IFERP
ISSN (Online) 2456-1304
International Journal of Science, Engineering and Management (IJSEM)
Vol 12, Issue 01, January 2025

Mental Stress Detection and Alleviation Application

[1] Muhammad Aqeel*, [2] Tharindu Udara, [3] Laksara Thilakarathna, [4] Navoda Sewwandi, [5] Kithsiri Samarasinghe

[1] [2] [3] [4] Graduate Student, Department of Electronic and Telecommunication Engineering, Faculty of Engineering, University of Moratuwa, Sri Lanka
[5] Senior Lecturer, Department of Electronic and Telecommunication Engineering, Faculty of Engineering, University of Moratuwa, Sri Lanka
Corresponding Author Email: [1] aqeeltm1998@gmail.com, [2] tharinduwijesinghe31@gmail.com, [3] olthilakarathna09@gmail.com, [4] blpnavoda@gmail.com, [5] kithsiris@uom.lk

Abstract— ***Stress has emerged as a significant contributor to various diseases in the modern world. Prolonged stress can lead to severe mental health issues such as depression, heart attack, and anxiety. Detecting and addressing stress in its early stages is crucial and is possible only through continuous monitoring. This paper presents the design of a cost-effective and accurate wearable device capable of detecting mental stress based on skin conductance, heart rate variability, and motion detected through an accelerometer. Additionally, it includes a mobile application that utilizes the device's camera to detect stress. The mobile application also features a chatbot and an alleviation feed to help alleviate stress. The wearable device captures readings from its sensors and transmits the data to a smartphone via Bluetooth Low Energy. Through intelligent analysis of the correlations between these signals using machine learning algorithms, the application predicts whether the subject is experiencing stress. This approach not only helps users gain a better understanding of their stress patterns but also provides reliable data to healthcare professionals for more effective treatment.***

Index Terms: Chatbot, Machine learning, Mobile application, Stress detection, Wearable sensors.

I. INTRODUCTION

Human mental health significantly impacts social, emotional, and psychological well-being [1]–[3]. In today's modern world, stress has become a prevalent issue. Long-term stress threatens the physical and mental health. University undergraduates, burdened by heavy workloads, particularly exams, presentations, and relationship problems, often neglect stress alleviation methods due to reluctance in sharing their situations with others. Early identification and timely alleviation of stress are crucial, as chronic stress can lead to severe problems such as depression, anxiety, and even suicide [1], [2].

During stress, the autonomic nervous system is triggered, resulting in increased blood pressure, heart rate, respiratory rate, and electrodermal activity [1], [4], [5], along with decreased heart rate variability and skin temperature [6], [7]. Biomarkers such as encephalography (EEG), electrocardiography (ECG), photoplethysmography (PPG), electrodermal activity (EDA), functional Magnetic Resonance Imaging (fMRI), thermal imaging (TI), and skin temperature (ST) [2], [8], [9] can capture these physiological responses. Among these, ECG, PPG, EDA, and blood pressure are widely used in wearable devices [1]. Our objective is to develop a wearable device, focusing on EDA and PPG as biomarkers.

Using heart rate alone as an indicator for mental stress may result in misclassification, as heart rate can increase for various reasons [7], [10] other than mental stress. Signal artifacts caused by motion, electrode placement, or respiratory movement while taking a reading further can affect the accuracy of measured recordings. Additionally, determining the ground truth of a user's stress level when labeling training data in a mobile environment is challenging. These factors pose difficulties in developing a pervasive mental stress detection and alleviation application suitable for everyday use.

While there are existing applications in the market, finding an affordable product that combines stress detection and alleviation remains a challenge for the average person [3], [9]. Cheaper solutions often lack accuracy and the interfaces of currently available mobile applications for stress detection and alleviation are complex for the average user to use it daily. In this work, we present a convenient, low-cost wearable device with a mobile application with improved accuracy.

Our application is designed for daily life, where individuals' movements are unrestricted, leading to artifacts in recorded data. To address this, we propose novel artifact detection and removal strategies. Additionally, we extract features from heart activity, skin conductance, and accelerometer signals using our sensors attached to the wearable device. These features are utilized to classify an individual's stress level through machine learning algorithms. Real-life testing of our system involved collecting physiological signals from participants using the designed wearable device and the mobile application camera.

This paper is organized as follows: First, we discuss related works in Section II. We introduce our application architecture together with the system design in Section III. Implementation of our application in Section IV. Data collection is included in Section V. Experiments and results are in Section VI. Finally, in Section VII important

ISSN (Online) 2456-1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 12, Issue 01, January 2025

conclusions are made while suggesting possible future directions of our application.

II. RELATED WORK

In this section, we discuss existing applications for mental stress detection and alleviation. The studies in [11], [12] describe the detection of mental stress based solely on EDA. However, using only EDA signals, the accuracy is around 80%. Stress detection using the PPG biomarker is described in [4], [13]. Most research in mental stress detection uses a combination of two or more biomarkers [5], [6], [14]. These studies have obtained higher accuracy compared to research using a single biomarker. According to the systemic review in [1], it is clear that using more biomarkers increases the accuracy of detection. In the studies mentioned above, ECG, EDA (GSR), PPG, and ST are the most commonly used biomarkers. However, EDA and PPG are the most suitable biomarkers [5] when designing a wrist-wearable device.

There is some research on mental stress detection using mobile phones, their features, and applications. In [15], data for detecting stress is monitored using mobile phone usage, such as calls, SMS, and screen on/off activity. Recognition of stress through the human voice using microphones embedded in smartphones is described in [16]. The study in [17] discusses using a mobile phone camera to obtain PPG signals by capturing a video of the fingertip. However, these studies focus only on stress detection.

Current studies regarding stress relief are discussed in the review [3]. Only 11 chatbots were included from an initial search of 1,000 applications related to stress relief. Woebot and Wysa are some popular chatbot applications for stress alleviation, but they do not have stress detection capabilities. The article [18] describes the utilization of chatbots for medical consultation. However, this chatbot is not used for any stress alleviation purposes.

To identify the noise caused by motion artifacts, the study in [19] presents a stress detection system that includes an accelerometer. The application SoDA, described in [20], involves a stress detection and alleviation system. However, there is no complete application that includes a wearable device to detect stress, a mobile phone application for stress detection, and a chatbot for alleviation.

III. SYSTEM DESIGN

In this section, we describe our application architecture, including the biomarkers and their physiological signals, the components of the wearable device, and the mobile application we developed. The overall architecture of the application, depicted in figure 1, includes the wearable device, mobile application, and other interconnected systems.

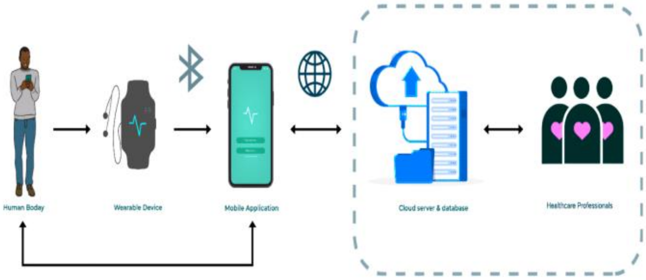

Figure 1 Overall Architecture

A. Photoplethysmography and Heart Rate Variability

Heart rate variability (HRV) is a crucial indicator of both physical fitness and mental well-being. Traditionally, electrocardiography (ECG) has been the primary method for measuring HRV. However, for our research focusing on wearable devices, ECG detection is not suitable. Instead, we use photoplethysmography (PPG) as a convenient alternative for HRV measurement. PPG signals are acquired either by placing the fingertip under a mobile phone camera or using a dedicated sensor attached to the fingertip.

Previous research has consistently shown that heart rate (HR) and heart rate variability (HRV) undergo changes during mental tasks. HRV and other features of PPG signals can be leveraged to measure the level of mental stress. In a study involving 28 subjects, it was demonstrated that HRV decreases during the performance of mental tasks or exposure to stressors [7]. Moreover, the study in [10] highlights the significant relationship between HRV and mental stress.

B. Electrodermal Activity and Galvanic Skin Response

Galvanic Skin Response (GSR), also referred to as Electrodermal Activity (EDA), measures changes in the electrical properties of the skin. When an individual experiences emotional arousal or stress, the body produces sweat, leading to an increase in skin conductance. EDA is computed by applying a small current and measuring the resistance of the skin between two electrodes.

GSR or EDA is widely recognized as one of the most discriminative signals [21], along with heart rate signals, for measuring stress levels in individuals. By analyzing GSR/ EDA signals, we can gain valuable insights into the physiological response to stress and emotional arousal.

C. Wearable Device

The wearable device includes a main microcontroller unit (MCU) that serves as the central processing unit, responsible for the seamless integration of various sensors. Specifically, the pulse sensor is utilized as a photoplethysmography (PPG) sensor, while the Grove GSR sensor is employed as an electrodermal activity (EDA) sensor. Additionally, an accelerometer is incorporated to effectively detect motion in the user's hand. The device also includes a voltage regulator to provide a stable power supply.

ISSN (Online) 2456-1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 12, Issue 01, January 2025

D. Mobile Application

To address the numerous limitations in the currently available mobile applications on the market, particularly their inability to comprehensively manage stress through both detection and alleviation functionalities, we have developed a novel mobile application specifically designed for Android platforms using the Java programming language.

The mobile application contains several features for stress detection and alleviation. The main features are as follows:

- Real-Time Stress Detection: The application detects stress using both a camera and a wearable device.
- Multi-Language Support Chatbot: The chatbot supports multiple languages, including English, Sinhala, and Tamil, using the Google Translate API.
- Interactive Feed: Based on the chat history and detected stress levels, the application suggests stress alleviation methods to users through an interactive feed.

IV. IMPLEMENTATION

This section describes how we implement the system based on previously discussed designs.

A. Wearable Device and PCB Design Implementation

The *STM32WB55RGV6* [22] is the microcontroller unit, and the *ADXL345* is the accelerometer used in the wearable device shown in figure 2. To ensure precise physiological measurements, the wearable device captures the photoplethysmography (PPG) signal at 64 Hz and the galvanic skin response (GSR) signal at 4 Hz using analog-to-digital converters (ADCs). The microcontroller unit (MCU) facilitates data reception from the accelerometer via the I_2C communication protocol, enhancing the device's functionality and versatility in capturing vital physiological information.

Figure 2. Wearable Device

The *LD39050PU33R* acts as a voltage regulator, providing a stable 3.3V power supply to essential components such as the microcontroller, pulse sensor, GSR sensor, and accelerometer, ensuring reliable and consistent operation. Additionally, the device incorporates an *M830520* 2.4 GHz chip antenna, enhanced by an *MLPF-WB55-01E3* passive filter network. The *MLPF-WB55-01E3* is a microscopically small, bumpless 6-pad chip-scale integrated circuit. The wearable device is equipped with a custom-designed PCB, as shown in figure 3.

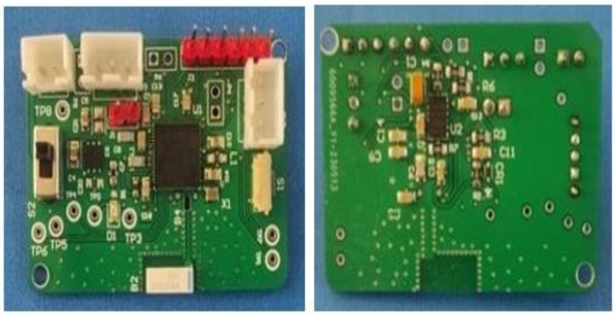

Figure 3. Left: Top Side of PCB, **Right**: Bottom Side of PCB

The microcontroller is programmed via *ST-LINK/V2*, and the Firmware Upgrade Service (FUS), and wireless stack is updated using *STM32CubeProgrammer* software. The *STM32CubeMX* software is used to generate the Bluetooth Low Energy (BLE) application. The code to acquire data from the sensors and transmit it to the mobile phone through BLE was built using the *STM32CubeIDE* software.

B. Mobile Application and Chatbot Implementation

Figure 4 illustrates the interfaces of the implemented mobile application, which includes features for stress detection and alleviation. The application provides a feed for users and incorporates a chatbot designed to offer personalized support.

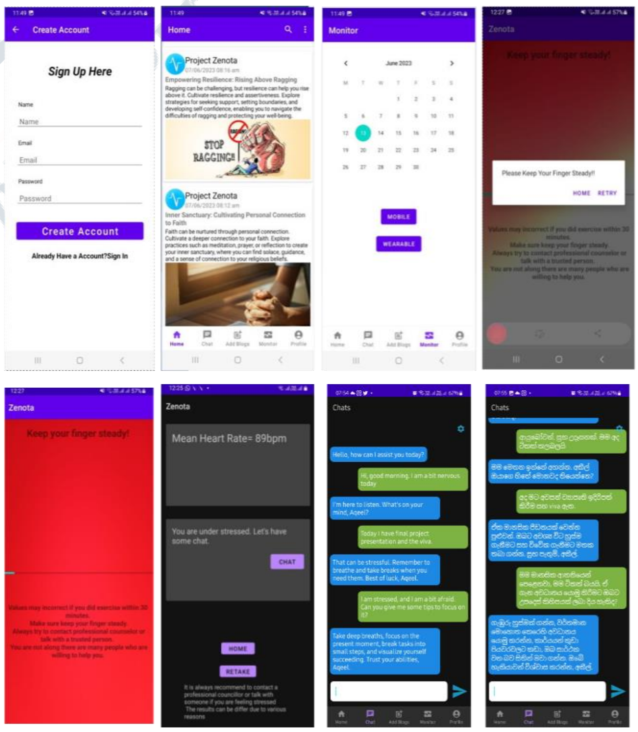

Figure 4. Mobile Application Interfaces

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 12, Issue 01, January 2025

A. Stress Detection

The mobile application facilitates stress detection using the mobile phone camera. We use only PPG to measure stress levels by capturing a video of the fingertip. Image processing techniques extract the PPG signal using the mobile phone camera. Since PPG is highly affected by motion, we first use a motion detection algorithm to identify motion. If motion is detected while the user is taking readings, the process will be stopped, and the user will need to restart. If no motion is detected, we analyze each frame and obtain the PPG signal value for every frame as proposed in [17]. Typically, mobile phones support a frame rate of 30 fps. We need to up-sample this before applying it to the classification algorithms. The up-sampling and classification algorithms are explained in the algorithm section.

B. Chatbot and Alleviation Feed Implementation

The mobile application's chatbot functionality is developed using OpenAI's Chat Completions API and prompt engineering techniques. To enhance the chatbot's performance, we configured the prompt to simulate a counselor with extensive experience, capable of understanding users' feelings. Additionally, the API receives chat history from recent conversations to provide context for generating appropriate responses based on the user's current emotions and situation. The generated response is then displayed within the application's interface. For this purpose, we utilized the GPT-3.5-turbo model.

Furthermore, the chat feature of the application supports multiple languages through the utilization of the Google Translate API. Each message from the chat history is added to an array, and a request is made to the API to obtain translations for each message. This enables users to engage in conversations in English, Sinhala, and Tamil languages.

To summarize the user's chat and extract emotions, a separate API is employed. This API utilizes the text-davinci-003 model and is responsible for generating a concise summary of the chat as well as identifying the user's emotions. By leveraging a recommendation algorithm, the extracted summary and emotions are used to suggest appropriate alleviation techniques.

C. Algorithm Training Dataset

The experiments are conducted using the publicly available Wearable Stress and Affect Detection (WESAD) dataset [23], which recorded physiological (BVP, ECG, EDA, EMG, RESP, and TEMP) and motion (ACC) data from two different devices: a chest-based and a wrist-based device. The dataset included data from 15 participants with a mean age of 27.5±2.4 years. To ensure the validity of the data, participants were carefully selected, and exclusion criteria were applied, including pregnancy, heavy smoking, mental disorders, and chronic and cardiovascular diseases. The dataset was labeled with four emotional states: baseline, stress, amusement, and meditation, which were examined during the data collection process.

D. Algorithms (1) PPG Algorithm

The PPG algorithm is designed to reduce noise and extract essential features from PPG signals, as shown in figure 5, involving the orchestration of multiple denoising and peak-detecting methods proposed in [13].

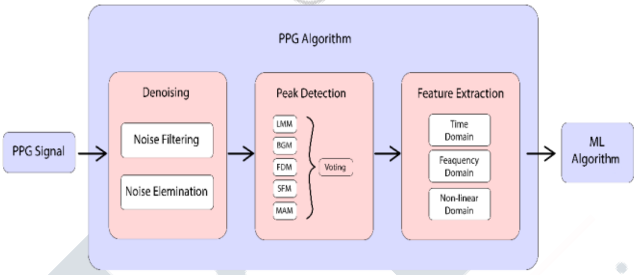

Figure 5. PPG Algorithm Flowchart

A. Step 1: Up-sampling

PPG signals in the WESAD dataset are stored at a 64 Hz data rate [23], the same rate used for feature extraction and machine learning model training. When generating PPG signals from the mobile phone camera, the frequency varies between 15 Hz and 30 Hz, determined by dividing the signal length by a fixed input time. The signal is then up-sampled to 64 Hz. Wearable devices provide PPG signals directly at a 64 Hz rate, eliminating the need for up-sampling.

B. Step 2: Noise Filtering

To effectively filter out unwanted noise and retain the pertinent features of a heart signal, a bandpass filter with a passband ranging from 0.5 Hz to 10 Hz is implemented. This passband range encompasses the critical heart signal features, ensuring that extraneous frequency components are eliminated.

C. Step 3: Noise Elimination

The noise elimination process involves segmenting the PPG signal into fixed-length segments. It is crucial to determine an optimized segment length that balances the accuracy of feature extraction, and the time required to collect a sufficient number of uncorrupted segments for subsequent analysis. Through rigorous experimentation on the dataset, multiple tests are conducted to identify the optimal segment length, which has been found to be 40 seconds. Upon partitioning the data, key statistical parameters such as standard deviation, kurtosis, and skewness are computed for each segment. These statistical measures serve as criteria for detecting segments corrupted by noise. By comparing these computed statistical data with threshold values derived from clean PPG signals, corrupted segments are effectively identified and eliminated from the dataset, thereby ensuring the reliability and integrity of

ISSN (Online) 2456-1304
International Journal of Science, Engineering and Management (IJSEM)
Vol 12, Issue 01, January 2025

subsequent analyses and machine learning model training.

D. Step 4: Peak Detection

We implemented five distinct methods for peak detection, as described in [13]:

- LMM: Local Maxima Method
- BGM: Block Generation with the Mean of the Signal Threshold Method
- FDM: First Derivative with an Adaptive Threshold Method
- SFM: Slope Sum Function with an Adaptive Threshold Method
- MAM: Moving Averages with the Dynamic Threshold Method

To determine the final peak detection result, a voting method is employed, considering the outcome that is shared among at least n out of the 5 methods. Based on [13], the most accurate results are obtained when n = 3.

E. Step 5: Feature Extraction

Upon peak detection, the intervals between consecutive main peaks are computed. Using these intervals, we calculate 26 distinct features as described in [13], most of which are associated with heart rate variability. Subsequently, these extracted features are input into machine learning algorithms to obtain the final result.

EDA Algorithm

Feature extraction of EDA signals is conducted using the pyEDA library [24]. As shown in figure 6, the signal initially undergoes down-sampling to 4 Hz, followed by noise removal using a moving average approach. For statistical feature extraction, the cvxEDA algorithm provided by pyEDA is employed. The features fed into the machine learning algorithms include:

- Number of peaks per minute
- Maximum peak value
- Average of the signal

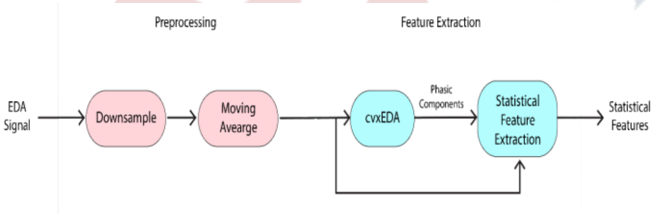

Figure 6. EDA Algorithm Flowchart

E. ML Algorithms

To classify stress into two levels, seven different classical machine learning models are employed. The models are trained using feature vectors extracted from the WESAD dataset, and the performance of the extracted features is evaluated. The machine learning models used are as follows:

- Gradient Boosting Classifier
- Support Vector Machines
- Linear Discriminant Analysis
- K-Neighbors Classifier
- AdaBoost Classifier
- Random Forest Classifier
- Decision Tree Classifier

Parameters are experimentally tuned to achieve the highest accuracy. Deep learning models could not be applied to our experiment due to insufficient data for training. To enhance the accuracy of the final result, a voting method is implemented, considering a total of 14 votes—seven for each model related to PPG features and seven for each model related to EDA features. The used evaluation metrics include F1 score, Area Under the Curve (AUC), and accuracy score for each model.

For tuning the weights of each vote, we consider the individual performance accuracy of each model for PPG and EDA features, as well as feature importance. Feature importance is taken into account to ensure the generalization of results across the dataset by increasing the vote weight of models that demonstrated a greater dependency on features related to heart rate variability.

V. DATA COLLECTION

To test and evaluate our application in real-life settings, we conducted a data collection experiment with twenty participants, consisting of 13 men and 7 women. All participants are undergraduate students at our university. This study was approved by the 56th UERC Committee of the University of Moratuwa. Prior to their involvement in the study, all participants signed a detailed informed consent form outlining the purpose and procedures of the research. Each participant was assigned a unique id to ensure anonymity throughout the study. Following the completion of data collection, all personal identifiers linking participant names to their assigned ids were anonymized.

Prior to obtaining readings from the wearable device, participants were instructed to sit down and relax for a brief period. To gauge the participant's mental state, an initial questionnaire was administered to determine the presence of stress.

A. Data Collection Using Wearable Device

The two sensors of the wearable device are attached to the participant's fingers, ensuring proper placement. Once the sensors are securely positioned, a Bluetooth Low Energy connection is established between the mobile application and the wearable device. A command is sent from the mobile application to initiate the signal reading process on the wearable device. The data capture phase lasts approximately 3 minutes, during which readings are recorded. Upon completion, the captured data is transmitted from the wearable device to the mobile application using Bluetooth Low Energy technology.

IFERP

ISSN (Online) 2456-1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 12, Issue 01, January 2025

B. Data Collection Using Mobile Application Camera

The participant is provided with a mobile phone that has the application installed and is instructed to place their index finger over the mobile phone camera. The video capturing process is initiated from the application, with the flash activated. If motion is detected by the Frame Difference Motion Detector while taking readings, an error message is displayed, and the participant is required to restart the reading process from the beginning. The mobile phone camera records video frames for a duration of 1.5 minutes. Subsequently, the values of the frames are calculated, and a request body is generated.

Finally, in both detection methods, the mobile application sends a request to the server to retrieve the stress results and heart rate information associated with the participant. The collected data from the wearable device or the mobile phone camera, along with the questionnaire responses, are used to create the dataset for further analysis and research purposes.

VI. EXPERIMENTS AND RESULTS

This section describes the experiments conducted and the corresponding results obtained for the application.

A. Feature Extraction and Sensor Calibration

Photoplethysmography (PPG) signals extracted from both hardware devices and mobile phone cameras are processed using the PPG algorithm. As the final stage of the PPG algorithm, PPG features are extracted by calculating the intervals between the detected peaks. To assess the performance of the input methods and the feature extraction algorithm, and to validate their accuracy, the extracted heart rates are compared with data collected simultaneously using a standard Philips multi-parameter patient monitor. The results for different test samples are depicted in figure 7. The overall deviation of the heart rates from the standard method is 10 beats per minute (bpm) for the hardware device method and 9 bpm for the mobile phone camera method.

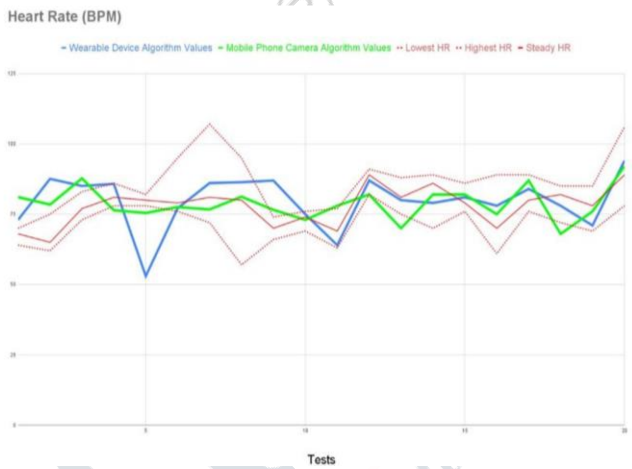

Figure 7. Comparison of Heart Rate

B. Results for WESAD Dataset

When applying the PPG algorithm to the validation data of the WESAD dataset, the results yielded an average machine learning model accuracy of 90.33%, an area under the curve (AUC) of 88.66%, and an F1 score of 81.50%. The individual results are presented in Table 1.

Table I: Accuracy for WESAD Dataset for PPG Data

ML Model	Accuracy (%)	F1 Score (%)	Area Under Curve (%)
Gradient Boosting Classifier	91.39	82.11	88.80
Support Vector Machines	93.39	84.38	90.62
Linear Discriminant Analysis	93.89	83.36	89.86
K-Neighbors Classifier	82.19	81.19	88.16
AdaBoost Classifier	93.60	84.01	90.18
Random Forest Classifier	90.62	79.26	87.90
Decision Tree Classifier	87.24	76.19	85.07

Similarly, upon implementing the EDA algorithm on the validation data of the WESAD dataset, the results showed an average machine learning model accuracy of 92.20%, an area under the curve (AUC) of 91.90%, and an F1 score of 87.42%. The individual results are provided in Table 2.

Table II: Accuracy for WESAD Dataset for EDA Data

ML Model	Accuracy (%)	F1 Score (%)	Area Under Curve (%)
Gradient Boosting Classifier	93.10	87.25	91.99
Support Vector Machines	93.88	89.31	93.30
Linear Discriminant Analysis	95.76	90.47	94.49
K-Neighbors Classifier	88.04	88.04	92.38

ML Model	Accuracy (%)	F1 Score (%)	Area Under Curve (%)
AdaBoost Classifier	90.97	86.65	90.88
Random Forest Classifier	94.61	89.52	93.77
Decision Tree Classifier	89.05	80.69	86.49

C. Results for Real-World Data

To validate the final generalized model, results from the collected data using both the mobile phone camera and the wearable hardware device were analyzed. The accuracy of both capturing methods is presented in Table 3.

Table 3: Accuracy for Real-World Data

Data Capturing Method	Accuracy (%)
Mobile Phone Camera	80.97
Wearable Hardware Device	83.42

VII. CONCLUSION

In this research, we addressed the significant impact of stress on modern society and presented the design of a cost-effective and accurate wearable device capable of detecting mental stress based on skin conductance and heart rate variability. Complementing the wearable device, we developed a mobile application utilizing the device's camera for stress detection.

Our wearable device effectively monitored users' mental stress levels and wirelessly transmitted stress-related data to their smartphones. To enable stress prediction, we employed various sensors in the wearable device, and through intelligent analysis of correlations between the input signals using machine learning algorithms, we predicted whether the user was experiencing stress.

In conclusion, our research presents a practical and affordable solution for stress detection and alleviation, fostering a better understanding of stress patterns and assisting healthcare professionals in providing more personalized treatment. Future work will focus on enhancing the system's capabilities and expanding its application to cater to a wider audience, ultimately contributing to better mental health management in society.

Acknowledgement: The authors would like to thank student counsellor Prof. J. Premachandra for his assistance in this research.

Funding Statement: The authors did not receive financing for the development of this research.

Data Availability: Data sharing is not applicable to this article.

Conflict of Interest: The authors declare that there is no conflict of interest.

REFERENCES

[1] A. Morales, M. Barbosa, L. Mor´as, S. C. Cazella, L. F. Sgobbi, I. Sene, and G. Marques, "Occupational stress monitoring using biomarkers and smartwatches: A systematic review," Sensors, vol. 22, no. 17, 2022.

[2] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," IEEE Access, vol. 9, pp. 84 045–84 066, 2021.

[3] A. Ahmed, N. Ali, S. Aziz, A. A. Abd-alrazaq, A. Hassan, M. Khalifa, B. Elhusein, M. Ahmed, M. A. S. Ahmed, and M. Househ, "A review of mobile chatbot apps for anxiety and depression and their self-care features," Computer Methods and Programs in Biomedicine Update, vol. 1, p. 100012, 2021.

[4] R. Castaldo, L. Montesinos, P. Melillo, C. James, and L. Pecchia, "Ultrashort term hrv features as surrogates of short term hrv: A case study on mental stress detection in real life," BMC Medical Informatics and Decision Making, vol. 19, 01 2019.

[5] T. Salafi, "Design of unobtrusive wearable mental stress monitoring device using physiological sensor," 01 2015.

[6] F.-T. Sun, K. Cynthia, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware mental stress detection using physiological sensors," vol. 23, 01 2012.

[7] J. Taelman, S. Vandeput, A. Spaepen, and S. Van Huffel, "Influence of mental stress on heart rate and heart rate variability," in 4th European Conference of the International Federation for Medical and Biological Engineering: ECIFMBE 2008 23–27 November 2008 Antwerp, Belgium. Springer, 2009, pp. 1366–1369.

[8] P. Schmidt, A. Reiss, R. D¨urichen, and K. V. Laerhoven, "Wearablebased affect recognition—a review," Sensors, vol. 19, no. 19, 2019.

[9] Y. S. Can, B. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: A survey," Journal of Biomedical Informatics, vol. 92, p. 103139, 2019.

[10] R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, "Acute mental stress assessment via short term hrv analysis in healthy adults: A systematic review with meta-analysis," Biomedical Signal Processing and Control, vol. 18, pp. 370–377, 2015.

[11] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Tr¨oster, and U. Ehlert, "Discriminating stress from cognitive load using a wearable eda device," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 2, pp. 410–417, 2010.

[12] Y. Liu and S. Du, "Psychological stress level detection based on electrodermal activity," Behavioural Brain Research, vol. 341, pp. 50–53, 2018.

[13] S. Heo, S. Kwon, and J. Lee, "Stress detection with single ppg sensor by orchestrating multiple denoising and peak-detecting methods," IEEE Access, vol. 9, pp. 47 777–47 785, 2021.

[14] A. Affanni, "Wireless sensors system for stress detection by means of ecg and eda acquisition," Sensors, vol. 20, no. 7,

2020.

[15] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in 2013 Humaine association conference on affective computing and intelligent interaction. IEEE, 2013, pp. 671–676.

[16] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury, "Stresssense: Detecting stress in unconstrained acoustic environments using smartphones," in Proceedings of the 2012 ACM conference on ubiquitous computing, 2012, pp. 351–360.

[17] G. Lovisotto, H. Turner, S. Eberz, and I. Martinovic, "Seeing red: Ppg biometrics using smartphone cameras," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops, 2020, pp. 818–819.

[18] N. Rosruen and T. Samanchuen, "Chatbot utilization for medical consultant system," in 2018 3rd Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), 2018, pp. 1–5.

[19] Y. S. Can, N. Chalabianloo, D. Ekiz, and C. Ersoy, "Continuous stress detection using wearable sensors in real life: Algorithmic programming contest case study," Sensors, vol. 19, no. 8, 2019.

[20] A. O. Akmandor and N. K. Jha, "Keep the stress away with soda: Stress detection and alleviation system," IEEE Transactions on Multi-Scale Computing Systems, vol. 3, no. 4, pp. 269–282, 2017.

[21] R. S´anchez Reolid, M. L´opez Bonal, and A. Fern´andez-Caballero, "Machine learning for stress detection from electrodermal activity: A scoping review," 10 2020.

[22] Datasheet - stm32wb55xx stm32wb35xx – stmicro electronics. Accessed: July 23, 2023. [Online]. Available: https://www.st.com/resource/en/datasheet/stm32wb55cc.pdf

[23] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing wesad, a multimodal dataset for wearable stress and affect detection," 10 2018, pp. 400–408.

[24] S. A. Hossein Aqajari, E. K. Naeini, M. A. Mehrabadi, S. Labbaf, N. Dutt, and A. M. Rahmani, "pyeda: An open-source python toolkit for pre-processing and feature extraction of electrodermal activity," Procedia Computer Science, vol. 184, pp. 99–106, 2021, the 12th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 4th International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops.