ECE 445

SENIOR DESIGN LABORATORY

PROJECT PROPOSAL

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A Wearable Device That Can Detect Mood

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Contents

1 Introduction **1**
1.1 Problem 1
1.2 Solution 1
1.3 Visual Aid 2
1.4 High-level Requirements List 2

2 Design **3**
2.1 Block Diagram 3
2.2 Subsystem Overview 4
2.2.1 User Interface Subsystem 4
2.2.2 Pre-processing Subsystem 4
2.2.3 Feature Extraction Subsystem 5
2.2.4 Classification Subsystem 6
2.2.5 Display Subsystem 6
2.3 Subsystem Requirements 7
2.3.1 User Interface Subsystem 7
2.3.2 Pre-processing Subsystem 7
2.3.3 Feature Extraction Subsystem 8
2.3.4 Mood Classification Model Subsystem 8
2.3.5 Display Subsystem 8
2.4 Tolerance Analysis 8
2.4.1 Pre-processing Subsystem 8
2.4.2 Feature Extraction Subsystem 9
2.4.3 Sensor Accuracy and Variability 9
2.4.4 Display Subsystem 10

3 Ethics and Safety **10**
3.1 Ethics 10
3.2 Safety 10

References **12**

1 Introduction

1.1 Problem

Understanding and managing our moods are important to both our mental well-being and physical health. Mood swings, if not appropriately addressed, can lead to long-term health issues, such as headaches, asthma, heart disease, and significantly impact our daily lives, productivity, and social interactions. The necessity to diagnose and provide care for individuals experiencing mental health issues, including stress, anxiety, and depression, has never been more critical. These conditions not only affect individuals on a personal level but also pose considerable challenges in workplaces, educational institutions, and care centers, thereby necessitating innovative solutions. The rising trend of mental health issues among citizens has encouraged researchers to develop wearable devices monitoring mental health issues, such as self-harming activities[4].

1.2 Solution

To address this pressing need, our project introduces a pioneering wearable device, a wrist worn smart device similar to Yang's[5], designed to track and record human mood dynamics. This device employs advanced sensor technology to monitor physiological signals—such as heart rate, successive heartbeat intervals, skin temperature, and skin conductance—that are closely linked to our emotional states. By leveraging these physiological markers, our device offers an objective and precise method for mood recognition, sidestepping the subjectivity and potential inaccuracies inherent in self-reported data. Our device stands out by integrating cutting-edge machine learning algorithms that analyze physiological data to identify mood patterns. This approach not only enhances the accuracy of mood detection but also provides real-time feedback to users, enabling immediate and personalized mood management strategies. Furthermore, by offering insights into an individual's mood fluctuations, our solution empowers users to better understand their emotional well-being, encouraging proactive mental health care.

The potential applications of our technology extend far beyond personal use. By providing accurate and objective mood assessments, our device can be a valuable tool for hospitals, schools, and caring centers. It can aid in the early detection of mental health issues, monitor the effectiveness of treatment plans, and support care strategies. In educational settings, understanding students' moods can help in creating a supportive learning environment, while in the workplace, it can contribute to a healthier, more productive work culture. Our project represents a significant advancement in the intersection of technology and mental health care. By combining psychological knowledge with wearable technology, we not only aim to enhance individual well-being but also to support institutions in providing better care for those with mental health concerns or those simply seeking to improve their mood management with the support of our mood detection results. Through continuous refinement and real-world application, we are committed to making a positive impact on both individual lives and society at large.

1.3 Visual Aid

This visual aid part includes a figure (Figure 1) demonstrating how our project resolves the mood detection in details. The user will wear the device combined with several sensors, the Arduino PCB design will record the signals and extract features we need. Our pre-trained machine learning model will output the corresponding potential mood based on these features, and display it on computer with the help of Graphical User Interface (GUI). Ideally, by connecting the wearable device along with the user, the system is able to reflect real-time mood.

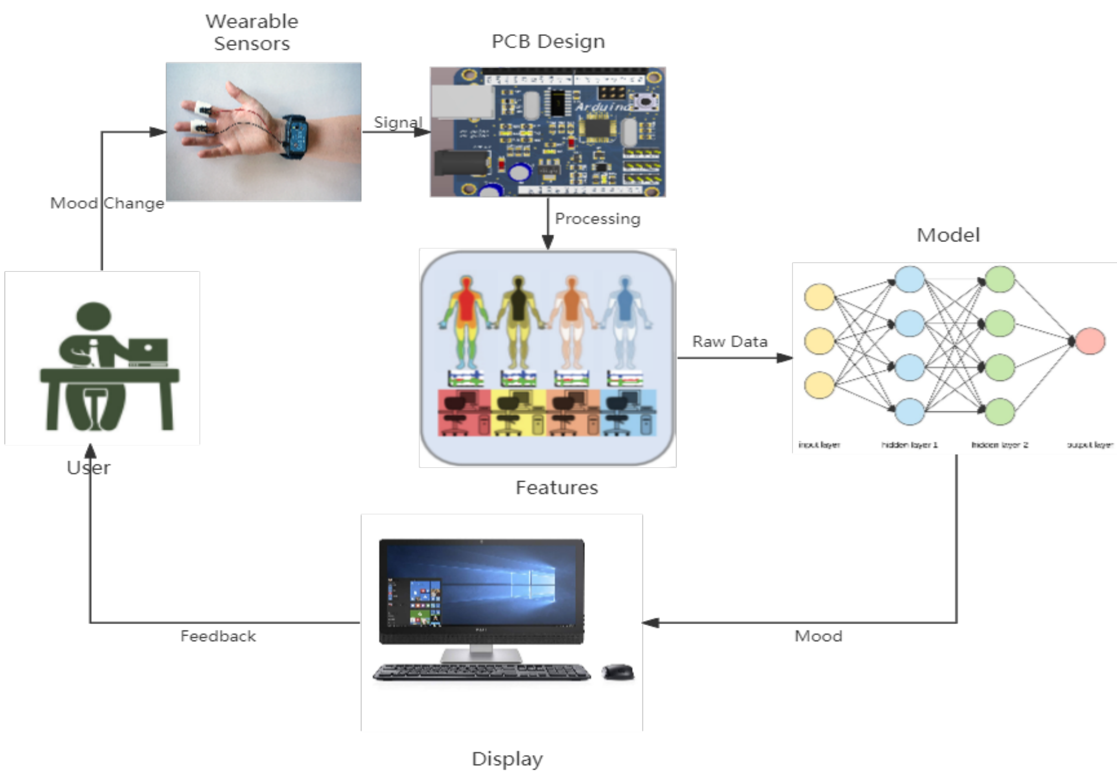

Figure 1: Visual Aid. The visual aid depicts the process where users wear integrated sensors to extract features based on the users' mood, and the machine learning model will predict mood based on features and the screen will display feedback to users

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 within an acceptable error rate, ideally, the accuracy should be greater than 0.55 indicated by the state-of-the-art. This involves distinguishing between three to five emotional states and providing reliable predictions that correlate strongly with self-reported mood condition. This requirement highly depends on the accuracy of machine learning models, we will focus on data processing and algorithm improvement to reach at least an accuracy of 0.55.

- Real-Time Processing and Feedback: The Mood Recognition Framework should be capable of processing data in real-time with our three sensors that can extract four features including heart rate, successive heartbeat intervals, skin temperature, and skin conductance to provide timely feedback to users by displaying on GUI system. To ensure timely feedback and reaction, the system should react to the users' input within 10 seconds and provide the result within 30 seconds on the screen. This enables immediate insight into mood states, allowing for prompt interventions or adjustments to activities and environments to improve mood. This leverages on Arduino programming, thus we must make sure the sensors can work together with Arduino and deliver data to the computer through wires and our PCB design.
- User Interface and Display: As a real-time mood detection wearable device, we will make sure the sensors are integrated into a user-friendly device that can fit in the wrist and fingers to produce real-time feedback on the screen. We plan to implement GUI display method on the computer reflecting users' mood with three to five kinds of emojis corresponding to the emotional states. Our system can collect data, feed it to the model, and display the result from the output of the model. This promises the feasibility of our systematic design.

2 Design

2.1 Block Diagram

The block diagram is divided into five subsystems, which can work together to realize the high-level requirements. The block diagram depicts a system designed to meet the requirements for accurate mood prediction, real-time processing and feedback, user interface and display, and user privacy and data security. The sensors collect physiological data that the system preprocesses with three steps: signal smoothing, outlier removal, and normalization to ensure quality and reliability, which is crucial for achieving the required accuracy of at least 0.3 in mood classification. The pre-processed data is then subjected to feature extraction with Time-frequency analysis, Frequency domain analysis, or nonlinear dynamic analysis and fed into trained machine learning models within the Classification Subsystem to predict mood states with desired accuracy. Real-time processing is facilitated through direct connections with an Arduino, which interfaces with the sensors for continuous data feed. User feedback is immediate via the Display Subsystem, which shows the mood predictions on a GUI, providing real-time insight and allowing for prompt user response. Additionally, by storing and processing data locally, the system aligns with privacy and security standards, ensuring user data is handled confidentially and securely.

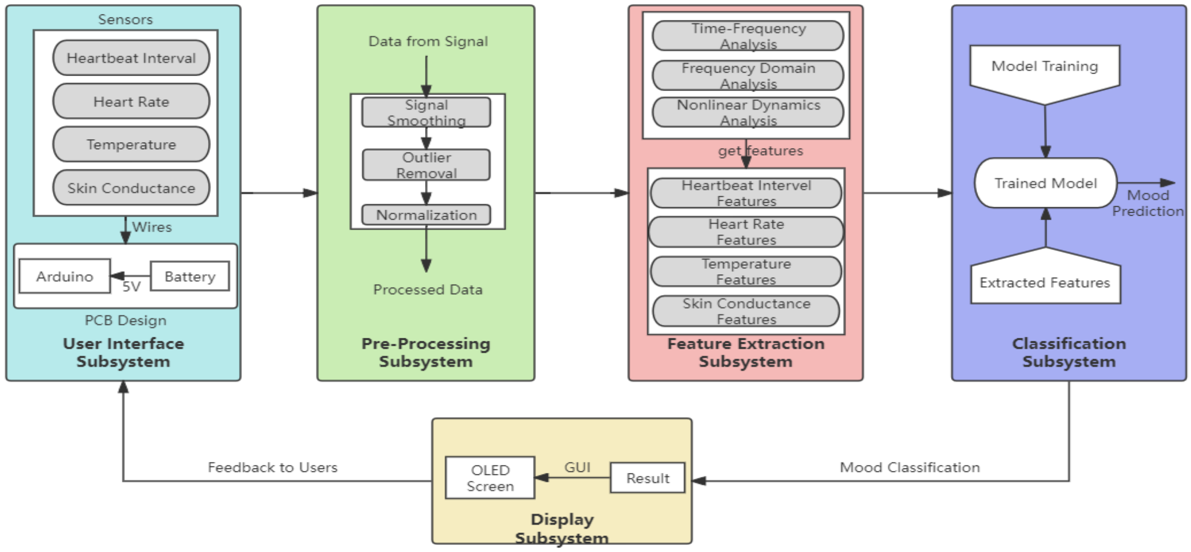

Figure 2: Block Diagram. It showcases a mood prediction system integrating sensors for data collection, pre-processing for quality (signal smoothing, outlier removal, normalization), and advanced analysis (Time-frequency, Frequency domain, nonlinear dynamics) for accurate classification. Features real-time Arduino interfacing, immediate GUI feedback, and prioritizes user privacy with secure local data handling

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 that measure signals such as heart rate, successive heartbeat intervals, skin temperature, and skin conductance. 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 subsystem involves 3 consecutive steps: Signal Smoothing, Outlier Removal, and Normalization.

- **Signal Smoothing** is the first step in the data preprocessing pipeline aimed at reducing noise and fluctuations in the raw sensor data. It involves applying various filtering techniques to achieve a smoother representation of the signal while preserving important features. We plan to use the moving average method that averages neighboring data points.
- **Outlier removal** is the second step in the data preprocessing pipeline aimed at identifying and eliminating data points that deviate significantly from the majority of the dataset. It employs statistical methods to detect and remove spurious outliers. We apply modified z-score statistical method to detect outliers, and then we remove outliers by directly deleting them.
- **Normalization** is the final step in the data preprocessing pipeline aimed at standardizing the range of features in the dataset. It scales the data to a predefined range or distribution, typically between 0 and 1 or with a mean of 0 and a standard deviation of 1. 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.

The feature extraction subsystem consists of 3 essential parts, which are Time-Frequency Analysis, Frequency Domain Analysis, and Nonlinear Dynamics Analysis. They share the same purpose of extracting features and they complement with each other.

- **Time-frequency analysis** is a method used to analyze signals in both the time and frequency domains simultaneously. It allows us to understand how the frequency content of a signal changes over time, which can be particularly useful for analyzing non-stationary signals such as physiological data. We apply Short-Time Fourier Transform (STFT).

- **Frequency domain analysis** is a technique used to analyze signals in terms of their frequency content. It provides insights into the distribution of signal power across different frequency components. We apply Power Spectral Density (PSD), and Frequency Band Analysis strategy.

- **Nonlinear dynamics analysis** explores the complex behavior of dynamical systems, which may exhibit nonlinear interactions and dependencies. It aims to uncover underlying patterns, structures, and properties that may not be apparent in linear analysis. We apply Phase Space Reconstruction and Poincaré Plot Analysis.

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.

The mood classification subsystem consists of 2 essential parts, which are Random Forest algorithm and Extreme Gradient Boosting(XGBoost) algorithm. They share the same purpose of extracting features and they complement with each other.

- **Random Forest** is an ensemble learning method that combines multiple decision trees to improve classification accuracy. It's robust to overfitting and works well for high-dimensional feature spaces.

- **XGBoost** is an efficient and scalable implementation of gradient boosting decision trees. It builds a series of decision trees sequentially, where each tree corrects the errors made by the previous ones, leading to improved overall performance.

2.2.5 Display Subsystem

The display subsystem is designed to display the detected mood and corresponding suggestions to the user in an intuitive and engaging way, which is crucial for enhancing the user experience. We plan to display the mood states in text ("Happy", "Sad", etc.) along with relevant icons or emojis, in accordance with the specific mood detected by classification subsystem. 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 that the user is sad. We can also advise some activities to users, such as hanging out or playing video games, to relax and please users themselves. Overall, this subsystem enhances user interaction by offering real-time feedback to improve or maintain people's emotional well-being.

We plan to implement Graphical User Interface (GUI) in Python to achieve this subsystem. The computer will firstly output the results of detected mood after utilizing neural networks in classification subsystem. Then the displaying subsystem will receive the processing results and give corresponding feedback. Designing a GUI that incorporates mood detection and provides appropriate suggestions requires careful consideration of user interaction, visual presentation, and integration with the mood detection subsystem. Here are components of our GUI:

1) Display Components: Design areas where the detected mood and suggested activities or content will be displayed.

2) Visual Elements: Use visual cues such as colors, icons and images to make the GUI visually appealing. We will utilize emojis to represent 3 to 5 kinds of moods.

3) Integration with Mood Detection Subsystem: Implement functionality (messaging protocols such as WebSocket, or direct function calls) to communicate with the mood detection subsystem to retrieve the user's current mood.

2.3 Subsystem Requirements

2.3.1 User Interface Subsystem

1) The user interface sensor subsystem is capable of obtaining at least four types of physiological data simultaneously. It should process the primary data and transmit the data to an external computer for further processing using wire.

2) The sensor must detect pulse rate changes within 10 seconds and maintain accuracy within ± 2 bpm.

3) The accuracy of the skin conductance sensor's output is within the range of $\pm 5\%$.

4) The infrared temperature sensor must stabilize to within ± 0.2°C of the target temperature in less than 10 seconds and exhibit a drift of less than 0.05°C per hour.

2.3.2 Pre-processing Subsystem

1) Smoothed signals should exhibit a significant reduction in noise compared to the original signal, with a minimum increase in SNR of 10 dB.

2) The mean squared error (MSE) between the original and smoothed signals should be below the threshold of

$$0.1 \times \text{noise variance} \tag{1}$$

,indicating minimal distortion.

3) The outlier removal process should effectively identify and remove data points that deviate significantly from the rest of the dataset.

4) All features in the dataset should be uniformly scaled to prevent dominance by features with larger scales. Also, the normalization process should not introduce bias or distortions in the data.

2.3.3 Feature Extraction Subsystem

1) **Resolution:** The feature analysis should accurately identify the dominant frequency components of the signal with an error margin of less than 5%

2) **Resolution:** The feature analysis should have a frequency resolution of at least 1 Hz to distinguish between closely spaced frequency components.

3) **Computational Efficiency:** The feature analysis method should process a signal of 1000 data points in less than 1 millisecond on a standard AMD Ryzen 9 5900x 12-Core CPU and 128GB RAM.

2.3.4 Mood Classification Model Subsystem

The mood classification model should achieve a classification accuracy of at least 55% when predicting mood states based on the given psychological data.

2.3.5 Display Subsystem

1) The interface must integrate with Mood Classification Model. After the model generates the detected mood based on our input, the interface should give corresponding feedback immediately.

2) The interface should provide appropriate suggestions to users based on the detected mood to make positive impacts on users.

3) The interface has aesthetic design elements including color schemes, typography, icons, and visual hierarchy to enhance usability and appeal.

2.4 Tolerance Analysis

2.4.1 Pre-processing Subsystem

Outlier Removal presents the greatest risk within this block, as it may lead to the inadvertent removal of valuable data or the retention of noisy data if not properly calibrated. A statistical analysis can assess the likelihood of true outliers versus false outliers based on the historical variability of the data. To mitigate this risk, it is imperative to employ robust statistical methods, such as the median absolute deviation (MAD), which is less sensitive to extreme values compared to the standard deviation.

Mathematically, the effectiveness of outlier removal can be evaluated by quantifying the change in the standard deviation of the dataset before and after the removal of outliers. Let's denote the standard deviation before outlier removal as σ_{original} and after outlier removal as σ_{removed}. The percentage change in the standard deviation ($\Delta\sigma$) can be calculated using the formula:

$$\Delta\sigma = \frac{\sigma_{\text{original}} - \sigma_{\text{removed}}}{\sigma_{\text{original}}} \times 100\% \tag{2}$$

The effectiveness of the outlier removal process can then be assessed based on the magnitude of $\Delta\sigma$. For example, if $\Delta\sigma$ is below a threshold of 10%, it indicates that the removal of outliers has effectively reduced the variability in the dataset without significantly altering its overall distribution.

To ensure success, the number of data points discarded during outlier removal should not exceed a certain threshold of 15% relative to the total dataset size. This threshold helps maintain the integrity of the dataset while still eliminating outliers. Additionally, conducting sensitivity analysis by varying the threshold can provide insights into the robustness of the outlier removal process and help optimize its parameters for different datasets.

We should also consider de-noising and extracting data accurately from the signal during the processing process, we will mathematically verify our data relying on what we mentioned at the R&V part, leveraging on advanced signal processing methods and our designed process including signal smoothing, outlier removal, and normalization to minimize the inaccuracy. At least 95% of the tested data should be within 5% of the average of all data in the dataset used for training.

2.4.2 Feature Extraction Subsystem

We can quantify the feature extraction tolerance using the root mean square error (RMSE) between the extracted features and the ground truth or expected values.

Root Mean Square Error (RMSE): The root mean square error measures the square root of the average of the squares of the errors between the extracted features ($\hat{f}_i$) and the ground truth or expected values (f_i). Mathematically, it is given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{f}_i - f_i)^2} \tag{3}$$

RMSE provide a quantitative measure of the deviation between the extracted features and the ground truth or expected values. A lower value of RMSE indicates better performance of the feature extraction method in terms of accuracy and reliability.

To ensure the success of feature extraction, the RMSE should be kept below a threshold of 15%.

2.4.3 Sensor Accuracy and Variability

As for the sensor accuracy, each sensor has a known accuracy interval (e.g., ±2bpm for heart rate, ±5% 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.

Considering the noise and other influencing factors on the sensors, we would decrease the influence of the environment as much as possible, for example, keeping the skin clear, keeping the users still, and decreasing weather influences by conducting the experiment indoors. With these methods, we wish to minimize the influences by other factors to the sensors.

2.4.4 Display Subsystem

For the GUI designed to provide suggestions to users based on their detected mood, a tolerance analysis involves evaluating various aspects of the interface to ensure that it remains usable, functional, and visually appealing despite potential variations or deviations. Using GUI is also crucial for our design for the purpose of displaying emojis, suggestions, and other potential feedback to the users. A proper integration between the model and display system is needed, which we decided to use Python to build the connection. To ensure timely feedback and reaction, the system should react to the users' input within 10 s and provide the result within 30 s on the screen.

Firstly, the crucial thing is that the suggestions provided to users may be misleading or irrelevant due to the accuracy of mood classification model. Moreover, we need to ensure that the layout remains visually appealing and functional despite changes in screen size, resolution, or content length. It is significant to determine acceptable tolerances for spacing, alignment, and content organization to maintain readability and usability.

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 usage, we will use the USB portal of computer as the power supply of Arduino, and the computer is powered by 220 volts of electricity. Our group fully understands and adheres to the guidelines for safe electricity usage. We will routinely check the computer and Arduino to ensure they operate in a proper environment. Moreover, we have wearable devices to measure the heart rate, body temperature and skin conductance, and those sensors will be connected with Arduino. Then Arduino will be connected to the computer to import data. There is a risk of getting an electric shock when we measure the physiological data of participants. We will strictly follow the safe current limits for electromedical apparatus [3] to ensure the safety of participants. We'll make sure the wires are intact and connected well to prevent the occurrence of electrical leakage.

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

References

[1] ACM. “ACM Code of Ethics and Professional Conduct.” (2018), [Online]. Available: https://www.acm.org/code-of-ethics.

[2] A. Khan, D. Windridge and J. Kittler, ”Multilevel Chinese Takeaway Process and Label-Based Processes for Rule Induction in the Context of Automated Sports Video Annotation,” in IEEE Transactions on Cybernetics, vol. 44, no. 10, pp. 1910-1923, Oct. 2014, doi: 10.1109/TCYB.2014.2299955.

[3] American National Standard Institute. ”Safe Current Limits for Electromedical Apparatus” (1993). Published By: Association for the Advancement of Medical Instrumentation (AAMI)

[4] J. Yang, Y. Li and M. Xie, ”MotionAuth: Motion-based authentication for wrist worn smart devices,” 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), St. Louis, MO, USA, 2015, pp. 550-555, doi: 10.1109/PERCOMW.2015.7134097.

[5] L. Malott, P. Bharti, N. Hilbert, G. Gopalakrishna and S. Chellappan, ”Detecting self-harming activities with wearable devices,” 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), St. Louis, MO, USA, 2015, pp. 597-602, doi: 10.1109/PERCOMW.2015.7134105.