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Title: **Calm Check**

Project Report

First-year Hardware Project

School of ICT

Metropolia University of Applied Sciences

1. Abstract

Heart rate variability (HRV) is an important measure of cardiovascular health and function, and photoplethysmography (PPG) is a non-invasive technique commonly used to measure HRV. However, accurate measurement and analysis of PPG signals can be challenging due to various factors that affect signal quality and variations across individuals. In this study, an algorithm for measuring HRV using PPG signals was developed using an embedded system approach with the Raspberry Pi Pico microcontroller and MicroPython firmware. The algorithm utilizes strategies for detecting the peak-to-peak interval (PPI) and heart rate (HR) in the PPG signal, as well as pre-processing techniques to reduce noise and artifacts. The implementation and results of the algorithm are presented and discussed, highlighting the potential implications for future developments in HRV monitoring using PPG signals.

Ver	Description	Date	Author(s)
1.0	Created structure for the project report. Added instructions for what should be included in the different parts of the document.	13.3.2023	Saana Vallius
1.1	Added Instructions (REMOVE WHEN READY), minor editions.	14.3.2023	Sakari Lukkarinen
1.2	Highlighted all instructions with red font.	19.3.2023	Sakari Lukkarinen
1.3	Updated Appendix 2 based on comments. Updated table of contents.	22.3.2023	Saana Vallius

Contents

2. *Introduction*

Heart rate variability (HRV) is a measure of the variation in time between successive heartbeats, and it provides valuable information about the health and function of the cardiovascular system. Photoplethysmography (PPG) is a non-invasive technique that uses light to detect changes in blood volume in the microvasculature of the skin, and it is commonly used to measure HRV.

However, accurately measuring, and analysing PPG signals can be challenging due to various factors that affect signal quality, such as motion artifacts, ambient light interference, and signal noise. Additionally, there can be significant variations in PPG signals across individuals, which can impact the accuracy and reliability of HRV measurements.

To address these challenges, this study aimed to develop an algorithm for accurately measuring HRV using PPG signals. An embedded system approach was used, specifically the Raspberry Pi Pico microcontroller and MicroPython firmware, for collecting and analysing PPG signals. A Txt file was used to test the algorithm.

This article is organized as follows. Section 3 provides a theoretical background on HRV and PPG, including an overview of the physiological factors that influence HRV, the challenges associated with measuring HRV using PPG, and the range of values in a PPG signal and variations across individuals. Section 4 describes the methods and materials used in the study, including details on the embedded system and software used for PPG signal processing and analysis. Section 5 presents the implementation of the algorithm, including strategies for detecting the peak-to-peak interval (PPI) and heart rate (HR) in the PPG signal. Finally, Section 6 provides a discussion of the results and potential implications of this research for future developments in HRV monitoring using PPG signals.

3. Theoretical background

Personalized medicine has exposed wearable sensors as new sources of biomedical data which are expected to accrue annual data storage costs of approximately $7.2 trillion by 2020 (>2000 exabytes). To improve the usability of wearable devices in healthcare, it is necessary to determine the minimum amount of data needed for accurate health assessment. (Bent B and Dunn JP, 2020, p.1)

Sampling rate refers to the rate, or frequency, at which data are collected per second. For continuous monitoring of the electrical activity of the heart and heart rate variability (HRV) using the electrocardiogram (ECG), data are typically sampled at 1000 Hz which requires approximately 192 kB/second of data storage. Because of the extensive storage requirements of continuous data and challenges surrounding its interpretability, the current data from continuous monitors like ECG are only stored in the EHR as summaries of the raw (signal-level) data. However, it would be useful to preserve this raw data for research and clinical applications that include the development of algorithms and digital biomarkers for improved patient care and understanding of physiology.
Monitoring of vital signs has traditionally been limited to clinical visits with few exceptions. This provides a very small window into a patient's daily health and wellness. Continuous monitoring using wearable sensors provides a more comprehensive view of a patient. While wearable sensors generally sample at a much lower rate than ECG to preserve battery life, they also provide longitudinal data, which could lead to a data deluge. Determining the minimum sampling rates required for wearable sensors to be relevant for clinical and research use will enable the use of this data within the clinical research ecosystem. Another motivation to decrease the sampling rate is the trade-off between battery power consumption and sampling rate. Higher sampling rates have increased power consumption, which decreases battery life. (Voss A, et al, 1995)

3.1 Heart Rate Variability(HRV)

HRV is simply a measure of the variation in time between each heartbeat. This variation is controlled by a primitive part of the nervous system called the autonomic nervous system (ANS). It works behind the scenes, automatically regulating our heart rate, blood pressure, breathing, and digestion among other key tasks. The ANS is subdivided into two large components: the sympathetic and the parasympathetic nervous system, also known as the fight-or-flight mechanism and the relaxation response. (Harvard Health Publishing Staff, 2021, p.3)

Heart rate variability (HRV) is the temporal variation between sequences of consecutive heartbeats. On a standard electrocardiogram (ECG), the maximum upwards deflection of a normal QRS complex is at the peak of the R wave (Figure 1), and the duration between two adjacent R wave peaks is termed the R-R interval. (QJM, 2005, p.87)

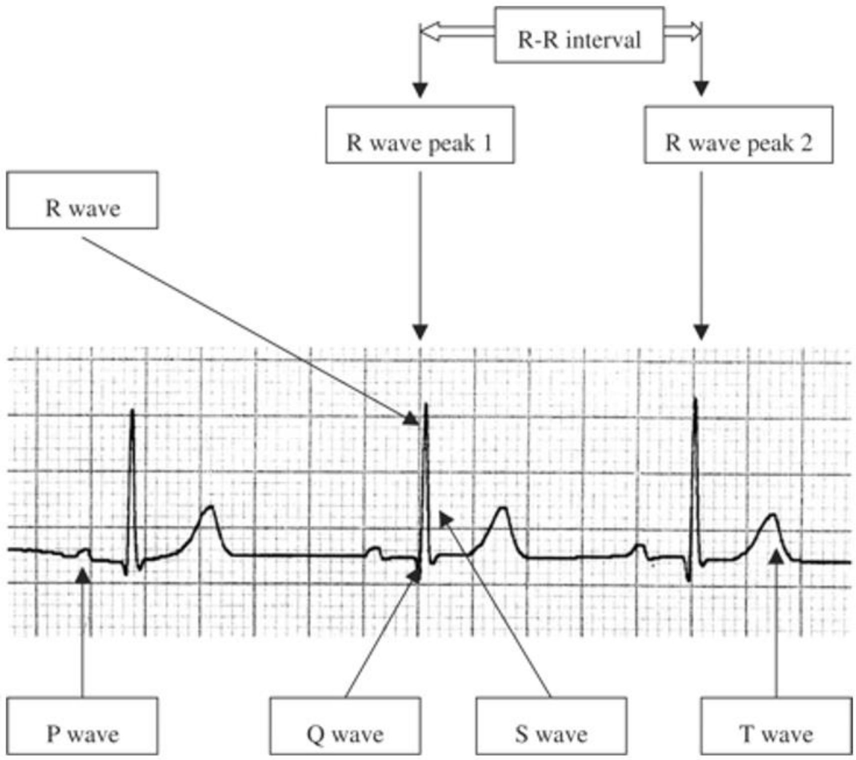

Figure 1. *The normal electrocardiogram with component waves labelled.*

The brain is constantly processing information in a region called the hypothalamus. The ANS provides signals to the hypothalamus, which then instructs the rest of the body to stimulate or relax different functions. It responds not only to a poor night of sleep, or that sour interaction with your boss, but also to the exciting news that you got engaged, or to that delicious healthy meal you had for lunch. Our body handles all kinds of stimuli and life goes on. However, if we have persistent instigators such as stress, poor sleep, unhealthy diet, dysfunctional relationships, isolation or solitude, and lack of exercise, this balance may be disrupted, and your fight-or-flight response can shift into overdrive. (Harvard Health Publishing Staff, 2021)

3.2 Problems with measuring HRV

To detect HRV changes over a period of hours or days requires a large volume of ECG data to be collected and analysed. This has traditionally been done with Holter devices that record the ECG in out-patients over periods from 24 h up to several weeks. Data can also be collected from patients who are monitored in the hospital (Figure 2). Data capture on dynamic changes in HRV in the period prior to arrhythmias or ischaemic events is harder to attain, due to the relative infrequency of such events. In the laboratory environment, studies of patients with exercise or electrically induced VT are possible, and implanted cardio-defibrillator devices (ICDs), are able to store information prior to an episode of ventricular fibrillation (VF) or ventricular tachycardia (VT). (QJM, 2005, p.89)

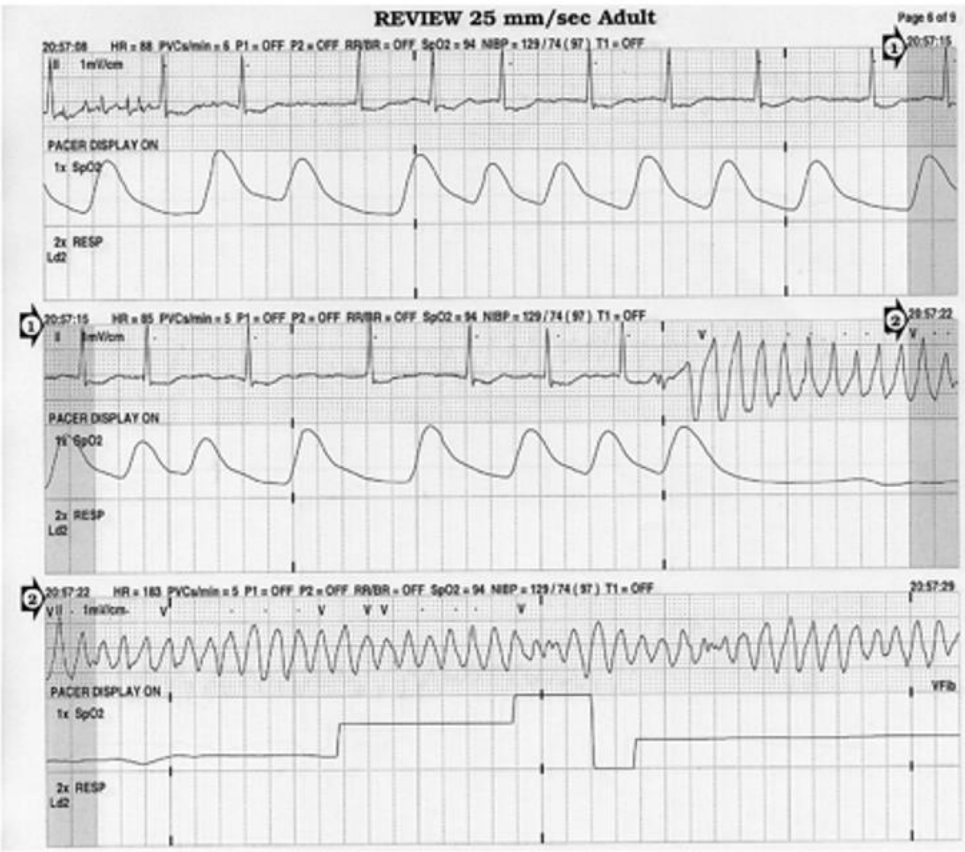

Figure 2. *A section of an ECG waveform and oxygen saturation waveform obtained from an Emergency Department monitor.*

3.3 *Photoplethysmography (PPG) signal*

Photoplethysmography (PPG) is a low-cost, non-invasive, and optical technique used to detect blood volume changes in the microvascular tissue bed, measured from the skin surface. It has traditionally been used in commercial medical devices for oxygen saturation, blood pressure monitoring, and cardiac activity for assessing peripheral vascular disease and autonomic function. There has been a growing interest to incorporate PPG sensors in daily life, capable of use in ambulatory settings. However, inferring cardiac information (e.g., heart rate) from PPG traces in such situations is extremely challenging, because of interferences caused by motion. Following the IEEE Signal Processing Cup in 2015, numerous methods have been proposed for estimating particularly the average heart rate using wrist-worn PPG during physical activity. Details on PPG technology, sensor development, and applications have been well-documented in the literature. (D. Biswas et al., 2019)

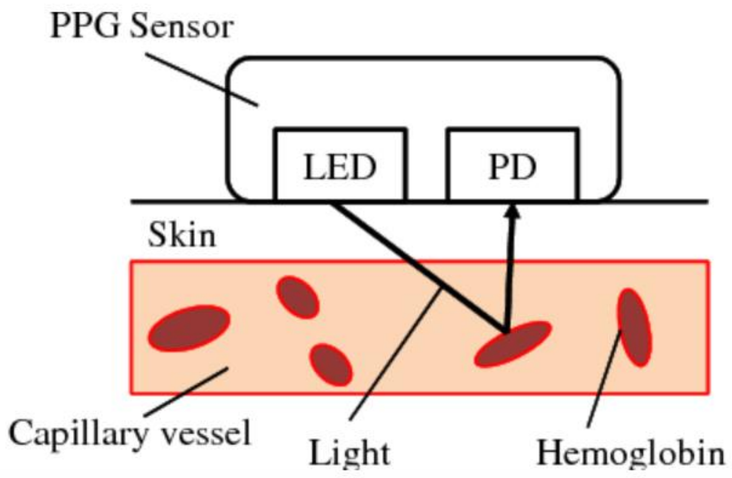

Figure 3. Structure of detecting PPG by receiving the reflected light.

3.4 Physiological factors

Non-influenceable physiological factors include age, gender, and circadian rhythm. A person’s HRV first increases sharply until they reach the age of one and continues to increase considerably until they reach the age of 15, while the resting heart rate decreases. Their HRV then decreases as they grow older. It also seems clear that there is a difference between men and women in the way the autonomous nervous system is regulated and thus in the sympathetic-parasympathetic balance, and this manifests itself in differing HRVs. This difference between the genders seems to become less prominent when people reach the age of 50, a fact that is attributed to the postmenopausal hormonal changes that take place in women. HRV, like a few other physiological parameters, is subject not only to age and gender but also to a circadian rhythm. This must be taken into account with short-term measurements ranging from a few minutes to a few hours are made. HRV increases at night and decreases considerably during the morning hours. (Summit S, Böckelmann I., 2016)

- ***Diseases***

The effects of various diseases on HRV have been examined in many studies. HRV is lower throughout among patients with the diseases concerned than healthy test persons. Lifestyle habits. In addition to these non-influenceable physiological factors, there are further factors, notably those related to the lifestyle habits of the test persons. These can have both a positive and a negative influence on HRV. They include physical fitness or sporting activity, increased body weight, which is sometimes negatively associated with the first two factors, active and passive smoking, and regular alcohol abuse. People who have an free fatifestyle and maintain a good or high level of physical fitness or above-average sporting activity can achieve an increase in their basic parasympathetic activity and thus an increase in their HRV. Cumulative or too-intensive sporting activity (e.g. competition series, overtraining syndrome), however, brings about a decrease in HRV52,54. In contrast, elevated body weight or elevated free-fat mass correlates with a decrease in HRV. Both active and passive smoking led to an increase in HRV. Regular chronic alcohol abuse above the alcohol quantity of a standard drink for women or two standard drinks for men reduces HRV, while moderate alcohol consumption up to these quantities does not change the HRV and is not associated with an increase. (Summit S, Böckelmann I., 2016)

- ***External Factors***

In addition to climatic conditions and job-related parameters, several harmful substances and medications also have a direct or indirect influence on HRV. Climatic factors lead to changes in HRV due to the physiological reaction of the vegetative nervous system. Heat increases sympathetic nervous system activity, reducing HRV. Long-term exposure to cold (e.g., at work or during the winter months) has not been found to have an influence on HRV. Due to adaptation effects, e.g., after 60 days. Exposure to noise likewise leads to a decrease in HRV because it increases sympathetic nervous system activity. Induced pain also results in a lowering of HRV due to the activation of the physiological sympathetic nervous system. (Summit S, Böckelmann I., 2016)

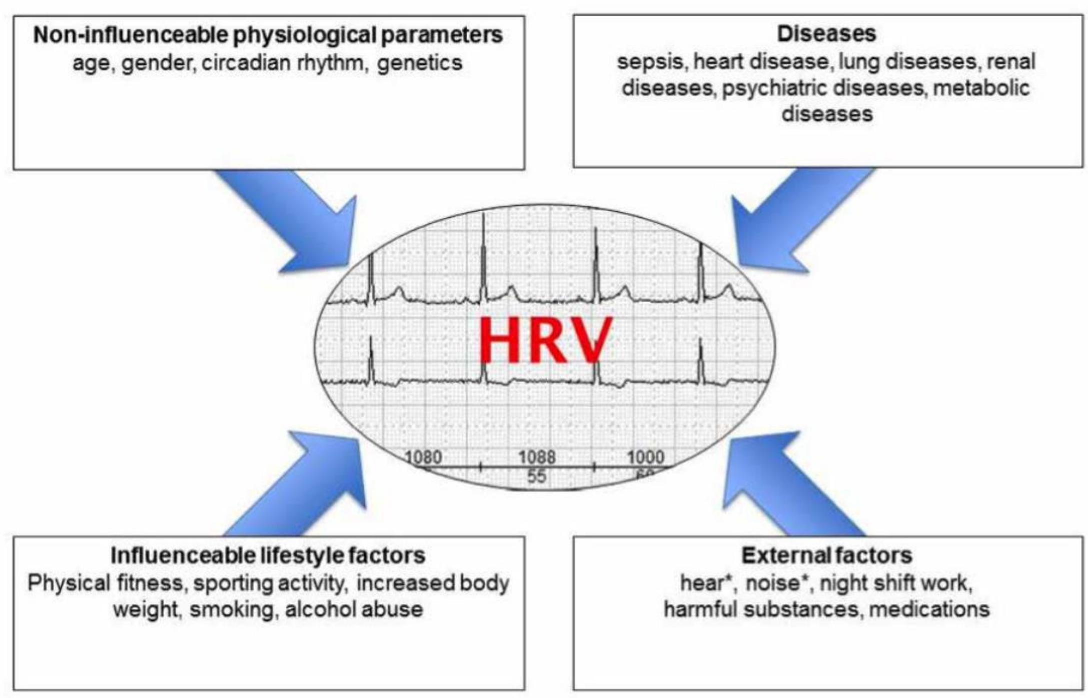

*Figure 4. The different factors influencing HRV grouped into four main areas, * = HRV decrease as a result of a physiological reaction to a physical stimulus. Provides a summary of the results referring to the factors and covers the four main areas, i.e. non-influenceable physiological factors, illnesses, influenceable lifestyle factors, and external factors*

3.5 PPG Signal (Variations Across Individuals)

The range of values in a PPG signal can vary from person to person depending on factors such as age, fitness level, and medical conditions. However, in general, the amplitude of the PPG signal is usually in the range of a few hundred millivolts to a few volts, and the frequency of the signal is typically in the range of 0.5 to 5 Hz.

The exact range of values can also depend on the type of sensor or equipment used to measure the PPG signal. For example, a photoplethysmography sensor attached to a finger may produce a different range of values compared to a sensor attached to an earlobe or forehead.

It's important to keep in mind that the absolute values of the PPG signal may not be as important as the relative changes in the signal over time, which are used to detect the heart rate and other physiological parameters. Therefore, it's more important to focus on the shape and characteristics of the PPG signal rather than the absolute values of the signal.

4. Methods and materials

4.1 Embedded Systems

An embedded system is a combination of both hardware and software, consisting of a microprocessor, memory for storing data and programs, converters microcontroller or digital signal processors (DSP), sensors, actuators, and other interfaces. It would not be wrong to say that there are computers on all devices. All into “embedded” computers there. Small devices with embedded systems such as Raspberry Pi, and Arduino can collect patient data and provide data processing with overwritten software, with a reduction in size and an increase in processing power. Similar small devices with embedded systems can make control decisions that can help provide better treatments and medications to patients.

Small designs with microcontrollers, sensors, motor drivers, and sensors are also increasing. It provides practical and inexpensive solutions applied in case of any urgent need. (Płaczek B, 2021)

Microcontrollers, one of the basic parts of embedded systems, can be defined as single-chip computers. They contain a microprocessor, memory, digital inputs-outputs, and other peripherals (a timer, interrupt, ADC, etc.)

The embedded system in this project is Raspberry Pi, Pico.

4.1.1 Raspberry Pi Pico

A Raspberry Pi Pico is a low-cost microcontroller device. Microcontrollers are tiny computers, but they tend to lack large-volume storage and peripheral devices that you can plug in (for example, keyboards or monitors).

A Raspberry Pi Pico has GPIO pins, much like a Raspberry Pi computer, which means it can be used to control and receive input from a variety of electronic devices.

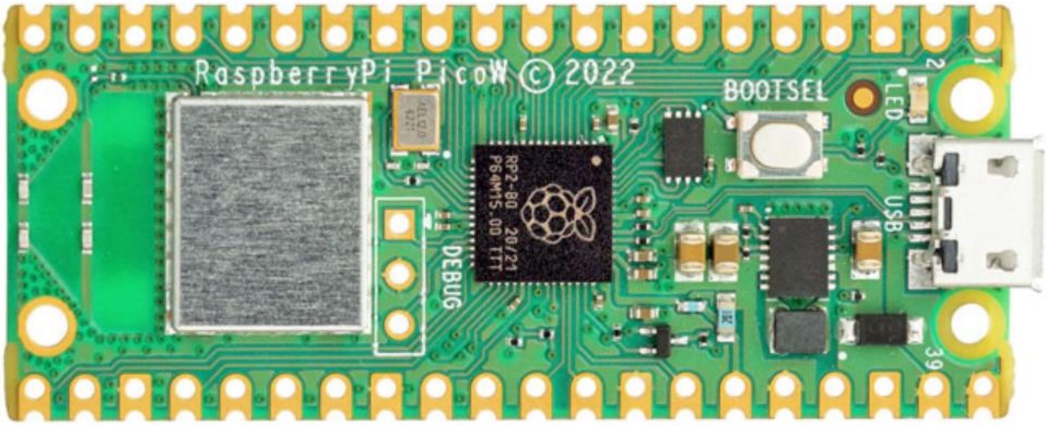

Figure 5. Raspberry Pi Pico

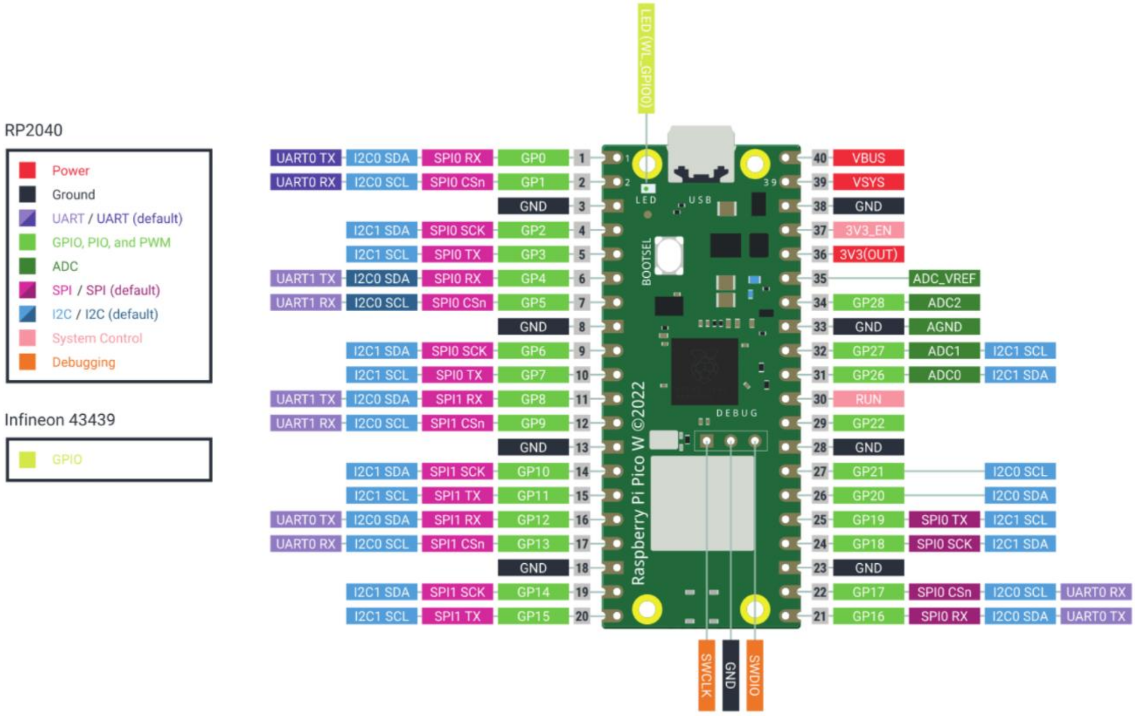

Figure 6. Raspberry Pi Pico components

4.2 Restrictions

When coding on an embedded system, it is necessary to pay attention to the detail between optimization and readability of the code. If there is enough memory, a readable code may be preferred instead of optimization. Many certification processes are required for the newly developed product.

4.3 Software

Embedded system development is also changing rapidly. While working with microcontrollers with small-sized resources in the past, it is possible to talk about products that reach very high speeds today. Nowadays, subjects such as internet protocols and encryption algorithms appear as new study areas. Naturally, it is becoming a necessity to use ready-made modules on the platforms we work with. As programming becomes increasingly complex, we now need platforms that support us. The structure known as the Internet of

Things (IoT) has modules called “gateways” that will connect other modules and devices to the network. (Płaczek B, 2021)

The project will run through the installation of:

4.3.1 MicroPython firmware for Raspberry Pi Pico

MicroPython is a lean and efficient implementation of the Python 3 programming language that includes a small subset of the Python standard library and is optimized to run on microcontrollers and in constrained environments.

The MicroPython board is a compact electronic circuit board that runs MicroPython on bare metal, giving you a low-level Python operating system that can be used to control all kinds of electronic projects.

MicroPython is packed full of advanced features such as an interactive prompt, arbitrary precision integers, closures, list comprehension, generators, exception handling, and more. Yet it is compact enough to fit and run within just 256k of code space and 16k of RAM.

MicroPython aims to be as compatible with normal Python as possible to allow you to transfer code with ease from the desktop to a microcontroller or embedded system.

4.3.2 The Thonny Python IDE

Thonny is an open-source IDE that is used to write and upload Micro Python programs to different development boards such as Raspberry Pi Pico, ESP32, and ESP8266. It is an extremely interactive and easy-to-learn IDE as much as it is known as a beginner-friendly IDE for new programmers. With the help of Thonny, it becomes very easy to code in Micro Python as it has a built-in debugger that helps to find any error in the program by debugging the script line by line.

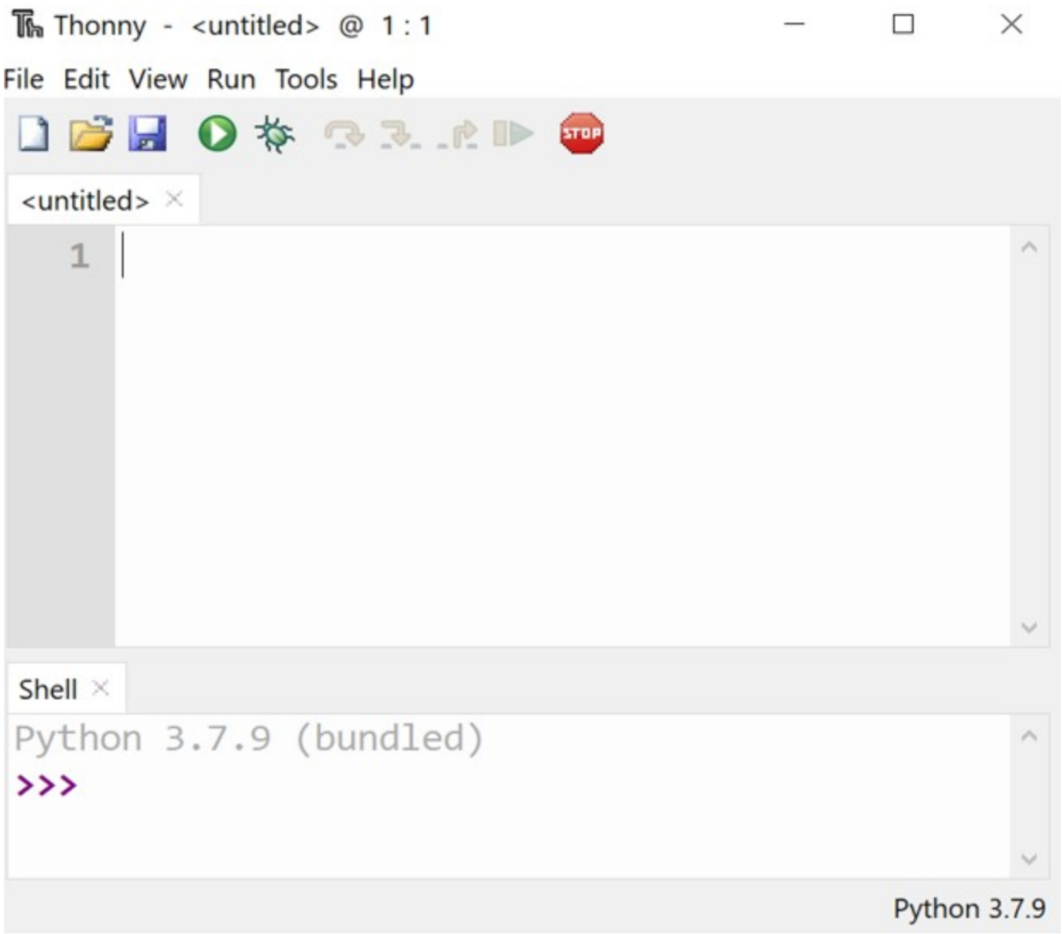

Figure 7. Thonny App overview.

4.4 Frequency and period

In MicroPython, timers can be set up either by specifying the frequency or the period.

Frequency refers to the number of cycles that occur in a unit of time, typically measured in Hertz (Hz), which represents the number of cycles per second. A timer with a frequency of 1 kHz would produce 1000 cycles per second.

Period, on the other hand, is the amount of time required for one complete cycle to occur. It is typically measured in seconds or fractions of a second. For example, a timer with a period of 1 ms would complete one cycle every millisecond.

The relationship between frequency and period is inverse: frequency can be calculated from period and vice versa.

4.5 Pulse detection

The PPG signal has periodic peaks, known as PPG waves or PPG peaks, which are caused by the expansion and contraction of the arteries during each heartbeat. These peaks can be detected and analysed to determine the heart rate. Typically, a PPG signal will have one peak per cardiac cycle, corresponding to the systolic phase of the cardiac cycle.

To detect the heart rate from the PPG signal, the time between successive PPG peaks needs to be measured. This time interval is called the peak-to-peak interval or PPI. Then the heart rate is calculated based on PPI.

Therefore, if the PPG peaks can be accurately detected, the heart rate can be calculated in real time by calculating the inverse of the peak-to-peak interval.

4.6 Peak-to-peak interval (PPI) and the heart rate (HR)

There are different ways to detect pulses from a PPG signal, and the most common methods are based on detecting either the positive peaks (maxima) or negative peaks (minima) of the signal or the rising/falling edges of the s Detecting rising or falling edges involves identifying the points in the PPG signal where the signal starts to rise or fall. This method is commonly used in research studies, as it provides a more accurate measure of the actual pulse waveform and can be used to analyse the shape of the pulse wave.

In practice, the choice of pulse detection method depends on the specific application and the characteristics of the PPG signal being analysed. Each method has its advantages and disadvantages, and different algorithms can be used to optimize performance based on the specific requirements of the application.

4.7 Finding the positive peak by slope inspection

The idea is to use numerical differentiation to approximate the slope of the PPG signal by calculating the difference between two successive samples of the signal. This method is known as finite difference approximation, and it provides an estimate of the slope at each point in the signal.

In the case of PPG signals, the shape of the signal often suggests that the slope is positive before the local maximum and negative after the maximum. This is because the PPG signal typically has a characteristic shape with a sharp rise and a slower decay, resulting in a positive slope before the peak and a negative slope after the peak.

By using the finite difference method to approximate the slope of the PPG signal, we can detect the local maximum (positive peak) by looking for the point where the slope changes sign from positive to negative. This can be done using a simple algorithm that compares the slope of each sample with the slope of the previous sample.

4.8 Challenges with PPG signal

While PPG signals can be a useful tool for measuring heart rate and other physiological parameters, there are several challenges that can make signal analysis difficult.

PPG signals can be affected by various types of noise and interference, such as ambient light, electrical noise, and physiological noise. These artifacts can make it difficult to detect the pulse accurately and can lead to erroneous results.

PPG signals can vary significantly between individuals, and even within the same individual under different conditions. This can make it difficult to establish reliable baseline measurements or to compare results between individuals or studies.

4.9 Dealing with challenges

To overcome these challenges, researchers and developers use advanced algorithms and signal-processing techniques to improve the accuracy and reliability of PPG-based measurements.

4.10 Pre-processing PPG signal with digital filtering signal

Digital filtering techniques are often used in combination with other pre-processing techniques, such as baseline correction and artifact removal, to improve the accuracy and reliability of pulse detection. The choice of filter depends on the specific characteristics of the PPG signal being analysed and the requirements of the application. It is also important to carefully tune

the filter parameters to balance noise reduction with signal distortion and avoid over-filtering or under-filtering the signal.

The threshold can be set between the minimum and maximum values of the signal, and when the signal crosses the threshold for the first time, the count begins. When the signal drops below the threshold (with some margin) the count is stopped, and the resulting count represents the interval between two beats.

The margin is typically added to account for noise and small variations in the signal, which can cause false detections if the threshold is set too close to the signal amplitude. The margin can be a fixed value or can be adaptive based on the signal characteristics or the estimated noise level.

Once the pulse interval is calculated, the heart rate can be derived by taking the inverse of the interval (i.e., HR = 1/interval). This approach is relatively simple and computationally efficient and can be implemented in real-time on microcontrollers or other embedded systems.

4.11How to test the system

To test measuring heart rate involves validating the accuracy of the algorithm's results against known or expected values, a set of data is typically used to compare the algorithm's outputs with the expected values.

In this case, the data used to test the heart rate measuring algorithm was provided in a Txt file format(capture03-250Hz), and this file contained data that falls within a suitable range. This means that the data provided for testing was representative of the range of heart rate values that the algorithm is designed to measure, and the data was suitable for use in validating the algorithm's accuracy.

This provides confidence in the algorithm's ability to accurately measure heart rate in other situations where similar ranges of data are expected while using the optical sensor.

5. Implementation

The whole idea is to collect heart rate data using MicroPython at a rate of 750 samples per second. The data was then processed to calculate the average heart rate and remove noise created by the sampling process.

To collect the data, a MicroPhython device was connected to a heart rate sensor, and the subject was instructed to remain still while the data was being collected. The data was recorded in a list with 750 characters, representing 250 Hz per second.

Once the data was collected, the average heart rate was calculated by taking the mean of the data points. To remove noise created by the sampling process, local maxima were determined, and any data points below the average were deleted. However, some local maxima were above the average, so a threshold of 70 percent of the average heart rate was used to filter out these outliers.

After filtering the data, the PPI (peak-to-peak interval) was calculated by finding the time interval between 2 or 3 sequential maximum values in the list. The list was then cleared, and the process was repeated to collect additional data.

The heart rate was calculated using this formula:

$$HR = \frac{60}{PPI/_{1000}}$$

Formula1:HR measurement

The resulting data was then analysed to determine the accuracy of the heart rate monitoring algorithm. Graphs were generated to visualize the data and illustrate the effectiveness of the algorithm.

Overall, the use of MicroPhython to collect and analyse heart rate data proved to be an effective method for monitoring heart rate. The algorithm was able to accurately calculate heart rate while minimizing the impact of noise created by the sampling process and outliers. By using the PPI method to analyse the data, the algorithm was able to provide more detailed information about heart rate fluctuations over time.

The steps that are done so far, take into consideration below.

The file provided on GitLab was used to not only develop a step-by-step process to write an algorithm but also to test the algorithm.

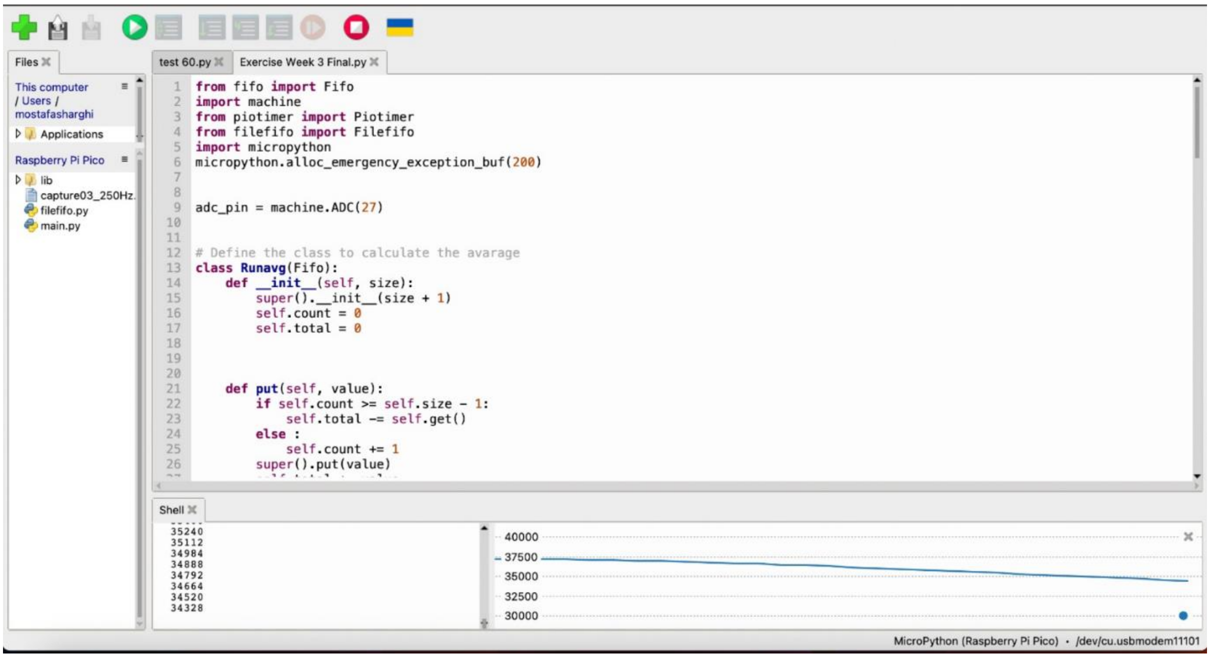

Figure 8. Using provided Txt file to test the algorithm.

6. Heart Rate Variability (HRV) Analysis

Heart rate variability (HRV) refers to the changes in time intervals between successive heartbeats. These changes are very small, measured in milliseconds, but can provide valuable information about the balance between the sympathetic and parasympathetic nervous systems, which regulate various bodily functions. HRV is typically highest when we are in a state of rest and relaxation and decreases during physical activity or stress, indicating increased sympathetic nervous system activity. The magnitude of HRV can vary between individuals and is influenced by a range of factors such as age, lifestyle, and health status. HRV analysis is a useful tool for monitoring health and can be used to diagnose or manage various medical conditions.

6.1 Basic HRV Analysis

To analyse HRV, various parameters are calculated, which can be divided into three categories:

- time domain:

HRV analysis in the time domain involves calculating parameters that describe the statistical characteristics of the inter-beat interval (IBI) time series. Two commonly used time domain parameters are RMSSD and SDNN.

- RMSSD measures the root mean square of the differences between successive IBIs, which provides information about beat-to-beat variability. This parameter is strongly associated with the activity of the parasympathetic nervous system, which regulates many bodily functions during rest and recovery.

  For stationary series, SDSD equals the root mean square of successive differences (RMSSD) given by:

$$\mathrm{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}(\mathrm{RR}_{n+1} - \mathrm{RR}_n)^2}.$$

Formula2: RMSSD measurement

- SDNN, on the other hand, measures the standard deviation of all the IBIs over a given period, providing a measure of overall HRV. This parameter reflects the activity of both the sympathetic and parasympathetic nervous systems, which work together to maintain the balance between bodily functions during rest and activity.

  The standard deviation of RR (or PP) intervals (SDNN) is defined as:

$$\mathrm{SDNN} = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(\mathrm{RR}_n - \overline{\mathrm{RR}})^2}$$

Formula3: SDNN measurement

HRV analysis in the time domain provides valuable information about the variation in the IBI time series, which is influenced by the autonomic nervous system activity. The choice of time domain parameters depends on the research question or clinical application and can provide different types of information about the autonomic function.

- frequency domain:

Frequency domain parameters use mathematical techniques to decompose the IBI time series into different frequency bands, such as low frequency (LF) and high frequency (HF), which represent different physiological mechanisms. LF reflects the activity of the sympathetic nervous system, while HF reflects the activity of the parasympathetic nervous system. The LF/HF ratio is also commonly used to indicate the balance between the sympathetic and parasympathetic nervous systems.

- nonlinear parameters:

Nonlinear parameters use more complex mathematical techniques to examine the complex and irregular patterns of the IBI time series. These parameters can provide insights into the complexity and adaptability of the cardiovascular system.

HRV analysis is a valuable tool for assessing autonomic nervous system function and can be used to monitor health and diagnose various medical conditions. Different HRV parameters can provide different types of information, and the choice of parameters depends on the research question or clinical application.

In this project, the time-domain parameter was used. In one measurement the parameters amounts were: (Appendic5)

- ✓ Mean PPI = 786 Ms
- ✓ Mean HR = 76 bpM
- ✓ SDNN = 154 Ms
- ✓ RMSSD = 205 Ms

These amounts can be different in every single measurement depending on the PPI and HR amount.

6.2 KubiosCloud Analysis

6.2.1 HRV In Evaluating Autonomic Nervous System (ANS) Function

The ANS, which controls the heart rate, has two branches - the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS). The PNS slows down the heart rate and increases HRV, while the SNS increases the heart rate and decreases HRV.

When individuals are at rest and fully recovered, the PNS is dominant, resulting in a low heart rate and high HRV. During stressful situations, the SNS is activated, leading to an increase in the heart rate and a decrease in HRV. This is because the SNS prepares the body for a fight or flight response, which requires a fast and regular heart rate to pump more blood to the muscles and vital organs. As a result, the heart rate becomes less variable, and the time between successive heartbeats becomes more consistent.

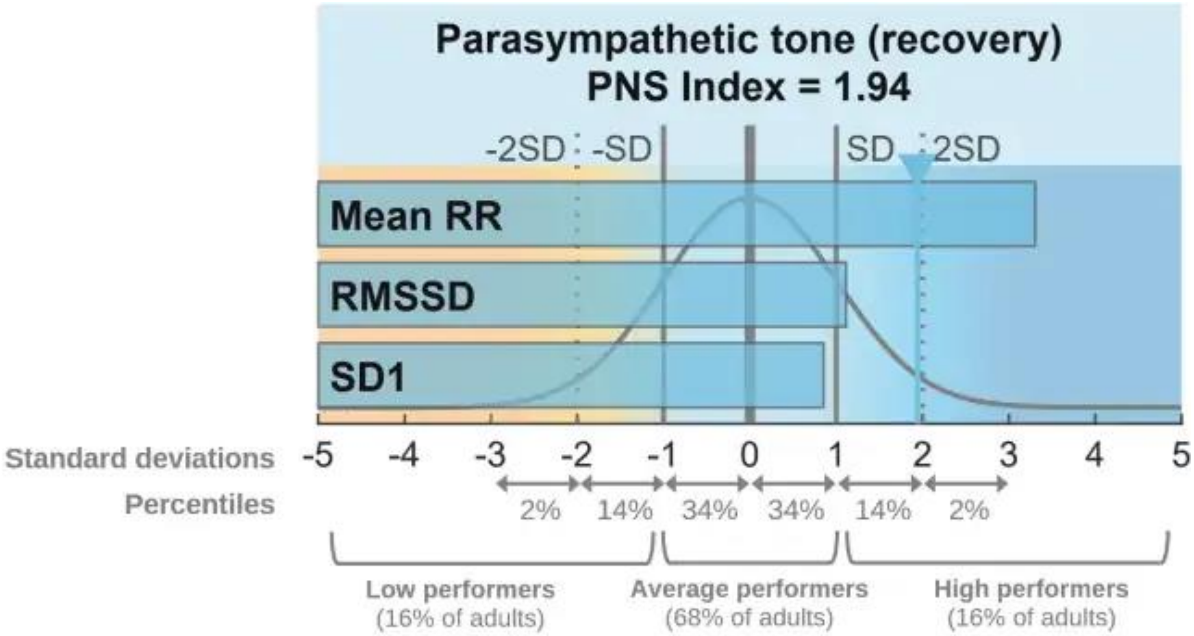

Figure9: Parasympathetic tone(recovery)

6.2.1.1 A brief interpretation of PNS:

During stress or high-intensity exercise, the PNS index value is expected to decrease below the average population level of 0 SDs. This is because sympathetic nervous system activity is increased, leading to a decrease in parasympathetic activity. A lower PNS index value during stress or high-intensity exercise may indicate a decreased ability to recover or adapt to the stressor. Tracking changes in PNS index values over time can provide insight into an individual's autonomic nervous system function and overall health status.

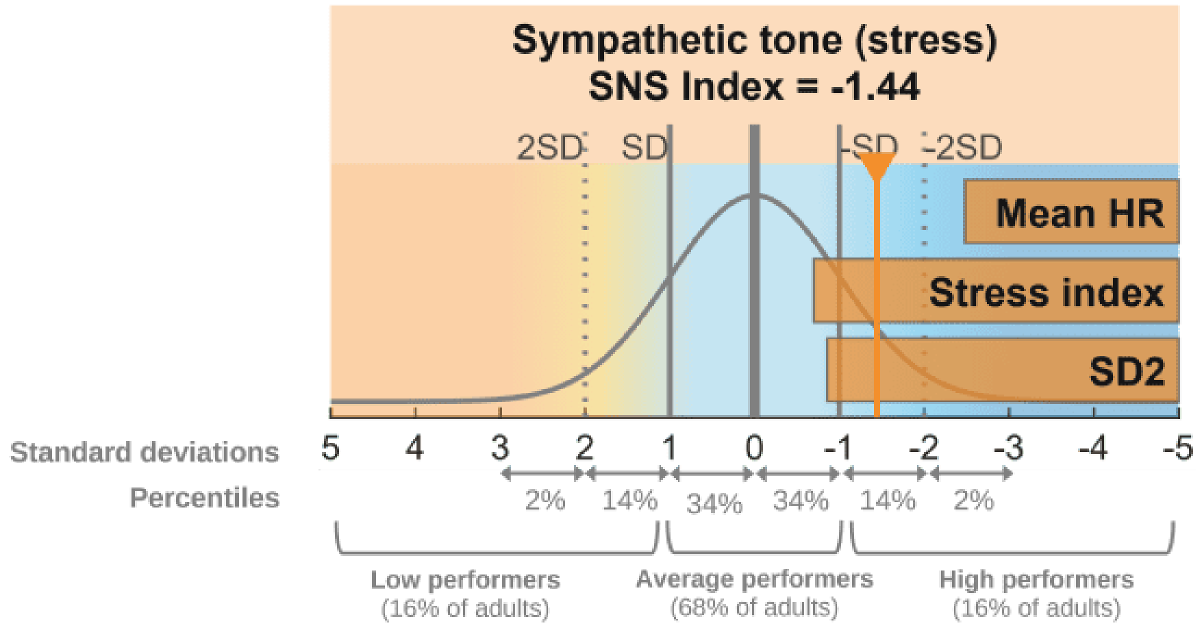

Figure10: Sympathetic tone(stress)

6.2.1.2 A brief interpretation of SNS:

During stress or high-intensity exercise, the SNS index value can increase above the average population level of 0 SDs. This is because sympathetic nervous system activity is increased in response to the stressor. A higher SNS index value during stress or high-intensity exercise may indicate a higher level of stress or a reduced ability to cope with the stressor. Tracking changes in SNS index values over time can provide insight into an individual's autonomic nervous system function and stress response. The SNS index can have values as high as 5-35 during stress or high-intensity exercise, depending on the individual's physiological response.

6.2.2 Kubios Analytics

Kubios Analytics helps analyse data related to heart rate variability (HRV). It uses algorithms that have been scientifically validated and widely accepted in research studies. The software can analyse short recordings of heart rate data, making it useful for studies that require frequent measurements. Kubios Analytics includes features such as beat correction and trend removal algorithms, which can help improve the accuracy of HRV analysis. The RESTful API enables Kubios Analytics to be integrated with other applications or platforms.

When using the Raspberry Pi Pico W, the uRequests module allows users to initiate communication with servers by making HTTP requests. The module supports various types of requests, such as HEAD, GET, POST, PUT, PATCH, and DELETE, which allow users to perform specific actions or retrieve certain types of data. By combining uRequests with a created HTTP packet, users can send and receive data to and from the cloud. This can be useful in a variety of applications, such as accessing online databases or sending sensor data to cloud-based servers. The integration of uRequests and HTTP packets provides a straightforward method for initiating and managing internet communication from the Raspberry Pi Pico W.

In this case study, data was gained by the sensor, and following that it was posted to Kubios (request). Data were analysed by Kubios, a response was sent by that, including a couple of parameters, PNS, SNS, and stress index were cases in point.

The amounts for once were: (Appendic7)

- ✓ Stress index = 5.6961
- ✓ PNS index = 1.53
- ✓ SNS index = -2.79

These amounts can vary depending on PPI, in addition to many other factors mentioned earlier.

7. Showing parameters on Raspberry Pi Pico W's OLED

All parameters explained above were shown on OLED in a specific order. To achieve that, a menu was designed where the user was able to choose an option. (Appendic4)

The selections on the menu were:

- Basic analysis
- KubiosCloud analysis
- Try again

The two first options are discussed earlier, the third is an option that provided users with doing the whole process as many times as they intend to gain information.

8. *Making Raspberry Pi Pico W work as an IoT system*

To carry out the plan, all necessary codes were saved on the Raspberry Pi Pico W, as the main.py file. As a result, when the Raspberry Pi Pico W was plugged in, the process was started.

It helps users to make use of the system without any need to connect any devices or take advantage of any software to run. (Appendic8)

9. *Conclusion*

Heart Rate Variability (HRV) is a non-invasive tool that has been widely used to evaluate the autonomic nervous system (ANS) function. HRV refers to the variation in the time intervals between consecutive heartbeats, and it has been associated with various physiological and pathological conditions. Photoplethysmography (PPG) is a popular technique for measuring HRV since it can be easily performed using a wearable device. However, there are challenges in measuring HRV using PPG due to variations across individuals and physiological factors, such as age, sex, and health status.

To overcome these challenges, pre-processing PPG signals with digital filtering signals is essential. In this context, the Raspberry Pi Pico microcontroller is a powerful embedded system that can be used to measure PPG signals and analyse HRV. The Raspberry Pi Pico is a low-cost, open-source microcontroller that is easy to use, making it an attractive option for researchers and practitioners. The Thonny Python IDE can be used to program the Raspberry Pi Pico microcontroller in MicroPython firmware, which allows for flexibility in signal processing and analysis.

KubiosCloud analysis is a cloud-based platform that provides an easy-to-use interface for HRV analysis. Additionally, Kubios Analytics can be used to analyse PNS and SNS functions. This method of HRV analysis using PPG signals and the Raspberry Pi Pico microcontroller has the potential to be used in various applications, including healthcare monitoring, fitness tracking, and stress management.

Finally, the Raspberry Pi Pico W's OLED can be used to show parameters and make it work as an IoT system. The OLED display allows for easy visualization of the parameters, and the IoT capability enables remote monitoring and data transmission. In summary, combining PPG signals, Raspberry Pi Pico, and Kubios Analytics offers a practical and effective solution for HRV analysis, which can contribute to health and wellness monitoring. Further research is needed to optimize this method and validate its accuracy and reliability in clinical and real-life settings.

10. References

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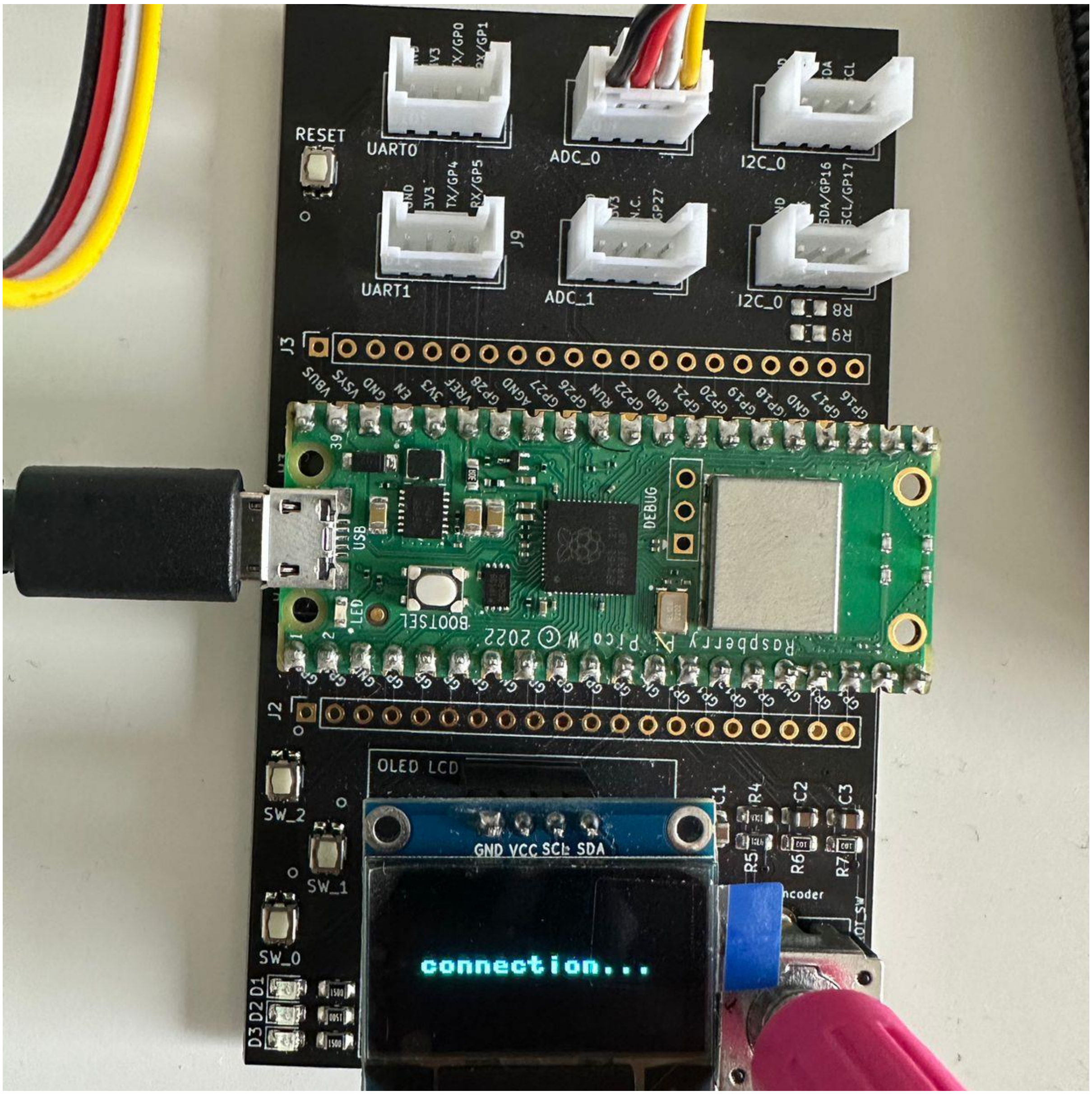
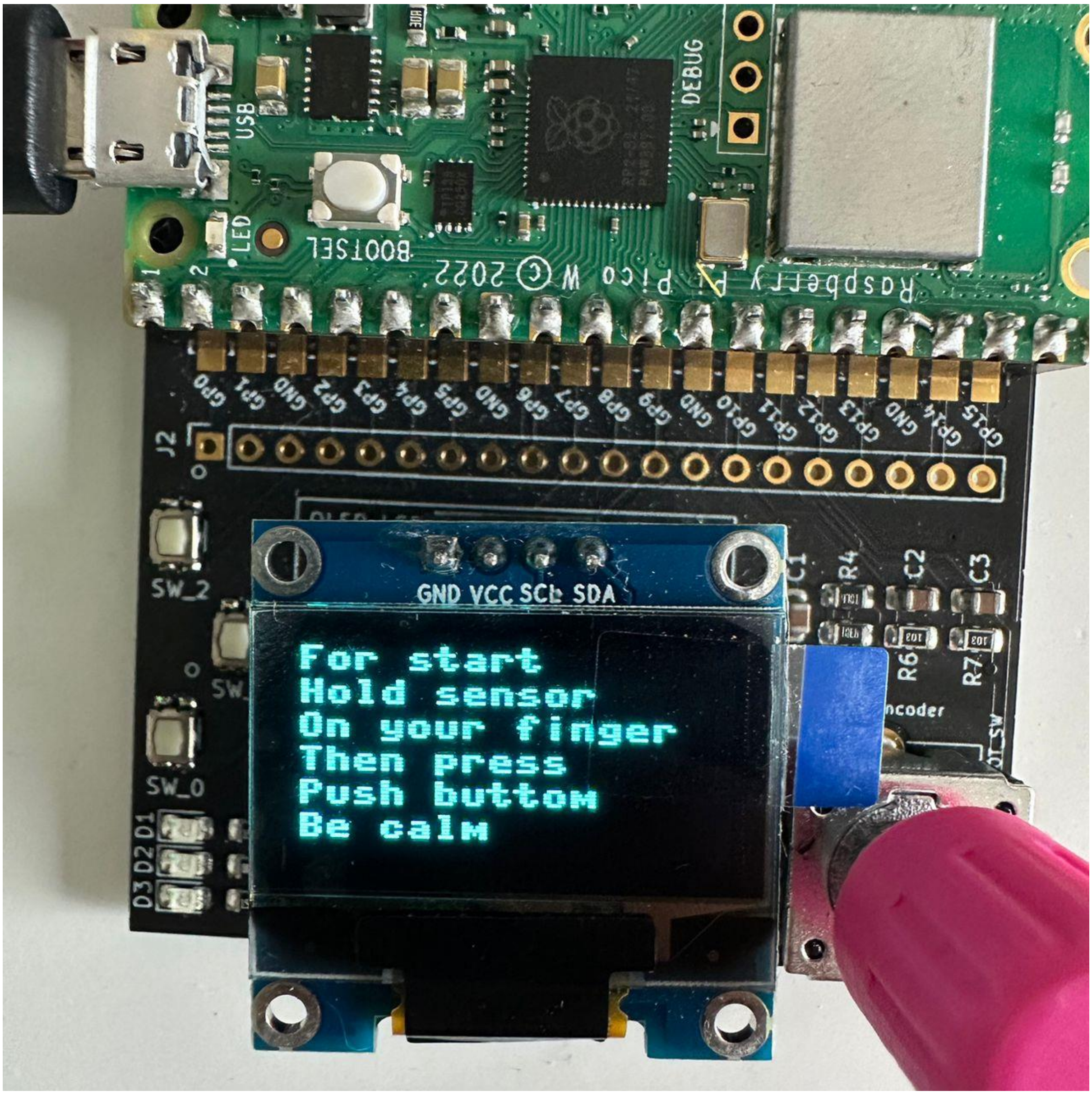
11. Appendices



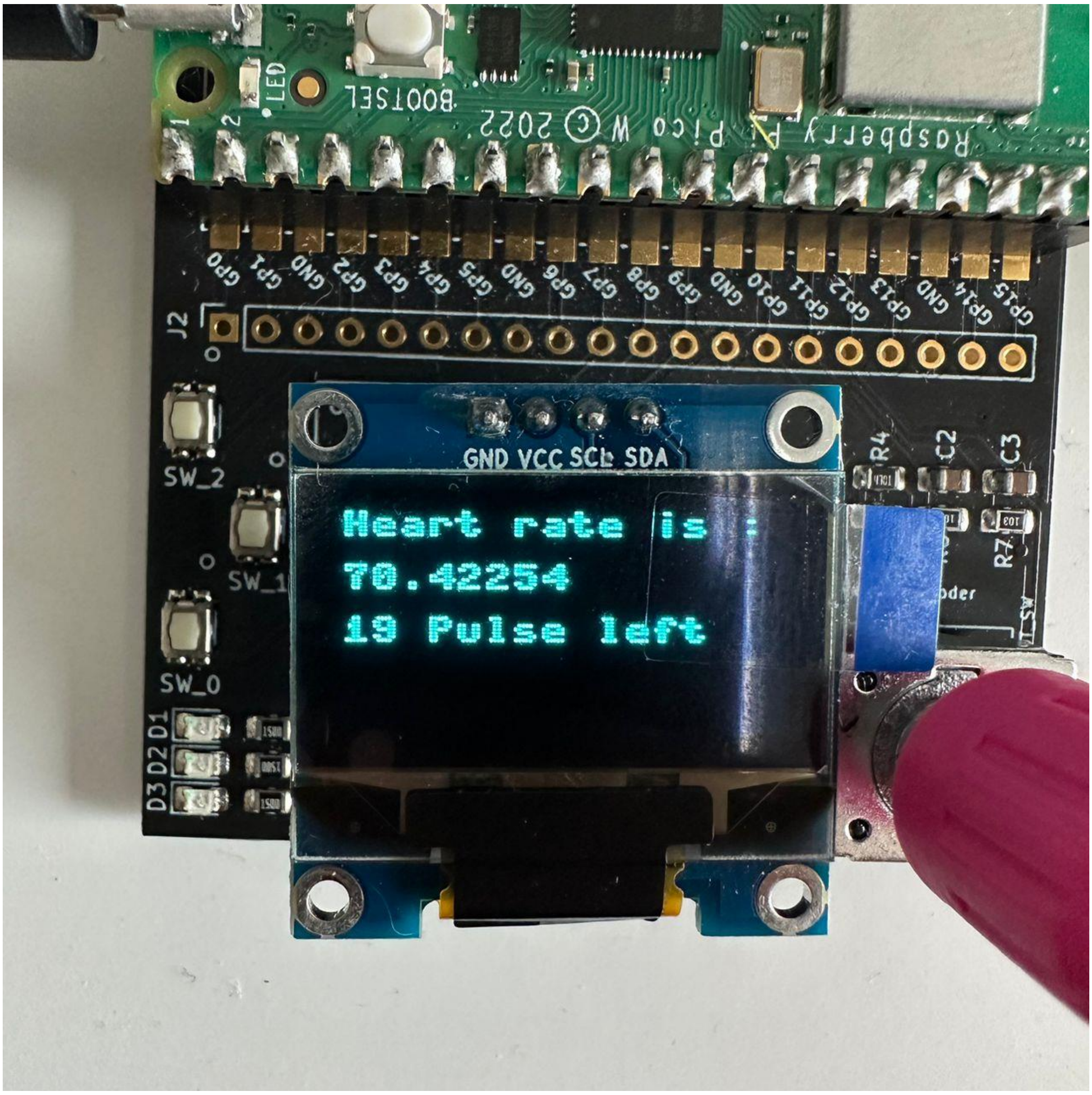
Appendic1: connecting to the internet.

When the Raspberry is connecting to the internet this message is shown on the OLED.



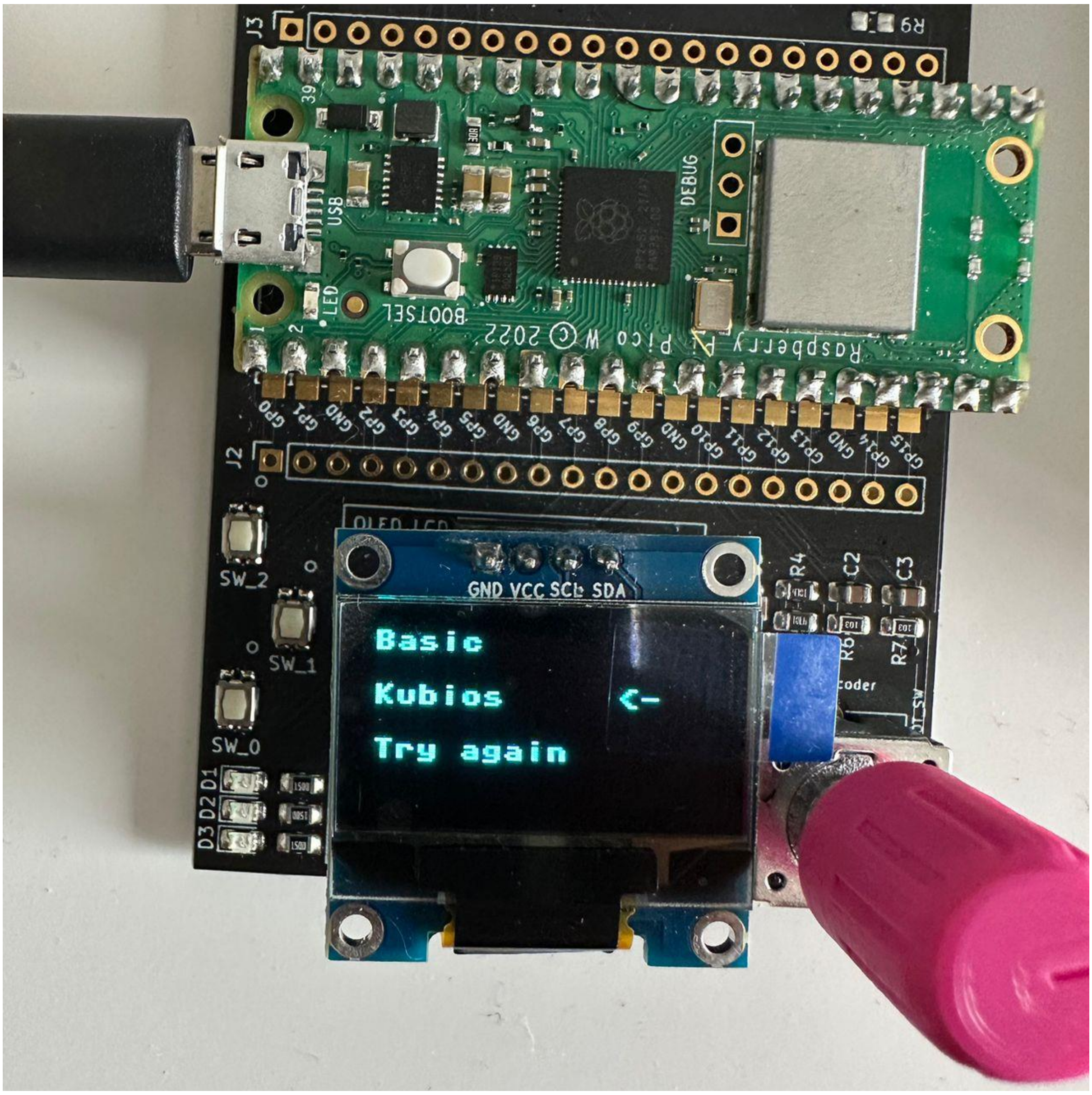
Apppendic2: request the user to put the finger.

First, the user should hold the sensor on their finger, then press the bottom.

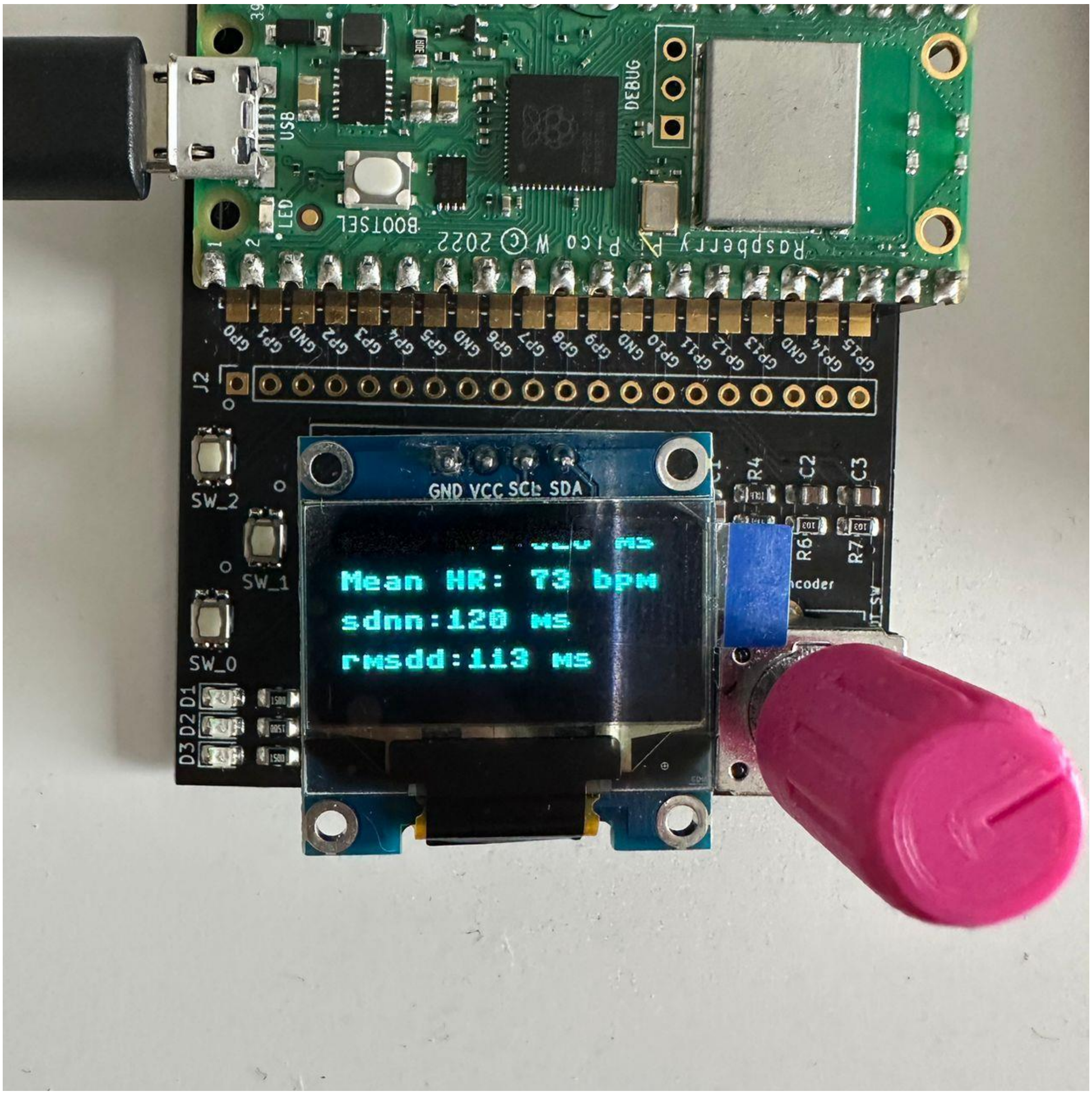


Appendic3: Showing heart rate.

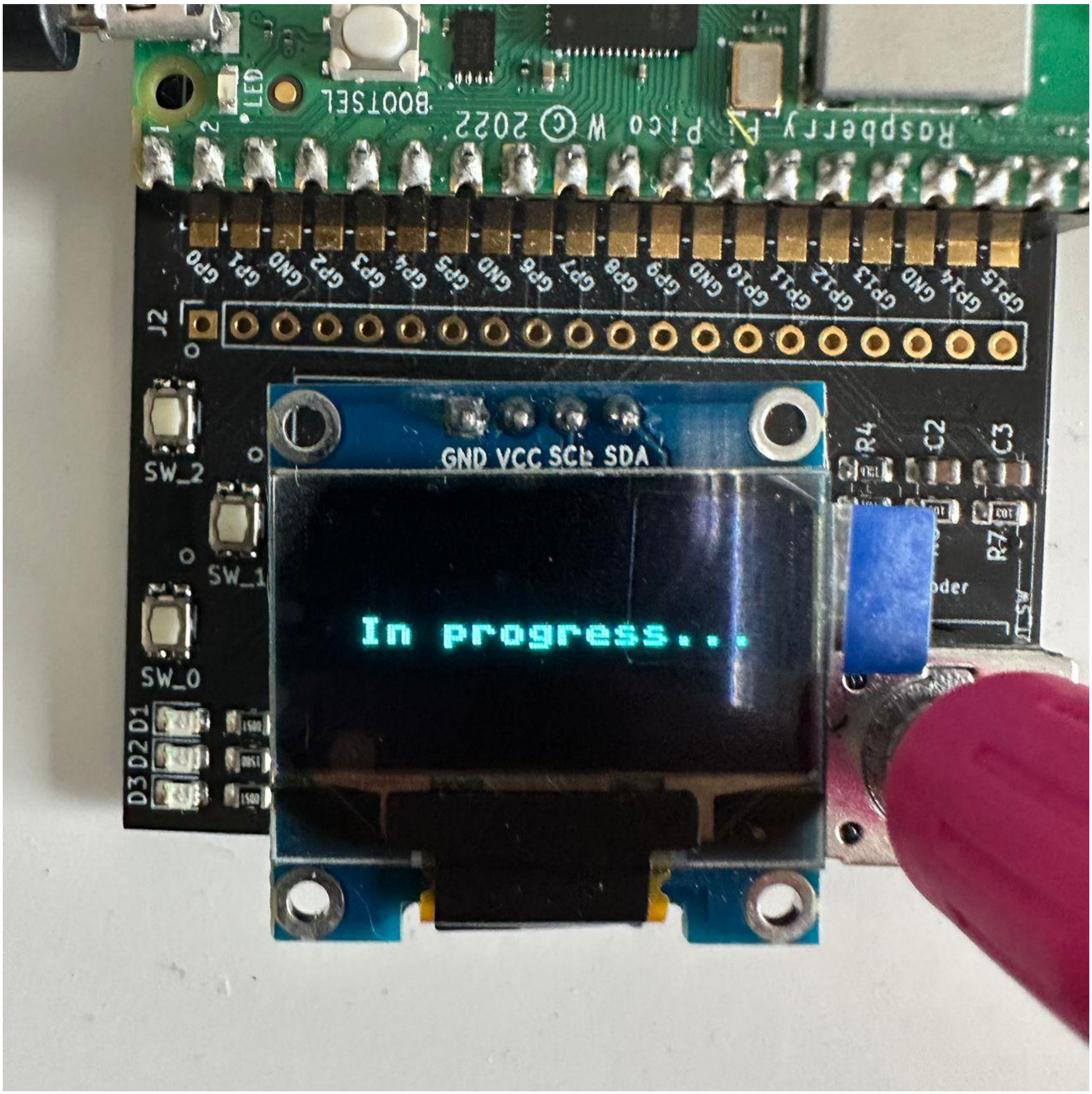
The counter informs the user the time.



Appendic4: Selecting from the menu.

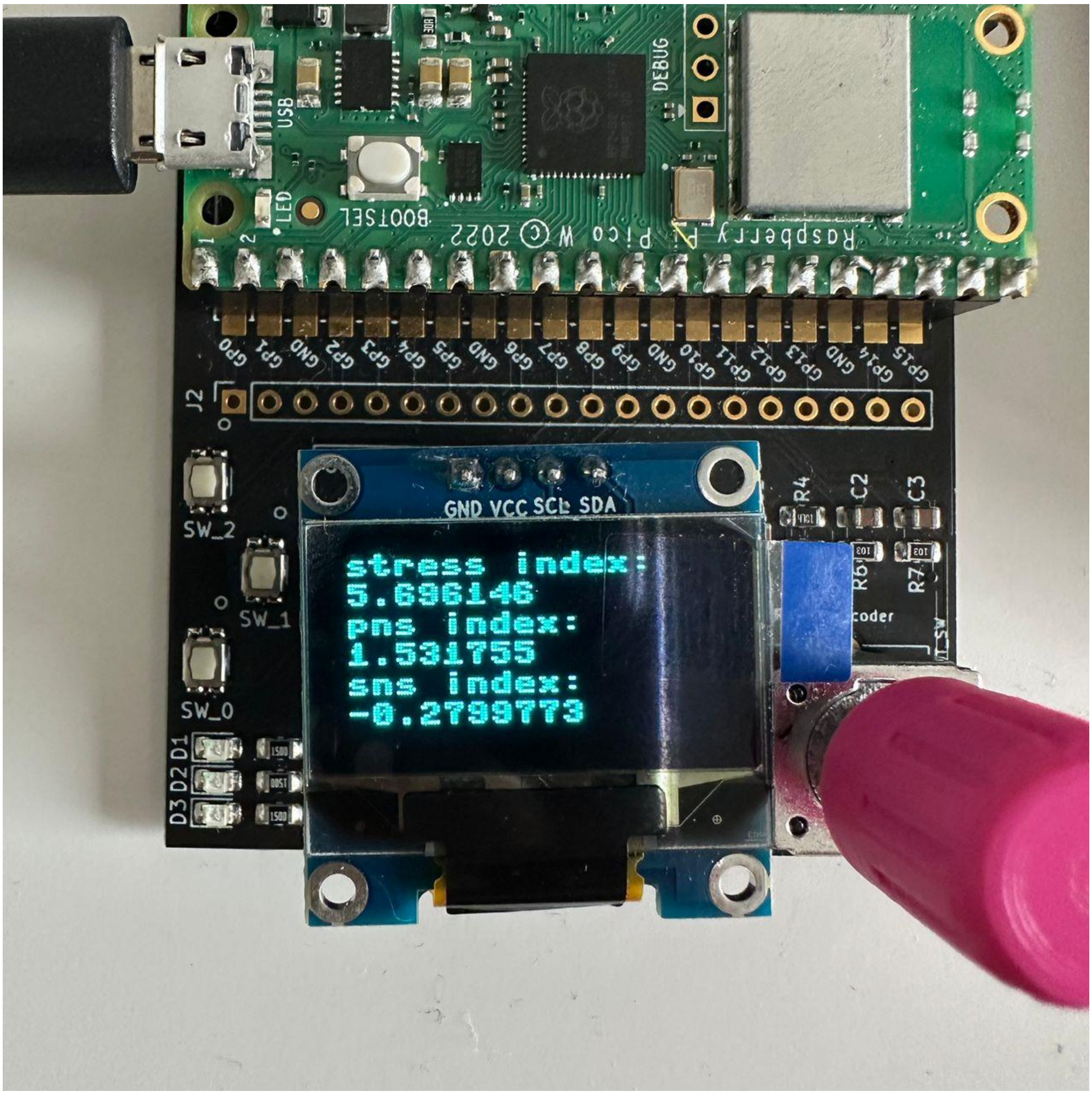


Appendic5: Basic analysis.

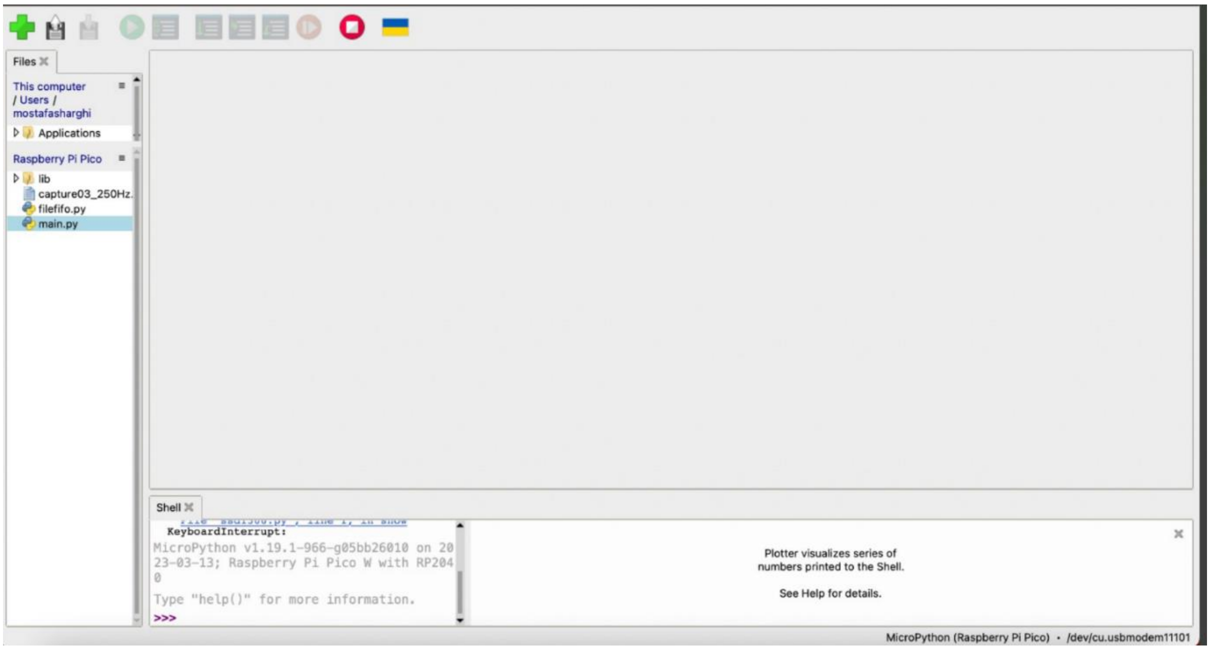


Appendic6: sending a request to Kubios.

This message is shown when Kubios is receiving the data and calculating the parameter, then get the response.



Appendic7: KubiosCloud analysis.



Appendic8: main.py and IoT system.

The main.py file is saved to Raspberry Pi Pico W, to run it without any need to any devices.