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Mantra Meditation: A Technology Based-Approach for Stress Detection and Mental Wellness

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ABSTRACT- Stress is a state that a lot of people experience while working on various activities at school or at work. As far as I noticed, stress begins in the brain. Moreover, stress manifests itself physically in some cases. Heart rate, heart-rate variability, electrical skin response, respiration, and blood flow are just some examples of body reactions to stress. Such manifestations may help to create stress detection technologies. However, only one body sign cannot serve as the only basis for stress assessment since movement, sitting position, temperature of the body, disease, medication, sensor placement and more may influence results.

In my attempt to integrate the body monitoring with meditation, I would like to focus on relaxation through the use of technology. At the moment, I have the prototype of the system that operates using the benchtop. The system uses an ESP32, optical sensor, and an SH1106 OLED display. The optical sensor captures data related to the light. This data is processed using the MAXIM algorithm to calculate heart rate and blood oxygen levels (SpO_2). When the readings are valid the screen shows heart rate, SpO_2 and a rough stress level. This stress level is based on fixed thresholds. It is not an assessment.I have also started using the WESAD dataset. This dataset contains stress and emotional data from people. One subject's file has been loaded into Python. The chest and wrist signals were checked. A short ECG segment was plotted. This step helps lay the groundwork for feature extraction and machine-learning model building. Now the system is still in stages. A machine-learning model has not been trained. A mobile app made with Flutter is not ready. Automated analysis before and, after meditation is not yet set up. The stress label used today is rule-based. It should not be treated as a measure of stress. This report goes over why the project was started what others have done in the field the hardware setup, how the software works what was done with the data, where things stand now what the limits are and what steps come next. The prototype is meant for teaching and wellness research. It is not meant for diagnosis. The prototype is the embodiment of the easy-to-use and non-invasive method of heart rate and SpO2 measurement, and stress estimation using some pre-defined rules. The application of machine learning methods for further stress classification was also considered within this study. Even though the suggested prototype is designed only for initial monitoring and education purposes, not for clinical diagnostics, it opens up possibilities for development of cheap technological solutions for stress monitoring and mental wellness.

Keywords: stress awareness, mantra meditation, ESP32, MAX30102, OLED, heart rate, WESAD, HRV, wearable sensing, machine learning.

I. INTRODUCTION

1. Context And Motivation

I notice that stress can happen when someone feels that the demands of a task exceed their ability to cope. Stress can happen when someone feels that the demands of a task exceed their ability to cope. Students for example can feel

stress about exams, due dates, speeches and changes in their schedule. The amount of work and what is happening in lives can also affect stress. Not everyone feels stress in the way. The same situation can cause different people to feel ways and how the body reacts can change over time. One common way to check for stress is to ask the person how they feel. Questionnaires and self reports help because what someone feels cannot be known by looking at a sensor. A questionnaire only shows what someone felt at one moment. Depends on how the person remembers and interprets things. Sensors that measure the body can give information by recording data all the time or at set times. A good system should use body data along with details. When needed what the person says, instead of just looking at one reading as the final answer. Wearable sensors have facilitated the study of various signals such as photoplethysmography, ECG, EDA,

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respiration, temperature, and motion. Photoplethysmography is an analysis of the variations in absorption due to changes in the volume of blood in the body.

ECG records the activity of the heart. Both can help look at heart rate. They are not the same. They work differently. They have problems with the quality of the data they collect. The Mantra Meditation System tries a mix of body monitoring. Repeating a mantra. The goal is to look at body data use a model to guess if someone is stressed give a guided meditation and then check some data before and, after the meditation. This version is a model and not a finished product.

2. Project Overview

I notice that stress can happen when someone feels that the demands of a task exceed their ability to cope. Stress can happen when someone feels that the demands of a task exceed their ability to cope. Students for example can feel stress about exams, due dates, speeches and changes, in their schedule. The amount of work and what is happening in lives can also affect stress. Not everyone feels stress in the way. The same situation can cause different people to feel stress in ways and how the body reacts can change over time.

One common way to check for stress is to ask the person how they feel. Questionnaires and self reports help, because what stress feels cannot be known by looking at a sensor.

3. Scope Of This Paper

This paper is about the hardware prototype that has been finished. The firmware works to show sensor data and gives a look, at the dataset. This paper also talks about the research background. The paper gives a plan that makes sense technically for work with machine learning and applications. This paper does not say that the mobile app, the stress classifier that is supposed to be trained or the way to check meditation results is already working.

4. Main Contribution At The Current Stage

- Running a bench-top ESP32 MAX30102 OLED prototype.
- Creating a measurement routine that holds samples and uses a heart-rate SpO2 algorithm.
- Designing display logic that keeps the result for a short time instead of changing it right away when there is an invalid calculation.
- Looking at a WESAD subject file. Finding the chest and wrist signal channels.
- Describing how the differences lie between the hardware demonstration and the entire process of monitoring and meditation.

II. BACKGROUD AND TECHNICAL CONCEPT

1. Physiological Stress Indicator

I have found that stress recognition research considers since the body exhibits diverse responses. The number of heartbeats per minute is indicated by heart rate (HR). HR may increase due to exercise, emotional arousal, fever, and others, while resting decreases HR. Thus, high HR does not indicate stress.

Heart Rate Variability (HRV) is the difference in the time intervals of one heart beat to the other. HRV attributes are determined from normal-to-normal beat intervals after preprocessing and error correction. The RMSSD is the time-domain index and relies on the difference of adjacent intervals, whereas the SDNN is the standard deviation of the interval series, over a set of time. I find that HRV features may be useful. How I read them depends on how long we record how clean the signal is, what the person is doing, breathing and the group of people we study.

2. Photoplethysmography And Max30102

Photoplethysmography works when light is sent into the skin and a photodetector measure how much light bounces back or passes through. The MAX30102 sensor has infrared LEDs and a photodetector to do this sensing. The raw data from the MAX30102 can change if the finger is placed wrong if pressure is too high if the user moves, if there is bright outside light if the skin is not well perfused or if the contact is unstable. A good reading from the MAX30102 depends not on the calculation algorithm but also, on how clear the optical signal is. Photoplethysmography really needs a signal to work well.

In the circuit the MAX30102 is wired to the ESP32 using an I²C bus. The firmware takes infrared and red-light samples puts them into buffers and runs the oxygen-saturation routine. The sensor does not give a certified stress score directly. The stress category shown in the demo is created by a software rule that looks at the estimated heart rate.

3. Esp32 Micro-Controller

The ESP32 is the controller in the prototype. The ESP32 runs the firmware and talks to the MAX30102. Oled over I²C. The ESP32 stores sample buffers to check if the calculated values are inside the programmed limits and update the display. The ESP32 is a platform for an educational IoT prototype because it mixes

microcontroller features with communication abilities. The current firmware shows output on the display; the current firmware does not send data to a phone yet.

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4. Oled Display

The OLED provides feedback when a demo is taking place. The firmware shows a title, heart rate in beats per minute SpO_2, as a percentage the preliminary stress estimate and a status line. When a valid measurement has just been calculated, the code keeps the result for a configured period. This makes the output easier to see during a demonstration although the displayed values remain estimates and should not be treated as a clinical report.

5. Machine Learning And The Role Of Wesad

A supervised machine-learning model learns how to connect input features with known labels. For stress recognition possible inputs can be HRV features, pulse features, EDA, respiration, temperature and movement. The models performance is affected by the labels, data quality, preprocessing, the features that are chosen the diversity of participants and the strategy used for evaluation. A model can seem accurate if the windows from the same person or recording are, in both training and testing; participant-wise evaluation can provide a more realistic idea of how well the model works in general. WESAD is a research dataset that holds types of physiological and motion data from people who went through a plan that included different emotional states. WESAD is useful for experiments because it gives kinds of signals and clear labels.

The problem with using WESAD is that it cannot directly apply to MAX30102 because of different types of sensors. The task requires to align the characteristics of the real-life prototype with those that were used to train the model.

III. PROBLEM DEFINATION AND OBJECTIVES

1. Problem Statement

Physiological sensors could provide data regarding changes in the state of the body. One measure, for example, the heart rate, may not always indicate whether the individual is experiencing any form of stress. A research-oriented system could demonstrate their ability to recognize stress from datasets or circumstances. In practice, an inexpensive device has to consider the quality of signals. It should be able to cope with individual variability as well. It should operate under the constraints

of the hardware. It should develop how monitoring can be linked to basic wellness practices. This project takes a systematic approach. It integrates monitoring of the future state of the body as an approach to estimating stress through data as well as mantras for meditation. It also makes sure that what works is distinguished from what was planned.

2. Aim

The objective is to design and research a technology-aided prototype for stress surveillance and awareness in the future, recommending mantra meditation as the relaxing exercise.

3. Objectives

- Build a working prototype using an ESP32, optical sensor, and OLED display.
- Collect infrared optical samples and then run a software algorithm to estimate heart rate and SpO_2.
- Show the measurements that were accepted and clearly labeled the rule-based stress category.
- I will explore WESAD. Learn about how its physiological signals are structured and sampled.
- I will prepare a process for signal preprocessing and extracting HR and HRV features.
- Later, I will. Evaluate suitable machine-learning models using an evaluation method that keeps participant-level data from leaking.
- I will acquire infrared optical samples and run a software algorithm to estimate heart rate and SpO_2.
- These measurements will be presented along with their names based on the stress rule category.

4. Functional Requirements

- FR-1
  Requirement: Read data from the MAX30102 sensor.
  Status: Implemented in the firmware.
- FR-2
  Requirement: Calculate heart rate and SpO_2 using an algorithm.
  Status: Implemented; accuracy has not been validated independently.
- FR-3
  Requirement: Show readings, on the OLED screen.
  Status: Implemented.
- FR-4
  -Requirement: Show a category based on programmed heart rate thresholds.

  -Current status: Implemented as a demonstration rule.
- FR-5
  -Requirement: Create a WESAD feature dataset.
  Status: Not completed; exploration has started.
- FR-6
  Requirement: Train and evaluate a stress classifier.
  Status: Pending.
- FR-7
  Requirement: Provide a Flutter app for data and meditation guidance.
  Status: Pending.

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- FR-8
  -Requirement: Compare measurements before and after meditation.
  -Current status: Pending

5. Non-Functional Requirements

- **Readability**: The OLED display should present the measurements and status messages in a certain format.
- **Reliability**: I don't want the results of algorithm computations to appear as new readings.
- **Maintainability**: The firmware and future Python pipeline should implement clear steps.
- **Privacy**: I want any transfer or storage of personal physiological data to be limited and protected.
- **Safety**: I would like all outputs to talk about estimations and wellness parameters and not diagnoses.

IV. LITERATURE REVIEW

I refer to the following literature to provide background on multimodal stress detection HRV-based feature extraction, wearable sensors, and the WESAD dataset. I try to summarize the relevance of each paper to my current research instead of summarizing the paper itself. The bibliographic information was cross-checked with that of the publishers prior to the final submission of the manuscript.

1. Abdelfattah Et Al. --- Multimodal Models On Wesad

Abdelfattah and colleagues compare machine-learning and deep-learning approaches for stress detection using physiological data. Their study matters because it looks at signals instead of just one. The comparison of chest and

wrist signals and the difference between testing on the subject and on unseen subjects points to a key problem, for wearable stress detection: a model that works well on people it has seen may not work as well on new people. For our project, this shows that cross-subject evaluation must become the next step.

2. Ashwin Et Al. --- Wearable Physiological Sensors

Ashwin and his team look at how to detect stress using sensors that measure body signals and machine-learning methods. The research looks at body signals and how to take important information from them. This is important for the projects plan to move from sensor data to a more organized way of representing the information. The results from a controlled setting shouldn't be seen as proof that the same results will happen in real-life situations. In life movement, where the sensor is placed and differences, between people can affect the data**.**

3. Dahal Et Al. ---Reduced Hrv Features And Random Forest

Dahal and colleagues investigate a stress-detection framework using a set of HRV features and a Random Forest model. I find the use of a feature set very useful for a student project because a smaller set can be easier to calculate inspect and potentially implement in a resource-constrained system. Dahals study also reinforces the need to evaluate the method on, than one dataset or setting before assuming broad applicability.

4. Bahameish Et Al. --- Reliable Stress Recognition From Hrv

Supervised machine learning with HRV feature selection for the recognition of stress and relaxation is examined by Bahameish et al. The study conducted by Bahameish et al. reveals that the efficiency of classification is contingent upon the manner of class definition and separation. Neutral states are more difficult to separate from each other than stressed vs. relaxed states.

5. Szakonyi Et Al Acute Stress From Hrv

Szakonyi and colleagues examine stress detection from HRV data obtained using portable ECG and compare time-domain, frequency-domain and nonlinear features. The study conducted by Szakonyi et al demonstrates the significance of choosing a feature family and measuring duration. The limitation in the number of participants may, nonetheless, hamper any generalization. The limited participant sample is relevant when designing the feature extraction and validation procedure.

6. Haque Et Al. ---Review Of Ai-Based Hrv Stress Prediction

Haque and other researchers look at how stress can be predicted using heart rate variability and artificial intelligence. A review paper is helpful because it gathers steps for preparing data, sources of signals, kinds of features of methods from machine learning and common problems that come up in studies. It gives a picture for the current project and helps with a step-by-step plan: checking the data, getting it ready, finding important parts training the model and testing it carefully.

7. Singh Et Al. ---Wearable Physiological Signals

Singh and other researchers study body signals from devices using computer-based methods. The inclusion of signals such as ECG and breathing explains why stress detection would

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benefit from information over heart rate. It is important to note that our current design has been implemented in a way that makes it necessary for the next design to implement the features that can actually be measured by the selected equipment.

8. Schmidt Et Al. ---Wesad Dataset

Schmidt and colleagues introduce WESAD, a multimodal dataset for stress and affect detection. The dataset includes recordings from devices worn on the chest and the wrist along with physiological and motion channels. It provides researchers with a shared benchmark, for testing their algorithms. For this project WESAD is being used first to understand the file structure to identify the signal modalities and to examine sample values. Dataset exploration is a preliminary step but it is not itself evidence that a trained model works.

9. Mishra Et Al. ---Continouous Stress Detection With Commodity Hardware

Mishra and colleagues investigate physiological stress detection using commodity hardware and look at both controlled settings and real-life situations. The difference between lab performance and everyday performance is important because data gathered in life contains motion, changing routines, and other changes. That is why Mishra and colleagues test the hardware under conditions first and only extend testing when a reliable protocol is available.

10. Abd Al-Alim Et Al. ---Free Living Wearable Stress Detection

Abd Al-Alim and other researchers look into detecting stress using machine-learning methods with sensors in real-life situations. This kind of research is very important for a wrist-worn device because a real person might walk, talk, change how they sit or wear the sensor in a loose way. A model created using a controlled data set should therefore be tested on the device and in the real setting before it is used to make claims, about users.

11. Literature Review Summary

There are a number of recurring themes that emerge in this review of research. The first is that the use of multiple forms of physiological data can provide additional data but it adds complexity to the system. Second heart rate variability features can give details than just average heart rate, but their quality depends on how well the heartbeats or pulse intervals are detected. Third getting results on a benchmark dataset doesn't mean the model will work well for new users or in real-life situations. Fourth public datasets are helpful for building models. Discrepancies in terms of signal types and sampling rates of the dataset versus the final hardware have to be considered. This is forming the basis of the phases of the project.

1. Abdelfattah et al. (2025) IEEE Access

- **Focus:** Multimodal ML/DL on WESAD – using machine-learning techniques on the WESAD data.
- **Relevance to this project:** Shows the value of comparing Multimodal ML/DL on WESAD modalities and models.
- **Caution / limitation to consider:** Unseen-user evaluation is more demanding – testing with users is harder.

2. Ashwin et al. (2022) IEEE ICECA

- Focus: physiological sensing and ML – collecting body signals with wearables and applying machine learning.
- Relevance to this project: Supports planning a feature-based pipeline for data.
- Caution / limitation to consider: Controlled results need validation – results may not be held in real life.

3. Dahal et al. (2023) Sensors

- Focus: Reduced HRV feature set and Random Forest – using heart-rate-variability features with a Random Forest model.
- Relevance to this project: Motivates using a set of features for easier deployment.
- Caution/Limitation for consideration: The ability of generalisation in the real world requires verification.

4. Bahameish et al. (2024) Sensors

- Focus on Heart Rate Variability Based Stress/Relaxation Recognition.
- Relevance to this project: Highlights how class definitions and feature choices affect results.
- Caution / limitation to consider: Neutral states can be difficult – distinguishing calm from states is hard.

5. Szakonyi et al. (2021) BioMed Eng Online

- Area of focus: Acute stress and HRV from ECG readings – using ECG heart rate measurement for determining stress.
- Relevance to this project: Enables assessment of families of features for stress classification.
- Important to note: Small sample sizes restrict generalization – larger number required.

6 . Haque et al. (2024) Cognitive Computation

- Focus: Review of AI and HRV stress prediction – outlining how stress prediction using AI is possible.

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- Relevance to this project: Provides an overview for the study.
- Note to be cautious about: The conclusions drawn from a review are dependent upon the research that was included.

7 . Singh et al. (2026) Procedia Computer Science

- Focus: Physiological ML – the use of machine learning on several bodily measures collected through wearables.
- Significance to this project: Highlights the significance of using physiological measures in combination.
- Warning / limitation to consider: May not be directly applicable as the dataset used might not be representative of our users.

8. Schmidt et al. (2018) ACM ICMI

- Topic: WESAD Dataset – the canonical dataset used in wearable stress and affect detection.
- Relation to this project: Data set source.
- Caution / limitation to consider: Research protocol differs from use – lab conditions may not reflect real life.

9. Mishra et al. (2020) ACM TCH

- Focus: Real-time detection using off-the-shelf technology – continuous monitoring using devices.
- Relation to current project: Inspires sensing assessment for wearable systems.
- Caution / limitation to consider: Free-living conditions are more variable – unpredictable everyday factors influence data.

10.Abd Al-Alim et al. (2024) Computers in Biology and Medicine

- Topic: Detection of stress in free living environments via wearables.
- Importance of topic to your project: Important for your project because of real world applications.
- Caveat/limitation to keep in mind: Context and device specific validation required.

V. EXISTING STRESS DETECTION TECHNIQUE

Stress-detection techniques include use of questionnaires and physiological measurements. Questionnaires measure perceived stress of the individual, whereas physiological measurements consider possible indicators of stress.

These indicators are:

Heart rate variability (HRV) Electrodermal activity (EDA) Skin temperature Photoplethysmography (PPG). HRV assesses changes in the intervals between heartbeats and provides information on the functioning of the autonomic nervous system. EDA is used to assess the changes in skin conductance and provides information on the functioning of the sympathetic nervous system. PPG technology is based on detection through light of blood volume change and allows the estimation of pulse rate. Nonetheless, the signals obtained may be influenced by activity, movement, environmental factors and inter-subject variations. Consequently, physiological measurements should be taken into account cautiously. Stress detection systems have to be properly validated.

I read that researchers use the methods below to investigate stress.

- **Heart Rate:** The frequency of heartbeats that takes place in a minute.
- **Heart Rate Variability (HRV):** The fluctuations that take place from one heartbeat to another.
- **Electrodermal Activity (EDA):** The changes in the electrical characteristics of the skin.
- **Photoplethysmography (PPG):** The light-based technique that determines the amount of blood flow in various bodily regions.
- **Questionnaire:** A method through which individuals can assess their level of stress.

5.1 Comparative Analysis

However, the research conducted differs from the discussed one in terms of the following aspects: perception method used, feature design, applied model, source of data, and experiment design. Applying several perception methods increases information about users' physiological state but requires specific sensors and processing which cannot be implemented in an affordable model. Employing HRV occupies less memory capacity but requires high-precision measurement of the interval between heartbeats. Research using ECG may lead to designing features which will not be applicable for a device employing only PPG. That's why the project needs to pick a way that works well and stays the same of mixing all the possible methods without thinking about the equipment.

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Technique	Advantages	Limitations
Questionnaires	Simple and inexpensive	Subjective & dependent on self-reporting
Heart Rate (HR)	Easy to measure using wearable sensor	Can be affected by exercise and physical activity
Heart Rate Variability (HRV)	Gives information about autonomic nervous system activity	Requires reliable signal processing and accurate measurements
Photoplethysmography (PPG)	Enables non-invasive measurements of pulse-related signals	It is sensitive to finger movements, sensor placement, and signal quality
Machine Learning (ML)	Identifies patterns in physiological data for stress classification	It requires suitable training, data and validation

VI. RESEARCH & DEVELOPMENT GAPS

Gap 1 - Monitoring ≠ Intervention. Detector detects bodily signals. Doesn't help user react to the signals. I think that this is an important gap. Project indicates a method which could connect the output with a mantra meditation practice. The connection is. It hasn't been coded yet.

Gap 2 -- Personalization stays a design challenge. A single heart-rate limit might not fit everyone. A future system might find a persons resting baseline. Look at past sessions but personalization must rely on enough observations and cannot be announced until it is built and tested.

Gap 3-- Generalization across people and settings. Stress-related signals change from one person to another. Stress-related signals differ based on the sensors used. Stress-related signals also vary depending on how active someone is. Stress-related signals are affected by the environment. Testing on a person-by-person basis is important. Later, data collected using hardware is needed. This helps to understand whether a model works well. This helps to understand whether a model works across situations. This helps to understand whether a model works for people. This helps to understand whether a model works in places.

Gap 4 -- Heart rate alone is not sufficient. The heart rate is variable because of some factors other than stress. HRV and signal quality criteria may enhance the analysis. These require accurate pulse measurement and correct processing. The current rule-based display is just a proof of concept.

Gap 5 -- Dataset-to-device mismatch. I notice that WESAD contains modalities and sampling characteristics that do not quite match the hardware. The final feature set must be restricted to signals that're available, from the target device or the mismatch must be studied explicitly.

Gap 6 -- Need a defined pre-/post-session protocol. A lower or higher reading after meditation does not automatically prove a change in stress. A future pilot should standardize rest duration, posture, sensor placement, session length and measurement of windows. Should record contextual factors.

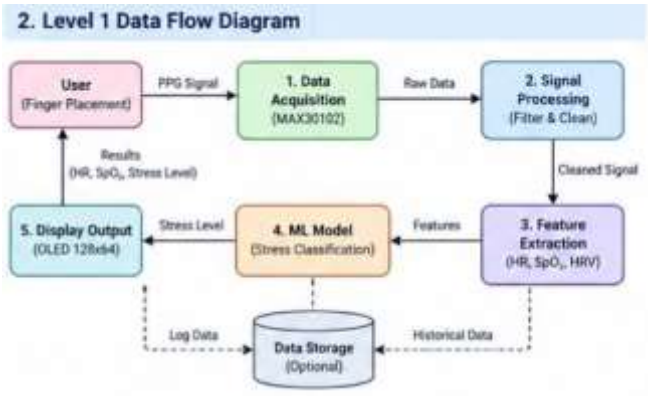
Gap 7 – Usability and clear feedback. The user-facing application must explain the meaning of the readings. The

user-facing application must explain what the readings cannot prove. The user-facing application must explain when the results might be inaccurate. The future application must convey uncertainty. The future application must not provide a diagnosis based on a category.

VII. PROPOSED SYSTEM DESIGN

1. System Overview

The planned complete system can be understood as a sequence of sensing, processing, interpretation, intervention, and feedback. Each stage has a purpose. Each stage should be evaluated separately before the stages are integrated.



1. Physiological acquisition

- Input: Red/IR samples
- Processing / action: MAX30102 samples collected by ESP32
- Output: Raw optical data

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- Status: Implemented in hardware
- Signal checks
- Input: Raw samples
- Processing / action: Check finger or contact. The number of available samples
- Output: Whether the measurement is ready
- Status: Basic logic is, in place.
- Physiological estimation
- Input: red and IR samples
- Processing / action: MAXIM algorithm calculates heart rate and SpO_2
- Output: Estimated heart rate and SpO_2
- Status: Completed.
- HRV feature extraction
- Input: Pulse. Suitable signals
- Processing / action: Compute RMSSD, SDNN and related features
- Output: Feature vector
- Status: Pending.
- ML classification
- Input: Prepared feature vector
- Processing / action: Run the trained and evaluated classifier
- Output: Model-estimated class
- Status: Pending.
- Intervention
- Input: Model output or user choice
- Action: Offer a guided session
- Result: Meditation session
- Status: Pending.
- Post-session analysis
- Input: -session measurements
- Action: Compare defined /post windows
- Result: Summary of changes
- Status: Pending.
- Mobile feedback
- Input: Measurements and session record
- Action: Show. Limits
- Result: User interface/history
- Status: Pending.

2. Current Hardware Flow

The current working path is - user places a finger on the MAX30102 → ESP32 receives red and infrared samples, over I²C → samples are stored in a buffer → the algorithm estimates heart rate and SpO_2 → the firmware checks validity flags and programmed value ranges → the OLED displays the accepted readings and a preliminary heart-rate category.

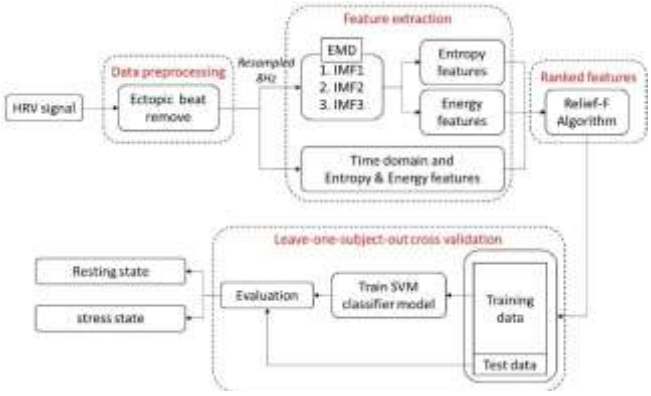
3. Intended App And Hardware Integration

A future mobile application could receive readings from the ESP32, over Bluetooth Low Energy or another supported connection. The team has not implemented this

data transfer yet. A first version of the application must keep the number of screens small: a home screen, a live measurement screen a measurement result screen, a mantra meditation guidance screen, pre-post session comparison and a history screen. The mobile application must not display an ML result until the model and its input pipeline have been tested**.**

4. Data Flow & Boundaries

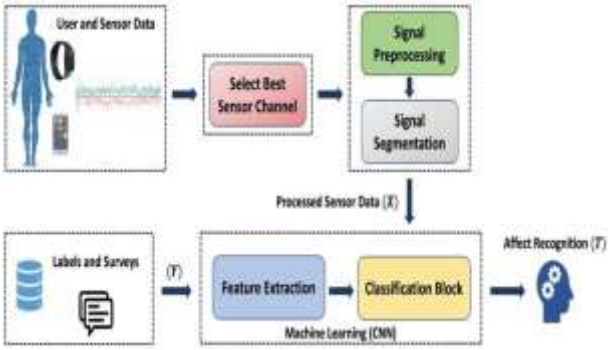
The project has two development paths that are connected but not yet combined. One path works on the embedded side running on the ESP32, where it calculates heart rate and SpO_2. The other path focuses on the side working with the WESAD dataset in Python and will later create features needed for training the machine learning model.



Above fig.1 Is the data Flow Diagram & Flowchart

A big challenge in engineering is making sure the model gets the kind of features when it's being used in real time as it did during training. For instance if the model was trained using heart rate variability (HRV) from ECG data it can't just be put onto the device unless we can reliably extract the kind of features, from the sensor that's actually on the device. Otherwise the model won't work properly.

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7.1 Hardware Design And Implementation Results

Components Used :

VIII. ESP32 DEVELOPMENT BOARD

1. Purpose: Microcontroller and I²C controller.

2. Implementation notes: Runs Arduino firmware and communicates, with sensor and display.

8.1 Max30102 Module

1. Purpose: red and infrared sensor.

2. Implementation notes: Provides samples used by the heart rate and SpO_2 algorithm.

8.2 Sh1106 Oled Display

1. Purpose: user feedback.

2. Implementation notes: Displays measurements and status text.

8.3 Jumper Wires

1. Purpose: interconnection.

2. Implementation notes: Connect sensor, display, controller and power/ground lines.

8.4 Usb/Power Connection

1. Purpose: Power and programming interface.

2. Implementation notes: Used during development and demonstration.

a. Pin & Bus Configuration

I am working with firmware that defines two I²C buses. The sensor bus uses SDA on GPIO 32. Scl on GPIO 33. The OLED bus uses SDA on GPIO 21 and SCL on GPIO

The OLED is created as an SH1106 display object using the second I²C bus (Wire1). Meanwhile, the MAX30102 uses the default Wire bus. The code tries to initialize the OLED display at the address 0x3C and print an error message, over Serial Monitor if the OLED is not found.

b. Max30102

1. Signal: SDA

2. ESP32 pin or setting: GPIO 32

c. Max30102

1. Signal: SCL

2. ESP32 pin or setting: GPIO 33

d. Oled Sh1106

1. Signal: SDA

2. ESP32 pin or setting: GPIO 21

e. Oled Sh1106

1. Signal: SCL

2. ESP32 pin or setting: GPIO 22

f. Serial Monitor

1. Signal: Debug output

2. ESP32 pin or setting: 115200 baud

g. I²c Speed

1. Signal: Sensor and OLED buses

2. ESP32 pin or setting: 100 kHz initialization setting

h. Max30102 Configuration

The firmware calls `particleSensor.setup(0x1F, 4 2 100 411 4096) `. In the library configuration used by the project, this sets the sensor operating parameters. These include LED power, sample averaging, LED mode, sampling rate, pulse

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width and ADC range. After that the code sets the infrared LED amplitudes. It also disables the LED. These settings are part of the prototype configuration. Their suitability should be confirmed through signal-quality testing.

i. Hardware Implementation

The physiological measurement setup suggested was implemented on a board containing an ESP32 microcontroller, a MAX30102 optical sensor, and an SH1106 OLED display. The ESP32 acted as the primary controller, whereas the MAX30102 sensor was wired to the board to read optical pulse signals. The OLED screen was connected to the microcontroller to show the processed results. Different I²C interfaces were used for the sensor and display to enable parallel functionality of both devices.

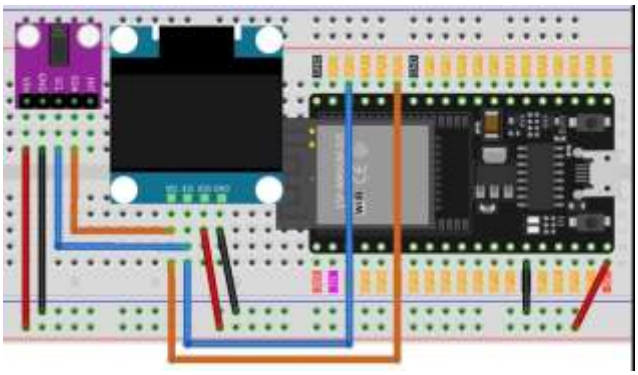


Fig.hardware implementation of ESP32-based physiological monitoring system

j. Sensor Data Acquisition

Red and Infrared optical signals from the finger of the user were captured through the use of the MAX30102 sensor.

The signals were analyzed using the ESP32 to measure heart rate and peripheral oxygen saturation (SpO2). Signal acquisition occurred once the user's finger had been correctly placed over the sensor's area of sensing. The accuracy of signal acquisition relied on the right placement of the user's finger.

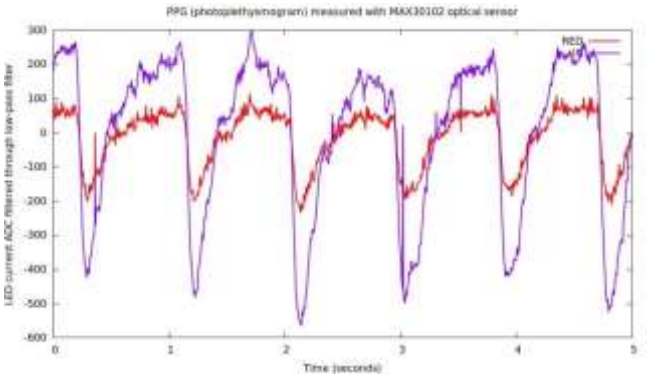


Fig.PPG waveforms from MAX10302

k. Oled Display Output

Physiological measurements that had been processed were shown in the SH1106 OLED display. The display interface had been set in such a way that it displays heart rate in beats per minute, SpO2 in percent form, and a stress classification estimate. The system updates the display information with the availability of measurements from the sensors. It enables the user to view the physiological measurements taken and their stress estimate.

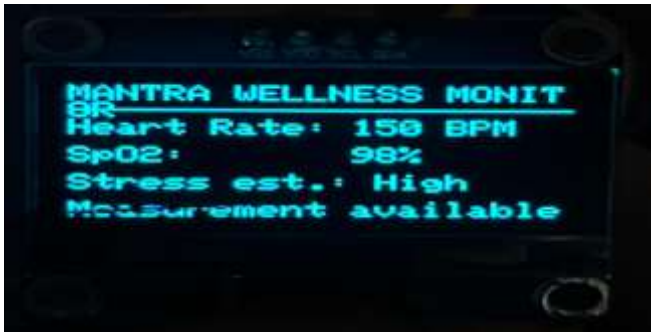


Fig. OLED Display results

l. Stress Level Estimation Results

The current prototype uses pre-programmed classification criteria to determine stress categories from the processed physiological data. The result falls into one of three categories – low, medium, and high. The ESP32 analyzes the available physiological data using the programmed criteria and shows the category on the OLED display. This process illustrates the connection between physiological data gathering and rule-based classification. Nevertheless, the determined stress categories represent only the result of an

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experiment and are not validated psychological measurements.



m. System Performance Evaluation

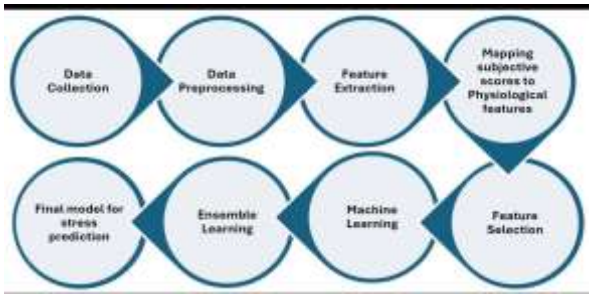
Assessment was carried out using the functioning of the sensor, microcontroller, and OLED screen. Assessment was done based on the detection by the sensor, acquisition of physiological data, signal processing and finally display of the results. Proper positioning of the finger was needed to get good readings. Any motion artifact and changes in the connection of the sensor would affect the stability of the reading. The prototype shows the possibility of having low-cost optical sensors integrated with embedded systems for physiological data acquisition.

n. Limitations Of The Implemented System

However, despite the prototype's real-time capability to monitor physiological signals, several restrictions should still be considered. First, readings taken by the MAX30102 chip may be influenced by the movements of the finger, sensor placement, and optical signal strength variations. Secondly, heart rate and SpO_2 alone are not enough to determine psychological stress. Finally, at the moment, the prototype is equipped with only predefined classification rules but lacks a machine learning algorithm trained on specific physiological data.

IX. . MACHINE LEARNING METHODOLOGY

Machine learning algorithms will enable the identification of patterns within the physiological measurements and provide conclusions about the stress level based on various features. As part of the proposed solution, the physiological signals obtained via MAX30102 will provide such features as heart rate, SpO_2 and, where possible, heart rate variability (HRV). All these features could then be fed into the machine learning algorithm trained with labeled data. The system would learn about the relationships between the features and stress level to predict the degree of stress. The result can then be shown by a monitoring system that uses ESP32. The systems success needs to be checked with data that has labels before it can be trusted.



9.1 Data Acquisition

I collect signals using the MAX30102 sensor. This sensor provides measurements that help estimate heart rate and blood oxygen saturation. I can take repeated measurements while at rest while meditating and during conditions that I label correctly. I can add another sensor, such as an electrodermal activity (EDA/GSR) sensor to get information, about physiological arousal.

9.2 Data Preprocessing

The gathered data are checked for missing values, noise, motion artefacts and bad readings. Bad measurements are. Treated properly and good samples are arranged into a clear dataset. Data Preprocessing improves the quality of the features that go into the machine learning model.

9.3 Feature Extraction

Relevant features are calculated from the processed signals. These may include:

- Heart rate (beats per minute).
- SpO_2 (percentage).
- HRV features if reliable beat-, to-beat intervals are available.
- EDA/GSR features, if an additional sensor is used.

9.4 Dataset Labelling

Make sure each training sample has a reference stress label that comes from an assessment or an experimental protocol. The stress label may represent moderate or high stress. The stress label must come from observations or an appropriate dataset and not be assigned only from heart rate.

9.5 Model Training And Classification

A supervised algorithm, like a Random Forest classifier can be trained using the labeled features. The dataset needs to be

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split into training and testing sets especially when there are participants involved it is better to separate them by subject. The model that is trained learns the patterns

that are linked to the reference stress categories. Then gives a category for new measurements.

X. CURRENT RESULTS AND PROJECT STATUS

1. Hardware Demonstration
Everyone, on the team says the ESP32–MAX30102–OLED circuit is working properly. The code that the team built covers sensor initialisation, finger-presence checking, sample buffering calls to the measurement algorithm, validity checks, output and OLED display updates. When the demonstration runs the code can display an estimated heart rate and SpO_2. Only if the readings are valid. The code also shows a category that depends on heart rate.

2. Dataset Exploration Results
The ESP32 MAX30102 OLED circuit is reported by the team to be working. The code includes sensor initialization, finger presence checking, sample buffering calls to the measurement algorithm, validity checks, serial output and OLED display updates. The current demonstration can show estimated heart rate and SpO2 when valid readings are returned. The code also displays a fixed-threshold category based on heart rate.

3. Interpretation Of The Current Output
The prototype shows a link, between an optical sensor, a microcontroller and a display. The prototype is an embedded-systems milestone because the prototype shows a working acquisition-and-feedback path. Still the displayed stress category is not proof that stress has been detected accurately. The model-related contribution will depend on feature extraction and evaluation while the meditation-related contribution will depend on a defined protocol and careful interpretation of pre-/post-session measurements.

XI. TESTING AND VALIDATION PLANS

1. Hardware Functional Test

1. H-1

1. Test procedure: I will turn on the circuit. Launch the firmware.

H-2

c. H-3

- Expected observation: A startup message should. The devices should initialise.
- Result to record: Pass or fail and any error.
- Test procedure: I will place a finger on MAX30102 and keep still.
- Expected observation: Finger is. Sample buffer fills.
- Result to record: Time until valid output.
- Test procedure: I will observe repeated HR/SpO_2 readings.
- Expected observation: Values update when algorithm reports results.
- Result to record: Record readings and stability.

1. Future Meditation Evaluation
Future evaluation could consider comparing the readings taken during the rest phase and after the mantra meditation intervention phase. This experiment needs to maintain posture, the position of sensors, the duration of reading, and the environmental condition if possible. This test should also take note of whether the subject is moving, talking, or experiencing contact with the sensor. Just physiological change cannot indicate stress as a psychological phenomenon.

XII. LIMITATIONS, SAFETY, PRIVACY AND ETHICAL CONSIDERATION

a. Technical Limitations

1. I have noted that the current prototype is a

b. H-4

1. Test procedure: I will remove the finger.

2. Expected observation: New sample accumulation pauses/resets and prompt returns after hold period.

3. Result to record: behaviour.

c. H-5

1. Test procedure: I will move finger slightly. Change contact.

2. Expected observation: Signal may become invalid or fluctuate.

3. Result to record: Document sensitivity, to movement.

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d. H-6

1. Test procedure: I will restart after disconnect/reconnect.
2. Expected observation: System initialises without fault.
3. Result to record: Pass or fail.

12.1 Model Validation Plan

Following feature extraction, the model needs to be tested using a -based split method. At one baseline model should be trained first. The team needs to take note of the total number of participants, the total number of windows, class distribution, feature definitions, window size, overlap, and class balancing. The performance needs to be illustrated via a confusion matrix and class-wise precision, recall and F1-score. In case of a small dataset, the performance estimate needs to state the limitations.

breadboard design rather than a wrist band.

- other measurement conditions.
- I have observed that the heart rate and SpO2 algorithm results have not been independently validated with respect to a reference device in this project.
- I have observed that stress categories include fixed values for heart rates without using any ML model.
- I see that dataset work has not yet produced a feature table or model evaluation.
- I notice that the app, data transfer, automated meditation guidance and session history are not implemented.
- I see that results, from WESAD may not generalize to the projects sensor, participants or daily-life conditions.

1. Health And Safety Disclaimer

The prototype is meant for demonstration and wellness research. It is not a device. It does not diagnose stress or any health condition. It should not be used to make decisions. The heart rate and SpO_2 values shown on the OLED are algorithm estimates. The individual having health-related issues needs to seek advice from health practitioners rather than using this prototype.

2. Privacy And Data Protection

Physiological data may sometimes be delicate. For a future application where this physiological data is collected by the project and is stored or transmitted, the necessary information needs to be gathered. The project must inform the participants on how this physiological data is to be used and obtain their consent. It is imperative that the data is kept safe from being leaked and the identity of the person is not revealed. In the case when a student performs a demo, the student should not gather peoples' physiological data without their consent.

3. Fair And Responsible Interpretation

Individuals will have varied reactions to stress. It all depends on the circumstances. The test will be incorrect if there is an assumption that someone experiences stress just because his/her heart rate is increased. On the other hand, people will not realize that they are under stress since they experience the normal heart rate. It means that the design should use wording that describes uncertainty and should not make medical claims.

XIII. FUTURE SCOPE

1. Improve A Wearable Hardware

The next hardware step is taking things to a wrist-worn design. The next hardware step includes having an enclosure that has stable sensor-to-skin contact, wired stability, power stability, and a charging method. In my opinion, the group needs to measure the data when resting and when moving, and see at which point does the data become inaccurate. If the device transmits data via BLE, then BLE transmission can be measured after the path is working properly.

2. Complete Data Pipeline

WESAD methodology is supposed to begin with the assessment of labels and selection of signals, data extraction of beats, interval cleaning, windowing, and features extraction. Each stage should be examined using segments first and then applied to the entire subject. The output of the process should be a set of feature tables containing unique identifiers for each subject to be assessed individually.

3. Train And Evaluate Models

Experiment 1 should involve comparing the baseline models with identical features and identical dataset split. The model selection process should be guided by performance, consistency across different classes, interpretability, and deployment requirements—rather than by single outstanding accuracy score. The research team should try to verify if the selected model works properly with those participants who did not participate in the training process. Then, the model should be tested separately using the MAX30102 prototype.

4. Develop A Flutter Application

I believe the following screens need to be provided in the mobile app: Home Screen, Live Monitoring Screen, Measurement Summary, Guided Mantra Meditation, Pre-

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/Post-Session Comparison and History. In the first version of the mobile app, measurements quality needs to be shown. Clarify that all the values are approximations. The development of the app starts from screens and dummy data and is followed by the addition of the actual communication with sensors once the protocol is developed. The connection of the trained model takes place afterwards.

5. Meditation Module And Feedback

This can include the ability for the device to select a specific mantra, give the user instructions on how to meditate, have an easy to use timer and also know when to start and stop. The next step would be taking a reading and then leading into the meditation for a fixed period and then taking another reading. This will then reveal the difference in the readings that occurred. The results should not say that the meditation definitely decreased the level of stress based on one reading.

6. Integration And Deployment

The structure of the last could incorporate the following elements: signal acquisition by the ESP32, communication over BLE, user action management in Flutter, and model processing which may be carried out either in a Python service or on the device. In the case where there is no cloud integration, a simple local connection would be more suitable. Otherwise, privacy, login, networking and data storage considerations should be taken into account.

XIV. CONCLUSION

This paper outlines the progress made on the Mantra Meditation System. Mantra Meditation System is a technological venture aimed at exploring the issue of body monitoring and creation of workflow support for mantra meditation.

The first big milestone is a working bench-top prototype made with an ESP32 microcontroller, a MAX30102 optical sensor and an SH1106 OLED display. The firmware of the prototype reads red. Infrared light samples. It then uses an algorithm to calculate heart rate and SpO_2. The firmware checks validity flags and stays inside programmed limits before it shows the results on the

display. It also shows a heart-rate category that is only a rough guide and not a trained stress detector. The team has begun working with data by loading WESAD subject S2 in Python. They find the chest and wrist channels check the shapes of the arrays calculate how long the chest ECG recording lasts and plot an ECG segment. They provide the foundation for signal processing. They do not complete any machine-learning training process. The Flutter application development, model testing, wearables enclosure, and automation of pre- and post-meditation analysis are all to be done in the future. In this stage of the Mantra Meditation System, it is important to concentrate on the reproducibility of heart rate and heart rate variability feature extraction, evaluation of the model per participant, validation of the sensors' measurements, and the implementation of meditation session protocol. The significance of the project will depend on its integration and on truthful presentation of the tests that have been performed. The project has to remain a wellness-oriented prototype and never be referred to as a medical diagnostics system.

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