Designing a device integrating neural and cardiovascular biosignals to classify emotional states in real-time

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Introduction

Emotion recognition refers to the process of identifying emotional states using observable behaviors such as facial expressions or speech, as well as physiological signals measured from the body (Cai et al., 2023). In humans, emotions involve complex bodily and neural responses, which can make it difficult to measure emotions directly. Biosignals are often noisy and vary between individuals, making accurate classification challenging. Two commonly used biosignals for emotion recognition are electroencephalography (EEG) and photoplethysmography (PPG), which measure brain activity and heart/blood activity, respectively.

Emotions are often mapped on the valence-arousal model, where valence represents how positive or negative the emotion is and arousal represents the intensity of the emotion. However, despite the usefulness of the framework and availability of physiological data, majority of existing emotion-recognition systems rely on offline analysis or computationally intensive hardware (Calvo & D'Mello, 2010). Additionally, self-reported emotional states tend to be unreliable. This project aimed to design and evaluate a low-cost, wearable system capable of classifying human emotions in real-time by integrating EEG and PPG biosignals with machine-learning algorithms.

Methods and Materials

The device was designed to be a wearable bracelet that integrates real-time physiological signal acquisition, processing, and visual feedback. It consisted of a Raspberry Pi Zero 2W which was connected to a NeoPixel LED grid and a battery pack. EEG and PPG data were streamed from the Muse 2 EEG headset to a Python script, which then processed the signals to remove noise before using a threshold-based classification system to classify an emotional state. The system was designed to classify four emotional categories: Excited/Up, Calm/Relaxed, Tired/Down, and Stressed/Tense.

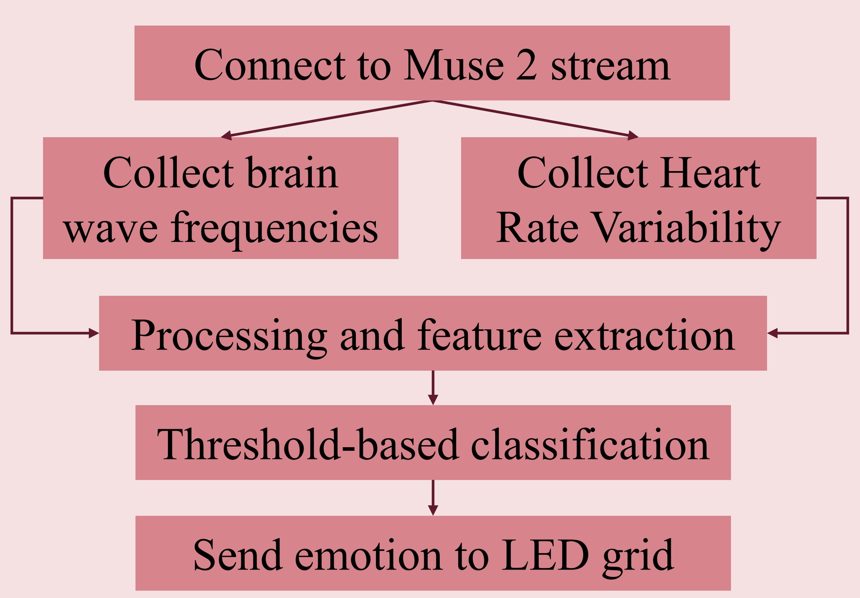


Figure 1 (left): The device's emotion classification system outlined. The Muse 2 headset automatically connects to the Raspberry Pi once both are powered on. Then, brain wave frequencies (alpha, beta, and theta) and Heart Rate Variability (HRV) are calculated in order to classify which emotional category the user is feeling.

Methods and Materials (continued)

The physical bracelet housing was designed using Autodesk Fusion to create an enclosure for all the electrical components. Openings and mounting spaces were incorporated to allow access for wiring, ventilation, and LED visibility. After completion, the model was printed using a Bambu Lab 3D printer.

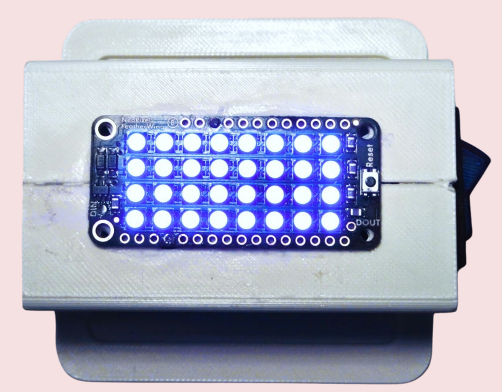


Figure 2 (above): Tired/Down displayed through blue.

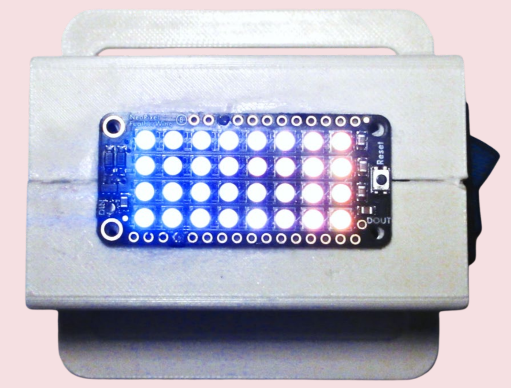


Figure 3 (above): Emotion changing from Tired/Down to Excited/Up in real-time.

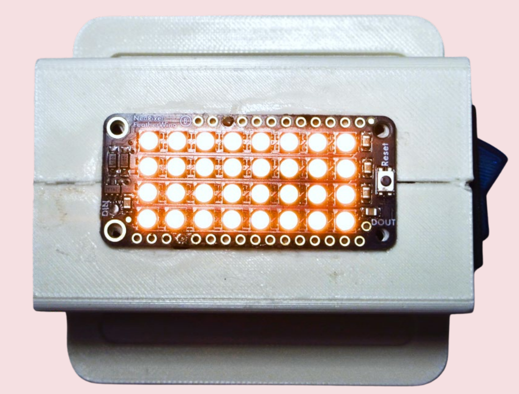
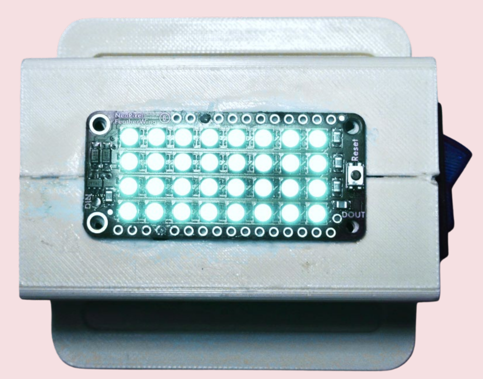


Figure 4 (above): Excited/Up displayed through orange.

Figure 5 (right): Calm/Relaxed displayed through green.



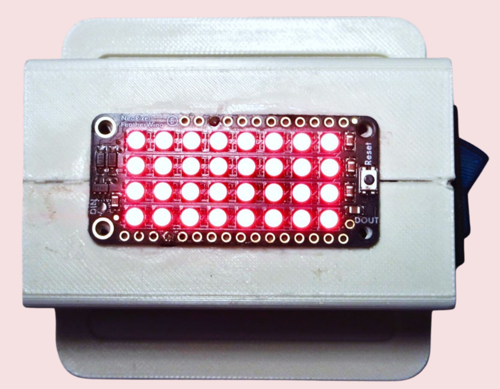
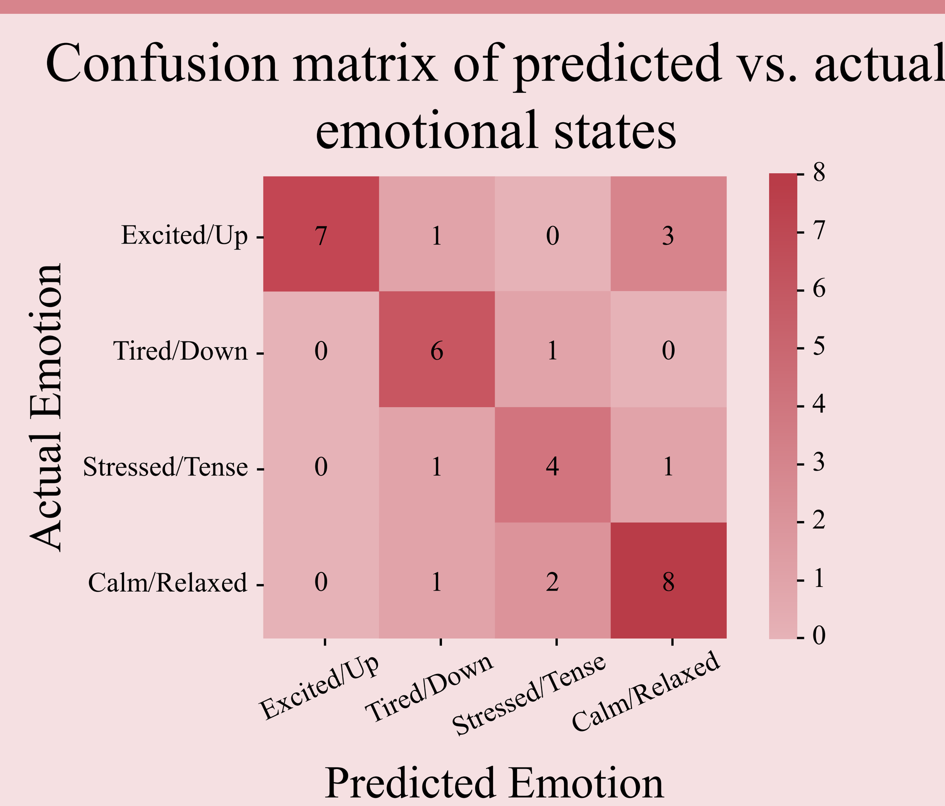


Figure 6 (left): Stressed/Tense displayed through a reddish-pink.

Twenty students were asked to complete a survey ranking which emotions they best felt at the time from highest to lowest and then complete an assessment by the device to determine whether the device's predictions were accurate to the top two categories ranked by the user.

Results

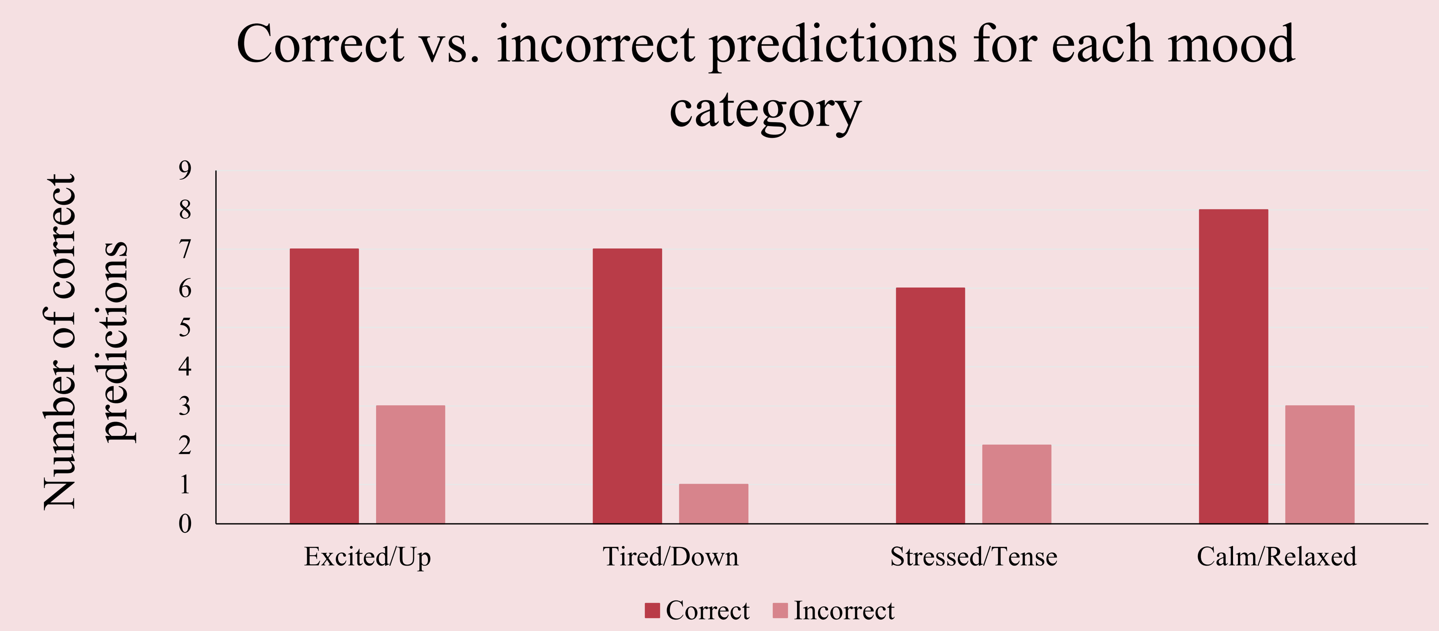


Graph 1 (above): A confusion matrix including the correct (diagonal) and incorrect (off-diagonal) predictions across emotional states.

A chi-square test for independence demonstrated a significant association between self-reported mood and device-predicted mood, $\chi^2(9, N = 35) = 44.34$, $p < .001$, suggesting that the device's predictions were not independent of participants' self-reported emotional states. Cohen's Kappa further indicated that the device demonstrated moderate agreement with participants'

Results (continued)

reported emotional states, $\kappa = 0.62$, suggesting that the classifier predicted emotions with some reliability beyond chance.



Graph 2 (above): Correct predictions exceed incorrect predictions across all four categories, with an overall accuracy rate of 75.7%. The highest accuracy observed was from the Tired/Down and Calm/Relaxed categories. The Excited/Up category showed a lower accuracy in prediction, indicating that the classification system may not work as well in determining that specific state.

Conclusion

This project demonstrates the feasibility of a portable, wearable system for real-time emotion classification using EEG and PPG signals. The device was successfully built and tested, with promising results of a highly accurate emotion classification system using a machine learning model.

A device as such has important implications for the sector of mental health, as it enables emotions to be objectively tracked rather than subjectively—which can be unreliable. Additionally, the device can be valuable for non-communicative patients, such as individuals that suffer from Amyotrophic Lateral Sclerosis (ALS) or advanced dementia because emotions can be monitored when verbal expression is limited. Overall, the results support the use of such systems for emotion recognition and provide a foundation for improving accuracy through larger datasets and refined modeling techniques.

References

Cai, Y., Li, X., & Li, J. (2023). Emotion recognition using different sensors: A survey. *Sensors*, *23*(5), 2455. https://doi.org/10.3390/s23052455

Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. https://doi.org/10.1109/T-AFFC.2010.1