AI-Powered Human-Machine Interface for Emotion Monitoring Using EXG Pill

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Abstract -

Human behavior, decision-making, and general well-being are significantly influenced by emotions. Emotion recognition has become crucial for creating user-centered and adaptive systems as artificial intelligence's influence grows. Traditional methods like sentiment analysis of voice, text, or facial expressions are frequently constrained by cultural bias, background noise, or deliberate masking, which renders them unreliable for real-time applications. Because physiological signal-based techniques, especially electroencephalography (EEG), directly record emotion-related brain activity, they have become viable substitutes for these difficulties.

The EXG Pill, a small, non-invasive bio-signal acquisition device that may be used on a daily basis, is used in this work to propose an AI-powered human–machine interface for emotion monitoring. The frontal lobe regions (Fp1, Fp2), which are closely associated with emotional processing, are where EEG data are obtained. Features are extracted following preprocessing procedures such as amplification, filtering, and noise reduction. Two important indicators are employed: Power Spectral Density (PSD), which measures alertness across frequency bands, and Frontal Alpha Asymmetry (FAA), which indicates emotional valence. To identify emotions like calm, happy, sad, and furious, they are categorized using SVM, CNN, and LSTM models.

Emotional states are visualized and adaptive feedback is given via a real-time dashboard. With prospective uses in personalized education, assistive technology, mental health, and emotion-aware interaction, the system exhibits increased accuracy, portability, and usability.

Key Words: Emotion recognition, EEG signals, EXG Pill, Frontal Alpha Asymmetry, Power Spectral Density, Human–Machine Interface, Real-time monitoring, Deep learning, Machine learning, Assistive technology, Mental health, Brain–computer interface.

1.INTRODUCTION

Human life is fundamentally shaped by emotions, which influence how people think, act, and engage with the world. Learning, memory, communication, decision-making, and overall psychological well-being are all impacted. As human-machine connection increases in the contemporary digital era, the ability of machines to sense and respond to human emotions is crucial for creating intelligent, flexible, and user-friendly systems. Accurate emotional state recognition is particularly important in domains including healthcare, mental health monitoring, education, assistive technology, entertainment, and workplace productivity where a deeper comprehension of emotions can provide valuable insights and improve outcomes.

Traditional techniques for determining emotions mostly rely on external cues such as text sentiment, speech signals, body language, and facial expressions. These methods have been somewhat successful, but they are often unreliable since situational, linguistic, and cultural factors can affect or intentionally mask emotions. For example, a smile may not always indicate happiness, and a person's conversational tone may not always reflect their true emotional state. Furthermore, because external approaches are very sensitive to ambient elements like illumination, background noise, and recording quality, their value for continuous, real-time monitoring is reduced.

To overcome these limitations, research has shifted toward physiological signal-based methods, particularly those that use electroencephalography (EEG). EEG signals are a more accurate way to identify internal emotional states since they give direct information about brain activity. Research has demonstrated that patterns of brain waves in particular frontal lobe regions can be used to predict arousal levels and emotional valence (positive versus negative). Nevertheless, the majority of EEG-based emotion recognition systems currently in use rely on large, costly, and lab-grade equipment that is unsuitable for daily use. This limits their utility in situations that need portability, affordability, and user comfort in the real world.

These issues are addressed by the EXG Pill, a small bio-signal collection device that provides a portable, non-invasive method of obtaining brain signals from the frontal lobe, namely at the Fp1 and Fp2 electrode sites. These areas are ideal for investigations on emotion recognition since they are intimately related to emotional processing. The EXG Pill provides a basis for reliable emotion classification by amplifying weak brain impulses in the microvolt range, filtering out noise, and preparing the signals for digital analysis.

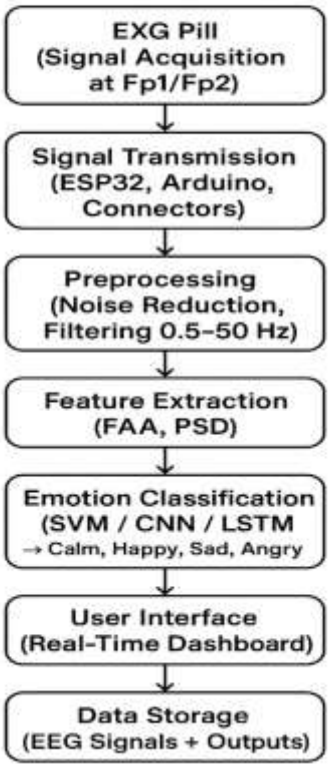
In this work, we introduce an AI-driven human-machine interface for emotion monitoring that integrates the EXG Pill with state-of-the-art AI models. The system processes EEG signals in three basic steps: preprocessing, feature extraction, and classification. At the feature extraction stage, important metrics are computed, such as Power Spectral Density (PSD), which gauges arousal levels, and Frontal Alpha Asymmetry (FAA), which gauges emotional valence. These features are then classified into emotional states such as calm, happy, sad, and furious using machine learning and deep learning techniques including Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). Built for real-time operation, the proposed system's user interface provides adaptive feedback and displays emotional states. This method allows for continuous tracking of emotions in ordinary circumstances by addressing the shortcomings of traditional systems and ensuring portability and usability. The system can be used for a variety of purposes, such as mental health monitoring, where patients and therapists can benefit from real-time insights into emotional states; assistive technologies, where devices can adapt to the emotional needs of individuals with disabilities; education, where individualized learning experiences can be created through emotional engagement; and entertainment, where immersive and adaptive experiences can be created.

2. Body of Paper

This section provides a comprehensive description of each module in the proposed AI-powered emotion monitoring system. The architecture follows a systematic pipeline from biological signal acquisition to real-time emotion visualization and adaptive response.

2.1. System Architecture Overview

The system architecture of the proposed AI-powered human–machine interface for emotion monitoring using Starting with signal gathering and concluding with real-time viewing, the BioAmp Electrophysiological Signal gathering (EXG) Pill is set up as a sequential process. In the initial phase, the EXG Pill is used to record brain signals from the frontal lobe (Fp1 and Fp2), which are then amplified and sent to an ESP32 microcontroller. Before wirelessly sending the signals to the processing unit, the ESP32 digitizes them and applies some basic filtering. The data is subsequently cleaned using preprocessing methods including artifact removal and bandpass filtering (0.5–50 Hz). Features including Frontal Alpha Asymmetry (FAA) and Power Spectral Density (PSD), which serve as the foundation for categorization, are extracted in the following step.Machine learning and deep learning algorithms—Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—are used to classify emotional states, which are finally visualized in a web-based dashboard with storage support.



2.2. Signal Acquisition Module

The BioAmp Electrophysiological Signal Acquisition (EXG) Pill is used in the system's initial phase to collect brain signals. Due to their strong correlation with emotional valence and processing, electrodes are positioned at the frontal lobe's Fp1 and Fp2 sites. These locations usually have weak brain signals that are vulnerable to noise and assessed in the microvolt

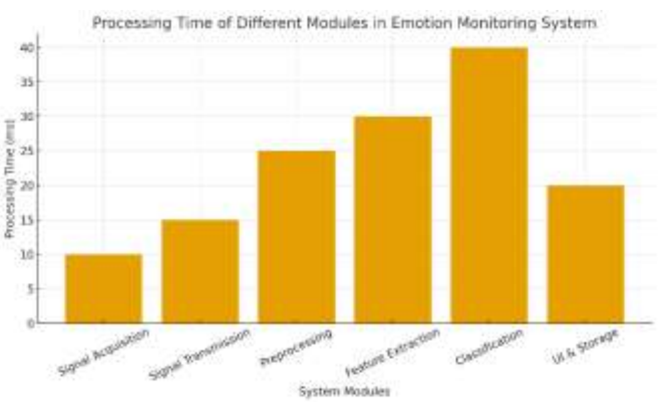
(µV) range. Without changing the frequency content of these signals, the EXG Pill's amplification circuitry raises them to a detectable level.
Additionally, this module incorporates analog bandpass filtering between 0.5 and 50 Hz. Important brainwave rhythms such as Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz) are protected for additional research thanks to this filtering. The acquisition stage enhances the recorded signals' quality by removing superfluous low- and high-frequency components. We explain the procedure by which these enhanced signals are sent to the following phase for additional processing.

2.3. Signal Preprocessing Module

The preprocessing stage aims to refine the digitized EEG data to make it suitable for feature extraction. While the EXG Pill already applies analog filtering, additional digital preprocessing is necessary to handle artifacts and background noise. Common noise sources include:

- **Electromyogram (EMG) artifacts** from facial or scalp muscle activity.
- **Electrode motion artifacts** due to poor contact.

A digital bandpass filter between 0.5–50 Hz is used to further isolate relevant frequency bands. In some cases, notch filters are employed to remove power-line interference at 50/60 Hz. Preprocessing also involves signal normalization and segmentation into smaller epochs for analysis.



2.4. Feature Extraction Module

After preprocessing, the signals are processed to extract features that characterize emotional states. Two primary features are employed:

1. **Frontal Alpha Asymmetry (FAA):** FAA is calculated as the difference in alpha-band power between Fp1 and Fp2 electrode sites. It is mathematically represented in Eq. (1):

   FAA=Pα(Fp1)−Pα(Fp2)FAA = P_{\alpha}(Fp1) - P_{\alpha}(Fp2)FAA=Pα(Fp1)−Pα(Fp2)

   where PαP_{\alpha}Pα denotes alpha power (8–13 Hz). Positive FAA values are linked with positive emotions (e.g., happiness), while negative values often correspond to negative emotions (e.g., sadness).

2. **Power Spectral Density (PSD):** PSD measures the distribution of signal power across different frequency bands. Higher beta and gamma activity may correspond to emotional arousal, while alpha rhythms are linked to relaxation.

For classification, a hybrid approach combining traditional machine learning and deep learning is adopted:

- **Support Vector Machine (SVM):** Effective for small datasets and provides baseline results.
- **Convolutional Neural Network (CNN):**Learns spatial relationships between EEG electrodes and identifies non-linear patterns.
- **Long Short-Term Memory (LSTM):** Captures temporal dependencies across time-series EEG data, essential for emotions that change dynamically.

These classifiers categorize the user's emotional state into four classes: Calm, Happy, Sad, and Angry.

2.5. Emotion Classification Module

An essential part of the system is the Emotion Classification Module, which maps retrieved data into distinct emotional states. The preprocessed electroencephalography (EEG) signals are used to extract features including Frontal Alpha Asymmetry (FAA) and Power Spectral Density (PSD). The input dataset for classification models is made up of these

features.
To guarantee reliable and accurate categorization, the module uses both cutting-edge deep learning techniques and conventional machine learning:

1. Support Vector Machine (SVM): This classifier is initially used as a baseline. By optimizing the margin between data points, it creates judgment boundaries between various emotion classes and performs well on smaller datasets. Simple situations are handled by linear kernels, but complicated distributions of EEG data are handled by non-linear kernels (such as the radial basis function).
2.

   2. Convolutional Neural Network (CNN): CNNs are made to recognize spatial patterns in EEG signals, especially when they are recorded from several electrodes. Discriminative characteristics like frequency shifts or asymmetry in brainwave activity are automatically detected by convolutional layers. Fully linked layers translate these features into particular emotional states, whereas pooling layers decrease dimensionality.

1. **Long Short-Term Memory (LSTM):** Since emotions evolve dynamically over time, LSTM networks are employed to capture temporal dependencies in EEG signals. LSTM units retain information across time steps, allowing the model to analyze transitions between emotional states more accurately. This is particularly useful for detecting subtle mood changes that occur over longer monitoring sessions.

By combining these models, the system classifies emotional states into four categories: **Calm, Happy, Sad, and Angry.** The use of hybrid classifiers provides improved robustness compared to using a single model.

2.6. User Interface and Data Storage Module

The user interface (UI), which offers real-time visualization of the categorized emotions, is the last phase of the system. Using graphical indications like timelines, charts, and colorful icons, a web-based dashboard created using JavaScript (frontend) and Flask (backend) illustrates emotional states. The interface guarantees ongoing emotional monitoring and the generation of adaptive reactions. For instance, the system might play relaxing music or offer relaxation advice if stress is sensed. Emotion-aware answers can also enhance user interaction in assistive technologies.
Another important component of this module is data storage. For additional investigation, EEG signals and classification outputs are recorded in a database. Long-term tracking of emotional patterns made possible by historical data can help with adaptive learning systems, therapeutic monitoring, and mental health evaluations.

3. CONCLUSIONS

Using the EXG Pill biosensor, this project effectively illustrates the design and execution of a working AI-powered human-machine interface for real-time emotion monitoring. The approach uses direct brain signal analysis through a portable, non-invasive device to effectively overcome major drawbacks of conventional emotion recognition techniques. Our implementation demonstrates that accurate classification of emotional states, such as calm, happy,

sad, and angry, can be achieved with a basic two-channel frontal EEG setup in conjunction with suitable data processing and machine learning methods.
In addressing the temporal dynamics of EEG signals, deep learning techniques—in particular, the Long Short-Term Memory (LSTM) network—performed better than conventional methods, according to a comparative examination of classification algorithms. The real-time dashboard effectively bridges the gap between raw biosignals and actionable emotional insights by converting complex neurological data into clear visual feedback.
This work lays a strong basis for real-world emotion-aware computing systems that are not limited by lab settings. Applications for the suggested design include improved human-computer interaction, adaptive learning systems, and mental health monitoring. This study advances the development of more responsive and sympathetic technologies that are better able to comprehend and adjust to human emotions by proving the viability of portable, EEG-based emotion identification.

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