Inspirit

A Capstone Project
by

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Abstract

The Inspirit is a wearable biofeedback device that tracks anxiety levels by monitoring physiological indicators of panic. It interfaces with a wearer's phone to give them an overview of their current stress level, helping them to communicate about their anxiety and track situations that cause them to panic. This represents a first step toward predicting panic attacks.

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Chapter 1: Introduction

1.1 Problem Statement

Anticipating and communicating episodes of anxiety can be challenging for sufferers, contributing to underlying stress.

1.2 Purpose Statement

The inspirit, a wearable smart device, tracks physiological indicators of stress and panic responses and predicts a wearer's current anxiety level, allowing them to track and communicate their anxiety. This is the first step in predicting panic attacks before they happen, so that wearers will have time to remove themselves from the situation and access the resources they need.

1.3 Context

Wearable computing devices have existed since the 1970s, mostly in the form of digital watches, and have interfaced with other personal electronics since the late eighties[19]. The first wearable device to integrate environmental sensors was the Pulsar Time Computer, which used light sensors to control the brightness of the screen[10]. Since then, wearable smart devices have evolved from novelties into specialized tools for data collection and alerts. Their position on the body grants them access to information about the activity and health of the wearer. This affordance has contributed to the proliferation of fitness-based wearables and wearable medical devices. Because they are measuring physiological data, they mostly track and predict physiological information, like expended energy or sudden falls[15][6].

Devices have been predicting emotional and behavioral information based on sensors since the invention of polygraph tests, but few have leveraged the information to benefit the wearer. Even other wearable devices that predict emotional information are often meant to provide this information to others. The Moxo sensor, developed at MIT uses skin conductivity data to track emotions of testers in consumer trials[7]. The Reveal[2] and Embrace[15] wearables both predict emotional information and communicate it to caretakers rather than to wearers. The inspirit will explore the utility of this information to the wearer.

When an individual suffers from panic attacks, sudden, intense episodes of fear and discomfort, they often come to fear the attacks themselves as much as whatever is causing them. This is called agoraphobia and it can lead to isolation and avoidance. Panic attacks are the result of a feedback loop where physiological signs of emotional distress are misinterpreted and signs of physical distress. Monitoring these metrics with biofeedback devices has been found to improve a sufferer's condition[3]. A 2011 study published in the Journal of Biological Psychiatry found that signs of a panic attack are visible in the body about forty-seven minutes before the onset of noticeable symptoms[23]. This means that with proper monitoring and prediction, sufferers should not have to live in fear of "spontaneous" panic attacks.

1.4 Significance of Project

Eighteen percent of the population suffers from an anxiety disorder, and one in three people who experience panic attacks will develop agoraphobia. Agoraphobia isolates sufferers and leads to avoidant behaviors that prevent recovery[4]. Successfully predicting panic attacks will help to alleviate the fear of a "random" episode since physiological predictors are visible before a panic attack begins. Prediction would also allow wearers to leave potentially dangerous or embarrassing situations before they panic. In addition, since panic disorders are largely invisible, it can be difficult for individuals to communicate the severity of their experiences and their level of need. This device would give them concrete metrics.

This project also helps helps those who build and use it to demystify technology and their own bodies. Since anxiety disproportionately affects women and women[4] are underrepresented in the space of open technology[18], the inspirit might introduce and acclimate people to technology they might not have otherwise encountered. Sensors like the ones we will be using are becoming cheaper and more abundant, but medical technology is still expensive, user-hostile, and inaccessible. Hopefully, this project could lower some of the barriers between consumers and the sensors that would let them understand their bodies.

Chapter 2: Literature

2.1 Literature Overview

Since this project addresses issues of mental health and has potential medical applications, we have referenced mostly medical and psychological papers and texts. These sources explore the causes of panic attacks and agoraphobia and address the physiological symptoms of these illnesses. By examining causes and somatic symptoms, we hope to learn what kinds of information will be most useful in predicting stress levels. We also hope to understand more about the conditions themselves so that we can address them and avoid causing any additional grief in testing. Since we are computer science students rather than psychologists, we have chosen texts that will offer some of the medical background information that we are lacking.

2.2 Software

There are many wearables that measure some of the same metrics we are measuring, like the fitbit, which also reads heart rate[1]. A small subset of these wearable systems focus on mood and prediction. Similar products include the previously noted Moxo, Reveal, and Embrace[7, 6, 15]. These technologies are meant to monitor symptoms and emotions for caretakers rather than for individuals. The most similar endeavor is the Snap bracelet, a wearable meant to monitor the emotional state of individuals with Asperger syndrome because of common sensory and anxiety issues[9], the designers, a group of psychologists, used their scientific expertise and focus group testing to refine their design and make sure it was desired by the target users. Their notes and preferences will likely inform some of our own design decisions. Another inspirational project is the Zephyr Biopatch used in the Cruz paper referenced above[8]. Though this project uses different sensors it also predicts panic attacks based on sensor data.

2.3 Research Articles

In their 2011 study, Walton et al. monitored the vitals of participants for 1,960 hours, examining the changes that occurred in the hour before and ten minutes following each panic attack[23]. The researchers found that skin conductance was elevated in the hour before the episode and other indicators, like respiration and heart rate, were unstable as early as forty-seven minutes before the onset of symptoms. This paper is essentially the basis of our project. If consistent changes precede panic episodes, then with constant monitoring it should be possible to predict panic attacks. This also means that we should be able to identify episodes based on stress level[23]. Unlike our project, this study used respiration. Instead, we will be using blood oxygen level, which should give similar readings considering that both measure the intake of air in the body. If we can replicate these results, then we should be able to predict panic attacks, which is a possible future application of this project.

In a paper published in Behavior Research and Therapy, Amering and Katsching examine the factors that lead to the development of agoraphobia in patients with panic disorder[3]. Accounts of first panic attacks were compared between groups with and without agoraphobia. Surprisingly, the age of the subject during, presence of others at, and even behavioral reaction to the first panic attack were not associated with the development of agoraphobia. Instead, agoraphobia is best predicted by feelings of embarrassment accompanying the first episode. This supports their assumption that agoraphobia would be predicted by first panic attacks occurring in a public setting. If embarrassment is one of the driving forces in the onset of agoraphobia, then a tool that allows a user to understand what physiological changes and stress patterns precede attacks, could possibly address the underlying causes of agoraphobia.

Story and Craske explore how subjects respond to false and accurate heart-rate feedback in a study conducted at The University of California, Los Angeles[20]. Their paper compares the responses of subjects with panic disorder to those of subjects without panic disorder. While all subjects were unsettled by false feedback, this relationship was stronger in subjects with panic disorder. Additionally, subjects were not unsettled by accurate feedback even when it indicated anxiety. This suggests that as long as the sensors read accurately, showing wearers their vitals is not likely to incite panic. If the readings are inaccurate though, we may provoke panic responses in our wearers, which is definitely not what we want to do. We should prioritize accuracy, or we could make the problem of anxiety worse for our wearers.

In a paper published in 1970, Lader and Matthews record the data from three polygraph tests during which subjects experienced spontaneous panic attacks[12]. This data is particularly useful because ambulatory monitoring does not include electromyography, but polygraphs do. This data includes the electromyograms of the three episodes, which the Walton study did not monitor because it relied on ambulatory recording[23], it is helpful to see the forearm electromyograph of a subject during a panic attack. In the first subject, the electromyograph shows increased instability in the period just before the onset of the attack. In the second, large spikes and dips dominate the initial stages of the attack. In the third patient's record, the forearm tension spiked just before the panic attack. This is reassuring because it indicates that the electromyography sensor will likely be useful in monitoring anxiety level. It is also reassuring to see that the heart rate data lines up well with the stages documented in the Walton paper, suggesting that these patterns are widely observable and repeatable.

Similar to the research of Story and Craske, Meuret, Wilhelm, and Roth address the possible results of giving people with panic disorder the ability to monitor their vitals in a paper published in Behavior Modification[16]. This experiment distributed handheld capnometry devices to patients with panic disorder. Subjects were instructed to use the device and observe its output when they were suffering from anxiety. They saw positive results in patient breathing over time. This rests on the theory that panic attacks result from misinterpretation of physical symptoms. Since hyperventilation often results from the belief that one is not getting enough oxygen when it is really over-oxygenating the blood, researchers believed that access to blood oxygen data might help compensate for the misinterpretation. Though we have been concerned that offering this kind of data could lead to obsessive behaviors and panic resulting from monitoring them, this study shows that even just reviewing their vitals may reassure subjects and lead to positive outcomes. This supports the use of biofeedback devices like the Inspirit in managing anxiety.

Taylor et al. explore heart rate during physical activity in patients with panic disorder and address the question of how panic responses differ from responses to physical activity in a 1987 study[21]. Researchers compare metabolic output with heart rate to examine how the two states differ. Panic attacks are clearly differentiable from periods of physical exertion even from heart rate alone despite the fact that heart rate is elevated in both situations. This addresses our fear that we might accidentally miscategorize periods of physical exertion, like running to class, as episodes of panic. This data is reassuring considering that this only examines heart rate and can still differentiate. We will be examining many other body metrics as well, so we should be able to differentiate between periods of physical exertion and episodes of increased anxiety.

Cruz et al. detail efforts to develop a system for predicting and preventing panic attacks consisting of a wearable device and mobile application[8]. Their mission is very similar to ours, but they are measuring different variables on different parts of the body. The products we produce would also have different applications. Their product is developed primarily for medical use and monitoring. In preliminary tests with small samples, they have seen initial success in predicting panic attacks, which bodes well for us considering that we will also have access to a very small amount of data. Their wearable device is an adhesive skin patch that measures breathing rate, body temperature, heart rate, and heart rate variability. We will be examining blood oxygen levels, muscle tension, heart rate, heart rate variability, body temperature, and skin conductivity. Their results are similar to those of the Walton study, finding symptoms that fall into distinct groups prior to each episode. We hope that we see similar success when reviewing our very limited data of different metrics.

In a journal article published by J. A. Hartigan and M. A. Wong, they describe the K-Means clustering algorithm and its use. K-Means is an algorithm dedicated grouping an arbitrary number of points. Each of those sets have the same number of dimensions, which is again arbitrary. Each of the points are put into K clusters, where K is an arbitrary number. The points are assigned into clusters based on the sum of the least squares. The goal is to minimize the value of the least squares in each cluster[11]. For our purposes, each point will be one of our users, and the dimensions will be made up of their vital signs. Each user will be placed into one of the K groups based on how similar the average of their vital signs are to the other users in the group.

Andy Liaw and Matthew Wiener describe the Random Forest algorithm in a journal article. Random Forests are a way of predicting some outcome based on multiple sets of data. They go on to describe how Random Forests are made up of Decision Trees. Decision Trees used by Random Forests are slightly different than normal. Instead of choosing the best predictor at each step of creating the tree, the algorithm picks the best predictor out of a random subset of predictors. Predictions made using Random Forests are made by making a prediction on each of the trees, and then picking the most common outcome. This randomized approach tends to perform better than a standard Decision Tree algorithm, and tends to be more accurate in the face of over-fitting[14]. We can use the Random Forest algorithm to create robust predictions on panic attacks. Random Forests tend to be more accurate than other prediction methods and offer us protection against over-fitting, a serious concern considering our potentially small dataset.

2.4 Books

The Oxford Textbook of Psychopathology is an academic resource for students of psychology[4]. It focuses specifically on emotional disorders, like panic disorder. This section proposes a theory on the source of panic disorder. Anxiety sensitivity is an unusually acute awareness of somatic symptoms of anxiety, like shortness of breath or accelerated heart rate. It is present in many people who develop panic disorder and can even be used to predict the onset of panic attack in young people. This section discusses a major difference between panic disorder and anxiety sensitivity. Anxiety sensitivity can lead to panic attacks over physical symptoms, just like panic disorder, but subjects are usually aware of the symptoms and have concrete and explicit fears about the consequences of these changes in their body. People who suffer from panic attacks are often responding to the feelings themselves, which have become associated with the pain and fear of previous panic attacks. They are often not even aware of the physical symptoms until they reach a critical point. This has implications for our project because the awareness of the symptoms before the attack would shift the trajectory of panic attacks in people with panic disorder to resemble those of people with anxiety sensitivity instead. Since these panic attacks are less frequent and extreme as well as more predictable to the patient, there could be benefits to people with panic disorder who developed greater conscious awareness of their physical symptoms.

Chapter 3: Methods

3.1 Design

3.1.1 Sensors

Before we can recognize high stress incidents, we need to record the vital signs that are valuable predictors. We acquired a series of sensors that that can aid us in this. They are:

- EMG Detector: When someone is anxious, they tend to shake or tremble. An electromyography sensor reads electrical signals from a person's muscles to determine how much they are trembling.
- GSR Sensor: People tend to sweat during stressful situations. This measures the electrical conductivity on the skin. Since sweat is salty and conducts electricity well, a very sweaty person will have high conductivity.
- Oximeter: Stress also tends to increase a persons heart-rate and cause a surge in blood oxygen levels. The Oximeter is a device that determines pulse and blood oxygen levels by measuring the frequencies of the reflections of red and infrared beams shown through the skin.
- Thermistor: A thermistor measures a person's body temperature. Anxiety has a complicated relationship with body temperature. Anxious movements can raise a person's body temperature. A higher heart-rate can also move heat from the core of a person's body to the extremities. In contrast, prolonged anxiety tends to lower a person's body temperature. Sweating, hyperventilation, and a higher pulse-rate, are all natural responses the body has to overheating. Because of this, a person's core body temperature will go down with time. Since our device will be on an extremity, we should notice a raise in temperature at the beginnings of a panic attack, and a drop after an extended period of time.

3.1.2 The Microcontroller

The Adafruit Feather MO Bluefruit LE is the microcontroller that connects all of our sensors. The microcontroller's small size is great for a wearable device, and it has built-in bluetooth capabilities. Bluetooth support is especially important for our wireless device. Since we use a phone application to show users information about their anxiety levels, we need to be able to reliably communicate with all types of phones. Bluetooth is the only protocol that can communicate with iOS devices without special certifications. Any cross platform solution will need to use a Bluetooth connection.

3.1.3 The Armband

Most wearable devices that try to predict panic attacks tend to be wristbands. Wristbands have their benefits, but we have chosen to build an armband two primary reasons. First, we use more sensors than many similar wearables. Our design will require more room to accommodate all of the sensors without increasing the profile of the device. The second reason is that wristbands can trigger and contribute to feelings of anxiety in wearers. A wristband is very similar to a bracelet, which provokes anxiety in people suffering from claustrophobia[13].

3.1.4 The Phone Application

We have created a phone application to interact with the wearable device. This program is an android application that will record a user's vital signs. The application occasionally accesses a server that runs predictions using the saved records. If the server predicts that the user is beginning to have a stressed event, the application will notify the user by updating a view on the phone. The application also allows the user to monitor their vital signs.

3.1.5 The Server

We have also created a server to go along with the phone application. The server is an Amazon EC2 micro instance. This is a type of free server that we can connect to whenever we want using a specific URL. It has an open HTTPS port that exposes a node server. The server collects JSON sent by the phone application. This JSON represents the person's vital signs for one instance in time. The server then validates it and converts it into a comma separated value format. Once the data is in a CSV format, it is compared against the saved Random Forest. The server then responds with the amount of predicted stress events, which is always zero or one, and the confidence of the forest.

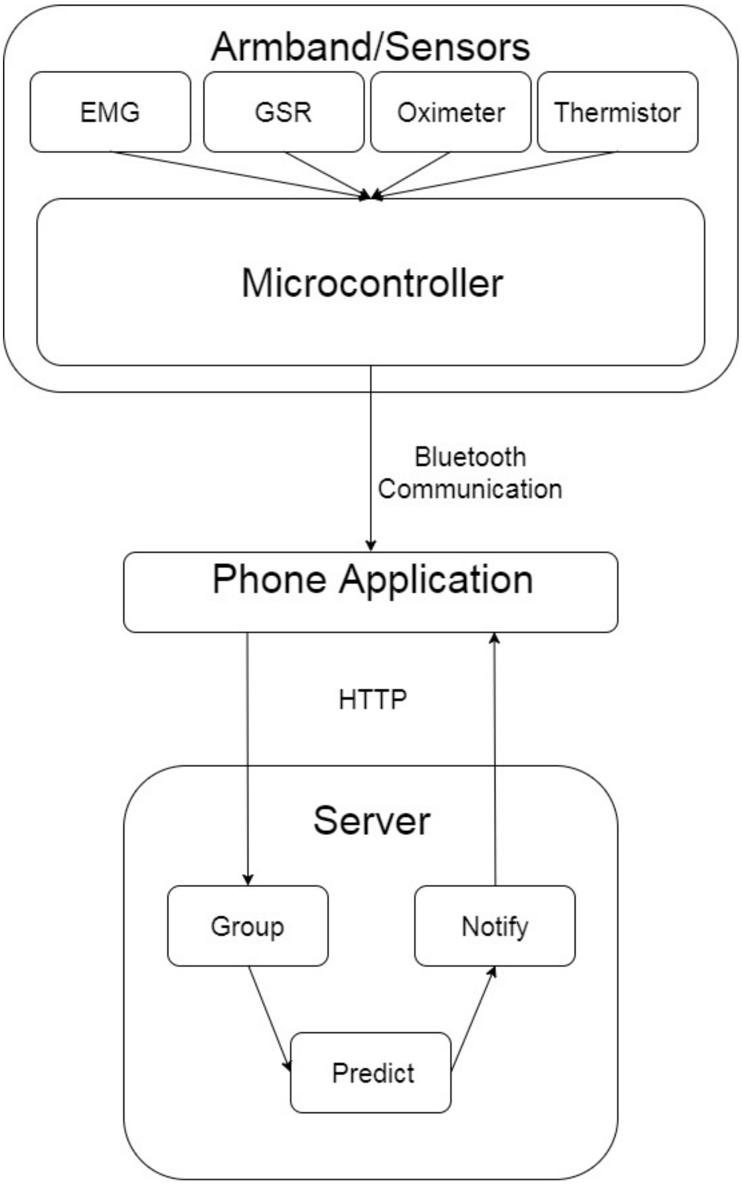
3.1.6 Process

The first step of our analytics process is collecting and modifying our data. The data will be collected as a user wears the armband, and the data will be saved onto their phone. In order to predict anxiety level, we need to know what a user's vital signs look like before and during a high stress incident. We gathered high stress samples and resting samples and associated that information with the data from that period. These samples are used to generate Random Forests that predict whether the sample belongs to a stressed or non-stressed event. Once the Random Forests have been made, predictions will start to be made for the users. While wearing the armband, the user's vital signs will be sent to a server that runs the vitals through the user's Random Forest.

3.1.7 Architecture

Data from each of the sensors will routinely be collected by the microcontroller. The data will then be transfered over Bluetooth to the wearer's phone. The application will collect and store this data. After a while, the phone will transfer the data to a server using HTTPS. Using the data collected, the server will use the stored Random Forest and make a prediction on whether the user is suffering from a high stress event. The server then sends a response back to the phone application to warn the user. This response includes a value that indicates the server's confidence in its prediction. We use this value to estimate the stress level of the user.

Figure 3.1: Basic Inspirit Architecture



3.2 Frameworks

3.2.1 Xamarin

Xamarin is a cross platform application development framework that can be used for mobile devices or desktop. Because Xamarin is not platform specific, it's great for prototyping mobile applications. We used Xamarin to make the entirety of the phone application.

3.2.2 Languages

We spent most of our time programming in two different languages. Xamarin is a C# framework for making cross platform applications. It has the added benefit of being able to use platform specific binaries in cases where the application needs to be platform specific. In addition, we used Python2 to run the analytics on the data collected by the microcontroller and application. Python2 is a solid choice because of our previous experience with the language and the availability of multiple data processing libraries. We also spent a small amount of our time writing a Node application for our server.

3.2.3 Development Environment

Development in Xamarin doesn't need to be done inside of Visual Studio, but the multitude of tools their IDE gives us made it an obvious choice. Our Python2 code doesn't have any UI requirements, so there is no 'best' development environment. The Python2 code was written in a variety of editors based on what was the most convenient at the time. We used Jupyter notebooks for some of the early testing of data analytics because of how easy it is to rerun one section of our code with minor tweaks. We used Sublime Text 3 to write a majority of the server code, since it has access to useful extensions like code highlighting and linting. And lastly we used lightweight editors like Vim to edit code whenever we needed a quick change, or to fix something on our EC2 instance. The project was saved to a private repository on Github.

3.2.4 Libraries

Most of the libraries we used are Python2 libraries. A few can be seen in basically every Python based data analytics project. Matplotlib is a library that mimics much of what Matlab does so well. We will use Matplotlib to graph our data and create visual representations of what we know. NumPy will be used to help create efficient lists and matrices. NumPy is also the basis of another library we will be using, Pandas. Pandas uses NumPy matrices to help create and modify small databases. The last Python2 library we used be using is Scikit-Learn. Scikit-Learn lets us run all sorts of data analytics algorithms on our dataset. We are the most interested in using random decision forests. These algorithms are useful to predict future outcomes based on some training dataset.

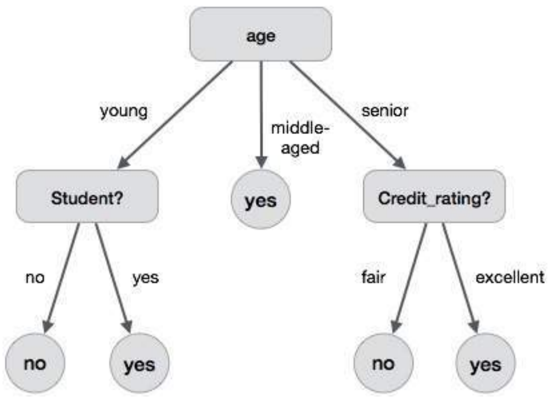
We also used two non-Python libraries. In order to utilize the bluetooth capabilities of the Adafruit Feather, we needed to install their bluetooth library, Adafruit Bluefruit LE nRF51. The library is pretty comprehensive and should work out of the box. While we intend to use the library, we do not expect to make changes to it. The second library we used was for the UI elements for our phone application. The Syncfusion libraries gave us a good looking and responsive UI without writing too much code.

3.3 Algorithms

3.3.1 Decision Trees

Decision Trees are the basis of the tool we plan to use for our predictions. Decision Trees ask a series of yes or no questions based on some target variable. Depending on the answer to each question, it either asks another question or it comes to some conclusion. In this case, the yes or no questions will be questions about the user's vital signs. For example, if the skin conductivity of the user is higher than a certain value, the tree may predict that the user might be suffering from a high stress event[17].

Figure 3.2: Example of a basic Decision Tree



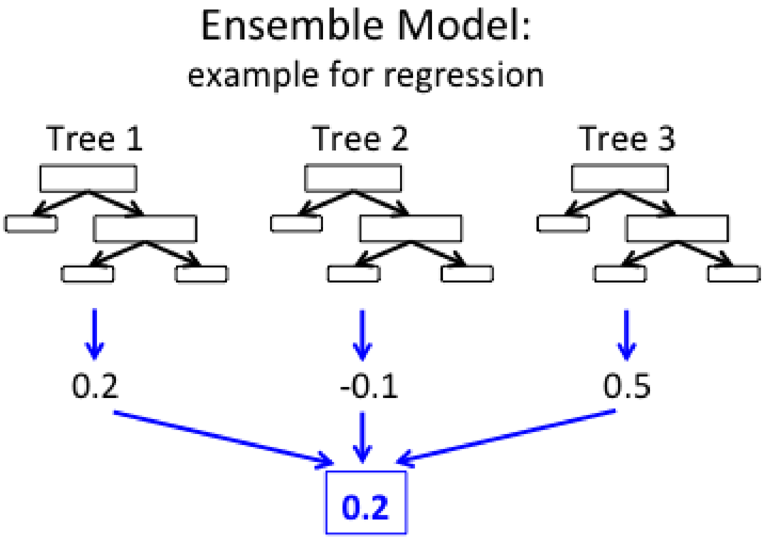
[22]

3.3.2 Random Forests

Decision Trees are useful, but they come with a major drawback. Finding out what questions to ask and what their target values should be at each step of the prediction is difficult. Random Forests solve this problem by creating a large number of Decision Trees with pseudo-random questions.

A subset of the data is used to create multiple Decision Trees. Each of these trees are slightly different, as each one randomly ignores some aspect of the data. After the trees are built, another subset is used to test the data. The output of the Random Forest is some average of each of its trees[14].

Figure 3.3: Example of a Random Forest



[5]

3.4 Analytical Methods

The quality of our project will be measured by the success of our predictions.

Before we created the random forests, we separated the data into two sections, a training set and a testing set. The training and testing set is created using a random sample of the whole dataset. The testing set is one fifth of the training set. The testing set and the training set do not overlap in any way. Since we are recording whether or not the user felt panicked in our data, that aspect is then removed from the testing set. The random forest is then created using the training set and predictions will be made on the testing set.

Success is be measured in two different ratios, true positives to false positives and true negatives to false negatives. A true positive or negative occurs when the forest correctly makes a prediction. A successful forest will minimize the number of false positives and negatives.

3.5 Features

The main feature we have implemented is the prediction of high stress events. If the application comes to the conclusion that a high stress event is occurring, the phone application will update its UI to match. The UI will give them the ability to communicate or realize their stress if they normally could not.

We also implemented a secondary feature for testing purposes. Users are able to monitor their vital signs through the phone application. This feature has the added benefit of allowing a user to ensure that all of the sensors are connected correctly. Vital sign monitoring would not be implemented outside of the capstone project. This is because we fear some users may compulsively check their application to see how they are feeling.

3.6 Test Plan

Testing this project required sensor data from both stressed and non-stressed events. To trigger stressed events, we collected data while playing Dark Souls 3, a notoriously stressful video game with a steep learning curve. Our trials consisted of one individual alternately completing the initial boss fight and resting. Data was stamped based on which group it belonged to.

After the data was collected and marked as stressed or relaxed, we randomly extracted twenty percent of the data into a testing set. We used the remaining eighty percent as training set to train the random forest and then ran our testing data through that model. We then compared the forest's predictions with the actual stamp of each segment in our testing data. We generated an ROC curve based on the results of that comparison to illustrate the accuracy of our model.

Once we had tested the accuracy of our predictions on our testing data, we uploaded the Random Forest up to the server and moved on to live testing. We ran an additional trial, consisting of the initial boss fight and a resting period, while monitoring the predictions from the server to verify the accuracy of our predictions.

3.7 Criteria and Constraints

3.7.1 Ethical

Our project originally had the intention of predicting panic attacks. One of the major concerns while collecting training data for this, is actually recording people in the middle of a panic attack. Since panic disorder is a serious medical diagnosis and people who suffer from it are a vulnerable population, we could not get approval to test on subjects with panic disorder since we could not provide resources to help address panic attacks or account for their mental health consequences.

While collecting data and testing, we also needed to make sure the events were stressful enough to be different from resting data, but not so stressful that it caused harm or embarrassment to whoever was wearing the armband. We settled on using video games as our stressful events because they're easy to back out of if the user is too uncomfortable.

3.7.2 Structural

In order to have the entire device fit onto an armband, the sensors and microcontroller have to be very small and flat. All wiring had to be flush and all pins had to be desoldered so that wires could be attached to the boards and sensors at a flat angle. Wherever possible, conductive thread was used preferentially over wire because of its flexibility and thinner profile.

The outside of the armband needed to be smooth so that a sleeve could lie flat over it. The wiring needed to be able to stretch with the fabric and the components needed to be mounted so that they also could move as the fabric stretched. Some sensors, like the thermistor and the oximeter needed to be against the skin, which meant that they needed to be on the inside of the band, so the wires would need to go through the material of the band.

Since it would be unrealistic to replace electrodes on a wearable device before every use, we used conductive fabric patches inside the band in place of electrodes, which required a small sacrifice in precision.

Figure 3.4: Armband With Sensors Exposed

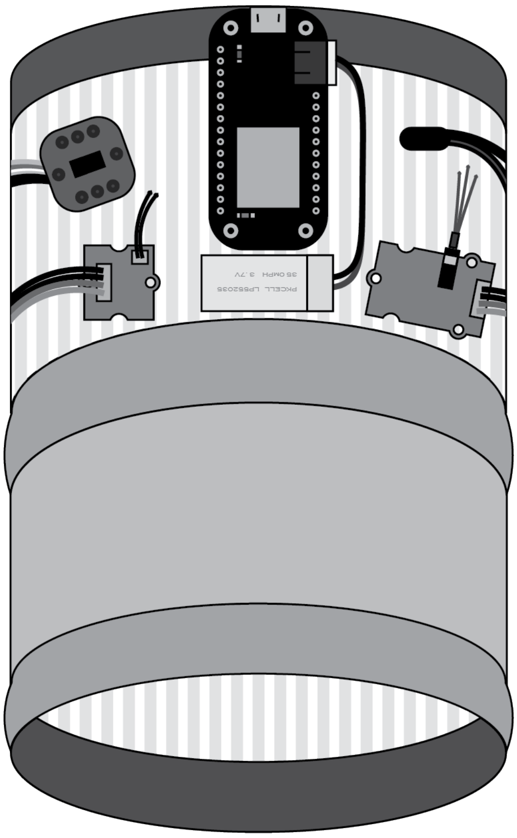
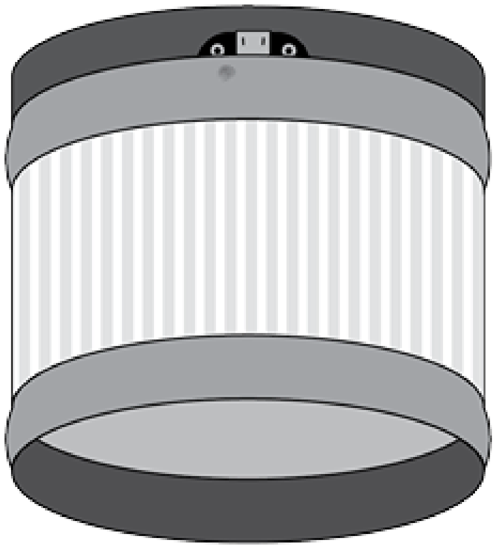


Figure 3.5: Armband With Sensors Hidden



3.7.3 Time and Budget Constraints

We could only afford parts to build one device, so we were limited in how much testing we could perform. We could only perform testing on one person at a time and had to be very careful with the device because we had no spare components. Instead of giving it to different subjects, it was safer to test it only when one of us would be supervising.

Additionally, it became unrealistic to wait for panic attacks to occur even if we had not faced the ethical constraints we did. Even in severe cases, panic attacks are relatively infrequent and there was a possibility that no testers would experience any during the testing period. This made it more practical to test high stress incidents which, unlike panic attacks, could be induced quickly and ethically by playing stressful video games.

Chapter 4: Results

4.1 Final User Interface

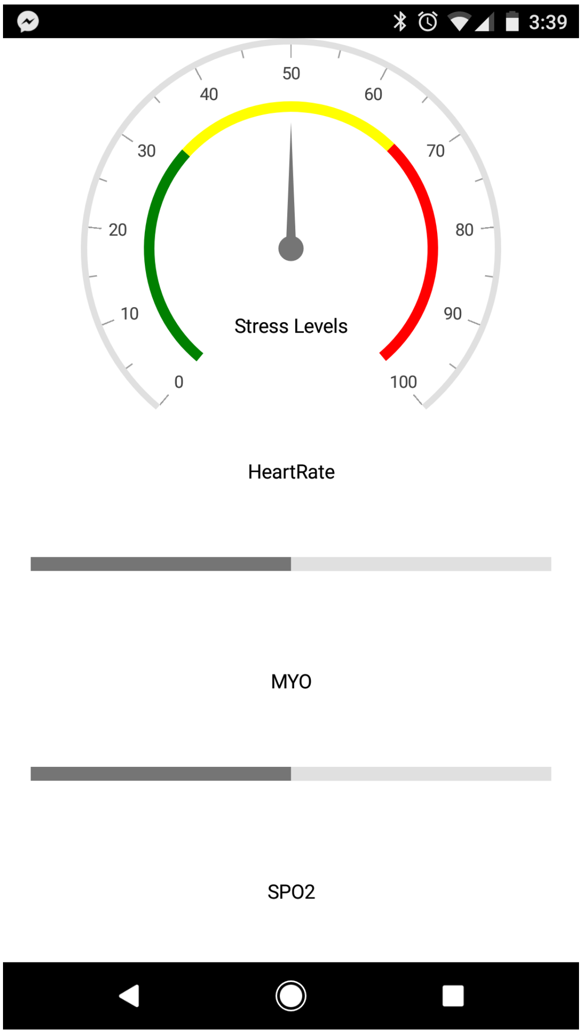
We had a few different qualities in mind while designing the user interface.

The first was that the user interface should be simple and easy to navigate. Since a person's stress level can change very quickly, information on the wearer's stress levels should be available as soon as the application is opened. This kept us from creating any sort of menu options for the user to fiddle with or an account for them to sign into.

We also wanted to avoid displaying actual numbers to the user. Displaying the values that each of the sensors read was concerning to many people who viewed the early stages of the application. This is because the data returned from our sensors isn't scaled in a standard format. For example, the application used to display a value for heart rate taken from our Oximeter. Some people would see the heart rate value, usually somewhere in the low twenties, and be concerned that the sensor was broken or the wearer was close to death. We solved this by replacing each of the individual numbers with valueless bars that were filled based on what the sensor returned.

The last thing we had in mind was displaying the predictions in a way that wouldn't be stressful to the users. We originally planned on displaying a boolean value for the user based on our predictions; the UI would display that the user was either stressed or relaxed with no in-between. Because we were concerned that inaccurate readings could be more stressful, we opted for a portion of the UI to be dedicated to our confidence in the user's stress level. We believe that allowing users to see that they're close to a stressed position will be more comfortable than being told that they aren't stressed.

Figure 4.1: User Interface Example



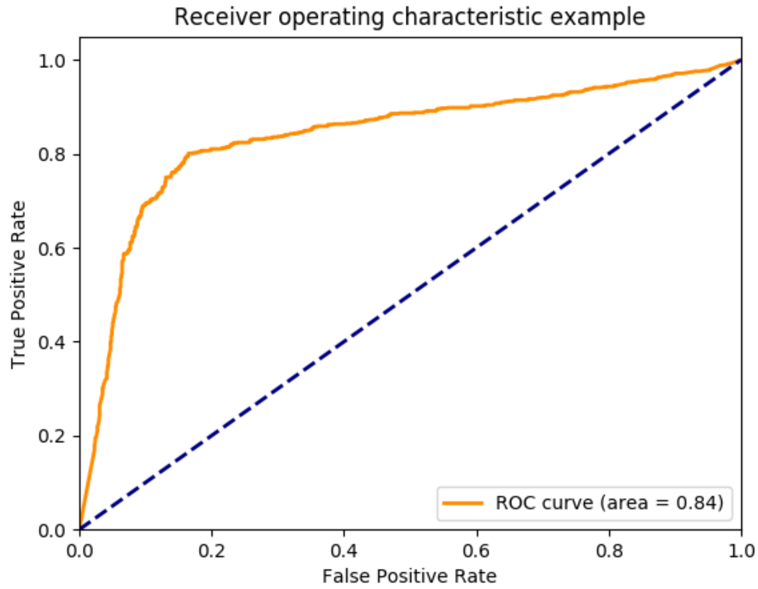
4.2 Analytical Results

We measured our analytical results by comparing our true positives to false positives and our true negatives to false negatives. A true positive is defined as a moment that we made a correct prediction. Our definition of a correct prediction was a moment where Robin was fighting a boss from Dark Souls 3. A false positive was an incorrect prediction made while she was relaxing. Negatives were defined in a similar way. A true negative is a correct prediction made while she was relaxing, and a false negative is an incorrect prediction made during a fight.

We found that 80.28% of our positive predictions were correct. In addition, 86.05% of our negative predictions were correct. Our total accuracy was close to 84%, shown by our ROC curve.

The ROC curve is a measure of the accuracy of our Random Forest at different thresholds. The yellow line on the graph follows our true positive rates verses our false positive rates.

Figure 4.2: ROC Curve for Predictions of Stress



4.3 Testing Results

We did three rounds of live testing throughout the life of our project.

The first round when extremely well. Robin wore the armband while fighting the first boss of Dark Souls 3, the same boss we used to train our model. The application returned what we believed to be very accurate predictions. When she wasn't playing the game, our application would almost always display that she was not stressed. While in the middle of fighting the boss, it almost always displayed that she was stressed. It is important to note that the data collection for this test and the test itself were all done in one sitting.

We did not have the same results for our second round of live testing. The application would always return that she was not stressed, even if she fought against Dark Souls bosses she had never seen before while being visibly stressed. At the time, we believed that this failed test was due to the accuracy of the readings from the armband. We were afraid that the connections made between the sensors and the wearer would be different every time the wearer put the armband on. We believed that this caused the readings to be much higher or lower than we prepared for. If this was true, the armband would need to be retrained every time it was put on.

Before our final trial, we made slight changes to the connections for our sensors. Afterwards, we noticed much better predictions. The application would rarely predict a stressed event, but it would often reach thirty to forty percent confidence that a stressed event was occurring. The application would also return much higher readings at the points where Robin reported she was most stressed. We were very surprised about how much better the predictions were at this point.

Our conclusion was that the sensors were working fine the whole time. The data between each training session was drastically different, which we would expect from a poor connection between our sensors and the wearer. What we didn't expect, was that the data collected between the beginning and end of our training sessions was also drastically different. We believe that is because we started training and testing too soon after putting the armband on. Before we can get accurate readings, we need to wait for the skin to become warm and sweat under the armband to help create a better connection between their skin and the electrodes.

There are also a lot factors that affect a person's vital signs. For example, drugs such as caffeine can make a person appear more stressed, being tired can make them appear less stressed, and going through a stressful event can make it less stressful in the future. Even though Robin reported that each of the boss fights were stressful experiences for her, how her body reacted to the stress was different each time. We believe that this vast combination of factors was keeping us from having consistent testing trials.

Chapter 5: Conclusion

5.1 Challenges and Solutions

We had initially planned to run trials on individuals with panic disorder and implement predictions about upcoming panic attacks. We pivoted for two reasons. First, we could not obtain permission to test our project on subjects who experienced panic attacks because they constitute a vulnerable population.

The second reason is the tremendous time necessary to collect that volume of data. This is, first and foremost, a computer science project. If we invested the time to recruit subjects and gather data on infrequent panic attacks from all of them, we would be spending more time running psychological experiments than developing a mobile application, developing a prediction model, and building a physical device. We would also be risking more damage to our device by passing it out to more wearers.

We only had one of each component necessary to build our project, and some of the parts had taken months to ship, so we were conscious throughout the testing process of the consequences of any damage to our components. Even if replacements arrived before the final presentation, we would lose precious weeks of testing.

In response to the time and ethical constraints, as well as the fragility of our device and our desire to focus primarily on the aspects of our capstone that demonstrated our competence in disciplines relevant to our major, we decided to focus on predicting current panic levels instead of approaching panic attacks.

Some of our research had already focused on the efficacy of biofeedback devices in treating the feedback loops responsible for panic attacks and we realized that a device that tracked anxiety level could have utility for many of the same users. Detecting high stress events is also a first step toward predicting them.

5.2 Future Work

While there are many applications for a biofeedback device that estimates the anxiety of its wearers, this project is both a proof of concept and jumping off point for our initial goal. If this device were worn by subjects suffering from panic disorder, and the server were set to record the times of any high stress events lasting longer than a set threshold, then that would become the new dataset.

Periods within an hour before sufficiently long high stress incidents would be stamped. Then one would only need to create a new random forest and train it to recognize those periods. This is, theoretically all that would be necessary to adapt our project to predict panic attacks.

There are other applications for this technology, though. With further testing, it could be used by educators and caretakers of young children or severely disabled people. If this product were rigorously tested for safety and durability, it could assist caretakers in interpreting the actions of those in their care. It could also help them recognize anxiety and work to soothe before it reached a critical point and caused an outburst.

Originally we had intended to make our parts list, process, and code available so that others could build their own armband and conduct their own testing. Unfortunately, fitting the parts in the band requires a lot of desoldering and very precise work that is not really approachable for beginners.

Many people could build the band based on our instructions, but it would probably not be a good introduction until we develop a more beginner-friendly instruction set. This would mean continuing to look online for more approachable sensors that could replace our current parts.

5.3 Project Importance

This project was a fascinating introduction for both of us to the process of conducting an experiment with human subjects. Even though we did not end up pursuing IRB approval, we filled out the majority of the forms and met with Barbara Colombo, who is chair of the school's IRB chapter. It was enlightening to learn how much effort goes in to ensuring the ethical integrity of experiments, and if either of us ever needs to go through this process in the future, we will be far better prepared.

We also learned a great deal about product design. There is an enormous gulf between knowing how to build a circuit and knowing how to build a device. This band required careful planning to make sure that everything was flexible and well-placed. Electrodes needed to be far from each other, but not too far from their parent sensors. The band had to be essentially flat against the arm. All of these structural and aesthetic constraints multiplied the difficulty of circuit design.

Similarly, making an attractive and easily readable interface was much harder than simply making an interface. We learned how much harder a project can be than the sum of its parts. Getting the phone, device, and server to communicate in real time was one of the biggest challenges we faced. Crucially, it was the challenge we most severely underestimated.

This project is also proof that medical sensors, despite being notoriously unfriendly and undocumented, can be used in the same types of projects as more traditional hobbyist sensors. The applications of these sensors in DIY projects are endless, and projects like this one will help to erode the barrier that keeps consumers from buying health sensors at the same rates as other sensors. This projects also provides cursory documentation on how to use all of the sensors inside of it. Some of these sensors had no schematics or pin information available online, so this is a solid improvement.

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