Princess Sumaya University for Technology
جامعة الأميرة سميّة للتكنولوجيا

Stress Detection System Using Machine Learning & Wearable Devices for Children in Crisis

Graduation Project

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Abstract

Stress is a psychological condition due to the body’s response to a challenging situation. If a person is exposed to prolonged periods and various forms of stress, their physical and mental health can be negatively affected, leading to chronic health problems. It is important to detect stress in its initial stages to prevent these negative effects. Biological signals including heart rate are known to be effective for stress state detection, In this regard, we propose a stress state detection system using physiological signals collected from wearable devices which can be carried during the daily life routines of individuals. Real-world data were collected to compare detection performances across various machine learning methods.

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1 Introduction

1.1 Introduction

Stress has become a pervasive and influential factor in modern life, with children in crisis settings—such as refugee camps—being among the most vulnerable to its mental and physical impacts. In these high-risk environments, where trauma, instability, and displacement are common, early identification of stress is critical. Timely intervention can help prevent stress from evolving into chronic conditions with lasting psychological and physiological consequences [89]. However, in such resource-constrained settings, traditional mental health services are often unavailable or inaccessible [90], and conventional diagnostic methods may not be practical.

This research aims to develop a machine learning-based approach for the early detection of stress, specifically tailored to the needs of children in low-resource and disconnected environments. By leveraging machine learning's ability to analyze subtle patterns in physiological data, the proposed solution offers a scalable, non-invasive, and offline-compatible tool for identifying stress—empowering frontline workers and caregivers to intervene early and improve children's well-being without the need for constant clinical oversight [91].

In both engineering and medical fields, early stress detection presents unique challenges and opportunities. Technological advancements have enabled the development of innovative tools for objectively collecting, analyzing, and interpreting stress-related data. Wearables, physiological sensors, and biometric data analytics have emerged as key components in the modern toolkit for stress monitoring [92]. This study harnesses data from wearable sensors and applies machine learning algorithms to detect nuanced physiological signals indicative of stress, even in the absence of overt symptoms [93].

From a medical perspective, stress is the body's response to adverse or demanding situations. While it may begin as a reaction to short-term triggers, if unaddressed, it can lead to serious health issues such as weight loss, cardiovascular diseases, sleep disturbances, immune dysfunction, anxiety, and depression [94]. Clinically, stress is understood as a psychological state marked by fear, anxiety, or emotional distress, all of which have a significant impact on both physical and mental health [94].

Research consistently shows that stress must be addressed at its onset to prevent escalation into chronic or debilitating conditions [89]. A successful stress detection approach should therefore be comprehensive, integrating both physiological indicators and contextual environmental factors. The precision of stress monitoring has improved substantially with the integration of machine learning into healthcare systems and the widespread use of wearable sensors in daily life [92][95]. This combination enables stress identification in real-world, uncontrolled conditions—meeting the individual needs of vulnerable populations [96].

Understanding both the physiological and environmental context of individuals exposed to stress significantly enhances early detection efforts. This dual perspective allows for more accurate identification, facilitates timely support, reduces the risk of chronic health issues, and ultimately improves the quality of life for those affected—especially children in crisis [97].

Traditional stress detection methods—such as interviews and self-reported questionnaires—are particularly ill-suited for children in refugee camps and similar settings. These methods are time-consuming, require trained professionals, and rely heavily on verbal articulation and emotional self-awareness, which may be limited in traumatized or developmentally young children [98]. In such contexts, responses may be shaped by fear, mistrust, or communication barriers, further undermining accuracy [99]. Moreover, cultural and language differences can distort the interpretation of questions and answers [100].

The structured, one-time nature of questionnaires also fails to capture the dynamic and evolving nature of stress. Stressors and coping mechanisms fluctuate over time, and predefined questions often miss nuanced or situational aspects of the lived experience [101]. These limitations underscore the need for alternative, non-verbal, and context-sensitive approaches that do not rely on introspection or language proficiency.

In response to these challenges, machine learning has ushered in a new era of stress detection. These algorithms can process and analyze large volumes of physiological data, uncover complex patterns, and detect correlations that traditional methods may overlook [91]. They are less susceptible to biases such as social desirability or inconsistent self-reporting and can be continuously fine-tuned to adapt to individual differences—making them ideal for scalable, context-aware stress detection systems [102].

This research introduces a machine learning-driven model for early stress detection in children, grounded in a holistic understanding of stress that considers both internal physiological responses and external environmental influences. A key requirement for this approach was sourcing a dataset containing real-world physiological signals, gathered under natural conditions rather than controlled laboratory settings. This real-life data foundation enhances the model's applicability and relevance to the chaotic and unpredictable environments where children in crisis live—paving the way for practical, field-ready solutions to a deeply urgent problem [93].

1.2 Problem Statement

Children in crisis environments—such as refugee camps and conflict zones—are particularly vulnerable to stress due to exposure to trauma, instability, and lack of psychosocial support. If left unaddressed, stress in children can evolve into chronic psychological and physiological disorders, including depression, anxiety, and cardiovascular disease, with long-lasting impacts on their development and well-being [89][90]. Early identification and intervention are critical to preventing these long-term consequences. However, in low-resource settings where access to professional mental health care is limited or non-existent, traditional stress assessment methods—such as interviews and self-report questionnaires—are not feasible. These approaches are time-consuming, require trained personnel, and are often ineffective for children due to developmental, linguistic, and cultural barriers [91][92].

1.3 Evaluation of Current Stress Detection Systems

Current stress detection systems predominantly rely on traditional methods such as self-report questionnaires and interviews, widely used in both clinical and non-clinical settings [103][104]. Instruments like the Perceived Stress Scale (PSS) and State-Trait Anxiety Inventory (STAI) have been validated across age groups and cultures; however, these methods come with significant limitations:

- **Subjectivity and Bias:** Self-report tools are prone to recall bias, social desirability bias, and misreporting—especially problematic in children who may lack emotional articulation or literacy [105].

- **Context Dependence:** These methods typically rely on retrospective assessments rather than real-time data, failing to capture the dynamic and fluctuating nature of stress [106].
- **Lack of Scalability:** These assessments require trained mental health professionals, making them inaccessible in low-resource or crisis settings [100].

In response to these limitations, digital health solutions have emerged—primarily mobile apps and cloud-based AI systems that use psychometric assessments, voice analysis, and video inputs to detect stress [107][108]. However, these also have major drawbacks in the context of refugee camps or underserved areas:

- **Dependence on Internet Access:** Many mobile and cloud-based solutions require stable internet, which is often unavailable in humanitarian settings [109].
- **Privacy Concerns:** Image and voice-based systems raise ethical and privacy issues, particularly with vulnerable children.
- **Cost and Complexity:** Some digital systems involve complex hardware setups or expensive software subscriptions, which are not feasible for large-scale deployment in low-resource contexts.

1.4 Comparison with the Proposed Approach

The following table illustrates and compares different features between traditional, digital and our proposed stress detection methods

Table 1.1 comparison with existing and proposed approach.

Feature/Criteria	Traditional Methods	Existing Digital Systems	Proposed Approach (ML + Wearables)
Suitability for Children	Low – dependent on verbal skills	Medium – limited emotional granularity	High – based on physiological data
Bias & Subjectivity	High	Medium – some implicit bias in models	Low – objective physiological indicators
Infrastructure Needs	High – need for professionals	High – internet, mobile devices	Low – offline, minimal training required
Scalability in Refugee Settings	Low	Low to medium	High – portable, adaptable to environments

Real-time Monitoring	No	Sometimes	Yes – real-time physiological sensing
Privacy & Ethics	Medium	Low – concerns with voice/image data	High – no sensitive visual/audio data
Cost-effectiveness	Medium	Low – costly hardware/software	High – simple wearables, reusable tools

The proposed approach stands out by addressing real-world constraints in humanitarian environments—namely, the lack of internet, low availability of mental health professionals, and the need for culturally agnostic, non-verbal stress indicators. By relying on physiological signals (e.g., heart rate variability, skin conductance) captured via affordable wearables and processed through offline machine learning models, the system enables early, scalable, and objective stress detection in children who are most at risk and least served by current systems.

2 Literature Review

Stress is a physiological and psychological response to environmental challenges or demands [1]. With the rise of wearable technology and Internet of Things (IoT) devices, it has become increasingly feasible to monitor physiological signals in real time. In this context, machine learning (ML) provides a powerful framework for interpreting large volumes of sensor data to detect stress patterns automatically and accurately [2], offering more objective, continuous, and scalable alternatives to traditional methods. This section reviews existing literature on machine learning techniques and their effectiveness in analyzing sensor data to identify stress patterns.

2.1 Machine Learning: Overview and Techniques

Machine Learning is a subset of artificial intelligence that enables systems to learn patterns from data and make decisions or predictions. It is categorized into:

- **Supervised Learning:** Supervised learning is a category of machine learning that uses labeled datasets to train algorithms to predict outcomes and recognize patterns. Unlike unsupervised learning, supervised learning algorithms are given labeled training to learn the relationship between the input and the outputs.. Common algorithms include Support Vector Machines (SVM), Decision Trees, k-Nearest Neighbors (k-NN), and Neural Networks [3].

- **Unsupervised Learning:** In this learning, models are not supervised using a training dataset. The models find the hidden patterns themselves and understand from given data. The task of unsupervised learning is to automatically develop a classification label as the algorithms are not provided with classification in it. The main goal is to find the fundamental structure of the dataset and group that data according to similarities and finally signify that dataset in a compressed format Clustering techniques such as k-means and DBSCAN are common.
- **Semi-supervised and Reinforcement Learning:** Combine aspects of both supervised and unsupervised learning or involve learning from interaction with an environment, respectively [4].

Deep learning, a branch of ML using neural networks with multiple layers (e.g., CNNs and LSTMs), has gained popularity in processing complex sensor data such as EEG and ECG signals [5].

2.2 Stress Detection Using Wearable Physiological Sensors

Sensors integrated into wearable devices are capable of capturing a variety of physiological signals, which serve as biomarkers for stress. This section describes the different wearable sensing technologies used by researchers to acquire physiological signals for stress detection and monitoring.

Various physiological signals that contribute toward stress detection are heart activity, skin conductance, skin temperature, brain activity, and activity-related signals [6].

2.2.1 ECG/PPG Sensors (heart activity)

ECG or PPG sensors allow capturing various heart activity-related parameters such as HR, BVP, IBI, and HRV [7][8][9][10]. Heart rate indicates the number of times the heart beats per minute (BPM), which reflects immediate feedback of physical activity, emotional stress, or environmental factors [11][12][13][14][15][16]. ECG measures the heart rate by capturing electrical signals using electrodes placed near the chest or arms [17][18][19][20][21][22][23][24][10][8][25][26][27][28], whereas PPG captures heart rate by capturing optical signals using light and measuring the blood volume from reflected light [7][11][29]. For heart rate measurement, ECG is considered to be more accurate than PPG [30]. However, ECG has motion artifacts and requires placing electrodes near the heart, which can lead to discomfort during long-term studies [31]. PPG, on the other hand, can collect heart rate from body positions such as the wrist, neck, or finger, making it feasible for long-term studies. Other heart activity parameters include BVP, which measures changes in blood volume [8]; IBI, which refers to the time interval between consecutive heartbeats, measured in milliseconds [9][21]; and HRV, which is the variation in the time intervals between heartbeats. HRV is a measure of the variations in the IBIs [10][32][33][34][35][36]. BVP is collected using PPG, whereas HRV and IBI can be collected using ECG or PPG techniques.

2.2.2 EDA/GSR Sensors (skin conductance)

Stress, which is psychological arousal, results in the generation of sweat; the rate of change of sweat generation results in a change in moisture level on the skin, thus leading to a change in skin conductance [37]. This change in skin conductance is measured using the EDA technique and is also known as GSR. Skin conductance also contributes toward stress detection and monitoring [38][39][11][29][26][40][23].

2.2.3 Skin Temperature

Studies have shown that changes in skin temperature correlate well with self-reported stress levels and other physiological indicators such as heart rate variability and electrodermal activity, increasing the reliability of stress detection models when used in multimodal sensor systems. Skin temperature typically decreases under acute stress due to peripheral vasoconstriction—a physiological response driven by activation of the sympathetic nervous system [41].

2.2.4 Respiration Rate

Respiration rate is a key physiological indicator used in stress detection systems, as it directly reflects autonomic nervous system activity and is highly responsive to emotional and psychological states. Under stress, the sympathetic nervous system is activated, leading to increased breathing rate, reduced variability, and shallower respiration patterns [42]. These changes often occur subconsciously and rapidly, making respiration rate a valuable non-invasive metric for continuous monitoring.

Stress-induced respiratory patterns—such as hyperventilation—can occur even in the absence of physical exertion and are often linked to psychological arousal, anxiety, or panic [43]. Wearable respiration sensors such as piezoelectric belts, respiratory inductance plethysmography (RIP), and accelerometers can be used to collect breathing signals in real-time. These signals can then be processed using machine learning models to detect deviations associated with acute or chronic stress [44]. Furthermore, respiratory signals can be combined with other physiological data—such as heart rate or electrodermal activity—for more robust, multimodal stress detection systems [45].

2.2.5 Activity Related Signals

Activity-related signals are crucial for improving the accuracy of stress detection systems by providing contextual information that helps distinguish between physiological responses due to emotional stress and those triggered by physical activity. For instance, elevated heart rate or respiration rate can occur due to either stress or exercise; incorporating data from accelerometers, gyroscopes, and inertial measurement units (IMUs) helps disambiguate these sources [45][27]. Wearable devices like smartwatches and fitness bands can monitor these activity signals in real-time with minimal intrusion, making them suitable for deployment in low-resource environments.

Machine learning models trained on multimodal datasets that include activity signals can significantly reduce false positives in stress detection by filtering out readings influenced by physical movement [46].

2.2.6 EEG

Electroencephalography (EEG) is a well-established, non-invasive method for recording electrical brain activity, widely used in cognitive and emotional state analysis, including stress detection [47][48]. EEG captures voltage fluctuations generated by neuronal activity, typically through electrodes placed on the scalp.

During stress, changes in EEG frequency bands are commonly observed:

- **Alpha waves** (8–13 Hz), typically linked to relaxation and low mental effort, often decrease under acute stress [49].
- **Beta waves** (13–30 Hz), associated with active thinking, anxiety, and alertness, tend to increase, particularly in the frontal cortex during stress [50].
- **Theta waves** (4–7 Hz), which relate to emotional processing and working memory, may increase under cognitive load or stress-inducing stimuli [51].

These shifts in brainwave patterns allow EEG to serve as an objective and sensitive marker for emotional and cognitive stress. When analyzed with machine learning algorithms, EEG features—such as power spectral density (PSD), frontal alpha asymmetry, or signal entropy—can be used to classify stress levels with high accuracy [52][53].

2.2.7 EMG

Electromyography (EMG) measures the electrical activity produced by skeletal muscles and is widely used to assess muscle tension and neuromuscular activation. In the context of stress detection, EMG serves as a valuable physiological indicator because muscle tension increases significantly under both physical and emotional stress due to heightened sympathetic nervous system activity [54][55].

Stress-induced muscle activation is often observed in specific muscle groups, such as:

- **Frontalis and temporalis muscles (forehead and jaw)**: Associated with facial tension [56].

- **Trapezius and shoulder muscles**: Often tighten in response to mental strain and anxiety [57].

These involuntary muscle contractions can be captured with surface EMG (sEMG) sensors and analyzed to distinguish between relaxed and stressed states [58].

2.3 Wearable devices with stress detection and monitoring capabilities

Stress detection and monitoring requires capturing various body-generated signals from the individuals, as discussed in the previous subsection. Wearable devices with embedded sensors allow automatic collection of these physiological signals. Let us now look at wearable devices used for stress detection and monitoring.

Traditional 12-lead electrocardiograms (ECGs) are the gold standard for cardiac diagnostics but come with notable limitations. Proper electrode placement is critical, especially for leads V1 and V2, which are frequently mispositioned, potentially compromising diagnostic accuracy . The setup process is often time-consuming and requires trained personnel, making it less suitable for continuous or ambulatory monitoring. Additionally, the immobility of the equipment restricts its use to clinical settings

To address these challenges, various wearable ECG devices have been developed, offering portability and ease of use. These devices vary in the number of leads and additional physiological parameters they can monitor

2.3.1 Chest-worn off-the-shelf devices

There are numerous chest bands available for commercial use. Along with heart activity, such chest bands are capable of collecting signals such as respiration, an inertial sensor, skin conductance, ambient temperature, and ambient pressure.

- **Polar H7 and H10**: These chest-worn sensors provide ECG-accurate heart rate monitoring. The H10, in particular, is known for its precision and is widely used in both clinical and research settings .AmazonPolar
- **Garmin HRM-Dual**: This device captures single-lead ECG data and transmits heart rate information via ANT+ and Bluetooth, making it compatible with various fitness equipment and applications .Polar+2Amazon+2DC Rainmaker+2
- **Shimmer3 ECG**: A versatile device that records multi-lead ECG signals and includes additional sensors like accelerometers and gyroscopes, facilitating comprehensive physiological monitoring .shimmersensing.com

- **Zephyr BioHarness 3**: This chest strap monitors single-lead ECG, respiration rate, and body movement, transmitting data in real-time for various applications, including stress detection .Honeywell
- **AutoSense Chestband**: Designed for stress monitoring, it records ECG, respiration, and movement data, providing a comprehensive overview of physiological responses autosenseproject
- **BIOPAC Systems**: Offers a range of chest-worn devices capable of measuring ECG, respiration, and other physiological signals, suitable for both research and clinical applications .BIOPAC

Devices and their sensing capabilities are listed on the table below.

Table 2.1 Chest-worn devices and their sensing capabilities

Device	ECG	IMU	RESP	SC	ST	EGG	AT	AP	References
Polar H7 & H10	✓	X	X	X	X	X	X	X	Montesinos et al., 2019; Mishra et al., 2020; Lee et al., 2022
Zephyr BH3	✓	✓	✓	X	X	X	X	X	Betti et al., 2017
Autosense	✓	✓	✓	✓	✓	X	✓	X	Hojjatinia et al., 2021
Shimmer 3 ECG	✓	✓	X	X	X	X	X	✓	Montesinos et al., 2019; Ashwin et al., 2022; Benchekroun et al., 2022
ADI-VSM	✓	X	✓	X	X	X	X	X	Anusha et al., 2019
BIOPAC	✓	X	✓	X	X	✓	X	X	Kim et al., 2020; Momeni et al., 2021

IMU, Inertial Measurement Unit; RESP, Respiration; SC, Skin Conductance; ST, Skin Temperature; AT, Ambient Temperature; AP, Ambient Pressure.

2.3.2 Wrist-worn off-the-shelf devices

Wrist-worn wearable devices have become increasingly prevalent in stress monitoring due to their convenience and integration of photoplethysmography (PPG) sensors. PPG measures heart rate by emitting light toward the skin and detecting changes in blood volume from the reflected light. This technique allows for accurate heart rate monitoring from various body parts, including the wrist.

Several wrist-worn devices have been utilized in research for stress detection and monitoring:

- **Empatica E4**: This research-grade wristband captures multiple physiological signals, including PPG, electrodermal activity (EDA), skin temperature, and accelerometry. It samples PPG at 64 Hz and EDA at 4 Hz, providing real-time data streaming and storage capabilities. The E4 has been widely used in studies assessing stress responses in various settings .MDPI+4Wikipedia+4WIRED+4MDPI+2PMC+2iMotions+2MDPI+4empatica.com+4MDPI+4

- **Fitbit Sense**: This consumer-grade smartwatch includes sensors for heart rate, EDA, and skin temperature. It offers stress management features, such as a daily stress score and guided mindfulness sessions. However, its accuracy in heart rate tracking during intense activities has shown variability .WIRED+1SELF+1SELF+1WIRED+1
- **Samsung Gear Sport Smartwatch**: Equipped with PPG sensors, this device monitors heart rate and supports various fitness tracking features. It has been used in studies focusing on stress detection through heart rate variability analysis .
- **Garmin Vivosmart 4**: This fitness tracker offers heart rate monitoring, sleep tracking, and a "body battery" feature that assesses energy reserves based on heart rate variability and other factors. While it lacks GPS functionality, it is praised for its ease of use and effectiveness in promoting lifestyle changes .

These diverse wearable technologies offer various options for stress detection and monitoring, each with its own set of features and applications.

The wrist-worn devices and their sensing ability are listed in table below.

Table 2.2 Wrist-worn devices and their sensing capabilities

Device	HR	IMU	SC	ST	AP	References
Empatica E4	✓	✓	✓	✓	X	Campanella et al., 2023; Moser et al., 2023; Shrestha et al., 2023; Park et al., 2018; Montesinos et al., 2019; Carreiro et al., 2020; Can et al., 2020; Aristizabal et al., 2021
Fitbit	✓	✓	✓	X	✓	Chalmers et al., 2021
Garmin Vivosmart 4	✓	✓	X	X	X	Shrestha et al., 2023; Han et al., 2022
Samsung Gear Sports 3	✓	✓	X	X	X	Tazarv et al., 2021; Aqajari et al., 2023; Can et al., 2019b

HR, Heart Rate; IMU, Inertial Measurement Unit; SC, Skin Conductance; ST, Skin Temperature; AP, Ambient Pressure.

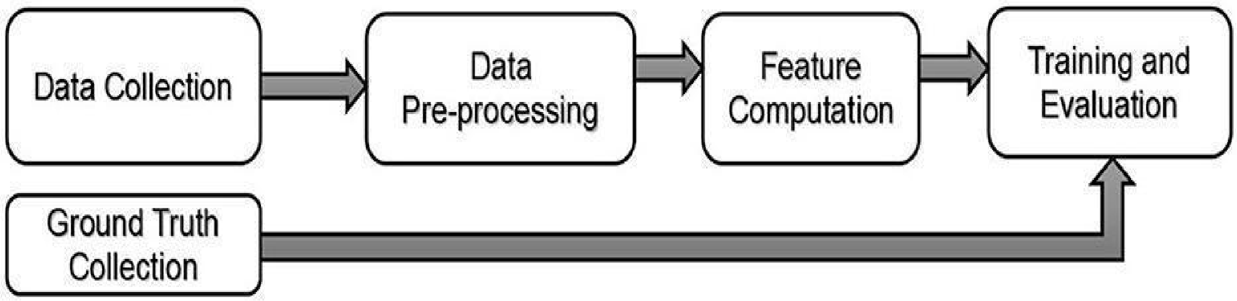
2.4 Stress detection approach

We identify and evaluate the standard machine-learning steps necessary for stress detection and monitoring.

A standard machine learning pipeline for stress detection and monitoring involves data collection, data pre-processing, feature computation, training, and testing the model. We present these steps in Figure 1. Data collection includes collecting physiological signals using wearable devices either (a) in a controlled environment by inducing stress using stressors or (b) in free-living conditions with domain-specific stress conditions. Then, during the data pre-processing step, the collected data is cleaned using various techniques. The next step is feature computation, which enables a meaningful representation of the data. These features are then used for training and evaluating the machine learning model.

The figure below illustrates the pipeline used to develop the stress detection machine learning model.

Figure 2.1 standard machine-learning steps for stress detection



2.4.1 Data Collection Methods

As described in Section 2.3, various off-the-shelf or custom-made devices can be employed for data collection in user studies aimed at detecting and monitoring stress. The process involves capturing physiological signals and ground truth data necessary for training machine learning models. Data can be collected either in controlled laboratory environments or through naturalistic, free-living studies.

Laboratory Studies

In controlled environments, stress is typically induced using standardized stressors, allowing researchers to observe physiological changes in response. A widely adopted protocol is the Trier Social Stress Test (TSST), which combines tasks such as public speaking and mental arithmetic, interleaved with rest periods [59]. Variants of TSST and other stressors have been applied by various researchers:

- **TSST and Variants**: Commonly used stressors include mental arithmetic and speech tasks [59][60][61][62]. Some studies replaced rest periods with neutral video clips to minimize residual stress [63].
- **Additional Psychological Stressors**: These include horror movies [64], memory search tasks [65], and emotional video clips [66][67].
- **Cognitive Tasks**: The Stroop Color-Word Test (SCWT) and complex arithmetic tasks are frequently used [68][69][70].
- **Physical Stressors**: Walking or treadmill activity [71], and the Cold Pressor Task (CPT) are also employed [72][73].

- **Acoustic Stressors**: High-decibel air horns were used to study stress under sudden auditory stimuli [74].

These stressors can be categorized as:

- **Psychological**: Mental arithmetic, speech tasks, SCWT, horror/emotional videos, acoustic stimuli.
- **Physical**: Walking, treadmill exercises, CPT [75].

Free-Living Studies

Free-living studies collect data in natural settings as participants go about their daily routines. These studies are useful for long-term monitoring and developing personalized stress detection models [76].

- **Short-Term Studies**: Studies lasting 3–12 hours have monitored stress during pre-surgical evaluations or daily activities [77][78][79].
- **Medium-Term Studies**: Collection over several days using devices such as the Empatica E4 allows for periodic sampling (e.g., three times daily) [80][81].
- **Long-Term Studies**: These can span weeks or months, offering rich datasets for modeling personalized stress patterns [82][83].

Despite their ecological validity, free-living studies face challenges like device malfunctions and participant non-compliance. Nonetheless, longer durations help to uncover more nuanced insights into stress triggers in real-life settings.

Ground Truth Collection

Accurate labeling of stress levels (ground truth) is vital for training reliable models:

- **Laboratory Studies**: Periods when stressors are applied are labeled as "Stressed," while interleaved periods are labeled as "Not Stressed." However, residual stress or ineffectiveness of certain stressors may lead to mislabeling [84].
- **Free-Living Studies**: Ground truth is typically obtained using Ecological Momentary Assessment (EMA), which sends prompts to participants throughout the day to assess mood, stress, and other states [82][85].

2.4.2 Data Pre-Processing

Sensor data collected from wearable devices may contain noise because of the presence of the body, the sensor's movement, and environmental noise. The most commonly used pre-processing steps involve noise and outlier removal, interpolation, and normalization.

Physiological signals obtained from various sensors such as ECG, PPG, EDA, Skin Temperature, and Accelerometer are passed through different filters to remove noise.

2.4.3 Feature Computation Methods

The next step in the process of stress detection and monitoring is feature computation. We will now look at the different types of features computed using various physiological signals.

Researchers compute time-domain and frequency-domain features from physiological signals such as ECG, PPG, EDA, Skin Temperature, and Accelerometer. Various time-domain and frequency-domain features are computed from the sensor data obtained from various wearables. Computing frequency domain features involves transforming time series data into the frequency spectrum using mathematical transformations like the Fourier Transform. These features help in understanding how the signals are distributed across different frequency bands.

Overview of the features computed are shown in table below.

Table 2.3 Physiological signals with their feature computation.

Physiological signal	Features computed	References
ECG (Time domain)	Mean, Standard Deviation, Minimum, Maximum, Median, RMSSD, SDSD, NN50, PNN50, HRV triangular index, TINN	Akbulut et al., 2020; Mishra et al., 2020; Rodrigues et al., 2018
ECG (Frequency domain)	VLF, LF, HF, LF/HF, Total Power, Energy, pLF, pH	Chalmers et al., 2021; Betti et al., 2017; Momeni et al., 2021; Wu et al., 2018
PPG	Breathing rate	Aqajari et al., 2023; Tazarv et al., 2021
EDA (Time domain)	Mean, Standard Deviation, Minimum, Maximum, Median, Mode	Campanella et al., 2023
EDA (Phasic and tonic)	Startle Mean, Startle SD, Rise Time Mean, Rise Time SD, Fall Time Mean, Fall Time SD	Wu et al., 2021; Betti et al., 2017
Respiration	Mean, Standard Deviation, Median	Akmandor and Jha, 2017; Momeni et al., 2021
Accelerometer	Mean X, Mean Y, Mean Z, Magnitude	Can et al., 2019b
Others	Mean Blood Pressure, Mean Blood Oximeter	Akmandor and Jha, 2017

2.4.4 Machine learning Classification Techniques

Researchers used machine learning and deep learning methods for detecting and monitoring stress. For stress detection and monitoring, the researchers perform two-class classification as stressed or not stressed.

Researchers considered a Decision Tree, which is a simple and versatile rule-based technique that can be used for a numerical type of data [86]. Decision trees are sensitive toward imbalanced datasets, and they can generate complex trees that may not be able to generalize, thus leading to overfitting the data. Hence, instead of using a single decision tree, an ensemble of decision trees is used for making predictions. Each of these decision trees makes a prediction and, based on majority voting, is the model's predicted output. This technique is called Random Forest. This random forest algorithm gives high accuracy and is robust to overfitting. It works well even with unbalanced datasets hence many researchers used this for stress detection and monitoring

SVM is another technique used for classification of stress. SVM aims to find a hyperplane that divides data into desired classes. It is robust to overfitting and its performance is dependent on class separability in the data. Physiological signal values for the classes of not stressed and stressed might overlap and are inseparable; in such cases, SVM may not work well, and a complex classification technique is needed.

Some researchers used KNN machine learning algorithm for stress detection and monitoring [19]. KNN works by computing distances between data points and forming groups of similar characteristics. Since KNN does not make any prior assumptions about the data, it is capable of capturing prominent insights from the data on its own. However, KNN has a challenge in choosing the value of K(number of nearest neighbors) and may also suffer when the boundaries of the two groups overlap. Some researchers also used Naive Bayes [21], Logistic Regression [16], and regression-based approach using linear regression [37].

Researchers experimented with other deep-learning approaches for stress detection and monitoring. Multi-layer Perceptron with hidden layer is capable of performing binary as well as multi-class classification [25]. Stress can cause gradual changes in physiological signals, which can be captured using LSTM [87][88] method. Some researchers also used CNN [22].

The classification techniques are summarized in the table below.

Table 2.4 Various machine learning techniques used to train the model.

Approach	Technique	References
Machine Learning	Decision Tree	Momeni et al., 2021
	Random Forest	Aqajari et al., 2023; Bin Heyat et al., 2022; Campanella et al., 2023; Can et al., 2019b; Momeni et al., 2021; Ashwin et al., 2022; Can et al., 2020; Liu et al., 2012
	XGBoost	Aqajari et al., 2023; Tazarv et al., 2021; Xefteris et al., 2023
	SVM	Aqajari et al., 2023; Campanella et al., 2023; Lee et al., 2022; Can et al., 2019b
	KNN	Akmandor and Jha, 2017; Aqajari et al., 2023; Tazarv et al., 2021; Can et al., 2019b; Anusha et al., 2019
	Naive Bayes	Bin Heyat et al., 2022; Ashwin et al., 2022
	Linear Regression	Park et al., 2018
	Logistic Regression	Can et al., 2019b; Campanella et al., 2023
Deep Learning	MLP	Can et al., 2019b, 2020; Tazarv et al., 2021; Rachakonda et al., 2020; Akbulut et al., 2020
	LSTM	Wu et al., 2021; Li and Sano, 2020
	CNN	Subash et al., 2023; Donati et al., 2023

2.4.5 Evaluation Metrics

The performance of the developed model can be evaluated using Accuracy. Accuracy is a good measure to evaluate the stress detection model if dataset is balanced Since the F1-score considers Precision and Recall, it is a good measure when the dataset is imbalanced. Other metrics used for evaluating the stress detection model are Specificity (True Negative Rate), Sensitivity (True Positive Rate) Using the specificity and sensitivity of the model, the ROC curve can be plotted, and AUC can be used to quantify the model performance.

The table below summarize the metrics used by different researchers.

Table 2.5 Various metrics used by researchers to evaluate the stress detection model.

Metrics used	References
Accuracy	Akmandor and Jha, 2017; Aristizabal et al., 2021; Benchekroun et al., 2022; Momeni et al., 2021; Park et al., 2018; Can et al., 2019b; Ashwin et al., 2022; Campanella et al., 2023; Can et al., 2020
F1-score	Szakonyi et al., 2021; Bin Heyat et al., 2022; Lee et al., 2022; Aqajari et al., 2023; Mishra et al., 2020; Smets et al., 2018b
Specificity & Sensitivity	Bin Heyat et al., 2022; Aristizabal et al., 2021; Zubair and Yoon, 2019
AUC	Benchekroun et al., 2022; Bin Heyat et al., 2022

3 Software Project Management Plan

3.1 Document Information

The table below holds the project management plan document information.

Table 3.1 Document Information

©	Information
Document Owner	Ahmad Emad, Ammar Al-Kilani
Issue Date	March 10, 2025
Document Description	The purpose of this document is to outline the goals and objectives of the project, list the activities, tasks and resources required to complete the project

File Name	GraduationProject

3.2 Document Change Control

The table below holds the project document change control.

Table 3.2 Document change control

Version	Issue Date	Changes
0.1	March 10, 2025	Issuing

3.3 Project Purpose, Goals and Objectives

The table below holds the project purpose, goals and their respective project objective.

Table 3.3 Project purpose, goals and objectives.

<table>
<tr><th colspan="2">Project Purpose</th></tr>
<tr><td colspan="2">The purpose of this project is to develop a stress detection system that identifies elevated stress levels in children experiencing crisis situations, with the goal of preventing this acute stress from progressing into chronic conditions that could hinder their development.</td></tr>
<tr><th>Project Goal</th><th>Project Objectives</th></tr>
<tr><td rowspan="3">Early Stress Detection</td><td>Develop real-time machine-learning algorithms to continuously monitor and detect early signs of stress from physiological data streams.</td></tr>
<tr><td>Implement a threshold-based early warning system that flags potential stress episodes before they become severe.</td></tr>
<tr><td>Evaluate detection latency by measuring the time from physiological signal change to system stress alert, targeting <10 seconds.</td></tr>
<tr><td rowspan="3">Field Adaptability</td><td>Design the hardware to be lightweight, portable, and battery-efficient for field use.</td></tr>
<tr><td>Ensure the system functions under minimal infrastructure (offline logging, local processing).</td></tr>
<tr><td>Allow for customizable configurations based on varying environmental and cultural factors.</td></tr>
<tr><td rowspan="3">Actionable Insights</td><td>Visualize stress trends through graphs and summary reports in a mobile or desktop interface.</td></tr>
<tr><td>Provide caregivers with contextual insights, including time-of-day and activity correlation.</td></tr>
<tr><td>Enable data export and integration with existing child health records or platforms.</td></tr>
<tr><td rowspan="3">Scalability</td><td>Modularize the system design to support different sensor combinations and ML models.</td></tr>
<tr><td>Optimize hardware and software for low-cost production.</td></tr>
<tr><td>Provide documentation and training materials for mass deployment.</td></tr>
<tr><td rowspan="3">Child-Centric Design</td><td>Use safe, hypoallergenic materials for wearable comfort and safety.</td></tr>
<tr><td>Validate the design with pediatric feedback or simulated user tests.</td></tr>
<tr><td>Minimize intrusion by reducing the number of sensors while maintaining accuracy.</td></tr>
</table>

3.4 Project Success Criteria

The table below holds the project success metric, measurement method and target corresponding to their respective categories.

Table 3.4 Project success criteria

Category	Success Metric	Measurement Method	Target
Scope	All core features (real-time monitoring, ML model, alert system) implemented	Feature checklist, system test report	100% of core features completed
Schedule	On-time delivery of project milestones	Sprint burndown charts and milestone tracking	All sprints delivered on schedule
Budget	Project stays within financial constraints	Budget tracking sheet and cost reviews	≤ 500 JOD
Quality	Accuracy and reliability of stress detection	Model evaluation (precision, recall, F1-score)	≥ 85% classification accuracy
Stakeholder satisfaction	Positive feedback from supervisor and users	supervisor reviews, user interviews, successful graduation project discussion	≥ 90% grade in GP1
Risk management	Effective handling of identified risks	Risk matrix and mitigation report	100% high-impact risks mitigated
Compliance	Adheres to NGO technical, ethical, and deployment standards	Compliance checklist, NGO evaluation report	100% compliance verified by NGO

3.5 Stakeholder Management Plan

3.5.1 Stakeholder Register

The table below holds the stakeholders involved in the project with their respective role, power, interest and dedicated engagement strategy.

Table 3.5 Stakeholder register

Name	Role	Power	Interest	Engagement Strategy
Patient	End user	High	High	Ethical research protocols, consent, empathy
Dr. Abdallah Al-Refai	Project Supervisor	High	High	Frequent updates, reviews, and approvals
NGO/Relief Organization Staff	deploying and operating the system in refugee camps.	Medium	High	Regular coordination, training, compliance
Healthcare Professionals	Interpret stress data, act on alerts	High	High	Involve in design validation and evaluation
Development Team	Build and test system	High	High	Daily scrums, Agile methodology

Device Suppliers	Supply sensors and components	Low	Low	Procurement contracts
Parents/Guardians	Consent providers; may assist children	Low	High	Clear communication, reassurance

3.5.2 Stakeholder Map

The table below categorizes the stakeholders on their contact level using influence and interest.

Table 3.6 Stakeholder Map

Level of Influence			
High	-	-	End user, Project Supervisor, Development Team, Healthcare Professionals
Medium	-	-	NGO
Low	Device Suppliers	-	Parents
	Low	Medium	High

Level of Interest

3.6 Scope Management Plan

'Dependencies' are logical relationships between phases, activities or tasks which influence the way that the project must be undertaken. Dependencies may be either internal to the project (e.g. between project activities) or external to the project (e.g. a dependency between a project activity and a business activity).
The table below holds the project tasks and their respective dependencies.

Table 3.7 Scope management plan

Scope Baseline			
Task	**Dependencies**	**Deliverables**	**Acceptance Criteria**
Identification of stress-related physiological signals.	Literature review completion, consultation with domain experts	List of key physiological signals (e.g., HRV, GSR, skin	Documented and validated by supervisor and relevant studies

		temperature) linked to stress	support selection criteria
Integration of multiple physiological sensors with an Arduino-based wearable system.	Availability of ECG, GSR, Temp sensors; Arduino Uno and supporting hardware	Sensor Integration Prototype	All sensors accurately transmit data to microcontroller
Collect and Preprocess Data	Ethical approval, access to the dataset	Cleaned and Annotated Dataset	No missing values, correct labels, usable for training ML model
Development and training of a machine learning model to classify stress levels.	Access to dataset, ML libraries (e.g., scikit-learn, TensorFlow)	Trained ML Model	Accuracy ≥ 85% with validation metrics (F1, confusion matrix)
Evaluation of model accuracy and real-world usability.	Functional model, test data	Evaluation Report	Detailed analysis of precision, recall, and performance
Build Wearable Device Prototype	Sensor integration completed, hardware casing available	Wearable Device Prototype	Durable, portable, and functional for field use
Develop Mobile Application for stress monitoring	Functional wearable device, Functional model	Mobile application with stress monitoring	User validation, project supervisor feedback
Compliance with NGO and humanitarian health requirements.	NGO guidelines access, feedback loop	Compliance Checklist	Reviewed and signed off by NGO collaborator

The table below holds the exclusions assumptions and constraints of the project

Table 3.8 Exclusions, assumptions and constraints

Exclusions, Assumptions and Constraints	
Exclusions	The system will not diagnose medical conditions beyond stress detection. Integration with third-party health monitoring systems or national databases is out of scope. Hardware mass production or commercialization.
Assumptions	Wearable sensors will function accurately under typical usage by. Data collected during the project will be sufficient for training and evaluating ML models. The environment for testing will simulate real-world conditions adequately. NGOs and supervisors will provide necessary guidance for ethical compliance and practical use cases.
Constraints	Budget limitations may restrict access to advanced wearable technologies. Time constraints require completion within one academic semester. Limited access to actual refugee camps for data validation.

The table below holds the project's milestones and their respective delivery date.

Table 3.9 Project's milestones

Milestone	Description	Delivery Date
Requirements Analysis Completed	Documentation of all system requirements including sensor specs, ML model needs, and user interface	19/5/2025
System Design Finalized	Completion of system architecture, hardware/software integration plan, and mobile UI/UX wireframes	25/7/2025
Sensor Integration & Calibration	Integration of physiological sensors and calibration with real-time data logging	7/9/2025
Machine Learning Model Training Completed	Final supervised ML model trained on labeled physiological datasets	19/9/2025
Final Mobile App Version Released	Fully functional mobile app with real-time stress feedback and user settings	19/10/2025

3.7 Software Development Life Cycle (SDLC)

The Software Development Life Cycle (SDLC) is a structured process used for planning, designing, developing, testing, and deploying software systems. It ensures that high-quality software is produced in a systematic, disciplined, and cost-effective manner.

For this project, which involves embedded hardware, physiological sensors, and machine learning, a careful and structured approach is crucial to minimize hardware/software integration issues and ensure the system works reliably in real-world, high-impact environments like refugee camps.

3.7.1 Justification for Choosing the Waterfall Methodology

The Waterfall model is a linear and sequential SDLC approach in which each phase must be completed before moving to the next. It is best suited for projects with well-understood requirements and low tolerance for changes once the development begins — both of which apply to embedded system development.

The table below holds the waterfall's criteria and justification for why it works best for this project:

Table 3.10 waterfall's criteria and project suitability

Hardware Dependence	Embedded systems with Arduino and physiological sensors require tightly coupled hardware/software integration. Waterfall supports early, fixed planning.
Fixed Requirements	Requirements for stress detection, especially in humanitarian use cases, are clearly defined upfront.

Low Tolerance for Change	Embedded development often involves flashing firmware and physical components — changes mid-project are expensive.
Regulatory/NGO Compliance	Working with NGOs often requires early documentation and sign-offs; Waterfall ensures clear milestones and documentation.
High-Reliability Needed	In critical applications involving children and health monitoring, robustness and predictability are essential.
Training & Handover Constraints	NGOs and field workers need stable systems and clear instructions — not continuously evolving solutions.

3.8 Project Schedule

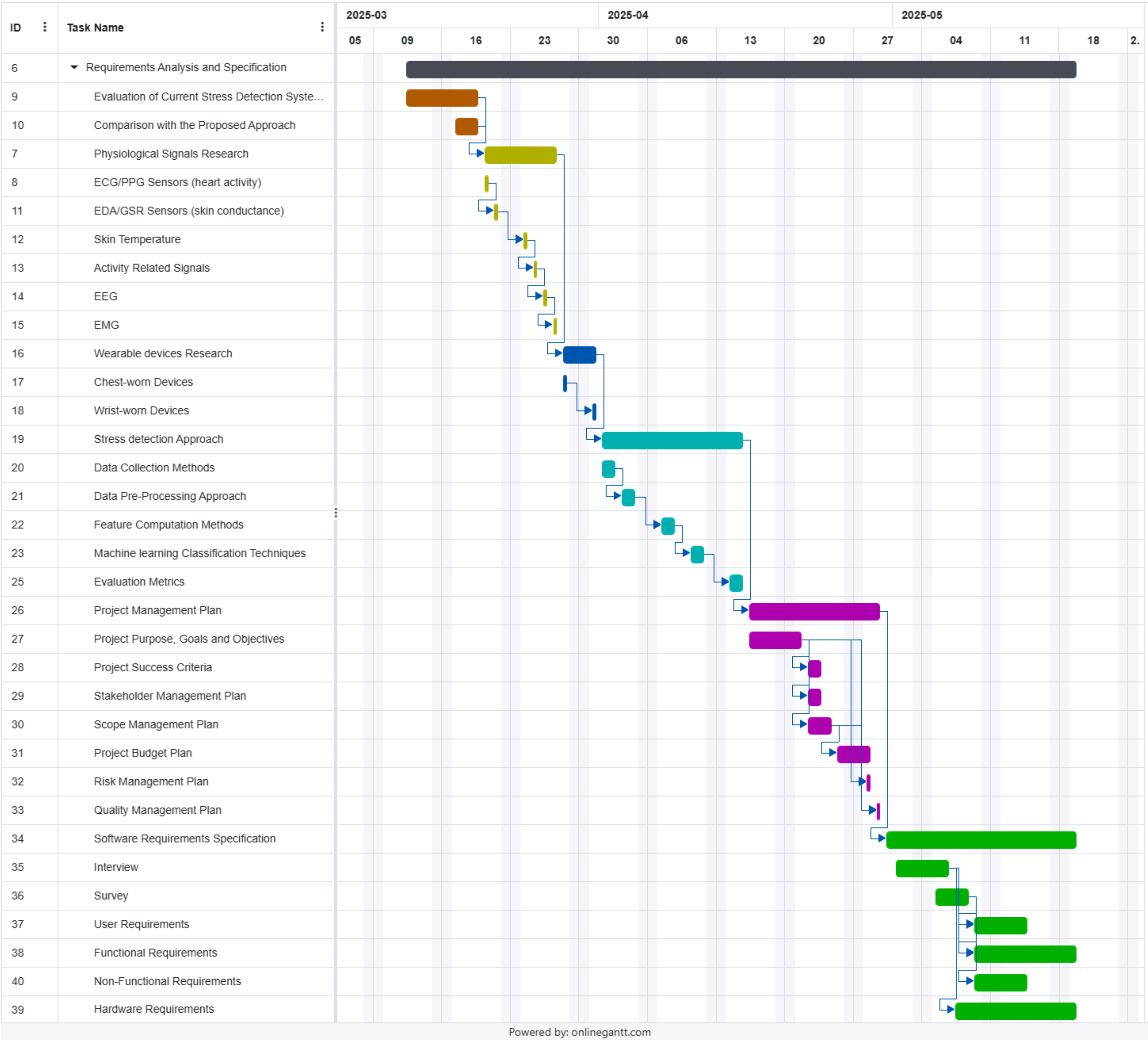
The project schedule indicates when the project tasks defined in the scope management section will be executed, including task dependencies, milestones and key deliverables.

3.8.1 Requirements Analysis and Specification Phase

Requirement Analysis and specification phase aims to understand the exact requirements of the customer and document them properly

The figure below illustrates the tasks and timeline to complete the requirements analysis and specifications phase.

Figure 3.1 Requirements analysis and specifications phase

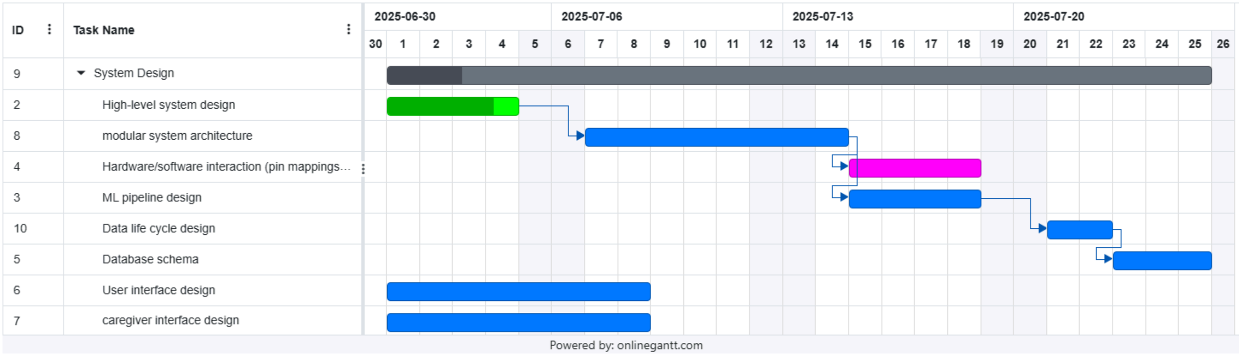


3.8.2 System Design Phase

The goal of this Software Design Phase is to convert the requirements acquired in the SRS into a format that can be coded in a programming language. It includes high-level and detailed design as well as the overall software architecture.

The figure below illustrates the tasks and timeline to complete the system design phase.

Figure 3.2 System design phase

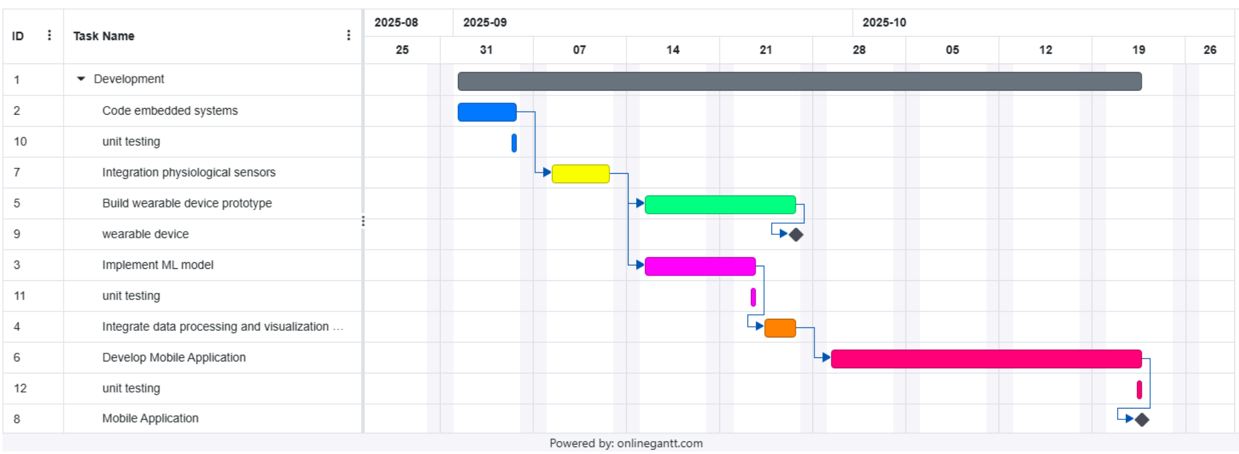


3.8.3 Development Phase

In the Development Phase software design is translated into source code using any suitable programming language. Thus each designed module is coded. The unit testing phase aims to check whether each module is working properly or not.

The figure below illustrates the tasks, milestones and timeline to complete the development phase.

Figure 3.3 Development phase

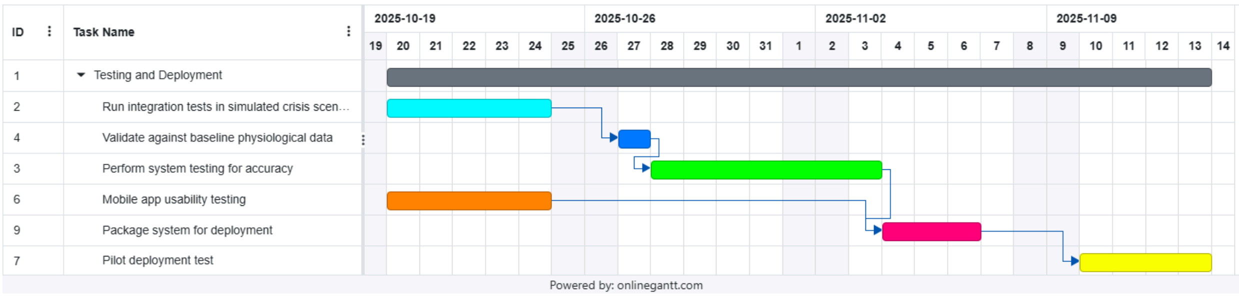


3.8.4 Testing and Deployment Phase

Integration of different modules is undertaken soon after they have been coded and unit tested. Integration of various modules is carried out incrementally over several steps. During each integration step, previously planned modules are added to the partially integrated system and the resultant system is tested

The figure below illustrates the tasks and timeline to complete the testing and deployment phase.

Figure 3.4 Testing and deployment phase



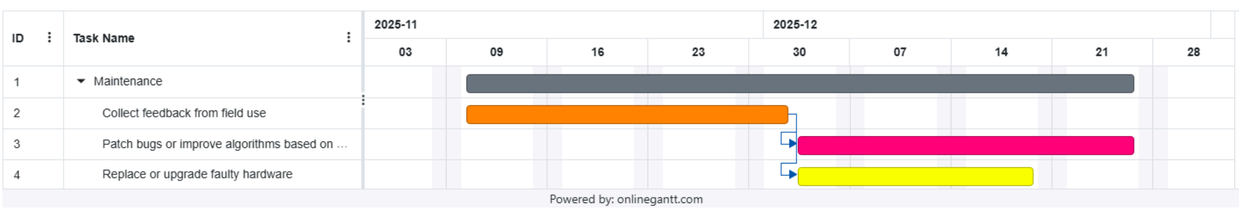
3.8.5 Maintenance

Corrective Maintenance: This type of maintenance is carried out to correct errors that were not discovered during the product development phase.

Perfective Maintenance: This type of maintenance is carried out to enhance the functionalities of the system based on the customer's request.

The figure below illustrates the tasks and timeline to complete the first iteration of the maintenance phase.

Figure 3.5 Maintenance phase



3.9 Project Budget

List the task and how much the labor and materials necessary to execute it will cost. Then add your budget to the appropriate column and the actual spend to the next column to track planned costs against actual costs.

The table below holds the spendable tasks with their respective costs.

Table 3.11 Project spendable

Task	Labor Costs	Material Costs	Other Costs	Budget	Actual
Sensors & Devices	0	-	Casing	500 JOD	-
Software & Tools	0	-	Licensing	0	0
Labor	0	-	-	0	0
Miscellaneous	0	-	-	-	-

3.10 Risk Management Plan

3.10.1 Risk Matrix

The table below holds the projects risks in a risk matrix with high risks in red, moderate risks in yellow, and low risks in green

Table 3.12 Risk matrix

Risk Matrix		**Severity**				
		Insignificant	Minor	Moderate	Major	Severe
Likelihood	Almost Certain	-	Sensor data noise	Machine learning model underperforms (<85% accuracy)	Model misclassifies stress levels frequently	Hardware malfunction in field
	Likely	-	Difficulty in obtaining real-world data	System failure in crisis environment	Device discomfort or refusal by children	Lack of NGO approval or misalignment with operational needs
	Possible	-	Inadequate training for field workers/NGO staff on using the system	Limited power supply or infrastructure in refugee camps	Ethical/privacy concerns in collecting children's health data	Inconsistent sensor readings
	Unlikely	-	Minor UI bugs	Unexpected cost overruns	Regulatory compliance failures (data protection, child safety laws)	Loss of NGO partnership
	Rare	-	Typos or cosmetic defects in UI	Mislabeling of non-critical data samples	Staff turnover during critical stages	Legal action due to data privacy breach

3.10.2 Risk Mitigation Strategies

The table below holds the risks with their respective mitigation strategies.

Table 3.13 Risk mitigation strategies.

Risk	Mitigation Strategy
Sensor data noise	Use filtering and signal processing techniques (e.g., moving average, Kalman filter); conduct calibration.
Hardware malfunction in field	Conduct pre-deployment stress testing; maintain spare parts and quick-replace kits in the field.
Model misclassifies stress levels frequently	Improve dataset quality, retrain with diverse ,real-world data; conduct frequent validation and real-world testing.
Limited accuracy in model training	Use cross-validation, hyperparameter tuning, and feature engineering to optimize model performance.
Difficulty in obtaining real-world data	Partner with NGOs and local institutions early; use simulation data if necessary for initial phases.
System failure in crisis environment	Build system with fail-safes and offline fallback modes; ensure hardware is robust and shock-resistant.
Device discomfort or refusal by children	Use child-friendly, lightweight, hypoallergenic materials; conduct trials to gather feedback before deployment.
Lack of NGO approval or misalignment with operational needs	Involve NGO stakeholders early in design; conduct regular reviews to ensure alignment with field requirements.
Inadequate training for field workers/NGO staff on using the system	Develop user-friendly manuals; conduct hands-on training workshops and remote support sessions.
Limited power supply or infrastructure in refugee amps	Use low-power devices; incorporate rechargeable batteries and solar power options.
Inconsistent sensor readings	Implement real-time calibration, redundancy (multiple sensors), and software-level signal validation.
Unexpected cost overruns	Allocate contingency budget (10–15%); monitor expenses regularly and adjust scope or sourcing if needed.
Regulatory non-compliance	Research and align with GDPR and local regulations; involve a legal advisor during design.
Loss of NGO partnership	Maintain regular communication, involve NGOs in planning, and demonstrate ongoing value.
Legal action due to data privacy breach	Conduct regular security audits; store data securely with encryption and access control mechanisms.

3.11 Quality Management Plan

We also include a quality management plan in our project documentation. It's made up of the following parts.

- **Quality Standards:** These are the criteria and benchmarks that measure the quality of a project's processes and deliverables. They enable the project to meet stakeholder expectations.

- **Quality Assurance Guidelines:** Next are quality assurance guidelines that help define quality standards and establish quality control procedures. These guidelines can help improve customer and stakeholder satisfaction.
- **Quality Control Procedures:** List the specific actions that you'll take to ensure the product, service or process meets the predetermined quality standards.

The following table holds the tasks along with the above-mentioned quality standards, guidelines, and procedures.

Table 3.14 Quality Management Plan

Task or Deliverable	Quality Standards	Quality Assurance Guidelines	Quality Control Procedures
Sensor Hardware Integration	Sensors must reliably collect physiological data with <10% error margin	Use medically validated sensors; test under lab and simulated field conditions	Calibration tests; compare sensor outputs to benchmark standards
Physiological Data Collection Module	Data should be collected in real-time with <1s delay	Data should be collected in real-time with <1s delay	Implement efficient data transmission protocols and buffering
Machine Learning Stress Detection Model	≥85% classification accuracy; no bias toward any group	Use a balanced dataset and cross-validation; assess model performance across age and gender groups	Confusion matrix analysis; periodic model evaluation and retraining
Wearable Device Comfort and Usability	Devices must be comfortable for children (no irritation or excessive bulk)	Child-centric design evaluation; test with sample users before deployment	Gather user feedback via surveys; assess usage compliance in pilot testing
Training Materials for NGO Staff	Materials should be clear, concise, and in local language	Involve NGO staff in early testing; ensure materials match local cultural and linguistic context	Pre/post-training quizzes; feedback collection
Software Interface (Dashboard or App)	Easy to use, intuitive, responsive interface (response time <2s)	Follow UI/UX best practices; usability testing with target user group	Usability testing; bug tracking logs; regular updates based on feedback
Data Privacy and Ethics Compliance	Full GDPR/ethical compliance; informed consent required for all data collection	Anonymize all data; encrypt sensitive information; gain IRB/ethics committee approval where needed	Consent form verification; audit logs of data access
System Deployment in Refugee Camps	System must operate reliably with minimal supervision for at least 48 hours	Field test under similar conditions; design for low power consumption and resilience	Pilot deployment test logs; usage monitoring reports

4 Software Requirements Specification

4.1 Requirements Elicitation

During our journey to gather requirements for our project, we've done two techniques. Interview and survey.

4.1.1 Interview

The interview was done with an occupational therapist, and a professor in the University of Jordan, by the name of doctor Hanan Madi. She worked as a pediatrician and in mental ward to cater for the needs of the children.

This interview not only deepened my appreciation for the role of occupational therapy in assistive design but also highlighted the importance of collaboration between healthcare professionals and developers to create meaningful, functional solutions. Below, I'll summarize the key takeaways from our conversation and how they influenced my work.

1. The system should cater to all children's needs
2. The system shall be as accessible as possible
3. the system should be as useful of a monitoring tool as possible for the caregivers and give meaningful data so that they can give the help they would be expected to give
4. Stress can be shown in different ways and we should look into possible solutions that would tackle those behaviors through the use of sensors

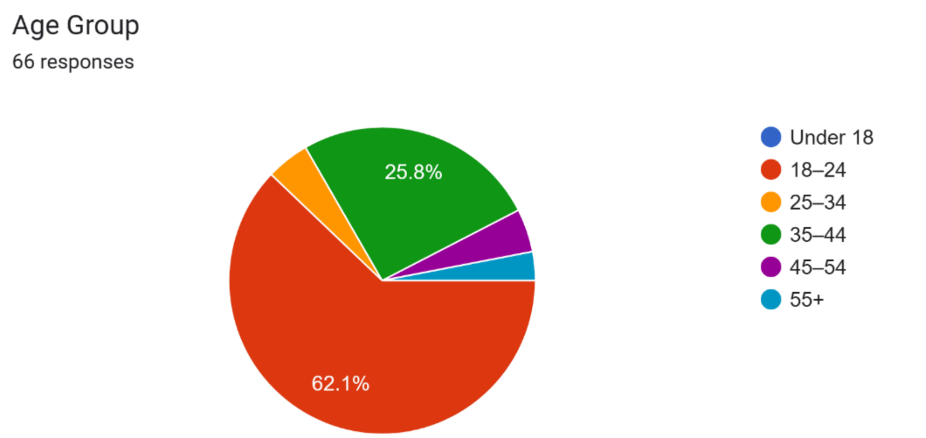
4.1.2 Survey

A survey was conducted as part of the initial data collection process to gather insights from potential users and stakeholders of the stress detection system. The primary purpose of using a survey was to understand the target audience's experiences with stress, their coping mechanisms, and their preferences regarding biofeedback methods and user interface features. This approach ensures that the system is built on a foundation of real-world needs and expectations.

The survey benefits the software development process by informing key design decisions, such as which feedback mechanisms to prioritize (e.g., visual vs. auditory), what types of calming activities to include, and how important features like offline functionality or caregiver access are. It also helps in defining user personas, functional requirements, and non-functional expectations. Ultimately, the survey ensures that the system is user-centered, practical, and more likely to be accepted and adopted by its intended users.

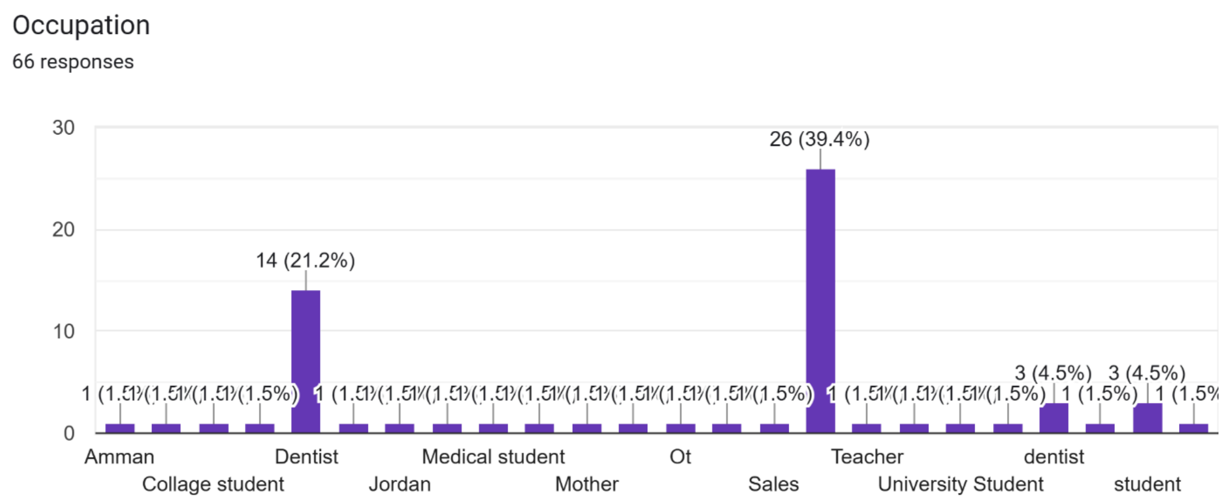
The pie chart below illustrates the age groups participated in the survey. Helps us to cater our project for individuals in different age groups.

Figure 4.1 Age groups from survey participation



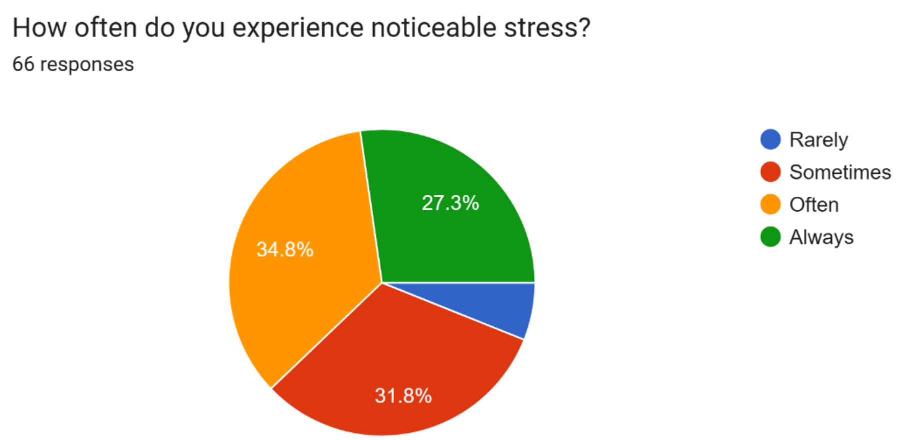
The bar chart below illustrates the occupation frequency of the individuals participated in the survey. Helps us to understand different needs for individuals from different backgrounds.

Figure 4.2 Occupation frequency from survey participation



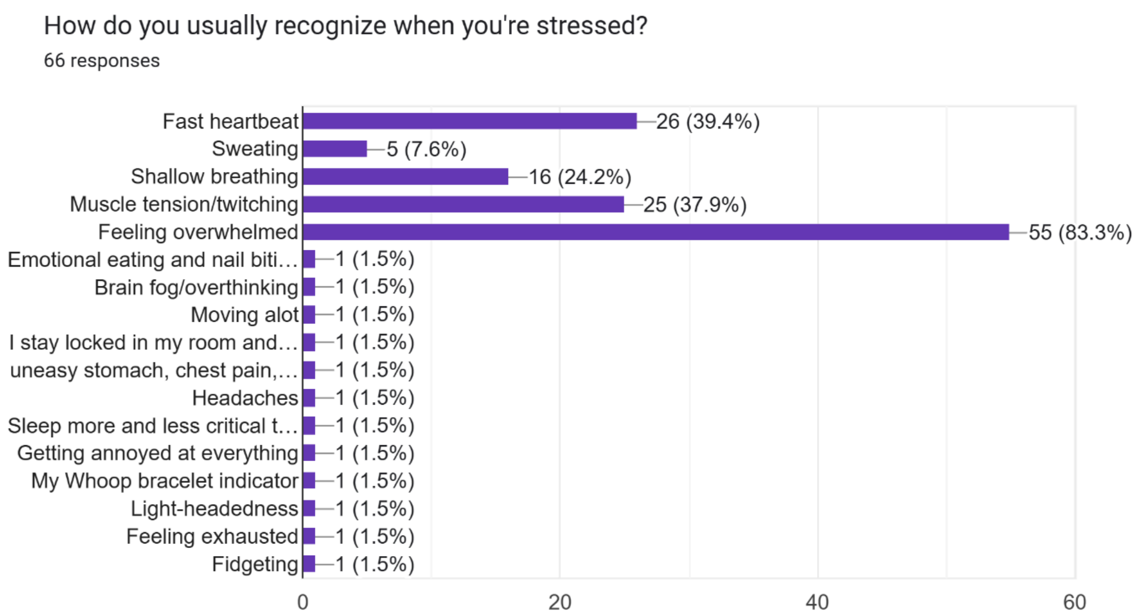
The pie chart below illustrates the frequency of noticeable stress in individuals who participated in the survey. Helps us to understand the ratio of affected people and their interest in our solution.

Figure 4.3 frequency of noticeable stress from survey participation



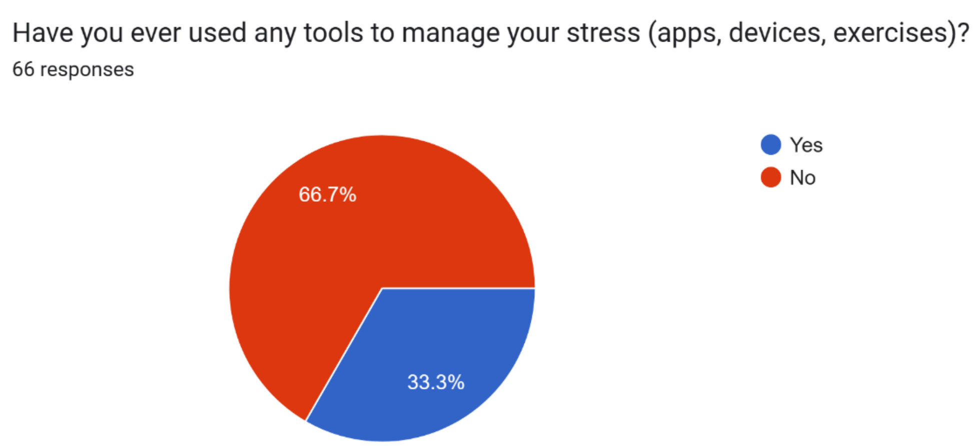
The bar chart below illustrates the repeated side effects of noticeable stress in individuals who participated in the survey. Helps us to recognize and capture physiological signals to detect stress

Figure 4.4 Repeated side effects of noticeable stress from survey participation



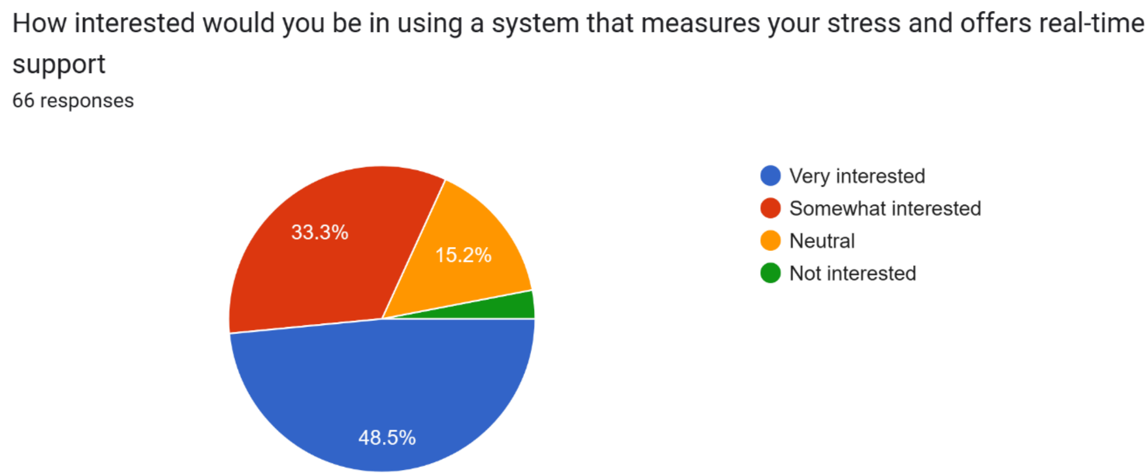
The pie chart below illustrates the ratio of participated individuals who used tools for stress detection. Helps us to understand the conversion rate of using our solution.

Figure 4.5 Ratio of previous stress detection tools usage from survey participation



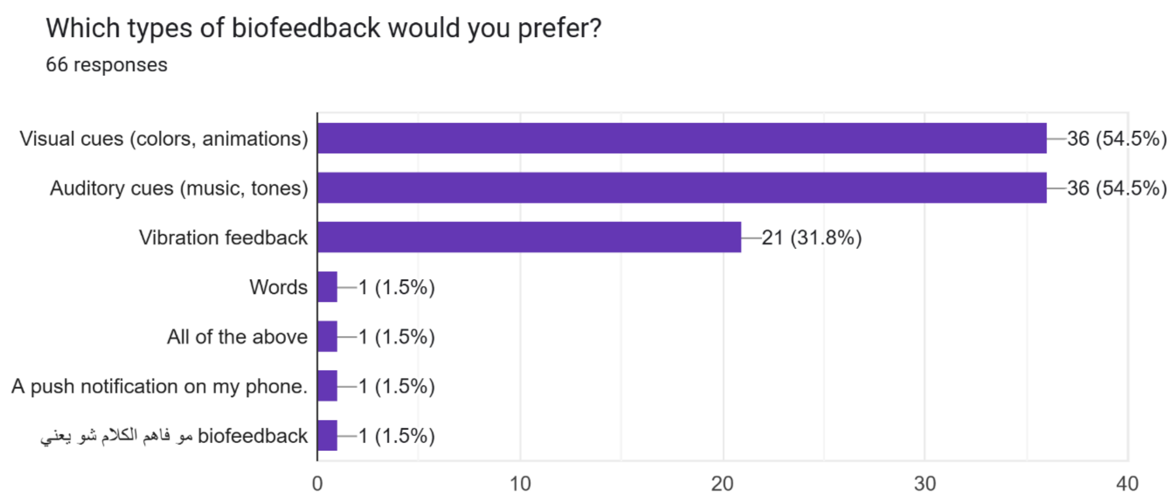
The pie chart below illustrates the ratio of participated individuals who are interested in using our solution. Helps us to determine the scale of our solution.

Figure 4.6 Ratio of interested participants in using our solution from survey participation



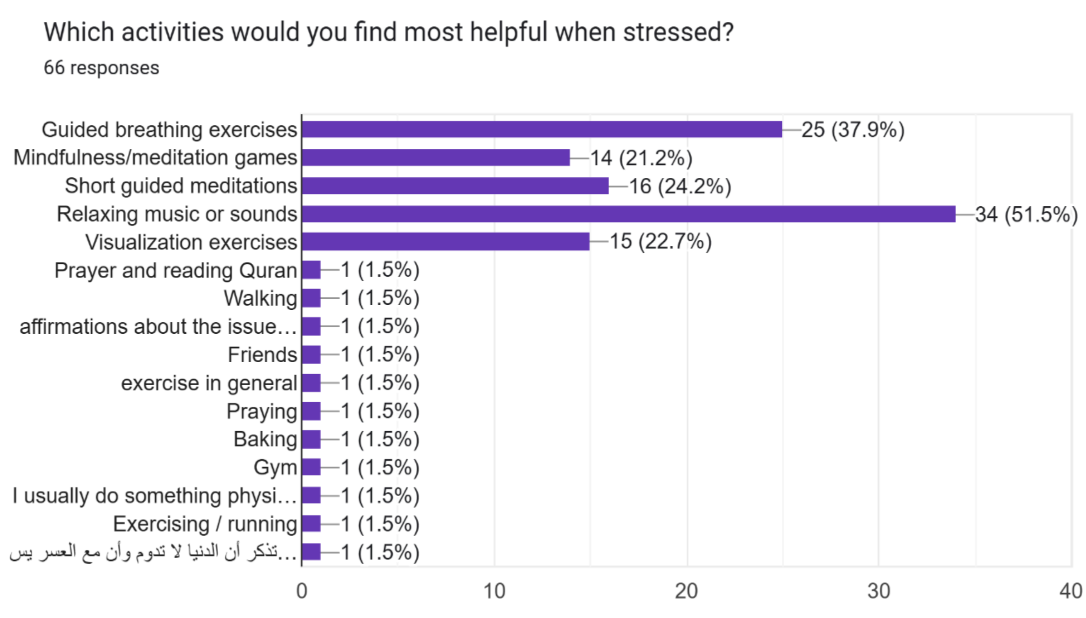
The bar chart below illustrates the frequency of preferred biofeedback in participants who are interested in using our solution. Helps us to determine the preferred biofeedback for our solution.

Figure 4.7 Frequency of preferred biofeedback in participants from survey particiaption



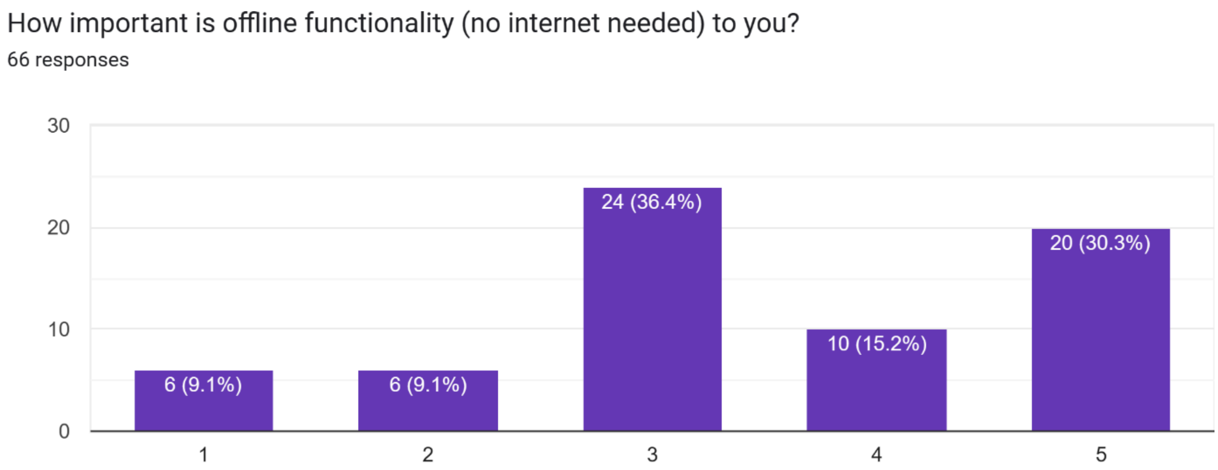
The bar chart below illustrates the frequency of preferred post stress activities chosen by participants. Helps us to add preferred activities in our solution.

Figure 4.8 Frequency of preferred post stress activities from survey participation



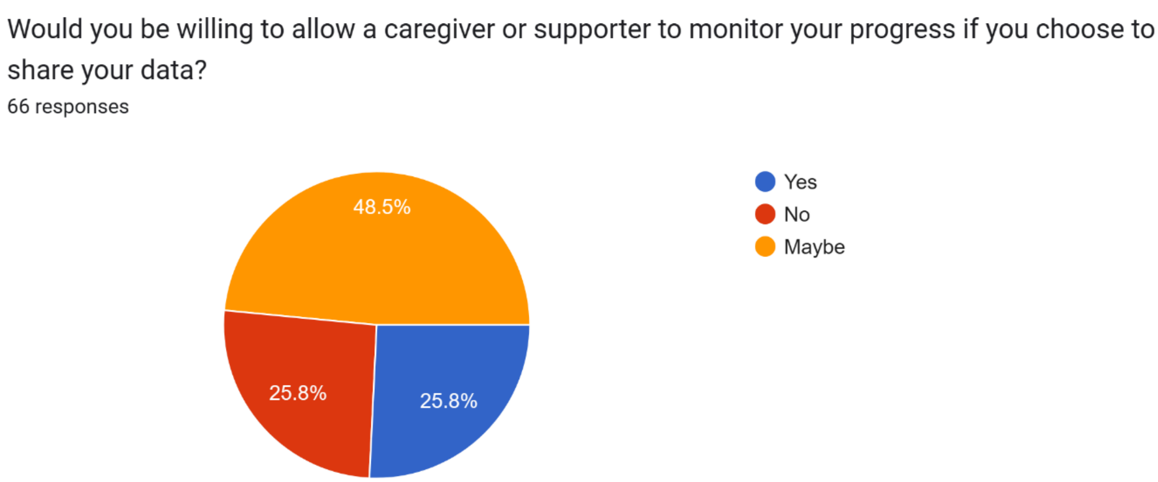
The bar chart below illustrates the degree and ratio of offline functionality importance to participants. Helps us to determine the priority of offline functionality in our implementation.

Figure 4.9 Offline functionality degree and ratio of importance from survey participation



The pie chart below illustrates the willingness ratio of sharing physiological data with caregivers. Helps us to find acceptance ratio for caregivers to monitor their respective data.

Figure 4.10 Willingness ratio of sharing physiological data from survey participation



The table below holds voluntary user answers about concerns in using our solution.

Table 4.1 concerns in using our solution from survey participation

inaccuracy
Protecting the data gathered
Leaked personal data
That it doesnt work
If it needs a log in every time you open it
forgetting about it
It not being helpful
I couldn't think of any major concerns when it came to this system
Its efficacy
N/A
Nothing
Privacy
Data privacy
Will it work or is it just talk
Privacy concerns
Practicality
Lose it
Boredom
I can try
Complex using and apply a lot of data
How effective it is, and privacy & security of sensitive personal data

Effectiveness
I using my information
Confidential
Consuming to much time
Takes too long while trying to calm down in public
no concerns
relaxation
Being complicated
To be offective in short time
Being not accurate in measuring the level of stress
Not be very helpful
Effectiveness
Affordability

4.2 Hardware Requirements

1. ESP32-S3

   a. Function: ESP32 variant with Bluetooth and Wifi capabilities.

   b. Key Features:

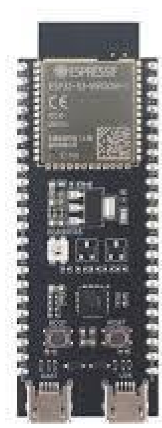
      i. The defining feature of the ESP32-S3 is its focus on AIoT (Artificial Intelligence of Things). Unlike the standard ESP32, the S3 includes additional vector instructions in its MCU, which specifically accelerate neural network computing and signal processing workloads.

      ii. More programmable GPIOs and flexible peripheral mapping compared to the standard ESP32.

      iii. Dual-Core Architecture for Reliable Data Acquisition

   c. Figure:

Figure 4.11 ESP32-S3 MicroController



2. GY-906 MLX90614

a. Function: Reliable temperature monitoring

b. Key Features:

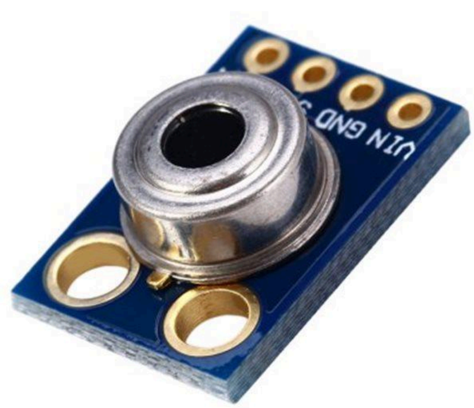
i. Unlike a thermistor that must be taped to the skin, this allows you to measure skin temperature (a key stress indicator) non-invasively, reducing user discomfort and "white coat" stress effects.

ii. Analog output, no calibration needed, low power.

iii. High-Resolution Digital Interface (SMBus/I2C)

c. figure:

Figure 4.12 GY-906 MLX90614sensor



3. Pulse Sensor (From Playground)

a. Function: The sensor employs reflective Photoplethysmography (PPG) using a 550nm green LED to maximize hemoglobin absorption contrast, enabling precise capture of the Blood Volume Pulse (BVP) waveform essential for Inter-Beat Interval (IBI) extraction.

b. Key Features:

   i. Integrated LEDs (red, IR) and photodetector.

   ii. Integrated Hardware Signal Conditioning (Amplification & Filtering).

   iii. Fast Analog Response for Real-Time Analysis.

c. figure:

Figure 4.13 Pulse Sensor

   i. 

4. GSR (Galvanic Skin Response) Sensor

    a. Function: Measures skin conductance (sweat levels) to detect stress/arousal.

    b. Key Features:

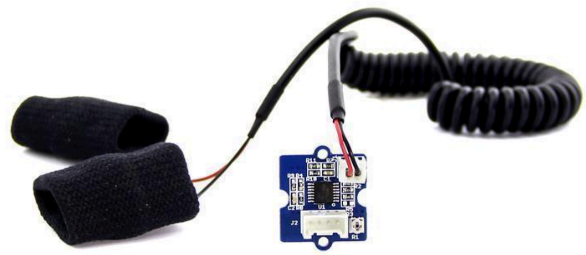
        i. Analog output (varies with skin moisture).

        ii. Often paired with an op-amp for signal conditioning.

        iii. Applications: Lie detectors, mental health monitoring, biofeedback systems.

    c. figure:

Figure 4.14 GSR (Galvanic Skin Response) Sensor



i.

5. ICM (ICM20948)

a. Function: 9-axis MotionTracking device.

b. Key Features:

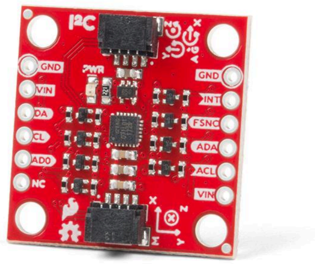
i. Ultra-Low Power Consumption (2.5 mW).

ii. I²C interface, built-in DMP (Digital Motion Processor).

iii. Applications: Drones, robotics, gesture control, gaming.

c. figure:

Figure 4.15 ICM 20948



6. ADS1115

    a. **Function:** 16-bit High-Precision Analog-to-Digital Converter (ADC).

    b. **Key Features:**

        i. **Ultra-Low Current Consumption:** (150 μA in continuous mode).

        ii. **Programmable Gain Amplifier (PGA):** Allows for the detection of minute voltage changes (up to x16 gain).

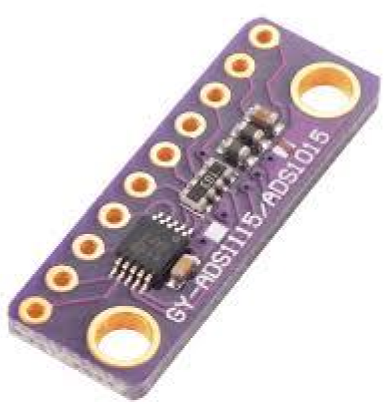
        iii. **I²C Interface:** Supports four pin-selectable addresses for multi-sensor scaling.

        iv. **Wide Supply Range:** Operates from 2.0V to 5.5V, ensuring compatibility with 3.3V and 5V systems.

7. **Applications:** Portable instrumentation, consumer goods, battery monitoring, and precision sensor interfacing (GSR/Pulse).

    a.

Figure 4.16 ADS1115



4.3 User Requirements

4.3.1 Child User

UR-1 The child should wear the microcontroller without needing to pair it manually.

UR-2 The child should be able to get into the system without needing to log in.

UR-3 The child should not see or adjust Bluetooth/technical settings

UR-4 The child should have all his physiological data recorded by the microcontroller

UR-5 The child should get gentle notifications directed to the app when he feels stressed .

UR-6 The child should tap/swipe to dismiss or start a calming activity.

UR-7 the child should be able to select one of the minigames that are available in the app.

UR-8 the child should be able to exercise breathing techniques available in the app

UR-9 the child should be able to tap in the screen when he plays a relaxing minigame.

UR-10 the child should be able to send one of his requests to the caregiver that are in the app

UR-11 the child should be able log his moods

UR-12 the child should able to log his current activity

UR-13 the child should be able to pause the current minigame he's playing

UR-14 the child experience a gentle vibration on his microcontroller when he gets stressed, if the caregiver sets the vibration on

UR-15 the child shouldn't encounter third party advertisements in the app

UR-16 the child should give his physiological data to train the AI model

4.3.2 Caregiver User

UR-17 The caregiver should either log in or signup to the app

UR-18 The caregiver should receive alerts if the child's device disconnects

UR-19 The caregiver should receive an alert if the child leaves a safezone

UR-20 During exams or sports, the caregiver should remotely pause stress alerts.

UR-21 The caregiver should view real-time stress status of the child's chosen mood

UR-22 The caregiver should get urgent alerts for when the child is in extreme stress.

UR-23 The caregiver should be able to control the thresholds of the child's stress levels

UR-24 the caregiver should see the data of the child's stress levels

UR-25 The caregiver should enable any types of feedback in the system

UR-26 The caregiver should be able to disable any specific feedback types

UR-27 The caregiver should share reports with doctors/schools via encrypted links

UR-28 The caregiver should enable location sharing during high stress

4.4 Functional System Requirements

4.4.1 Child functional requirements

FSR-1 The system should automatically connect to the child's microcontroller without manual input.

FSR-2 The system should establish a secure Bluetooth connection with the supported biosensors

FSR-3 The system should reconnect automatically to paired devices when they are within range

FSR-4 The system should display a confirmation animation, such as an emoji, upon successful pairing.

FSR-5 The system should Hide all Bluetooth/technical settings from the child interface.

FSR-6 The system should let the child in without the need to log in.

FSR-7-The system should automatically give out an id number for the child user.

FSR-8 The system should be established with voice note capabilities.

FSR-9 The system should continuously acquire heart rate data from connected biosensors.

FSR-10 The system should collect skin conductivity (GSR) readings at configurable intervals.

FSR-11 The system should measure temperature data and report any deviations from baseline.

FSR-12 The system should validate incoming sensor data for completeness and accuracy.

FSR-13 The system should incorporate AI models trained to identify stress patterns in physiological data.

FSR-14 The system should apply predefined thresholds for physiological signals to detect signs of stress.

FSR-15 The system should locate and update the location of the child's whereabouts

FSR-16 The system should support updating AI models dynamically via cloud synchronization or manual upload.

FSR-17 The system should trigger vibration alerts on connected devices for immediate attention.

FSR-18 The system should display a calming user interface for the child user.

FSR-19 The system should display a set of minigames in the interface with the games' pictures representing what the activity would be.

FSR-20 The system should display a selection of emojis from (sad, worried, blank, smile, happy) to determine the user's mood.

FSR-21 The system should provide guided breathing exercises via auditory masked as a minigame.

FSR-22 The system should provide a stress relieving tapping game (popping bubbles) masked as one of the available stress relieving games on the app.

FSR-23 The system should allow vibrations on the microcontroller device to be turned on or off, depending on the child needs.

4.4.2 Child non-functional requirements

NFSR-1 When stress is detected, the system should notify the user within 5 seconds

NFSR-2 The system should be as easy to navigate as possible

NFSR-3 The system should be viewed with bright colors on the user interface

NFSR-4 The system's microcontroller should be as resilient as possible from damage

NFSR-5 The system should have high levels of accuracy in determining whether the child was stressed or not.

4.4.3 Caregiver functional requirements

FSR-24 The system should offer a log in/signup button in the top corner of the screen designed as a box icon for the caregiver users.

FSR-25 The system should require the following information for logging in:

A. username

A. password

A. id/s of the child/children getting monitored

FSR-26 The system should require the following information for signing up:

A. username

A. password

A. confirmed password

A. id/s of the child/children getting monitored

A. disability of the child (if any)

A. agreement for terms and conditions

FSR-27 The system should let caregivers be able to adjust detection thresholds through the settings menu.

FSR-28 The system should send out notifications that include details about the detected signal patterns with the combination of:

A. Heart rate spike

A. Extreme hand movement

A. Extreme sweat

A. High temperature

FSR-29 The system should generate line graphs of heart rate, GSR, and temperature over time.

FSR-30 The system should present a timeline view showing correlations between stress events and user activities.

FSR-31 The system should allow toggling between;

A. Daily trend view

A. weekly trend view

A. monthly trend view

A. yearly trend view

FSR-32 The system should highlight time periods of user-reported stress alongside physiological data.

FSR-33 The system should periodically upload user data to a secure cloud server for backup.
FSR-34 Users shall configure the upload frequency (e.g., hourly, daily, or weekly).

FSR-35 The system should be able to turn off stress alerts for the caregiver during the child’s sports

FSR-36 The system should have the location of the child’s device

FSR-37 The system should let the caregiver be able to disable any trigger inducing feedback for the child’s device

4.4.4 Caregiver non-functional requirements

NFSR-6 The system should have a secure connection to the child’s device as necessary

NFSR-7 The system should be able to have high levels of accuracy for the data readings for the physiological patterns

NFSR-8 During caregiving multiple child users, the system should optimize the list of priority to be for the ones with the highest level of stress.

NFSR-9 The system should be updated with the most recent data from the child’s device

NSFR-10 The system should be working 24/7 for both the child and the caregiver.

4.5 External Requirements

Hardware Interfaces

- The system shall interface with:
    - ESP32-GSM
    - LM35 (analog, 10mV/°C).

    - SpO_2 Sensor (MAX30102)
    - GSR (Galvanic Skin Response) Sensor
    - IMU (MPU6050)
- Hardware communication will be managed via the platform's native Bluetooth API or SDK.

Software Interfaces

- The backend shall expose RESTful APIs or Firebase Cloud functions for:
    - User authentication
    - Data synchronization (sensor data, user logs)
    - Stress classification and feedback triggering
- The system shall integrate with third-party authentication services (e.g., Google/Firebase Auth).
- Compatibility with health data standards such as HL7 or FHIR is desirable for medical integrations.

Communication Interfaces

- Bluetooth 4.0+ (BLE) will be required for sensor connectivity.
- HTTPS protocol shall be used for all cloud communication.
- The system shall support WebSocket or MQTT (optional) for real-time data streaming in advanced use cases.
- Data must be securely transmitted using TLS 1.2 or above.

4.6 Requirements Traceability

Table 4.2 child's functional traceability matrix

-	UR-1	UR-2	UR-3	UR-4	UR-5	UR-6	UR-7	UR-8	UR-9	UR-10	UR-11	UR-12	UR-13	UR-14	UR-15	UR-16
FSR1	x															

FSR2	x															
FSR3	x															
FSR4					x											
FSR5			x													
FSR6		x														
FSR7		x														
FSR8												x				
FSR9				x												
FSR 10				x												
FSR 11				x												
FSR 12				x												
FSR 13				x												
FSR 14																x
FSR 15									x	x						
FSR 16																x

FSR 17															x	
FSR 18						x										
FSR 19							x									
FSR 20											x	x				
FSR 21								x								
FSR 22													x			
FSR 23														x		

Table 4.3 child's non-functional traceability matrix

-	UR-1	UR-2	UR-4	UR-6	UR-15
NSFR 1	x				
NSFR 2		x			

NSFR 3				x	x
NFSR 4	x		x		
NFSR 5			x		

Table 4.4 caregiver’s functional traceability matrix

-	UR-17	UR-18	UR-19	UR-20	UR-21	UR-22	UR-23	UR-24	UR-25	UR-26	UR-27	UR-28
FSR-24	x											
FSR-25	x											
FSR-26	x											
FSR-27					x		x					
FSR-28				x								
FSR-29						x						
FSR-30						x						
FSR-31								x				
FSR-32									x			
FSR-33									x			
FSR-34											x	
FSR-35				x								
FSR-36			x									

FSR-37										x		x

Table 4.5 caregiver's non-functional traceability matrix

-	UR-16	UR-19	UR-20	UR-26
NFSR-6	x			
NFSR-7		x		
NFSR-8			x	
NFSR-9				x
NFSR-10	x		x	

4.7 Requirements Prioritization

For our requirements prioritization we used the MoSCoW method which categorizes features into 4 levels of priority: Must Have, Should Have, Could Have and Won't Have. This gave us a clear framework for decision making and ensured our resources were allocated efficiently and the most important features were prioritized according to stakeholder needs.

Table 4.6 Functional Requirements Prioritization

Requirements ID	MoSCow ID	Requirements ID	MoSCoW ID
FSR-1	Must Have	FSR-20	Should Have
FSR-2	Must Have	FSR-21	Should Have
FSR-3	Must Have	FSR-22	Could Have
FSR-4	Must Have	FSR-23	Should Have
FSR-5	Must Have	FSR-24	Must Have
FSR-6	Must Have	FSR-25	Must Have
FSR-7	Must Have	FSR-26	Must Have
FSR-8	Should Have	FSR-27	Must Have
FSR-9	Must Have	FSR-28	Must Have
FSR-10	Must Have	FSR-29	Must Have
FSR-11	Must Have	FSR-30	Should Have
FSR-12	Must Have	FSR-31	Should Have
FSR-13	Should Have	FSR-32	Must Have
FSR-14	Must Have	FSR-33	Must Have
FSR-15	Must Have	FSR-34	Could Have
FSR-16	Must Have	FSR-35	Should Have
FSR-17	Should Have	FSR-36	Must Have

FSR-18	Must Have	FSR-37	Must Have
FSR-19	Should Have	NFFR-1	Should Have

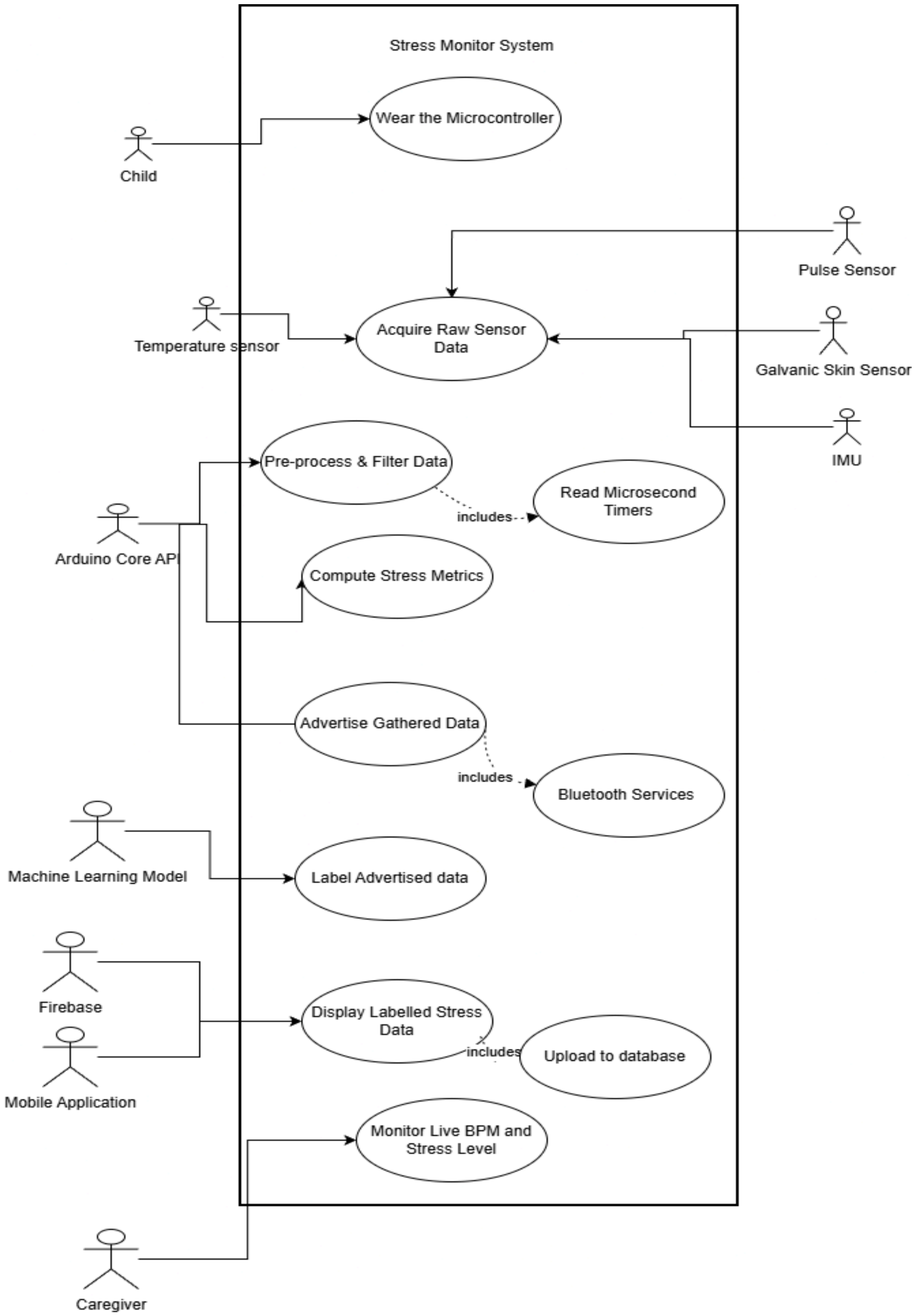
Table 4.7 Non-functional Requirements Prioritization

Requirements ID	MoSCoW ID
NFSR-2	Must Have
NFSF-3	Must Have
NFSR-4	Must Have
NFSR-5	Must Have
NFSR-6	Must Have
NFSR-7	Must Have
NFSR-8	Should Have
NFSR-9	Must Have
NFSR-10	Must Have

5 Design

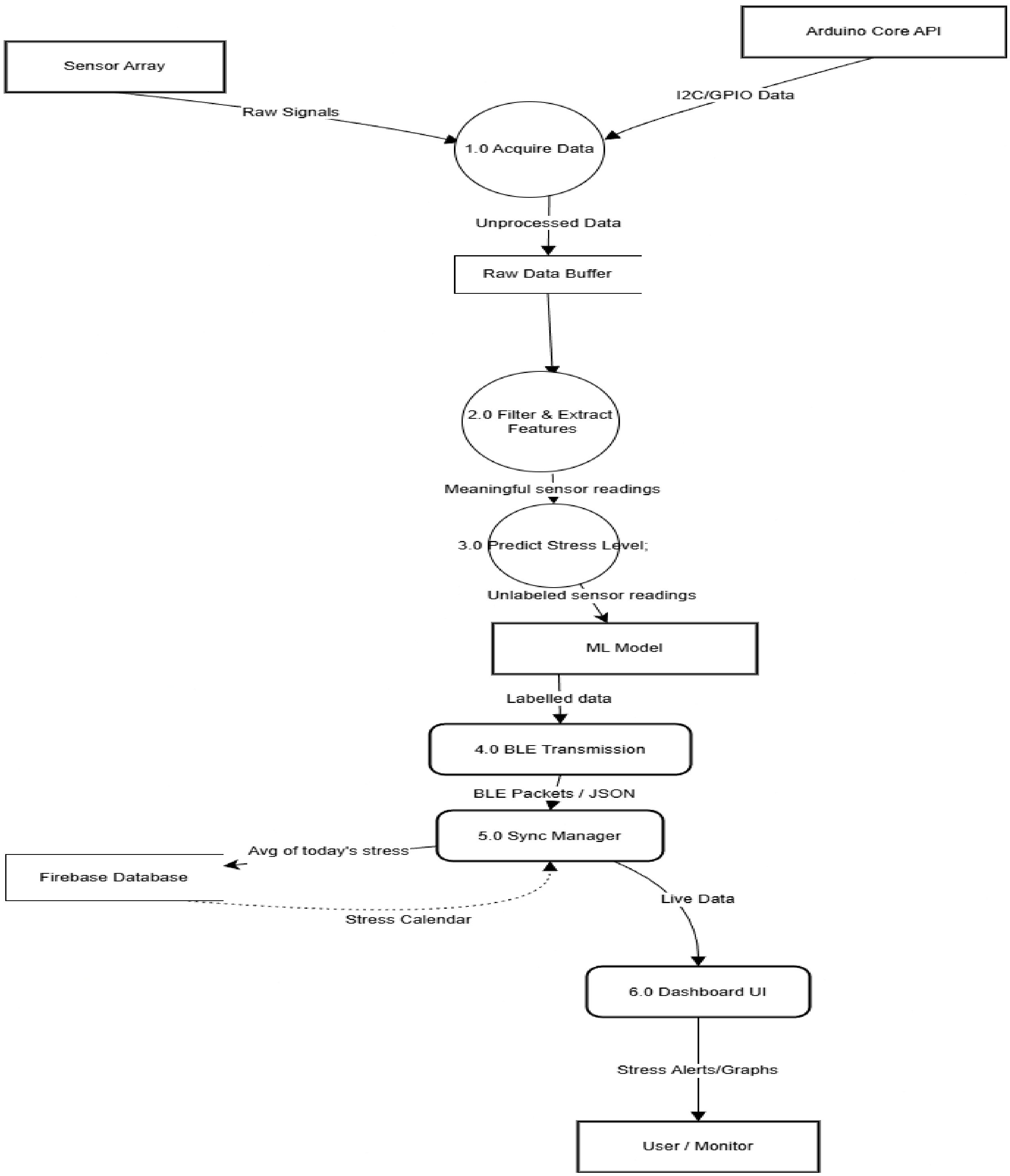
5.1 Use Case Diagram

Figure 5.1:Use Case Diagram


Stress Monitor System
Wear the Microcontroller
Child
Pulse Sensor
Temperature sensor
Acquire Raw Sensor Data
Galvanic Skin Sensor
IMU
Pre-process & Filter Data
includes
Read Microsecond Timers
Arduino Core API
Compute Stress Metrics
Advertise Gathered Data
includes
Bluetooth Services
Machine Learning Model
Label Advertised data
Firebase
Display Labelled Stress Data
includes
Upload to database
Mobile Application
Monitor Live BPM and Stress Level
Caregiver

5.2 Data Flow Diagram

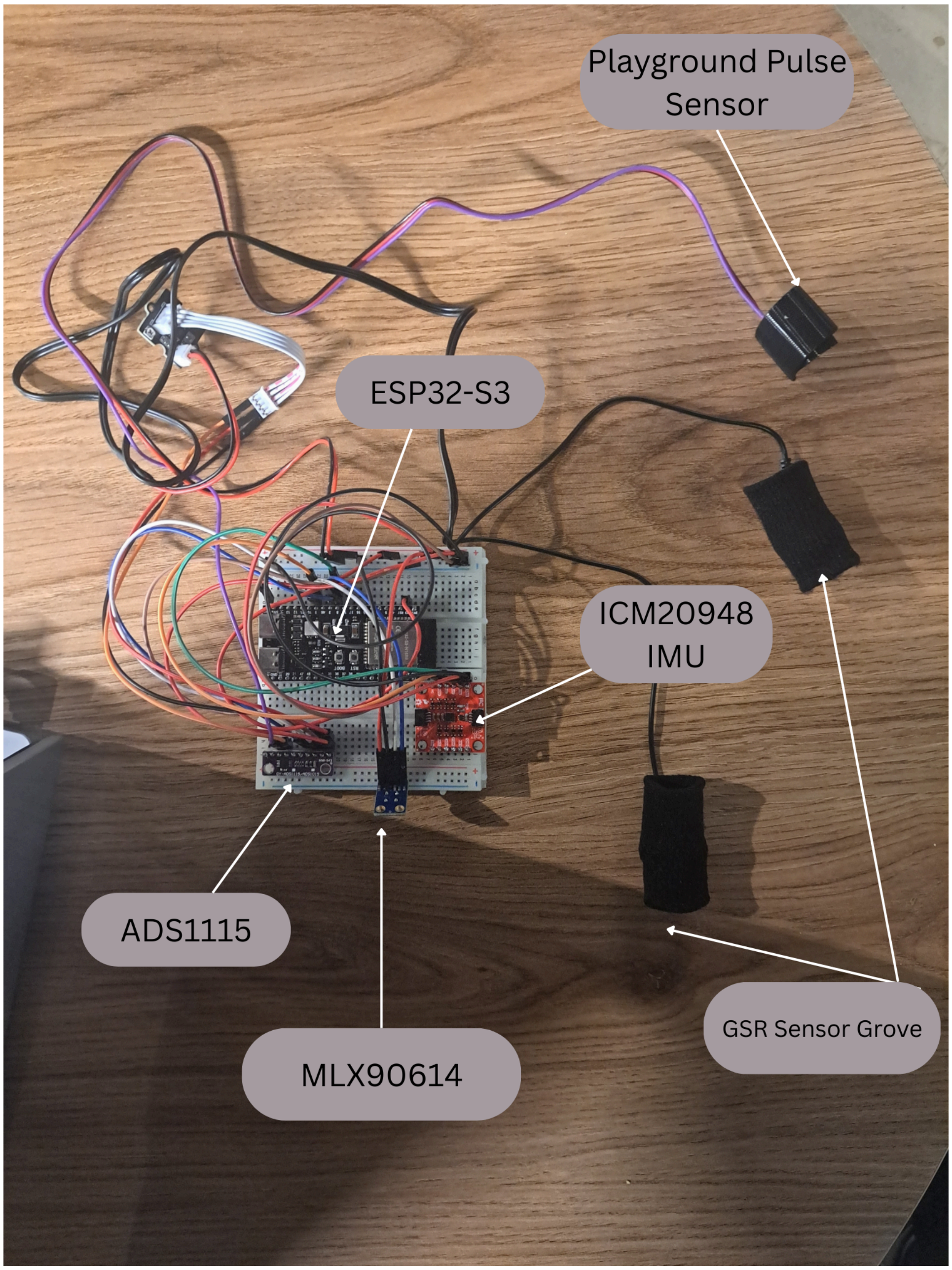
Figure 5.2:Data Flow Diagram



6 Implementation

6.1 Hardware Implementation

Figure 6.1 Hardware Wiring



The hardware architecture of the Stress Monitor System is designed to acquire multi-modal physiological data with high precision while maintaining processing efficiency. The system is built around a high-performance 32-bit microcontroller, which serves as the central processing unit, interfacing with a diverse array of sensors via I2C and analog protocols.

6.1.1 ImplementationMicroController Unit (MCU)

The core of the system is the **ESP32-S3**, chosen for its dual-core Xtensa LX7 processor running at up to 240 MHz. This MCU was selected specifically for its ability to handle high-speed signal processing and its built-in Wi-Fi/Bluetooth capabilities, which allow for future wireless data transmission. The ESP32-S3 operates on 3.3V logic and manages the synchronization of all sensor data streams.

6.1.2 Precision Data Acquisition (ADC)

To overcome the limitations of standard on-board analog-to-digital converters, the system utilizes the **ADS1115**, a high-precision 16-bit ADC. This component is critical for the project as it allows for the detection of minute voltage changes in the physiological sensors.

- **Role:** The ADS1115 acts as an intermediary between the analog sensors and the ESP32-S3.
- **Protocol:** It communicates with the MCU via the **I2C protocol** (Inter-Integrated Circuit), utilizing the SDA and SCL lines. This setup ensures that the subtle variations in bio-signals are preserved without loss of resolution.

6.1.3 Sensor Integration

The sensor array is divided into three distinct categories based on the physiological metrics being monitored:

A. Electrodermal Activity (GSR) The **Grove GSR (Galvanic Skin Response)** sensor is used to measure the electrical conductance of the skin.

- **Implementation:** The sensor is powered by 5V but interfaced with the 3.3V system via the ADC. It outputs an analog voltage corresponding to the skin resistance, which varies with sweat gland activity—a key indicator of physiological stress.

B. Cardiovascular Monitoring (PPG) A **Pulse Sensor** (from pulsesensor.com) is implemented to capture the Blood Volume Pulse (BVP).

- **Implementation:** This optical sensor uses photoplethysmography (PPG) to detect changes in light absorption caused by blood flow. The analog signal is routed through the system to calculate Heart Rate (BPM) and Inter-Beat Interval (IBI).

C. Thermal and Motion Sensing

- **Temperature:** An **MLX90614** infrared temperature sensor is integrated to measure non-contact skin temperature. Unlike the analog sensors, the MLX90614 is a digital sensor that connects directly to the I2C bus alongside the ADS1115.
- **Motion (IMU):** To account for motion artifacts and monitor physical activity, an Inertial Measurement Unit (IMU) is included. This sensor provides 3-axis accelerometer (X, Y, Z) data, allowing the system to correlate stress spikes with physical movement or stillness.

4.4 Circuit Topology

The hardware is assembled using a shared bus architecture to minimize wiring complexity:

1. **The I2C Bus:** The MLX90614, ADS1115, and IMU all share the same I2C lines (SDA/SCL), distinguished by their unique hardware addresses.
2. **Power Distribution:** The system manages a dual-voltage requirement, supplying 5V to the analog sensors for optimal sensitivity while maintaining a stable 3.3V reference for the ESP32-S3 and digital communication lines.

6.2 Firmware and Software Architecture

The system software is divided into two distinct layers: the **Embedded Firmware** running on the ESP32-S3 and the **Mobile Application** running on the user's smartphone. The development workflow utilized **GitHub** for version control, ensuring synchronization between the hardware code (C++) and application code (Dart).

6.2.1 Development Environment & Tools

The project leveraged a multi-platform development ecosystem to ensure robust performance and ease of debugging:

- **Embedded Development:** The **Arduino IDE** was used for writing and uploading firmware to the ESP32-S3. The **Arduino Core API** served as the underlying hardware abstraction layer, allowing for high-level C++ implementation of low-level hardware interrupts and I2C communication without direct register manipulation.
- **Mobile Development: VS Code** was utilized as the primary editor for **Flutter** and **Dart** development, chosen for its extensive extension support. **Android Studio** provided the necessary Android SDKs and emulators for compiling and testing the application on mobile devices.

6.2.2 Embedded Software Implementation (Arduino/C++)

The firmware for the ESP32-S3 was developed using the **Arduino IDE** and the **Arduino Core API**. The code is architected to perform three critical tasks simultaneously: sensor polling, digital signal processing (DSP), and Bluetooth Low Energy (BLE) transmission.

To ensure that high-frequency data (like the heart rate signal) is not lost during slower operations (like reading temperature), the software utilizes a **Non-Blocking Cooperative Scheduler** rather than a linear execution flow.

6.2.2.1 Initialization and Configuration (setup)

Upon boot, the system initializes the hardware peripherals via the I2C bus. The setup routine performs a "Health Check" sequence:

1. **I2C Bus Init:** The specific SDA and SCL pins are assigned to the Wire library to establish the sensor network.
2. **Sensor Verification:** The firmware attempts to handshake with the ADS1115, MLX90614, and IMU. If any sensor fails to acknowledge (ACK), the system halts and outputs an error to the serial console, preventing undefined behavior during runtime.
3. **Filter Settlement:** A dummy reading is taken from the ADC to initialize the "DC Offset" variables, ensuring the filters start with valid data rather than zero.

6.2.2.2 The Scheduler (Time-slicing)

The main *loop()* function avoids the use of *delay()*, which would pause the processor and cause data loss. Instead, it uses *micros()* to track time deltas, effectively multitasking between sensors with different sampling rate requirements:

- **High-Priority Task (64 Hz):** The Pulse Sensor (BVP) is read every 15,625 microseconds. This high sampling rate is necessary to capture the sharp peaks of the heart beat waveform.
- **Medium-Priority Task (32 Hz):** The IMU (Accelerometer) is polled to detect motion artifacts.
- **Low-Priority Task (4 Hz):** The GSR and Temperature sensors, which change slowly, are read every 250 milliseconds.

6.2.2.3 Digital Signal Processing (DSP) Algorithms

Raw sensor data is often noisy or drifting. The firmware implements on-device filtering before transmission:

- DC Blocker (High-Pass Filter): The raw optical signal from the pulse sensor contains a large DC component (ambient light and skin reflection) that obscures the tiny heartbeat signal. An algorithm is implemented to dynamically subtract this drift:

  Signal_AC = Signal_RAW - Average_ROLLING

  This centers the waveform around zero, making it suitable for peak detection.
- **GSR Calibration & Smoothing:** The skin conductance data is passed through a Low-Pass Filter (LPF) to remove high-frequency electrical noise. Additionally, a "Ghost Value" threshold is applied to zero out readings when the sensor is not in contact with the skin.

6.2.2.4 Data Packetization & BLE Streaming

Once all sensors are sampled for a given timeframe, the data is serialized into a single JSON string (the "Snapshot").

- **Format:** *{"a":[0.01,-0.98,0.22],"b":12.45,"t":36.5,"g":2.15}*, where “a” is the IMU x,y, and z axis, b is the BVP, t is the temperature by celcius, and g is the GSR’s conduction
- **Transmission:** This string is written to a BLE Characteristic. The ESP32 utilizes the "Notify" property, pushing the data to the mobile application immediately without waiting for a read request, ensuring low latency.

6.2.3 Stress Learning Model

To ensure robust stress detection that generalizes well across different users, the system utilizes a machine learning pipeline developed using AutoML (Automated Machine Learning) techniques. The final deployed model is an **ExtraTreesClassifier** (Extremely Randomized Trees), selected for its high performance in handling non-linear physiological data and resistance to overfitting.

6.2.3.1 Stress Learning ModelData Preprocessing & Windowing

Raw physiological data is non-stationary and cannot be fed directly into the classifier. The system applies a "Sliding Window" approach to segment the continuous streams into analyzable chunks:

- **Window Size: 30 seconds**. This duration was empirically selected to capture sufficient physiological context (e.g., a full respiration cycle or GSR peak) while maintaining a responsive system.
- **Step Size: 1 second**. The window slides forward every second, providing a near real-time classification rate (1 Hz).

6.2.3.2 Stress Automated Feature Engineering(FLIRT)

The system employs the **FLIRT** (Feature LineIR Tools) framework to extract interpretable features from the raw signal windows. A total of **71 distinct features** are calculated to represent the signal characteristics, including:

- **Time-Domain Features:** Mean, Standard Deviation, Min/Max, and Dynamic Range of the GSR and BVP signals.
- **Frequency-Domain Features:** Fast Fourier Transform (FFT) coefficients to analyze the spectral density, specifically identifying High-Frequency (HF) components associated with parasympathetic activity (relaxation) and Low-Frequency (LF) components associated with sympathetic activity (stress).
- **Peak Detection:** Number of GSR peaks (SCR) and peak amplitude/duration, which are direct indicators of emotional arousal.

6.2.3.3 Model Architecture (ExtraTreesClassifier)

The core classification engine was optimized using the **TPOT** (Tree-based Pipeline Optimization Tool) genetic algorithm.

- **Algorithm:** The **ExtraTreesClassifier** is an ensemble learning method similar to Random Forest but with two key differences: it uses the entire original sample (no bootstrapping) and selects cut-points completely at random. This reduces variance and makes the model computationally lighter for mobile deployment.
- **Hyperparameters:**
    - `n_estimators`: **50** (Number of trees in the forest).
    - `min_samples_split`: **14** (Prevents the model from creating overly specific rules for single data points).

- `criterion`: **Gini Impurity**.

6.2.3.4 Performance & Explainability

- **Validation:** The model was trained on the industry-standard **WESAD** (Wearable Stress and Affect Detection) dataset. It achieves an **F1-Score of 0.87** on unseen users, balancing Precision (avoiding false alarms) and Recall (detecting actual stress events).
- **Explainability (SHAP):** To ensure the model is not a "black box," **SHAP** (SHapley Additive exPlanations) values were used during development to verify that the model prioritizes physiological features (like GSR Mean) over noise artifacts when making a prediction.

6.3 Mobile Application

6.3.1 Application Architecture

The application follows a **Clean Architecture** principle to ensure separation of concerns and maintainability. It is structured into three distinct layers:

1. **Presentation Layer (UI):** Built using Flutter’s Material Design widgets, providing a responsive and intuitive interface for the user.
2. **Logic Layer (State Management):** Utilizes the **Provider** pattern (or BLoC) to manage the state of the application. This ensures that when new data arrives via Bluetooth, the UI components (like charts and text labels) update instantly without redrawing the entire screen.
3. **Data Layer (Services):** Handles background tasks such as Bluetooth scanning, data serialization, and local database storage.

6.3.2 Key Functional Modules

1. Connectivity Module (BLE Manager) This module is responsible for the handshake between the phone and the ESP32.

- **Scanning:** The app scans for nearby BLE peripherals and filters them by the unique **Service UUID** of our hardware, ensuring it doesn't accidentally connect to other devices (like headphones or watches).
- **Subscription:** Once connected, the app subscribes to the **Notify Characteristic**. This establishes a continuous stream where the hardware "pushes" 20-byte data packets to the phone automatically.

2. Real-Time Dashboard The main screen of the application serves as a live monitor.

- **Data Visualization:** It features dynamic charts (using `fl_chart`) that plot the GSR and Heart Rate values in real-time. This allows the user to visually correlate spikes in the graph with their current activity.
- **Stress Indicator:** A prominent gauge displays the current classification result (e.g., "Relaxed," "Low Stress," "High Stress") derived from the ML model.

3. On-Device Inference Engine To protect user privacy and ensure offline functionality, the Machine Learning model is executed locally on the smartphone.

- **Implementation:** The trained model (exported as `.tflite`) is loaded into the app using the `tflite_flutter` plugin.
- **Process:** The app buffers the incoming sensor data into 30-second windows, extracts the necessary features (Mean, Slope, Peaks), and passes this tensor to the interpreter. The result is returned in milliseconds.

4. User Authentication & History

- **Authentication:** A secure login system allows users to create personal profiles. This ensures that calibration data (baseline physiological levels) is specific to the individual user.
- **History Logs:** Stress events are timestamped and stored in a local database (SQLite/Hive). The "History" screen allows users to review their stress patterns over the last week or month, helping them identify long-term triggers.

6.3.3 User Flow

Pairing: User opens the app -> Taps "Connect Device" -> Selects "StressMonitor_ESP32".

Monitoring: The Dashboard opens, showing live bio-signals. The background color changes (Green/Red) based on the detected stress level.

Alerting: If "High Stress" is detected for more than 1 minute, the app triggers a haptic notification and suggests a breathing exercise.

6.3.4 Challenges and Solutions

During the development of the Stress Monitor System, several technical challenges arose related to signal fidelity, hardware resource management, and cross-platform synchronization. Below are the primary issues encountered and the engineering solutions implemented to resolve them.

A. Signal Noise and "Ghost" Readings

Challenge:

The Grove GSR and Pulse sensors are highly sensitive to electromagnetic interference (EMI) and motion artifacts. A significant issue encountered was the "Floating Input" phenomenon (or "Ghost Values"), where the ADC would detect a voltage of ~1.98V even when the sensors were not in contact with the skin. This created false positives, sending invalid data to the machine learning model.

Solution:

A dual-layer filtration strategy was implemented:

1. **Hardware Thresholding:** A software "Silence Threshold" was established. Any conductance reading below a specific micro-siemens (μS) floor is treated as noise and clamped to 0.00.
2. **Digital Signal Processing (DSP):** A High-Pass Filter (DC Blocker) was applied to the Pulse Sensor data to remove baseline wander caused by ambient light changes, while a Low-Pass Exponential Moving Average (EMA) filter was applied to the GSR data to smooth out high-frequency electrical jitter.

B. Concurrency and Blocking Latency

Challenge:

The system requires multi-rate sampling: the Heart Rate sensor must be read at 64 Hz (every 15ms) to capture the systolic peak, while the GSR and Temperature sensors are slower (4 Hz). Using standard delay() functions caused the processor to pause, leading to "missed beats" in the heart rate signal and erratic BLE transmission.

Solution:

The firmware was rewritten using a Non-Blocking Cooperative Scheduler. Instead of halting the CPU, the system checks the micros() clock in every loop iteration.

- **Result:** This allows the ESP32-S3 to interleave tasks—reading the heart rate sensor exactly every 15,625 microseconds while handling Bluetooth stack operations in the idle time between samples.

C. BLE Data Fragmentation

Challenge:

Transmitting raw float values (4 bytes each) for every sensor individually created high overhead on the Bluetooth Low Energy bandwidth. This resulted in packets arriving out of order or being dropped by the Android/iOS networking stack, causing the mobile app charts to "lag" behind real-time.

Solution:

A Data Serialization (Snapshot) approach was adopted.

- Instead of sending individual characteristics, the firmware aggregates all sensor readings (GSR, BVP, Temp, IMU) into a single **JSON string** (e.g., {"G": 5.4, "B": 120, "T": 36.6}).
- This ensures that the Machine Learning model always receives a complete, synchronized "frame" of data for every inference step.

6.3.5 Results

The performance of the Stress Monitor System was evaluated through a series of unit tests and integrated system trials. The primary objective was to verify the accuracy of the physiological data acquisition and the responsiveness of the real-time classification engine.

6.3.6 Physiological Signal Validation

A. Electrodermal Activity (GSR) Response

The Grove GSR sensor was tested under two distinct conditions: a baseline "Rest" state and a controlled "Stress" state (induced via a breath-holding and rapid exhalation test).

- **Resting State:** During the relaxation phase, the subject remained seated with hands stationary. The system recorded stable skin conductance values ranging between **6.21 μS** and **6.25 mu S**. The low variance ($\pm 0.04 \mu S$) indicates that the implemented Low-Pass Filter successfully removed high-frequency noise.
- **Stressed State:** Upon initiating the stressor (breath retention), the system detected an immediate rise in skin conductance. Values increased from the **6.22 μS** baseline to a peak of **8.64 mu S** over a duration of approximately 20 seconds. This **39% increase** in conductance validates the sensor's sensitivity to sympathetic nervous system arousal.

B. Blood Volume Pulse (BVP)

The Pulse Sensor successfully captured the cardiac waveform. The implementation of the DC Blocker algorithm resulted in a centered signal (oscillating around 0), allowing for distinct systolic peak detection.

- **Observation:** The Inter-Beat Interval (IBI) showed clear variability, which is essential for Heart Rate Variability (HRV) analysis. The raw signal-to-noise ratio was improved significantly after enabling the digital filters.

6.3.7 System Performance & Connectivity

A. Wireless Latency

The ESP32-S3 BLE Server maintained a stable connection with the mobile application within a range of 10 meters.

- **Throughput:** The data serialization method (JSON Snapshot) allowed the system to transmit all three sensor values (GSR, BVP, Temp) in a single packet.
- **Latency:** The average time delta between the sensor reading (Hardware) and the chart update (Mobile Screen) was measured at approximately **150ms**, which is sufficient for "real-time" bio-feedback applications.

B. Noise Handling (Calibration Results)

Initial testing revealed "Ghost Values" (readings of ~1.98V / 5.8mu) when the sensor was placed on non-conductive surfaces.

- **Result:** The calibration threshold implemented in firmware successfully eliminated these false positives. In final testing, removing the sensor from the skin immediately resulted in a **0.00 muS** reading, preventing false stress classification during idle periods.

6.3.8 Classification & Application reults

The mobile application successfully subscribed to the BLE stream and performed on-device inference.

Visual Feedback: The dashboard successfully plotted the transition from "Low Stress" (Green indicator) to "High Stress" (Red indicator) coinciding with the rise in GSR values during the breath-holding test.

Model Latency: The specific inference time for the ExtraTreesClassifier on the mobile device was negligible (< 50ms per window), confirming that the chosen model architecture is lightweight enough for mobile deployment.

6.3.9 User Interface

Figure 6.3.1 Welcome_to_app

Figure 6.3.2 Sign_in

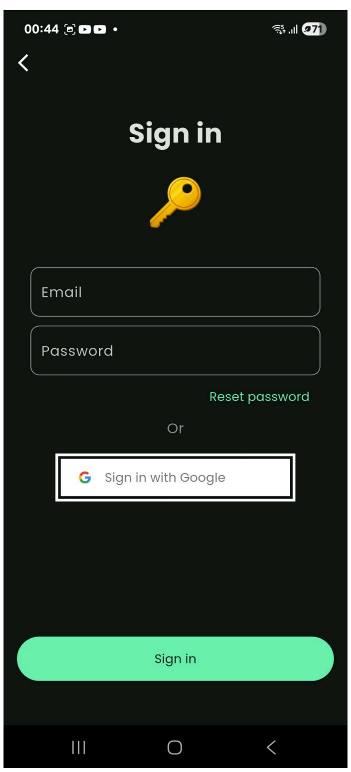


Figure 6.3.3 login

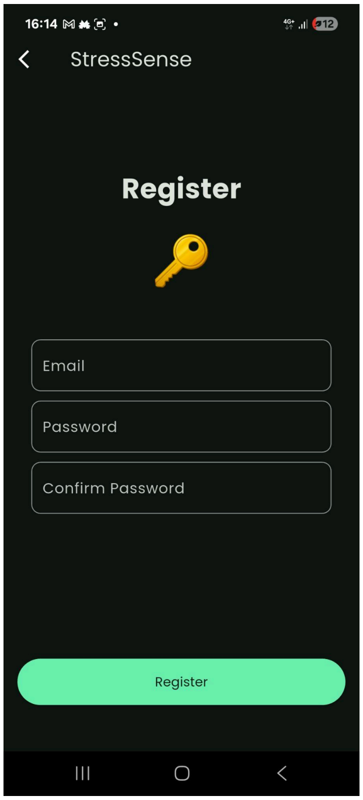


Figure 6.3.4 unconnected_state

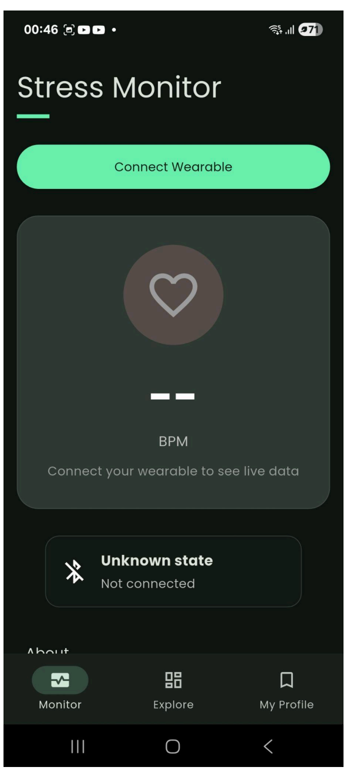


Figure 6.3.5 connected_state

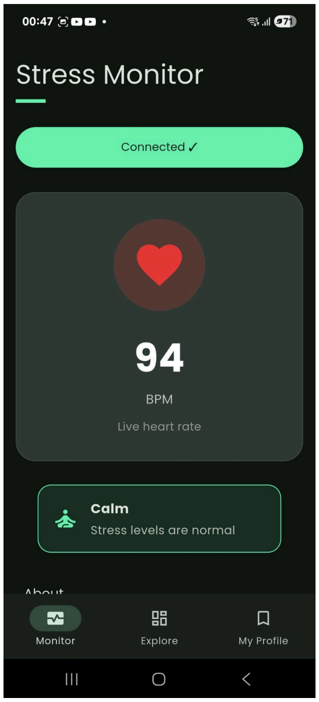


Figure 6.3.6 Stress_Graph

Figure 6.3.7 Stress_of_last_seven_days

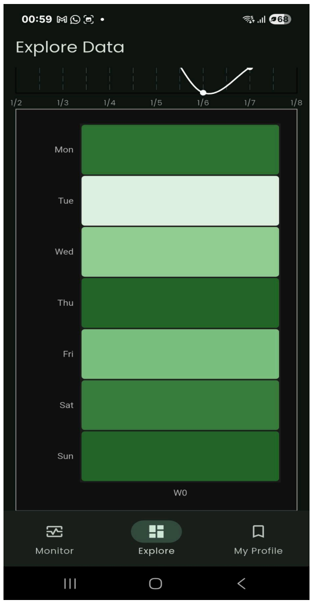


Figure 6.3.8 Bar_chart_seven_days

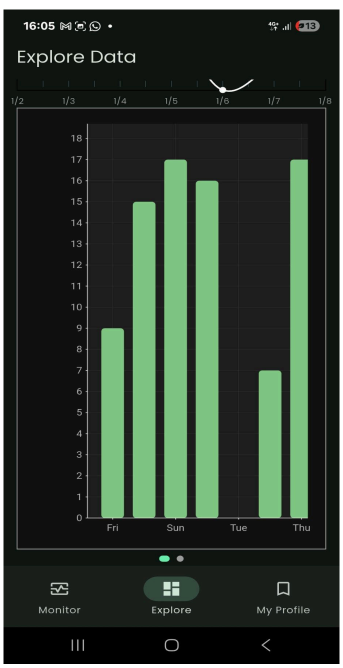
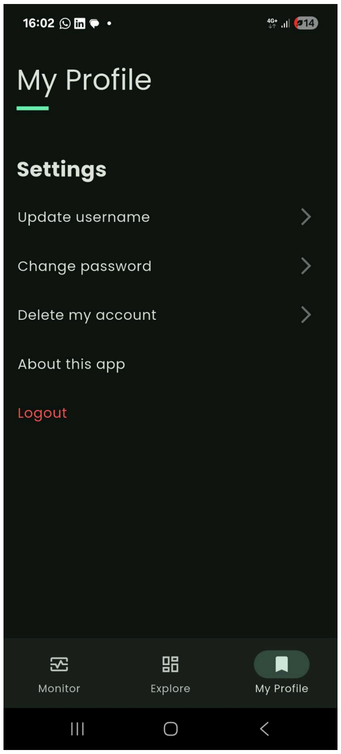


Figure 6.3.9 My_profile



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