ECE 445
SENIOR DESIGN LABORATORY
PROJECT PROPOSAL
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A Wearable Device That Can Detect Mood

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1 Introduction

1.1 Problem

The influence of mood on our daily lives and work is significant. Mood not only serves as an indicator of one's mental well-being but also exhibits a profound connection to physical health. Negative emotions have emerged as a pivotal factor impacting human health, with long-term exposure linked to various issues such as headaches, asthma, and heart disease. The pervasive effects of workplace stress, anxiety, and depression are recognized as critical challenges that compromise individual well-being and overall productivity.

The escalating social problems in recent years can be attributed to a lack of resources for diagnosing and treating psychological issues like depression and anxiety. Mood recognition techniques have the potential to enhance both human-computer interaction and psychological treatment to some extent. While commonly used methods rely on behavioral parameters or physiological signals for emotional recognition, the former, though intuitive and convenient, can be deliberately disguised in certain situations, diminishing reliability and accuracy. It is widely acknowledged that physiological signals, influenced by the human endocrine and autonomic nervous systems, are less susceptible to subjective consciousness. They provide a more objective and accurate reflection of the real emotional state. Therefore, from this perspective, emotion recognition based on physiological signals yields more objective results.

Motivated by the need for proactive solutions, we aim to provide a wearable device equipped with advanced sensors and a unique mood recognition framework. The progress of Wristband technology is also being used in interdisciplinary domains. For instance, wrist-worn technology has further been used to detect motion-based authentication [4] and self-harming activities [5]. By integrating psychological knowledge and wearable technology, our solution objectively monitors and manages mood-related challenges, offering timely feedback. The goal is to contribute to a healthier work environment, and our project represents a significant step at the intersection of technology and mental health in modern workplaces.

1.2 Solution

Participants may be asked to report their mood at various points using standardized questionnaires or scales, such as the Positive and Negative Affect Schedule (PANAS) or the Profile of Mood States (POMS).

Wearable sensors collect physiological data that can indicate mood, such as blood pressure, heart rate, skin temperature, and skin conductance. Machine learning models analyze this data to recognize patterns that correlate with the self-reported mood states.

The models' predictions of mood states are compared against the self-report measures to validate their accuracy. This involves statistical analysis to determine how well the predicted moods match up with the reported moods.

The framework will undergo iterative testing, where the feedback from both subjective reports and sensor data is used to refine the mood prediction models. Besides, the framework will be tested in real-world settings to ensure that the system can handle the complexities of daily life. Users may provide feedback on the accuracy of the mood predictions, which can be used to further refine the models.

1.3 Visual Aid

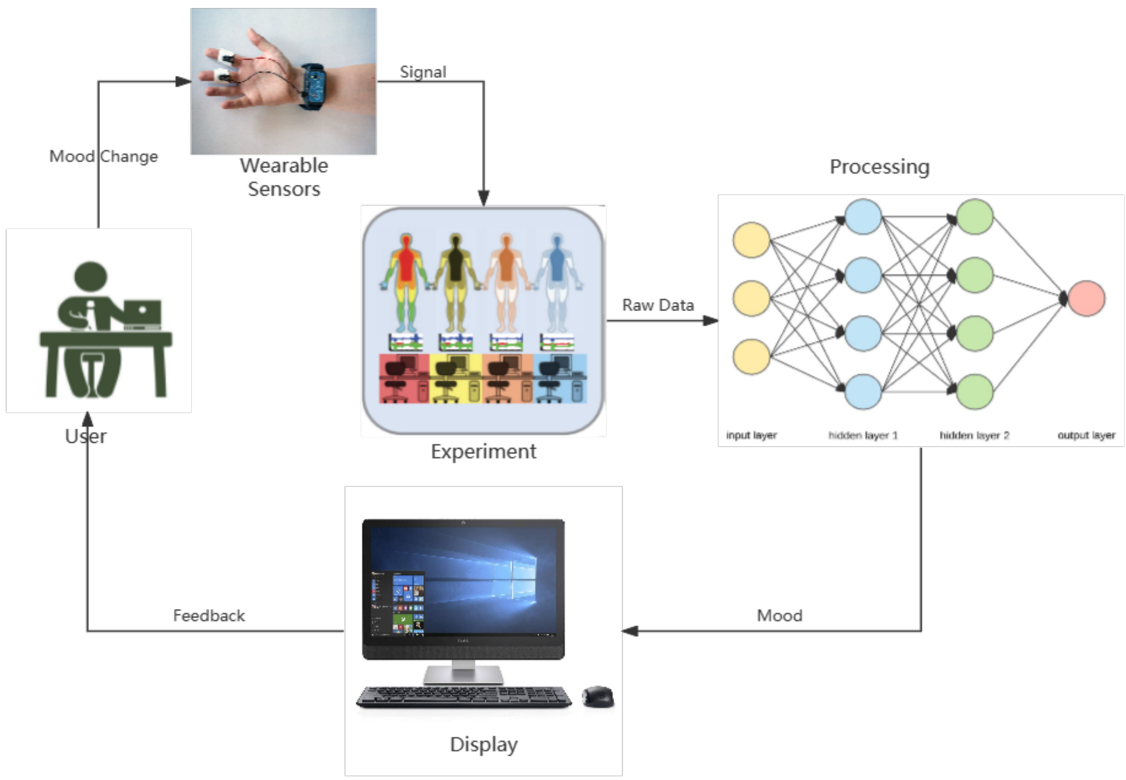

Figure 1: Visual Aid

1.4 High-level Requirements List

Accuracy of Mood Prediction: The system must accurately identify and classify an individual's mood states based on the data collected from wearable sensors. This involves distinguishing between various emotional states and providing reliable predictions that correlate strongly with self-reported mood data.

Real-Time Processing and Feedback: The Mood Recognition Framework should be capable of processing data in real-time to provide timely feedback to users. This enables immediate insight into mood states, allowing for prompt interventions or adjustments to activities and environments to improve mood.

User Privacy and Data Security: Given that the system handles sensitive personal data, it must adhere to strict privacy and data security standards. The system should ensure that individual data is kept confidential, with appropriate measures to prevent unauthorized access or data breaches.

2 Design

2.1 Block Diagram

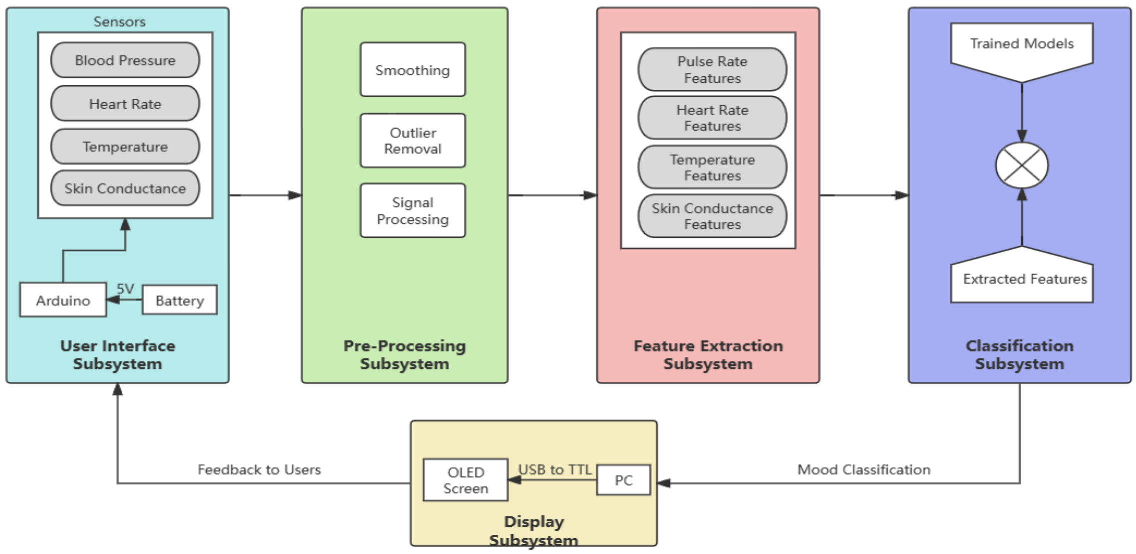

Figure 2: Block Diagram

2.2 Subsystem Overview

2.2.1 User Interface Subsystem

The User Interface Subsystem is designed to monitor various physiological signals to infer the user's mood more accurately. It includes various sensors such as heart rate sensor, skin conductance sensor, temperature sensor, and blood pressure sensor. We will utilize the Arduino Uno to manage data collection from these sensors. Each sensor is connected to the Arduino Uno via its digital or analog input pins, depending on the sensor output type. For example, the skin conductance sensor may require an analog input to measure varying levels of skin conductivity, while a digital heart rate sensor can output pulse data directly to a digital pin.

This user interface sensor subsystem has close connection with the extraction subsystem. The Arduino Uno collects raw data from each sensor, performing initial processing such as filtering and normalization. Given the Uno's limited computational resources, data can be sent to an external computer for processing. For dynamic content sent to the computer, serial communication can be established between the Arduino and the computer. The extraction subsystem on the computer will then extract the features of those signals and data.

2.2.2 Pre-processing Subsystem

The pre-processing subsystem serves as the initial filter for the data collected from wearable sensors. Its main function is to clean the raw data by removing noise and irrelevant information that could negatively impact the accuracy of mood recognition. This involves techniques like signal smoothing, outlier removal, and normalization. The preprocessed data is then a more reliable representation of the user's physiological and behavioral states.

This subsystem interfaces directly with the feature extraction subsystem, providing it with high-quality input data. The quality of pre-processing directly affects the efficiency and effectiveness of the subsequent feature extraction stage, making this a critical part of the mood recognition process.

2.2.3 Feature Extraction Subsystem

The feature extraction subsystem's function is to distill key indicators from the preprocessed data that are relevant for mood recognition [2]. It translates raw sensor data into a set of features that reflect the user's physiological and behavioral patterns associated with different moods. For instance, heart rate variability may indicate stress levels, while temperature changes could relate to physical activity or emotional arousal. This subsystem must extract features that are both informative and discriminative for different mood states.

It interfaces with both the pre-processing subsystem, from which it receives the cleaned data, and the mood classification model, to which it sends the extracted features. The success of this block is measured by its ability to provide meaningful features that improve the classification performance of the mood recognition model.

2.2.4 Classification Subsystem

This subsystem is the heart of the mood recognition framework, where the actual classification of the user's mood occurs. It employs machine learning algorithms to interpret the features extracted from the user's data and classify them into mood states such as happy, sad, stressed, or relaxed. This subsystem may utilize a variety of modeling techniques, including supervised learning, to train models on labeled mood data.

The mood classification model interfaces with the feature extraction subsystem, receiving features as input, and with the display subsystem, providing the mood predictions. Its performance is critical, as it directly determines the accuracy and reliability of the mood recognition the framework provides.

2.2.5 Display Subsystem

The display subsystem is designed to display the detected mood to the user in an intuitive and engaging way, which is crucial for enhancing the user experience. This subsystem contains an OLED or LCD screen to display the mood state in text ("Happy", "Sad", etc.), along with relevant icons or emojis. To further strengthen the feedback, we can also display tips or recommendations based on the detected mood. For example, some encouraging sentences can be placed on the screen after detecting someone is sad. Overall, this subsystem enhances user interaction by offering real-time feedback to improve or maintain people's emotional well-being.

The computer will output the results of the emotion after utilizing neural networks. The displaying subsystem will accept the processing results from computer. The microcontroller acts as the bridge between the OLED screen and the computer. It receives commands from the computer, processes these commands, and controls the OLED display accordingly.

2.3 Subsystem Requirements

2.3.1 User Interface Subsystem

1) The user interface sensor subsystem is capable to of integrating with a minimum of four types of sensors (e.g., skin conductance, heart rate, temperature, blood pressure) for mood detection.
2) The system must continuously acquire data from all connected sensors with a minimum sampling rate sufficient for accurate mood detection.
3) After collecting data, the system should be capable of transmitting collected data and analysis results wirelessly to an external computer for further processing.

2.3.2 Pre-processing Subsystem

1) Noise reduction algorithms should achieve a signal-to-noise ratio improvement of at least 20 dB.
2) Outlier detection should correctly identify and handle at least 95% of nonconformant data points.
3) Data smoothing techniques must not distort the original signal by more than 5% when assessed by root-mean-square error (RMSE).
4) Data privacy standards, such as GDPR or HIPAA, should be strictly adhered to from the beginning.

2.3.3 Feature Extraction Subsystem

1) The feature extraction process should reduce data dimensionality by at least 50% without losing more than 5% accuracy in mood prediction.
2) Extracted features must have a correlation coefficient of at least 0.7 with the mood states to ensure relevance.
3) The extraction process should be optimized to run within 200 milliseconds for each data window to maintain real-time performance.

2.3.4 Mood Classification Model Subsystem

1) The mood classification accuracy should be at least 80% for generalized models and 85% for personalized models.
2) The model should be trained on a dataset with a minimum diversity representing at least 80% of the targeted user demographics.
3) The system should update or retrain the model with new data at least once every 24 hours to adapt to new patterns.

2.3.5 Display Subsystem

cThe OLED screen must accurately depict at least three distinct mood states. Both texts along with its relevant icons should be displayed on the screen. Mood detection results must be updated on the screen within 5 seconds of being processed by the mood analysis subsystem.

2.4 Tolerance Analysis

2.4.1 Pre-processing Subsystem

The Outlier Removal is the greatest risk within this block. The outlier removal block risks discarding useful data or retaining noisy data if not properly calibrated. A statistical analysis can determine the likelihood of true versus false outliers based on historical data variability. The number of data points discarded should not exceed a certain threshold of the total data (e.g., 5%). To assure success, use robust statistical methods (e.g., median absolute deviation instead of standard deviation) to reduce the sensitivity to extreme values. Mathematically, the effectiveness can be measured by the change in the standard deviation of the dataset before and after outlier removal.

2.4.2 Feature Extraction Subsystem

The Dimensionality Reduction is the greatest risk within this block.There is a risk of losing significant information during dimensionality reduction. Principal Component Analysis (PCA) can be employed, and the amount of variance explained by the retained components can be calculated to ensure a certain level of data integrity (e.g., 95% variance retained).To assure success, the selection of features can be informed by calculating the mutual information or correlation with mood states to ensure only the most predictive features are retained.

2.4.3 Sensor Accuracy and Variability

As for the sensor accuracy, each sensor has a known accuracy interval (e.g., $\pm 5\%$ for heart rate, $\pm 2\%$ for Skin Conductance). The data obtained by the sensors are also determined by various factors. For example, the variation in pulse detection accuracy can be due to motion artifacts, skin tone, and ambient light, and the variation in skin conductivity readings can be due to factors such as skin moisture, temperature, and sensor placement. In this case, we'll be focusing on all the physiological information that a person has at rest. We will use signal-to-noise ratio (SNR) to quantify the heart rate sensor's ability to distinguish pulse signals from noise under different conditions. We will assess the acceptable range of SNR where the heart rate can be accurately detected. This tolerance analysis emphasizes the importance of robust sensor selection.

3 Ethics and Safety

3.1 Ethics

Our initiative addresses the widespread influence of workplace stress, anxiety, and depression, acknowledging them as pivotal challenges that undermine individual well-being and overall productivity. Driven by the imperative for proactive interventions, we aspire to introduce a wearable device integrated with sophisticated sensors and an innovative mood recognition framework. Our objective is to foster a healthier work environment, marking a substantial advancement at the crossroads of technology and mental health within contemporary workplaces. This endeavor aligns seamlessly with the ACM code's commitment to contribute to society and human well-being, recognizing the universal stakeholder role of all individuals in the realm of computing [1].

The collection and use of personal and potentially sensitive data to train our model could infringe on an individual's privacy if not handled correctly, especially in compliance with the ACM Code regarding to respect privacy and confidentiality [1]. We promise to collect only the data necessary for mood recognition to reduce the risk of privacy breaches, and we will ensure that users are fully informed about what data is collected, how it will be used, and obtain their consent. Moreover, we will implement strict access controls so that only authorized personnel can access sensitive data.

3.2 Safety

Ensuring safety is a top priority in our project. We have successfully finished the UIUC online safety training. Adhering to safety guidelines, it is compulsory to have a minimum of two team members present in the lab during experiments.

For electrical safety, we will use electricity as the power supply of Arduino. Our group fully understands and adheres to the guidelines for safe electricity usage. We will routinely check the device to ensure it operates in a proper environment. Moreover, we have wearable devices to measure the blood pressure, heart rate, body temperature and skin conductance, and those sensors will be connected with Arduino. We will strictly follow the safe current limits for electromedical apparatus [3] to ensure the safety of participants.

If the system inaccurately assesses a user's mood, it could lead to inappropriate recommendations or actions. Ensuring high accuracy of the mood prediction algorithms and providing users with context about the limitations of the system can minimize this risk.

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