MACHINE LEARNING ENABLED WEARABLE STETHOSCOPE: DESIGN DOCUMENT

ECE 445 – 2/22/2018

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Table of Contents

Introduction....2
- Objective....2
- Background....2

High-Level Requirements....3

Design....3
- Block Diagram....3
- Physical Design....4
- Functional Overview....4
- Software Overview....12
- Tolerance Analysis....15

Cost and Schedule....17
- Cost Analysis....17
- Schedule....19

Ethics and Safety....19

References....22

Appendix A....25

Introduction

Objective

Millions of people in the United States suffer from chronic conditions related to the lungs and heart. Many more are in professions or positions which place them at risk of sudden afflictions of these two organs. In these cases, the time of response and diagnosis is crucial to the survivability of the individual.

We propose a wearable device, which constantly monitors the heart and lungs of a patient much like a doctor would with a stethoscope. Databases of lung and heart sounds used to train machine learning models like [1], [2] would allow this device to recognize conditions and communicate to the appropriate parties immediately.

Background

There are many conditions that can be diagnosed from listening to the sound produced by the organs, a practice called auscultation. In our proposal we are focusing on the conditions afflicting the heart and lungs, mainly: chronic obstructive pulmonary disease (COPD), pertussis, pneumonia, heart murmurs and irregular heartbeats (a longer list of conditions that can be diagnosed through auscultation can be found in Appendix A).

In the United States, there are 40 million people living with some chronic respiratory disease. There are also 735,000 Americans which have heart attacks, with 610,000 Americans a year dying from a heart condition [12]. When it comes to either heart or lung conditions, the quality of life and survivability can be improved by constant monitoring and early detection of emergency events.

In the current market, heart rate monitors are available commercially. The most extensively used product requires the user to put a band around the chest and wear a watch that displays the heart rate the band is picking up. The band uses electrocardiography to pick up heart electrical activity and requires moisture, whether you put water on the band or your sweat gets on the band, in order to pick up the electrical signal. The band contains a microprocessor that analyzes the electrical signals given off by the heartbeat and transmits the data to the watch via Bluetooth [13]. In the more recent years, the data has been able to transmit to mobile apps as well. Our product deviates from this heart rate monitor in the fact that it also measures lung sounds. Instead of using electrocardiography, our wearable stethoscope uses multiple microphones to pick up sound, therefore not requiring the band to be damp and uncomfortable. Our proposed project also doesn’t just listen to sounds, it’ll detect any abnormalities within the heart and lungs. It is important to note, however, that it is not intended to replace a stethoscope. The main goal is to monitor patients with pre-existing heart or lung conditions outside of the doctor’s office.

High-Level Requirements

The system must be able to

- Use its microphones to capture the heart and lung sounds which occur at frequencies between 20 and 150 Hz and between 50 and 2500 Hz respectively, as well as filter out the ambient noise to reduce it to a maximum of 10% of the total measured incoming signal
- Take the captured audio input and determine if it corresponds to an abnormal heart or lung condition with an accuracy of ~90%
- Detect an abnormality in the heart or lung sounds within four seconds once the incoming signals have been filtered

Design

Block Diagram

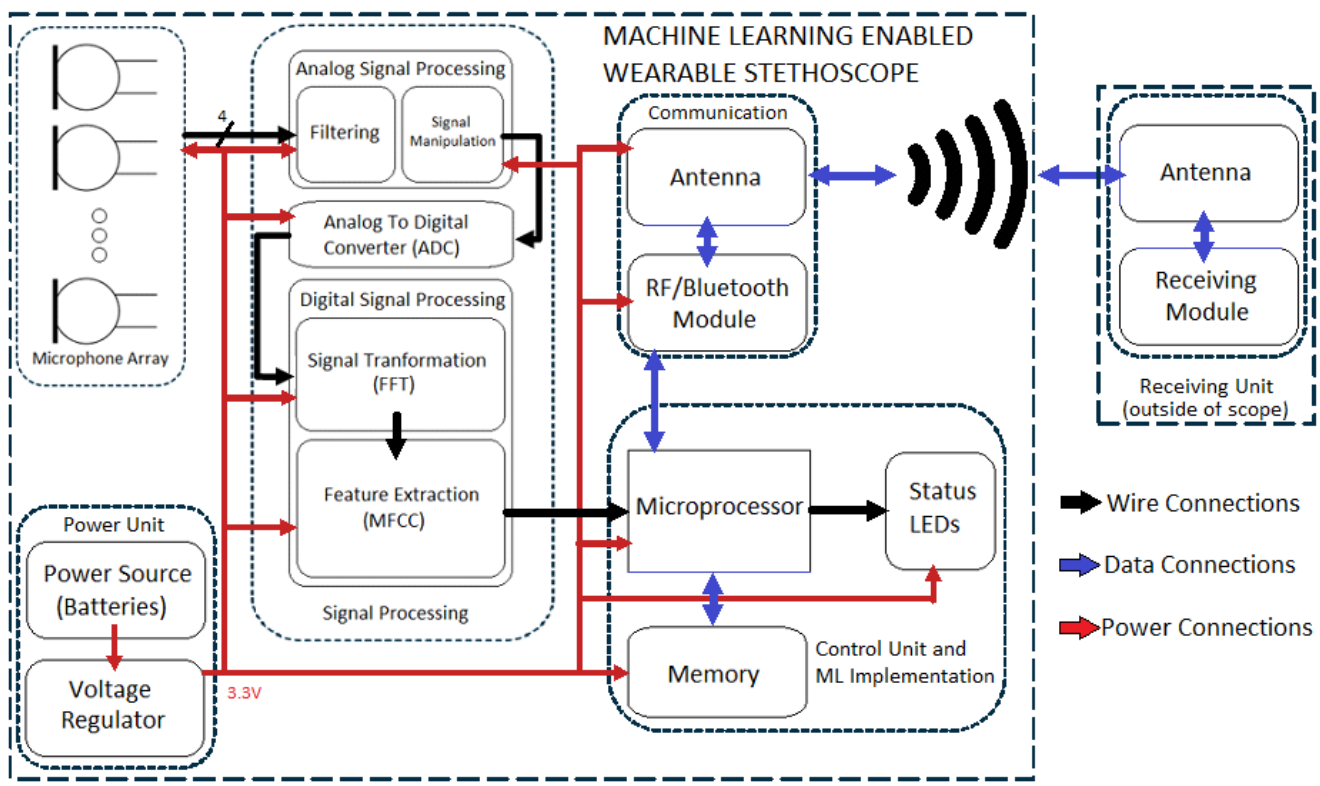

Fig. 1: Overall block diagram following audio signal path

The block diagram design described in Figure 1 (above) fulfills the high-level requirements described and follows the path of the audio signals. First, the microphone array and associated analog and digital signal processing fulfills the system's ability to sense the sounds produced by the heart and lungs. Second, the microprocessor and memory (parts of the control unit) will allow the implementation of the machine learning algorithms required to detect conditions of the organs. Finally, the wireless capability will enable the system to warn the user (or doctor) of any detected issues.

Physical Design

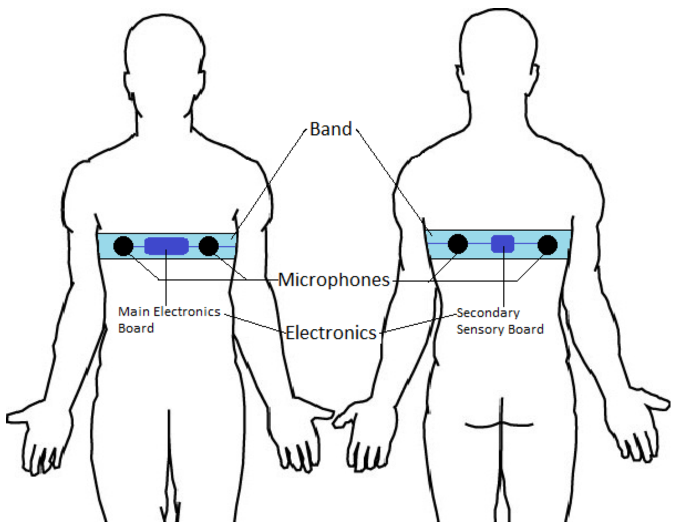

Fig. 2: Physical design of system

The physical design of the system will comprise of a band to be worn around the chest with an appendage to help with comfort and placement – shown in Figure 2. The main band is placed around the circumference of the chest and there will be four microphone sensors. These are placed strategically to record sounds from the heart and both lungs, as well as to analyze different sensor outputs for filtering out noise. The electronics will be embedded in the band and the electronics boards will perform all the necessary signal processing and computation to fulfill the high-level requirements. The material of the band is discussed in the Safety and Ethics portion due to the wide range of materials that are plausible and the concerns it raises. We propose the band to be similar to a gauze bandage that is 100% cotton.

Functional Overview

Microphone Array

The microphone array acts as the system's sensors. The sensors are the interface between the organs we are monitoring and the system we are designing. For the microphone array to function as required, it must be able to detect sounds and vibrations in the range corresponding to the conditions we are trying to detect. Heart sounds occur in the range between 20 and 150 Hz and lung sounds between 50 and 2500 Hz [6]. We're using four microphones to pick up the sounds, two for the heart and two for the lungs. Two of the microphones, strategically placed to pick up the heart or lung sounds better, will output to an analog signal processing unit to be filtered by the correct frequencies. The outputs of the other two microphones, strategically placed to pick up more ambient noise, will be fed directly into the microprocessor to compare the signal closer to the source of sound and the signal with ambient noise in order to filter out the ambient nose. The following schematic and board layout were built based off of the datasheet for the CMA-4544PF-W microphones we intend to use [14].

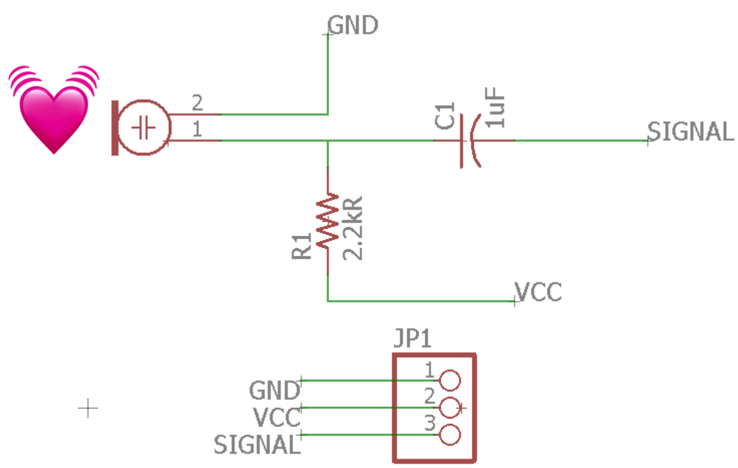

Fig. 3: Microphone unit schematic

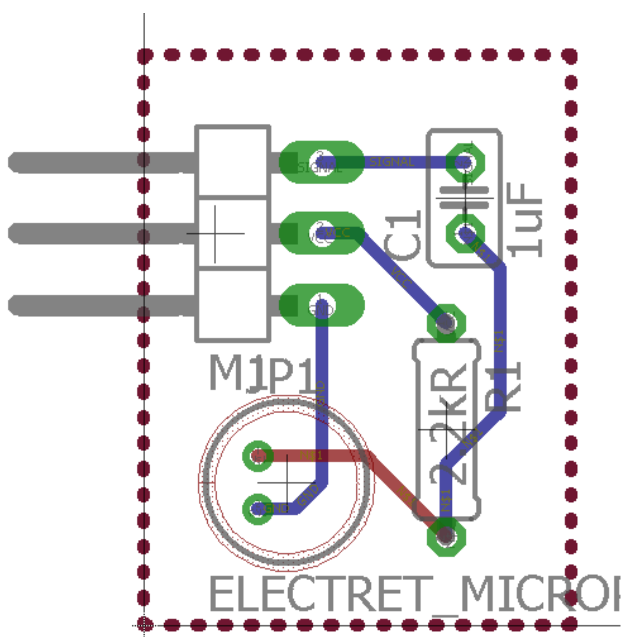

Fig. 4: Microphone unit board

TABLE I
MICROPHONE ARRAY REQUIREMENTS

Requirements	Verification
• Have a response in the frequency range between 25Hz and 25kHz • Operate on 3.3V +/- 0.1V	• Produce audio through the entire range and use an oscilloscope to plot the voltage response • Attempt to power microphones with a Vcc between 3.2V and 3.4V

Power Unit

The power unit provides the power required to operate all the other components in the system. The system is comprised of components which operate at 3-5V. As such, it should be possible to use a single power line to power all the components of the system.

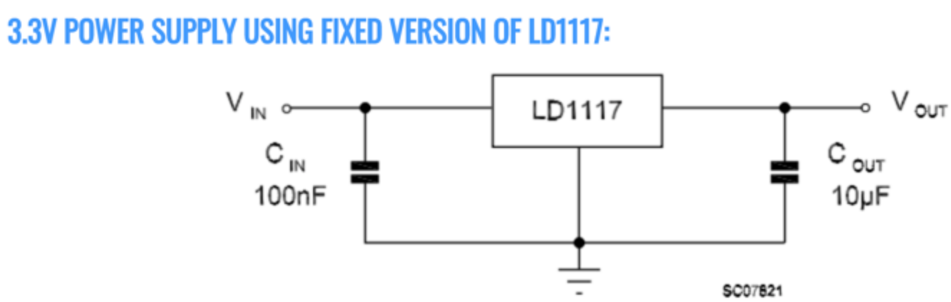

Fig. 5: Power supply circuit [19]

TABLE II
POWER UNIT REQUIREMENTS

Requirements	Verification
• Generate 3.3V +/- 0.1V • Can operate at currents 0-200mA • Batteries provide 2500mAh of power	• Measure the output voltage from the voltage regulator and verify that it stays within 3.3V +/- 0.1V • Use a constant current circuit to draw 200mA from the power supply and voltage regulator • Connect the battery to a discharging circuit. Verify that at the maximum current (200mAh), it runs for 12.5 hours

Analog Signal Processing

The analog signal processing takes care of filtering out noise coming from outside the frequency range for which we are interested in, between 20 and 150 Hz for the heart and between 50 and 2500 Hz for the lungs [6]. This sub-unit takes its input from the microphones and manipulates the signals before sending them to the Analog-To-Digital Converter (ADC).

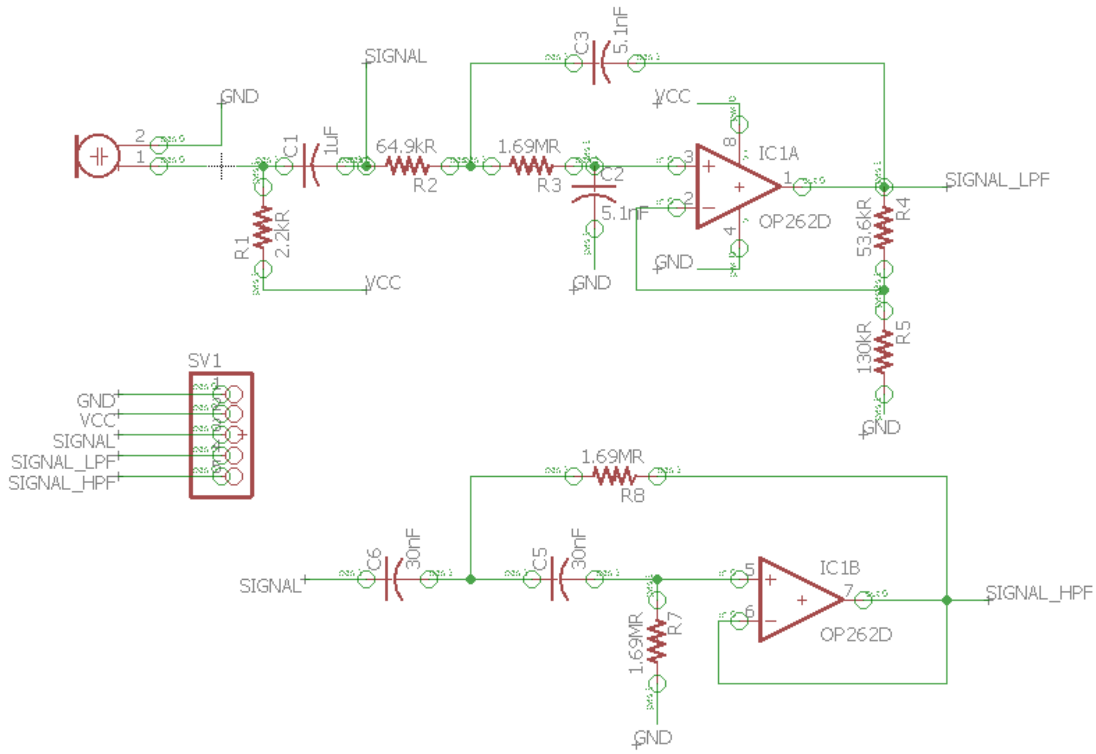

Fig. 6: Analog signal processing circuit

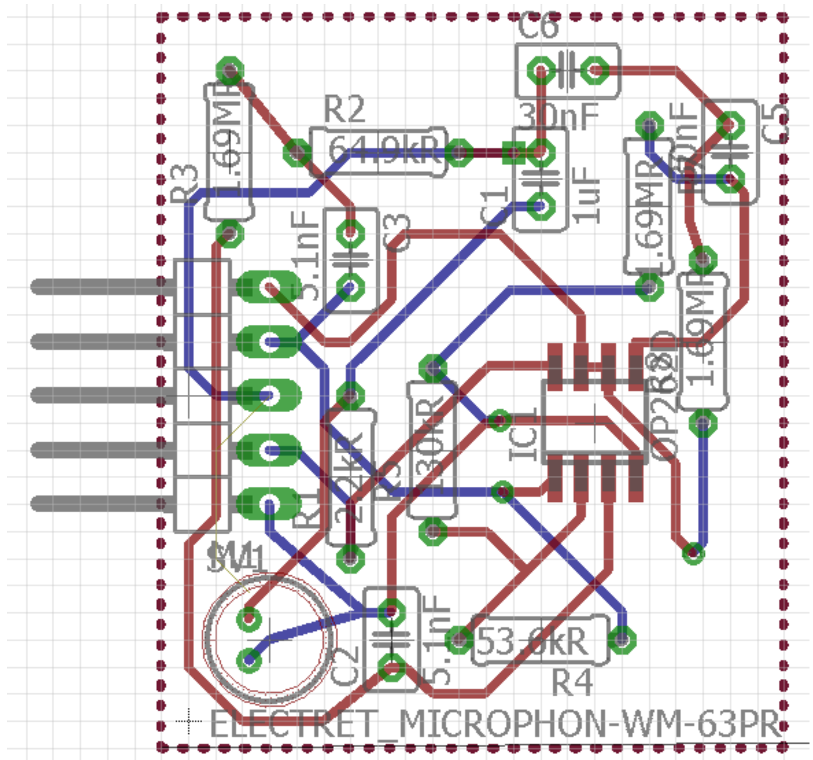

Fig. 7: Analog signal processing board

TABLE III
ANALOG SIGNAL PROCESSING REQUIREMENTS

Requirements	Verification
• -3dB response below 25Hz and above 300Hz for filtering out heart sounds. • -3dB response below 50Hz and above 2500kHz for filtering out lung sounds.	• Use signal generator to generate signals at 25Hz and below. Measure frequency response to verify -3dB below. Do the same for signals above 300Hz. • Use signal generator to generate signals at 50Hz and below. Measure frequency response to verify -3dB below. Do the same for signals above 25kHz.

Analog to Digital Converter

The ADC will then take the output from the analog signal processing unit and convert it into digital readings. These will allow for the processing required that cannot be done through analog signals alone. The conversion to digital enables the transformations for features to be generated (MFCC). The analog to digital converter will have to be quick and have a large enough accuracy to prevent bias. It will also require a good bit-width so as not to quantize the readings too much. The microprocessor we into to use includes an analog to digital converter we can use.

TABLE IV
ADC REQUIREMENTS

Requirements	Verification
• 10 Bit ADC with 60ksps • 8 Analog Input Lines for ADC	• Generate a signal with Nyquist frequency requirement >60Hz. Use ADC to look for biasing of signal. • Generate 8 independent signals. Read values converted to digital for all signals, compare to input signals.

Microprocessor

The microprocessor will be the unit which does all the computations necessary for the filtering the incoming signals, converting to Mel Frequency Cepstrum Coefficients (MFCC), and implementing a machine learning algorithm to do the diagnosing. It will also handle the preparation of the data for sending through the communication unit and will choose the data to be stored in the memory.

TABLE V
MICROPROCESSOR REQUIREMENTS

Requirements	Verification
• Can receive and transmit through UART at a rate of >10Mb/s • Can receive and transmit through SPI at a rate of >10Mb/s	• Send a 100 Mb random message through the UART port. Verify signal received is the same as signal sent. Verify that it took less than 10s. • Send a 100 Mb random message through the SPI port. Verify signal received is the same as signal sent. Verify that it took less than 10s.

Memory

The memory will be both embedded and external. Due to the sensitivity of the type of data, medical data, it is crucial to store the history of the patient. Therefore, there needs to be a means of permanently storing the patient history gathered by the device.

TABLE VI
MEMORY REQUIREMENTS

Requirements	Verification
• Write/Program memory at 102 kbits/s • Have a total usable memory of > 256 kbit • Operate on 3.3V +/- 0.1V	• Record the time it takes to write a large file (~2 MB). Attempt multiple times. • Try to fill the memory with > 256 Kbit • Attempt to power chip with a Vcc between 3.2V and 3.4V

Communication

The communication unit interfaces our device to the outside world, where actionable information can reach the right people and lives can potentially be saved. The communication unit will need to consume little power and ideally it would be powered on only when a message needs to be sent.

TABLE VII
COMMUNICATION REQUIREMENTS

Requirements	Verification
• Able to communicate through UART or SPI • Have at least 250 kBit/s data communication rates (due to small size of files) • Operate on 3.3V +/- 0.1V	• Check in manufacturer datasheet for UART or SPI pin capability. Verify by sending simple message to chip. • Program to send a file of known size from Bluetooth chip to a microcontroller. Measure the time for transmission. • Attempt to power chip with a Vcc between 3.2V and 3.4V

Additional Circuits

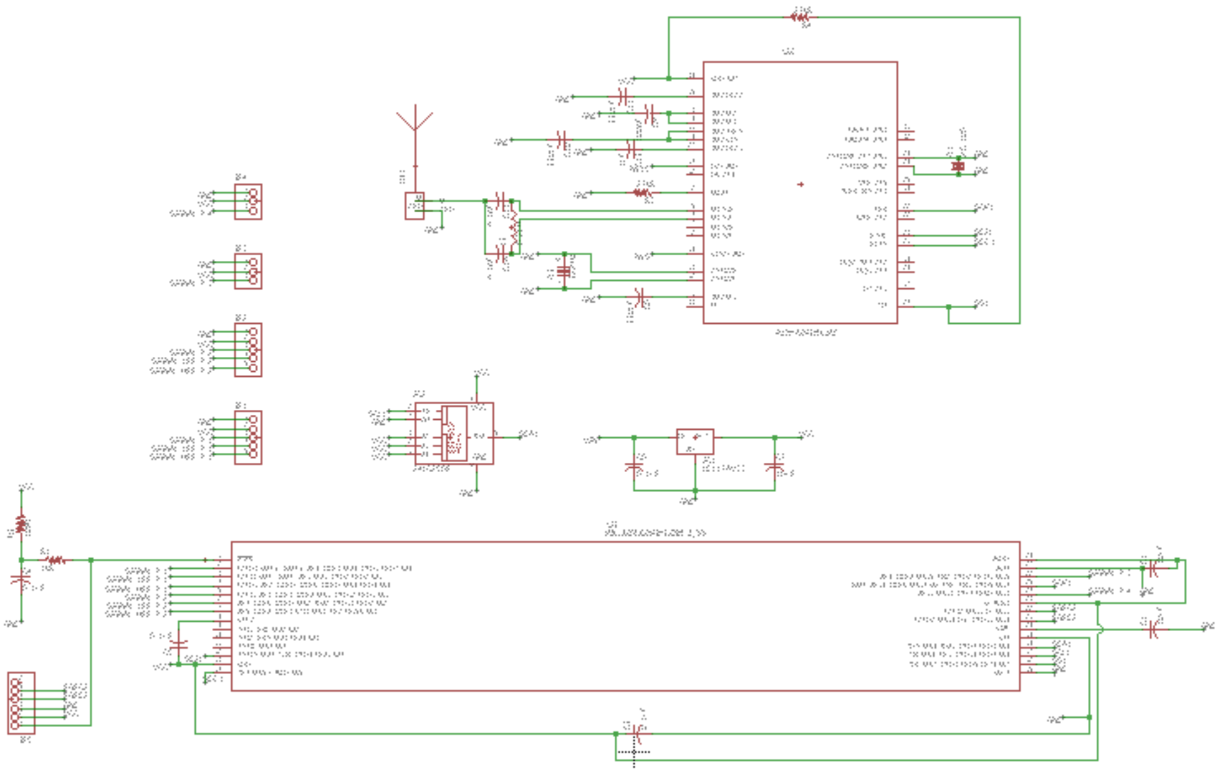

Fig. 8: Microcontroller + communication + memory + power circuit

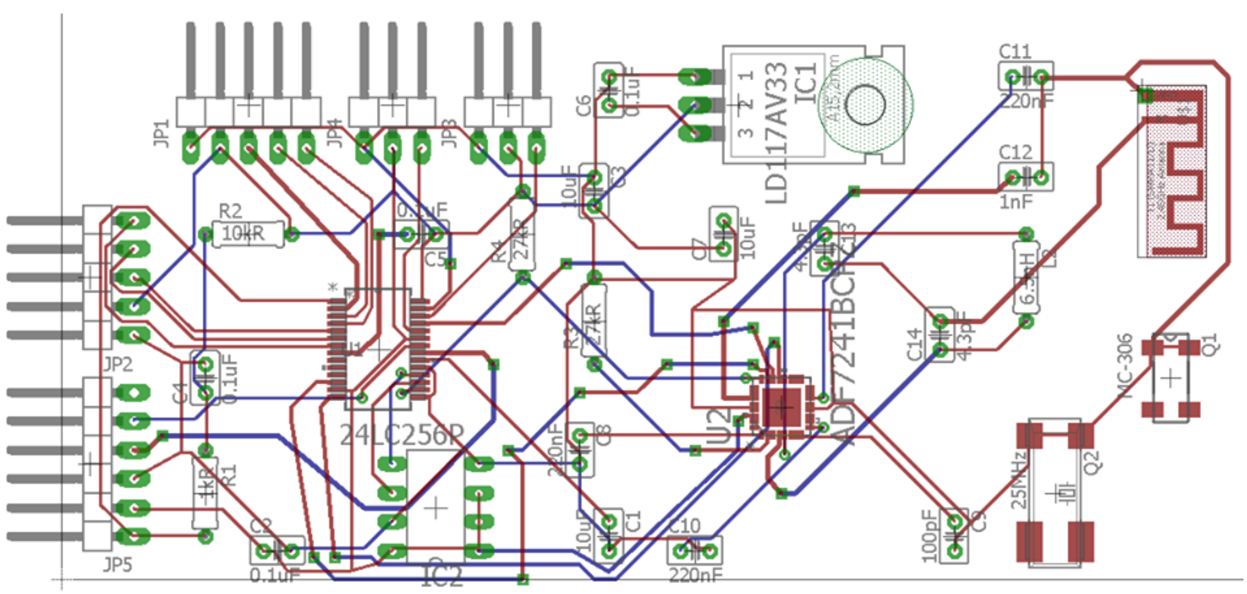

Fig 9: Board layout for circuit in Fig. 8

Software Overview

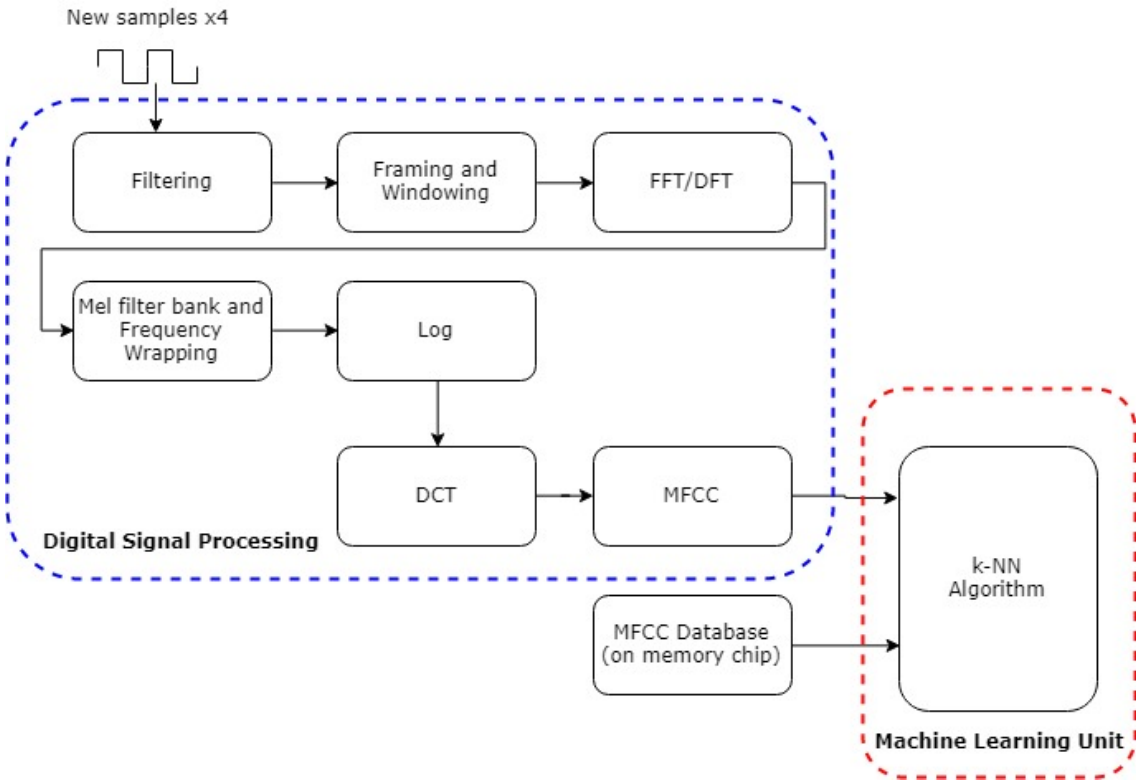

Fig. 10: Software flowchart

Digital Signal Processing

The digital signal processing unit handles the processing of the converted and filtered signals into meaningful data to be used by the control unit (microcontroller) to detect and diagnose abnormalities. This unit will have to do this quickly and reliably. It will either be done through a dedicated microprocessor that will handle the computations.

TABLE VIII
DIGITAL SIGNAL PROCESSING REQUIREMENTS

Requirements	Verification
• Processor speed needs to be larger than 2.8MHz.	• Complete an FFT transform of a measured heartbeat (file size of 1.4Mbits) in less than half a second (which would be the processing time for a >2.8MHz processor).

Filtering

The incoming samples need to first be processed to filter out the ambient noise from the main two signals near the heart and lungs. As we mentioned earlier, there are two microphones for the heart and two for the lungs. The reason why we use two microphones for each source is so that one microphone is as close to the source of sound as possible, to pick up the signal as accurately as possible, while the other microphone is placed to pick up the external noise. These two samples are fed into this adaptive filtering unit in the microprocessor where we compare the two signals and subtract the ambient noise. We are using an adaptive algorithm, the Least Mean Square (LMS) algorithm, to get a better estimate of the signal by changing the value of the filter coefficients. You can see a visual representation of the algorithm in Figure 11. LMS starts by filtering the reference input using weights (w) of the adaptive filter and creates an estimate of the primary input. It then creates an error signal using the equation,

$$error = primary\ input - estimate\ of\ primary\ input. \tag{1}$$

The error signal is then sent into the adaptive filter to update the weights (w) and increasingly make the algorithm more efficient. The weights are updated using,

$$w(n+1) = w(n) + 2 * \mu * e(n) * x(n), \tag{2}$$

where w(n + 1) is the new vector of filtering weights, w(n) is the current vector of filtering weights, μ is the size step parameter (determined through experimentation), e(n) is the error signal, and x(n) is the vector of recorded reference signals x with length of n [15].

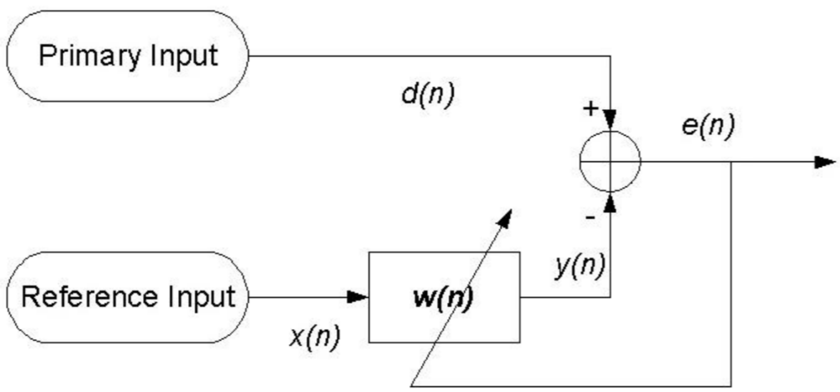

Fig. 11: Block diagram of adaptive filter [15]

From Filtered Signal to MFCC

In the microprocessor, we convert the filtered signal from the adaptive filtering unit to the final MFCC that we can send to the machine learning unit. In order to do so, we are using the process discussed in [16]. Describing this in high-level, the incoming audio signal is first separated into frames of length N separated by M, where N and M will be determined by experimenting with the incoming audio signal. Each frame will then be windowed to minimize any discontinuities in the beginning and end of the frames. The next step is to then convert each frame from the time domain into the frequency domain in the FFT block of the diagram above. It then goes on to scale the frequency from a linear scale to a Mel scale, where the logarithm of that output is taken and the log Mel spectrum is converted to the time domain, finally giving us the MFCC [16].

Machine Learning Unit

The machine learning unit will take two sets of inputs: 1) the MFCC from the digital signal processing unit, and 2) the pre-existing MFCC's stored on a memory chip for machine learning implementations. The overall idea of this unit is to determine if a person has an abnormality in their heart or lungs using the *k*-nearest neighbor (*k*-NN) algorithm. While there are many other machine learning algorithms to choose from, the *k*-NN is easy to implement, its accuracy is relatively high, and only k and the distance metric need to be defined. Table IX shows a comparison between different machine learning algorithms from a study that detected different kinds of arrhythmia using a database of 48 electrocardiogram results [18]. Sensitivity (Sen) is the percentage of people correctly identified with an illness. Specificity (Spec) is the percentage of healthy people correctly identified as healthy. Accuracy (Acc) is the percentage of the ability to differentiate between the healthy and ill individuals [17]. As you can see in the table below, using *k*-NN gives us the best results when it comes to accuracy.

TABLE IX
COMPARISON OF ALGORITHM FOR DETECTING ARRHYTHMIA [18]

Algorithm	Arrhythmia		
	Sen	*Spec*	*Acc*
k-NN	95.2%	99.7%	99.4%
SVM	89.3%	99.7%	98.9%
MLP	93.1%	99.4%	98.9%
C4.5	94.1%	99.6%	99.2%
LDA	82.0%	95.6%	94.6%

k-NN Algorithm

k-NN is a type of instance-based learning where the function is approximated locally and all computation is deferred until the classification stage. The algorithm assigns weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where *d* is the distance to the neighbor. We'll be calculating the distance metric using the Euclidean distance between points. The neighbors are taken from a set of objects for which the class (for *k*-NN classification) or the object property value (for *k*-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. In Table IX, the study used a *k* value of three to get the accuracies for their arrhythmia detection [18]. We will use this *k* as out starting point. However, because we're also looking for lung conditions, we may have to experiment around with *k* to optimize the *k*-NN algorithm.

Tolerance Analysis

There are several steps of signal processing in the system. They comprise of the analog signal processing and the digital signal processing and are crucial in this system because they are necessary for the removal of irrelevant signals and noise, which is necessary if we are to isolate the heart and lung sounds and perform diagnosis.

Beginning with the analog signal processing, here we remove signals outside the ranges of frequency produced by the two organs we are listening to – heart and lungs. The biggest unknown here is around the component tolerances and how their behavior affects the magnitude response of the incoming signal. Using Analog Devices software [20], we simulated our analog signal processing filters. The below graph shows the deviation of the magnitude response given worst case tolerances for the components – 10% for capacitors, 1% for resistors and 20% for Op Amp GBW.

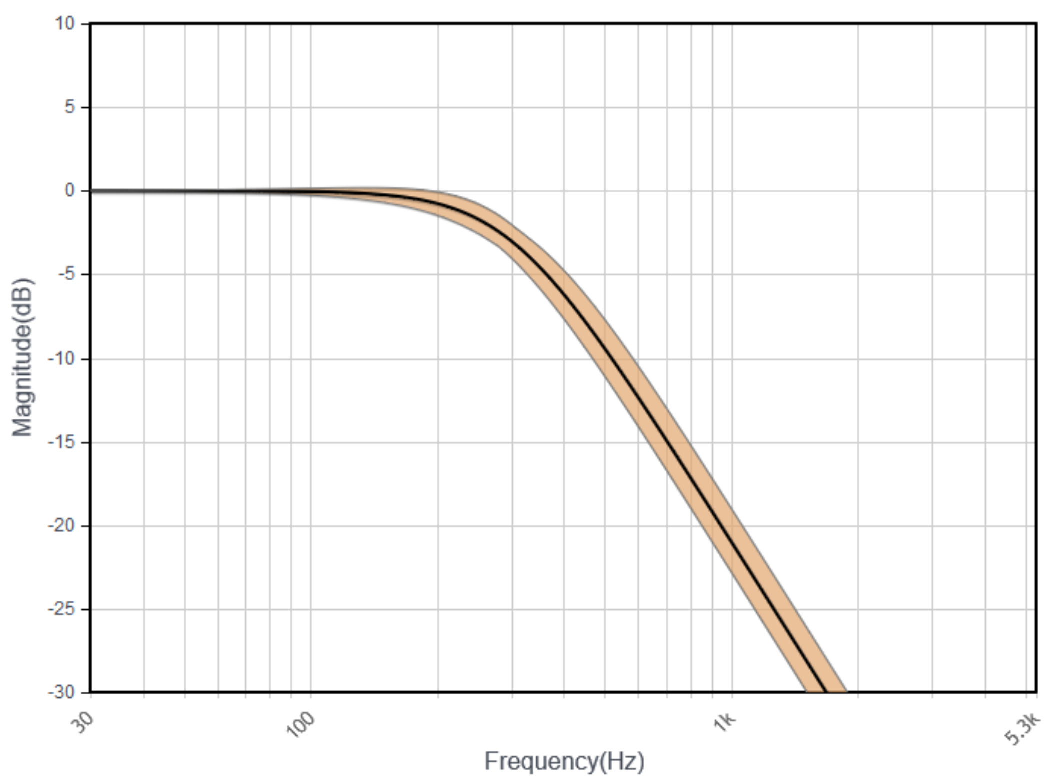

Fig. 12: Magnitude response at worst-case tolerances

As we can see even under the worst-case performance, the circuit still represents a roughly 3dB difference between the main pass band and between 290Hz and 350Hz. Therefore, under reasonable tolerances of the passive and active components in the filter circuit, we will get acceptable filtering results. Below, we show the same magnitude response for the high pass filtering for the lung sounds.

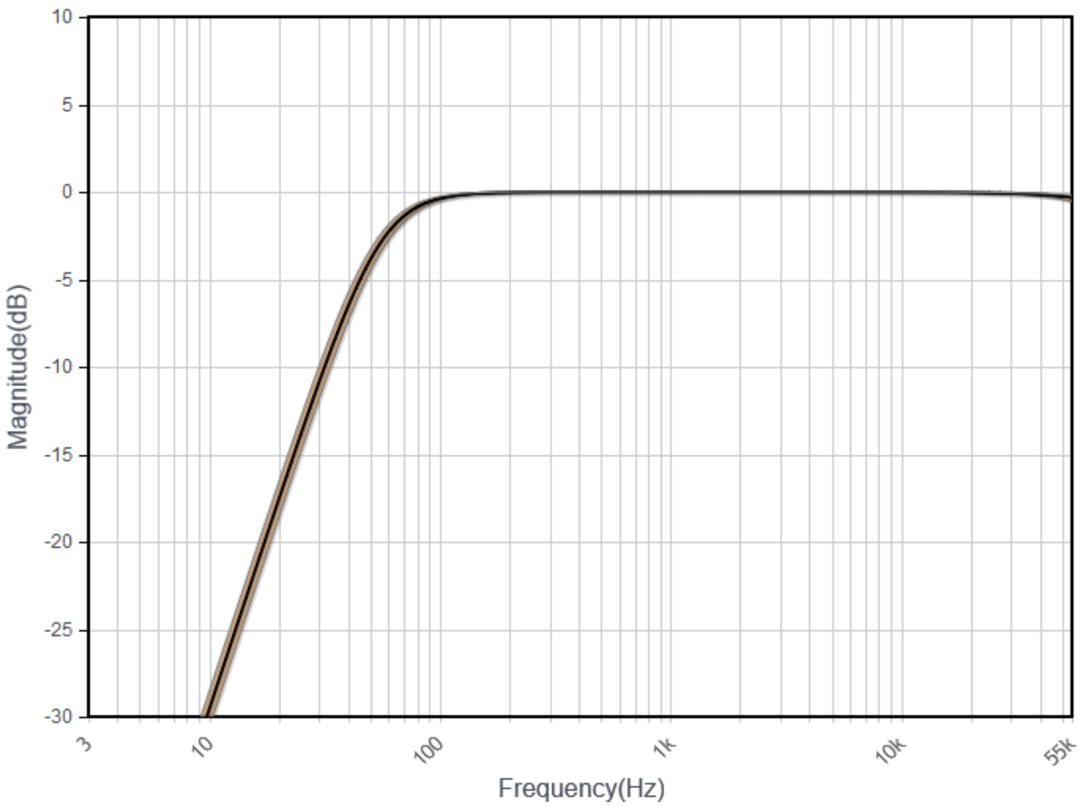

Fig. 13: Magnitude response for high pass filtering with lung sounds

We can see that for this circuit the magnitude response range is very good, and the behavior around the cutoff frequency is good given the component tolerances.

Should the filtering of the signal using this analog signal processing method not be sufficient, we could add a mechanical filter – a diaphragm stretches over a cavity. This is the same as the diaphragms used in typical stethoscopes and can filter the sounds coming from the heart and lungs – but is not ideal as the performance depends on the pressure applied on the filter against the human body.

On the digital signal processing side, there are several tolerances that we need to worry about. One is the ADC – analog to digital conversation. Using the PIC32 MCU built-in ADC, we can convert analog input to digital at a rate of 1 Mega samples per second. This is more than sufficient than the 75 kilo samples per second required to avoid any biasing. The analog signal is converted to 10-bit digital values. This represents a quantization of 0.003V or less than 0.1% of the range. If this should not be sufficient for the ability to detect abnormalities by competing to database entries, we are left with one option. We would need to incorporate a separate ADC chip which would convert the analog signal to 12-,16-, or 32-bit digital values, then feed these values serially to the MCU. The MCU we have chosen has the capability to incorporate another chip should we use a separate ADC, but this would slow down the reading of analog signals since we would have to multiplex the ADC through each microphone. Note it is unlikely that we will need a separate ADC since we are not using the raw signal but MFCC values, and that machine learning models require high accuracy when training but are more robust when recalling.

Cost and Schedule

Cost Analysis

Labor

We expect to work 10 hours a week across 14 weeks. Using a salary of $40/hour, the labor cost per person comes out to,

$$salary * \ 2.5 * total\ number\ of\ hours = total \tag{3}$$

$$\frac{\$40}{1\ hr} * 2.5 * 14\ wks * \frac{10\ hrs}{1\ wk} = \frac{\$14{,}000}{laborer}.$$

Therefore, the total labor cost for all three of us is,

$$\frac{\$14{,}000}{laborer} * 3\ laborers = \$42{,}000.$$

Parts

TABLE X
PARTS AND COSTS

Description	Manufacturer	Model #	Units	Unit Cost*	Total
Microcontroller	Microchip	PIC32MX230F256B-I/SS	1	\$2.53	\$2.53
Lithium coin cell battery	Renata	CR2477N.IB	5	\$1.74	\$8.70
Memory chip	Microchip	24LC256	1	\$0.72	\$0.72
Microphones	CUI Inc.	QN9022/DY	4	\$0.82	\$3.28
Bluetooth	Analog Devices	ADF7241	1	\$2.24	\$2.24
Operational Amplifier	Analog Devices	OP262GSZ	2	\$2.56	\$5.12
Resistors	Various	Various	20	\$0.10	\$2.00
Capacitors	Various	N/A	24	\$0.30	\$7.20
Inductor	Various	Various	1	\$0.22	\$0.22
Oscillator	Various	Various	2	\$1.40	\$2.80
Connectors	Various	Various	4	\$1.00	\$4.00
Voltage Regulator	STMicroelectronics	LD1117	1	\$1.95	\$1.95
PCB	PCBWay	N/A	1	\$4.00	\$4.00
100% Cotton gauze roll	Curad	N/A	1	\$2.26	\$2.26
Total Parts Cost					\$47.02

*Parts assumed to be bought in bulk

$$\boldsymbol{Grand\ Total} = Labor\ Cost + Parts\ Cost \quad (4)$$

$$= \$42{,}000 + \$47.02$$

$$= \$42{,}047.02$$

Schedule

TABLE XI
PROJECT TIMELINE

Deadline (Sundays)	Natalia	Erlis	Sam
03/04	Build, Test and Verify Power Supply Circuitry. Test Voltage Stability.	Order Voltage Regulator and Analog Signal Processing Parts	Build, Test and Verify Power Supply Circuitry. Test Voltage Stability.
03/11	Verify Microphone Datasheet Characteristics. Test Frequency Response.	Build, Test and Verify Analog Signal Processing. Verify Magnitude Response.	Build, Test and Verify Analog Signal Processing. Verify Magnitude Response.
03/18	Program and Test DSP Filtering. Use Test Signals to Verify Noise-to-Signal Ratio.	Extract Signal Features from Database Samples and Test Samples.	Train the Learning Algorithm – Programming.
03/25	Test the Learning Algorithm and Find Accuracy, Order PCB.	Verify DSP. Use Test Signals as Well As Database Heart/Lung Signals to Test Performance.	Build and Verify Bluetooth Circuitry, Send and Receive Test Signal.
04/01	Microprocessor Programming – I/O, ML Algorithm.	Build, Test and System Integration.	Build, Test and System Integration.
04/08	Buffer for Setbacks.	Buffer for Setbacks.	Buffer for Setbacks.
04/15	Prepare Final Presentation.	Begin Final Paper, Final Presentation.	Prepare Final Presentation.
04/16-04/20	Mock Demonstrations		
04/23-04/25	Demonstrations		
04/26-04/27	Mock Presentations		
04/30	Presentations		
05/02	Final Paper Due		

Ethics and Safety

There are a few safety hazards to highlight with our proposed project. Starting from the simplest, there is a chance that the battery in the band can overheat, resulting in user discomfort or worse, an exploding battery. In order to avoid this, we are taking extra precaution in testing our circuitry in the safety lab and making sure the battery does not overcharge. There are a few things we can do to improve the safety of out product. For example, we can add a fire retardant chemical to the physical band material or use a material that protects the body against heat if the battery starts overheating. Both of these, however, can increase irritation, which is explained a few paragraphs below. For the scope of our project, we will do our best not to overheat the battery. However, we won't be providing any change in physical design to protect the user just yet. In order to follow IEEE Code of Ethics #1, we plan to fully disclose the safety issues with our product [7]. In the future, we hope to work on the potential battery hazards once we get the main function of the product working.

Another circuit-related hazard in our project is potential water damage to the device. Getting water onto the band can result in shorting the circuits, ultimately hurting the user as well. Our product is not yet intended to protect against water, so here it is incredibly crucial that the user is aware of the product's flaws, which correlates with IEEE Code of Ethics #3, as well as #1 again [7].

The material of the band is another important concern to the individual using the wearable stethoscope. Certain materials have the ability to induce an allergic reaction or create an uncomfortable rash on the individual where the band is placed. To avoid any kind of reaction, we plan on coating the device with a gauze bandage. Gauze bandages are prevalent in the medical world and are used specifically to protect the body. In order to decrease the chances of getting textile contact dermatitis from the gauze bandage, we are using a gauze bandage that is 100% cotton and dye-free [8].

The last safety concern we want to highlight is that our device will not be 100% effective. With our goal of 90% efficiency, there is a 10% chance that the device fails to detect a lung or heart problem for a user that may be completely dependent on the device. The initiative we are taking with this safety hazard is ensuring that, again, we follow the IEEE Code of Ethics #3 and to be transparent about the product's success rates as well as the potential flaws mentioned above [7]. The other issue with this is receiving too many false alarms. Not only would the doctor receiving the false alarm lose time trying to analyze it, but the doctor would be taken away from real-life threatening situations that could be occurring at the same time, ultimately decreasing the total quality of care. However, for the safety of the patients using our device, we prefer to output more false positives if that prevents more false negatives from occurring. In our implementation, a false negative can occur when a new symptom that perhaps isn't in the training data set yet gets fed into the k-NN algorithm where the nearest neighbors are normal heart or lung sounds. We recognize that there are ways to reduce false negatives, for example by feeding in more inputs into the microprocessor such as whether the user is sitting or jogging at that moment to further analyze the heart or lung signal. For the scope of this project, reducing false negatives won't be a goal because as we mentioned above, the k-NN algorithm alone should get us an accuracy of at least 90% when it comes to detecting the abnormal or normal condition in the user.

Some studies [9], [10] show that heart rates are directly related to racial or gender differences. Although this is just a theory, we want to enforce equality and not segregate heartbeats or lung sounds into different groups, essentially following IEEE Code of Ethics #8 [7]. We know that machine learning training sets can create bias towards groups. So in order to prevent discrimination, we will continuously audit our algorithm and create a standard that works best for our device.

Because our medical device requires human participants, it's necessary that we go through the Institutional Review Board (IRB). It's particularly important because we need to access heartbeat and lung sound data from public records. Although there is an exception for using public data if the subjects cannot be identified [11], in order to both connect the public data to any kind of related heart or lung illness and to continuously get new data over time, we indeed need to identify the subjects. We do, however, qualify for the expedited process because our research is neither invasive and it only requires digital voice recordings [11].

References

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Appendix A

Irregular rhythm, heart murmurs, signs of congestive heart failure, fluid in the lungs, valve leakage, aortic stenosis, pneumonia, atelectasis, pulmonary fibrosis, acute bronchitis, bronchiectasis, interstitial lung disease or post thoracotomy or metastasis ablation, hypersensitivity pneumonitis, alveolitis, asthma attacks, though it can also be a symptom of lung cancer, congestive heart failure, and certain types of heart diseases, Caused by narrowing of airways, such as in asthma, chronic obstructive pulmonary disease, foreign body. epiglottitis, foreign body, laryngeal oedema, crouppertussis (whooping cough) pneumonia, pulmonar edema, tuberculosis, bronchitis, inflammation of lung linings, lung tumors, pneumomediastinum, pneumopericardium

https://en.wikipedia.org/wiki/Crackles

https://en.wikipedia.org/wiki/Auscultation

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