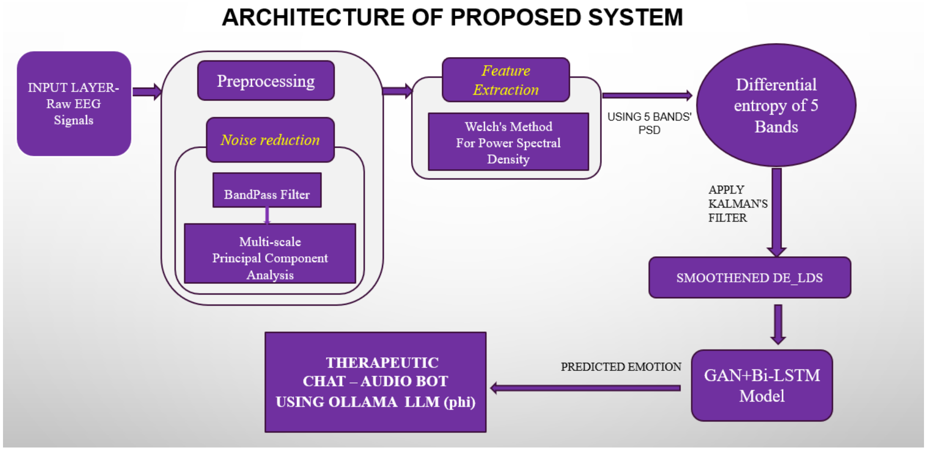

Figure 1. Emotion Prediction EmoPy Bot System Architecture

3.2 System architecture and workflow

The modules of the proposed system of the EmoPy Bot are as followed in the figure 1 and a detailed description is given below:

3.2.1 Input Layer - Raw EEG Signals

The process begins with raw EEG signals collected from brainwave monitoring devices. These signals are typically noisy and contain a lot of irrelevant data, so they require preprocessing.

3.2.2 Preprocessing

This step is crucial to clean and prepare the EEG signals for analysis.

Down sampling:

It converts high-frequency EEG data (2500 Hz) to a lower rate (200 Hz) for easier and faster processing.

3.2.3 Bandpass Filter

A bandpass filter isolates a specific range of frequencies in a signal, allowing only the frequencies within that range to pass and blocking others. For example: Delta (1–4 Hz): Passes frequencies between 1–4 Hz, Theta (4–8 Hz): Passes frequencies between 4–8 Hz.

Multi-scale Principal Component Analysis (MSPCA):

A technique that decomposes the signal into components at multiple scales and removes low-variance components, thereby reducing noise while preserving important signal features.

3.2.4 Feature Extraction

Once the signal is cleaned, features need to be extracted to represent the data meaningfully for the model.

- Signal Segmentation: The signal is divided into small segments (e.g., 1-second segments).
- Windowing: A window function (like Hann) is applied to reduce edge effects.
- FFT (Fast Fourier Transform): Converts the signal from the time domain to the frequency domain.
- Power Calculation: The amplitude of the FFT is squared to get the power at each frequency.
- Averaging: Power is averaged across all segments to get the Power Spectral Density (PSD).

3.2.5 Differential Entropy of 5 Bands

Differential Entropy (DE) is a statistical measure used here to quantify the complexity or randomness of EEG signals within each of the 5 bands. Differential Entropy (DE) is computed for each frequency band (e.g., delta, theta, alpha, beta, gamma). DE represents brain activity levels, with higher DE indicating stress and lower DE indicating calm states.

$$DE = \frac{1}{2} log\ (2\pi e\sigma^2) \quad (1)$$

- σ is the variance of the distribution, which measures how spread out the values are.
- e is Euler's number (~2.718), appearing due to its role in the Gaussian probability density function.
- 2π comes from the normalization constant in the Gaussian distribution.
- The logarithm (usually base-2 for bits or natural log for nats) converts the expression into a measure of information.

3.2.6 Kalman's Filtering for Signal Smoothing

Once the differential entropy (DE) features are extracted across the five frequency bands, they often contain noise and fluctuations due to the dynamic nature of EEG signals. To enhance the stability and reliability of these features, Kalman Filtering is applied. The Kalman Filter is an optimal recursive filter that estimates the true state of a system from noisy observations. It works in two phases: Prediction Equation (State Evolution) (2) – estimates the current state based on the previous state and Update Equation (Observation Update) (3) – refines the prediction using the current noisy observation.

$$x_t = Ax_{t-1} + w_t \quad (2)$$

x_t: The current state at time t

A: The state transition matrix, which describes how the previous state x_{t-1} evolves to the next state.

w_t: Process noise at time t, typically assumed to be Gaussian.

$$y_t = Cx_t + v_t \quad (3)$$

y_t: The observation or measurement at time t

C: The observation matrix that maps the state x_t to the observed output y_t.

v_t: Measurement noise, typically assumed to be Gaussian

3.2.7 GAN + Bi-LSTM Model

GAN (Generative Adversarial Network):

Used to enhance feature quality or generate synthetic training data to overcome limited dataset size.

Bi-LSTM (Bidirectional Long Shorty-Term Memory):

A deep learning model that captures both past and future dependencies in sequential data like EEG, improving emotion classification accuracy.

The model predicts the user's emotional state based on the processed EEG features as Happy, Sad, Surprise, Fear, Anger, Disgust or Neutral.

3.2.8 EmoPy bot using Ollama (phi model)

The Figure 4.2 presents the EEG Emotion Therapeutic (audio/chat) bot also known as the EmoPy Bot which integrates speech recognition, emotion detection via EEG data, and a local language model to create an empathetic and context-aware conversational system. It uses EEG data to detect the user's emotional state, which drives the bot's responses, ensuring that the conversation feels personal and emotionally intelligent. The system allows users to interact via text or speech, with the bot generating responses based on the user's emotional context and conversation history.

The bot leverages Ollama, a local language model, to generate thoughtful, empathetic responses and Zira's TTS voice to speak these responses aloud, making interactions more engaging and human-like.

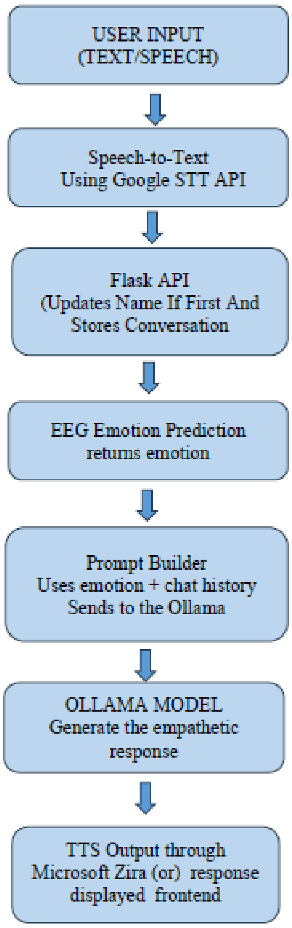

Figure 2. Workflow of the EmoPy bot

4. Dataset Preparation

The SEED-IV dataset, developed by the Brain and Cognitive Intelligence Lab at Shanghai Jiao Tong University, is a curated EEG dataset tailored for multi-class emotion recognition. It involves data collection from 15 participants (aged between 23–28), each undergoing three experimental sessions spaced at least one week apart to evaluate the temporal robustness of emotional EEG patterns.

The SEED-VII dataset, developed by the Brain and Cognitive Intelligence Lab at Shanghai Jiao Tong University, is a comprehensive multimodal resource designed for emotion recognition research. It encompasses EEG and eye-tracking data from 20 right-handed participants (10 males and 10 females, aged 19–26) who viewed 80 video clips intended to evoke seven emotional states: happiness, sadness, fear, disgust, surprise, anger, and neutral. Each video lasted between 2 to 5 minutes, totaling approximately 14,098 seconds of stimuli. EEG signals were recorded using a 62-channel ESI NeuroScan System, while eye movements were captured with Tobii Pro Fusion eye-tracking devices. The raw EEG data underwent preprocessing steps, including bandpass filtering (0.1–70 Hz), notch filtering at 50 Hz, and downsampling from 1000 Hz to 200 Hz.

Subsequently, Differential Entropy (DE) features were extracted across five frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–31 Hz), and gamma (31–50 Hz). These features were further refined using a Linear Dynamic System (LDS) approach to enhance temporal stability. The dataset is organized into several folders, including raw and preprocessed EEG data, DE features, eye-tracking features, and accompanying metadata such as stimulus labels and subject information. This rich dataset supports the development of advanced models for emotion recognition and is accessible to researchers upon request through the official BCMI Lab website.

5. Experimental Setup

5.1 Hardware Requirements

- RAM: 4 GB minimum
- Storage: 10 GB free space
- Microphone & Speaker: For voice input/output
- Internet: Required for API and model access

5.2 Software Requirements

- Operating System: Windows 7/8/10/11
- Tools: PyCharm, Google Colab (for EEG emotion detection), Ollama (for local AI model)
- Programming Language: Python 3.8+
- Libraries: win32com.client, speech_recognition, flask, flask_cors, requests, numpy , pandas , matplotlib , scipy , torch, PyWavelets

6. Results and Discussion

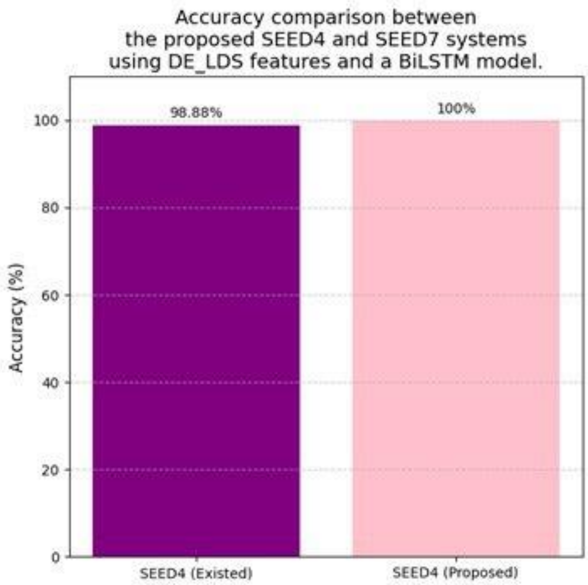

Figure 3. Proposed System results comparison

The proposed system addresses the limitations like struggles to effectively capture long-range temporal dependencies in EEG signals by incorporating advanced feature extraction methods such as Welch's Power Spectral Density (PSD), Differential Entropy (DE), and modeling temporal dynamics using a Linear Dynamic System (DE_LDS) with Kalman filtering. These enriched features are processed using a Bi-Directional Long Short-Term Memory (Bi-LSTM) network, enabling the model to recognize complex emotional patterns with greater precision. As a result, the proposed system achieves an accuracy of 98.88% on the SEED4 dataset and a perfect 100% on the SEED7 dataset, highlighting its superior generalization capability.

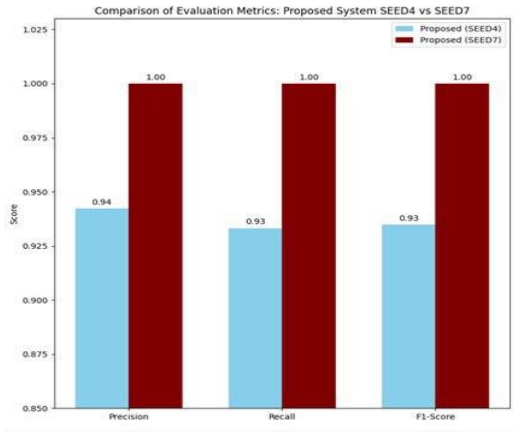

Figure 4. Performance Analysis of the Proposed System

Figure 4 compares Precision, Recall, and F1-Score of the Proposed System on SEED4 and SEED7. The bar chart presents a comparative analysis of evaluation metrics—Precision, Recall, and F1-Score—for a proposed emotion recognition system tested on the SEED4 and SEED7 EEG datasets. The system demonstrates outstanding performance on the SEED7 dataset, achieving perfect scores (1.00) across all metrics, indicating flawless classification of emotional states. In contrast, the system also performs strongly on the SEED4 dataset, with scores of 0.94 for Precision and 0.93 for both Recall and F1-Score, reflecting its robustness and generalization capability. The slight performance gap suggests that SEED7 may provide more diverse or better-quality emotional features, possibly due to its richer multimodal structure or more distinct emotional stimuli. Overall, the results validate the effectiveness of the proposed system across different datasets.

7. Conflict of Interest

The SEED and SEED-VII datasets utilized in this study were obtained from the Brain and Cognitive Intelligence Laboratory at Shanghai Jiao Tong University solely for academic and research purposes. No financial, commercial, or personal relationships with the dataset providers have influenced the outcomes or interpretations of this work. All data usage strictly adheres to the licensing and ethical guidelines set forth by the SEED organization.

8. Acknowledgement

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9. Conclusion

In conclusion, the proposed EEG-based emotion recognition system effectively combines advanced signal processing and deep learning techniques to achieve accurate and real-time emotional classification. By integrating MSPCA, DE_LDS, GANs, and Bi-LSTM, the system addresses challenges like noise, temporal dynamics, and data scarcity. The addition of a voice-enabled therapeutic Emopy chatbot enhances its real-world applicability in mental health support. This approach provides a more objective and dynamic alternative to traditional emotion detection methods. Overall, it lays a strong foundation for future emotion-aware healthcare and human-computer interaction systems.

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