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# SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

# Are You Stressed? Detecting the onset of stress using mobile phones

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# **Abstract**

**Dedication**

*I would like to thank the University of New South Wales as a whole with a special mention to Salil Kanhere. You have helped me on a week-by-week basis to help give me direction in what I aimed to achieve in this thesis. May this thesis also help you in future endeavours to find our solution.*

*Secondly, I would like to acknowledge the support that the Veerakumar family has given me for as long as I can remember, let alone with my thesis. Their efforts have furthered me to become a person more than I could have imagined, and I know I could not have written this without them.*

*To my partner of 7 years, Fiona De Silva, who has stuck by my side through thick and thin: your willing nature to help me through my feats is the reason I don’t come close to stressing so much, and I don’t know what tertiary education would have been like without you.*

*Most of all, I dedicate this thesis to all those whom are exposed to distress to unhealthy levels – let there be a solution not only to our problems, but to stress detection and prevention.*

*“It is only natural to stress in our life –the key is to not let it turn into distress.”*

*- HtM, 2014.*

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# 1. Introduction

A “stress response” can be defined as:

*“A physiological reaction caused by the perception of aversive or threatening situations”* [1]

Humanity’s problems can always be related to stress. If any one person is stressed, they experience “stress responses” – that is, they are feeling a consequence of some form of burden that has been placed upon them physically or mentally. Stress is inevitable in a person’s life, and the amount that people experience can only be minimized through the choices we make – simply because they do not enjoy the stresses that result from risky decisions as an example.

Nevertheless, no matter who you are, the human body can react badly to the stress which you experience: whether it is directly from the stressor, or the stress response. A common example to relate to is an elderly person suffering a heart attack due to an emotional stress. Whilst the stressor is not actually stressing the person through physical means, a physical stress response is still triggered – and a dangerous one at that. On a larger scale, it has been found that physiological responses have significant adverse long-term effects on our health when dealing with continuous stressors, as opposed to episodic stressors. [1]

Bearing this in mind, we have a strong reason to identify stress responses and assess the levels of stress we are experiencing at the point in time. In understanding what stress responses we experience, we can then act to minimise them. Currently, whilst there are technologies to determine significant stressors and stress responses in our lives, we cannot say it is to a point that it is readily accessible. Furthermore, people do not make conscious efforts to assess their stress, especially during their times of stress. If people were more aware of what stressors and stress responses were doing to them both mentally and physically, the problems that people experience would be reduced or eliminated. In particular, this would be most effective if people were made aware of dangerous physiological reactions at the time they are experiencing it.

For something as important as what has been discussed, and with the new and ever-changing technological world we live in, the issue can now start to be addressed effectively. There are current technologies that we use on a day-to-day basis that can have a further enhanced capability to detect stress responses and, essentially, assess levels of stress.

One particular technology that fits this category is a mobile smartphone (“phone”). Those who associate with current technology will be well aware that phones are capable of doing more than making a voice call. Phones have evolved from simply making vocal communication to messaging, and now have progressed to completely different user experiences and interactions with touch screens replacing buttons. What people are less aware of is the hardware that is contained within a standard phone. Phones are now equipped with hardware that provides us with more information than older phones. This allows applications to interact with the physical world we live in and, in particular, the user. The hardware can be utilised to interact with the user and gain information regarding the onset of stress through the user’s stress responses.

Hence, we have a probable solution to the problem. Our inability to analyse our stress levels to a certain degree of accuracy is a valid and significant problem. The knowledge we can gain from a valid solution can result in many benefits: a key benefit being a reduction in dangerous stress responses from conscious effort due to awareness. This path of research will further open up avenues to deal with stress. Ultimately, especially with further technological advancement, we will be able to minimise stress responses from a person, and the knowledge regarding our own stress responses is a good first step and foundation towards the solution.

This paper is a proposal for research into this problem a complementing solution that we can implement. We will explain the differences between the current state-of-the-art technologies, as well as slightly older applications that were considered the latest technology at the time. Such technologies go from current, all the way back to 2007. Here, we will be able to identify not only key differences between each of the application, but how these inspire ideas to the proposed solution. Furthermore, we will discuss a feasible timed structure to approach and implement the solution, which will include slowly integrating the solution into real-world applications.

# 2. Background

## 2.1 Literature Review

There are many attempts at implementations that can be noted both using and not using a mobile phone. Such successful implementations include “AutoSense” [2], “Sociophone” [3], “MoodScope” [4] and “Mood Meter” [5], as well as a methodology to remotely manage hypertension [6]. As seen here, a majority of successful implementations to address the larger problem uses external hardware to work with the mobile phone.

In studying these methodologies, we can identify accurate procedures used to determine the onset of stress. We can also note dangerous physiological reactions from these implementations, which address the big picture of a key benefit in identifying the onset of stress. On the other hand, with the restricting aspect of measuring stress using a specific means, there is a hole in the accuracy of these applications. It also does not cater for everybody’s personal reactions, but rather defines stress at a certain point and determines the onset of stress according to that definition.

### 2.1.1 Mobile-application solutions, and data collection methods

Measuring hypertension (high blood pressure) is an extremely important for stress management [1, 6]. Hypertension is a prime danger, and has a strong association to stress, hence being one of the leading significant stress responses. As a result, methods in [6] to remotely manage it can prove rather helpful as a key element of stress management as a whole. This particular application also specifically applies to concerns for diabetic patients, however is not restricted to that. Using a blood pressure monitor with an active Bluetooth connection, a mobile phone can interact with the hardware to process the data and send it to the respective physician(s). This particular application, however, does not use the mobile phone for direct methods of input – rather it takes care of everything else.

AutoSense ( [2] ) uses “an unobtrusively wearable wireless sensor suite that can collect continuous measurements” [2]. This external hardware communicates with a phone via an application to collect data regarding stress. The solution “focuses on physiological measures monitoring cardiovascular, respiratory, and thermoregulatory systems.” [2]. This allows detection of physiological reactions from the hardware, which is then sent to the phone through a low-frequency radio signal. An algorithm is used to collate the data and, ultimately, provide a judgement of stress.

In a similar manner, studies have been conducted to assess stress using other factors [7]. In particular, one application recognises stress using skin conductance, the production of cortisol and pupil diameter, whilst looking at the previously discussed heart rate and blood pressure variables. A binary classification algorithm was used to further increase accuracy – in particular, a linear Support Vector Machine (SVM). Furthermore, in the production, data was also collected manually to detect stress. This produced accurate results, however we must bear in mind it is different to other applications as it uses external hardware.

Sociophone ( [3] ) is an application which monitors face-to-face conversations at the core to investigate social interaction. It is classified as an “interaction-aware application” [3]. Whilst the focus is not around stress, human interaction often leads to the revealing of other stress responses in the event the person is stressed [1, 3]. The symptoms of different characteristics that the application checks for are also similar to those that can be analysed to detect the onset of stress, namely: “sound signals, online turn segmentation[[1]](#footnote-1) and meta linguistic feature extraction[[2]](#footnote-2)” [3].

MoodScope ( [4] ) is a sensor that measures the mental state of a user that does not use physical properties. Rather, the aim of the project is to detect the mood of a user to provide a context as an input for other applications which, in turn, enables “context-aware computing” [4] – something that is highly important in creating a successful application, since it allows the application to act dynamically and enhance human-computer interaction, as opposed to acting statically [8]. MoodScope does not use physiological signals as most do, but rather uses the activity a user has with their phone to determine what mood they are in. MoodScope further uses customised data sets for each user to gradually improve the accuracy of the application for each user. Whilst it starts off inaccurate, it uses a 2-month training period to increase the accuracy of the application in its inferences, raising the accuracy from 66% to 93%, when analysing 32 participants [4]

MyWalk [9] is a mobile application that, rather than being based around stress in particular, was developed to help reduce gait asymmetry. Gait asymmetry involves physiological reactions to cause abnormal movements of the human body and limbs, and is very common in the event of a stroke. This is particularly useful to this project for us to understand how sensors are used to detect changes in movement as someone walks. Using the accelerometer, the application was able to determine how the person walks, and measure to what degree they were able to walk “normally” - that is, in a straight line, as per the instructions provided. Making use of all three axes of motion and space, the degrees of asymmetry were calculated on average and the variance between each sampled value could be used to assess recovery progress.

Data collection techniques involving speech were also studied, as this is a key factor that is proportional to the mood of a person. The product, AMMON [10], is a library used to detect stress through speech in mobile phone applications specifically. It was developed in C, and tested on a number of subjects. This is partially inspired by a previous project, SoundSense [11]. It uses a linear SVM to predict the nature of the mental health. However, it is completely supervised learning, and so was done completely offline with all data included in the library. Ultimately, the outcome was a success, as it achieved its aim in being as accurate as state-of-the-art technology for the same purpose on a PC.

We can draw a number of parallels between each of the applications, whilst also noting key differences in achieving certain elements of our common goal. We can see in [2], [3], [4] and [6], phones are used for the collecting and processing of data to generate information regarding human interaction. In particular, [2], [3] and [6] collect physiological information, with [2] and [3] specifically using this to calculate one’s mood, which we can directly infer one’s level of stress. [6], on the other hand, collects physiological data to specifically respond to a dangerous, and very key, stress response. [4] does not utilise physiological reactions, yet still manages to detect stress through other interesting means. [5] is very different, since it uses other technologies to collect useful data, analyse the data and produce results based off one parameter to scale what mood the person is in.

The methodology used in [2] and [3] are one of the most advanced, despite [2] being a relatively older use of phone applications for this purpose. In [2], the hardware itself is very intricate – it has the capacity to collate many parameters within a very small device that is “comfortable to wear for long hours in the field” [2]. However, we can agree that not having hardware attached to us is, in itself, a superior advantage. [3] further inspires the idea of collecting data using the phone’s hardware, which is, of course, a much more comfortable option for the user. It also results in the user being much less conscious of the analysis, since the phone simply runs in the background and causes less disruption with the user’s activities whilst collecting and analysing data.

As such, [3] inspires the idea of utilising the phone’s hardware. We can note that the physiological reactions sensed in [2] can now be sensed using current mobile phone technology. There are methods to calculate one’s heart rate, such as in the application “Stress Check” [12]. This application uses the phone’s camera and flashlight to detect one’s heart rate. We can detect respiratory function using the phone’s inbuilt accelerometer to detect a rate of displacement on one’s lung area, hence allowing us to accurately calculate changes in volume of air within one’s lungs [13]. [2] also detects skin temperature, which can be found using the phone’s thermometer. All these inbuilt hardware render the external hardware used by [2] as redundant. The advantage that the external hardware offers, however, is that people still claim accuracy, however [2], despite using dated technology, still determines one of the highest accuracies out of all the solutions. This can be attributed to many factors, with the inaccurate nature of using the internal hardware of a phone being one of them.

Whilst both [2] and [3] uses static information for its inferences, [2] has a 90% accuracy rate for 20+ participants, and [3] has an overall accuracy of 60%, with variations of ±5% due to different phones. A phone’s internal hardware can cause inaccuracies specifically due to its physical placement upon collecting of data, as well as the design of the hardware itself. [2] conveniently places the hardware on the person’s chest. Whilst this is possible to achieve using internal hardware, it is highly inconvenient for one to place their phone on their chest – this would take the element of convenience by using a mobile phone’s internal hardware to create less interference with their daily activity. [3] only uses the common camera and microphone hardware in a phone. Depending on where it is positioned, it can be used conveniently for analysis. However, at the same time, there is a degree of inaccuracy, depending on at what distance the phone is placed at during its inaccuracies. Whilst the hardware is of relatively good quality, it is found that dedicated hardware to these purposes are still of better quality.

One significant advantage that each of the solutions offer is the use multiple parameters to determine its results. These use algorithms that can weigh the importance of each of the parameters and make a decision from there. This is highly advantageous, as it allows us to hone in on the specific reasoning behind the physiological reactions. We must remember that physiological reactions can apply to more than one type of response [1]. The use of multiple parameters offers a distinguished combination of symptoms which can be more accurately associated with stress. However one disadvantage of these applications is that these are static algorithms that do not account for differences in human nature from user to user. These algorithms can be improved so as to cater for users more accurately.

[4] has a contrasting aspect to its ability to cater for multiple users. It uses aspects of machine learning over a period of time to increase the accuracy of the application. Using only static inferences, the application offers a very low accuracy (66%), whilst post-training, the application was able to provide an accuracy of 93% to the two users [4]. This is a highly significant change attributed solely to concepts of machine learning, and hence a large factor to consider in achieving our own personal goal. The application actually uses less reliable methods of detecting moods than as per previously mentioned, but achieves the same degree of accuracy as those applications.

The application uses a supervised learning algorithm referred to as Sequential Forward Selection (SFS). SFS involves machine learning via regression. Unknown data inputs estimate and produce an inference using regression techniques. The algorithm is used hand-in-hand with a personalised data model to create an even more accurate data model on a case-by-case basis. Whilst the personalised data model can be used by itself to create inferences, it also involves a much longer time-frame for the model to reach its potential. This issue is solved by complementing with the SFS algorithm, which acts as a “one-size-fits-all” model to give the application a starting idea of how to process the information, as opposed to developing it from scratch [4]. The following graph gives us the best idea of how the application evolves over the 60-day learning period.

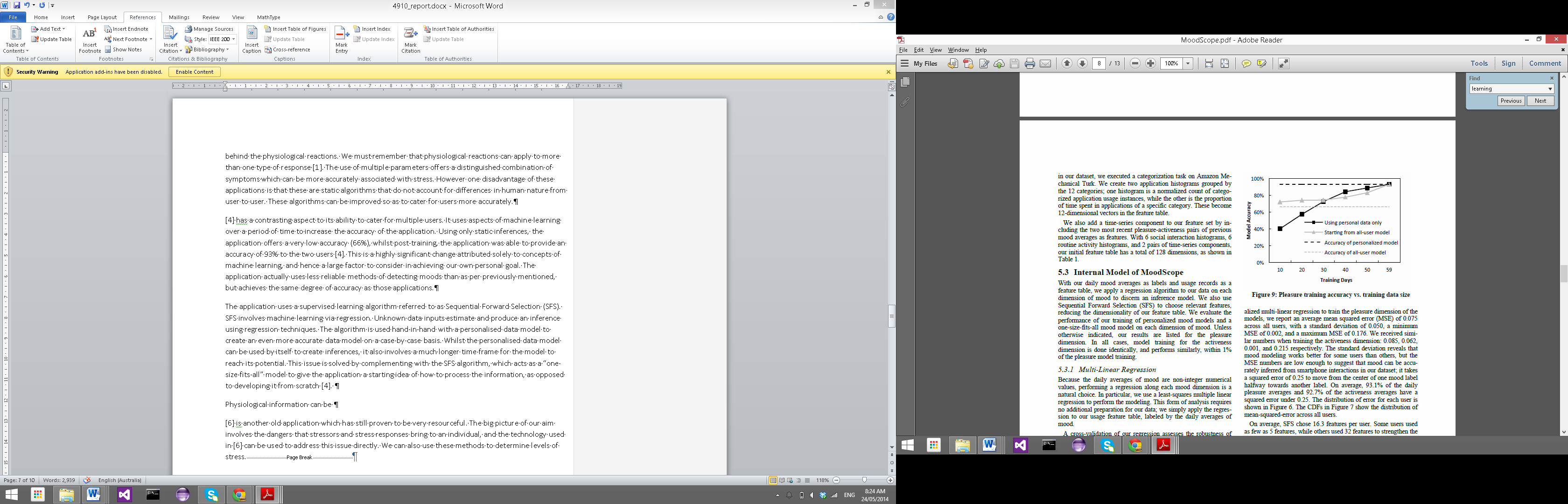


Figure 1 – Improvement in accuracy over a 60-day period due to machine learning

The initial concept of how to detect mood, however, is not as superior for the purposes of detecting stress. The application is not reliant on physiological stress responses, but rather stress responses based on direct phone activity. This, of course, leads to a low degree of accuracy; as such activity widely differs from person to person, with very little overlap of common activities for all potential users. This is let alone how people’s activities vary upon the onset of stress. We can directly conclude this from [1, 14, 15].

As such, the main aspect of the application to take as inspiration is the concept of supervised machine learning to create an accurate model. Whilst the methods of collecting data are respectable, other applications have more accurate results from methods of collecting physiological data to detect the onset of stress.

[6] is another old application which has still proven to be very resourceful. The big picture of our aim involves the dangers that stressors and stress responses bring to an individual, and the technology used in [6] can be used to address this issue directly. We can also use these methods to determine levels of stress. This methodology still uses external hardware to obtain the raw data regarding blood pressure. However, the application is used for the processing of this data, after it is received from the external hardware. The information is then sent to a central server for notification using mobile technology.

The application uses one of the most direct symptoms of stress responses possible, however is currently not very feasible to achieve only using a phone’s hardware. Whilst there have been developments, such as the enterprise iHealth Wireless Blood Pressure Wrist Monitor [16], none have progressed past the stage being restricted to using external hardware to determine this parameter accurately. As such, it is currently infeasible to achieve our goal until the necessary hardware is incorporated into mobile phones.

The application, however, inspires the idea of further refinement of the application, by sending the data to relevant places. Being a problem that has only been brought to attention as of recent, we do not have much data that is collated and sourced from using such means. This application, however, takes this data. Hence, this solution proves useful for the collection of data, as well as the benefits of alerting the appropriate people, for monitoring purposes, in a non-invasive manner.

Whilst not all projects studied used machine learning techniques, it is still important to recognise the importance of it in the research and projects thus far. Another namely example we can look at shows how the different methods of machine learning act to give varying accuracies of results [7]. This was especially important in ensuring the accuracy of the product in determining stress from a multitude of different symptoms. They implemented three models, using various techniques including the use of the linear SVM. Each model used machine learning, but varied between levels of supervised and unsupervised learning.

Machine learning is particularly helpful in determining use-cases that are tailored to the user – especially if unsupervised or semi-supervised learning is allowed. In this case, semi-supervised learning is used to develop their model. Their “supervised adaptation” involves “a user explicitly contributes labelled data for adaptation” whereas the “unsupervised adaptation”, i.e. self-training, involves “leverages self-train technique by utilizing unlabeled data”. What we see when we compare two of their models, where one was universal (fully supervised) and the other was personalised (fully unsupervised), was that the personalised one was the most accurate model, whereas the universal one was the least accurate. As an example, for an outdoor environment, the models achieved accuracies of 77.9% and 66.6% respectively. We also note that the variance of the results for the supervised learning is much higher, as seen in the diagram below.

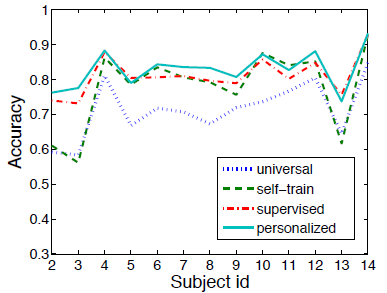


Figure 2 – Varying accuracies dependent on level of supervision in StressSense

Thus, we cannot reject the notion of unsupervised learning completely. Whilst it is very risky to use [17], it also produces the most correct results [7]. The risks involved are if:

* Algorithms are implemented correctly, and
* if the users use the application correctly, and do not feed it bogus data – be it intentional or unintentional

The second point is the most important regarding the risks regarding machine learning, and is one we shall consider later in this paper.\*\*\*TODO – where is it addressed?\*\*\*

### 2.1.2 Non-mobile-application solutions, and data collection methods

There are many applications that do not include using a mobile phone that are used to detect stress – most of which are as effective, if not more than current state-of-the-art technologies using a mobile phone. Good examples to illustrate this are as per below.

Mood Meter [7] was not a mobile-phone based application, but still uses technology that mobile phones are currently able to use today. A camera is used to detect people’s “smiles”, and rate them on a scale according to the “Shore framework” [9] – a geometric algorithm that detects a smile, and its intensity, with a high degree of accuracy even from a distance [7]. The data is then processed and sent to a central server for collating and further processing.

The use of a heart rate monitor to detect stress is a particularly useful one, with one of the main symptoms of stress being an increase in heart rate. We must note that the type of stress detected is of all kinds, and even beyond the scope of research. However, we must appreciate the advantages offered before us. One particular application involves sensors of minimal obstruction [18]. The sensors are used to collect data regarding a variable heart rate over time. This is statistically analysed to determine changes in stress levels.

Similarly, blood pressure can also be analysed using a blood pressure cuff. This, complemented with changes in heart rate, gives us ample information, as seen before. Experiments involving these signals, as well as changes in eye activity have been done in [19]. Through the watching of films, stresses were incited. From here, the changes from the person's different states were matched up with the bodily activity of the person. The data underwent statistical analysis, and machine learning algorithms were applied to determine stress. These, once again, produced meaningful results.

Cardio-respiratory systems are most evident in continual physical stress in particular, such as physical shocks from running, or simply having a bucket of ice poured over your body. However, experiments have been done to observe symptoms due to mental stress [20]. As a result, experiments have been done so as to analyse oscillations not only in heart rate variability, but also in breathing patterns and sweating. This is performed in a similar manner to that as of above, and has produced significant results that are actually positive.

Ideally, the developed solution would involve remote data collection. Frameworks have been produced to detect heart rates remotely i.e. without physical contact. This is done through a number of physiological reactions associated with the heart rate, such as reading the human face (an extremity of the body) using thermal infrared imaging [21]. This produced significant results that actually determined changes between stress and a lack thereof.

We must note that the extremity of the human body is a particularly good source of detecting changes in heart rate. This is due to the nature at which blood collects and empties at this particular point. Whilst the human body extremities also include smaller features such as toes and fingers, the face is an optimal place to analyse blood flushes. Most blood rushes to this extremity due to the size of the head in comparison to other extremities. Thus, this produces the largest changes in visual flush as well as temperature due to blood flushes. We must also remember that the rate of flushes in and out of the extremity is directly proportional to one’s pulse i.e. their heart rate. Thus, thermal imaging, which can detect small changes in colour due to blood flushing [21], namely, can be used effectively to detect the nature of one’s heart rate.

We have seen good methodologies to look into regarding what to look out for with stress. Throughout all papers, we notice one of the ways of detecting a stress symptom is via detecting heart rate volatility (HRV) [18, 19, 20, 21], with each research paper deeming different importance on it. As aforementioned, this is extremely important due to the strong correlation between one’s heart rate and their emotional state i.e. their stress levels. In particular, those that used HRV to detect stress levels ended up with a very positive result that showed strong significance.

In one particular instance, machine learning is still used. We have mentioned the advantages of machine learning previously. In the case of [19], universal optimised search algorithms were used in their SVM and artificial neural networks (ANNs). All test subjects used were between the age of 18 and 30. What we noticed is the machine learning algorithm used was not significant enough of a factor to change the accuracy. The more significant case involved method of detection. Methods involving detections in physical reactions labelled as “primary stress signals” returned an accuracy of 95%. However, when using electroencephalography (EEG) to detect physiological changes, the accuracy was determined to be 91%. With all factors deemed constant, we see that physical symptoms are, indeed, very powerful in determining stress.

We also note that in this experiment, the heart rate was not a key determining factor as a data source. This was a very intricate set up with a large amount of excessive equipment, since it was to simulate a virtual environment. A lot of data samples were taken from various sources, allowing the increased accuracy without the high dependence on HRV – something that is not common.

In the other three cases, we use a less complex form of machine learning and less equipment than the previous example. We notice that despite the complexity of algorithms, we end up with a lower accuracy. One example is a 83% accuracy when still detecting heart condition, muscle tension and respiration [18]. This used a non-linear Volterra series to establish stress levels[[3]](#footnote-3). In the same way that the charge of a battery deteriorates over time, we note that the heart signals observed over time from the heart monitor has varying importance. This procedure of detecting stress, in particular, places a higher importance on HRV than the other factors. Therefore, we can appreciate machine learning as an important factor, as well as the other factors that determine stress that are not weighted as importantly.

Speech was the second most prominent factor in these determinations. Namely, in non-mobile-phone applications, we notice its use in [19] as a very good example. However, this uses an undiscussed hardware – ECG and GSRs. These are highly accurate pieces of equipment that can be used to detect one’s conductivity of the skin. This has a strong correlation with sweating, a symptom of stress. This is due to the high electrolyte content of sweat – hence dry skin has a much higher resistance than wet skin. The difference is significant enough to detect a change in.

Again, we’ve noted the accuracy it’s produced, and can attribute a part of that to the many factors that it takes into account. We must still consider the importance of the use of the SVM to create further accuracy, as well as the detection via eye-ball – something that no other relevant paper has considered and produced a strong accuracy.

\*\*\*make mention of all speech pathology described, what kind of accuracy it gives, and how they obtained this data. Was machine learning used?\*\*\*

Overall, the accuracies determined throughout these experiments have a much higher accuracy than that of those described in section 2.1.1 – up to 95%, versus a maximum of 83%. What these procedures don’t have that those did are the restrictions that a mobile phone system uses. In particular, we must note that specialised external hardware provides a significant advantage in accuracy over those of a mobile phone.

### 2.1.3 Research regarding stress factors generally

There are a number of articles that describe the changes in emotions and stress due to various factors. A few different cases were analysed for the sake of diversity and a better understanding of the problem and potential solutions at hand. These were also assessed for relevancy in applying to our proposed methodology.

One particular study involves the changes of the human emotional state based on social media patterns, and resulted in the development of “Moon Phrases” [22]. This is increasingly relevant in this current time, considering the amount that social media is used. One of the key factors that can be used to detect emotional disturbances is changes in linguistics. In particular, people express their emotions through Facebook, Twitter, etc. when interacting with friends or strangers. Initially, 6 subjects had their social media use analysed with feedback as to their current mood at the time. From here, a framework was developed which isolated linguistic factors to determine the mood in which a person was in based on their activity. Whilst it has not achieved its aim in acting as an intervention mechanism, it has still progressed towards it through accurate identification of emotional wellbeing and has the potential to have a positive impact on reducing negative behaviour of heavy social media users.

Whilst our main focus has been on physiological and physical reactions thus far, there are also deeper biological reactions to stress as well that can be analysed. It has been reported that prominent stressors that cause this include general stress, heat shock, cold shock, cytoplasmic stress, and starvation. The experiment involved the extraction of the biosensor (a trigger for our biological stress responses) and seeing under what conditions they survive. A study of this was conducted successfully [23]

In terms of capabilities, phones are not equipped with all the hardware required for the analysis which we require currently. One example is obtaining biological data to help determine stress levels [23]. For this reason, one disadvantage of the use of a mobile phone is that it is more probable that we achieve a better accuracy in all cases with other hardware.

## 2.2 Conclusions and Aim

Detecting the onset of stress using a mobile phone involves capitalising on stress responses from the user, measuring their intensity and making a judgement. As mentioned before, we are in need of a method of stress detection that acts dynamically, and responds to stress immediately as opposed to only upon user request.

A key thing that defines people as different is what we respond to in a stressful manner, and what the physiological and mental reactions are. With the many different personalities everyone has, there are many responses. However, there are stress responses people experience are involuntary, and common amongst the majority of people. Hence, stress responses, which are a unique combination of physiological reactions, can be detected and identified strictly as stress. We are, of course, familiar with common stress responses. Whilst there is a large variety, examples of some common symptoms [1, 24, 14] include:

* Changes in vocal pitch and amplitude
* Pacing up and down a certain distance
* Increased heart rate
* Perspiration via palms
* Increased blood pressure
* Brain damage – specifically learning and memory
* Weakened immune system, and associated nervous system

Current methodologies that are successful account for specific symptoms. The aim of the next part of the chapter is to explain the current solutions to the problem at hand, what they offer for the detecting the onset of stress, and what each of the latest resolutions are lacking from the perfect solution.

# 3. Proposal

## 3.1 Deductions

The aim of this chapter is to show a plan of how to fill the voids of the problem through other means. We have discussed where the current applications and solutions stand, and so from here we can utilise the benefits to fulfil the ultimate objective. We can combine these benefits, with slight additions, to form a long-term project. The current goal is to lay down a strong framework that can be built upon for future generations of research. The overall goal is to minimise stress responses and the dangers associated with stressors and stress responses.

From our previous analysis, we can deduce requirements of the following:

* We are in need of a system that detects the onset of stress in a convenient manner
* A mobile phone has been deemed the most appropriate equipment. It is portable, and allows easier detection of the onset of stress with less conscious effort. Mobile phones are also equipped with a lot of helpful hardware, and are equipped with more as time passes due to technological advancement. Due to the capabilities of a mobile phone, we will eliminate the need for external hardware, as most are used to detect stress responses are now integrated into the latest phones.
* Machine learning algorithms are a key part of the project, in order to ensure accuracy for all users – there is no one size fits all, and there is always room for improvement due to the varying nature of stress responses from different users.
* Mobile phones also have abilities to communicate, not only with the user, but globally by utilising data connections such as Wi-Fi and mobile data networks. Hence, we will require a form of persistence to collect data that can easily be sent by users of the application. This data can assist with the machine learning process and, combined with the initial data provided, allows a unique form of semi-supervised learning that has not been used in any state-of-the-art applications to date

As explained before, a person experiencing stress responses is not necessarily acting rationally. We require a solution that will collect our data through natural means. This include when the phone is on standby next to us or in our pocket, when we are using our phone for remote video or vocal communication, or simply through interactions when using other applications such as games, the Internet, video viewing, etc.

A mobile phone is a convenient gadget to use, with over two thirds of Australians owning a smart phone [25]. In particular, we will initially target specific stress responses and expand on these further. Stress responses to analyse include heart rate, vocal communication, and use of sweaty palms and a person’s rate of pacing. Each of these has been determined as a stress response by [1, 26, 24]. It is a unique combination of physiological activity that is most often related to mental stress. These are also feasible symptoms to measure using the latest mobile phone technology. The associated hardware with each of these responses is the camera and flash, microphone, hygrometer[[4]](#footnote-4) and accelerometer respectively. With technological advancement and time, the project will be able to expand further and detect other stress responses, such as detecting blood pressure using only the phone’s internal hardware.

Concepts of machine learning are sure to be adopted to increase accuracy. Initially, the application prototype will consider binary classification of experiencing an onset of stress or not. Future developments will involve a non-binary classification of how much stress is experienced by the user, on a scale involving more than two options. In considering binary classification, we will start with a simple Bayesian model, and change the model according to what results we start to obtain, as well as what algorithm will be used. The model could be SFS, as mentioned in [4], or random forest decision tree, as discussed in [17]. The application will also be fed test data, to provide a supervised environment which the application can learn around using the appropriate algorithms. This will ensure a more acceptable degree of accuracy, whilst improving to perfection over time. As we will discuss next, we will actually adopt semi-supervised learning techniques to ensure efficient learning processes with maximal accuracy.

We are also well aware of the communication abilities that a phone has. Being able to send data globally allows global users to send their data regarding physiological stress signals, as well as whether the determined result was correct or not. We can thus use the concept of a persistence model to collate useful data sourced solely from a mobile phone, and use this in future research. Furthermore, whilst the initial process of supervised machine learning involves having a set of test-data, we can also collect more initial data for future users by collecting from the current application users themselves. In having more data, we are adopting a semi-supervised learning process [17] - we are using data that is sent without interference from the developer. Whilst we run the risk of false data being sent for use, the risk of corrupted test data is minimised using the original test data, and giving it more weighting when used in modelling.

Thus, upon research, we have determined a seemingly perfect solution that has not been exercised yet. A proof of concept has been partially developed, where we are testing the hardware and the degrees of accuracy to which the hardware hold true.

With the progression that stands as is, as well as a partial proof of concept that has been developed, we now have the following to consider over our time period of Tuesday May 27th 2014 – Friday 3rd October 2014, which is described in Figures 2 and 3.



Figure 3 – Planning until preliminary demonstration



Figure 4 – GANTT chart representation of plan

## 3.2 Breakdown

The aim of this section is to justify the necessity for the breakdown of our project.

A proof of concept is especially important in research, as this will give a true assessment of what we can do with mobile phone technology for the purpose of the project. Categorically, we can break the assessment of each of the hardware into determining the accuracy, and how functional it is for the purpose. Whilst we are aware of how the hardware can be used theoretically. However, the investigation in the allocated time period will give a true assessment of how it can act functionally.

The hardware of a phone can be used for many purposes. We must consider how to use the each hardware's API works towards the final goal. In some cases, we have left minimal time, as the algorithms required to collect relevant data are not complex. However in other cases, namely the camera as a prime example, require more complex algorithms, since we must detect dynamic changes in a hardware which we do not normally consider. The camera’s functional purpose is to capture images for storage. However, we are using the camera to simply analyse each capture and take relevant data dynamically. For such purposes, we have allocated more time.

We then finalise the functionality assessment using a statistical analysis of collected data when using the hardware for the specific purpose. This data is not only used for a furthered proof of concept, but as an initial set of test data to help build our initial starting algorithm, as per our semi-supervised learning process.

From here, we can create our stress-detection algorithm using certain regression techniques, and potentially implementing machine learning concepts – in particular, the Bayesian model for binary classification. Considering we are using a small sample of data at this point for testing purposes, we do not expect the model to be completely accurate. We also do not intend on implementing unsupervised learning at this point.

The testing process is a supervised method of collecting further data to assess how effective the application works. This will be used in our evaluation process when assessing the effectiveness of the application without implementing unsupervised machine learning processes. This data will also be used as raw data to help assist with the supervised learning process.

The new data is summarised, and from here the algorithms can further be refined. Hence, an efficient machine learning process is integrated into the system. Once this is complete, the application is ready to be used. The application is packaged, with the collated data incorporated for supervised learning purposes.

We then re-collect the data through having a final testing session with the same sources, as well as other people. This will end our collection of data for evaluation, and the information will be summarised.

# 4. Bibliography

|  |  |
| --- | --- |
| [1] | N. R. Carlson, Physiology of Behavior, Amherst, USA: Pearson, 2007. |
| [2] | E. Ertin, N. Stohs, S. Kumar, A. Raij, M. al'Absi and S. Shah, “AutoSense: Unobtrusively Wearable Sensor Suite for Inferring the Onset, Causality, and Consequences of Stress in the Field Onset, Causality, and Consequences of Stress in the Field,” SenSys, Seattle, WA, USA, 2011. |
| [3] | Y. Lee, C. Min, C. Hwang, J. Kee, I. Hwang, Y. Ju, C. Yoo, M. Moon, U. Lee and J. Song, “SocioPhone: Everyday Face-to-Face Interaction Monitoring Platform Using Multi-Phone Sensor Fusion,” MobiSys, Taipei, Taiwan, 2013. |
| [4] | R. LiKamWa, Y. Liu, N. D. Lane and L. Zhong, “MoodScope: Building a Mood Sensor from Smartphone Usage Patterns,” MobiSys, Beijing, China, 2013. |
| [5] | J. Hernandez, W. Drevo, R. W. Picard and M. E. Hoque, “Mood Meter: Counting Smiles in the Wild,” UbiComp, Cambridge, MA, USA, 2012. |
| [6] | A. G. Logan, W. J. McIsaac, A. Tisler, M. J. Irvine, A. Saunders, A. Dunai, C. A. Rizo, D. S. Feig, M. Hamill, M. Trudel and J. A. Cafazzo, “Mobile Phone–Based Remote Patient Monitoring System for Management of Hypertension in Diabetic Patients,” *American Journal of Hypertension, Ltd,* vol. 2007, no. 20, p. 7, 2007. |
| [7] | H. Lu, M. Rabbi, G. T. Chittaranjan, D. Frauendorfer, M. S. Mast, A. T. Campbell, D. Gatica-Perez and T. Choudhury, “StressSense: Detecting Stress in Unconstrained Acoustic Environments using Smartphones,” UbiComp, Pittsburgh, USA, 2012. |
| [8] | A. K. Dey and G. D. Abowd, “Context-Awareness, Towards a Better Understanding of Context and Context Awareness,” Graphics, Visualization and Usability Center and College of Computing, Georgia Institute of Technology, Atlanta, GA, USA, 1999. |
| [9] | T.-V. How, J. Chee, E. Wan and A. Mihailidis, “MyWalk: A Mobile App for Gait Asymmetry Rehabilitation in the Community,” University of Toronto, Toronto, Canada, 2013. |
| [10] | K.-h. Chang, D. Fisher and J. Canny, “AMMON: A Speech Analysis Library for Analyzing Affect, Stress, and Mental Health on Mobile Phones,” University of California at Berkeley, Berkley, CA, USA, 2011. |
| [11] | H. Lu, W. Pan, N. D. Lane, T. Choudhury and A. T. Campbell, “SoundSense: scalable sound sensing for people-centric applications on mobile phones,” ACM, New York, 2009. |
| [12] | Azumio, “Stress Check | Azumio,” Azumio, 2012. [Online]. Available: http://www.azumio.com/apps/stress-check/. [Accessed 3 April 2014]. |
| [13] | V. Chandrasekeran, “Measuring Vital Signs Using Smart Phones,” University of North Texas, Denton, TX, USA, 2010. |
| [14] | R. Segal, M. Smith and J. Segal, “Stress Symptoms, Signs &Causes: Effects of Stress Overload,” HelpGuide.org, May 2014. [Online]. Available: http://www.helpguide.org/mental/stress\_signs.htm. [Accessed 12 May 2014]. |
| [15] | American Psychology Association, “Stress The different kinds of stress,” 2014. [Online]. Available: http://www.apa.org/helpcenter/stress-kinds.aspx. [Accessed 20 May 2014]. |
| [16] | iHealth, “iHealth Wireless Blood Pressure Wrist Monitor Mobile Health Products,” iHealth, 2012. [Online]. Available: http://www.ihealthlabs.com/wireless-blood-pressure-monitor-feature\_32.htm. [Accessed 23 May 2014]. |
| [17] | P. Flach, Machine Learning: The Art and Science of Algorithms that Make Sense of Data, Cambridge, CB2 8RU, UK: MPG Books Group, 2012. |
| [18] | J. Choi and R. Gutierrez-Osuna, “Using Heart Rate Monitors to Detect Mental Stress,” Texas A&M University, Texas, 2009. |
| [19] | N. Sharma and T. Gedeon, “Modeling Stress Recognition in Typical Virtual Environments,” Australian National University, Canberra, Australia, 2013. |
| [20] | J. Choi and R. Gutierrez-Osuna, “Estimating Mental Stress Using a Wearable Cardio-Respiratory Sensor,” Texas A&M University, Texas, 2010. |
| [21] | F. Bousefsaf, C. Maaoui and A. Pruski, “Remote assessment of the Heart Rate Variability to detect mental stress,” Laboratoire de Conception, Optimisation et Modelisation des Systemes (LCOMS), Metz, France, 2013. |
| [22] | M. De Choudhury, M. Gamon, A. Hoff and A. Roseway, “"Moon Phrases": A Social Media Faciliated Tool for Emotional Reflection and Wellness,” Microsoft Research, Redmond WA, USA, 2013. |
| [23] | S. Abraham, J. Chin, H. J. M. Brouwers, B. Turner, R. Zhang and T. A. Chapman, “Green Fluorescent Protein-Based Biosensor To Detect and Quantify Stress Responses Induced by DNA-Degrading Colicins,” American Society for Microbiology, Woolongong, NSW, Australia, 2011. |
| [24] | National Institutes of Health, “Stress and Anxiety: MedlinePlus Medical Encyclopedia,” U.S. National Library of Medicine, 22 May 2014. [Online]. Available: http://www.nlm.nih.gov/medlineplus/ency/article/003211.htm. [Accessed 16 6 2011]. |
| [25] | P. Stafford, “Australians go local with smartphones – and three other trends from Google’s latest research,” SmartCompany, 22 July 2013. [Online]. Available: http://www.smartcompany.com.au/technology/online/32768-australians-go-local-with-smartphones----and-three-other-trends-from-google-s-latest-research.html. [Accessed 7 May 2014]. |
| [26] | WebMD, “Stress Symptoms Effects of Stress on the Body,” 2 July 2013. [Online]. Available: http://www.webmd.com/balance/stress-management/stress-symptoms-effects\_of-stress-on-the-body. [Accessed 23 May 2014]. |
| [27] | C. Küblbeck and A. Ernst, “Face detection and tracking in video sequences using the modified census transformation,” *Journal of Image Vision Computing,* vol. 24, no. 6, p. 9, 2006. |
| [28] | HowStuffWorks, “HowStuffWorks Hygrometer,” 15 September 2009. [Online]. Available: http://science.howstuffworks.com/nature/climate-weather/meteorological-instruments/hygrometer-info.htm. [Accessed 15 April 2014]. |
| [29] | V. Volterra, “Theory of Functionals and of Integrals and Integro-Differential Equations,” Dover Publications, NY, USA, 1959. |

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1. A “turn” is a continuous speech segment where a person starts and ends her speech [3] [↑](#footnote-ref-1)
2. Meta-linguistic features include characteristics of speech that are not classified as the “language”. Examples include pace of speech, and whether the type of speech used is assertive or dominant [↑](#footnote-ref-2)
3. A Volterra series is an old algorithm used to predict the decay of a device’s ability to hold electrical charge [29] [↑](#footnote-ref-3)
4. Hygrometer is defined as “a device for determining the humidity of the atmosphere” [28]. It can also be used to measure the moisture of one’s palms when holding the phone. [↑](#footnote-ref-4)