Alleviating Stress through Sensors

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Date of Talk: 5 Dec 2018

Abstract

Stress is very prevalent in today's society and is one of the leading causes of a multitude of health problems. The goal of this project is to be able to relieve stress in an autonomous way without the person having to be conscious of choosing specific methods to alleviate stress such as breathing techniques.

Some vital and easily obtainable parameters, such as heart rate and galvanic skin response, can be used to detect someone's stress level. We have proposed to create a system that not only accurately detects stress using the parameters mentioned above but is also capable of managing a user's stress such that the device relieves stress autonomously without the user having to make a conscious effort to take steps to calm down. Our proposed system aims to detect stress using a machine learning algorithm that uses Heart Rate, Heart Variability Analysis, and Galvanic Skin Response to learn what signals or combinations thereof can be used to detect stress in an individual. Once stress is detected, the system will attempt to alleviate a user's stress through a technique that mimics acupressure on the user's wrist and thus relieves the user of stress. The main goal of this paper is to create multiple stress-detecting algorithms and determine which might be the most effective in determining when a user is stressed. We have found that a machine learning stress detection algorithm that uses multiple different combinations of physiological signals to determine stress is relatively accurate in terms of the data sets that it has been tested against.

1. Introduction

1.1 Problem Statement

When a person enters a stressful situation, a number of chemicals and hormones are released in the body that are meant to prepare the person for survival [1]. This response is commonly termed as a "fight or flight" response. These survival responses are triggered each time a person may enter a stressful situation in his or her daily life [1]. This response can be considered a highly useful innate survival strategy, but oftentimes a human body will not receive the needed ample amount of recovery time necessary after an episode of stress responses in order for the body to return to its normal state [1]. Every day can become tainted with constant, stress-invoking events that keeps the body continually responding in a "fight or flight" manner and, in the long run, this can take a toll on the health of an individual and potentially shorten their lifespan [1].

1.2 Previous Work (Literature Search)

1.2.1 Devices for Stress Detection or Alleviation

Throughout our research, we have found devices currently available to the public at a relatively affordable price that can either detect stress or alleviate stress. We have not found any devices at this time that can do both.

***Device Type A**: Detects Stress*

There are currently devices available on the market that are capable of measuring an individual's stress levels and provide proper feedback to the user. The device typically will provide the user with some suggested form of relief. However, these devices do not alert the user at the precise moment they may be stressed; a user must look at a chart of their signals throughout the day and decide for themselves when it was they felt stressed. This makes it particularly difficult for a user to alleviate their stress as they cannot relieve stress at the very moment they are experiencing it. If the user chooses to partake in the stress relief later on after the stress event has passed, the activity and effort may not be as effective. There is also the possibility that a user may choose not to partake in the "stress-relieving" activity as it may seem to require too much effort. These devices are as follows:

a. *Garmin Vivosmart 3, Fitbit, Apple Watch, Feel Wristband:* These are overall fitness tracker that maintain data about a user's health and presents it in an organized manner [2]. If any of these devices detect stress levels, a user can choose to participate in a stress-reducing activity provided by the device.
b. *Muse*: This is a headband-like device worn by a user to monitor stress levels [20]. A user typically would choose to wear the device if they feel stressed. The device leads them through a series of exercises or activities designed to lower stress and normalize vital signs.

Device Type B*: Alleviates Stress*

There are a number of devices currently available for purchase that work by sending signals to the brain during a stress event. A user must indicate to the device when they feel stressed whether that be by turning on the device or clicking a button. These devices reportedly work well; however, since the stress alleviation involves the direct sensory stimulation of the nervous system, it can trigger unwanted responses in individuals, especially those with any form of brain disorder [7]. These devices are also not capable of monitoring stress levels. Thus, a user must be consciously aware of the current stress they may be under, and the user must consciously choose to receive stress relief. These devices are as follows:

a. *Thynks Vibe:* This device sits on the back of a user's neck and sends signals to the brain to reduce stress. It is typically worn when a user feels stressed.
b. *The Touch Point Solution:* This device is worn on both wrists. It sends signals to the brain to reduce stress. When the user feels stressed, he or she must turn on the device to receive the treatment they desire. Users typically are drawn away from the device due to it being worn on both wrists, as well as its manual alleviating feature.

Both classes of the devices do one functionality implemented very well; the device can either detect stress but not alleviate it, or the device can alleviate stress but not detect it.

1.2.2 Signals that Indicate Stress

The Autonomic Nervous System is responsible for the bodily responses to a stress event [24]. The responses given can be utilized and measured quantitatively through sensors to detect when a user is stressed. As can be seen in Figure 1, the sympathetic nervous system facilitates immediate action in response to a stress event. Increased sympathetic activity is associated with bodily indicators such as increased heart rate, increased blood pressure, and sweating [24].

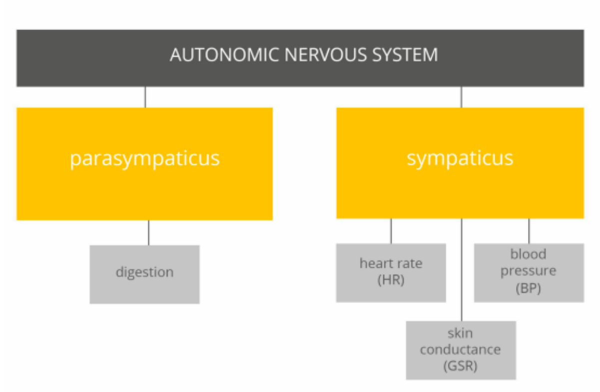

Fig.1 Autonomic Nervous System[24]

Skin conductance has been found to increase as stress increases [14]. A study measuring stress was conducted on soldiers in the military using GSR (Galvanic Skin Response) with the intention to discover if GSR by itself was an accurate indicator of stress [11]. The study reported results with 78.03% accuracy in detecting stressful moments when the soldiers utilized a wristband with two electrodes that monitored GSR.

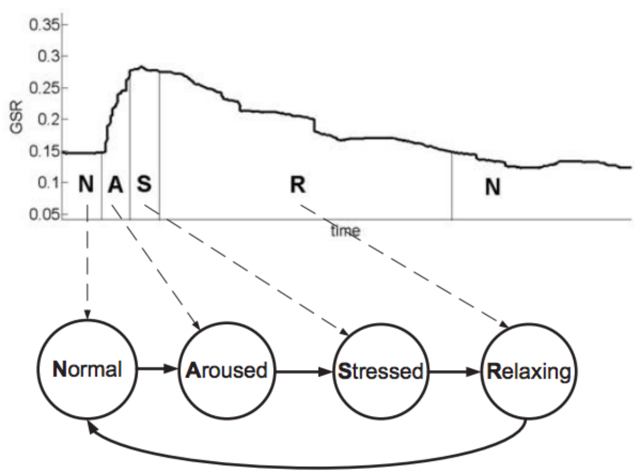

Fig. 2 Relationship between GSR and mental state[11]

More recently, Heart Rate Variability (HRV) has been found to determine the stress level of a user with great accuracy. HRV measures the variation in the beat-to-beat interval of the heart rate. The frequency bands associated with the HRV are analyzed by measuring the ratio of low frequencies (LF) that span from 0.04 Hz- 0.15 Hz and high frequencies (HF) that span from 0.15 Hz - 0.4 Hz [21]. The user is considered stressed if the frequencies are predominantly LF or if the LF/HF ratio is above 1.06. The level of stress the user may be experiencing is determined by how far his or her specific LF/HF ratio deviates from 1.06 [21].

An experiment using an algorithm that includes analysis of the rMSSD, pNN50, and mean HR values extracted from HRV calculation proved to be efficient in finding stress in individuals [21]. If a sudden increase is seen with all of the values associated with these components, an individual would be considered stressed in that moment even if his/her vitals would display otherwise.

1.2.3 Stress Detection Algorithms

In "Design and Implementation of a Real Time Stress Monitoring System with the Help of ECG Using Matlab Tool", a stress detection algorithm was created by measuring Heart Rate (HR), Respiration Rate (RR), and Galvanic Skin Response (GSR), and determining if each of the signals measured at a particular point in time had values that resided above a certain threshold pertaining to each measurement respectively [11]. A stress event would be determined to exist if all the signals measured had values above their respective thresholds. At this point, the system implemented would send an SMS message to the user's cell phone indicating that they were experiencing stress, thus allowing a user to decide if he or she would want to partake in some form of activity that would relieve his or her stress [11]. The algorithm would then return to monitoring signals until all three signals would cross their respective thresholds and once again signal that the user is stressed. In the case where stress is not detected, the system will repeat this this process until stress is detected.

The algorithm may work for some users, but it is highly unlikely that it would function correctly for every user possible as each individual has a unique body and thus has unique stress signals associated with it; not everyone's vital signals will pass a given threshold when someone is stressed.

In [12], an algorithm is proposed that uses physiological parameters of HR and Blood Pressure (BP) and machine learning to detect stress. The algorithm takes in HR and BP signals and filters them to remove noise. It then extracts the features of the signals and determines if the associated values indicate stress through a classification system such as Support Vector Machines. This method works fairly well in detecting stress as the algorithm can "learn" what values of each physiological signal used can indicate stress for each unique user. However, in the particular algorithm presented in [12], BP is used; this can be a relatively difficult signal to acquiesce accurately using rather simple sensors. We thus use other physiological signals, such as GSR, in place of BP.

1.2.4 Stress Alleviation

Acupressure is a Chinese medical technique; one receives an acupressure treatment when pressure is applied to acupuncture points on the body [27]. In "Four-Week Self-Administered Acupressure Improves Depressive Mood", twenty-five college students conducted acupressure sessions three times a day where pressure was applied to acupuncture points in the neck [27].

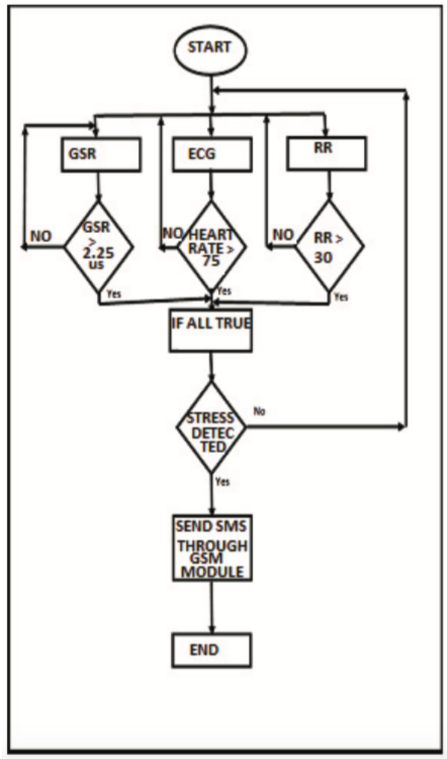

Fig. 3 Flowchart for system implemented in "Design and Implementation of a Real Time Stress Monitoring System with the Help of ECG Using Matlab Tool"[11].

Within two weeks, the level of depression held by the group conducting acupressure sessions had overall decreased; the control group's depression levels had increased in the same time period. It was thus concluded that acupressure can be effective in terms of lowering stress.

The previous study discusses a rather long-term impact of acupressure; one might then wonder how efficient and/or effective acupressure might be in the instant it is applied. In "Acupressure for prevention of pre-operative anxiety: a promised, randomised, placebo controlled study", acupressure

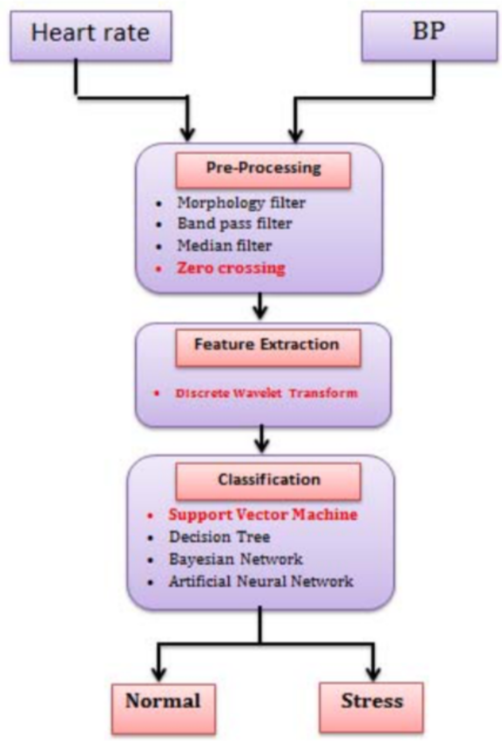

Fig. 4 Flowchart for system implemented in "Effective Stress Detection Using Physiological Parameters"[12].

was used to alleviate symptoms of anxiety. Results were measured by use of a visual stress scale (VSS) and concluded that acupressure was effective in lowering anxiety while it was being administered [17]. We thus can conclude that acupressure is effective as it is being applied; however, it is important to note that anxiety rose again in the patients in the study within thirty minutes after the acupressure treatment finished.

2. The Technical Approach of Adopted Solution

The goal of this project is to create a wearable device that will rest on the acupressure point in the wrist that is triggered by stress. Our stress detection and alleviation system design is now described. We devised two separate stress detection algorithms to determine when a user is indeed stressed.

Algorithm 1: *Threshold-Based Detection*

The first algorithm is based on each measured signal at a given moment in time surpassing its respective threshold. The HR, RR, and GSR signals are used and would be monitored constantly against our thresholds (75 bpm for HR, 30 bpm for RR, and 2.25 us for GSR). If all of these thresholds are passed, the device would immediately enter the Stress Detection phase where it would analyze the rates of rMSSD, pNN50, and mean HR values. If the rates are increasing, the individual would be considered stressed and the device will begin using the alleviation technique described in 3.

Algorithm 2: *Using Machine Learning*

The second algorithm uses the machine learning algorithm "K Nearest Neighbors" and learns the physiological signals that indicate stress through a number of training sets compiled from data sets found in [J]. The algorithm is trained to identify stress with different feature combinations and extracts each feature combination from live physiological signals to determine if the user is stressed. Different combinations may be used, although each combination will have varying accuracies when predicting stress.

The current version of the algorithm uses two combinations: The first combination uses GSR, pNN50, and rMSSD (pNN50 and rMMSD are both HRV measures), and the second combination uses GSR and LF/HF ratio (also an HRV measure).

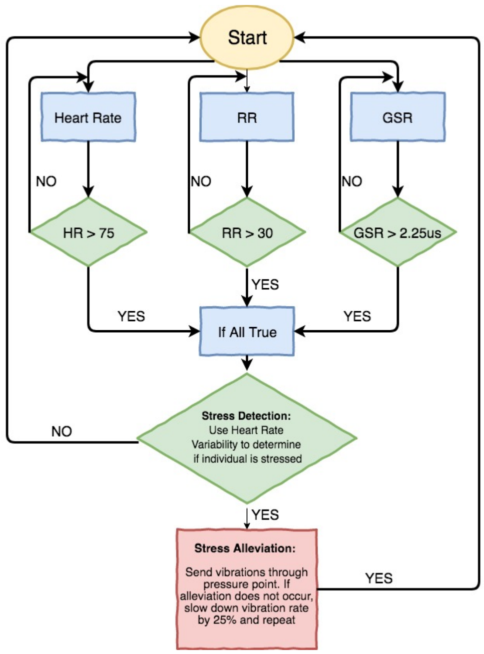

Fig. 5. Proposed Algorithm 1 for threshold-based stress detection

Each time the device predicts if the user is stressed using current physiological signals, it returns a "confidence" level that indicates how confident the algorithm is that the prediction is true. The prediction with the highest confidence level is used when determining if the user is stressed. If the algorithm detects stress, the device will begin the alleviation pattern mentioned in 3.

Stress Alleviation

When the device senses that the user is stressed, it will begin sending vibrations in order to mimic pressure at an interval on the acupressure point. This should continue until the device receives readings from the user that no longer show signs of stress. The device will determine the vibration speed to use when alleviating a user based on his/her calculated stress level. If he/she has a high stress level, the device will use a fast vibration pattern.

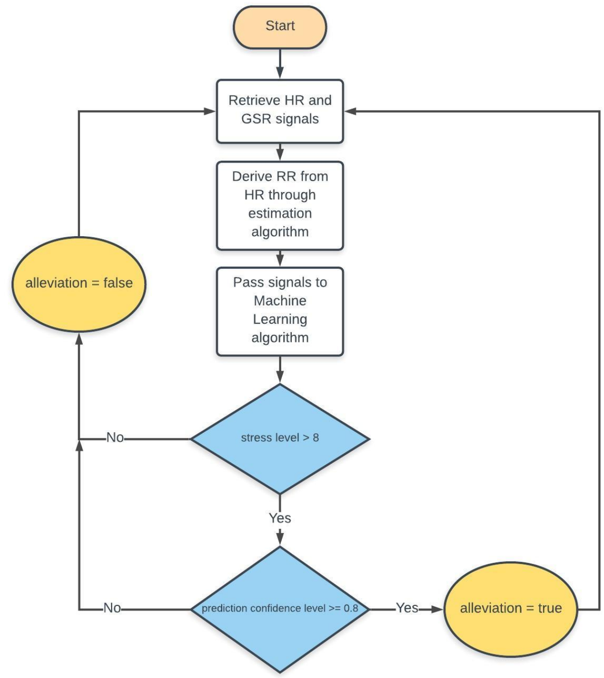

Fig. 6. Proposed Algorithm 2 for stress detection through machine learning.

If the level of stress of the user is relatively low, the vibration speed will be slower. The user will also have a companion app that will allow the user to manually set vibration speed and intensity. The device will repeat the alleviation each time it senses the user is stressed.

The **current focus** of the project is to determine which stress detection algorithm is the most accurate when it is given a set if input of signals, whether it be pre-recorded signals from a data set or live signals from a participant.

3 Results

Both algorithms described in the previous section were tested using data sets from "Stress Recognition in Automobile Drivers" [29]. These data sets were crucial in testing the algorithm itself as (i) the data sets measured and used the same physiological signals that we used in programming the device, being HR, GSR, and an optional Respiration Rate (RR), (ii) the data sets included a literary stress level that was deduced by the author of "Stress Recognition in Automobile Drivers" when measuring stress levels of participants that were driving through traffic-congested areas through the use of MATLAB algorithms, video monitoring of facial expressions, and questionnaires, and (iii) the accuracy of the algorithms themselves would be able to be isolated and tested specifically as the signals provided in the data sets had already been filtered.

As previously mentioned, the data sets used to test our algorithms contain a literary stress measure for each data point in the set [29]. The accuracy of this literary stress level was reported to be 96% [29]. We thus assume this to be our standard of truth in regards to whether the user is stressed or not when testing our algorithms.

Algorithm 1: Threshold-based Detection

The algorithm that uses thresholds to detect stress was found to be highly inaccurate. While the algorithm was capable of detecting seven of the eight moments in time where a user was stressed, it would also detect multiple false positives throughout a test run. The results can be seen in Figure 7.

Algorithm 2: Machine Learning

The machine learning algorithm has gone through multiple changes as it has been tested against data sets. The first iteration of the algorithm would use one combination of signals including HR, GSR, and RR derived from HR.

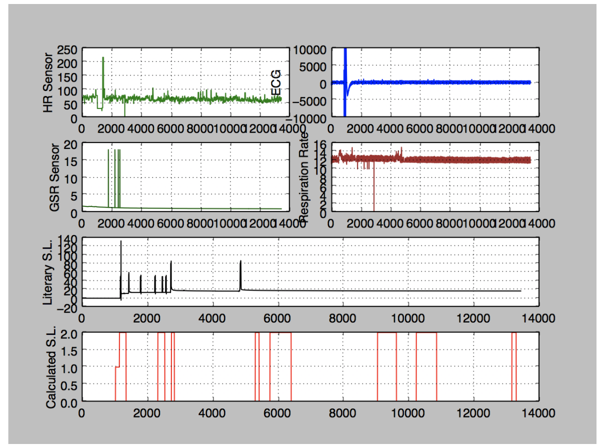

Fig. 7.Results from example test run of threshold-based stress detection algorithm against data set from [29]

When this iteration was run against an example test set, it would catch only three of eight moments of stress and return a false positive. These results can be seen in Figure 8.

The next iteration of the machine learning algorithm included Heart Rate Variability within its training sets and thus would use Heart Rate Variability Analysis when predicting if a user was stressed. This resulted in the algorithm catching four of the eight moments of stress in the example run as can be seen in Figure 9.

As can also be seen in Figure 9, the predicted stress moments from the machine learning algorithm aligned at the same moments in time that the GSR would increase dramatically; thus, it can be concluded that the algorithm was relying on GSR to predict stress with a high confidence level. We then decided to create another iteration of the algorithm that uses multiple combinations of different signals to determine if any of the other combinations would be capable of picking up moments of stress.

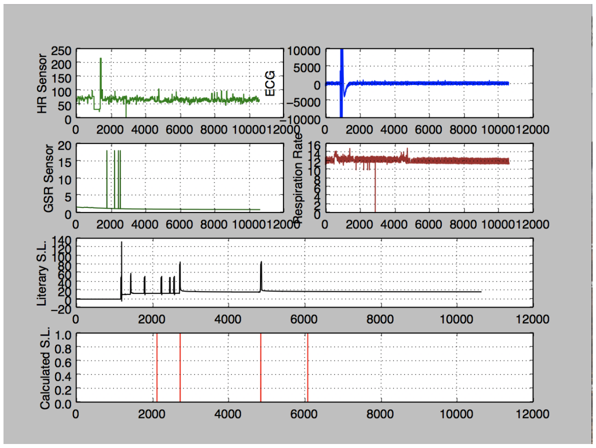

Fig. 8 Results from example test run of first iteration of machine learning stress detection algorithm against data sets from [29].

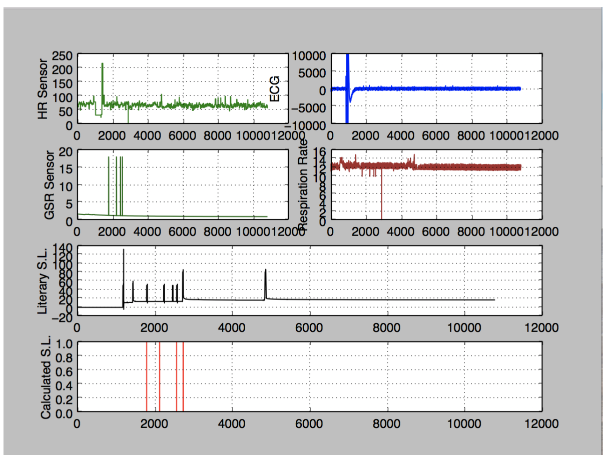

Fig. 9 Results from example test run of second iteration of machine learning stress detection algorithm against data sets from [29].

This iteration of the algorithm, using the combinations described in section 2, was found to be the most accurate of all iterations of the machine learning algorithm, and was found to be more accurate than the algorithm that uses thresholds. From an example of eight stress moments within a data set, the machine learning algorithm would detect six of the eight moments within a test run and would not return any false positives. The associated results can be seen in Figure 10.

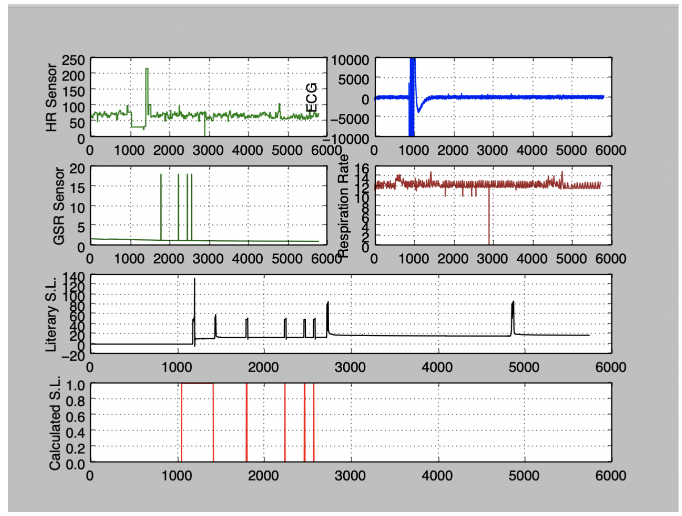

Fig. 10 Results from example test run of last iteration of machine learning stress detection algorithm against data sets from [29].

4 Concluding Remarks

The scope of this project was to create a device that would be capable of detecting stress and alleviating it through the use of acupressure. Our emphasis at this time is to create, compare, and determine the most accurate algorithm that will detect stress through the use of HR, Heart Rate Variability Analysis, and GSR. We focused on two types of algorithms: one determined stress through checking if the signals received passed specific thresholds, and the other determined stress through the use of the machine learning algorithm K Nearest Neighbors. These algorithms were tested against data sets that contained a literary stress level determined to be 96% accurate; we used this as our standard of truth and compared the algorithms to this value [29]. We found that the machine learning algorithm that used multiple combinations of different signals to determine stress was the most accurate. This solution is particularly advantageous as it should be able to learn an individual's unique stress signal combinations and detect stress relatively accurately based off of this. Our algorithms do indeed need more testing both with more data sets and with live participants; we intend to continue testing in this manner in the future. We also intend to connect the stress detection algorithm to the device's sensors in the future to be able to complete the overall goal of the project.

5 Acknowledgements

The author would like to give a great and special thanks to her advisor, Dr. Ahmed Helmy, for his guidance, advice, direction, and encouragement from the very start of this project.

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7 Biography

Sylvia Lujo was born in 1996 and raised in Flagler Beach, Florida. She began attending the University of Florida in August of 2014 and expects to receive her Bachelors of Science in Computer Science with a minor in Mathematics in December of 2018. She has completed an internship with a software company, Greenway Health, and currently works as a software consultant for Motorola Solutions through a startup that they have helped her fund. She has accepted employment from Infinite Energy in Gainesville, Florida and plans to start in January of 2019. In her spare time, Sylvia enjoys playing piano, building websites, and refurbishing furniture. She hopes to pursue an advanced degree in Computer Science while employed in the upcoming year.