Imperial College London

Department of Electrical and Electronic Engineering

Interim Report 2023

Status on measurements
is good → A-
background and so is
improved with respect to
previous drafts → B
Check after adding or updating
sections whether the rest of the
report is still relevant. → B
References → some do not exist.

Overall B

Project Title: **A smart breathing mask for breathing training**

Student: **Matthew Setiawan**

CID: **01917068**

Course: **EIE3**

Project Supervisor: **Dr Kristel Fobelets**

Contents

1 Abstract

Building on Dr Kristel Fobelets' pioneering research in knitted breathing coils [1], this project introduces an Internet of Things (IoT) smart breathing mask designed to enhance respiratory health insights by collecting new user data from integrated sensors. The current device features heart rate, movement, temperature, and CO_2 sensors positioned around the facial area, enabling monitoring of users' breathing patterns.

The primary and final objective of this project is to analyse and correlate data from the mask and the knitted breathing coil. By doing so, it will be possible to predict the inputs from one device using data from the other. For example, if machine learning is employed to detect asthma attacks, the correlated data from just one device could offer enough information to make accurate predictions. This would be useful when wearing both devices is impractical, but data collection remains necessary. For instance, wearing a smart breathing mask may be impractical when monitoring proper inhaler usage. By using a knitted coil to predict breath temperature ~~and CO2~~ levels, we can still obtain valuable insights without requiring the mask.

not possible

When you have figures you must refer to them in the text otherwise they don't make sense

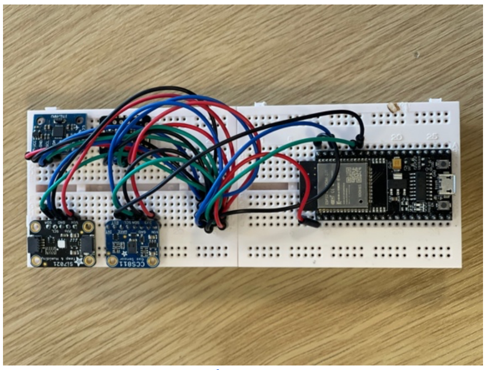

Figure 1.1. Graphical Abstract: ~~Circuit Configuration of~~ test circuit for Smart Breathing Mask

Figure 1.2. Graphical Abstract: Knitted Coil Device [1]

2 Acknowledgement

I would like to express my sincere gratitude to Dr Kristel Fobelets from the Department of Electrical and Electronics Engineering at Imperial College London for her invaluable guidance and support throughout the course of this project, and her expertise and insights have been instrumental in shaping the direction of this research. I would also like to thank my friend and colleague in the embedded systems group project, Mr James Jun Hao Ong, for his assistance in designing an initial minimum viable product using a Raspberry Pi.

3 Ethical, Legal and Safety Plan

I still think this should be at the end rather than the beginning.

This project involves a hardware-based approach that requires frequent interaction with electrical components. In addition, the project focuses on the health technology sector, which necessitates the regular analysis of user data. Given these considerations, it is crucial to establish a comprehensive ethical, legal, and safety plan to guide the project's design and development, however since this project is currently in its initial development phase, no testing will be conducted with volunteers at this stage. The following guidelines outline important considerations that must be addressed to ensure that the project is safe, legal, and ethical throughout its progression.

Ethical

1. Respect user privacy and ensure that user data is always protected, such as by using encryption methods to secure user data.
2. Obtain informed consent from users before collecting and analysing their health information and provide clear and concise information about the purpose of collecting user health information.
3. Ensure that the device is not used to discriminate against individuals based on their health status and take appropriate measures to prevent such discrimination.
4. Regularly review and update the ethical plan to ensure that it reflects the evolving ethical considerations related to the use of the device.

Legal

1. Ensure that the device complies with all applicable laws and regulations, such as data protection laws and health information privacy laws, such as the EU's General Data Protection Regulation (GDPR) [2].
2. Obtain any necessary licenses or permits for the design, manufacture, and sale of the device, and ensure that the device meets all applicable safety standards.
3. Protect any intellectual property associated with the device, such as patents, trademarks, and copyrights.

Safety

1. Test the device thoroughly and safely to ensure that it functions properly and does not pose a risk to users or testers, and regularly conduct safety assessments to identify and mitigate any potential safety risks. These include reviewing the wiring, ensuring limited exposure to electrical components, and verifying that the device is properly grounded.
2. Provide clear and concise instructions for users on how to properly use and maintain the device and include appropriate warning labels on the device to alert users to any potential safety hazards. These could typically include hazards to swallowing small electrical components, exposed wiring or electrical shocks from live wires or improper grounding.
3. For safe wireless communication, adhere to safety protocols such as ensuring devices are within regulated limits like the FCC's radio frequency exposure limit of 1.6 watts/kg [3]. Additionally, maintain a safe distance from transmitting antennas, use protective gear when required, and follow manufacturer guidelines for proper device usage and maintenance.

What are the maximum currents & voltages that are allowed when a fault occurs? → reference [?]

4 Introduction

4.1 Background

chest diameter changes

The ability to observe respiration is at the core of healthcare diagnosis and monitoring, as numerous health conditions manifest themselves in characteristic breathing patterns. One innovative approach to monitoring respiration, mentioned in the abstract, involves knitted coils that obtain respiration information based on chest muscle movement [1]. These coils, integrated into wearable garments, detect changes in inductance as a function of ~~elongation~~ circumference, providing valuable insights into breathing patterns.

However, developing smart breathing masks was proposed as a solution to gain a more comprehensive understanding of respiration. These masks would track key respiration indicators, such as CO2 levels near the mouth, movement, breath temperature, and heart rate, offering a richer dataset than the knitted coils relying solely on muscle movement. These additional parameters could enable healthcare professionals to diagnose better and manage various health conditions that affect respiration. → this is no longer consistent with abstract however it can also be a target.

The integration of advanced sensor technology in smart breathing masks not only provides a non-invasive and unobtrusive method for monitoring respiration but also has the potential to revolutionize the way healthcare professionals approach respiratory health management. By offering a more in-depth analysis of respiration patterns, smart breathing masks have the potential to significantly improve patient care and outcomes across diverse populations.

This interim report aims to outline the fundamental concepts of a smart breathing mask, including its design and power management considerations. Furthermore, the objective by this period in the project is to develop a minimum viable product (MVP) that demonstrates the core functionality of the smart breathing mask and provides early testing results to confirm the feasibility of this project. By assembling circuits and integrating essential components, this report will serve as a foundation for further research and development in the integration with the knitted coil device.

4.2 Project Objective

The project has two primary ~~milestones~~ deliverables: the interim and final deadlines. By the interim deadline, the goal is to develop an MVP that showcases essential functionality and some data analysis capabilities. The final objective involves completing research and testing on Dr Fobelets' knitted coil device, enabling the identification of correlations between the knitted coil and the smart breathing mask. Table 4.2.1 outlines the specific objectives of the device.

Period	**Objectives**

Interim	1. Complete background research on similar smart mask concepts and market demographic
	2. Create a working MVP for proof of concept including
	    a. Microcontroller with integrated and functional sensors
	    b. Communication and processing of sensor data from microcontroller to web application using Bluetooth and/or Wi-Fi
	    c. Server-side processing and analysis of data including, but not limited to machine learning, filtering, data aggregation and feature extraction.
	    d. Intuitive and engaging frontend features that effectively visualize and communicate processed data to clients
	3. Outline plans and designs for improvement of form factor, including enhancing the power management system for increased efficiency, transitioning from breadboards to printed circuit boards (PCBs) for greater reliability and

	compactness, and incorporating a modular design approach to facilitate easy customization and scalability 4. Provide early implementation and testing results to determine feasibility of the project
Final	1. Complete research and data collection on knitted coil device 2. Improve data processing and feature extraction for both devices 3. Attempt at discovering a correlation between mask and breathing coil predictors 4. Create system with improved form factor and power management

Table 4.2.1. Project Objectives

4.3 Evaluation Plan

To assess progress and ensure success at different stages of the project, I will conduct weekly, interim, and final evaluations. At the end of every weekly meeting, I will review progress towards the weekly goals and identify any challenges that need to be addressed. Before the interim deadline, I will conduct a thorough evaluation of progress towards the project objectives, including a review of project documentation and results. This evaluation will help identify areas where improvements can be made to ensure the project's success. Finally, before the final deadline, I will conduct a comprehensive evaluation of the overall success of the project, including a final review of project documentation and product. By conducting these regular evaluations, I can identify any issues early on and make necessary adjustments to ensure the project is completed successfully.

Evaluation	**Description**	**Response**		
		Weekly	**Interim**	**Final**
Outstanding	The project exceeded expectations, with all targets being completed smoothly and outstanding results achieved with minor or no setbacks.	If development appears to be faster than expected, set more tasks for future weeks.	Set higher goals and expectations for final objective and modify project plan as such.	Optimize report to include findings.
Meeting Expectations	The project successfully met expectations, with goals and objectives being achieved on schedule and with satisfactory quality.			
Below Expectations	The project did not fulfil all expectations due to setbacks, or shortcuts had to be taken to fulfil expectations which resulted in reduced quality.	Identify whether the issue is a simple bug that requires more time or a major logic hole, and in the latter case, consider unconventional methods to solve the issue.	Identify causes for below-expectation achievements, adjust weekly goals for time management issues, and set more realistic final goals for unexpected challenges.	Explain in final documentation why the project fell short of original goal and what was attempted.

Table 4.3.1. Evaluation Plan

Table 4.3.1. shows the descriptions and responses to weekly, interim, and final evaluations. In the case that these evaluations were above or below expectations certain responses are warranted depending on severity.

4.4 Project Plan

Table 4.4.1. outlines the agreed-upon meeting times along with specific milestones at each date.

Meeting Count	Scheduled Date	Milestone	Scope
1	4th April	- Discuss project scope, goals, and objectives - Conduct literature research on similar projects to common standards and best practices - Identify metrics for success	Research, Planning
2	11th April	- Integrate sensors with microcontroller and ensure all data is being read at a reasonable rate - Establish communication between microcontroller and server using appropriate communication protocols - Display test data on frontend to verify that communication is working properly	Software Development
3	18th April	- Refine data processing to ensure that data being sent is in the final, presentable form - Improve visualization and other application layer features - Create data processing features for proof of concept, including filtering and machine learning	Software Development
4	25th April	- Refine Minimal Viable Product (MVP) based on unit testing and comments - Perform analysis and design on next steps including PCB design and layout, improving the form factor, and power management. - Agree upon structure of Interim Report and key areas to cover	Software, Research, Planning
5	3rd May	- Complete and review Interim Report and identify areas for improvement - Revisit current progress and identify any changes to project scope and objective	Research, Planning
6	9th May	- Conduct testing and simultaneous data collection on knitted coil and breathing mask to ensure accurate and reliable results.	Testing
7	16th May	- Create different PCB designs on board that complements form factor more effectively ? - Explore different power management options for improved form factor and battery life ?	Research, Software
8	23rd May	- Analyse the collected data to identify patterns and explore different techniques to uncover relationships between the data.	Software
9	30th May	- Create several more advanced models that can extract more features using new insights from Dr Fobelets' device	Hardware ?
10	6th June	- Assemble prototype of final product	Hardware
11	13th June	- Run tests and obtain results of final product - Identify structure of final report and revaluate our objectives	Testing, Planning
12	20th June	- Revise final report and identify any areas of improvement	Planning

is this the plan?

could be via software

Table 4.4.1. Arranged Meeting Times and Milestones

5 Literature Research

5.1 Importance of personal devices in monitoring health

general statement but reference limited to face mask.

Personal devices, such as wearable sensors, are increasingly important in monitoring health and improving overall well-being. These devices offer a range of benefits, including continuous monitoring, early diagnosis, personalised care, and cost-effective treatment, which collectively contribute to better health outcomes for individuals [4].

Continuous monitoring is a crucial advantage of using wearable sensors. These devices can track physiological data throughout the day, such as heart rate, blood pressure, and activity levels. This constant flow of information allows for a more comprehensive understanding of an individual's health, as it captures variations that periodic clinical tests might miss. In addition, with continuous monitoring, it is easier to identify abnormal patterns or deviations from healthy baselines, which can be crucial for early diagnosis and intervention.

Reference does not exist

Early diagnosis is another benefit offered by personal devices [5]. As wearable sensors can detect abnormal conditions in real-time, they enable prompt medical attention, reducing the risk of complications and improving the chances of successful treatment. In addition, early diagnosis often leads to less invasive and more effective treatment options, improving health outcomes and reducing the burden on healthcare systems. For example, a study in the Guardian [6] outlined how Fitbit devices could allow doctors to “step in before patients must be sent to the hospital”; beyond offering early diagnosis, this also saves medical costs.

Personalisation is a significant aspect of using wearable sensors for health monitoring [7]. By collecting individualised data, these devices enable healthcare professionals to tailor their approach to each patient, considering their unique circumstances and needs. Personalised care has been shown to lead to better patient engagement, improved compliance with treatment plans, and, ultimately, better health outcomes.

Lastly, wearable sensors can contribute to cost-effective healthcare solutions. By enabling early diagnosis and personalised care, these devices can reduce the overall costs associated with diagnosing and treating illnesses. Additionally, the real-time monitoring offered by personal devices may help prevent unnecessary hospital visits, further lowering healthcare costs.

5.2 Importance of monitoring Breathing

Monitoring breathing is essential for maintaining optimal health, as abnormalities in respiration can indicate various illnesses. Respiratory illnesses can range from common conditions [8], such as asthma and chronic obstructive pulmonary disease (COPD), to more severe disorders, such as lung cancer and pulmonary fibrosis. Early diagnosis of these conditions is crucial for effective treatment and improved health outcomes.

Personal devices, such as wearable sensors, can potentially discover and diagnose respiratory illnesses early by continuously monitoring respiratory patterns and other vital signs. These devices can detect subtle changes in breathing that may be indicative of underlying health issues, facilitating early intervention and improving health outcomes.

The use of big data analytics and machine learning plays a significant role in enhancing the capabilities of personal devices for health monitoring. By processing and analysing large volumes of data collected from wearable sensors, advanced algorithms can identify patterns and correlations that might not be apparent through traditional analysis. This can lead to more accurate detection of respiratory abnormalities, enabling timely diagnosis and treatment [9].

Furthermore, the accessibility of this information through user-friendly software applications allows individuals and healthcare professionals to easily monitor and interpret the data, leading to top-notch early diagnoses. By making the insights derived from big data analytics and machine learning readily available, patients can take a more proactive role in managing their health, while healthcare providers can make better-informed decisions about treatment plans.

For example, in the case of asthma, a chronic condition characterised by inflammation and narrowing of the airways, monitoring respiratory patterns can help identify early warning signs of asthma exacerbations, allowing for timely intervention and management [10]. Machine learning algorithms can be utilised to analyse the collected data, improving the accuracy and predictive capabilities of the monitoring system.

Similarly, for chronic obstructive pulmonary disease (COPD), early diagnosis and monitoring can lead to better management of symptoms and reduced risk of complications, such as respiratory infections and heart problems [11]. Big data analytics and machine learning can further enhance the effectiveness of wearable sensors in detecting and monitoring COPD by uncovering patterns and trends in respiratory data.

The same principles apply to more severe respiratory diseases, such as lung cancer and pulmonary fibrosis. Early detection of these conditions through continuous monitoring of respiratory patterns and other biomarkers, combined with the power of big data analytics and machine learning, can significantly improve survival rates and treatment outcomes.

5.3 Techniques for monitoring Breathing

Various techniques have been developed to measure breathing, including the use of infrared (IR) cameras and inductance plethysmography. These methods provide doctors with valuable data to analyse and discover early signs of respiratory problems. By continuously monitoring respiratory patterns, physicians can detect subtle changes in breathing that may indicate the onset of an illness or the worsening of an existing condition.

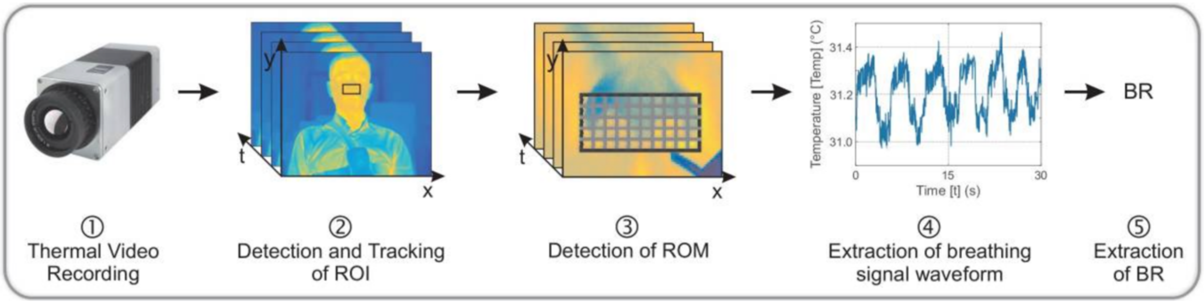

Figure 5.3.1. Utilising Infrared Cameras and Computer Vision to estimate breathing rate (BR): (1) Video Sequence is Recorded (2) Detection of Region of Interest (ROI) is performed (3) Identification of Region of Measurement (ROM) (4) Extract mean temperature of ROM (5) Extract BR from temperature [12]

Infrared cameras enable doctors to visualise the airflow and temperature changes associated with respiration, which can help identify irregularities in breathing patterns or airflow obstructions. Figure 5.3.1. demonstrates the research and device presented by Dr Pereira from RWTH Aachen University [ref] where infrared cameras were used to identify nasal regions, and then using the temperature around the region, extract a temperature time series which could be used to measure breathing rate in a contactless way.

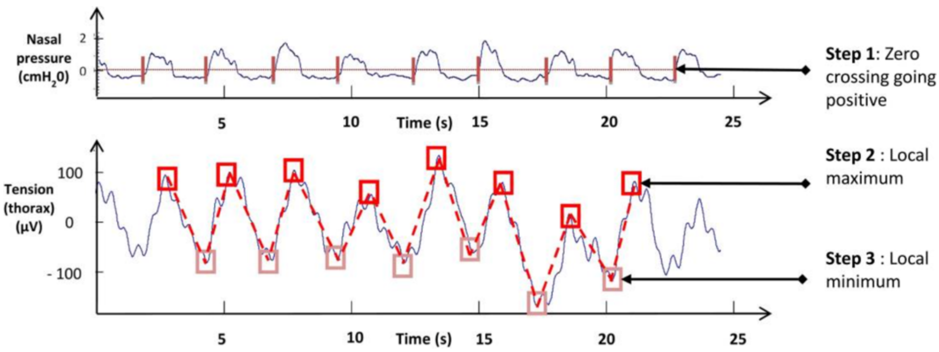

Figure 5.3.2. Nasal Pressure and Respiratory Inductance Plethysmography (RIP) Signals [13]

Another technique called inductance plethysmography, offers a quantitative approach to respiratory monitoring, providing information on respiratory rate, volume, and rhythm. Figure 5.3.2. shows the signals that can be obtained using this method, which offers similar information regarding breathing rate to using temperature. Generally using RIP is considered more accurate as RIP provides a more direct measurement of breathing rate as it focuses on the mechanical aspect of respiration whereas using temperature might take advantage of indirect correlations to determine breathing rate.

In both cases, the early detection of abnormalities in respiratory patterns can significantly improve patient outcomes. By identifying potential problems at an early stage, doctors can initiate timely interventions and develop personalised treatment plans, ultimately enhancing the overall quality of care.

5.4 The use of masks in monitoring Breathing

Smart breathing masks have emerged as a promising solution for monitoring respiratory health, offering several advantages over other types of wearable sensors. Face masks provide easy access to critical aspects of respiration, such as respiratory rates and patterns, exhaled breath for measuring volatile biomarkers of disease, respiratory droplets and aerosol particles originating from the wearer or present in the environment, and toxic gases in the environment. Ref?

By incorporating sensors into face masks, it becomes possible to continuously analyse respiratory airflows and measure respiratory rates and patterns. This allows healthcare professionals to monitor patients' breathing in real-time, aiding in the early detection of abnormalities and facilitating timely interventions.

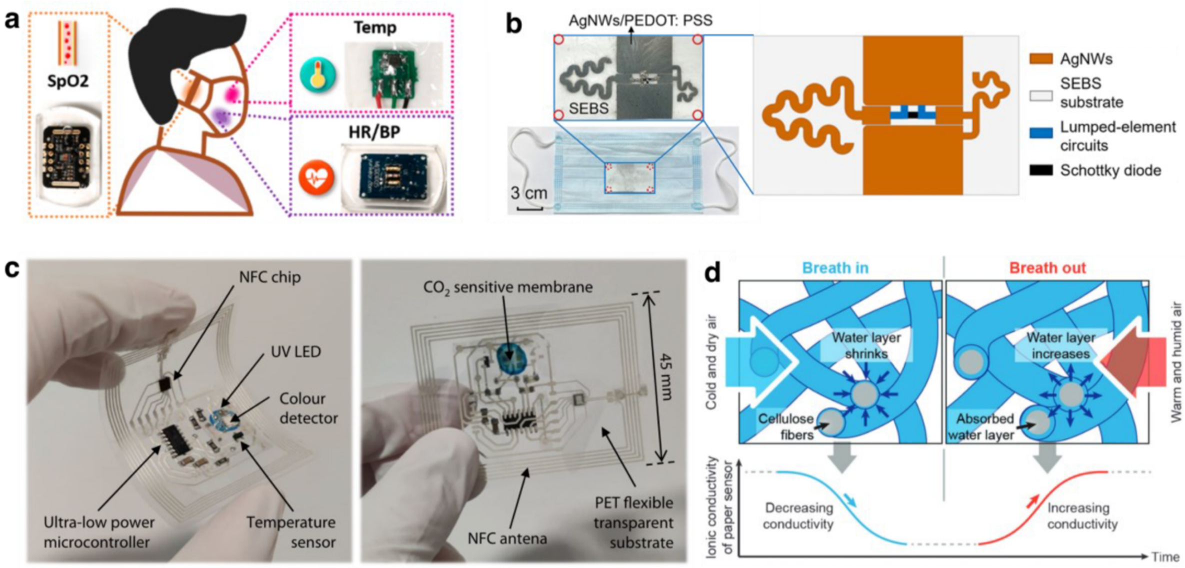

Figure 5.4.1. Passive detection in masks: (a) smart mask integrated with a sensor system to remotely monitor values (b) mask which utilizes deformation to detect coughs (c) mask component with CO2 sensitive membrane to wirelessly detect CO2 levels around the facial area with near field communication (NFC) (d) cellulose-based paper mask functioning as a moisture sensor [14]

Figure 5.4.1. illustrates several techniques for developing sensors and masks that could be useful for the passive monitoring of users [14]. These devices can be integrated with healthcare professionals or automated systems to provide feedback on the user's respiratory functions.

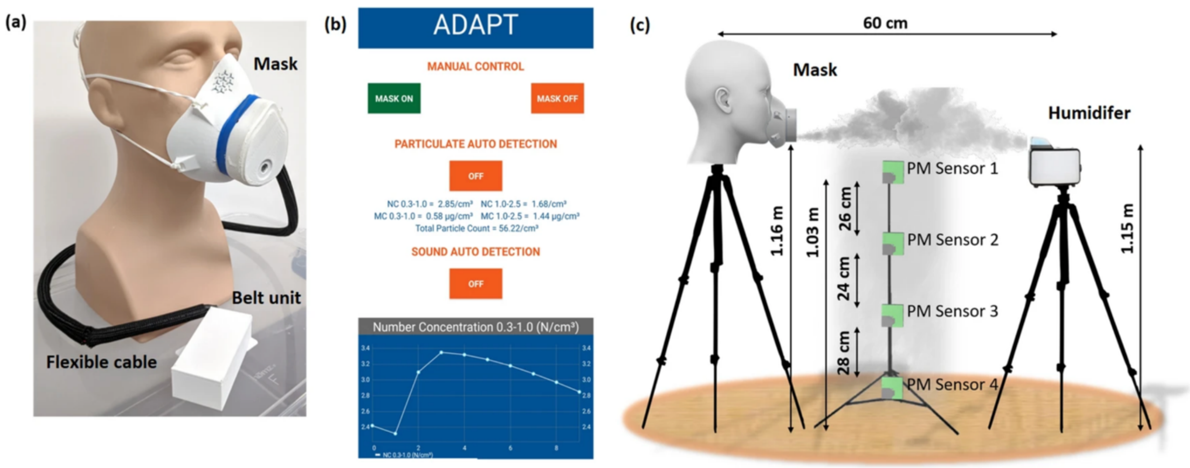

Figure 5.4.2. ADAPT Smart Mask: (a) Prototype (b) User Interface (c) Experimental Setup [15]

Beyond passive monitoring, smart masks can also be made to interact and respond to the environment [15]. The ADAPT smart mask is shown in Figure 5.4.2. has the capability to monitor nearby airborne viruses and react with a spray which would bond with the airborne particles, increase their size and mass, and thus cause them to rapidly fall to the ground. This feature is particularly useful for tracking airborne diseases, such as influenza or COVID-19, or air pollution and then reacting accordingly. OK

5.5 Common Designs

Regarding design, various approaches have been adopted to incorporate advanced features and improve the performance of traditional protective masks. One common method involves attaching sensors directly to established rigid masks, such as N95 respirators. By integrating sensors into existing mask designs, researchers can quickly demonstrate proof of concept and showcase the potential benefits of smart mask technology, such as real-time monitoring of air quality, respiratory health, and other relevant factors. More sophisticated smart mask designs make use of advanced materials and manufacturing techniques to enhance mask performance. For instance, some researchers have explored the use of nanofibers in mask construction, optimizing filtration capabilities without compromising breathability [17]. These cutting-edge materials can effectively capture and filter out airborne particles while maintaining a comfortable, lightweight design that is ideal for prolonged wear. Another innovative approach to smart mask development involves 3D printing, which offers a high degree of customization and precision in mask design. By using 3D printing techniques, researchers can create tailor-made masks that conform closely to the wearer's facial contours, ensuring a secure and comfortable fit [18].

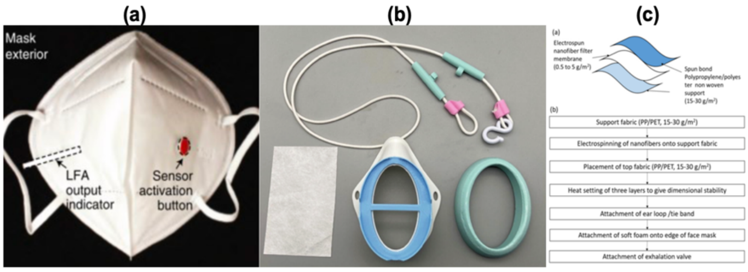

Figure 5.5.1. (a) standard N95 mask stuck with different components (b) custom 3d printed skeleton of a smart mask (c) nano-fibre mask filter design [18]

Copy-paste figures need Reference

6 Analysis and Design

The preliminary version of the device was developed in the ELEC96018 Embedded Systems course, where our team employed a Raspberry Pi and successfully integrated four sensors: heart rate, CO2, accelerometer, and temperature. Data was transmitted to our AWS server via MQTT, demonstrating the effective use of communication protocols. However, this initial iteration did not include data processing improvements and utilized a less efficient Raspberry Pi instead of a dedicated microcontroller.

6.1 Architecture Overview

To maintain a structured approach, the analysis and design of the IoT device will be divided into four main categories: perception, communication, middleware, and application layers. The perception layer is responsible for gathering data from the environment and sensors, including power and form factors, as they are closely related. The communication layer, which is sometimes referred to as the network layer, has been renamed to accommodate the section's focus on application layer communication protocols such as HTTP. The communication layer handles the transmission and reception of data, while the middleware layer is responsible for data processing and device management. Finally, the application layer is responsible for providing end-user functionality, including data visualization and analysis. This categorization allows for a clear understanding of the device's architecture and the role of each layer in achieving its intended purpose.

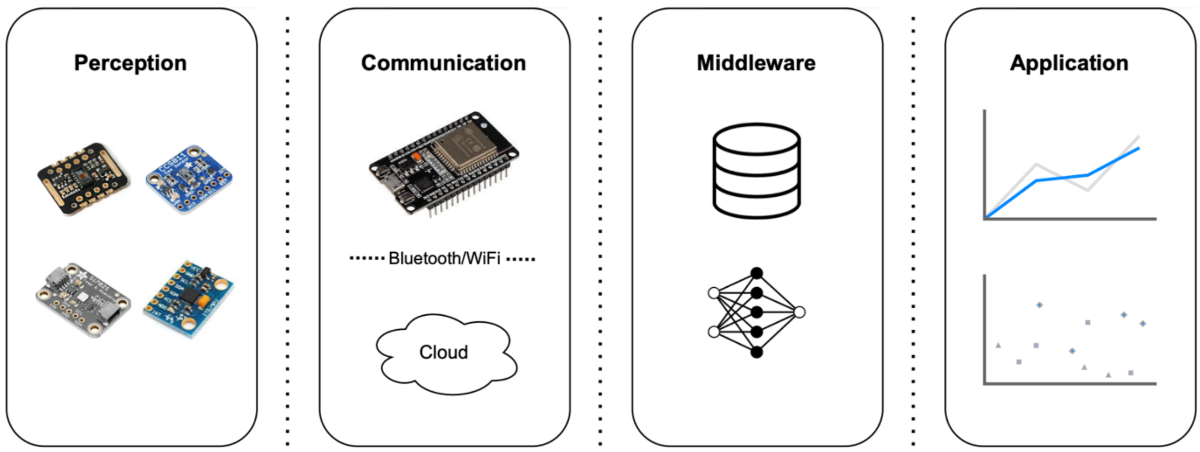

Figure 6.1.1. Visualization of Internet of Things Layers

6.2 Perception

The research was conducted on sensors suitable for a smart breathing mask. The sensors were primarily evaluated based on their accuracy and speed. The sensors were also evaluated based on their suitability for wearable technology, as the sensor package would need to be compact enough to fit into a wearable device for breathing training. The selected sensors are detailed below, along with justifications for their selection based on their specifications, ideal placements, and suitability for the mask.

MAX30102 PPG Sensor [19]

Rationale

The MAX30102 is an integrated pulse oximetry and heart rate module. It functions as the primary sensor which will be used to measure heart rate. The core requirements for a heart rate sensor were reasonably accurate measurements, low power requirements and a small form factor.

This sensor was finally chosen as it fulfilled the core requirements on top of other advantages and features taken from the MAX30102 datasheet:

- Heart rate Monitor and Pulse Oximeter Sensor in LED Reflective Solution
- Tiny 5.6mm x 3.3mm x 1.55mm 14-Pin Optical Module
    - Integrated Cover Glass for Optimal, Robust Performance
- Ultra-Low Power Operation for Mobile Devices
    - Programmable Sample Rate and LED Current for Power Savings
    - Low-Power Heart-Rate Monitor (< 1mW)
    - Ultra-Low Shutdown Current (0.7µA, typ)
- Fast Data Output Capability
    - High Sample Rates (50-400 samples/second)
- Robust Motion Artifact Resilience
    - High SNR
- 40°C to +85°C Operating Temperature Range

Data Collection

The MAX30102 PPG sensor outputs a raw signal that needs to be filtered and processed to obtain the heart rate. A PPG sensor uses light to detect blood volume changes in the microvascular bed of tissue. To obtain heart rate from PPG readings, the PPG sensor measures the variations in blood volume and converts them into an electrical signal.

Data Processing

The Pan-Tompkins algorithm was originally created for the ECG signal but can be applied with minor changes to make it suitable for PPG signals [20]. The primary adaptation involves modifying the pre-processing step to better accommodate the characteristics of PPG signals. For example, you can use a bandpass filter with appropriate cut-off frequencies (e.g., 0.5 Hz to 4 Hz) to remove noise and baseline wander. Additionally, as PPG signals may not exhibit the same prominent QRS complex as ECG signals, the peak detection method needs to be adjusted to accurately identify systolic (pulse) events in the PPG signal. This can be achieved by using a threshold-based approach or employing more advanced techniques like the continuous wavelet transform or the autocorrelation method. By making these adjustments to the Pan-Tompkins algorithm, it can be effectively applied to PPG signals for estimating heart rate. The following steps provide the steps for a Pan-Tompkins modified heart rate estimator:

1. Pre-processing: Apply a bandpass filter to the raw PPG signal with appropriate cut-off frequencies (e.g., 0.5 Hz to 4 Hz) to remove noise and baseline wander.
2. First derivative: Calculate the first derivative of the filtered PPG signal to emphasize the high-frequency content and rapid changes associated with the pulse events.
3. Square the signal: Square the derivative of the PPG signal to emphasize high-frequency content and accentuate pulse events further.

4. Moving average: Apply a moving average to the squared signal with a window size roughly equivalent to the expected pulse duration. This step integrates the signal, forming an integrated signal emphasizing the pulse events.
5. Peak detection: Identify the peaks in the integrated PPG signal that correspond to the systolic (pulse) events using a threshold-based approach or more advanced methods like the continuous wavelet transform or the autocorrelation method.
6. R-R interval calculation: Measure the time intervals between consecutive peaks in the PPG signal. These intervals correspond to the time between successive heartbeats.
7. Heart rate calculation: Calculate the heart rate by taking the average of the R-R intervals and converting it to beats per minute (BPM).

Placement

Due to the nature of the smart breathing mask the sensors need to be placed within the facial area. It is important, however, to ensure that heart rate readings in the facial areas are not significantly worsened.

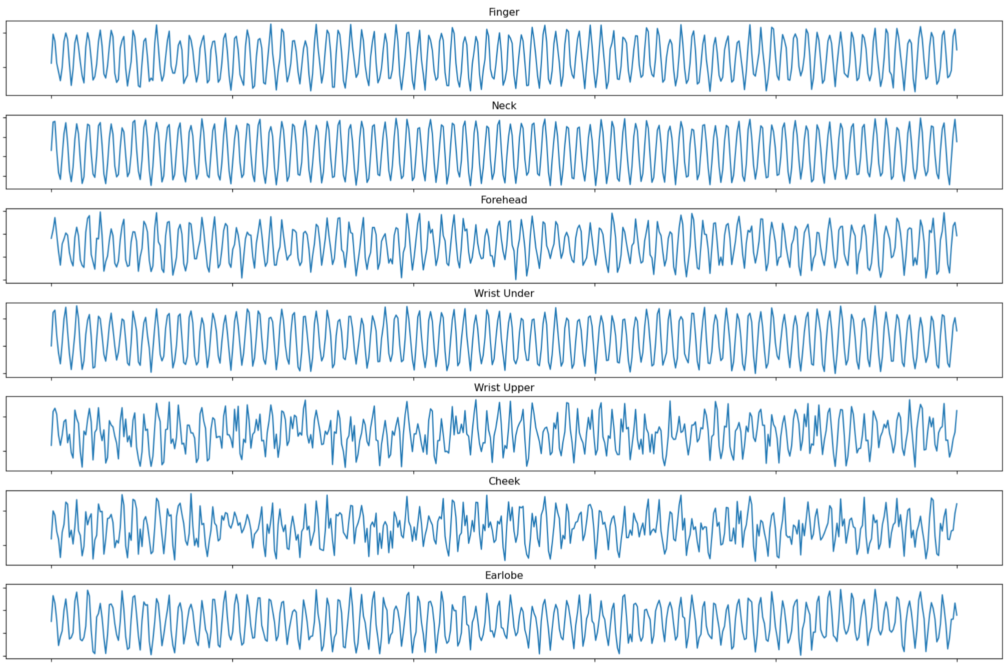

Figure 6.2.1. Raw PPG Signals Measured at Different Areas of the Body of a Volunteer

good stuff

The signal-to-noise ratio (SNR) is an important factor to consider when placing a PPG sensor. The SNR is the ratio between the power of the desired signal and the power of the background noise. A higher SNR indicates that the desired signal is more distinguishable from the background noise, leading to improved measurement accuracy. Placing the PPG sensor on a body site with a strong response maximizes the signal strength and SNR.

In Figure 6.2.1. the raw PPG measurements from different areas of the body are given. The first 5 readings show common locations where heart rate is measured, and the final two readings show PPG measurements from the cheek and possibly earlobe, which are both within the range of a mask. The values that were obtained were similar to a recent publication, *"Accurate Extraction of Respiratory Frequency"* [21].

It is noticeable that in the cheek the signal strength is lower compared to the others indicating an expected lower SNR, however, the SNR is still at a reasonable level whose data would still provide a reliable heart rate reading, given proper pre-processing.

CCS811 CO2 Sensor [22]

Rationale

The CCS811 sensor is an air quality sensor that can measure volatile organic compounds (VOCs) and equivalent breath CO2 (eCO2) levels. The following are some of the reasons for using this sensor on the device:

1. Monitoring CO2 levels can help assess the quality of the air being inhaled and exhaled during breathing training. High CO2 levels can lead to discomfort and reduced cognitive function while monitoring CO2 levels can help users adjust their breathing patterns for optimal performance.
2. CO2 is a by-product of cellular respiration and tracking its levels can provide valuable feedback on the user's metabolic activity and the efficiency of their breathing technique.
3. Proper CO2 levels are essential for maintaining the body's acid-base balance, which impacts overall health and performance. By monitoring CO2 levels, users can ensure they maintain a healthy balance during their training [23].

Data Collection and Processing

The CCS811 sensor outputs digital data in the form of eCO2 and TVOC (total volatile organic compounds) values. These values can be collected and read through an I2C interface, which is compatible with most microcontrollers. For the CCS811, data processing may be required to convert eCO2 levels to the concentration of CO2 in the air (in parts per million) and provide real-time feedback on air quality and breathing performance. However, this may not be necessary as during monitoring, the relative changes in eCO2 levels can be more important than knowing the precise CO2 concentration. Furthermore, implementing data processing for this sensor could increase complexity and worsen power management for this device.

Placement

The ideal placement for the CCS811 sensor in a smart breathing mask would be in the front of the mouth. This position ensures the sensor accurately measures the concentration of CO2 in the air being inhaled and exhaled by the user. The mask should create a placement spot in the front to accommodate the sensor, allowing it to function effectively without obstructing the user's breathing or comfort. This location also minimizes the chance of the sensor being affected by external environmental factors and ensures a more accurate representation of the user's breathing patterns.

Si7021 Humidity and Temperature Sensor [24]

Rationale

The Si7021 is a digital humidity and temperature sensor that provides accurate and reliable readings. A few of the reasons for tracking temperature include:

1. Monitoring temperature is very common amongst when dealing with patients with breathing problems including asthma [25].
2. Temperature regulation is essential for optimal performance during training. By tracking temperature, users can ensure they maintain a comfortable environment for their breathing exercises.
3. The temperature of inhaled air is usually lower than exhaled air because inhaled air is at the ambient temperature, while exhaled air has been warmed by the body. This allows us to use temperature to get insights on breaths.

Data Collection and Processing

The Si7021 sensor outputs digital data in the form of temperature and humidity values. The data can be collected and read through an I2C interface, compatible with the ESP32. Minimal data processing is needed since the sensor provides temperature readings in Celsius, and we are mainly interested in relative temperatures.

Placement

The optimal placement for the Si7021 sensor in a smart breathing mask would depend on the specific health metric that needs to be tracked. Since we are more interested in monitoring the temperature of the inhaled and exhaled air, placing the sensor near the mouth within the mask would be most appropriate.

MPU6050 Accelerometer and Gyroscope [26]

Rationale

Incorporating the MPU6050 can provide insights about breathing by detecting subtle movements and vibrations associated with respiration. The MPU6050 is a popular and cost-effective inertial measurement unit (IMU) that combines a 3-axis gyroscope and a 3-axis accelerometer, enabling it to measure both linear acceleration and angular velocity. By placing the sensor on the chest, abdomen, or other relevant body parts, it can monitor the expansion and contraction of the respiratory muscles, thus providing valuable information about breathing patterns, rate, and depth. This approach has been employed in various research studies to develop non-invasive and wearable respiratory monitoring systems [27]. Using the MPU6050 for breath monitoring can potentially help in assessing respiratory health, tracking physical activity, and monitoring sleep quality, among other applications.

Data Collection and Processing

The MPU6050 outputs digital data, in the form of 16-bit signed integers (2's complement representation), for each of the axes. These values represent the measured angular velocities (for gyroscope) and linear accelerations (for accelerometer) along the X, Y, and Z axes. The data can be collected and read through an I2C interface, compatible with the ESP32. Very minimal data processing is needed for this sensor, although it is quite common to take the L2 norm of the three axes to simplify analysis further [28].

Placement

The MPU6050 inertial sensors, which include accelerometers and gyroscopes, can be placed on various parts of the body to capture motion data. However, breathing would normally be correlated with areas close to the chest and abdomen [29]. Since the device being created is a mask, the closest area where these movements could have useful insights would be the thyroid which is directly below the chin.

ESP32 Microcontroller

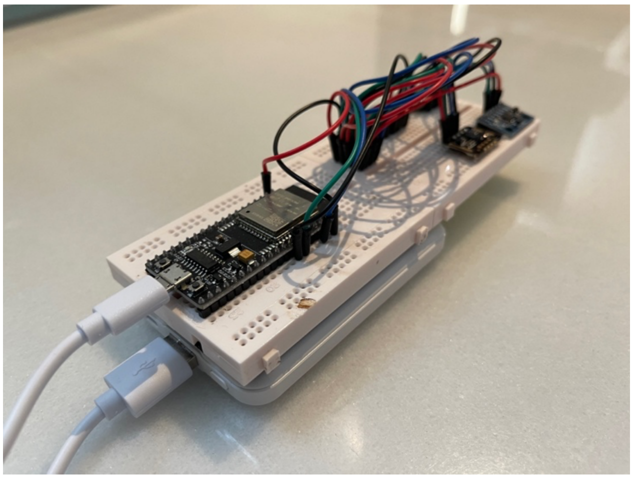

Figure 6.2.2. Initial integrated prototype: ESP32 and sensor I2C interface, powered by micro-USB

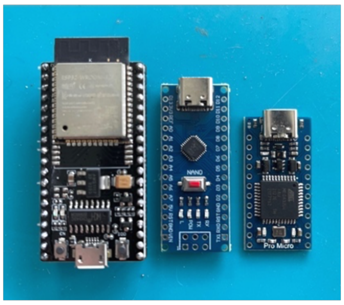

Figure 6.2.3. Development Boards in Consideration (Left to Right): ESP32, Arduino Nano, Pro Micro

Rationale

The ESP32 development board (as shown in Figure 6.2.3) was selected for its versatility and compatibility with a wide range of sensors and peripherals, and for its built-in Wi-Fi and Bluetooth capabilities, which allowed for easy communication with a server. Although the Raspberry Pi Zero was initially considered due to its ease of use with Python, it was later dropped from consideration due to several limitations. Compared to the ESP32, the Pi Zero had higher power consumption, a larger form factor, limited real-time performance, and required additional modules to add Wi-Fi and Bluetooth capabilities. Additionally, the ESP32 was more cost-effective than the Pi Zero, making it a better fit for the project's budget requirements. Overall, the ESP32 proved to be the ideal choice for integrating the sensors and establishing communication with the server, and its selection helped to ensure the project's success.

Several development boards, with smaller form factors that could support the exact same software created, with minor changes, were shown in Figure 6.2.3. However, the Arduino Nano and Pro Micro had issues as Wi-Fi was not built in and purchasing an additional Wi-Fi component would counteract the idea of a smaller form factor on top of creating more complexity.

Power Supply

The microcontroller in Figure 6.2.2. was initially powered via the micro-USB port using a power bank with a voltage of 5V, a current of 2A, and a capacity of 5000mAh. Because the ESP32 relies heavily on the Wi-Fi and Bluetooth modules for communication, it is estimated to consume around 800mA when active. With this implementation, the device has an estimated battery life of 6.25 hours when operating continuously.

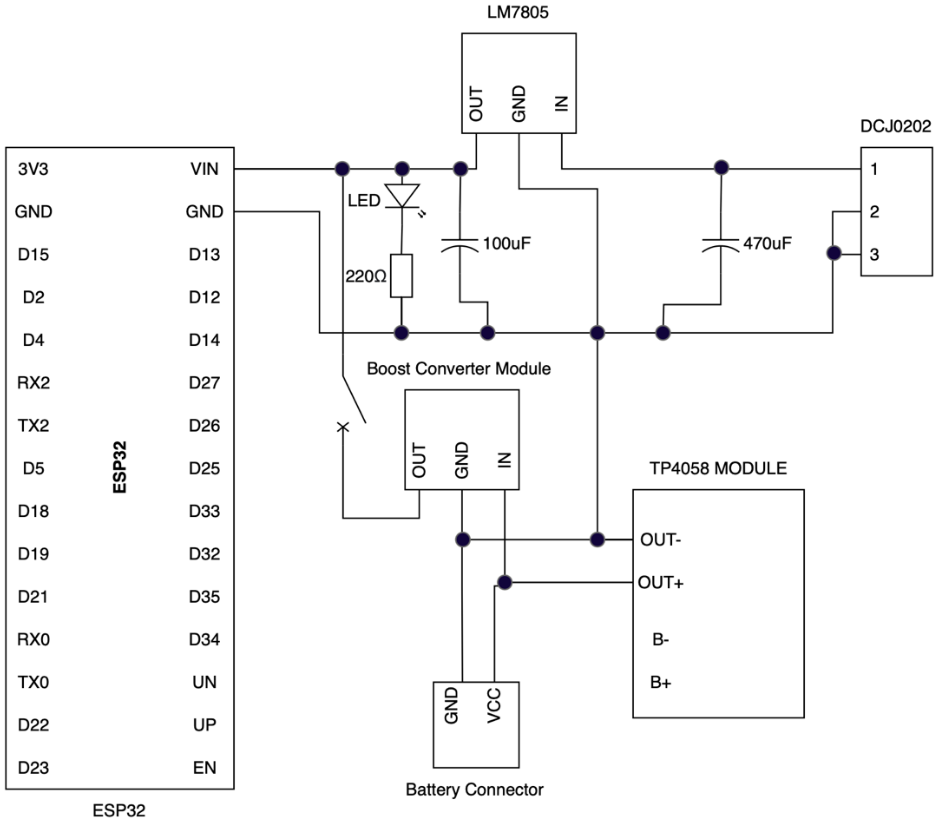

Figure 6.2.4. Proposed Battery Configuration Design [30]

Although convenient for early testing, the battery configuration with a power bank had portability, flexibility, efficiency, and cost issues, therefore the configuration using a lithium-ion battery and a step-up boost converter (shown in Figure 6.2.4) could be used in the final design.

Form Factor

The initial design of the smart breathing mask was created using Maya Autodesk, utilising basic geometric shapes for the sensors and slightly more complex shapes for the mask. The design took inspiration from the standard N95 mask which has been approved by leading organisations such as the FDA and CDC for its high filtration efficiency and tight seal, making it an ideal model for the smart breathing mask design.

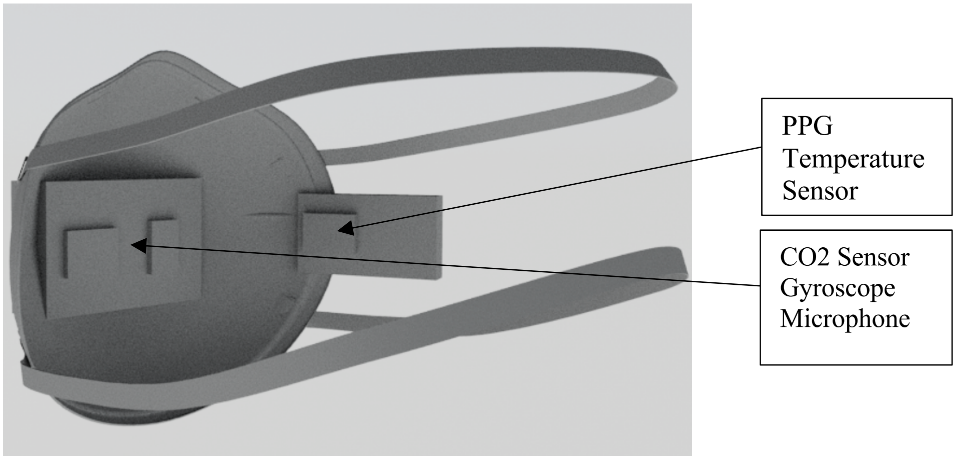

Figure 6.2.5. Sensor Placements: Back of Mask

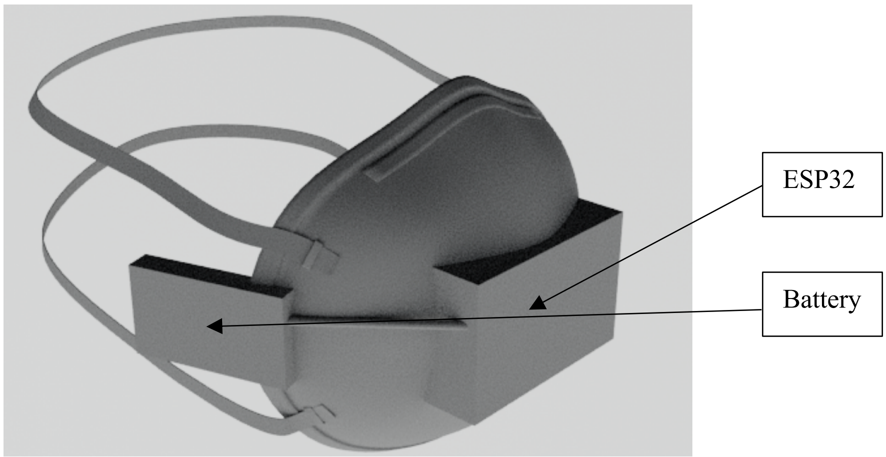

Figure 6.2.6. Battery and ESP32 Placements: Face of Mask

Figures 6.2.5. and 6.2.6. depict various perspectives of the smart breathing mask, highlighting the optimal locations for hardware placement. The ESP32 microcontroller is placed in the mask's main compartment, which offers more space for larger hardware, and is connected to the separated sensors via a tube that protects the wires and connects to the power and I2C interface.

→ No longer objective as we will integrate sensors in commercial mask. E.g. cycle mask.

6.3 Communication

The ESP32 is built with support for both Bluetooth 5.0 and 802.11 b/g/n Wi-Fi protocols allowing it to transmit data over short and long distances.

Bluetooth

When it comes to Bluetooth, the ESP32 supports the latest version of Bluetooth, Bluetooth 5.0. This allows it to establish a wireless connection with other Bluetooth-enabled devices such as smartphones, laptops, and IoT devices. The ESP32 also supports Bluetooth Low Energy (BLE), which is a power-efficient protocol that allows for long battery life in devices that use it.

Wi-Fi

When it comes to Wi-Fi, the ESP32 supports 802.11 b/g/n Wi-Fi protocols, which means it can connect to almost any Wi-Fi network. This allows it to send and receive data wirelessly over the internet or local network. Differently from Bluetooth, a communication protocol needs to be used to establish communication between the ESP32 and the web server. The three most common communication protocols which come to mind are HTTP, MQTT and COAP. As testing the speed of these three protocols could be done quite easily, testing was done during this initial analysis and design phase rather than further down the line where code could be larger and more complex. The results of sending strings of different byte sizes were as follows:

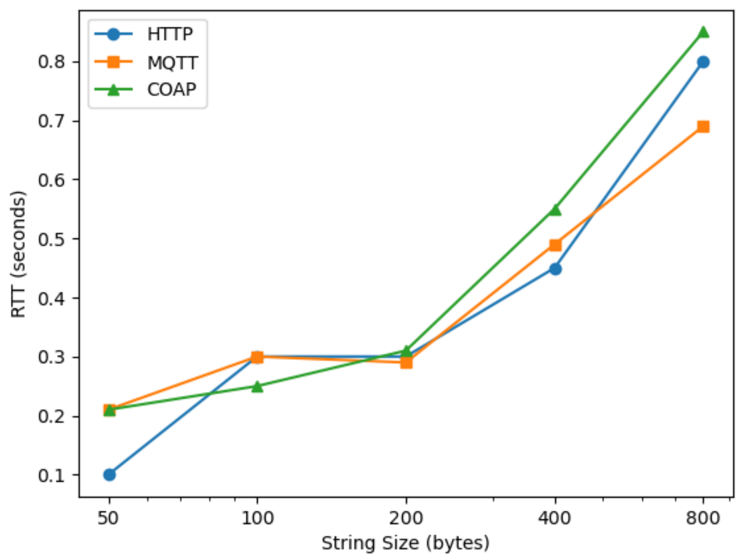

Figure 6.3.1. RTT vs Payload of Different Communication Protocols

Figure 4.3 shows that HTTP is the optimal choice for the thesis project. The analysis of the payload vs. round trip time (RTT) suggests that HTTP is the fastest and most suitable protocol for the application, which requires sending small payloads. In addition, HTTP GET requests are simple to implement and scalable, making them an ideal choice for the project's communication requirements. The well-established nature of HTTP as a protocol for the web makes it a familiar and straightforward option to use, with simple implementation and easy integration with web servers and APIs. Overall, the use of HTTP will allow the project to meet its communication needs efficiently and effectively.

6.4 Middleware

Data Processing

When creating this mask, I plan to go beyond just displaying basic health indicators and leverage the power of machine learning and other algorithms to analyse the data and extract deeper insights. In addition to converting raw sensor data into useful information such as heart rate, which was discussed in the earlier section, I plan to implement exponential or mean filtering to improve the quality of data being seen. I also plan on applying machine learning algorithms to the data, so I will be able to detect irregularities and anomalies in heart rate data and monitor physical activity levels using step counts: this may require training data that we would have to find in online datasets, by generating synthetic data or by manually collecting data. By doing this, I will be able to provide personalized exercise plans and suggestions to users based on their respiratory health data. Overall, the middleware layer will enable real-time monitoring and analysis of vital signs and facilitate the extraction of valuable insights to improve users' respiratory health.

Filtering

The two common filtering techniques used in finance are exponential in eq. (6.4.1) and Gaussian filtering in eq. (6.4.2):

$$K(\sigma, x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \tag{6.4.1}$$

$$y[n] = \alpha x[n] + (1 - \alpha) y[n-1] \tag{6.4.2}$$

Figure 6.4.3. Yahoo Finance FTSE [32]: Real Price (Blue), Gaussian Kernel (Red), Exponential Kernel (Purple)

Although both kernels are effective at reducing noise and improving the quality of the data, they offer slightly different results. Gaussian kernels are centred around the present and are more responsive to small variations in the data. On the other hand, exponential kernels place more weight on more recent information and are more responsive to larger trends in the data. This can be further observed when carefully looking at Figure 6.4.3. This means that exponential filtering tends to provide a smoother result with a slight forward shift in the data, while Gaussian filtering tends to preserve more of the original signal's features and is centred around past information. Given that we aim for the data to be as recent as possible, an exponential filter may be preferable.

Heart Rate Indicator

The following data from the American health association can help us create a model to provide an indication of health based on heart rate [33]. In this instance, resting heart rate indicates that the target has minimal movement usually during sleeping or sitting activities, moderate intensity indicates light exercise such as jogging, and vigorous activity indicates heavy exercise such as sprinting.

Age (years)	**Heart Rate (bpm)**			
	Target Resting (30-50%)	**Target Moderate Intensity (50-70%)**	**Target Vigorous Physical Activity (70-85%)**	**Absolute Maximum (100%)**
20	60-100	100-140	140-170	200
30	57-95	95-133	133-161.5	190
35	55.5-92.5	92.5-129.5	129.5-157.25	185
40	54-90	90-126	126-153	180
45	52.5-87.5	87.5-122.5	122.5-148.75	175
50	51-95	85-119	119-144.5	170
55	49.5-82.5	82.5-115.5	115.5-140.25	165
60	48-80	80-112	112-136	160
65	46.5-77.5	77.5-108.5	108.5-131.75	155
70	45-75	75-105	105-127.5	150

Table 6.4.4. American Health Associate Optimum Heart Rate Levels

The main issue with using this data is that we have no knowledge of the target's activity level. Which is what we can train a model to estimate. For this model, we will be using the Human Activity Recognition Using Smartphone dataset collected from the UC Irvine Machine Learning Repository. Our final model would take in 6 inputs (x, y, z angular velocity and x, y, z linear acceleration) and output the most likely class of activity. From there we can use user-inputted age and class to find the difference between the optimum heart rate and actual heart rate. The percentage difference could be used as a score to provide the user.

For this dataset, there is an option to use either a decision tree or a neural network to train and estimate the target activity. The decision to use one of these would depend on factors such as the size and quality of the dataset, the complexity of the relationship between the inputs and the target, and the desired accuracy and interpretability of the model. Decision trees are easy to interpret and can handle non-linear relationships between inputs and targets, making them a good option for small datasets or simple relationships. In contrast, neural networks are better suited for larger and more complex datasets, where they can capture more nuanced relationships but require more computational resources and training time. Given this, it would be most optimum to test both decision trees and neural networks with different hyperparameters and pick the model with the highest F1 score.

For a neural network, a suitable architecture would be a multi-layer feedforward network with 6 input nodes and 3 output nodes using the SoftMax activation function. The output node with the highest assigned probability would be chosen as the predicted class. We can experiment with different activation functions, number of layers, and number of hidden nodes.

For a decision tree, we can assign the model to 3 different classes and experiment with different hyperparameters such as maximum depth, minimum number of samples per leaf node, and splitting criteria to optimize the model's performance.

Breathing Rate

Both the CCS811 CO2 Sensor and Si7021 Temperature Sensor placed in front of the mouth can be used to estimate breathing rate.

Temperature sensors measure the temperature of the air passing over the sensor, and changes in temperature can be used to detect the respiratory cycle. Exhaled air is typically warmer than inhaled air, and by measuring the temperature of the air, the sensor can detect when the user exhales and inhales. Temperature sensors are simple and inexpensive and can provide accurate measurements of breaths per minute under controlled conditions. Furthermore, the use of temperature to keep track of respiration has been demonstrated in our literature research.

CO2 sensors measure the concentration of CO2 in the air, and changes in CO2 concentration can be used to detect the respiratory cycle. Exhaled air contains higher concentrations of CO2 than inhaled air, and by measuring the CO2 concentration, the sensor can detect when the user exhales and inhales. CO2 sensors are also relatively inexpensive and can provide accurate measurements of breaths per minute under similarly controlled conditions.

A naive algorithm to detect breathing rate would be a simple peak detection algorithm to detect the local maxima of these sensor readings, alternatively, we could combine these two readings using a weighted average approach which may offer better accuracy. The weights could be determined using gradient descent or other empirical techniques. The following, eq. (6.4.5), shows a weighted sum of both readings.

$$f(x) = \alpha_1 g(x) + \alpha_2 h(x) \tag{6.4.5}$$

Multimodal Sensor Approach

After extracting several key features from the sensor data using the aforementioned techniques, we can delve deeper into finding correlations between the smart mask values and the knitted coil device measurements.

A straightforward approach might involve employing machine learning algorithms to predict the knitted coil time series measurements based on the key values obtained from the mask sensors. However, in some cases, if a clear correlation is identified between the sensor values and the knitted coil measurements, more analytical techniques, such as regression analysis or curve fitting, can be employed instead of machine learning, which can simplify the process of finding a personalised model for each user. It is crucial to recognise that the model's effectiveness could vary between individuals, necessitating a calibration process to account for these differences.

The calibration process could involve collecting data from both devices while operating on a user for a short period of time. This initial data will help adjust the analytical model to better capture the unique characteristics of each individual. This approach can enhance the model's accuracy and generalisation capabilities, ultimately improving the prediction of respiratory rate measurements.

Data Management

Minimal data had to be kept for our system: device data and user data. The following Figure 6.4.6. highlights the entity relationships between elements in the database.

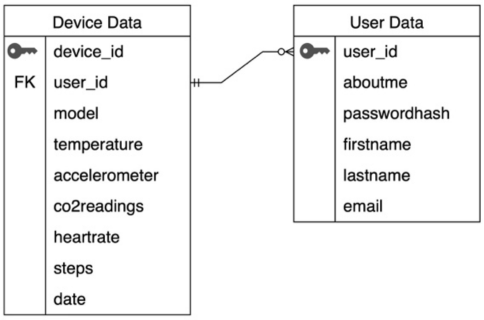

Figure 6.4.6. Database Entity Relation

In managing data, it was important to create a system that was scalable and easily modifiable. Each device would be assigned a unique ID, like a MAC address, users can then create their account and link their designated account to the specified device ID. This creates a system where multiple users can connect to multiple different devices as well instead of creating a system that only works for one individual.

Data Security

There were several measures that needed to be taken to reduce the number of vulnerabilities in such IoT devices, these included packet sniffing, password attacks, SQL/XSS injections or firmware vulnerabilities. The following measures were taken to reduce the likelihood of these occurring.

During transmission, we decided to use public key cryptography techniques, where our web server would launch a publicly accessible API to obtain the public key and the private key would be generated purely on the server side. Hence the following steps were taken for the transmission of data:

1. ESP32 obtains RSA public key and encrypts the data before transmission
2. Data is sent over HTTPS using GET requests
3. The server contains a private key used to decrypt the transmitted data

To secure the passwords in my database, I used a technique called password hashing with salt. First, I generated a unique random salt for each user's password. Then, I concatenated the salt with the password and passed it through a cryptographic hashing function. The resulting hash was then stored in the database. By using a unique salt for each user, I ensured that even if two users had the same password, their hashes would be different, which makes it more difficult for attackers to reverse-engineer the passwords. Additionally, by using a strong cryptographic hashing function, I ensured that it would be computationally difficult and time-consuming for attackers to guess the original password from the hash. This approach provided an additional layer of security to my password database and helped protect my users' passwords from being compromised.

To prevent SQL injections, it is important to maintain the use of prepared statements throughout my site. Furthermore, SQLMap can be run against the web server to ensure that no SQL vulnerabilities were found.

Given that the site is developed using the Django framework, cross-site scripting attacks are usually protected against, however, it is always important to maintain the latest firmware to prevent bugs in these frameworks.

6.5 Application

Data Visualization

To display real-time data on the website, Chart JS and AJAX can be used in the application layer of the system. The following steps show how data goes from the sensors all the way to the frontend system:

1. The ESP32 reads sensor data.
2. The data, including the device ID, is sent to the backend via HTTPS for storage in the database.
3. When a user requests real-time data, the front end sends an AJAX request to the backend.
4. The backend responds to the AJAX request with the latest sensor data from the database.
5. The frontend JavaScript updates the UI with the received sensor data and renders it in charts using Chart JS.

Interaction

In the application layer of the smart breathing mask, the user experience is designed as follows:

1. Account creation: The user begins by downloading the companion app for the smart breathing mask and creating an account. This involves entering personal information such as name, age, weight, and height, which will be used to tailor insights and recommendations.
2. Device pairing: Next, the user pairs their smart breathing mask and knitted coil with the application. This is typically done through a Bluetooth or Wi-Fi connection. Once connected, the app will display the status of both devices and sync data in real time.
3. Calibration: The calibration process is initiated through the app, guiding the user through a series of steps to ensure accurate measurements between the smart breathing mask and the knitted coil. This may include performing specific activities or breathing exercises to generate a baseline of data for comparison.
4. Viewing key values and insights: Once calibration is complete, the user can access a dashboard within the app that displays real-time data on breathing rate, heart rate, CO_2 levels, movement, and temperature. The dashboard also provides insights and recommendations based on the data, helping the user understand their respiratory health and make informed decisions about their training and overall well-being.
5. Saving calibration data: After the initial calibration, the app stores the calibration data for future use. This allows users to switch between using the smart breathing mask and the knitted coil for single predictive use. By leveraging the stored calibration data, the system can predict all values using only one of the devices, providing a flexible and convenient monitoring solution.
6. Ongoing interaction: Users can continue to interact with the app, updating their personal information, recalibrating devices as needed, and reviewing the insights generated by the smart breathing mask and knitted coil. The app may also include features such as goal setting, progress tracking, and sharing capabilities, further enhancing user engagement, and promoting a healthy lifestyle.

Additional Features

The following additional features were added to improve the interactivity of the application:

1. **Leaderboard**: Given that an algorithm is developed for step counts, a leader board system can also be developed publicly or between friends to increase engagement of the platform
2. **Search for Others**: Given that the database contains users, we can utilize this further to show public information of other users when searching

7 Implementation and Results

7.1 Visualization

Real Time Graphs

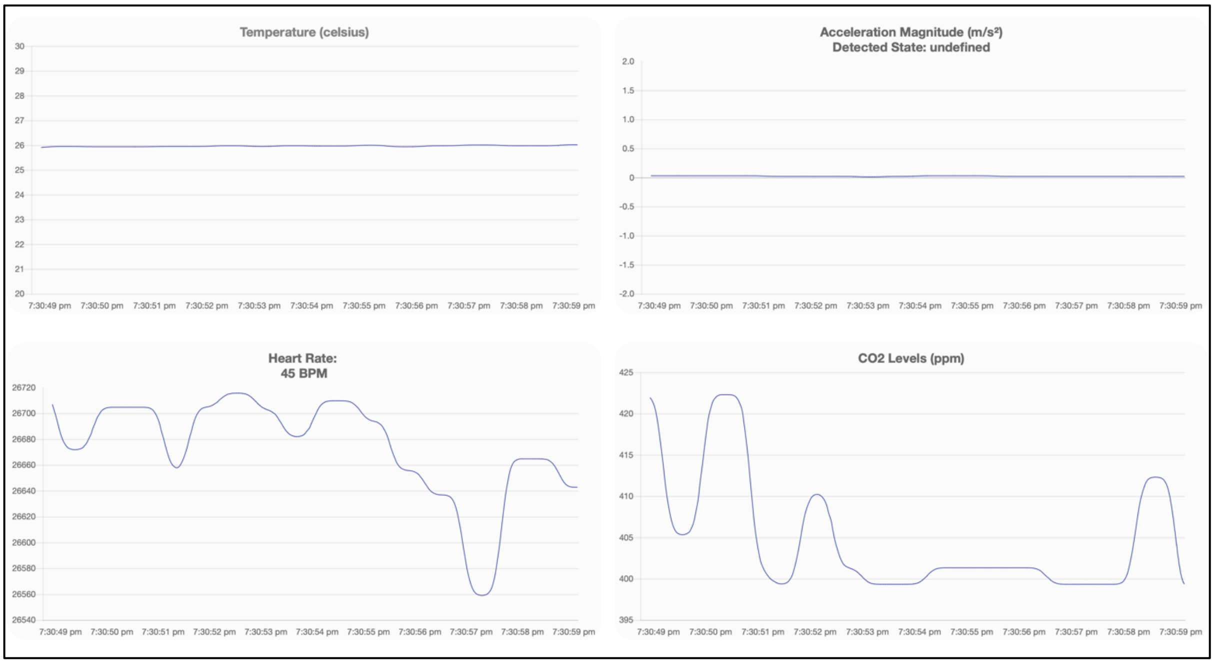

Figure 7.1.1. Real Time Graphs

The real time graphs utilized Chart JS and AJAX discussed in 6.5.

Health Indicators

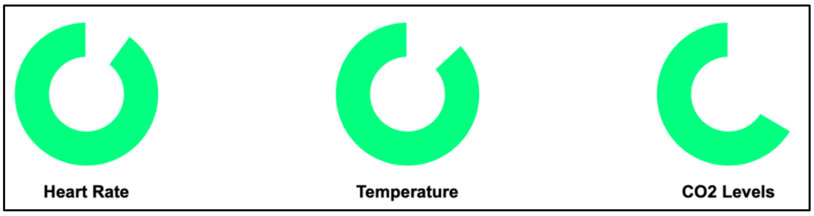

Figure 7.1.2. Health Indicators

The heart rate indicators similarly utilized Chart JS and AJAX discussed in 6.5.

Leader boards

Rank	Name	Steps	Calories Burnt
1	matthewsetiawan	535	21
2	mattset123	500	20

Figure 7.1.3. Leader boards

A leaderboard system was implemented to keep track of different users and their daily activities. Beyond demonstrating the ability to count steps it also demonstrates the scalability of the current created model, which is not only optimized for a single user.

7.2 Data Processing

Heart Rate Processing

When calculating heart rate, I initially implemented a peak-to-peak-based algorithm by simply counting the number of local extrema, as it was easier to execute and required less computational complexity. However, the simple peak-to-peak method has certain limitations that can affect the accuracy and reliability of the results.

Subsequently, I transitioned to using a modified Pan-Tompkins algorithm adapted for PPG signals, which offered several benefits over the simple peak-to-peak method. These benefits include:

1. Noise resistance: The modified Pan-Tompkins algorithm employs filtering and differentiation techniques to reduce the impact of noise and artifacts present in the PPG signal. This improves the accuracy of heart rate detection, as it reduces the likelihood of false positives caused by noise.
2. Robustness: The modified Pan-Tompkins algorithm is designed to adapt to variations in the PPG signal shape and heart rate, making it more robust and reliable across different individuals and situations. The simple peak-to-peak method, on the other hand, can be susceptible to errors when confronted with variations in the signal.
3. Improved accuracy: By using specific features of the PPG signal as the basis for detecting heartbeats, the modified Pan-Tompkins algorithm can achieve better accuracy in heart rate estimation compared to the simple peak-to-peak method, which may not account for all the complexities of the PPG signal.

In summary, the modified Pan-Tompkins algorithm for PPG signals provides a more reliable and accurate approach for calculating heart rate when compared to the simple peak-to-peak method. While the initial implementation of the peak-to-peak method was easier, the transition to the modified Pan-Tompkins algorithm has led to better results, making it a more suitable choice for PPG-based heart rate detection.

Filtering

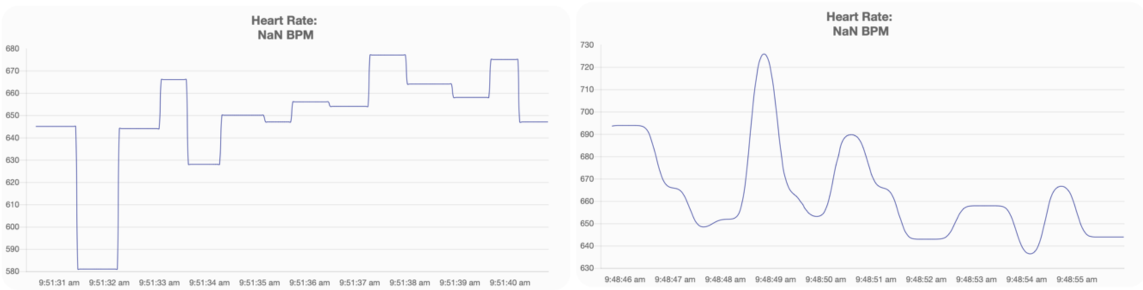

Figure 7.2.1. Pre-Filtered PPG Signal (Left), Post Filtered PPG Signal (Right)

In my analysis of time series data, I implemented a kernel-based filtering approach, which provided flexibility and ease of customisation. With kernel-based filtering, it is straightforward to switch between different kernel functions, such as exponential or Gaussian kernels, by simply adjusting the kernel values in a 1D array.

To determine the most suitable kernel for our application, I compared the performance of the exponential kernel and the Gaussian kernel across various time series data. The exponential kernel was hypothesised to work better for our specific use case, as it focuses more on "real-time" data by giving higher weight to recent observations. The Gaussian kernel, on the other hand, gives equal importance to both past and future observations within the window, which may result in a smoother output but may not be as responsive to recent changes in the data.

Upon evaluating the two kernel functions, I found that the exponential kernel indeed performed better than the Gaussian kernel, in line with our hypothesis. Consequently, we decided to stick with the exponential kernel values for processing our time series data, as it provided a more accurate representation of the data's underlying trends while still being responsive to real-time changes.

Heart Rate Indicator

The heart rate indicator shown in Figure 7.1.2 was a result of the machine learning algorithm that we implemented following our design plan in 6.4. The results of using a neural network and decision tree for classification were as follows (note that to use the neural network as a classifier we simply chose the class with the highest probability).

		Actual		
		Resting	Moderate Intensity	Vigorous Intensity
Predicted	Resting	275	24	12
	Moderate Intensity	54	292	67
	Vigorous Intensity	21	34	271

Figure 7.2.2. Decision Tree Model

		Actual		
		Resting	Moderate Intensity	Vigorous Intensity
Predicted	Resting	241	58	9
	Moderate Intensity	84	242	59
	Vigorous Intensity	25	50	282

Figure 7.2.3. Neural Network Model

In the context of training accelerometer data to detect whether the target is resting, moderately exercising, or vigorously exercising, the decision tree model achieved an accuracy of 80%. In contrast, the neural network model obtained an accuracy of only 73%. This discrepancy in performance could be attributed to several factors.

The decision tree model may have been more effective in capturing the relationships between the features in this specific problem, as it involves a smaller number of features and relatively simpler relationships between variables. The decision tree's hierarchical structure can efficiently separate the different activity levels based on the accelerometer data, leading to higher accuracy. On the other hand, the neural network's lower accuracy could be due to its inherent complexity and the potential for overfitting, especially if the dataset used for training is relatively small or noisy. Additionally, the neural network's performance is highly dependent on its architecture and hyperparameters. An inappropriate choice of these factors could also contribute to the lower accuracy.

In this case, the decision tree model outperformed the neural network model for the given problem, providing a more accurate classification of the target's activity levels based on the accelerometer data. This highlights the importance of evaluating different models on a specific problem and dataset to determine the most suitable approach for the task at hand.

Breathing Rate

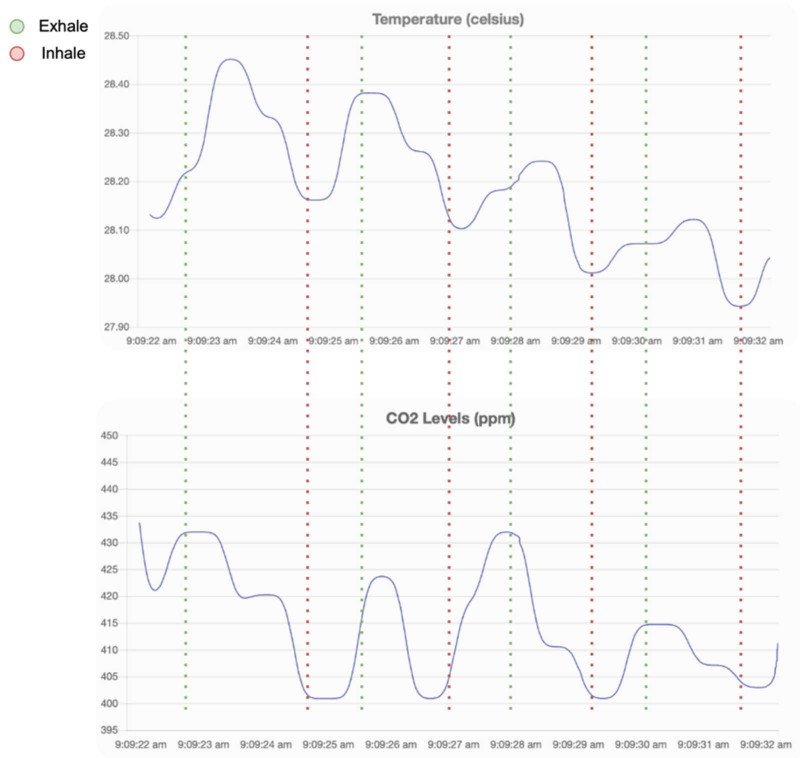

Figure 7.2.4. Temperature and CO2 Readings Overlayed with Breathing Periods

When overlaying inhales and exhales with temperature and CO2 levels using sensors placed in front of the mouth, several observations can be made. First, both CO2 levels and temperature appear to increase during exhales, followed by a gradual decrease. This trend likely results from the warm, CO2-rich air being expelled from the lungs during exhalation. Second, inhales do not exhibit a strong response in the data, potentially due to their minimal impact on temperature and CO2 levels. This can be explained by the inhalation of cooler, fresh air with lower CO2 concentrations, which may not cause significant changes in the sensor readings. Additionally, it's worth noting that the exhale periods do not align perfectly with the troughs of the graph. This observation further supports the idea that inhales have a minimal impact on the temperature and CO2 levels, as their influence is not as clear in the data.

Upon closer examination of the data, it appears that CO2 levels have a faster response to exhales than temperature. This faster response could be attributed to the higher concentration of CO2 in the exhaled air, which causes a more immediate change in the CO2 sensor readings. On the other hand, the temperature change may be slower due to the heat dissipation dynamics, as it takes more time for the warmth of the exhaled air to affect the surrounding environment and consequently the temperature sensor.

Although the troughs of the graph are not perfectly in sync with the exhale periods, the overall peaks align well with the breathing pattern. This alignment suggests that the sensor data can still provide highly accurate breathing rate measurements. The peaks in the CO2 and temperature readings correspond to the timing of the exhales, enabling precise tracking of the user's breathing pattern and allowing for reliable estimation of breathing rates.

good status on measurements

8 Conclusion

The current progress of the project is roughly following the expected schedule. The extensive background research I conducted on similar smart mask concepts and the market demographic provided valuable insights that helped me make informed decisions about the direction of my project.

The current MVP developed includes a microcontroller with integrated and functional sensors, which can communicate and process sensor data to the web application using Bluetooth and/or Wi-Fi. The server-side processing and analysis of data currently include basic machine learning, filtering, data aggregation, and feature extraction. Furthermore, the application layer was designed to effectively visualise and communicate processed data to clients. This front end features robust and interactive visualisations, allowing for better data comprehension and analysis.

For future work, the main area of development is for integration and research on the original knitted coil device, which would allow for a lot of functionality. Beyond this, it is also an industry standard to transition from the current breadboard state of the project to a more suitable PCB, along with custom power management.

9 References

[1] Fobelets, K. (2020). Knitted coils as breathing sensors. Sensors and Actuators A: Physical, 306, 111945. https://doi.org/10.1016/j.sna.2020.111945

[2] General Data Protection Regulation (GDPR). (2022, September 27). Official Legal Text. https://gdpr-info.eu/

[3] Federal Communications Commission. (n.d.). Radio Frequency Safety. https://www.fcc.gov/general/radio-frequency-safety-0

[4] Adeel, M., Cotur, Y., Naik, A., Gonzalez-Macia, L., & Güder, F. (2022). Face masks as a platform for wearable sensors. Nature Electronics. https://doi.org/10.1038/s41928-022-00871-2

[5] Steinhubl, S. R., Waalen, J., & Edwards, A. M. (2018). Digital medicine: A primer on measurement. Digital Medicine, 1(1), 1-11.

This reference does not exist!

[6] The Guardian. (2018, June 1). Cancer patients could be saved by 'Fitbits for the tumour'. https://www.theguardian.com/technology/2018/jun/01/cancer-fitbit-treatment-chemotherapy

[7] Dunn, J., Runge, R., & Snyder, M. (2018). Wearables and the medical revolution. Personalized Medicine, 15(5), 429-448.

[8] NHS Inform. (n.d.). Illnesses and conditions - Lungs and Airways. https://www.nhsinform.scot/illnesses-and-conditions/lungs-and-airways

[9] Chen, A., Zhang, J., Zhao, L., Rhoades, R. D., Kim, D. Y., Wu, N., Liang, J., & Chae, J. (2020). Machine-learning enabled wireless wearable sensors to study individuality of respiratory behaviors. Biosens Bioelectron, 173, 112799. https://doi.org/10.1016/j.bios.2020.112799

[10] Tsang, K. C. H., Pinnock, H., Wilson, A. M., & Shah, S. A. (2022). Application of Machine Learning Algorithms for Asthma Management with mHealth: A Clinical Review. J Asthma Allergy, 15, 855-873. https://doi.org/10.2147/JAA.S285742

[11] McDowell, A., Kang, J., Yang, J., Jung, J., Oh, Y.-M., Kym, S.-M., Shin, T.-S., Kim, T.-B., Jee, Y.-K., & Kim, Y.-K. (2022). Machine-learning algorithms for asthma, COPD, and lung cancer risk assessment using circulating microbial extracellular vesicle data and their application to assess dietary effects. 30 September 2022.

[12] Pereira, C. B., Yu, X., Czaplik, M., Rossaint, R., Blazek, V., & Leonhardt, S. (2017). Remote monitoring of breathing dynamics using infrared thermography. Biomedical Optics Express, 8(11), 4838-4850. https://doi.org/10.1364/BOE.8.004838

[13] Retory Y, Niedzialkowski P, de Picciotto C, Bonay M, Petitjean M. New Respiratory Inductive Plethysmography (RIP) Method for Evaluating Ventilatory Adaptation during Mild Physical Activities. PLoS One. 2016 Mar 23;11(3):e0151983. doi: 10.1371/journal.pone.0151983. PMID: 27008313; PMCID: PMC4805261.

[14] Li, J., Yin, J., Ramakrishna, S., & Ji, D. (2023). Smart Mask as Wearable for Post-Pandemic Personal Healthcare. Biosensors, 13, 205. https://doi.org/10.3390/bios13020205

[15] Kalavakonda, R. R., Masna, N. V. R., Mandal, S., & Bhunia, S. (2021). A smart mask for active defense against airborne pathogens. 7 October 2021.

lacks information & doi

[16] Escobedo, P., Fernández-Ramos, M. D., López-Ruiz, N., et al. (2022). Smart facemask for wireless CO2 monitoring. Nat Commun, 13, 72. https://doi.org/10.1038/s41467-021-27733-3

[17] Akduman, C., & Akçakoca Kumbasar, E. P. (2018). IOP Conf. Ser.: Mater. Sci. Eng. 460, 012013.

[18] Hyysalo, J., Dasanayake, S., Hannu, J., Schuss, C., Rajanen, M., Leppänen, T., Doermann, D., & Sauvola, J. (2022). Smart mask – Wearable IoT solution for improved protection and personal health. Internet of Things, 18, 100511. https://doi.org/10.1016/j.iot.2022.100511

[19] Maxim Integrated Products. (2019, October 29). MAX30102 Datasheet. https://www.analog.com/media/en/technical-documentation/data-sheets/MAX30102.pdf

[20] Esgalhado, F., Batista, A., Vassilenko, V., Russo, S., & Ortigueira, M. (2022). Peak Detection and HRV Feature Evaluation on ECG and PPG Signals. Symmetry, 14(6), 1139.

[21] Hartmann, V., Liu, H., Chen, F., Hong, W., Hughes, S., & Zheng, D. (2019). Toward Accurate Extraction of Respiratory Frequency From the Photoplethysmogram: Effect of Measurement Site. https://www.researchgate.net/publication/333854219_Toward_Accurate_Extraction_of_Respiratory_Frequency_From_the_Photoplethysmogram_Effect_of_Measurement_Site

[22] Advanced Manufacturing Services. (2016, December 23). CCS811 Datasheet. https://cdn.sparkfun.com/assets/learn_tutorials/1/4/3/CCS811_Datasheet-DS000459.pdf

[23] West, J. B. (2012). Respiratory physiology: The essentials. Lippincott Williams & Wilkins.

[24] SiliconLabs. (2017, April 26). Si7021-A20 Datasheet. https://www.silabs.com/documents/public/data-sheets/Si7021-A20.pdf

[25] Dragonieri, S., et al. (2007). An electronic nose in the discrimination of patients with asthma and controls. Journal of Allergy and Clinical Immunology.

[26] InvenSense. (2013, September 19). MPU 6000 Datasheet. https://invensense.tdk.com/wp-content/uploads/2015/02/MPU-6000-Datasheet1.pdf

[27] Massaroni, C., Nicolò, A., Lo Presti, D., Sacchetti, M., Silvestri, S., & Schena, E. (2019). Contact-based methods for measuring respiratory rate. Sensors, 19(4), 908. https://doi.org/10.3390/s19040908

[28] Khan, A. M., Lee, Y. K., Lee, S. Y., & Kim, T. S. (2010). A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. IEEE Transactions on Information Technology in Biomedicine, 14(5), 1166-1172. https://doi.org/10.1109/TITB.2010.2051955

[29] Massaroni, C., Nicolò, A., Lo Presti, D., Sacchetti, M., Silvestri, S., & Schena, E. (2019). Contact-based methods for measuring respiratory rate. Sensors, 19(4), 908. https://doi.org/10.3390/s19040908

[30] How2Electronics. (n.d.). Power Supply for ESP32 with Boost Converter & Battery Charger. Retrieved May 5, 2023, from https://how2electronics.com/power-supply-for-esp32-with-boost-converter-battery-charger/

[31] MathWorks. (n.d.). Kernel covariance function options. Retrieved May 2, 2023, from https://www.mathworks.com/help/stats/kernel-covariance-function-options.html

[32] Yahoo Finance. (n.d.). Financial Times Stock Exchange. (FTSE) stock price, news, quote & history. Retrieved May 2, 2023, from https://finance.yahoo.com/quote/FTSE

[33] American Heart Association. (n.d.). Target heart rates chart. Retrieved May 2, 2023, from https://www.heart.org/en/healthy-living/fitness/fitness-basics/target-heart-rates