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Progress Report

PREDICTION OF SEIZURES DURING SLEEP

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1.0 Overview

Sudden Unexpected Death in Epilepsy (SUDEP) is believed to be the leading cause of epilepsy-related deaths, affecting 1 in 1000 people with epilepsy. Although little is known about the causes of SUDEP, one known risk factor is having seizures during sleep [1]. By alerting a patients to impending seizures during sleep, this group aims to reduce the risk of SUDEP in epileptic patients and enable them to get the care they need.

2.0 Changes from Preliminary Report

2.1 Project Need

No changes were made to the project need.

2.2 Project Scope

No changes were made to the project scope.

2.3 Team Responsibilities

Most of the team responsibilities have remained the same. One addition is that Jack is responsible for writing the weekly reports and submitting them to Blackboard. All three members have contributed to the progress report. Nikhil focused on the signals and machine learning algorithms, Jack focused on transducers and Josh focused on the device architecture and data transmission. The rest of the paper was collaborated on as a group.

2.4 Design Schedule

The design schedule is presented in Appendix A.

3.0 Design Specifications

Table 1: Specifications

Specification	Unit	Value	Description
Safety	Unitless	Unitless	Device should be safe to wear during sleep. It should minimize sharp edges or cords that can tangle, and should be properly insulated
Comfort	Unitless	Unitless	Device should not prevent the user from sleeping comfortably
Size	cm^2	100 cm^2	Part of the device in contact with the patient should not hinder the patient's ability to sleep and should be large enough to be able to collect the relevant data
Weight	g	250 g	Part of the device in contact with the patient should not hinder the patient's ability to sleep
Operating time	Hours	12 Hours	Device should function throughout the night
Consumer Cost	$	$1,000	Device consumer cost is predicted by client to be of similar cost to current AED devices
Production Cost	$	$300	Device production cost is estimated to be ⅓ of the consumer cost
Transmission	unitless	unitless	Device should transmit data to the receiver with minimal wiring and time delay
Prediction Interval	Min	5-60 min	Device should be able to alert the patient of impending seizure 5 to 60 min prior to onset
Prediction Alert	Unitless	Unitless	Device should acoustically alert the patient when an impending seizure is predicted
Detection Alert	Unitless	Unitless	Device should alert emergency services when an active seizure is detected
Sensitivity	%	99%	Device should accurately predict an impending seizure within a certain percentage
Range	m	20 m	Device should be able to receive signals from the sensor within 20 meters
Security	%	100%	Data collected will only be accessible to the user and to emergency services
Time to Completion	Months	5 months	A prototype must be completed by May 2018.

4.0 Design Alternatives/Analysis

There are five primary components to our device: the physiological signal used for prediction, the type of transducer used for recording, the architecture of the recording devices, the methods of data transmission, and the machine learning algorithm used to make the final prediction. Several possibilities for each component are described in this report. Other options were considered, but are not included here due to space constraints. A list of these solutions can be found in Appendix E.

4.1 Signals

4.1.1 EEG

Given that seizures are caused by abnormal electrical activity in the brain, EEG data provides a significant amount of valuable information that could be used to predict seizures [2]. Because EEG is closest to the source of the seizure, it serves as the strongest predictor of an impending seizure and is available from our client. However, this device will be used in the home, therefore, putting any recording equipment on the head, as would be required by EEG, would require significant risk mitigation. Additionally, our client has indicated that EEG recordings through the scalp can be inaccurate due to obstruction from the skull, skin, and hair. Although intracranial EEG could serve as an alternative, this requires an invasive surgery, and was not considered.

4.1.2 Surface EMG

Surface EMG on the scalp is another signal that our client has available to give to us. It is valuable in detecting seizures because convulsive muscle activity increases dramatically during a seizure. However, there is currently no literature to support the predictive value of the surface EMG from the scalp and similar to with EEG, this signal requires recording at the head which poses safety and comfort concerns for our device.

4.1.3 2-Channel ECG

While ECG is not a direct measure of neural activity, research shows that there is predictive value in the ECG signal [3][4]. Information such as the magnitude of the R and S peaks or the presence of various arrhythmias can change significantly in patients who are pre-ictal. Additionally, information such as heart rate and heart rate variability, which have known predictive value, can be extracted from this signal [5]. This signal can be measured easily using electrodes on the chest, which will not significantly interfere with sleep. Our client has 2-channel ECG data available for us. While there is greater predictive value in a 12 lead ECG, similar information can be extracted from a 2 channel ECG and a full 12 lead ECG is not practical for use in patient homes and, therefore, was not strongly considered.

4.1.4 Electrodermal Activity

Electrodermal activity is observed as the change in resistance of the skin to small currents [6]. This is something that can be easily recorded from the arm or leg and has been seen to change in the pre-ictal period [7], however it has only been tested in conjunction with other physiological signals. It is unknown if this signal has enough predictive power to be used on its own. Additionally, this is not something that our client has data available for.

4.1.5 Optimal Solution

As seen in Table 2, the best signals for us to use are the heart rate and the 2 channel ECG. These two signals are both safe and easy to acquire, will be have predictive value for seizures and have testing data available from our client.

Table 2: Pugh Matrix - Signals to Measure

Specification	Weight	Potential Solutions			
Concept Selection Legend 10: Most Preferred 0: Least Preferred		EEG	Surface EMG (head)	2 Channel ECG	Electrodermal Activity
Safety	10	6	6	8	8
Comfort	8	4	4	8	10
Prediction Interval	9	10	0	10	10
Sensitivity	10	10	0	8	8
Time to Completion	10	10	10	10	0
Weighted Total		382	192	414	330

Table 2 - Signals Pugh Chart: Safety and comfort were defined by the recording location and potential for electric shock. Prediction interval and sensitivity was defined by the known predictive value of the signal. Time to completion was defined by the availability of the signal from our client.

The next highest scoring signal is EEG, which requires data collection from the head. This is not safe or easy to collect in an individual's home at night and therefore will not be used.

4.2 Transducers

4.2.1 Invasive Electrodes

The main two types of invasive electrodes are subdural and micro electrodes. Subdural electrodes are surgically implanted on the surface of the brain and micro electrodes are implanted within the depth of the brain. Invasive electrodes are able to obtain very accurate recordings, but can be costly (often involving surgery) and have many safety concerns (such as infection). For this device, the use of invasive electrodes significantly compromises the safety and comfort of the user, despite the accuracy benefits.

4.2.2 Wet Electrodes

Wet electrodes are most commonly defined as Ag/AgCl electrodes that utilize an electrolytic gel to form a conduction between the skin and electrode. These electrodes can minimize motion artifact, a source of noise in physiological measurements. One concern with wet electrodes is that gel dehydration can occur with extended use. Frequent reapplication of the gel may be necessary and in some cases, infeasible. Wet electrodes also require hair removal and can cause skin irritation from repeated gel application [8]. Below are examples of wet electrodes that offer possible solutions. Diagrams of these electrodes are shown in Appendix B.

4.2.2.a Suction Electrodes

The rubber bulb is compressed to build suction, holding the electrode in place [9]. While straps and adhesives are not required, these electrode can only be used for short periods of time. These electrodes are also quite large but have a small contact area resulting in a high source impedance. A diagram of a suction electrode is presented in Figure 1a.

4.2.2.b Hydrogel Electrodes

The film provides efficient conduction and a sticky material so that no additional adhesive is needed, which reduces the interfacial motion between the two surfaces [9]. These electrodes are also flexible which provide a better fit to the body, which is valuable for monitoring patients that might move during sleep. One concern with hydrogels is that the concentration of ions is generally lower than the other electrolytic solution in the other models, resulting a higher source impedance. A diagram of a hydrogel electrode is presented in Figure 1b.

4.2.2.c Floating Electrodes

In floating electrodes, the gel does not move with respect to the metal disk, which will isolate the electrode-electrode interface from motion artifacts [9]. Another issue is that floating electrode are fairly rigid and therefore is unable to fit certain body contours, which could affect the device's accuracy for patients who move during sleep. A diagram of a floating electrode is presented in Figure 1c.

4.2.3 Dry Electrodes

Dry electrodes do not use artificially applied electrolyte solutions or gels. Most sensors are held with the use of elastic bands and tape and, therefore, are generally safer and longer lasting because there is no adhesive. However, due to the absence of a gel there is an unstable electrochemical interface, resulting in high contact impedances, drift and noise. Dry electrodes such as the metal plate electrodes are not ideal for sleep use due to their larger size. Furthermore, metal plated electrodes are generally inflexible and would result in a higher motion artifact. Textile electrodes may solve the problem with weight and flexibility but involve complex circuitry and require cables for power.

4.2.4 Optimal Solution

As seen in Table 3, the best type of transducer for our device is the hydrogel electrode. Hydrogel electrodes have a simple design and are fairly lightweight. They are readily available, inexpensive, easily disposable and have a low initial contact impedance. The next highest score is for textile electrodes. Though textile electrodes maybe better for long-term monitoring, they having a low sensitivity due to artifacts will make prediction difficult, especially in a supine position.

Table 3: Pugh Matrix - Transducers

Specification	Weight	Potential Solutions						
Concept Selection Legend 10: Most Preferred 0: Least Preferred		Microelectrodes	Needle Electrodes	Suction Electrodes	Floating Electrodes	Hydrogel Electrodes	Metal Plated Electrodes	Textile Electrodes
Safety	10	2	2	8	5	5	7	7
Comfort	8	2	2	8	5	5	7	7
Size	6	10	10	3	3	5	5	3
Weight	6	10	10	3	3	5	3	8
Operating Time	8	10	10	5	10	10	10	10
Consumer Cost	6	1	1	5	3	9	3	3
Sensitivity	9	10	10	5	5	7	3	3
Time to Completion	10	2	2	10	10	10	10	10
Weighted Total		352	352	395	369	447	399	417

Table 3 - Transducers Pugh Chart: Safety and comfort was defined by invasiveness, irritation and number of wires. Operating time was defined by the ability to record continuously overnight. Sensitivity was defined by impedance, noise and motion artifacts.

4.3 Device Architecture

The architecture of the device refers to the organization of the sensor components that lie between the transducers and the receiver (either a computer or a mobile device). For this device, the combination of the sensor components and the receiver must be able to:

1) Input an analog signal from the transducers.
2) Process and store the data from the signal.
3) Run the prediction algorithm to determine whether or not a seizure will occur.

While there are many types of microcontrollers and single-board computers, in this analysis an Arduino Uno was chosen for the microcontroller component, and a Raspberry Pi was chosen for the single-board computer. When the receiver is not explicitly stated as part of the "possible solution," it is implied that the sensor component is connected in series with the receiver. However, the receiver itself is not performing any of the data analysis. The receiver in these instances is only acting to alert the patient and relay information to EMS. When the receiver is explicitly listed as part of the "possible solution," it is implied that the receiver is performing the data analysis and alerting the patient. Diagrams of each design can be found in Appendix C.

4.3.1 Arduino Only

For this solution, shown in Figure 2a, the transducer feeds directly into the Arduino, which performs the data analysis. An Arduino does not consume much power (~180 hour battery life) and is relatively inexpensive (~$35). Although it can transmit data to the receiver wirelessly, it has very little processing power and is unable to store very much data at once [10]. It is designed to take in analog signals, but has a built in 10-bit analog-to-digital converter[1]. Although our signal may require a higher number of bits, it should be noted that it is possible to overcome this problem by oversampling and amplifying the signal [11][12]. However, it would be nearly impossible to build the proposed device if the Arduino was the only component storing and analyzing data because the Arduino is designed primarily for data acquisition, not data analysis [13].

4.3.2 Raspberry Pi Only

For this solution, shown in Figure 2b, the transducer feeds directly into the Raspberry Pi. A Raspberry Pi is relatively inexpensive (~$40), but consumes a lot of power (~4 hour battery life), making it impossible to use the Raspberry Pi throughout the night without an external power source [10]. It can transmit data to the receiver wirelessly but has a slower processing speed than that of a mobile device or a computer that are part of the sensor

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[1] With VDC of 10V and a 10-bit A/D converter, the resolution will be roughly 10 mV/step. To more accurately represent the signal (which will be about 1-10 mV) and obtain a better resolution, the bit number will have to be increased or the signal will have to be amplified.

architecture in other possible solutions. A Raspberry Pi is not designed to read analog data which makes it impossible to measure the signal of interest without an AD Converter. Therefore, this setup would be insufficient if the Raspberry Pi were the only sensory component. While it would not be very difficult to program the Raspberry Pi to run the analysis using Python, there is less flexibility with the design of the analysis on a Raspberry Pi than there is on a computer [14][15].

4.3.3 Analog/Digital Converter to Raspberry Pi

For this solution, shown in Figure 2c, the analog signal from the transducer feeds into an A/D converter, outputting a digital signal into the Raspberry Pi. This solution is largely the same as that described in 4.3.2, however, this solution would solves the problem of taking in analog data. This solution also allows more flexibility regarding the choice of bit size for the A/D converter in this solution than we would have in 4.3.1.

4.3.4 Arduino to Receiver (Computer)

This solution, shown in Figure 2d, is identical to 4.3.1, except a computer will take the place of the Arduino in storing the data and performing the analysis. This greatly improves upon using only an arduino and will allow for a complete data analysis, which is not possible without the storage capacity and processing speed of the computer. Additionally, because of the minimal programming constraints when using a computer, the data analysis software will be easier to implement using this structure. The programmability of Arduino allows the data to be autonomously exported during recording, which allows for real time processing.

4.3.5 Arduino to Receiver (Mobile Device)

This solution, shown in Figure 2e, is identical to 4.3.4, except a mobile device will take the place of the Arduino in storing the data and performing the analysis. Because the team lacks experience in programming on a mobile platform, the device will take much longer to complete using this architecture, and because the device is designed to be used during sleep, portability is not a major concern.

4.3.6 Arduino to Raspberry Pi

For this solution, shown in Figure 2f, the transducer feeds into the Arduino, which is connected in series with a Raspberry Pi. The Arduino performs the analog sensing, and the Raspberry Pi performs the data processing and analysis. This solution has the benefits of the Arduino described in 4.3.1 as well as the benefits of a Raspberry Pi described in 4.3.2. However, this solution will have a much higher cost resulting from the need to purchase both devices as well as the difficulties with programming flexibility as described in 4.3.2.

4.3.7 Data Acquisition Chip to Computer

For this solution, shown in Figure 2g, the transducer feeds into a data acquisition chip, which connects to a computer. This allows acquisition of data without having to use an intermediate device like an Arduino, while still allowing processing to occur on the computer. It also allows for analog data input and an A/D converter with a bit number of 12 (compared to 10 for an Arduino). However, the data acquisition chip requires an external power source and is more expensive than an arduino. The software used by these chips do not allow data processing to occur in real time because it is not possible to autonomously record and export the data like it is on Arduino. This will make real time prediction impossible using this structure. Furthermore, these chips cannot transmit the data to the computer wirelessly [16].

4.3.8 Optimal Solution

As shown in Table 4, the optimal solution for sensor architecture is Arduino to Computer. This solution can take in an analog signal, transmit wirelessly to a receiver, store a large amount of data, and perform prediction using software written in the programming language of choice. It should be noted that this is the optimal solution for the working prototype of this team's device. If the proposed device were to be taken to market, a more consolidated solution would be sought out, such that the sensor and receiver were physically combined into a single device.

Table 4: Pugh Matrix - Architecture								
Specification	Weight	Potential Solutions						
Concept Selection Legend 10: Most Preferred 0: Least Preferred		Arduino Only	Raspberry Pi Only	A/D Converter to Raspberry Pi	Arduino to Computer	Arduino to Mobile Device	Arduino to Raspberry Pi	Data Acquisition Chip to Computer
Operating Time	8	10	8	8	10	10	8	8
Consumer Cost	6	10	10	10	10	10	8	9
Production Cost	6	10	10	10	10	10	8	9
Transmittion	6	5	8	8	10	9	8	5
Sensitivity	9	8	0	10	8	8	8	10
Time to Completion	10	0	0	9	10	5	9	8
Weighted Total		302	232	412	432	376	370	372

Table 4 - Architecture Pugh Chart: Operating time was defined by the power consumption. Transmission was defined by the wireless capabilities of the devices used and the processing speed. Sensitivity was defined by the ability of the device to accurately intake analog signals. Time to completion was defined by the ability of the device to provide data in a form that can be analyzed in real time as well as team members' familiarity with the hardware and software. It is assumed that the patient possesses a computer and mobile device with WiFi and Bluetooth capabilities.

4.4 Data Transmission

Data transmission refers to the mode by which the signal travels from the sensor to the receiver. It is assumed that consumers have Wi-Fi/Bluetooth accessible devices. All transmission methods are functional within a range of 20 meters.

4.4.1 Wired

A cable (likely a USB) would run directly from the device to the receiver. While this solution has the highest data throughput (>100 Mbps), it does not satisfy the wireless specification. This solution is very secure, given that the data is not remotely accessible and easy to implement given that most computers are equipped to handle a wired input [17].

4.4.2 Wi-Fi

This solution has a high data throughput of 72 Mbps and is password protected, though any wireless connection could be hacked. Wi-Fi is currently the most ubiquitous mode of wireless connectivity, and it is compatible with desktop/mobile device receivers, making it easy to use for most users [18].

4.4.3 Bluetooth

This solution received the same score for every design specification as 4.4.2 except for transmission, receiving a slightly lower score due to an intermediate data throughput of 2 Mbps. Like 4.4.2, this solution is password protected and compatible with desktop/mobile device receivers [18].

4.4.4 Thread

Thread is useful for connecting to multiple devices at once and has a data throughput of up to 250 Kbps. Thread also has low power consumption and provides a secure connection. While Thread is a relatively cheap wireless transmission option, the major drawback of Thread is that its infrastructure is not already widely deployed in most homes (certainly not to the degree that Wi-Fi and Bluetooth are), and it is not readily compatible with desktop/mobile device receivers [18].

4.4.5 ZigBee

A popular alternative to Thread, ZigBee can also be used to connect multiple devices and has a data throughput of 250 Kbps. ZigBee received low consumer/production costs and time to completion scores for the same reasons given in 4.4.4.

4.4.6 Optimal Solution

As shown in Table 5, the top scoring solutions for data transmission are Wi-Fi and Bluetooth. Both of these options are

Table 5: Pugh Matrix - Transmission							
Specification	**Weight**	**Potential Solutions**					
Concept Selection Legend 10: Most Preferred 0: Least Preferred		Wired	WiFi	Bluetooth	Thread	Sub 1-Ghz: TI 15.4	Zigbee
Operating Time	8	10	10	10	10	10	10
Consumer Cost	6	9	10	10	5	5	5
Production Cost	6	9	10	10	5	5	5
Transmission	6	5	10	9	8	8	8
Range	6	10	10	10	10	10	10
Security	10	10	10	10	10	10	10
Time to Completion	10	8	10	10	5	5	5
Weighted Total		458	520	514	398	398	398

Table 5 - Transmission Pugh Chart: Operating time was defined by power consumption. Transmission was determined by the wireless capability and the data throughput of the solution. Range was determined by the solution's ability to transmit data at least 20 meters. Security was defined by the difficulty for the system to be hacked by a third party. TIme to completion was defined by the compatibility of the solution with the optimal device architecture.

wireless, have a low power consumption, have a secure connectivity, work well within the specified range, and are compatible with desktop and mobile device receivers. The one advantage that Wi-Fi appears to have over Bluetooth is data throughput—72 Mbps for Wi-Fi, 2 Mbps for Bluetooth. Because we do not currently know what the sampling rate will be or how much data will need to be transmitted, we plan to use Wifi as our method of data transmission in preparation for large amounts of data.

4.5 Machine Learning Algorithm

There are seven machine learning algorithms outlined in the Pugh Matrix. Given that our project will rely on using several seizures to train a model, we selected only supervised learning algorithms to be included in our analysis. We were interested in finding an algorithm that is capable of classifying a set of data as either positive or negative for being in the pre-ictal period. There are a variety of classification algorithms capable of doing this:

1. Random forest
2. Support vector machine (SVM)
3. Artificial neural network (ANN)
4. Nearest neighbors
5. Naive bayes
6. Decision trees
7. Regression

One key specification in this piece of the design is the sensitivity. A study by Acharya et al. compared several machine learning techniques in detecting normal, pre-ictal, and ictal states from EEG data [19]. The results of this study contributed to the sensitivity rankings on the Pugh Matrix. Some algorithms do not perform well on small datasets (Support Vector Machine and Artificial Neural Networks) [20]. Because we will have data from approximately 50 patients with roughly 1-3 seizures each, we will not have a very large sample size. This also impacted prediction interval score on the Pugh Matrix because a more data is required to make an accurate prediction. Another important piece of the prediction algorithm is how familiar our team is with the algorithm. Because we have experience with some of these algorithms (Random Forest, Decision Trees, and Regression), but not others, the specification that scores the estimated time to completion of the project was considered, with algorithms that are new to our team receiving lower scores.

4.5.1 Optimal Solution

The optimal machine learning algorithm was determined by the Pugh Matrix shown in Table 5 to be the Decision Tree algorithm. It is able to make classifications using small data sets, which is what we will have after reducing our data down to a small set of features. It also performed well in the study performed by Acharya et. al. This algorithm is a common element of machine learning software packages and has been used before by members of our team.

Table 6: Pugh Matrix - Algorithms

Specification	Weight	Potential Solutions						
Concept Selection Legend 10: Most Preferred 0: Least Preferred		Random Forest	Support Vector Machine	Artificial Neural Network	Nearest Neighbors	Naive Bayes	Decision Trees	Regression
Prediction Interval	9	10	5	5	10	10	10	10
Prediction Alert	10	10	10	10	10	10	10	10
Detection Alert	10	10	10	10	10	10	10	10
Sensitivity	10	8	10	6	10	8	10	6
Time to Completion	10	10	6	6	6	6	10	10
Weighted Total		470	405	365	450	430	490	448

Table 6 - Algorithms Pugh Chart: Prediction interval was defined by the ability of the solution to work well on small data sets. Sensitivity was determined by the results of a study performed by Acharya et. al. [17]. Time to completion was defined by the team's familiarity with the algorithm.

5.0 Overview of Chosen Solution

Based on Pugh Chart analysis, our device will use data from a 2-channel ECG recording to predict seizures. Hydrogel electrodes will be used to collect data into an Arduino, which will simultaneously transmit the data to a computer via WiFi. Finally, a random forest algorithm will process the data to determine if the patient is in a pre-ictal state alert them when this occurs.

This design allows data to be recorded safely and comfortably from the patient with inexpensive electrodes that can be disposed of after use. An Arduino with an integrated WiFi is an inexpensive and easy-to-use method of acquiring analog data that can securely transmit the data to a computer. Furthermore, sensing cables and a 2-channel ECG board are made for Arduino that will make it easy to record these signals. The random forest algorithm will work well with the small amount of data that we will have and can be easily implemented on almost any software platform. A diagram of the device structure is presented in Appendix D.

6.0 Proposed Budget

An overview of our budget is shown in Table 7. We are requesting $59.80 for sensor cables, an ECG sensor, and an Arduino microcontroller (with an integrated WiFi module). This equipment is necessary to be able to collect data and send it to the computer that will perform the analysis. We are assuming that the user has a computer as well as WiFi available to them.

We will be using hydrogel electrodes from Professor Patricia Widder's lab at no additional cost. We will also use software and computers from Washington University in order to view and test the data we will be obtaining from our client.

Table 7: Proposed Budget

Item	Quantity	Cost	Source
Adhesive Hydrogel Electrodes	50	$0	Professor Widder
Sensor Cable - Electrode Pads (3 connector)	1	$4.95	SparkFun [21]
SparkFun Single Lead Heart Rate Monitor	1	$19.95	SparkFun [21]
Arduino Uno Wifi Microcontroller	1	$34.90	RobotShop [22]

Appendix A: Design Schedule

SUDEP	start	end	46%
	08/28/17	**05/01/18**	**46%**
Client ID	08/28	09/18	100%
Project Selection	08/28	09/25	100%
Preliminary Report	09/11	10/06	100%
Preliminary Presentation	10/09	10/09	100%
Web Page	10/23	05/01	40%
Design Brainstorming	10/06	12/01	100%
Pugh Chart	10/30	12/01	100%
Budget Proposal	10/30	12/01	100%
Progress Report	10/23	12/01	100%
Progress Report Presentation	12/04	12/04	0%
Verification Plan	01/01	02/01	0%
Proof of Concept ID	02/01	03/02	0%
Validation/Verification/Proof of Conc...	12/01	03/02	0%
Software/Hardware Dev.	03/02	04/20	0%
Final Paper	03/02	04/20	0%
Prototype Demo	04/23	04/23	0%
BME day	05/01	05/01	0%

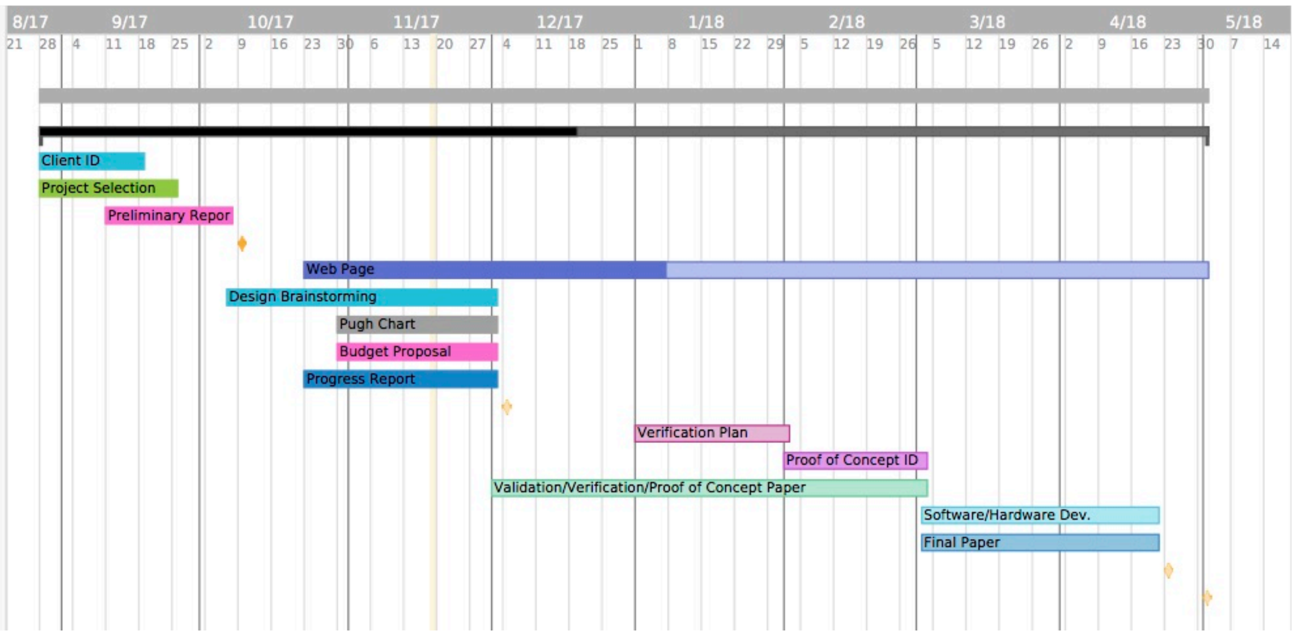


Figure 1a: Suction Electrode [9]

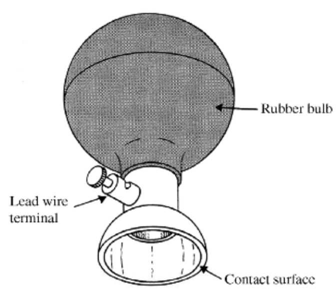


Figure 1b: Hydrogel Electrode [9]

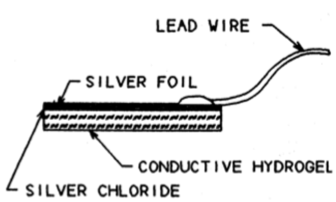
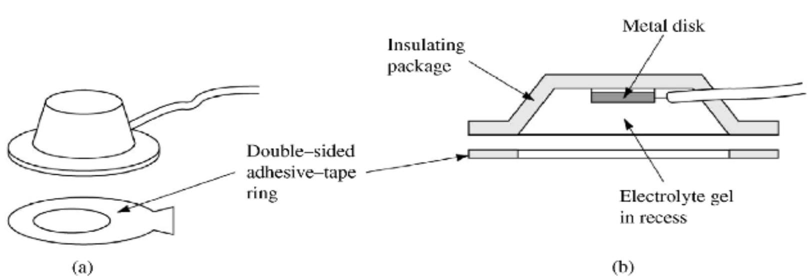


Figure 1c: Floating Electrode [9]



Appendix C: Diagrams of Device Architecture

Figure 2a: Arduino Only

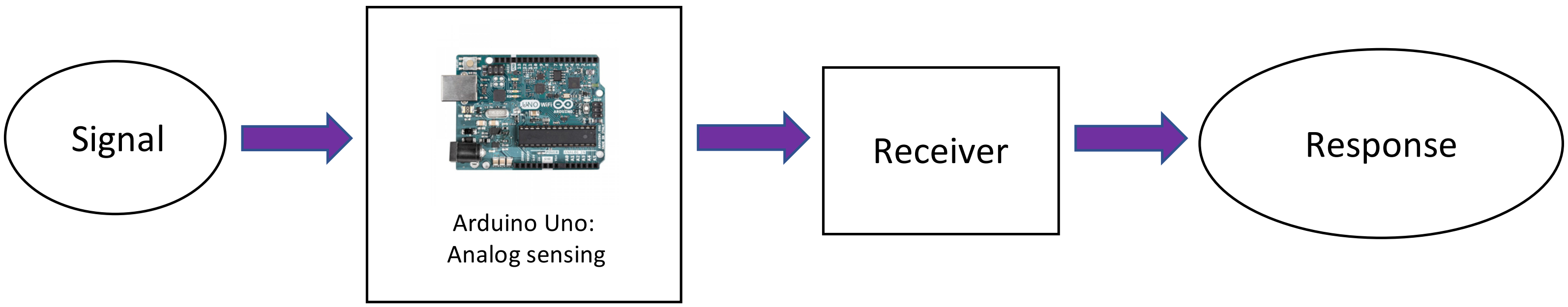
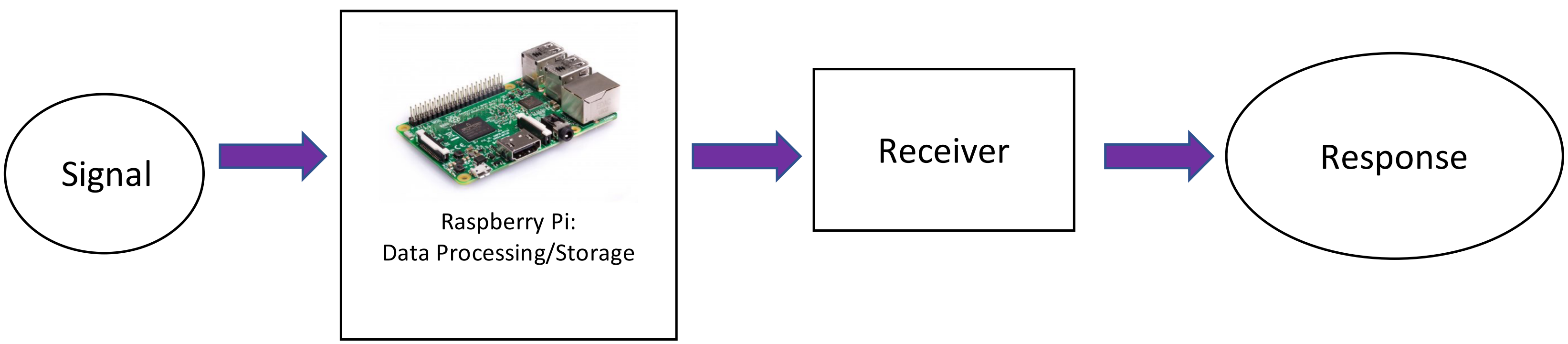


Figure 2b: Raspberry Pi Only



Appendix C: Diagrams of Device Architecture

Figure 2c: A/D Converter to Raspberry Pi

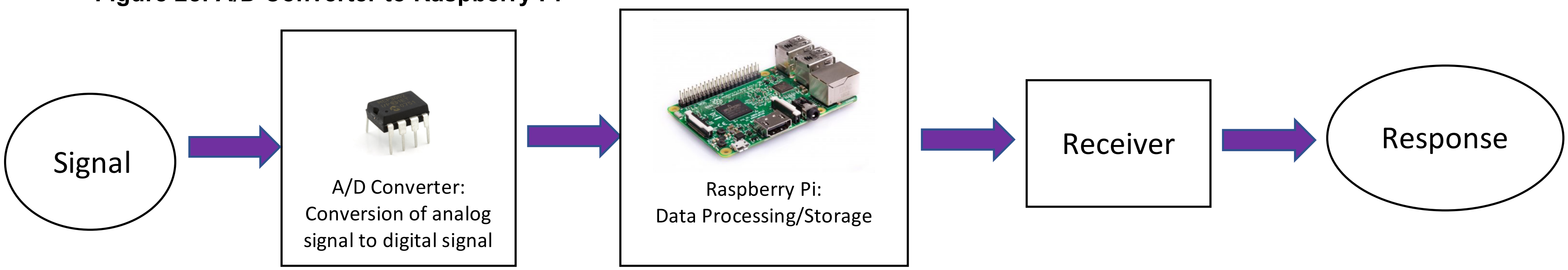


Figure 2d: Arduino to Computer

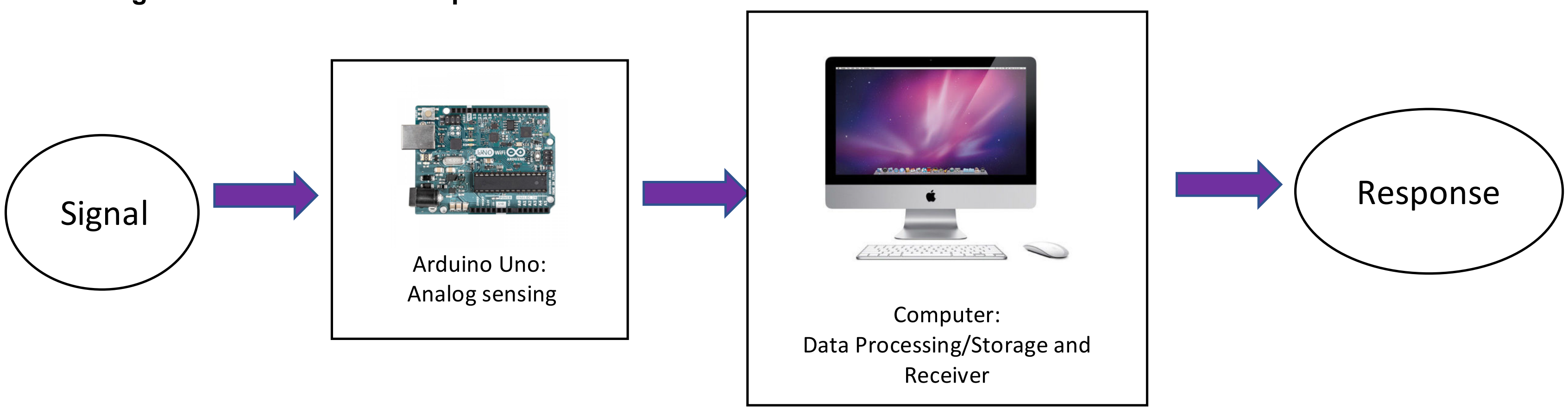
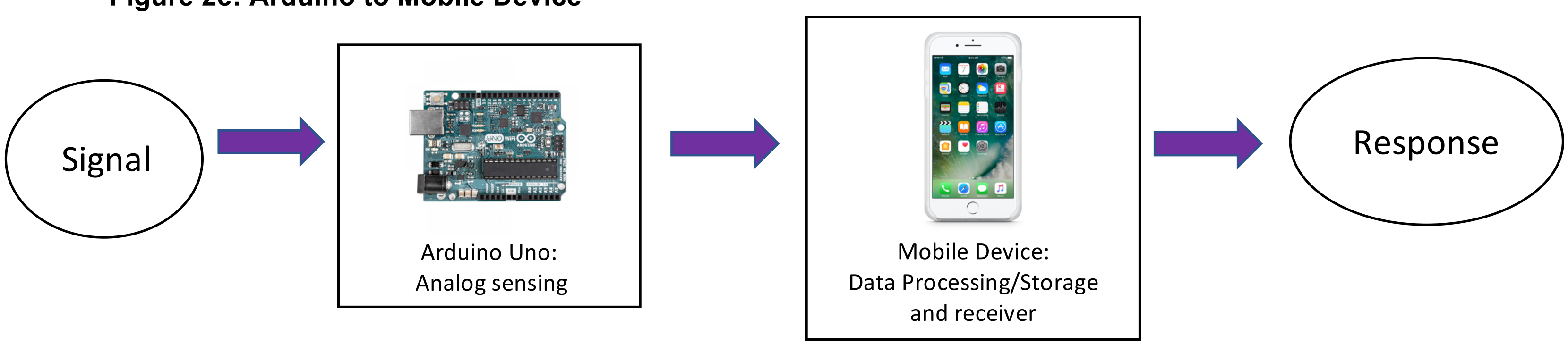


Figure 2e: Arduino to Mobile Device



Appendix C: Diagrams of Device Architecture

Figure 2f: Arduino to Raspberry Pi

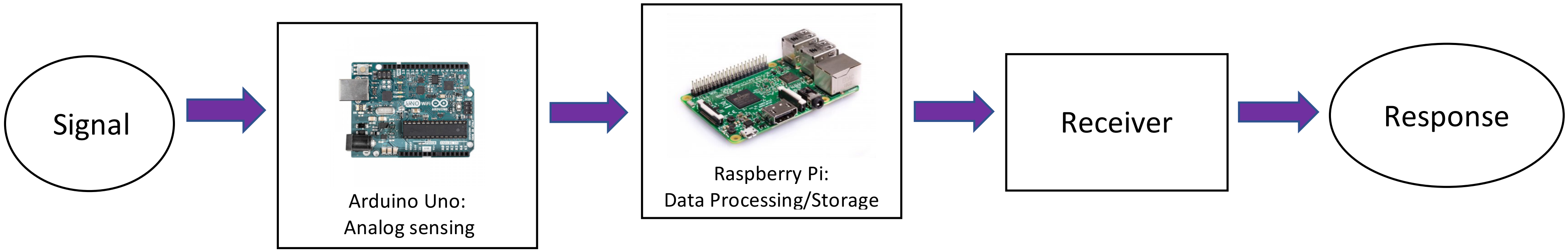
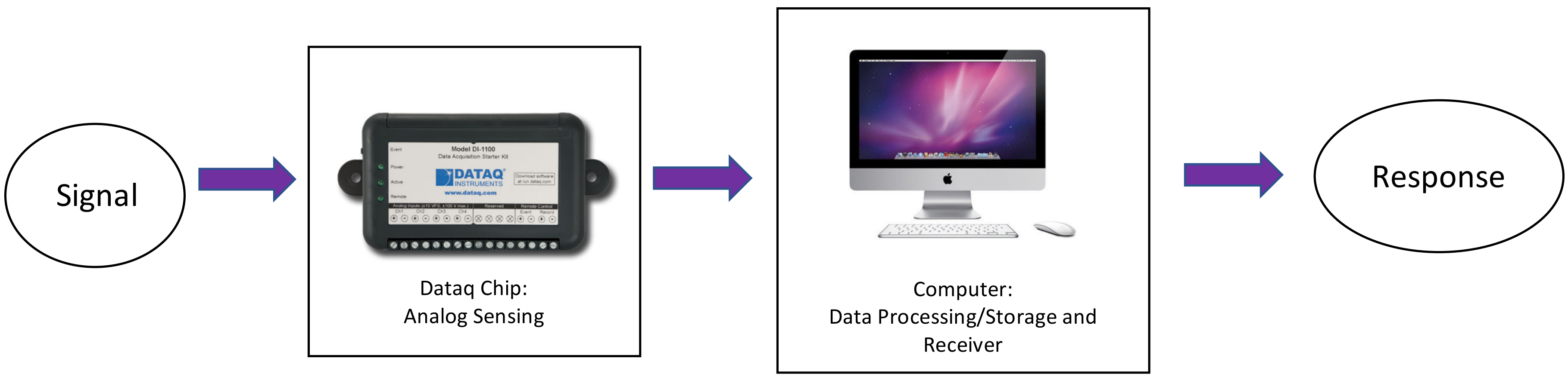
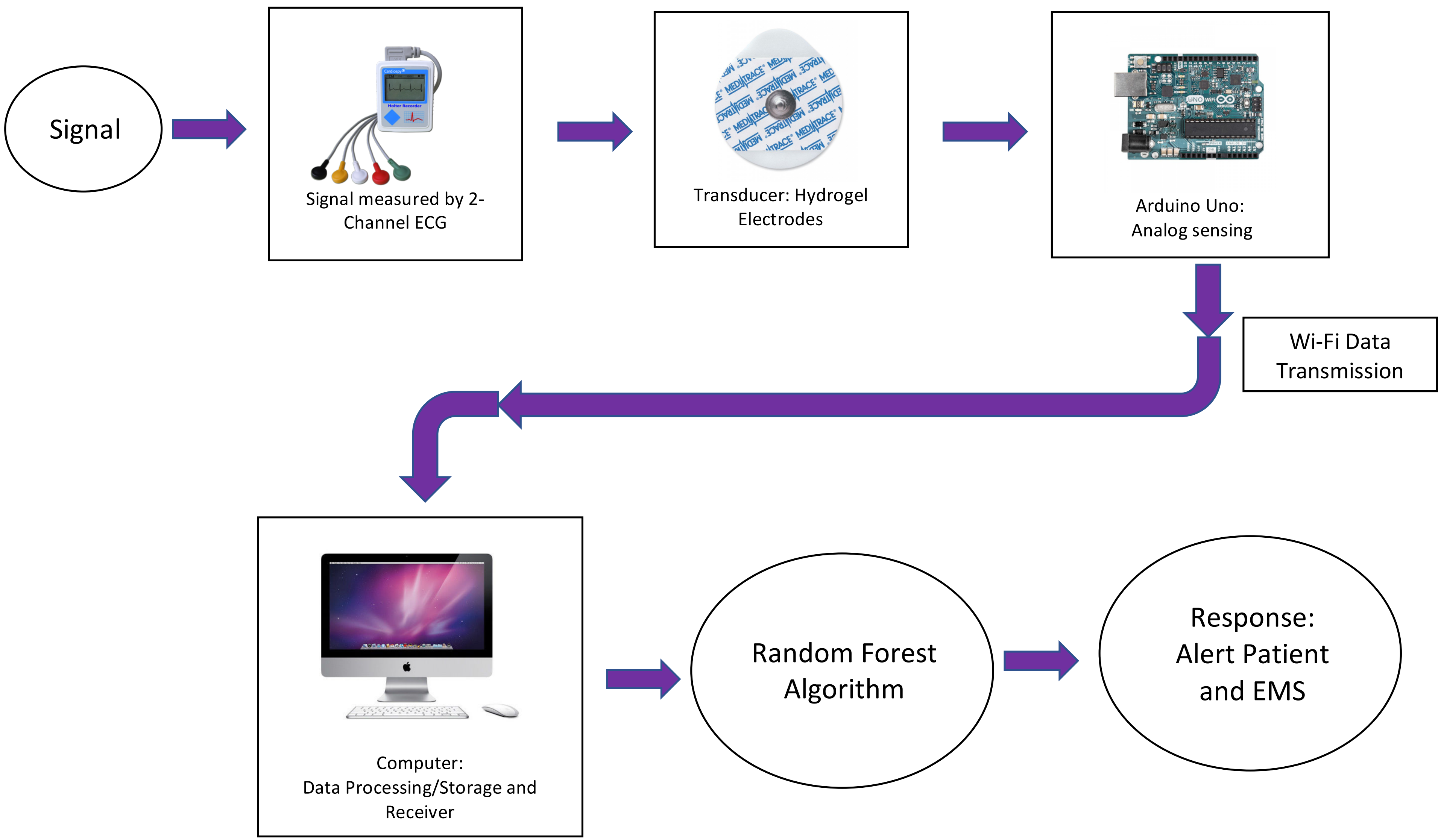


Figure 2g: Data Acquisition Chip to Computer



Appendix D: Diagram of Optimal Solution

Figure 3: Optimal solution architecture



Solution	Reason for exclusion
Signals	
Intracranial EEG	Requires an invasive surgery
EOG	Recording on the head No known predictive value
Surface EMG (bicep)	Data not available from our client No known predictive value
ECG	Full 12 lead ECG is not prectical to record from a patient durting sleep
SiO2	No known predictive value
SiCO2	No known predictive value
Blood Pressure	Can be difficult to measure continuously during sleep in a patient home No known predictive value
Respiration	No known predictive value
Transducers	
Spiked Electrodes	Has sharp needles designed for penetration of human skin
Sensor Architechture	
Raspberry Pi to Computer	Redundant to have to data processing/storage devices in series with each other, ineffective for the same reasons as the Raspberry Pi only option
Raspberry Pi to Mobile Device	Redundant to have to data processing/storage devices in series with each other, ineffective for the same reasons as the Raspberry Pi only option
NI C Series Multifuction I/O Module	No discernable advantage over Dataq or Arduino for the purposes of this project, costs roughly 8 times as much as these perfectly adequate options
Transmission	
Sub 1-GHz: TI 15.4	Typically used in industrial applications. Identical to Thread and Zigbee regarding the design specifications of this project
Sub 1-GHz: Sigfox	Typically used in industrial applications. Identical to Thread and Zigbee regarding the design specifications of this project
Algorithms	
Gradient Boosting	Not commonly found in machine learning software packages
Q-Learning	Not commonly found in machine learning software packages
Temporal Difference	Not commonly found in machine learning software packages
Markov Modeling	Not commonly found in machine learning software packages
k-means Clustering	Not a supervised learning method
Association Rules	Not a supervised learning method
Genetic Algorithm	Not a supervised learning method
Gaussian Mixture Model	Not a supervised learning method
Bayesian Linear Discriminant Analysis (BLDA)	Not commonly found in machine learning software packages
Generic Osorio-Frei Algorithm (GOFA)	Algorithm constructed specifically for the Yang lab Not found in any machine learning software packages

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