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# A Project Report on Stress-Monitoring Mouse: Enhancing IT Workspaces for Well-being

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## 1. Introduction :

Stress, an intricate and widespread aspect of modern life, has an impact on a wide range of disciplines, from the workplace to healthcare. Understanding and efficiently managing stress have become critical in today's culture, when the demands of daily living are frequently accompanied with the threat of increased emotional strain. This report begins a thorough investigation of stress detection and physiological monitoring, diving into a tapestry of research endeavours spanning novel methodology, technical developments, and user-centric designs. This report tries to demystify the complexity of stress evaluation by an in-depth examination of important studies, providing insights into cutting-edge methodologies and their consequences for both workplace dynamics and healthcare practises.

The evaluated literature covers a wide range of aspects of stress detection. Each study adds a unique layer to the evolving landscape, from hybrid models that leverage sophisticated algorithms, such as the integration of the smart fly algorithm and least square support vector regression, to user-friendly innovations, such as the multi-photoplethysmography (PPG) sensor module embedded in a computer mouse. The introduction of real-time monitoring devices, particularly for older persons, highlights the dynamic nature of this subject, where technology meets healthcare to provide practical answers.

As we negotiate the complexities of stress, this paper intends to provide light on the importance of physiological markers in stress evaluation, such as heart rate and skin conductance. The investigation of user modelling, particularly in the context of understanding stress dynamics in older persons during computer interactions, offers a human-centric perspective to technology advances. By going into these investigations, we hope to not only explicate the techniques and conclusions, but also to create links between these disparate contributions, developing a comprehensive understanding of stress detection that goes beyond individual studies.

In an age when well-being is becoming increasingly entwined with technology, the combination of physiological monitoring and stress detection shows promise for improving our ability to buffer the impact of stressors. We hope to pave the way for future endeavours that seamlessly integrate technological advancements with healthcare treatments, encouraging a more robust and responsive approach to stress management.

## 2. Literature Survey :

In this section the authors have covered various research methods conducted previously in the literature.Androutsou et al. took a unique way to addressing the issues of stress detection in office environments in their study. The researchers created a hybrid model based on their integration of the smart fly algorithm with least square support vector regression. This model, which incorporated data from several sources in North America, Australia, and America, performed admirably, with a promising MAPE of 18.95%. However, a significant gap in the study is the lack of documented correlations between features and elucidation on the interpretability of the applied models. This detailed investigation highlights the efficacy of hybrid models while emphasising the significance of transparency and interpretability in guaranteeing the practical implementation and comprehension of such advanced approaches in stress detection research. The importance of heart rate in the investigation of physiological factors for healthcare cannot be emphasised. This paper goes into the field of pulse rate detection, emphasising the usefulness and convenience of photoplethysmography (PPG). Recognising the difficulties presented by motion artefacts and spatial limits associated with PPG signals, the study proposes a unique solution—a user-friendly multi-PPG sensor module integrated into a computer mouse. The major goal is to improve real-time pulse rate detection while maintaining stability and accuracy even in dynamic conditions.

The authors' methodological approach in Lin et al. is based on a weighted average technique applied to signals from numerous PPG sensors. This technique modifies the weight allocated to each signal channel dynamically in order to improve the overall accuracy and stability of the detected signal. The goal is to reduce noise interference, especially in motion-intensive circumstances. Experiment results verify the suggested method's efficacy, demonstrating its capacity to improve usability and the chance of successful PPG signal identification on palms.

The introduction of a real-time pulse rate monitoring mouse with a multi-sensor structure is important to the investigation. The weighted average approach emerges as a critical component, changing signal weights intelligently based on channel quality to optimise PPG peak detection accuracy and stability. Despite the nuanced performance outcomes for individual participants not constantly reaching the summit, the processed signal's aggregate sensitivity and failed detection rate outperform most single channels. The extensive four-stage experiment supports the notion that the multi-sensor structure and weighted average approach considerably increase the utility of detected PPG signals, increasing the likelihood of successful detection on palms.

Aside from the technological advances, the proposed design's simplicity, user-friendliness, and cost-effectiveness stand out. This device, positioned as a real-time monitoring mouse with a low-cost multi-sensor structure, appears not only as a technological innovation but also as a realistic solution for illness diagnosis. Its potential value as a measurement instrument for collecting physiological data offers special promise for breaking down healthcare obstacles in low- and middle-income nations. In conclusion, this study makes an important contribution by giving a practical and accessible solution that combines technology and healthcare, demonstrating the potential for new designs to have a positive influence in a variety of healthcare contexts.

Motivated by the delicate interplay between stress and physiological responses, Belk et al.'s study aims to contribute to a more nuanced understanding of stress among older persons in the workplace. Stress, which is characterised by negative feelings such as anxiety, worry, and uneasiness, has been extensively researched, particularly in relation to physiological manifestations such as increased heart rate, blood volume, pupil dilation, and skin conductance. Based on this foundation, the current study takes a novel approach by imagining real-time detection of such physiological reactions as a means of implicitly identifying stress during older persons' interactions with a computer system.

The process requires the development of an in-house computer mouse outfitted with embedded sensors capable of measuring a variety of physiological data such as heart rate, skin conductance, skin temperature, and grip force. The incorporation of these sensors creates the framework for a thorough evaluation of the user's physiological status during computer interactions. The paper presents a probabilistic classification technique to analyse and use this richness of physiological data. This programme uses real-time physiological measures to identify episodes of emotional stress in older persons.

The importance of this work extends into the broader realm of user modelling, connecting with a large body of research dedicated to detecting stress in computer users. The overarching goal is to inform intelligent actions and personalised solutions rather than simply detect stress. By detecting stress episodes in real time, the proposed algorithm opens the door to targeted interventions that can alleviate frustration and proactively prevent unfavourable health outcomes in older persons who work on computers.

This study adds a new dimension to user modelling by concentrating on the often-overlooked demographic of elderly individuals. Understanding their stress levels during computer interactions is especially important since it paves the way for solutions that address the specific needs of this demographic. The inclusion of physiological data, such as heart rate and skin conductance, emphasises the research's holistic nature, offering a comprehensive foundation for stress detection and intervention.

Finally, our study contributes to the growing landscape of user modelling by providing a technologically unique way for implicitly detecting stress in older persons during computer interactions. The combination of physiological measures and a sophisticated classification algorithm has the potential to advance not just our understanding of stress dynamics, but also to shape intelligent interventions that promote user well-being in the area of computer usage.

In conclusion, this review of the literature has spanned a wide landscape of research endeavours aiming at understanding and solving various elements of stress detection and physiological monitoring. Each contribution adds a unique layer to the evolving field of stress detection and physiological assessment, from the innovative hybrid model proposed by Androutsou et al., integrating the smart fly algorithm and least square support vector regression, to the user-friendly multi-PPG sensor module embedded in a computer mouse designed by Lin et al., and the real-time pulse rate monitoring mouse for older adults in the study by Belk et al.

The work of Androutsou et al. highlighted the potential of hybrid models in stress detection, emphasising the need of transparency and interpretability in advanced techniques. Lin et al.'s method, which used a weighted average technique for multi-PPG sensors, demonstrated the effectiveness of minimising noise interference and enhancing the overall usability of PPG data. Furthermore, the introduction of a real-time monitoring mouse with a multi-sensor structure provides a practical and cost-effective solution with potential for healthcare applications in a variety of situations.

The work by Belk et al., driven by the delicate interplay between stress and physiological reactions in older persons, added a new dimension to user modelling. The use of physiological measures in conjunction with a probabilistic classification method proved the possibility of detecting implicit stress during computer interactions. The research's emphasis on addressing the special needs of the senior demographic, as well as its holistic nature, contribute greatly to our understanding of stress dynamics and potential solutions.

These studies, taken together, demonstrate the fluid nature of research in stress detection and physiological monitoring. The literature evaluated demonstrates a determined effort to bridge knowledge gaps and provide practical answers, ranging from technology advancements to user-centric designs. As we traverse the convergence of technology and healthcare, these varied contributions pave the path for a more comprehensive knowledge of stress and open doors to intelligent interventions that improve well-being in a variety of user populations.

Table 1: Literature covering various studies embedded in computer mouses

| **Authors** | **Participants** | **Input** | **Aim** | **Methodology** |
|---|---|---|---|---|
| Kaklauskas et al. [3] | 239 | Heart rate, temperature, humidity, skin conductance, touch intensity | Detection of stress dependencies on physiological parameters | Linear regression models |
| Tran et al. [4] | 10 | PPG | PPG peak detection | Robust peak detection algorithm |
| Chigira et al. [5] | 5 | PPG | Mental stress monitoring | Signal amplification, filtering and digitization |
| Lin et al. | 21 | PPG | Pulse rate detection | Weighted average method |

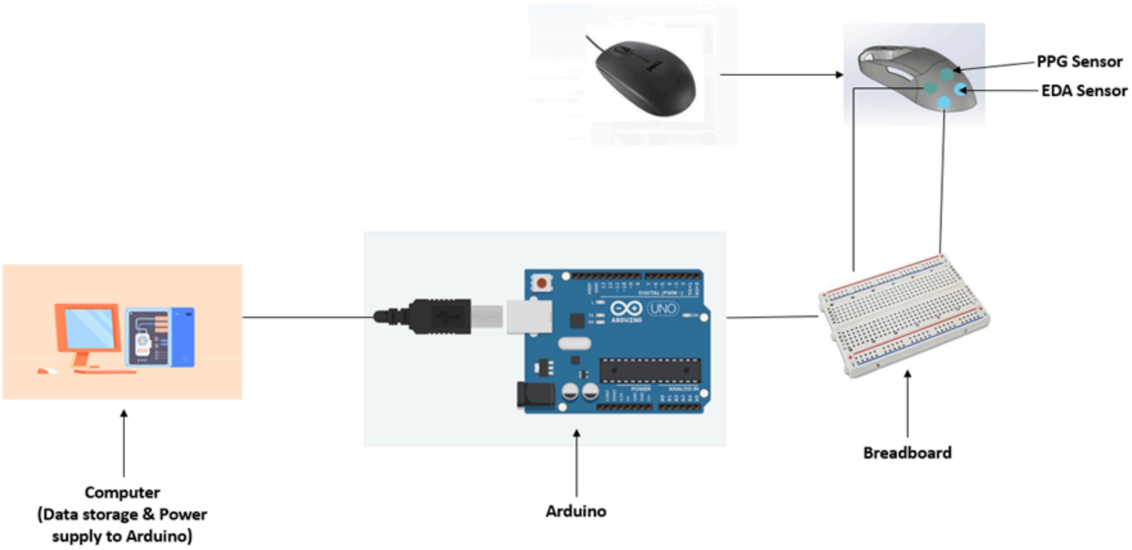
## 3. Materials and Methods :

- ### Materials:

1. Arduino UNO
2. PPG sensor
3. EDA sensor
4. Bread board
5. Computer mouse case

- ### Design

- ### Schematic Design




The PPG and EDA sensors have been positioned on the upper surface of the computer mouse. To facilitate attachment and detachment, the mouse case has been specifically designed, and the sensors have been strategically placed on the case. Connections from the sensors extend to the breadboard and subsequently to the Arduino. The computer serves as the power source for the Arduino, and it also manages the collection and storage of data from the sensors.

- ### Technical Property:

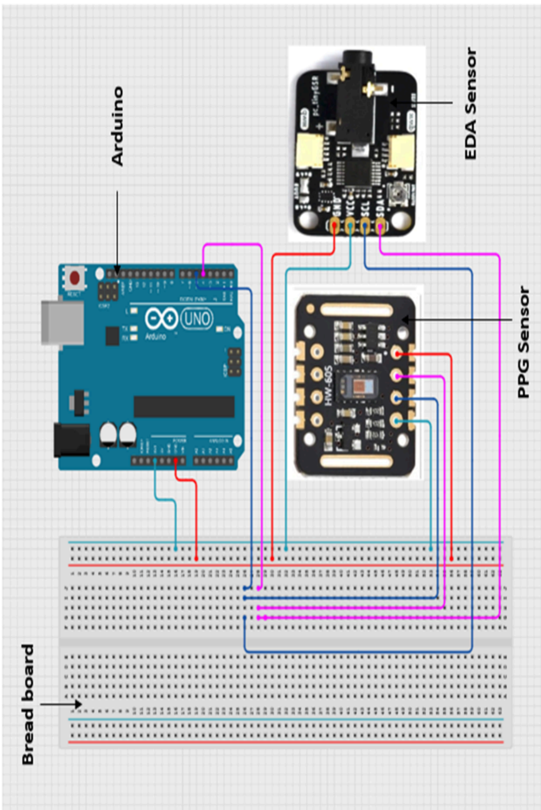
- ### Sensing working principle:

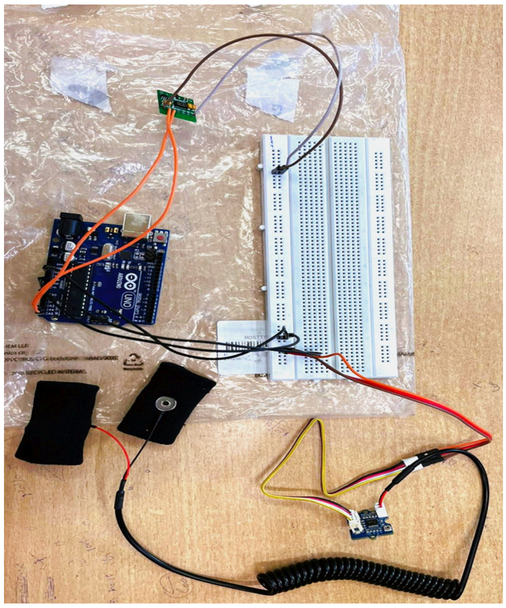
The PPG sensor utilizes red or infrared light rays. These light rays are emitted into the skin, and as they traverse biological tissues, they undergo absorption by bones, skin pigments, and both venous and arterial blood. The absorption is more pronounced in blood than in the surrounding tissues due to its higher absorption coefficient. As blood is pumped through the arteries, it induces periodic changes in blood volume. The photodetector absorbs a portion of the emitted light, and the absorbed light by the photodetector varies with the changes in blood volume. Consequently, the PPG sensor captures measurements from the body in this manner.

Electrodermal Activity (EDA) is a physiological response that gauges skin conductance, a parameter sensitive to emotional and physiological arousal. The EDA sensor comprises two electrodes in direct contact with the skin. One electrode administers a minimal, innocuous electrical current, while the other electrode gauges the ensuing electrical conductance across the skin. This conductance is intricately tied to the quantity of sweat present on the skin's surface, a factor modulated by the activity of sweat glands under the influence of the sympathetic nervous system.

During episodes of stress, the activation of the body's sympathetic nervous system prompts an elevation in heart rate and triggers responses in sweat glands. The PPG sensor is capable of discerning these physiological changes, offering valuable insights into the cardiovascular response to stress. Concurrently, the EDA sensor captures alterations in sweat gland responses, furnishing information pertaining to the emotional and psychological facets of stress. Through the integration of data from both sensors, a comprehensive understanding of stress responses is achieved, encompassing both the physiological dimension, represented by heart rate, and the psychological dimension, characterized by sweat gland activity.

- Circuit Diagram:



A photoplethysmography (PPG) sensor, an electrodermal activity (EDA) sensor, and an Arduino UNO R3 board, which is an Atmel ATmega328 microcontroller make up the proposed construction of the stress monitoring computer mouse shown in this project. The Arduino board contains 6 analog inputs, a 16 MHz ceramic resonator, a USB port, a power jack, an ICSP header, and a reset button. It also has 14 digital input/output pins, six of which can be used as PWM outputs. The Arduino IDE software, which can be downloaded for free, can be used to program it. The ADC boasts a resolution of 10 bits.

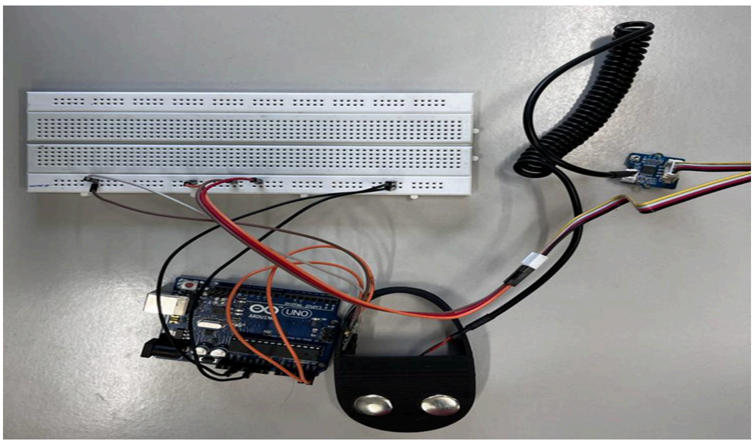
A breadboard made specifically for use with the Arduino UNO R3 board is the Protocentral breadboard. It is organized in a 5 by 5 grid and includes a total of 830 tie points. The power bus on the breadboard can be utilized to power the Arduino board and the sensors.

The designed system structure is shown in the above figures. Analog pins A0 and A1 of the Arduino board are connected to a PPG sensor since it has two outputs, one for each of the two light wavelengths it emits. The electrical conductivity of the skin is the sole output of the EDA sensor so it is connected with the A2 analog pin. This output is read by the Arduino board, which then determines then computes the heart rate and the stress level respectively. The ground and voltage pins on the Arduino board must be linked to both sensors. The system's goal is to assess users' levels of stress by examining physiological factors resulting from the processed data. The signals produced by the system's sensors are transferred to the microcontroller for recording. Algorithms for reducing noise and motion artifacts are used there to process and filter the data. Finally, the output is transferred through USB to the computer so it can be displayed.

## Experimental Setup:

A computer mouse cover that was 3D printed houses the entire setup. This makes it portable and simple to use.

The Techtonics MAX30102 Heart Rate and Pulse Oximeter Sensor that we are using in this project runs between 3.3 and 5 volts and communicates with other devices using the I2C protocol. It uses two LEDs with peak light emission wavelengths of 660 nm and 880 nm and operates on the idea of sensing light reflection signals (PPG). The sensor determines changes in blood volume brought on by heartbeats by detecting the reflected light, which enables the determination of heart rate. With a sampling rate range of 100Hz to 10kHz, the MAX30102 enables accurate data capturing.



The non-invasive Protocentral tinyGSR EDA sensor that was chosen is intended to measure changes in skin's electrical conductivity. It uses the I2C interface to exchange data and functions in the 3.3V to

5V voltage range. It guarantees precise data capture with a sample rate ranging from 1Hz to 1kHz. This sensor measures the electrical resistance between two electrodes that are in close proximity to the skin. According to the amount of perspiration, the resistance varies. Its output is a voltage signal that is proportional to the skin conductance. This is significant because the sympathetic nervous system, which is also in charge of the fight-or-flight response, activates sweat glands. Therefore, a rise in skin conductivity is a sign of increased stress. The ADC then converts the voltage signal to a digital signal for further analysis.

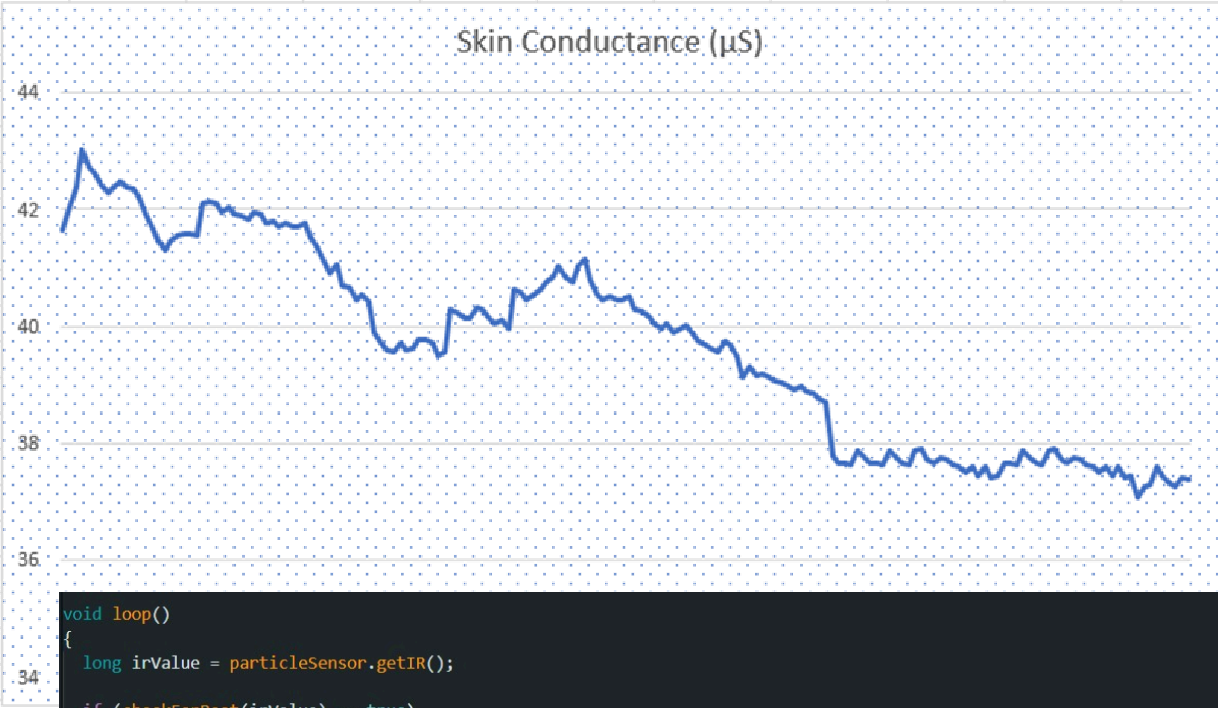
## Computation:

The system sensors picked up the EDA and PPG signals and sent them to the microcontroller. Filtering and preprocessing methods were used during the data capture to reduce the noise component and extract the required information for further processing. Artifacts like body movements and gestures or inappropriate electrode-to-skin contact have an impact on the EDA signal. In the suggested experimental setting, the electrodes are not fastened to a wearable object but rather are embedded in a mobile surface, i.e., as a computer mouse case, which is frequently moved by the user's hand. A moving average filter is used to smooth the data, and a modified version of the manufacturer's formula is used to convert the raw sensor data to human skin conductance (SC) in Siemens, reducing the signal artifacts.

$$SC = \frac{2048 - V_{out}}{4096 + 2 \cdot V_{out} \cdot 10000}$$

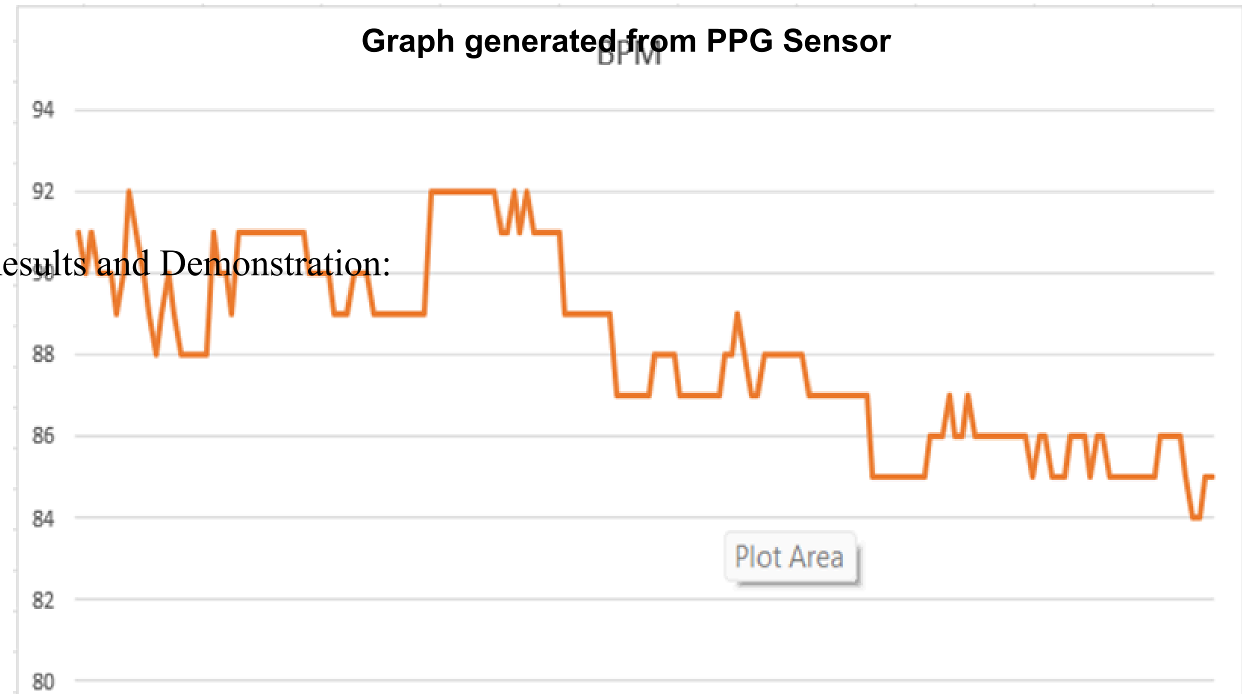
From the obtained PPG, finding the precise moment of each heartbeat despite obstacles like baseline noise and inaccurate readings from the dicrotic notch is crucial for obtaining reliable outcomes. To remove noise and motion distortions from PPG data and modify the measured sensor value based on previous sensor data, Kalman filtering is employed in this situation to reduce the noise of the sensor value. It follows a process that may be broken into two sections for this purpose: prediction and update. The algorithm determines the subsequent sensor measurement in the prediction phase using the historical data. To get closer to the real value, the prediction value is adjusted during the update process based on the measured value. The code of the algorithm is attached below.

```
#include <Wire.h>
#include "MAX30105.h"
#include "heartRate.h"

MAX30105 particleSensor;

const byte RATE_SIZE = 4; //Increase this for more averaging. 4 is good.
byte rates[RATE_SIZE]; //Array of heart rates
byte rateSpot = 0;
long lastBeat = 0; //Time at which the last beat occurred

float beatsPerMinute;
int beatAvg;

void setup()
{
  Serial.begin(9600);
  Serial.println("Initializing...");

  // Initialize sensor
  if (!particleSensor.begin(Wire, I2C_SPEED_FAST)) //Use default I2C port, 400kHz speed
  {
    Serial.println("MAX30105 was not found. Please check wiring/power. ");
    while (1);
  }
  Serial.println("Place your index finger on the sensor with steady pressure.");

  particleSensor.setup(); //Configure sensor with default settings
  particleSensor.setPulseAmplitudeRed(0x0A); //Turn Red LED to low to indicate sensor is running
  particleSensor.setPulseAmplitudeGreen(0); //Turn off Green LED
}
```




```
void loop()
{
  long irValue = particleSensor.getIR();

  if (checkForBeat(irValue) == true)
  {
    //We sensed a beat!
    long delta = millis() - lastBeat;
    lastBeat = millis();

    beatsPerMinute = 60 / (delta / 1000.0);

    if (beatsPerMinute < 255 && beatsPerMinute > 20)
    {
      rates[rateSpot++] = (byte)beatsPerMinute; //Store this reading in the array
      rateSpot %= RATE_SIZE; //Wrap variable

      //Take average of readings
      beatAvg = 0;
      for (byte x = 0 ; x < RATE_SIZE ; x++)
        beatAvg += rates[x];
      beatAvg /= RATE_SIZE;
    }
  }
Serial.print(beatAvg);
  Serial.print(",");
  Serial.print(analogRead(A0));

  if (irValue < 50000)
    Serial.print(" No finger?");

  Serial.println();
}
```

Bi

Graph generated from PPG Sensor

Results and Demonstration:

By using the above-mentioned algorithm to carefully distinguish between the tonic and phasic components of EDA, the baseline curve for electrodermal activity was created. The baseline conductance level of the skin, which indicates the person's general level of arousal, is reflected in the tonic component. The phasic component, on the other hand, records quick, transient variations in conductance that are frequently brought on by unexpected stimuli or emotional reactions. The defined baseline provides a trustworthy starting point for evaluating EDA fluctuations under typical conditions. The EDA baseline curve, however, experiences observable changes under stressful circumstances. Increased phasic responses and elevated tonic levels are seen, indicating heightened sympathetic nervous system activity. This thorough baseline curve offers an essential framework for analyzing EDA data, providing a detailed comprehension of physiological reactions and supporting tailored therapies for stress.

The Photoplethysmogram (PPG) baseline curve was the same. This method successfully distinguished between the core elements of the PPG signal, such as the dynamic pulsatile fluctuations and baseline. The baseline depicts the typical level of light absorption, which is mostly controlled by the positioning of the sensor and the characteristics of the tissue. In contrast, pulsatile variations are rhythmic changes in blood volume that are timed to the heartbeat. This baseline curve offers a steady frame of reference for assessing PPG changes in typical physiological situations. But under stressful circumstances, the baseline curve shows clear variations. This established baseline curve provides a fundamental framework for analyzing PPG data, enabling targeted therapies for stress reduction and offering a comprehensive understanding of cardiovascular responses to stress.

## Conclusion

The proposed multimodal system has a great deal of potential to improve IT professionals' quality of life. It gives people the ability to monitor their stress levels, enabling them to adopt proactive measures for a better and more effective lifestyle. Additionally, this technology extends its advantages to IT firms by providing insightful data on the dynamics of staff well-being and stress. This knowledge can be used to create specialized stress management plans, which will ultimately promote a more encouraging and beneficial work atmosphere. The adoption of this cutting-edge system is a big step towards a healthier, more balanced work-life for IT professionals because of its potential to benefit both individuals and organizations. It not only takes care of current issues, but it also paves the way for a more resilient and prosperous professional environment.

## References :

1) Androutsou, Thelma, Spyridon Angelopoulos, Evangelos Hristoforou, George K. Matsopoulos, and Dimitrios D. Koutsouris. 2023. "A Multisensor System Embedded in a Computer Mouse for Occupational Stress Detection" *Biosensors* 13, no. 1: 10. https://doi.org/10.3390/bios13010010
2) Lin, Shu-Tyng, Wei-Hao Chen, and Yuan-Hsiang Lin. 2017. "A Pulse Rate Detection Method for Mouse Application Based on Multi-PPG Sensors" *Sensors* 17, no. 7: 1628. https://doi.org/10.3390/s17071628
3) Kaklauskas, A.; Zavadskas, E.K.; Seniut, M.; Dzemyda, G.; Stankevic, V.; Simkevicˇius, C.; Stankevic, T.; Paliskiene, R.; Matuli- auskaite, A.; Kildiene, S.; et al. Web-Based Biometric Computer Mouse Advisory System to Analyze a Users Emotions and Work Productivity. *Eng. Appl. Artif. Intell.* **2011**, *24*, 928–945.
4) Tran, T.V.; Chung, W.Y. A Robust Algorithm for Real-Time Peak Detection of Photoplethysmograms Using a Personal ComputerMouse. *IEEE Sens. J.* **2015**, *15*, 4651–4659
5) Chigira, H.; Kobayashi, M.; Maeda, A. Mouse with Photo-Plethysmographic Surfaces for Unobtrusive Stress Monitoring. In Proceedings of the 2012 IEEE Second International Conference on Consumer Electronics—Berlin (ICCE-Berlin), Berlin, Germany,3–5 September 2012; pp. 304–305.
6) Lin, S.T.; Chen, W.H.; Lin, Y.H. A Pulse Rate Detection Method for Mouse Application Based on Multi-PPG Sensors. *Sensors* **2017**,*17*, 1628.