School of Engineering, Faculty of Applied Science

The University of British Columbia Okanagan

ENGR 499 Capstone:

Final Design Report

Group 45:

Stress Monitoring and Mitigation

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1. Project Introduction

First responders encounter extremely challenging situations in the line of duty. Over time, the accumulation of stress poses a significant risk to physical and mental health. PTSD can arise from a single traumatic event or from continuous exposure to stressful situations. Research indicates that instances of PTSD are twice as high in Canadian First Responders than compared to the general population (Canadian Mental Health Association, 2016). Prolonged high stress can also give rise to hypertension, heart disease, obesity, diabetes, and arthritis. Research has shown that over the last 20 years, access to stress management solutions for first responders has been very limited (Haugen et al. 2012). It is therefore the primary function of this project to develop an effective stress monitoring and mitigation system for first responders. **This work aims to address a lack of stress monitoring tools for first responders by creating a stress assessment protocol which combines both wearable stress-tracking technology and cortisol rapid testing.** Key partners in this project are UBC Star, Gemina Labs and the RCMP. It is the expressed intent of this project to create a useful product that will improve the mental and physical health of first responders, as well as the communities in which they serve.

1.1 Need and Constraint Identification

Stress is a mental and physiological response to a perceived threat or challenge. When the brain perceives a stressor, it activates the sympathetic nervous system (SNS) which is responsible for the body's "fight or flight" response. During this process, the adrenal glands are stimulated to produce and release cortisol. Once released into the bloodstream, cortisol supports the "fight or flight" response by increasing blood sugar levels, regulating metabolism, interacting with the central nervous system, and increasing immune system suppression. While it is an essential and effective hormone for dealing with short term bouts of stress, cortisol at elevated levels over long periods of time is associated with an array of health issues.

Traditional stress monitoring has been heavily reliant on the measurement of cortisol as a biomarker of stress. Cortisol levels are found expressed in blood, urine, saliva and sweat. In the past, blood serum or urine samples were often required which posed an obtrusive means of data collection for the patient. This, coupled with the need for expensive lab analysis equipment have made frequent or real-time stress monitoring a challenge. Studies have since demonstrated that salivary cortisol is often present at levels comparable to blood serum cortisol (Hellhammer 2009). Saliva samples are less obtrusive than blood and can be analysed using a few different methods. One such method is the Salimetrics Cortisol ELISA kit which can be used as a benchmark for high accuracy salivary cortisol testing. The ELISA method allows this kit to achieve a high accuracy and a sensitivity of less than 0.007 ug/L cortisol. Despite its high accuracy, this kit is limited in its scope as it requires a 2hr assay time, careful sample preparation and sophisticated equipment (~$20,000), precluding its use outside of a lab.

Lateral flow tests (LFT) have emerged as a cheap alternative to traditional diagnostic lab testing. Lateral flow tests consist of a paper-based membrane and rely on similar principles to the ELISA method but are cheaper, faster, and easier to conduct. A sample is applied to one end of the paper-based membrane at which time the sample interacts with labeled particles (latex beads or gold beads). The label particles travel down the membrane to the reaction zone. If the target analyte is present, they will be immobilized, triggering the appearance of a visible line. While LFTs have been available for some time (pregnancy tests, HIV), they have become far more widespread in response to the rapid testing needs of the Covid-19 pandemic. The primary advantages of LFTs are low cost, ease of use and quick results. However, they are typically disadvantaged by limited sensitivity and a lack of quantitative results (Koczula, K. M., & Gallotta, A. 2016).

Gemina labs, in partnership with ReadyGo and RAPIvD has developed a LFT salivary cortisol test which is cost-effective and easy to use. This technique is a novel form of lateral flow testing which is achieved by incorporating the use of the ReadyGo Sampler. The ReadyGo Sampler is a tool in which the swab and collection buffers are integrated into a single device (Figure 1a). The Sampler collects identical sample quantities on the “nib” each time. After

sample harvest, a consistent amount of buffer is released from within the Sampler, and the sample is thereby mixed and delivered simultaneously into the diagnostic testing device. The significance of this approach is that it allows the lateral flow test to be used quantitatively. Given that the Sampler exerts precise control over the quantity of sample taken and the amount of buffer solution released, the visible strength of the lines of the LFT can be found proportional to salivary cortisol concentration (see Figure 1b). Although the human eye can recognize these variations in line strength, accurate quantitative measurement requires the use of a lateral flow test reader. Existing devices, such as the Dialunox ESEQuant Flex and MedIUL iPeak are large lab oriented LFT readers with low portability that require a power supply and are expensive (greater than $2000). These devices are accurate, but unsuitable for field work amongst first responders.

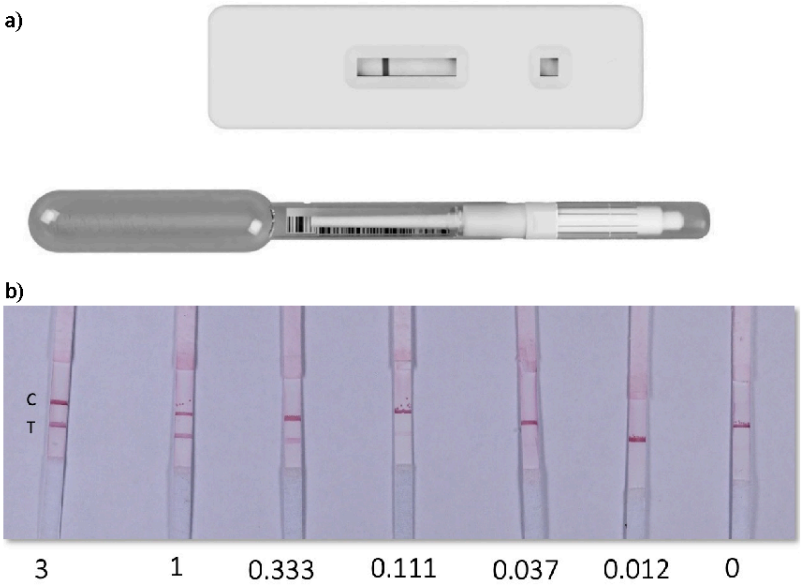

Figure 1a: Lateral Flow Test Kit (top). The ReadyGo Sampler used by Gemina Labs (bottom)

Figure 1b: Example of lateral flow strips with increasing levels of Cortisol (ug/dL). Note the test line strength visibly increases with cortisol concentration.

Figure 1: Lateral Flow Testing

The physical measurement of cortisol from a bio sample such as saliva or urine sample is normally a reliable indicator of stress in the individual. This method, however, has limitations. The physical collection and sampling of saliva for analysis, while relatively easy compared to other testing methods, is still obtrusive. And while cortisol is an important indicator, its use as a biomarker alone may generate a narrow interpretation of an individual's overall stress condition.

Cortisol levels peak within 30 minutes of a stressful event, and typically remain elevated for several hours after an event – testing outside of this time frame may fail to capture an individual's exposure to stress. It has thereby become desirable to find new ways of monitoring stress continuously and in real-time.

In the past few years, there has been a dramatic rise in the popularity of wearable electronic devices. Most of these wearables are integrated with some form of biosignal sensors which provide health monitoring and feedback to users. The commercialization of these products has led to the availability of wearables with a wide range of features and efficacies. The most common sensor types consist of heart rate (HR), electrocardiogram (ECG), respiration (Resp), blood oxygen (SpO2), skin temperature (ST), electrodermal activity (EDA) and inertial measurement units (IMU). Although many of these devices are data rich and can collect enormous amounts of data, some sensors and data types are more valuable than others. It has been shown that the sensors which are the most useful in stress detection are heart rate (HR or ECG) and EDA (Gradl, S., 2019). Heart rate monitors are also typically capable of measuring heart rate variance, (HRV) which when properly analyzed, informs about the state of stress. EDA relies on measuring variances in the electro conductivity of the skin. Changes in this variance are often due to activation of the sympathetic nervous system (SNS) and the corresponding increase in gland activity at the skin.

Another important feature of modern wearable technologies is the high computational power of the "smart" devices. Apple Smart Watches, Fitbit and Garmin are all popular smart devices with built in data processing. Specifically, the Apple Health Kit makes it easy for developers to design and tailor apps to meet their health monitoring needs. Despite the glut of wearable fitness technology available, only a few devices offer near medical grade sensor capability. These include Empatica, SHIMMER, and Sentio devices. Of these, Empatica is the least obstructive, with a size comparable to a wristwatch (Shimmer and Sentio have sophisticated sensors, but they are bulky and more cumbersome to wear). Empatica devices consist of HR, EDA, and IMU sensors and benefit from high quality raw data collection, allowing flexibility for data analysis and machine learning. A recent publication listed Empatica as having one of the highest potentials for stress detection, based on sensor quality and compatibility with machine

learning (Gedam, S., 2021). Apple was also listed as a contender for high stress monitoring capability due to its good HR sensor and machine learning capability. It is noteworthy that Empatica Embrace2 and EmbracePlus are the first devices to be approved for FDA use in epilepsy treatment. Currently, Empatica wearables can only be obtained with a prescription or for research purposes.

A variety of machine learning algorithms have been tested for stress monitoring (Appendix Table 1). Further research is required to determine what type of machine learning algorithm will be best suited to first responders in a work setting. Designing an algorithm that accurately predicts stress is an important requirement of this work and will be discussed further below.

Figure 2: Apple Watch (left) is a versatile device, offering connectivity, apps and fitness tracking. Apple Watch contains HR, PPG and motion sensors. The Empatica EmbracePlus (right), while less versatile, is a medical grade device dedicated to collecting high quality HR, PPG, EDA and motion sensors.

Despite the promising direction of wearable technologies, they have disadvantages. Improperly worn devices and can dramatically influence data quality. User health issues, relating to blood pressure, blood sugar, sleep, and substance use are all likely to have dramatic effects on data reliability. Finally, real time data collection may be challenged by the physical environment of the first responder (Gradl, S. 2019). For these reasons, this work aims to combine the real-time stress monitoring capabilities of a wearable with the reliability of Gemina Lab Cortisol saliva test as a means of verification.

The key partners for this project are UBC Star, Gemina Labs and the RCMP. UBC Star is a group of university researchers that work directly with industry partners to create products and

solutions for health, sport, and defense. The industry partner, Gemina Labs, is a Vancouver based pharmaceutical company having strategic partnerships with RAPIvD and ReadyGo. West Riding Consultancy (Phil Lancaster) has served as a liaison between this project, Gemina Labs and the RCMP. RAPIvD is a UK based pharma company responsible for developing the LFT saliva cortisol test. Gemina Labs has licensing agreements with ReadyGo to use the ReadyGo Sampler for lateral flow testing and diagnostics.

The RCMP are the primary stakeholder for which this product is being tailored. The Royal Canadian Mounted Police are the federal policing organization with over 19,000 officers. RCMP officers are often exposed to high levels of stress which over time can affect their mental health and performance in the field. Police incidents involving improper judgment or excessive force have been linked to officers combating high levels of stress (Craddock and Telesco, 2021). There has been a significant increase in public scrutiny of police action in recent years, and this highlights the need for stress management tools that will improve officer health and wellbeing. Privacy and the secure handling of RCMP officer data is a significant concern. Any protocol that is implemented must be discrete and the data obtained cannot somehow be used to harm the reputation or career of an officer. The union of the RCMP, the National Police Federation will not permit a stress protocol if it has the potential to harm its members.

Empatica is an MIT based technology company. They design medical grade wearables, such as the Empatica E4 and the Empatica Embrace Plus which are devices dedicated solely to health monitoring. Empatica also offers a suite of developer tools which allows users/researchers to collect and process their data as desired. Empatica devices are the first and only devices to be FDA approved for epilepsy treatment. Empatica offers access to their full platform on a subscription basis, with plans starting at $2000 per device per 3 years. Given these fees, Empatica may incur considerable financial gain if the Empatica Platform is chosen for distribution to thousands of RCMP officers.

Apple, the technology giant, designs a large suite of personal electronics which include the Apple Watch. The Apple Watch itself is a versatile package that offers communications, lifestyle apps, and fitness tracking. Apple Watches are limited to only electronic, optical heart and motion sensors. Despite this, Apple has free developer tools which make app design and data analysis easy. Apple Watches range in price from 400 to 1200 dollars.

Future expansion of this protocol could ultimately impact Firefighters, Paramedics, Canadian Armed Forces. This protocol may also affect the procedures of mental health professionals such as psychiatrists and counsellors. Ideally, users will be referred to mental health professionals when a stress threshold has been passed and therefore this protocol could increase the number of referrals to health professionals.

2 Problem Specification

Although this project aims to create a product suitable for all types of First Responders, the primary focus of the design process is to build a product suitable for an RCMP officer. Police officers often endure physical work in many extreme environments, therefore a protocol that meets these needs will ideally be appropriate for other first responders such as Firefighters, Paramedics, and the Armed Forces.

The end-product must be a stress detection protocol that accurately recognizes when a user has experienced an above normal level of stress. Figure 3 illustrates the conceptual design of the stress protocol. The protocol will consist of 3 stages: In the 1st stage, the wearable will provide an alert to the user when a stress threshold has been crossed. Assuming an alert has been triggered in the 1st stage, the user will proceed to the 2nd stage and administer a cortisol saliva test. The result of the 2nd stage cortisol test must be quantified by a digital reader. For cortisol readings above 0.5 ug/dL, users will proceed to the 3rd stage. The 3rd stage will consist of the user's referral to a stress management professional, such as a counsellor or union representative, for assistance.

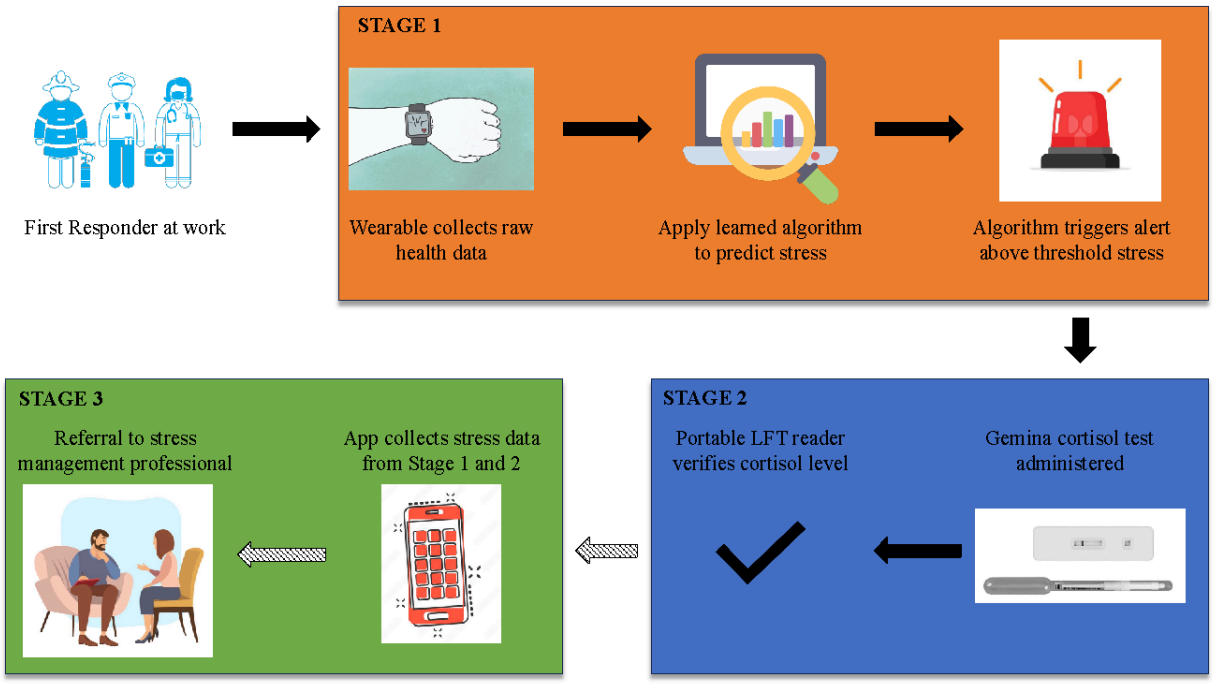

Figure 3: Conceptual Design of Stress Protocol.

2.1 Stage 1 Problem Specification

RCMP officers regularly conduct field work and are away from the office. While they are working, they must be able to operate freely, without distraction or discomfort. A wearable sensor must be small and lightweight and must exclude wires or electrodes that would make it difficult to remove in the course of duty. Therefore, a smart watch or similar device with a radius of less than 5 cm, and a weight of less than 50 g is required. The wearable must also have a battery life of at least 18 hours, so that it can function into an extended workday or emergency overtime shift. At a minimum the wearable must have HR, HRV, PPG and motion sensors. Preferably it should also have an EDA sensor. Previous research has shown that EDA may be one of the best health metrics for stress detection (Liu and Du, 2018). Sensors must sample at a minimum frequency of 10 Hz and data must be available in raw format for data analysis.

The chosen wearable will preferably be compatible with a suite of developer tools, either in Python or C++ which could enable subsequent app design. Furthermore, personal health data must be treated with high sensitivity and data access must be secured with password protection at a minimum.

The capability of the wearable to detect stress will be largely dependent on the quality of the machine learning algorithm that is trained. For the purposes of this work, a suitable algorithm must accurately predict if **a)** A stressful event has occurred **b)** and the length of the event (expressed in minutes). Research has shown that stressful events that surpass 30 minutes are the most likely to induce a strong cortisol response (Yehuda et al. 1998). The algorithm must be capable of analyzing wearable data in real time and it should alert after a stressful event exceeding 30 minutes has occurred. Given the sensitivity of medical data, data collection must be handled by a secure platform (Empatica or Apple).

2.2 Stage 2 Problem Specification

Conventional lateral flow test readers are large, expensive, lab-oriented devices. An accurate but compact alternative is needed to meet the portability needs of an officer in the field. Most likely this device would be stored and used in a police cruiser, or at the officer's place of residence for at-home testing. Given these constraints, the portable LFT reader must be smaller than 20 cm x 20 cm x 5 cm and weigh less than 300 g. The sensitivity of the reader must ideally detect thresholds as low as 0.012 ug/dL and up to 3 ug/dL which coincides with the sensitivity of the RAPIvD cortisol test kit. The reader must be battery powered with a battery life of at least 24 hours. It must also be fast, and capable of scanning and uploading a cortisol value within 3 minutes of start-up. The portable LFT reader should have a display which at minimum reads out the determined cortisol value. Ideally it will have Bluetooth connection for direct upload to a wearable or computer of the user's choosing. The reader should ideally also have a button which uploads the cortisol result to Bluetooth, as well as a button which resets and runs a new measurement. Ideally, the portable LFT reader will have a material cost of less than $100.

2.3 Stage 3 Problem Specification

The objective of Stage 1 and Stage 2 is to establish a strong data driven basis for referring a user to a stress management professional. Based on the past evidence, if the wearable detects over 30 minutes of cumulative stress in the day, a Stage 2 cortisol test should be implemented. If a saliva cortisol reading exceeding 0.1 ug/dL is readout from the portable reader, the user should be referred. Ideally, the results of both Stage 1 and Stage 2 shall be integrated into a user-friendly app which could be accessed by phone or desktop. The app will integrate the stress findings of

the Stage 1 wearable data with that of the Bluetooth transmitted result of the Stage 2 test. The purpose of the app is to simplify the data handling and its primary output should be either a Yes or No for referral to a professional.

3 Solution Generation and Selection

3.1 Stage 1 Solution Generation

Selecting the appropriate wearable is the first step of the Stage 1 solution. Based on the project constraints, Apple Watch and Empatica are both contenders, however there are key differences between both. Apple Watch offers the versatility of a smart device with many apps, and compatibility whereas the Embrace Plus is a dedicated medical grade device with almost no lifestyle functions for the user (apart from a clock). Nonetheless, the Embrace Plus comprises a more robust sensor package that includes EDA (not available on Apple), HR and PPG sampling at 64 Hz, and a battery life of 7 days versus 18 hours for Apple. Both Apple and Empatica offer secure developer platforms with Python programming, although the Empatica Care Platform is purpose built for medical research. Empatica devices are better tailored to remote health monitoring, by offering a seamless continuous raw data upload to the Empatica Care Platform. There are also many pre-existing Empatica data sets online which makes algorithm design and programming possible without needing to possess an actual watch. Based on these findings, this project has determined that an Empatica wearable, such as the Embrace Plus will be the most effective for stress detection in first responders. Apple Watch could be considered as a secondary option if needed.

Once raw stress data is collected, a prediction of whether the user is experiencing stress is produced. A prediction is made for each data entry, which happens at 64 Hz. These predictions are saved and used to determine stress event duration. The stress event duration is calculated by using a ‘rolling window’ calculation. Once a positive stress event is predicted, a window of data is observed by the code. The event duration is determined by starting a timer at the first stress event, and ending when the ‘window’ of observed data has no more positive predictions. This step does not employ machine learning but the parameters of the rolling window were tuned to produce the most accurate event duration predictions we could achieve. In short, the first stage of

the project collects raw biological data, detects stressful psychological states of the user, and outputs the predicted length of the stress event.

3.2 Stage 2 Solution Generation

If the stress threshold is crossed in Stage 1, it becomes necessary to enter Stage 2-verification using a cortisol test. To allow timely stress detection in the field, the saliva test should ideally be taken within 1 hour of the stressful event. The portable LFT reader is used to quantify this result in the field and allow for immediate cortisol verification. Existing devices are large, heavy, lab style instruments, many of which are designed for multi-strip analysis. While these products are accurate, they are too cumbersome, overpowered, and expensive for field work or at-home use.

A possible solution considered was to allow officers to perform the saliva test in the field, without immediate quantification by an LFT reader. This would require officers to bring their test strips into the station for quantification using a centralized LFT reader at the end of the workday, or work week. This option eliminates the need for portable LFT verification but offers less privacy. It is also prone to poor follow-through given that strips could be lost, forgotten, or ignored with increasing times following sampling. Instead, this work aims to create a smaller, robust LFT scanning solution which can be implemented immediately following the saliva test. The idea for a rapid, portable LFT reader was inspired by the ReadyGo Snapshot. The Snapshot is a device proposed by ReadyGo to offer handheld LFT reading and portability. However, the Snapshot is still in development, and not yet available for commercial use. The device being built for this project is being developed as an alternate prototype of the conceptualized ReadyGo Snapshot.

3.3 Stage 3 Solution Generation

Harnessing the data of Stage 1 and Stage 2 is the primary function of Stage 3. This project envisions the creation of an app, ideally phone compatible, that utilizes the machine-learned algorithm with a live feed from the Empatica wearable. The app will also collect the quantified LFT reading from the saliva test and add it to the stress profile of the user. Based on the inputs of Stage 1 and Stage 2, the app will then provide referral, if necessary, to a stress management professional. App design is beyond the scope of the projects' members

expertise, and therefore it is only offered in concept. Future efforts should ideally expand on the proposed app design of Stage 3.

4. Design Process

4.1 Stage 1 Design Process

The first step of designing the stress detection algorithm was determining which data channels to use. Empatica watches capture multiple data types, but after statistical analysis and multiple iterations of machine learning models, we found that the best predictor of stress was electrodermal activity. The test data we acquired from a public dataset provided by WESAD (Schmidt et al.). This data was collected from fifteen users whose biological data was collected while being subjected to multiple test conditions. For our purposes, the only relevant test condition was the stress event. The data was collected and stored chronologically such that the user's psychological and biological state can be observed at the same moment in time, which is identical to how data would be collected in real-time. Below is an example of one user's input data and the predicted stress data.

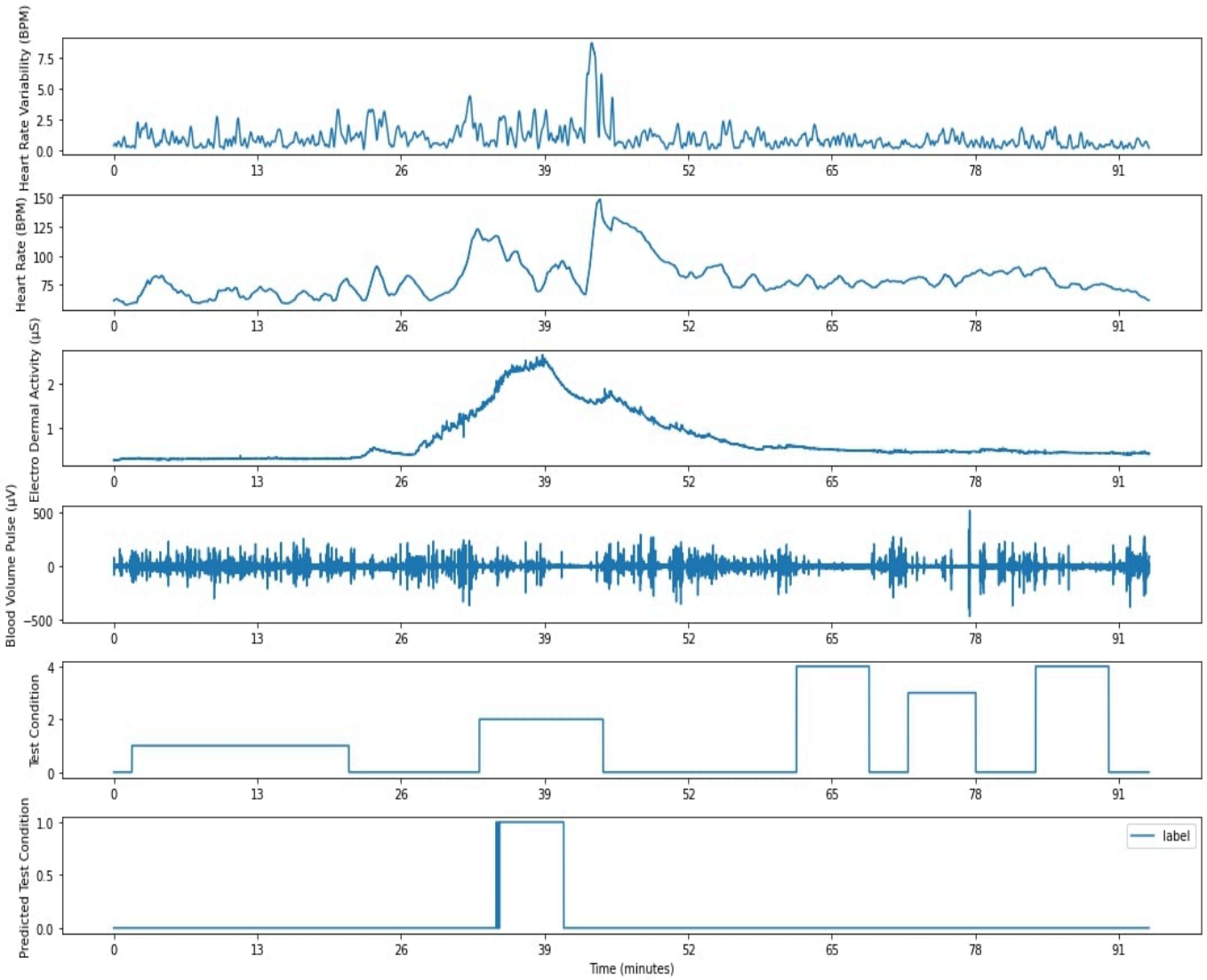

Figure 4: Example of Input Data and Output Data For a Single User

The first row is the user's heart variability (the amount their heart rate changed over time). This is calculated based on the second row, which is the user's heart rate data. The third row is the user's electrodermal activity over time. The fourth row is the user's blood volume pulse, which is how the heart rate data is derived. The fifth row is the true state of the user based on the test procedure. The sixth and final row is the predicted stress event based on the input data. As mentioned in the stage one solution generation, the only data channel that was used to train the model was the electrodermal activity as the other data channels exclusively decreased

the model by introducing noise, rather than any meaningful correlation. The fifth row, the user's true test condition, is mapped numerically using the following encoding map:

Test Condition Encoding Map	
0	Transient / Not Defined
1	Baseline
2	Stress
3	Amusement
4	Meditation

Now, with test data that perfectly replicates our proposed field data, we could create a machine learning algorithm that takes, as an input, the biological state and outputs their psychological state. Multiple model structures were tested to find the best predictor. The models tested were a logistic regressor, a random forest classifier, and an XGBoost classifier. All three models were tested with a wide range of model parameters using a GridSearchCV library. The data we are trying to predict is heavily class-imbalanced because most users are not in a stressful state most of the time. This means that decreasing the number of false positives is valuable to creating a model that functions correctly. With this in mind, the grid search algorithm employed was optimized for F1-Score. This metric is very useful for class imbalanced data sets as it takes into account both precision and recall. After testing all three models under a wide range of parameters, we found that a logistic regressor with an 'L2' penalty and a 'saga' solver offered the best results.

4.2 Stage 2 Design Process

An early design plan for the portable LFT reader considered combining a basic app with a phone camera to assess LFT strips. This was a tempting option because it would preclude the need for an additional device given that most users are already carrying a personal phone. Problematic, however, is the variance in lighting and optical conditions using this method.

Instead, as a 2nd iteration, this project recognized the need for building a consistent optical environment under which the strips could be analyzed. An enclosed space, free of ambient light

is needed. Strips are to be inserted into the chamber, and the chamber will contain a controlled light source for measurement. Different modes of measuring the intensity of the test bar have been considered. The first option was to use a spectrometer, whereby a diode emitter would shine light directly at the test line of the sample strip. A photodetector, or all-in-one spectrometer would be placed opposite to the light reflecting off the test region. Ideally, the current generated from the photodiode would be proportional to the darkness of the test line. Upon further evaluation of this design, it was deemed unlikely to offer the high sensitivity needed. Positioning of the photoemitter and diode would have been critical, and slight variations in relative positioning of the control line and test line would result in high degrees of error.

In a 3rd iteration, use of a mini high-definition camera for measurement was considered. The camera is to be positioned at an appropriate distance, focusing on the test strip within the box. The camera is controlled and powered by a small microcomputer. LEDs within the box provide a controlled amount of light to illuminate the strip. The camera then takes an image of the test strip. The image is processed by a program on the microcomputer which compares the relative darkness of the control line and the test line to yield a cortisol reading. Given the high resolution of modern mini-HD cameras, short focal distance and flexible programming, a camera-based reader has been chosen for this device. Initially, white light photoemitter was considered for the controlled light source. Instead, in a 4th iteration this was substituted for a green emitting LED. Most salivary cortisol tests, such as the Gemina Labs use colloidal gold nanoparticles which absorb more green light. Below is an example of each test line value taken by the mini-HD camera:

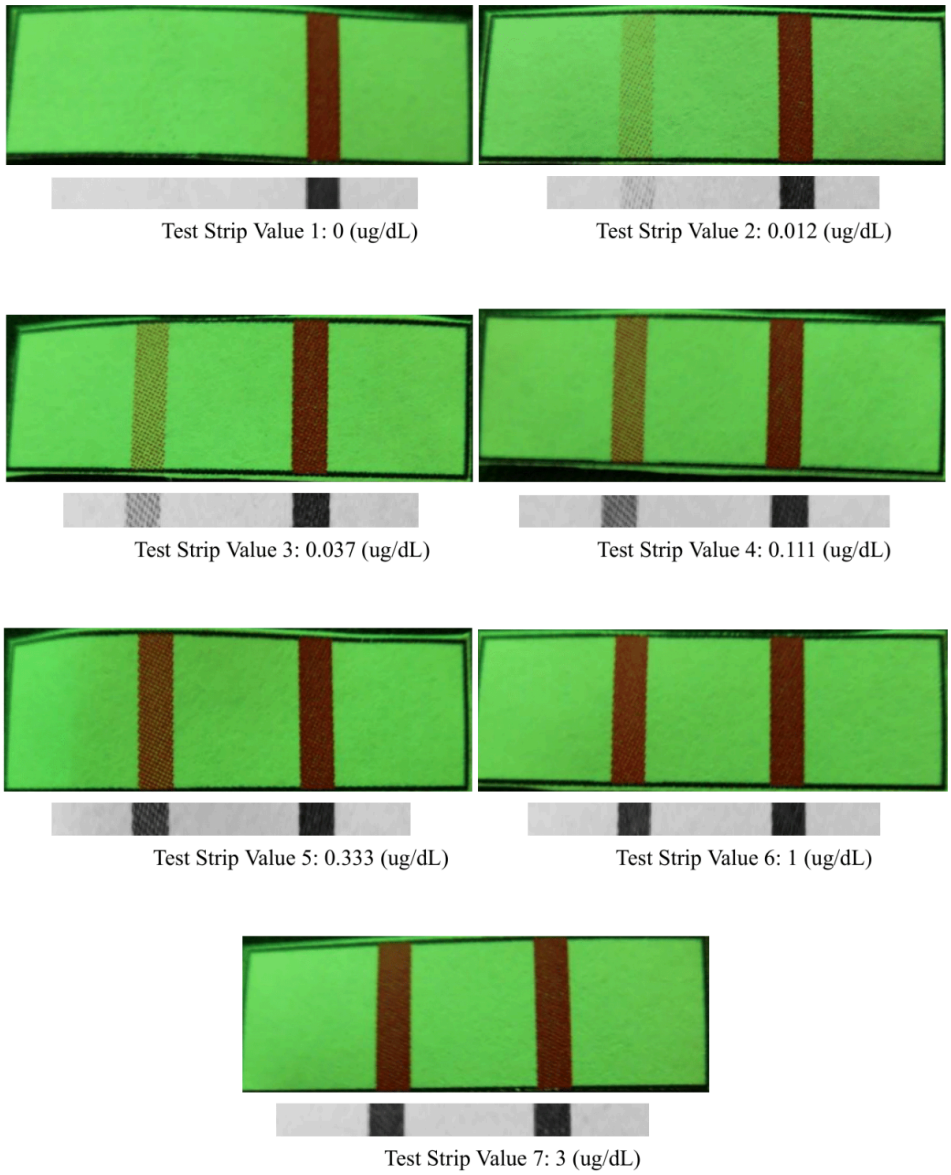

Figure 5: Test Line Pictures

The results of the image analysis are held on the microcomputer. This data, however, cannot be easily accessed without some external control features on the LFT reader. In a further iteration, a micro display was added to the device. The display will read out the cortisol level obtained from the program. Buttons included on the display module will be programmable to take a new measurement and transmit the result via Bluetooth to the app in Stage 3.

5. Final Design Details

5.1 Final Design Stage 1

Stage 1 of the Final Design begins with an officer wearing an Empatica watch. The watch collects sensor data and is synced with the Empatica Care App which transmits and stores the data securely. Data stored on the Empatica Care App is then securely shared with the learned algorithm. The algorithm takes the user's data, predicts a triggered stressful event, and aggregates these predictions into a stress event duration. This stress event duration is used as a marker to identify the user of a noteworthy stress event. Given this event marker, the user will be encouraged to move to Stage 2 of our protocol.

5.2 Stage 2 Final Design Details: Assembly

While designing this stress mitigation device, software was not the only thing taken into consideration to execute a sound engineering design. The box where all the necessary equipment is housed had careful design choices made, to allow for maximum efficiency and compactness. Upon first glance it's easy to miss the design considerations that went into the cut-outs and patterns found throughout the box, and why they work for the components inside them. Three designed parts make up the box: the base, the body, and the lid. The base and lid are 10mm thick, while the body has 10 mm thick walls with a height of 100 mm. This means the final dimensions are a length of 150 mm, a width of 100 mm, and a height of 120 mm. The body can be broken down even further, as it is easily the most detailed piece forming the device's housing.

Two major body sections are found when the box is opened: one to store the Raspberry Pi, and another is the space necessary for the distance between the test strip and camera. Test strips are inserted/removed on one side of the box where the camera can see them. To ensure the camera obtains accurate footage, there is a sliding door that can be opened to insert/remove test strips, and closed during testing. The camera is housed in a partition wall. In the wall is a cut out to house the camera using mounting screws to securely fix the position. To aid the camera's ability to capture the image, two green LEDs are installed on each of the side walls, shining the light at a 45-degree angle. There are channels cut-out within the walls for wiring to power the lights. The

height of the lights was carefully selected to coordinate with that of the camera, to allow the lights to be as useful as possible enhancing the data the camera collects. The camera itself needs to connect to the Raspberry Pi, via a Raspberry Pi camera cable. Since the camera and Raspberry Pi aren't mounted in the same section of the box, a channel can be found in the center wall: feeding down the wall and out the side towards the Raspberry Pi, near the base of the box. This cable has different dimensions than the typical wire sizes found elsewhere in the stress mitigation device, so the channel was adjusted accordingly.

The Raspberry Pi is mounted on 10 mm standoffs, to allow for sufficient cooling and clearance for wiring. This ensures the Raspberry Pi remains in place, and also helps align the bottom piece of the box to the main body during construction with all components in place. The bottom, and top were fastened to the main body using screws allowing for required maintenance. Below is a sectioned view of the final design.

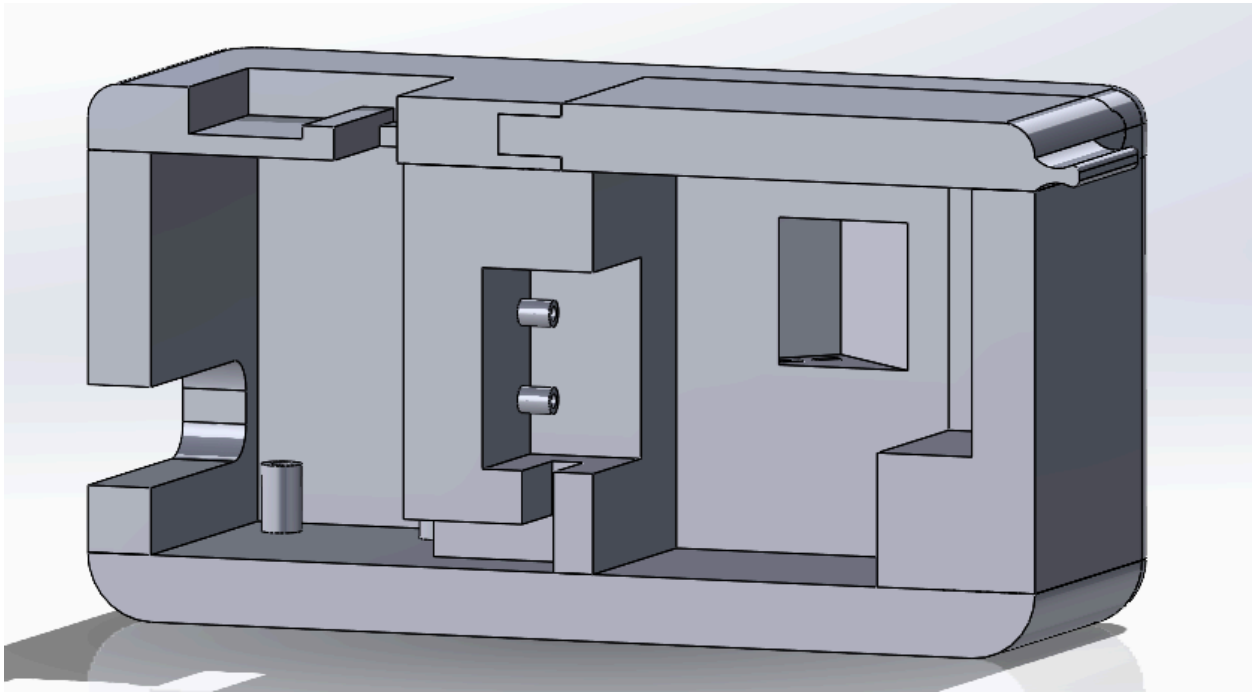

Figure 6: Final Lateral Flow Test Reader Design

6. Final Design Evaluation

6.1 Final Design Evaluation: Stage 1

To evaluate the first stage of our protocol, we need to evaluate both the machine learning model and the corresponding prediction of stress event duration. Firstly, the logistic regressor model chosen has the following predictive statistical markers:

Logistic Regressor Model	
Accuracy	94%
Precision	97%
Recall	96%
F1-Score	97%

The following figure is all model predictions graphed against the true test condition. As can be seen, the logistic regressor not only had the best statistical accuracy, but it also qualitatively predicted the stress event better than the other two models. The random forest classifier was an unsuitable predictor and the XGBoost classifier had an inconsistent positive prediction rate which reduced its viability as an input to the event stress duration calculation. This is because using a moving window calculation requires a relatively consistent positive prediction, otherwise the moving window would detect many small events rather than the true larger event.

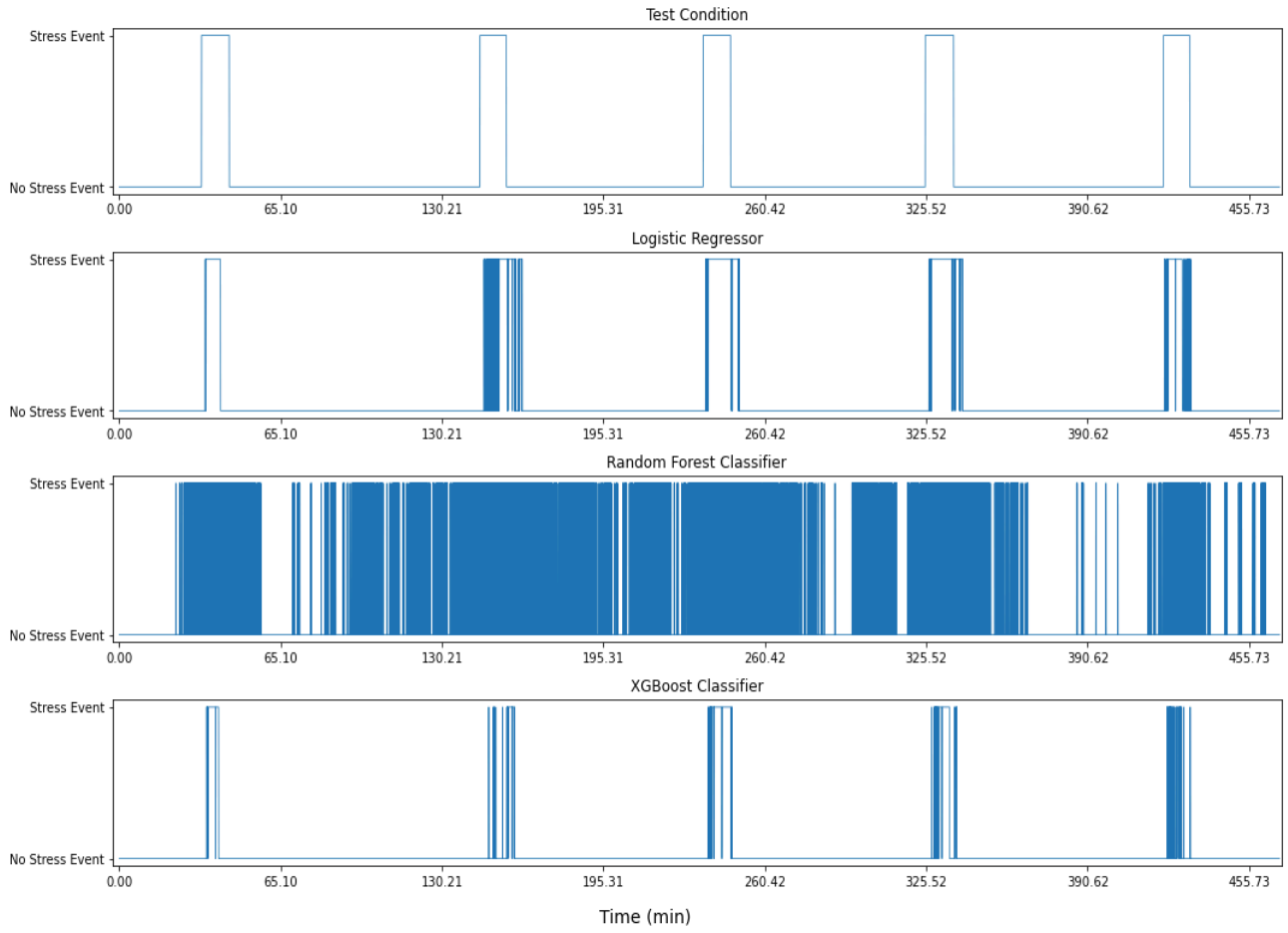

Figure 7: Predictive Model Results For all Users Not Included in Training Data (Test Data)

The following figure 8 shows the accuracy of the model's stress event duration calculation. As can be seen, the prevailing error of the model is to slightly over estimate the duration of the event. Comparing the test condition and the logistic regressor prediction in the above figure (Figure 6) it can be seen that the moving window algorithm correctly calculated the model's stress event. This leads to the conclusion that the small error predicted from the users data comes from the machine learning model, not the moving window algorithm. It is possible that the training data for the model was not absolutely perfect, as an example it is possible that the user was somehow aware that the stressful portion of the test was forthcoming and therefore their biological markers increased preemptively. Alternatively, it is also likely that the users biological markers did not return to baseline immediately after the stressful event, even after the true test condition goes back to a transient state. This is highly likely and would explain why the model over-estimated the event duration length and can be accepted as a valid prediction in spite

of the test data provided. Also, observing Figure 6 it can be seen that in most cases the model correctly predicted the start of a stressful event but not the end, this further supports this claim.

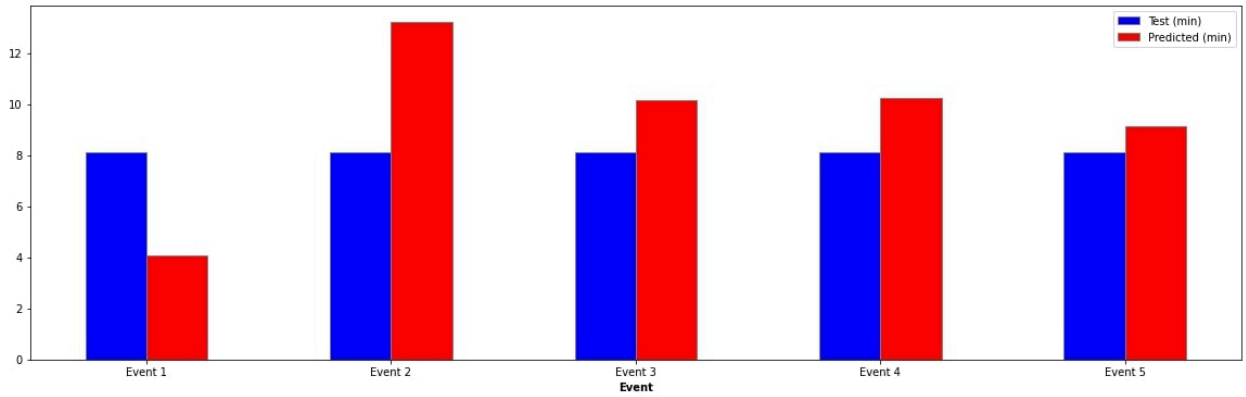

Figure 8: Stress Event Duration Predictions and True Values

6.2 Final Design Evaluation: Stage 2

The performance of the portable LFT readers is simple to evaluate. It assesses the cortisol level associated with a lateral flow test. After testing each lateral flow test value ten times, our portable LFT reader got the following results:

Test Strip		0	1	2	3	4	5	6
(ug/dL)		0	0.012	0.037	0.111	0.333	1	3
Test	1	0	0.012	0.037	0.111	0.333	1	3
	2	0	0.012	0.037	0.111	0.333	1	3
	3	0	0.012	0.037	0.111	0.333	1	3
	4	0	0.012	0.037	0.111	0.333	1	3
	5	0	0.012	0.037	0.111	0.333	1	3
	6	0	0.012	0.037	0.111	0.333	1	3
	7	0	0.012	0.037	0.111	0.333	1	3
	8	0	0.012	0.037	0.111	0.333	1	3
	9	0	0.012	0.037	0.111	0.333	1	3
	10	0	0.012	0.037	0.111	0.333	1	3

Figure 9: Portable LFT Reader Results

As can be seen above, the portable LFT reader was 100% accurate in assessing the lateral flow test value. The accuracy achieved can be attributed to the consistent imaging environment in the portable LFT reader. The box is enclosed so the only source of light comes from the LEDs. Inside of the box there is a shelf to place the lateral flow test on that guarantees it is in the same location for every test, and the camera is securely oriented in the same position for every test. Also, there is enough light provided by the LEDs to accommodate wide light sensitivity parameters in the test assessment code. This means that slight deviations from the expected values will still be categorized correctly by the software.

7. Conclusion

The development of a stress mitigation protocol is crucial to monitor the physical and mental health of first responders. Our suggested three step strategy could be implemented to detect and mitigate high stress events. Elevated levels of stress for prolonged periods of time have been shown to cause negative long term effects. The first step in mitigation is to identify prolonged stress events which our machine learning algorithm is able to successfully detect using data sampled from the Empatica watch. If an event is detected it is suggested that the user take the lateral flow cortisol test. After taking the test, the LFT reader can precisely identify the level of cortisol in the salivary sample and quantify the data to be collected and stored. The development of the stage 3 app, would allow the individual to track and store their data. From the collected data we would be able to determine the stress profile of an individual and suggest options for treatment from health care professionals. Our LFT reader is a portable and cost efficient solution to cortisol testing in the field, which eliminates the barriers caused by existing solutions. The goal is that the implementation of a system like this will increase the health and well-being of first responders leading to a decrease in PTSD and depression.

8. References

About UBC. (n.d.). The University of British Columbia. https://www.ubc.ca/about/ Helios Global Technologies - Survivability Tech. (n.d.). https://heliosglobaltech.com/

Barney, C. E., & Elias, S. M. (2010). Flex-time as a moderator of the job stress-work motivation relationship: A three nation investigation. Personnel Review, 39(4), 487-502. https://doi.org/10.1108/00483481011045434

Bryson, L., Warner-Smith, P., Brown, P., & Fray, L. (2007). Managing the work–life roller-coaster: Private stress or public health issue? Social Science & Medicine (1982), 65(6), 1142-1153. https://doi.org/10.1016/j.socscimed.2007.04.027

Burchell, B., Miller, J., Brewin, C., Soffia, M., & Wang, S. (2023). The association between job quality and the incidence of PTSD amongst police personnel. Policing : A Journal of Policy and Practice, 17. https://doi.org/10.1093/police/paac054

Craddock, T. B., & Telesco, G. (2021). Police stress and deleterious outcomes: Efforts towards Improving Police Mental Health. *Journal of Police and Criminal Psychology*, *37*(1), 173–182. https://doi.org/10.1007/s11896-021-09488-1

Fries, E., Dettenborn, L., & Kirschbaum, C. (2009). The cortisol awakening response (CAR): facts and future directions. *International journal of Psychophysiology*, *72*(1), 67-73.

Gedam, S., & Paul, S. (2021). A review on mental stress detection using wearable sensors and machine learning techniques. *IEEE Access*, *9*, 84045-84066.

Gradl, S., Wirth, M., Richer, R., Rohleder, N., & Eskofier, B. M. (2019, May). An overview of the feasibility of permanent, real-time, unobtrusive stress measurement with current wearables. In *Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare* (pp. 360-365).

Haugen, P. T., Evces, M., & Weiss, D. S. (2012). Treating posttraumatic stress disorder in first responders: A systematic review. *Clinical Psychology Review*, *32*(5), 370–380. https://doi.org/10.1016/j.cpr.2012.04.001

Hellhammer, D. H., Wüst, S., & Kudielka, B. M. (2009). Salivary cortisol as a biomarker in stress research. *Psychoneuroendocrinology*, *34*(2), 163-171.

Hickey, B. A., Chalmers, T., Newton, P., Lin, C. T., Sibbritt, D., McLachlan, C. S., ... & Lal, S. (2021). Smart devices and wearable technologies to detect and monitor mental health conditions and stress: A systematic review. *Sensors*, *21*(10), 3461

Kinnamon, D., Ghanta, R., Lin, KC. *et al.* Portable biosensor for monitoring cortisol in low-volume perspired human sweat. *Sci Rep* **7**, 13312 (2017). https://doi.org/10.1038/s41598-017-13684-7

Koczula, K. M., & Gallotta, A. (2016). Lateral flow assays. *Essays in biochemistry*, *60*(1), 111-120.

Larzelere, M. M., & Jones, G. N. (2008). Stress and Health. *Primary Care: Clinics in Office Practice*, *35*(4), 839–856. https://doi.org/10.1016/j.pop.2008.07.011

Liu, Y., & Du, S. (2018). Psychological stress level detection based on electrodermal activity. *Behavioural Brain Research*, *341*, 50–53. https://doi.org/10.1016/j.bbr.2017.12.021

Schmidt, Philip, et al. "Introducing WESAD, a multimodal dataset for wearable stress and affect detection." *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, 2 Oct. 2018, https://doi.org/10.1145/3242969.3242985

Torrente-Rodríguez RM, Tu J, Yang Y, Min J, Wang M, Song Y, Yu Y, Xu C, Ye C, IsHak WW, Gao W. Investigation of cortisol dynamics in human sweat using a graphene-based wireless mHealth system. Matter. 2020 Apr 1;2(4):921-937. doi: 10.1016/j.matt.2020.01.021. Epub 2020 Feb 26. PMID: 32266329; PMCID: PMC7138219.

Yehuda, R., McFarlane, A., & Shalev, A. (1998). Predicting the development of posttraumatic stress disorder from the acute response to a traumatic event. *Biological Psychiatry*, *44*(12), 1305–1313. https://doi.org/10.1016/s0006-3223(98)00276-5

ZRT Laboratory. (2019). *Diurnal cortisol curves*. ZRT Laboratory. https://www.zrtlab.com/landing-pages/diurnal-cortisol-curves/

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