Portable Blood Monitor : PBM

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Summary

As we know that alcohol consumption is on the rise, and many people drive after drinking which increases the chances of accidents tremendously. Here comes the usage of the breathalyzer, the current breathalyzer is a threat to our health safety. So we have decided to propose a device that is a better and safer version of the breathalyzer called Portable Blood Monitor with some added features like measuring your blood sugar. Also, there will be an application attached which will help the users to keep track of their data and make possible changes to their drinking habits. This paper explains the necessity, benefits, equipment, development process, and cost of the device. This information in this paper can be relevant to the engineers/manufacturers that develop breathalyzers or similar devices. The overall cost is estimated to be $315,731 if the project takes a year. However, this device is pretty simple to build so it might take less than a year.

Author’s Note

This paper was prepared for English 21007 taught by Professor Susan Delamare.

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Introduction

Now more than ever, our health is our number one concern. After a pandemic that shut down the entire world, everyone internationally has become more aware of what they eat, where they eat it, and where their food or utensils have been. One huge issue that has sparked from this is the existence of breathalyzers and their implementation in law enforcement. As things stand, breathalyzers are a health risk. Offenders are instructed to blow into a tube that has been used by others who have committed the same infraction. This poses a health risk due to the shared device collecting pathogens from a number of hosts, spreading these malicious bacterium during a time of recovery from inebriation. These health risks could end up endangering the very idea of the breathalyzer over time due to how important health and safety is, which is why a compact version of this device that anyone could carry with them would be preferred. Driving under intoxication is a crime that unfortunately occurs incredibly often. Many times it is due to irresponsibility, but sometimes drivers simply aren't aware of how much they have had to drink. About "20% of traffic accidents where there are serious or fatal injuries" stem from driving under intoxication (Alvarez et. al., 1995). The Portable Blood Monitor, or PBM, will allow its users to monitor their blood alcohol content, or BAC, and as an added bonus will offer a feature to monitor blood sugar.

The reasoning for these features is simple: Alcohol consumption and sugar consumption are issues that plague people to this day. Many adults take in around "46.8 g of sugar" in a twenty four hour period (Moss et. al., 2013-2016). Many drivers are unaware of the fact that they are intoxicated until they get behind a wheel and as such are unable to stop themselves from endangering the lives of those around them on the road, pedestrian or otherwise. This could lead to the arrest and fining of these people for a simple mistake. More often than not, drivers who take a breathalyzer test as things stand now are usually already fined or under arrest. Blood sugar levels are also a dangerous issue for drivers. A high blood sugar level with a lack of insulin to process the sugar intake could potentially lead a driver to get behind the wheel minutes before going into shock. According to many studies,“hypoglycemia causes physical and psychological symptoms associated with disruption of cognitive function” (Ahmed, 2010). This lack of attentiveness due to being unaware of their condition could get people killed, including themselves. The PBM will be a small device around the size of a conventional cellular device. The device will be much smaller than the average iPhone and will come in a dark color so as to not stand out in a traditional bag. This will ensure that the device can be stored easily and securely while also not exposing its users to any kind of shame in a social situation. The device will be bluetooth compatible and will transmit data with an application that can be installed on a cellular device. This will allow users to keep a record of their habits and make the necessary adjustments to their lifestyle so as to achieve better results. While seemingly arbitrary, the feeling of accomplishment could foster a need for users to improve their lives one step at a time. After all, dopamine can inspire “invigoration of…motivation”, and these adjustments would cause a rush of dopamine (Karin et. al., 2022).

The PBM will monitor blood sugar via a groove located in the center that will house a transmitter and receiver. The transmitter will push a signal through the user’s finger and the receiver will take that output and process it. This processing will allow the user to know how much sugar content is present in their blood and will then allow them to adjust accordingly. This method is far less invasive compared to the current method of pricking a hole into the finger to draw blood, and is less dangerous as well. Not only is the pricking method causing a wound on the body, but it is also exposing the body to harmful pathogens in the air. People with hemophilia would be put at immense risk due to their inability to form proper blood clots, which is why using a non-invasive current is a necessity.

The PBM will not come cheap, but it will be a durable and long lasting device due to the lithium ion batteries that power it and the shell that encases the delicate internals. Although the expenses may seem egregious, the consequent ability for the average citizen to have greater knowledge and control of their own physical situations will justify the cost. Bartenders will be able to better monitor clients and adjust their habits to a more personal degree, the inebriated will be less exposed to harmful microscopic organisms that could induce sickness, and the diabetic will have a non-invasive method for checking their blood sugar levels.

Objectives

The main goals of this proposal are:

1.1: To detail the necessity of the Portable Blood Monitor in a field of similar technology.

1.2: To detail the schematics of the Portable Blood Monitor and the logistics of production.

1.3: To further detail the specific mechanisms in the device for the purpose of better outlining how the device will work.

Preliminary Literature Review

A multi-functioning device involves an understanding of how compatible the contrasting aspects of the device are. The device will be operated to measure both blood glucose levels and breath ethanol levels. As for detecting the two organic compounds, both electrical and optical sensors have been suggested to be possible methods. The proposed theory of applying optical sensors directly on a subject's skin to measure blood glucose concentration has been explored for the past several years (see Appendix A). Its limitations, however, appear to supersede its strongpoints with its low accuracy readings due to sparse glucose concentrations in blood, which are below a spectrometer's threshold (Gonzales et. al., 2019). Yet, there holds some promise with recent research which employs new methods such as machine-learning, to circumvent the technology's restrictions. Our device also opts to use electrical sensors for measuring breath alcohol content; an electrical component has been synthesized in the past with infrared spectroscopy to develop more accurate non-invasive glucose readings. This can establish the groundwork for our proposed device (Kasahara et. al., 2018).

Similar to our own device, Javid et. al. (2018) sought to integrate a mobile application interface with their monitoring apparatus via bluetooth technology. Their approach uses both optical sensors and electrical sensors with machine-learning models as a way to combat the low accuracy results of direct optical readings (see Appendix B). They utilized near-infrared spectroscopy (NIRS), performed by an infrared receiver, to identify and target glucose compounds in 19 blood sample solutions (see Appendix A). Using a transmitter and a receiver, they correlated glucose concentrations with the output voltage, and noted that as glucose concentration increases, the output voltage increases as well. This information was used as training data, which was fed to their mobile application for it to calculate a prediction model which converts voltage to glucose concentration (see Appendix B). They tested this method on a subject's body by placing a transmitter and receiver on either side of a finger and measuring the output voltage, which was then converted to a supposed blood glucose concentration. The sample group for this phase of the study was five subjects. The team verified the accuracy of their method by comparing it to invasive glucose monitoring and reported margins of error as low as 4% (Javid et. al., 2018). As for bluetooth configuration, Javid et. al.'s (2018) printed circuit board supports a bluetooth module which communicates with their mobile application (Figure 1). Their method of identifying a statistical correlation between glucose concentration and a transmitter's voltage proves to be a more reliable method towards approaching NIRS and glucose monitoring. In addition, their research also proves that this method is compatible with bluetooth technology. However, they seemed to have only scratched the surface on applying machine-learning algorithms (see Appendix B), and have a rather small sampling group. This may risk the accuracy and consistency of results of any future experiments. Our research aims to explore broader fields of machine-learning capabilities to design higher-calibrated prediction models using more test subjects.

Figure 1

"The Printed Circuit Board"

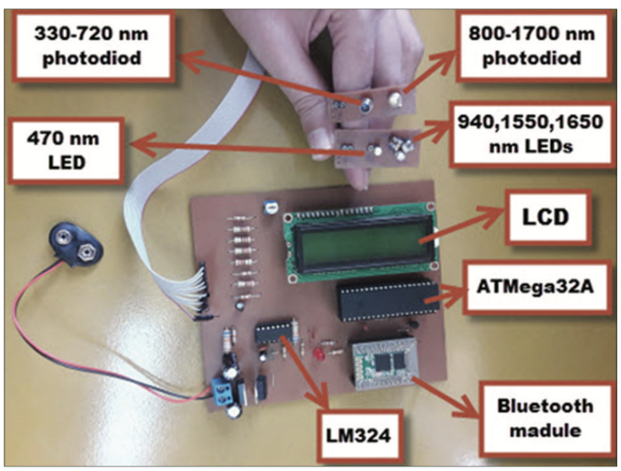


Figure 5: The printed circuit board to measure the blood glucose and bilirubin in transmittance mode

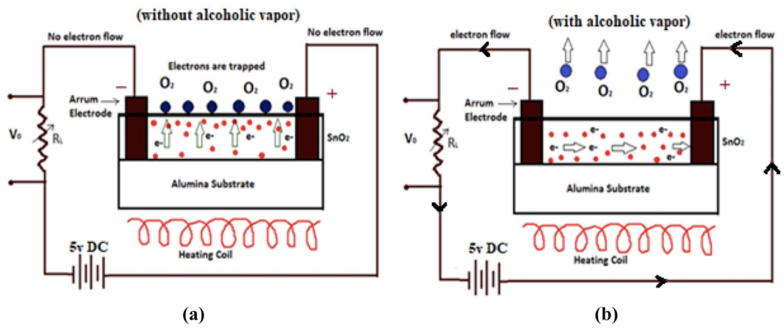
Note. Reprinted from "Noninvasive Optical Diagnostic Techniques for Mobile Blood Glucose and Bilirubin Monitoring," by B. Javid, F. Fotouhi-Ghazvini, F.S. Zakeri, 2018, *Journal of Medical Signals and Sensors.*

Kasahara et. al. (2018) had a similar approach of synthesizing machine-learning with optical sensing. They integrated mid-infrared spectroscopy (MIRS) (see Appendix A) with domain adaptation (DA), a form of deep learning which adapts to differences between training data and test data (see Appendix B). They concluded that DA enhances the prediction accuracy of the model. They proceeded to compare the accuracy between the DA model and other machine-learning models they used, and noted that the DA method displayed the most optimal results. One of their key observations, however, was that the prediction accuracy of the DA method improves if the device acquired data from the subject multiple times: “the user of the glucose-monitoring device could improve the prediction accuracy for the acquired data series by applying the DA method” (Kasahara et. al., 2018). The application of domain adaptation can therefore be incredibly valuable to our own device. Of course, since it is meant for medical and commercial use, the machine-learning model must be fed more data points from more varied subjects so it can be applicable to the general population. Research must be done to test how many attempts it takes for the DA model to reach complete-near accuracy on an arbitrary individual. In addition, we need yet to see if Javid et. al.’s approach of correlating voltage with glucose concentration could possibly be synthesized with the DA method to develop more accurate prediction models.

There is minimal research to prove that infrared spectroscopy can be similarly used to measure breath alcohol content. On the other hand, Biswas and Saha (2020) tested electrical sensors to function as a breathalyzer. Similar to Javid et. al., who correlated voltage with glucose concentration, this team designed their apparatus to obtain “a measurable voltage corresponding to concentration of ethanol” (Biswas & Saha, 2020). Their working principle was to use tin oxide (SnO_2) as a semiconductor of ethanol (C_2H_6O), which would react and simultaneously allow greater electron flow, therefore yield a greater measurable output voltage (Figure 2). The results prove that ethanol concentration and voltage have a correlational relationship, therefore a prediction model can be developed. This research proves valuable towards creating a device with a similar calibration. However, research must be done to replicate Biswas and Saha’s mechanism

Figure 2

Sensing Mechanism (a) With Ethanol and (b) Without Ethanol



Note. Reprinted from “Probing Volatile Liquid Through an Electrical Sensor with Up Gradation to a Breathalyzer for Drunken Drivers,” by R. Biswas, D. Saha, 2020, *Applied Physics A.* https://doi.org/10.1007/s00339-020-03479-5

and to gather more data points for a prediction model. The team did not experiment with applying machine-learning into their algorithm, which would be more ideal for a small portable device like the one we propose.

Our proposed device also strives to include a bluetooth module which transports the measured data to a mobile application, allowing seamless and accessible user interface. Javid et. al. briefly mentioned integrating such a module into their circuit board, however they did not go over the logistics of their mechanism. Sidibe et. al. (2022) managed to design and implement an apparatus that transfers data between a temperature/humidity sensor and a bluetooth low energy (BLE) transceiver (see Appendix C), along with other systems which manage the node’s power consumption. Figure 3 presents their block diagram of the node; the boxed section indicates the subsystems relevant to our device. This component of the design outlines the communication interface between a sensor, such as an electrical transmitter and receiver, and a bluetooth module, such as a transceiver. Sibide et. al. integrated a temperature & humidity sensor HDC2080 which communicates with the BLE transceiver QN9080 using an I2C protocol. They programmed the

QN9080 to follow an algorithm which directs it to send received data (see Appendix D). Our device aims to follow a similar pattern. However, before the data from the sensor—in our case, a measured voltage—is transferred to the transceiver, the voltage must be converted into an approximated glucose or ethanol concentration. Further research must be conducted to understand how the conversion can be integrated into the bluetooth mechanism. An I2C interface can be similarly used to connect a central processing unit (CPU), which converts the measured voltage into an estimated concentration, with a sensor and a transceiver (see Appendix D), however more studies must be conducted to test this theory. The research presented not only provides insight towards how both the glucose and ethanol monitoring functions would work, but how they can be harmonized as well. Rather than compartmentalizing the device's functions into

Figure 3

"Block Diagram of the Architecture of the Implemented Sensing Node."

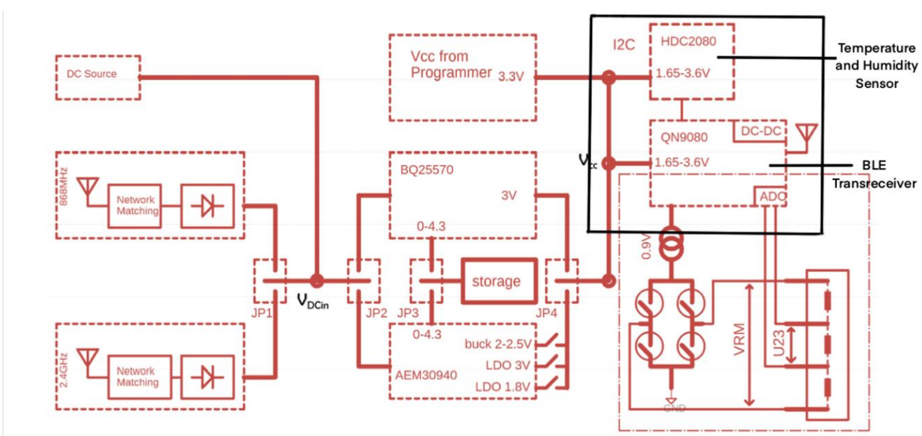


Figure 2. Block diagram of the architecture of the implemented sensing node.

Note. Adapted from "A Multifunctional Battery-Free Bluetooth Low Energy Wireless Sensor Node Remotely Powered by Electromagnetic Wireless Power Transfer in Far-Field," by A. Sibide, G. Loubet, A. Takacs, D. Dragomirescu, 2022, *Sensors 2022.* https://doi.org/10.3390/s22114054

optical glucose sensors and electrical ethanol sensors, it is possible to use electrical sensors to measure both compounds and to apply a form of machine-learning for more accurate predictions.

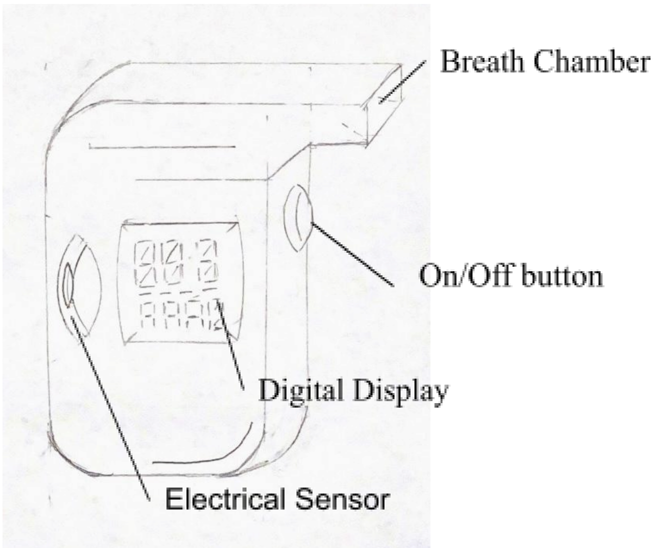
These studies, however, appear to lack proper depth in uncovering the extent to which machine-learning can provide near-accurate models and how they can be implemented into a tangible, portable device. We have yet to research how machine-learning, preferably domain adaptation like Kasahara et. al. exhibited, can be used to pinpoint an approximated ethanol concentration from a measured voltage. In addition, we have yet to understand possible data transfer methods (such as I2C) between a sensor, bluetooth transceiver, and a third subsystem.

Technical Description of Innovation

The components of the breathalyzer are quite simple. The device's main components include the breath chamber, the digital display, the on/off button, and the power source [Figure 4]. The breath chamber components will include a chemical-based apparatus that will detect ethanol content. Our innovative design will be an adapted version of a typical breathalyzer with additional features that will also analyze blood sugar content. This cutting-edge device has two separate apparatus that make our design stand out, and both apparatus will revolve around the utilization of electrical current that records data. This device will contain 7 functional parts for full operational capabilities . The following parts are displayed below.

Figure 4

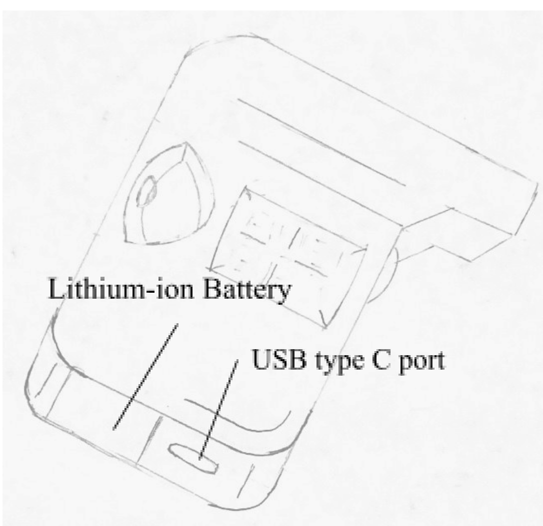
Frontal view of device model



Note. Reprinted from " Device Sketch #1" by W. Ng, 2022, November 30, Final Proposal.

Figure 5

Bottom view of device model



Note. Reprinted from " Device Sketch #2" by W. Ng, 2022, November 30, Final Proposal.

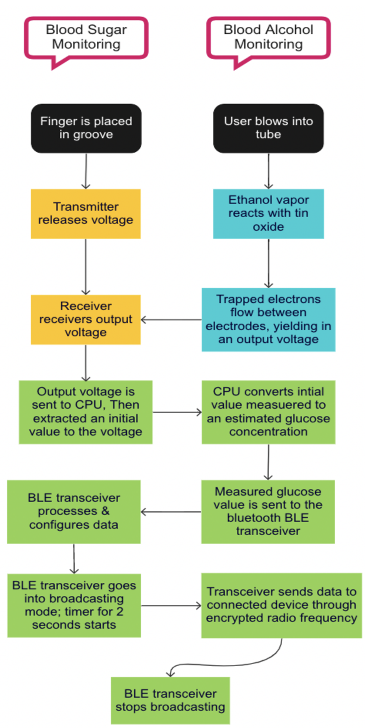
IV. Electrical sensors - this sensor is located on the opposite side of the mouthpiece and includes a transmitter and receiver that are parallel to each other with spacing in between [Figure 4]. The user can place their finger in between the sensors to allow the electrical current transceiver to record data. This sensor is a noninvasive diagnostic to analyze the blood sugar (glucose) content. (Javid et. al., 2018)

V. USB type C port - The port is located on the bottom right of the device. The charging port allows the user to recharge the lithium-ion battery. [Figure 5]

VI. Lithium Ion Battery - Rechargeable lithium-ion battery unit, can hold up to 1000 mAh of battery charge. Weighs approximately 35 grams. It is located internally within the device. [Figure 5]

Figure 6

Process Flow



Note: Reprinted from " Process flow" by W. Ng & A. Rahman, 2022, November 30, Final Proposal.

While the external functional parts are logistical, there are more functionality that sets this technology apart from the rest. The goal of this innovation is to track and analyze the blood alcohol content, as well as a non-invasive procedure to track blood glucose content. This process can be shown in the process chart [Figure 6]. In addition, to allow the device to create a track record for the external device/application. This can be done by machine learning and bluetooth transceiver. This feature not only provides an additional service but has many potential for further development in medical technology and data analysis. This ergonomics application will provide a better user interface as well as user experience.

Figure 7

Bluetooth Transceiver Module

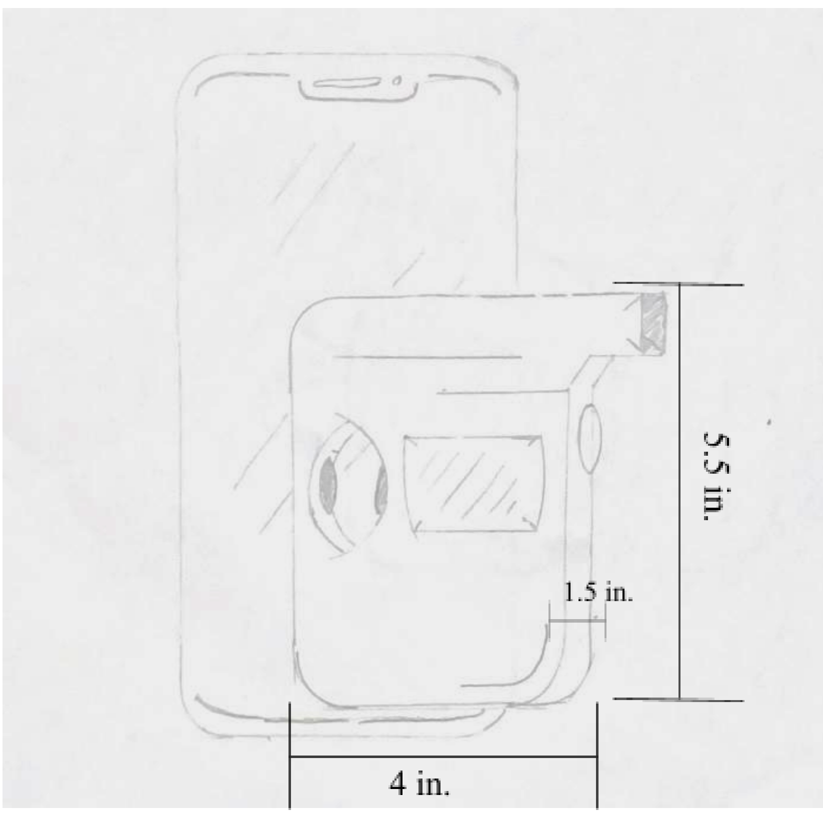
Note. Reprinted from "*Interfacing Bluetooth Module (HC-05) with Arduino Uno*." by J. Akshay, 2020, April 19, Arduino Project hub. https://create.arduino.cc/projecthub/akshayjoseph666/interfacing-bluetooth-module-hc-05-with-arduino-uno-f5209b

Bluetooth Transceiver - This transmitter simplifies the transfer of data wirelessly and effectively, the wireless data transfer is performed over BLE radio frequency (see Appendix C). This is located internally within the device. [Figure 7]

When determining the size of this device, we have to consider the dimensions of all components. The weight of the device is 80 grams including the lithium battery. The device will have a peculiar design and ergonomic look. The dimensions of this device are 4 in x 1.5 in x 5.5 in , the size can be comparable to the size of a portable charger. The image shown below are the device size comparison to an iPhone [Figure 8].

Figure 8

Live size display vs Iphone



Note. Reprinted from “ Device Sketch #3” by W. Ng, 2022, November 30, Final Proposal.

Budget

As shown in Table 1, the spending for the Portable Blood Monitor can be divided into two parts, one is the cost of the equipment and other is the manufacturer. Now both costs can vary depending on . Most of the equipment can be bought from Amazon.This project would require an app developer to make the application where the users can see the results, electrical engineers to figure out how to put the electrical components together, then a manufacturer company that can produce the Portable Blood Monitor and a supervisor who will make sure the project finishes on time efficiently. The optimal time to finish the whole project can be about 6 months. Also, it wouldn't be a good idea to make many pieces at once, so at first it would be better to make about 1,000 of them and would pay the manufacturer accordingly.

Table 1.

Budget Details

Line Item	Cost	Time	Per Total
Biomedical engineers	50,000	Annual	50,000
Electrical engineers	$101,780	Annual	$101,780
App developers	$85,735	Annual	$85,735
Manufacturer (General Electric Co)	$59000	One Time	$59,000

Total Cost of Workforce			≈ $365,000
Equipment	Per each Portable Blood Monitor		
Lithium Ion Battery	$11.89	One Time	$11.89
Breath chamber	$61.95	One Time	$61.95
Digital Display	$8.99	One Time	$8.99
USB type C port	$8.99	One Time	$8.99
Bluetooth Transceiver	$29.99	One Time	$29.99
On/off Button	$5.99	One Time	$5.99
Electrical Sensors	$22.85	One Time	$85
Equipment Total			$150
Total			≈ $365,150

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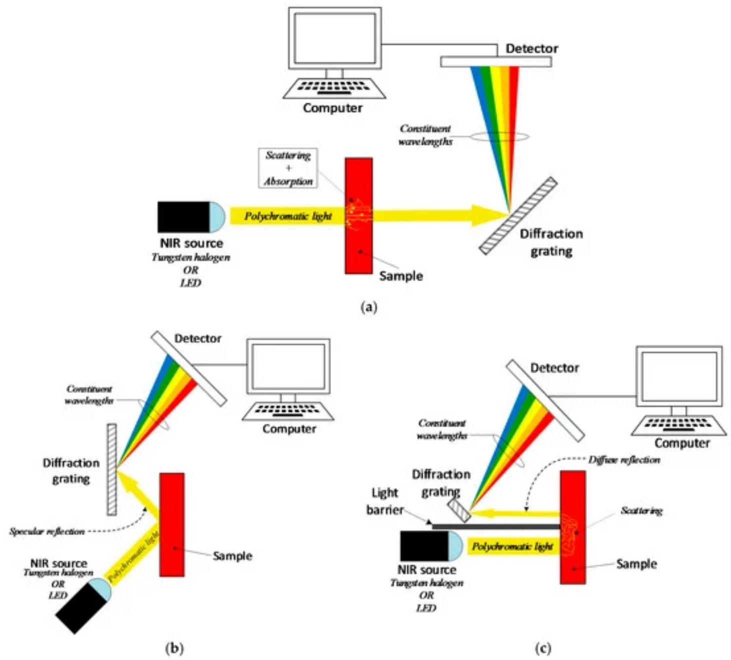
Appendix A: Infrared Spectroscopy

Infrared spectroscopy (IRS) is a form of optical sensing that has been proposed as a non-invasive modus operandi of measuring glucose concentration (Gonzales et. al., 2019). Optical sensors emit electromagnetic light—in this case, infrared light—and study its change in properties to approximate a returned wavelength (Gonzales et. al., 2019). A spectrometer would emit the infrared light which would diffract and return vibration frequencies which can correspond to a different molecular bond or functional group (Gonzales et. al., 2019). Functional groups are molecular substituents commonly found in organic compounds. IRS can therefore be used to identify glucose present in the bloodstream and henceforth measure its concentration. The two most practiced modes of IRS are Near-infrared spectroscopy (NIRS), which emits infrared light at a range of 780-2500 nm , and Mid-infrared spectroscopy (MIRS), which emits infrared light at a range of 2500-10000 nm (Gonzales et. al., 2019). NIRS has three measuring modes: transmittance, reflectance, and interactance (Figure 8) (Gonzales et. al., 2019). All three modes involve a light source interacting with a sample and emitting a new measurable frequency by means of diffraction grating. Under transmittance mode, the light passes directly through the sample and onto the diffraction grating; reflectance mode has the sample reflect the light onto the diffraction grating; interactance mode also functions with reflected light except a light barrier separates the detector from the light source (Gonzales et. al., 2019). Although NIRS has been a popular method of glucose monitoring, it tends to take a gamble on whether or not measured frequencies are that of glucose or of other proteins and biological acids of similar frequencies (Gonzales et. al., 2019). On the other hand, MIRS deals with greater penetration and absorption rates compared to NIRS; this makes it more viable for molecular recognition, therefore less likely to miscount other compounds for glucose (Gonzales et. al., 2019).

Figure 9

Visual Representation of the Three Modes of NIRS



Note. Reprinted from "The Progress of Glucose Monitoring—A Review of Invasive to Minimally and Non-Invasive Techniques, Devices and Sensors," by W.V. Gonzales, A.T. Mobashsher, A. Abbosh, 2019, *National Library of Medicine*, https://doi.org/10.3390/s19040800

Appendix B: Machine Learning

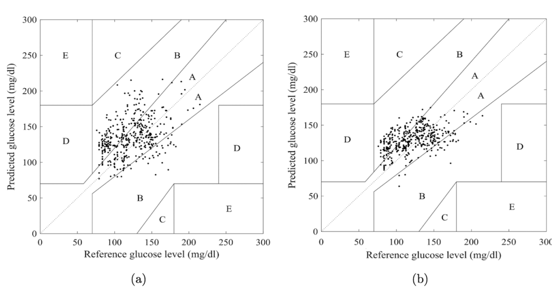
Due to NIRS and MIRS's unstable rate of accuracy, machine learning (ML) can be applied to predict their results instead. ML is a form of artificial intelligence (AI) which statistically analyzes input data, contextually called training data, in order to yield a predicted output (Pant, 2019). The three main machine learning algorithms are supervised, unsupervised, and reinforcement learning. Supervised algorithms have initial data sets with tagged labels; the prediction model henceforth analyzes and learns from such labels to properly identify and classify the data sets into their respective labels autonomously (Pant, 2019). For example, when distinguishing between spam emails and non-spam emails, the algorithm must first be fed with examples of both types of emails (which are labeled). Unsupervised algorithms are provided with unlabeled data sets; therefore the AI must distinguish patterns amongst the data through code (Pant, 2019). Reinforcement learning takes place when the AI interacts with its environment (Pant, 2019). Similar to how humans and other living beings can learn through operant conditioning, AI can also be taught appropriate and inappropriate courses of actions when approaching certain situations through a reward and penalty system. The AI system receives rewards if it assumes the appropriate course of action, and penalties if it assumes the inappropriate course of action, thereby allowing it to learn what is expected of them in the future (Pant, 2019).

Javid et. al. (2018) applied ML in order to form a predicted glucose concentration from output voltage from a transmitter and receiver. The training data they used was the statistical correlation between their measured glucose concentrations and voltages. When they tested the results to see if they matched with in-vivo readings, however, there were some noticeable contrasts between the predicted data and the actual data. This brings the question on if there are better ML algorithms which can account for these differences.

Kasahara et. al. (2018) used a particular type of machine learning known as domain adaptation (DA). DA can be applied when there are stark contrasts between the training data and test data. This can account for external variables which may affect glucose concentration readings, such as a meal a subject may have eaten beforehand. Kasahara et. al. extracted two data sets: the labeled data set and unlabeled data set. Both data sets were extracted from a range of subjects who were provided with meals before measurement as a way to consider external variables. The team then went on to apply DA and other machine-learning models onto the labeled data set to create prediction models which provided the team with predicted glucose levels (mg/dL). They compared the prediction accuracy with the unlabeled data set which was used as reference glucose levels (mg/dL) with and without DA on a Clark error grid, with correlation coefficients of 0.38 and 0.47 respectively (Figure 10).

Figure 10

"Clark Error Grid of the Unlabeled Dataset for the Estimation models."



Note. Reprinted from "Unsupervised Calibration for Non-invasive Glucose Monitoring Devices Using Mid-Infrared Spectroscopy," by R. Kasahara, S. Kino, S. Soyama, Y. Matsuura, 2018, *Journal of Innovative Optical Health Sciences."* https://doi.org/10.1142/S1793545818500384

Appendix C: BLE Transceiver

Wireless data communication can be completed by bluetooth, but for our particular device we will be using a specific frequency called the Bluetooth Low Energy (BLE) radio. This data frequency is designed for efficient and effective communication in a low power operation. Transmitting data in the 2.4GHz frequency band, the BLE radio provides developers flexibility to build their products that allows their innovation to accommodate the connectivity requirements of their market (Bluetooth® Technology). The development of this connectivity relies on its configured state where observer mode performs well over low energy usage. Using BLE frequency, broadcasting begins through the device initialization with its main component, the central processor unit (CPU) . According to (Bluetooth® Technology), Bluetooth LE can handle multiple communication in its frequency, this technology has expanded from point-to-point to broadcast and enable Bluetooth technology to support the creation of reliable, while still maintaining large-scale networks. Furthermore, BLE was very well known for its communications capabilities, but now their frequency can be used as a device positioning technology to address the increasing demand for high accuracy indoor location services. Additionally, their new features enable devices to allocate the presence, distance, and direction of another device through the BLE network.

Appendix D: Communication Interface between Sensor and Transceiver

Sibide et. al. (2022) programmed the QN9080 to follow an algorithm which directs it to send received data (Figure 11). They utilize an I2C protocol (inter-integrating system), which is a message transferring system that conducts serial communication (Campbell, 2016). The algorithm commands the transceiver to provide an initial value to the measured data, validates the data, and converts the format of the data for accuracy and accessibility (Sibide et.al., 2022). After this process, the device is tuned to automatically start advertising the data so that they can be sent to possible recipients. The advertising event is timed for 1 second, with four evenly spaced advertising events within that second (Sibide et. al., 2022). This allows the transceiver to send the measurements four times to four separate devices. After the fourth event, the transceiver automatically stops advertising.

Figure 11

"Flowchart of the Functioning of the BLE SN in Broadcasting Mode."

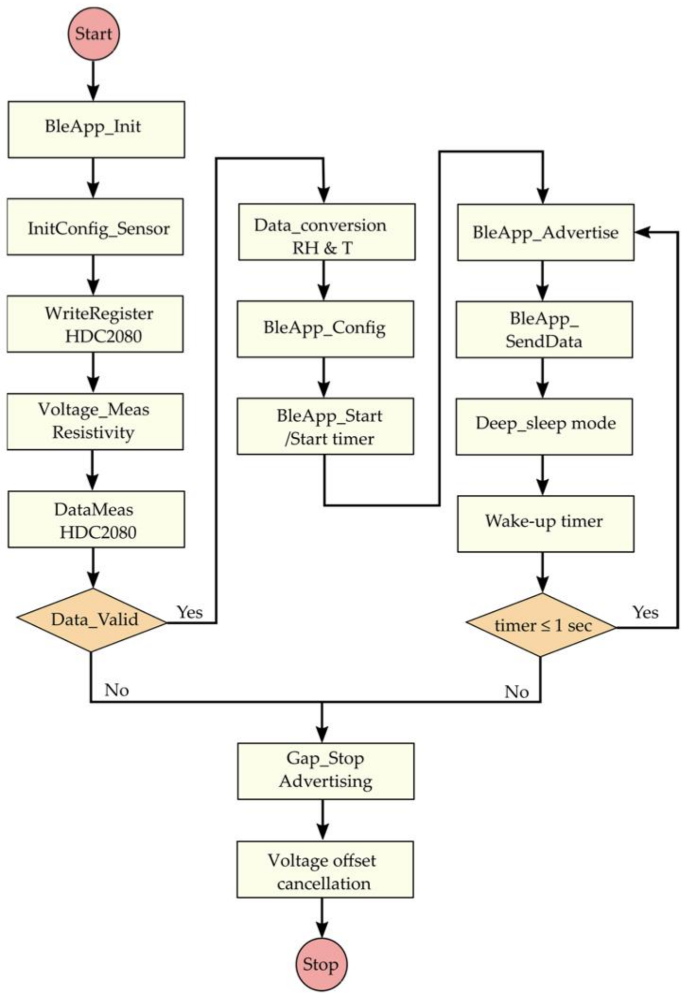


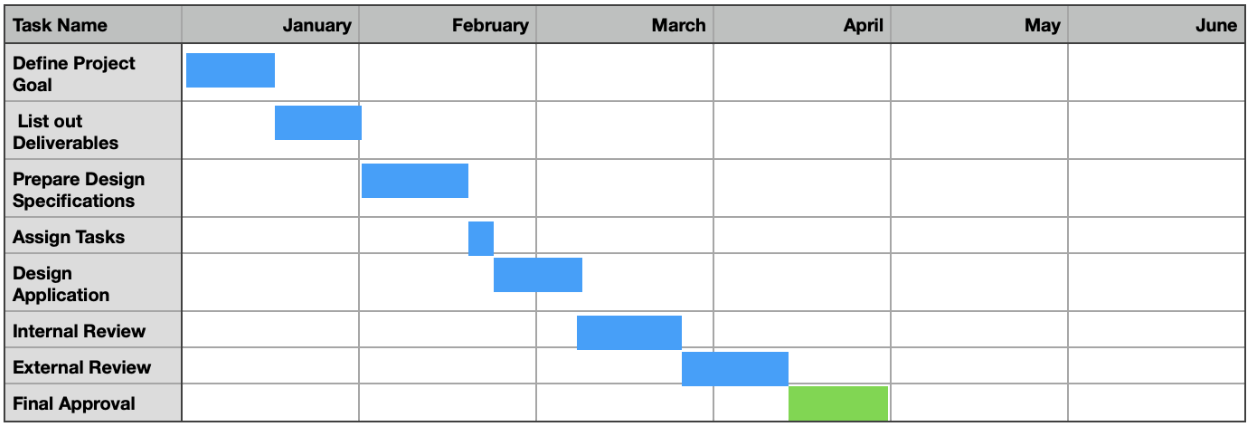
Figure 4. Flowchart of the functioning of the BLE SN in broadcasting mode.

Note. Reprinted from "A Multifunctional Battery-Free Bluetooth Low Energy Wireless Sensor Node Remotely Powered by Electromagnetic Wireless Power Transfer in Far-Field," by A. Sibide, G. Loubet, A. Takacs, D. Dragomirescu, 2022, *Sensors 2022.* https://doi.org/10.3390/s22114054

Appendix E: Task Schedule

Figure 12.

Table 1



Note. Adapted from “Free project schedule template”. ProProfs. (n.d.). Retrieved December 8, 2022, from https://www.proprofsproject.com/templates/project-schedule/

As shown in figure 12 the tasks are divided into multiple parts and project length is expected to be about months. Also the supervisor will make sure each task gets done on time.