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QUANTITATIVE APPROACH TO ASSESSING STRESS IN AUTISM INDIVIDUALS

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ABSTRACT

A harness and shirt were created to measure and analyze the stress in individuals with autism. Stress was measured using heart rate (ECG), muscle activity (EMG), and an accelerometer to measure breathing rate. Coupled with a software filter, a machine learning algorithm was developed and implemented to increase detection accuracy. An android application was developed to allow the user to see their biometrics in real-time on their smartphone wirelessly. To train the machine learning algorithm, biometric data was collected from 17 individuals who went through a controlled experiment designed to measure stress. The data was then labelled for stress and no-stress regions, and fed into several machine learning algorithms such as Support Vector Machines, Decision Trees, K-Nearest Neighbors, etc. It was found that the Support Vector Machine with an RBF kernel performed the best among all the algorithms that were tested. The test accuracy for the SVM-RBF was ~67% without any feature extraction applied to the three raw physiological signals. The model was then deployed in the Android app to detect stress from individuals in real-time through the harness and shirt, and send a notification based on the outcome of the model to the user's smartphone.

NOMENCLATURE

ASD – Autism Spectrum Disorder

BITalino – A hardware and software toolbox that is designed specifically for handling and processing biometric signals.

ECG – Electrocardiogram: a common method of measuring the electrical activity of the heart using voltage measuring equipment through electrodes secured to the surface of the skin.

EMG – Electromyogram: a method of measuring the electrical activity of the muscles through electrodes secured to the surface of the skin.

GSR – Galvanic skin response: also known as electrodermal activity (EDA), it is a method of measuring the changes in the electrical conductivity of the skin.

IRB – Institutional review board: committee that reviews proposed methods of research to ensure that those methods are ethical in nature and do not put the subjects in any form of danger

PCB – Printed Circuit Board

QRS (peak) – The repeating part of the echocardiogram wave that signifies the ventricular depolarization of the heart

RBF Kernel – A specification of the SVM algorithm

RR interval – The time between the QRS peaks in the echocardiogram that is used to determine heart rate

Respiratory rate – The breathing rate of an individual

Support Vector Machines (SVM) – A class of machine learning algorithm

TensorFlow - A framework for machine learning

INTRODUCTION

Autism spectrum disorder (ASD) is a developmental disorder affecting communication and social interaction. Difficulties in cognitive and emotional processing can lead to states of increased stress that manifests as inappropriate social behavior. It is challenging for caretakers and individuals with autism to eliminate stressors since they range from real to perceived, and pleasant or unpleasant. Therefore, adapting to or identifying states of stress is important in the management of ASD. There is currently no clearly defined measure of stress, since it manifests differently in individuals. Recent work has assessed stress using physiological measurements, the easiest of which to monitor is heart rate variability [1]. To increase the accuracy, additional physiological information should be explored, such as skin conductivity and respiratory rate. Portable devices capable of processing data can be used to monitor and assess stress in the daily life of individuals with ASD. One limitation to current stress detecting devices is the lack of including additional biometrics and limited data processing techniques. This allows for a broad project scope, to explore additional biometrics and data processing methods.

In order to help these individuals become more independent, a device was desired that would detect their stress and send an alert to both the user and their caretaker. This system was not allowed to be on the wrists because individuals with autism are usually uncomfortable with objects wrapped around their wrist. Rather, it was required to be placed on the torso area using a shirt or a harness. It was determined that a machine learning algorithm would be the best approach to determine stress in an individual person. Through research on what is currently on the market, it was found that the industry primarily currently uses heart-rate variability using mobile phone sensors [1]. Research has demonstrated that mental stress can be detected solely through a heart rate monitor with a successful discrimination rate of 83% within subjects [2]. To increase the accuracy, additional data information was desired, so skin conductivity and breathing rate were chosen for inclusion [1][2].

The MSD team from the previous year accomplished the design of a wearable device that tracks muscle activation during exercise. The team integrated a microcontroller and system of sensors in an athletic compression garment (P01722). This provided knowledge that provided feasibility that the form factor was possible with today’s technology. Through research, it was discovered that a similar device exists on the market but in the form of a device worn on the wrist similar to a watch [3]. The major drawback of current design is that it is worn on the wrist rather than seamlessly integrated into the users clothing, which could lead to discomfort and aggravate the user. This device is also limited to only using heart rate monitoring, which ignores other useful biometrics like respiratory rate or muscle activity. Lastly, the current device does not have a feature to notify a third party, such as a parent or guardian. With current wearable stress tracker devices as our benchmark, we sought to improve upon these main features. Our objective was to design a device that is seamlessly integrated into the users clothing, captures a greater range of biometrics, and interactive with caretakers of children with autism.

PROCESS

The customer requirements pertaining to a wearable system that could detect the stress of an individual were defined in terms of the biometrics that were detected, the method of calculating stress levels, the profile of the wearable, and the operating time of the system. In addition to this, it was required that an application was to be created for the use on a mobile device such as a smartphone, so that the end-user of the system could easily operate the system and monitor the person who is wearing the device. Another function of the front-end application was to alert the user and the user's guardian of the detection of stress, so that proper actions to calm the user down could be performed. The system was also to be removable or washable, since the desired wearable was to be a shirt that was in direct contact with the user. While obtaining the customer requirements, it was determined that the device to be designed would be considered a lifestyle device, rather than a medical device, so Federal Drug Administration (FDA) regulations would instead serve the purpose as a guide to good engineering and device development practices.

The most emphasized component of the system to be designed was the stress detection algorithm, which had to implement the patterns of the measured biometrics to determine if the user was in a state of stress or in a state of non-stress in real-time of near real time, to relieve the stress of the individual as soon as possible. In conjunction with the stress detection algorithm, it was required to use at least three of the five proposed physiological signals. The customer defined physiological signals were ECG, EMG, respiratory rate, skin conductance, and skin temperature. The selection of these sensors was confirmed through available research [4]. The system to detect these biometrics was to be able to operate for at least eight hours. The system was to perform the desired stress detection in a concealed profile, meaning that it was not to be detected under the user's normal clothing.

The engineering requirements that met the customer requirements were then defined to determine design goals of the project. The engineering requirements were ranked by importance to determine which aspects of the design would be the most vital in the completion of the design that best satisfies the customer requirements. The most important engineering requirement was the accuracy of the heart rate monitor, which is also known as the ECG, after some processing of the signal. The ECG was determined to be the most influential in determining stress through the research that was conducted [5]. The other biometrics to be used in the stress detection machine learning algorithm were of the next highest importance, since it was determined that the accuracy of the signals was fundamental in the desired machine learning algorithm. Without the proper operation of the wearable, physiological signal measuring system and the machine learning algorithm, the front-end mobile application would not serve its full purpose. While developing the full package of the prototype, the shirt, the machine learning, and the app, it was determined that the app would have concise functionality to fulfill its intended purpose. The app was created to have a user login to it, connect to the BITalino biometrics acquisition system, visualize the data that was being collected, and notify the user of detected stress.

There were multiple forms of constraints that were recognized throughout the design of the prototype which include constraints created by the customer, constraints from team composition, and constraints created by limited time frames. Constraints provided to the team by the customer included the following: it must be worn on the torso of the user, it must incorporate some form of machine learning to detect stress, and it must be able to integrate with an app developed for a mobile device. Constraints created by the composition of the engineering team limited the viable solutions. For example, there was only one electrical engineer on the team, so the development of a custom printed circuit board was not feasible, so existing solutions on the market for microcontroller boards were desired. In addition to this, there was only one team member that had extensive knowledge in computer programming languages that were used to develop a mobile application that could function appropriately. The time frame constraint mainly pertained to the creation, approval, and execution of human subjects' research. There were only a few months in which this research could be conducted, and it was vital to the training of the stress detection algorithm that this data be collected. It took the IRB committee over two months from submission to approve the human subjects testing that the team proposed, which significantly delayed the development and training of the stress detection algorithm. It was originally planned that the team was going to do human subjects research on those individuals that were on the autism spectrum, however it was ascertained that this form of testing would never be approved by the IRB committee, so research on healthy, college-aged persons was conducted as a substitute.

The initial concept generation began with the discussion of what the vital functions of the device were based on the engineering requirements and how they would be broken down into sub-functions using functional decomposition chart. Solutions to the functions and sub-functions were brainstormed and organized into a morphological chart, which displayed all the practical solutions that would satisfy the engineering requirements. These workable solutions were further grouped into four overall feasible solutions, which included a wristband/wristwatch, a single chest band, a vest or shirt, and an adjustable harness. A concept sketch was then created for the design of each of the four viable solutions. Of the four, the vest/shirt and the adjustable harness were the two most promising concepts that would meet all the customer requirements and remain within the constraints that were defined.

Applicable engineering standards to the device were based on IEEE standards. The standards were as follows: IEEE 11073-10406-2011 (Basic electrocardiograph (ECG) (1- to 3-lead ECG)) [6], IEEE 11073-10441-2013 [8], IEEE C63 011-2000 (American National Standard for Limits and Methods of Measurement of Radio Disturbance Characteristics of Industrial, Scientific, [9]. IEEE 11073-10406-2011 distinguished ECG devices that monitored the heart from those that were used as diagnostic equipment, including wearable ECG device that were limited to three leads; the standard also defined the fact that the capability of annotating or analyzing the detected electrical activity to determine known cardiac phenomena was not required. IEEE 11073-10441-2013 establishes the need for plug-and-play interoperability of the device and defines a method of communication between a medical device and a personal device, such as a smartphone. IEEE C63 011-2000 attempts to limit spurious radiation by establishing which radio frequencies are fundamental frequencies and which frequencies are harmonics of those fundamental frequencies.

The original budget set by the customer at the beginning of the process was $2,000. After the initial designs were completed and it was determined that the skin temperature would not contribute to the detection of stress reliably, it was estimated that the two iterations of the design would cost $654.10. This budget estimate also included the equipment that was needed in the research study. The majority of the budget was toward the purchase of the BITalino, which was determined to be the best off the shelf package for the needs of the project.

The development of the harness and the shirt began with the testing of reliable locations on the skin to determine the placement of the electrodes, along with the acceptable sampling rates at which the integrity of the physiological signal could be maintained. The placement of the electrodes was restricted by the space in which a shirt would cover the body. The testing was conducted using a PowerLab26T manufactured by AD Instruments. The data was collected using this equipment along with the LabChart 7 software package. The data was then run through a MATLAB script to determine which series of electrode placements would be the most effective for each signal. The MATLAB script focused on the visualization of the raw data plotting, looking for the electrode placement and the minimum sampling rate that resulted in the clearest set of P-waves, QRS-waves, and T-waves in the ECG, the sinusoidal nature of the respiratory rate, the subtle changes in the GSR, and activation of the muscles for the EMG. The MATLAB script also calculated the signal to noise ratio for each combination.

Throughout all of the signals, it was determined that 100Hz would be sufficient for the collection of data to be fed into the stress detection algorithm that would extract the defining features of the signals. The ECG feasibility of electrode placement and sampling rate resulted in the selection of a custom placement of the electrodes [10] [11]. The negative electrode was placed just under the right clavicle, the positive electrode was placed on the left side of the abdomen just below the bottom-most rib bone, and the reference electrode was placed on the right side of the abdomen also directly under the bottom-most rib bone. Testing for the EMG determined that the shoulder would be the best placement for the electrodes, both positive and negative, to minimize the heart activity that may be interfering with the muscle activity. The skin conductivity testing determined that the most ideal placement of the electrodes would be below, but not in the armpit, since it was one of the more abundant areas of eccrine sweat glands aside from the hands and soles of the feet [12]. The respiratory rate was measured with a respiratory-transducer belt, which outputs a certain voltage reading based on the amount of tension on the belt [13]. This method was useful in determining the sampling rate, however it was not feasible to have a transducer belt on the user in the final design of the prototype. The alternate solution was to have an accelerometer perform the same usage as the respiratory-transducer belt. Skin temperature was also tested but discarded from inclusion in the design of the prototype because it did not provide reliable data, and the sensor that would need to be purchased that was sensitive enough to detect miniscule changes would be too expensive.

For the machine learning algorithm to produce a meaningful output, a meaningful input must be supplied. In the case of biometrics such as the ones used in this project, a low pass noise filter must be implemented for the signals. The filters designed were Butterworth filters, which are a type of low pass filter with a frequency response as flat as possible in the passband. This flatness is desired to ensure the signal integrity of the system while still filtering out the noise from the signal. There were two separate filters designed – a 9th, and a 7th order butterworth filter with a cut off frequency of 4Hz. The parameters are empirically optimized to maximize the desired features for the signals. A sample of the filtered ECG signal can be found in Fig. 1.

To deploy the machine learning model, an Android phone and a BITalino Revolution BLE Kit were chosen. The phone was used as a monitoring device for the user and the BITalino was used to collect the biometrics. A user could make a log-in account in the phone and once logged in, the phone would pair with the BITalino and start showing the biometrics. In the event when a user is stressed, the phone would send a notification to the user. The prototype of this app is shown in Fig. 2.

The detection of the stress was done in the phone using the biometrics in real time. The TensorFlow framework was used for deploying the machine learning model in Android, because of its compatibility and speed in Android.

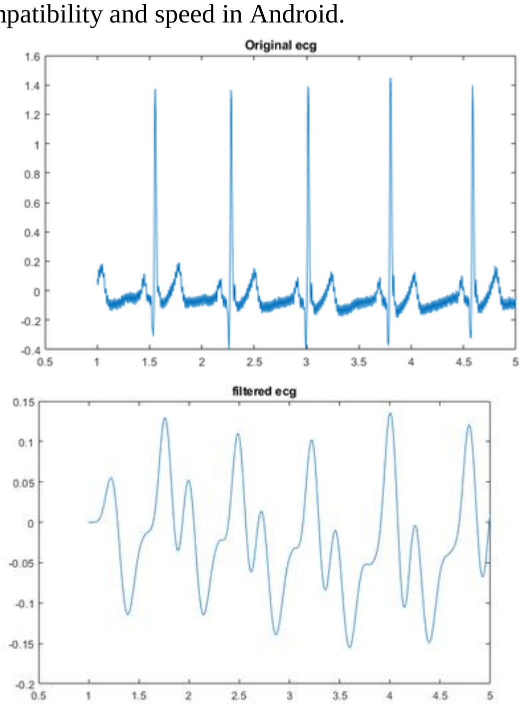

Figure 1. Lowpass filtering example

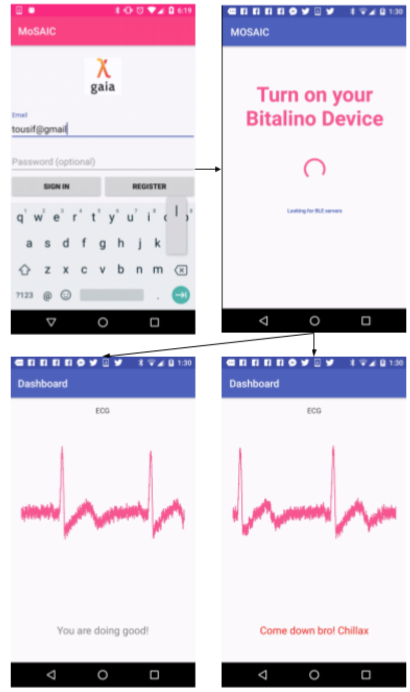

Figure 2. Android app prototype

A backend in Loopback.js was also created which stored basic information about the user and when a user got stressed. No stress data was stored when using the app because of inadequate storage capacity of the team's system.[14][15]

To train and evaluate the accuracy of the machine learning model, a research study was conducted in which 17 voluntary human participants were subjected to a stressful and non-stressful situation. Subjects were instructed to read and sign an informed consent form and participate in an anonymous questionnaire prior to testing. The proctors collected these forms and documented a unique identifier on each questionnaire to protect anonymity. The electrode placement feasibility testing was used to determine electrode placement on human subjects during the study except for the respiratory belt instead of the accelerometer. ECG, EMG, and respiratory rate were collected using 5 electrodes and a respiratory belt. EMG electrodes were placed on the shoulder of the non-dominant arm. All biometric data was collected in one continuous dataset. After attaching the 5 electrodes and respiratory belt, subjects were instructed to remain still for the remainder of the study. Each subject was asked prior to beginning data collection how stressed they felt on a subjective scale of 1-10, with 1 being less stressed, and 10 being most stressed. This question was asked after every segment of the study a total of 8 times. The first segment of the study was a 5-minute dataset collected for each subject in order to establish a baseline. During the second segment of the study, an onscreen prompt instructed the subjects to perform basic arithmetic problems by hand for 2 minutes while the proctor periodically read out how much time remained. During the third segment of the study, subjects stopped performing the arithmetic and were presented with a slideshow of calming images for 2 minutes. The second and third segments of the study were each repeated in their respective order 2 more times for a total of 17 minutes of continuous data collection, with one baseline for 5 minutes, three timed arithmetic sections for 6 minutes, three calming images slideshows for 6 minutes, and 8 stress level indications. Stress level indications were retrospectively added to the dataset as comments at the time they were obtained (Time T=0, 5, 7, 9, 11, 13, 15, and 17 minutes). All 17 datasets were exported separately as txt files for further analysis.

The data of each subject from the research study was then modified by extracting the following raw data: time, respiratory rate, ECG, and EMG. A column of ground truth data, zeros or ones depending on the difference of reported stress from the baseline, to the existing raw data columns. The ones were added in a case of "stress" and the zeros were added for "non-stress" time periods of the study. The data was then concatenated in the order of the subjects, so that it was one large dataset. The time column of the dataset was replaced to reflect if it were one trial of data taken to make the processing of the data more straightforward.

The first iteration of the prototype (Fig. 3) was the adjustable harness, which was built to ensure that the system of measuring the biometrics was not affected by the wiring or any other connections. The main purpose of this system was to test the machine learning algorithm on a person, while having confidence that the system would be measuring biometrics without the addition of recurring artifacts. The wiring was secured to the harness, along with the separate sensors at various points along the harness, central to the area of the electrode placement for each physiological signal.

Figure 3: The harness iteration of the monitoring system

The second iteration of the prototype (Fig. 4) was a shirt that was sewn with stainless steel conductive thread as the method of transferring the measured biometrics from the electrodes to the BITalino. The conductive thread that was sewn into the shirt was covered with the same fabric as the shirt to maintain the elasticity of the shirt, and to make sure the signals being sent through the conductive thread were not interfered with. The BITalino was soldered to a housing that snapped onto the shirt using button snaps. This design of the housing allowed for the shirt to be machine washable after the housing was removed.

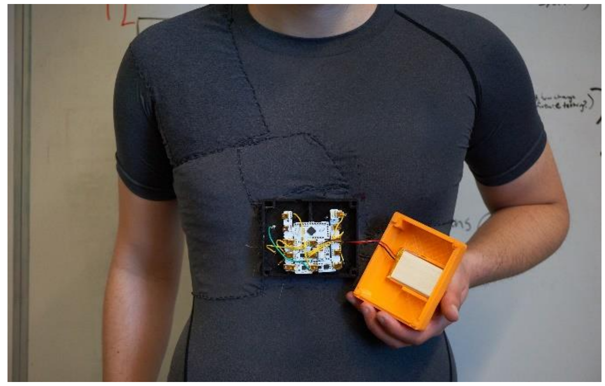

Figure 4: The final, shirt iteration of the system

RESULTS AND DISCUSSION

The test plans were developed based on the engineering requirements, with the majority of the testing comparing the physiological signal acquired by the BITalino to an established system of physiological data acquisition. The system that was considered to be the "industry standard" that the data from the BITalino was compared to was the AD Instruments PowerLab 26T with LabChart 7 software. For ECG, EMG, GSR and respiratory rate, the data was collected at the same time and in relatively the same electrode location on the body. After the data was collected, it was analyzed through MATLAB code that aligned the data in the time domain, and analyzed the data using various data comparison methods. The methods used were signal-to-noise ratio, correlation and measuring the percent accuracy of the data based on the results from the correlation matrix, the fast Fourier transform and magnitude-squared coherence and power spectral density comparison using Welch estimation in the frequency domain, and data normalization in the form of feature scaling for an absolute difference of the signals. The heart rate and heart rate variability of the signals were compared only for the ECG signal.

All of the sensor testing of the BITalino had to be within a marginal value of ±20% and ideal of ±5% of the industry standard, with the industry standard being the AD Instruments system. The heart rate measured by the BITalino was within 10% accuracy of the standard. The mean heart rate variability was 22.4% accurate to the standard, however the error may have been compounded by the method of calculating the RR intervals and the moving window in which they were calculated across the dataset. The signal to noise ratio of the BITalino was greater than the AD Instruments for the ECG. 99% of the BITalino was within a 95% accuracy interval of the AD Instruments data for the ECG signal. The fast Fourier transform along with the power spectral density estimation using the Welch method both had similar trends with only slight differences in the signals at all of the frequencies measured. There was an absolute of normalized difference between the signals of 0.086, which is negligible since the QRS peaks are the most important aspect of the ECG.

The respiratory rate testing results displayed the fact the accelerometer does not detect as miniscule of motion as the respiratory transducer belt of the AD Instruments setup. However, the overall sinusoidal nature of the signal was still obtained, even though it was not as clear as the AD Instruments. 99.9% of the BITalino data was within a 95% accuracy interval of the AD Instruments. The mean absolute normalized difference was 0.0205, but the signal was of the sinusoidal nature, which was more important than any other aspect.

The EMG signal was not as conclusive as the other signals. After running the data through the correlation function and generating a correlation matrix, it was ascertained that 99% of the data was within a 95% accuracy interval of the AD Instruments data. There was an abundance of additional frequencies seen in the fast Fourier transform, along with the power spectral density. Since most of the data was collected at rest, there would not be any significant muscle activity being recorded. The additional frequencies seen may have been from the detection of some of the less obvious muscle activations.

The GSR signal had 90.1% of the data within a 95% accuracy interval of the AD Instruments data. The raw data plots appeared to be similar after a bandpass filter was applied to the data. The GSR data was difficult to obtain a reliable and accurate signal for because the typical placement of the sensors was not used. In the testing, since the design of the prototype is limited to the torso, the signal had to be measured from under the arm on the right side of the body, which is not the most abundant location of eccrine sweat glands.

Another focus of the test plans was to determine the accuracy of the machine learning model in terms of the stress detected and if the stress is psychological or stress from exercise. The overall accuracy of the stress detection algorithm was accomplished through running unit tests and acceptance tests at multiple frequencies in the development time using the data acquired by the IRB research study. Table 1 summarizes the different test scores that was achieved for the machine learning models that were tested. Figure 5 shows the confusion matrix of the SVM/Gaussian Process model that used in the app.

Table 1 Summary of Machine Learning Algorithm Scores

Algorithm	**Accuracy Score**	**Avg Precision Score**	**F1 Score**	**Recall Score**
Nearest Neighbor	0.47	0.36	0.41	0.48
Linear SVM	0.57	0.37	0.22	0.15
SVM RBF	0.63	0.37	-	-
Gaussian Process	0.63	0.37	-	-
Decision Tree	0.62	0.37	0.02	0.01
Random Forrest	0.63	0.37	-	-
Neural Net	0.55	0.39	0.41	0.43
AdaBoost	0.61	0.38	0.22	0.15
Naive Bayes	0.63	0.38	0.03	0.02
QDA	0.58	0.38	0.31	0.25

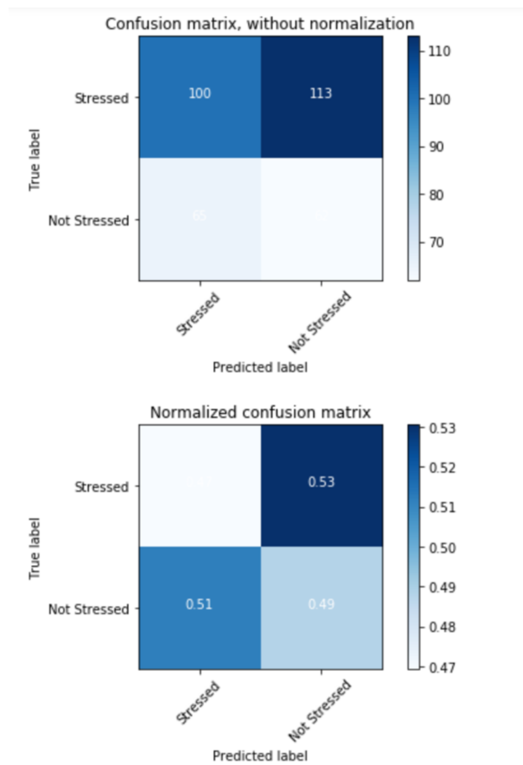

Figure 5: Confusion Matrix for Linear SVM/Gaussian Process

The stability of the front end mobile application was also tested. The app successfully connected to the BITalino each time it was turned on, followed by opening the app. The visualization was tested by continuously streaming the signals and seeing how the app performed visually. It was found that the app lagged quite a bit when displaying all the signals. Hence, only the ECG signal was displayed in the final app. It was concluded that the library used for visualization (GraphView) is not efficient enough to handle real time visualization. The unit tests for machine learning inference passed in the TensorFlow for Android framework implemented in the app.

The customer requested that the device be machine washable or removable, so the garment can be washed. The team went for a sweat-proof housing with the ability to easily remove and replace the device. Due to limited resources, the team was unable to verify that the shirt can be washed, but this would be a good opportunity for future improvement and testing.

Overall, the project was a success because the team was able to create and deliver on our customer's requirements and specifications. The final prototype exceeds their requirement in terms of accuracy. With a reduced budget the team was unable to get a plastic injected molded housing to satisfy waterproof requirement. In lieu, the team developed a water-resistant housing that the customer can take and produce through the use of plastic injection molding when manufacturing has been initiated.

CONCLUSIONS AND RECOMMENDATIONS

The system is able to discriminate stress with 67% accuracy. With additional time and training, this number could be improved.

A major issue the team encountered was the constant change of customer requirements after significant progress has been made. To address this issue, the team pointed to previous documentation about the requirements. One of the additional requirements for complete waterproofing was made after the final design and method has already been developed and would have required a complete redesign as well as significant additional cost for plastic injection molding, something they were not willing to provide funds for.

Another conflict the team encountered was the customer's reduction of financial support which led to more affordable designs and components being utilized. This was most notable during testing where it was difficult to get volunteers to give up their time for the study. Had the team been able to give a financial benefit for participating, more data could have been gathered for the machine learning model, increasing the accuracy of the model.

Freedom for selection of design is important. Had the customer not required certain sensors to be used, a more compact device could have been developed with greatly reduced cost.

Using off-the-shelf components provided the team with proven technology and equipment that was readily available. This enable the team to focus more on the implementation of the equipment, rather than debugging a custom PCB board. It also led to reduced expenses.

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