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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.*

Contents

Abstract i

Dedication ii

Contents iii

List of figures v

1. Introduction 1

2. Background 4

2.1 Literature Review 4

2.1.1 Mobile-application solutions, and data collection methods 4

2.1.2 Non-mobile-application solutions, and data collection methods 11

2.1.3 Research regarding stress factors generally 14

2.2 Conclusions and Refined Aim 16

3. Own Work 19

3.1 Proposal 19

3.1.1 Deductions 19

3.1.2 Breakdown 24

3.2 Specific Learning 25

3.2.1 Android API 25

3.1.2 Machine learning algorithms 25

3.3 Process 25

3.3.1 Data Gathering 25

3.3.2 Manual Inteferences 25

3.3.3 Machine learning 25

3.3.4 Refine Algorithm 25

3.4 Implementation 25

3.4.x <talk about each package> - half a page per class on average 25

4. Evaluation 26

4.1 Testing procedure 26

4.2 Method 26

4.3 Results 26

4.4 Discussion 26

5. Conclusion 27

5.x Future work 27

6. Bibliography 28

# List of figures

[Figure 1 – Improvement in accuracy over a 60-day period due to machine learning 9](#_Toc401681143)

[Figure 2 – Varying accuracies dependent on level of supervision in StressSense 11](#_Toc401681144)

[Figure 3 – Planning until preliminary demonstration 22](#_Toc401681145)

[Figure 4 – GANTT chart representation of plan 23](#_Toc401681146)

# List of tables

[Table 1 Data collected from accelerometer\*\*\*INSERT REFERENCE\*\*\* 25](#_Toc401681277)

[Table 2 Data collected from hygrometer\*\*\*INSERT REFERENCE\*\*\* 25](#_Toc401681278)

# 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 research thesis regarding this problem, where we will develop 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 – giving us an idea of historical research whilst still being state-of-the-art. It is particularly important to understand what has been attempted. This gives us an appreciation for what has currently been created, further inspires our own ideas, and allows us to innovate further based on these solutions. Lots of current implementations use interesting concepts regarding the various signals that were detected, the collection of data from a variety of instruments, and the processing of the physiological and physical data using interesting algorithms – from machine learning algorithms such as the use of support vector machines (SVMs), to the use of the Volterra series, which is commonly used in electrical engineering applications. Lastly, we can also identify untapped areas of research that may offer a better solution, such as the use of alternate machine learning algorithms like a random forest decision tree [2].

Thus, we will be able to identify not only key differences between each of the application, but their strengths and weaknesses and how these will inspire ideas for 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.

From here, we discuss our own work. Firstly, we discuss any further technical research in areas of study concerning machine learning and the use of an API of a mobile phone for a technical standpoint. These are important to understand before we discuss the methodologies in which the application was built. For methodologies, each step is as important as each other in ensuring the optimal solution is developed. We will walk through the justifications for each process, and what values it added to our solution.

We will go through our testing methodologies, which is used to ensure that the application is developed robustly. These are done under a strict methodology, and the results were assessed. From here, we gauged whether the data collected was of an accurate nature, and what would cause these inaccuracies.

Once the application was perfected, the system was evaluated, as will be discussed. This evaluation returned a number of results. An evaluation method was also created so as to measure the accuracy of the application – namely using machine learning metrics. This allows us to draw conclusions from our solution and assess its effectiveness.

# 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” [3], “SocioPhone” [4], “MoodScope” [5] and “Mood Meter” [6], as well as a methodology to remotely manage hypertension [7]. 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, 7]. 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 [7] 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 ( [3] ) uses “an unobtrusively wearable wireless sensor suite that can collect continuous measurements” [3]. 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.” [3]. 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 [8]. 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 ( [4] ) is an application which monitors face-to-face conversations at the core to investigate social interaction. It is classified as an “interaction-aware application” [4]. 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, 4]. 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)” [4].

MoodScope ( [5] ) 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” [5] – 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 [9]. 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 [5]

MyWalk [10] 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 [11], 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 [12]. 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 [3], [4], [5] and [7], phones are used for the collecting and processing of data to generate information regarding human interaction. In particular, [3], [4] and [7] collect physiological information, with [3] and [4] specifically using this to calculate one’s mood, which we can directly infer one’s level of stress. [7], on the other hand, collects physiological data to specifically respond to a dangerous, and very key, stress response. [5] does not utilise physiological reactions, yet still manages to detect stress through other interesting means. [6] 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 [3] and [4] are one of the most advanced, despite [3] being a relatively older use of phone applications for this purpose. In [3], 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” [3]. However, we can agree that not having hardware attached to us is, in itself, a superior advantage. [4] 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, [4] inspires the idea of utilising the phone’s hardware. We can note that the physiological reactions sensed in [3] 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” [13]. 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 [14]. [3] also detects skin temperature, which can be found using the phone’s thermometer. All these inbuilt hardware render the external hardware used by [3] as redundant. The advantage that the external hardware offers, however, is that people still claim accuracy, however [3], 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 [3] and [4] uses static information for its inferences, [3] has a 90% accuracy rate for 20+ participants, and [4] 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. [3] 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. [4] 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.

We must draw a further parallel between SocioPhone [4] and AMMON [11] as two of the key applications used to detect changes in speech during times of emotional stress or distress. As mentioned before, SocioPhone has produced an accuracy of 60±5%. On the other hand, AMMON produced an accuracy of 93.6% accuracy. Whilst these both are dependent on speech variations

AMMON in particular has used a balanced data set to ensure a 50% degree of accuracy. Balanced data is essential as training data. Whilst we can note that data that is biased towards one particular result can still produce results of decent accuracy, it can fundamentally be proven that balanced data will produced more accurate results [15]. Thus, we recognise this as one particularly important characteristic regarding machine learning.

[5] 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 [5]. 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 [5]. The following graph gives us the best idea of how the application evolves over the 60-day learning period.

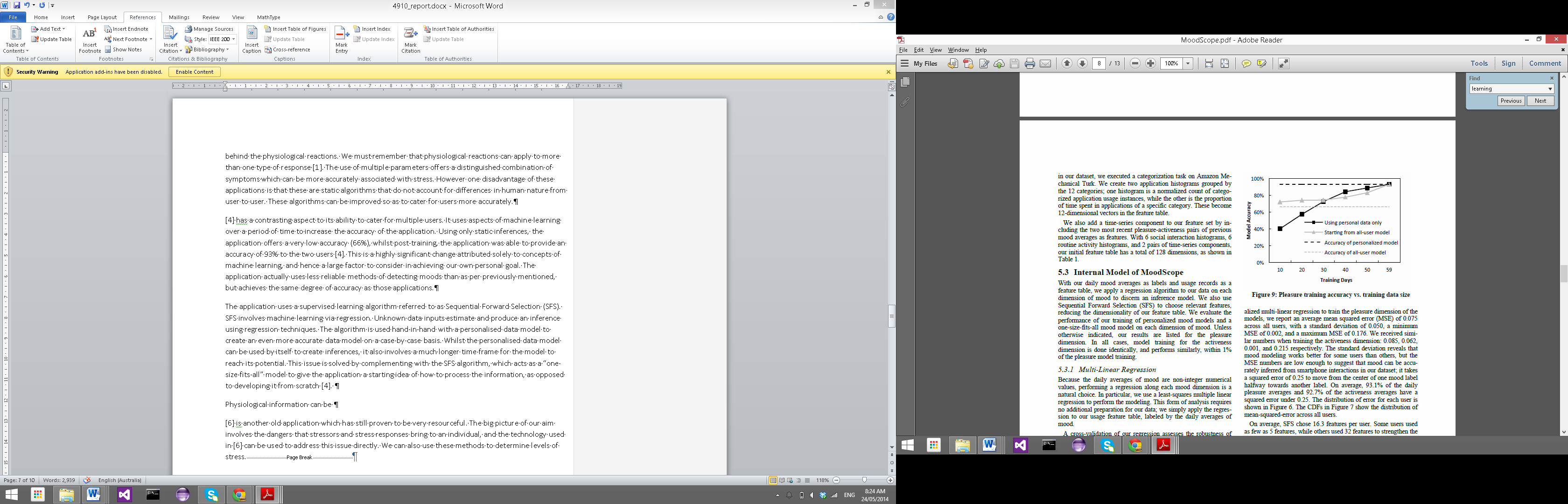


Figure 1 – Improvement in accuracy over a 60-day period due to machine learning

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, 16, 17].

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.

[7] 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 [7] 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 [18], 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 [8]. 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.

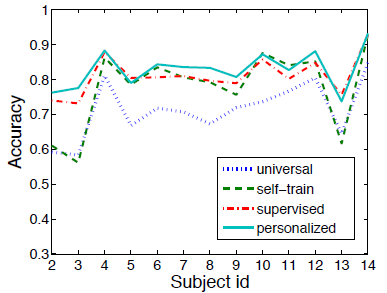


Figure 2 – Varying accuracies dependent on level of supervision in StressSense

Thus, we cannot reject the notion of unsupervised learning completely. Whilst it is very risky to use [2], it also produces the most correct results [8]. 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 [19]. 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 [20]. 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 [21]. 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 [22]. 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 [22], 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) [19, 20, 21, 22], 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 [20], 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 [19]. 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.

Respiration was the second most prominent factor in these determinations. Namely, in non-mobile-phone applications, we notice its use in [20] 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.

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. Their usage is also less applicable to the practical world, as the equipment is optimised for simulations rather than day-to-day use. This is a significant disadvantage to a lot of non-mobile solutions and, thus, is a further inspiration for our proposed solution.

### 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” [23]. 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 [24]

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 [24]. 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 Refined 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, 25, 16] include:

* Changes in vocal pitch and amplitude
* Erratic movement, e.g. 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

Our reviews have taught us a lot about physiological, physical and biological symptoms of stress, as well as how they are detected and strong determinants of whether one is exhibiting stress symptoms or not. We also note that some methods have produced stronger accuracies than others. Whilst accuracy is one of the most important factors, we must also consider other factors such as practicality in the real world. Such practicality for the user includes portability and ease of use.

We have decided to use a mobile phone application to take advantage of the portable hardware within the phone itself. However, the disadvantage of this is the inability to use the intricate software offered by some of the non-mobile solutions. Thus, we must investigate what hardware offers a high accuracy and are integrated into a phone.

For a start, we noted that biological symptoms [24] cannot be detected with a phone, as discussed above. Thus, the main concerns for our conclusions will revolve around physiological and physical symptoms of stress. Although these offer less accuracy at times, under certain conditions, they are the most practical symptoms to make use of.

We notice that heart rate is an extremely good indicator of stress, both mentally and physically. This has been mentioned previously in the literature review, let alone within the papers themselves on numerous occasions. A phone has the potential to recognise one’s heart rate using the camera[[4]](#footnote-4). Such an example is its application in Azumio’s “Heart Rate Monitor”. Whilst this development is somewhat of an innovation based on a undedicated hardware, the camera, the logic to deduce one’s heart rate through imagery is correct, Thus, we will be able to take use of this signal using a mobile phone.

Another key signal we would like to observe is respiration symptoms due to stress. Respiration occurs in the form of cardio-vascular activity or perspiration. Again, papers that used respiration techniques had a furthered accuracy which we would like to take advantage of.

Perspiration can be measured in a phone using the hygrometer, which we will discuss later in this thesis. Again, this is not the dedicated purpose of the hygrometer[[5]](#footnote-5), however the logic behind its use is correct and, provided we can provide a proof of concept to ourselves for its application, it is a feasible option to use for detecting perspiration.

Lastly, we take note of two mobile applications that make use of speeh patterns and their associations with stress. By itself, speech has the potential to provide one of the highest accuracies. We have also noted that libraries have been developed regarding speech patterns – in particular, specifically for stress [11]. This is expected behaviour, with phones having a microphone dedicated to detecting speech for one of their primary uses, phone calls, and other uses such as recording. Thus, this is the last physical stress reaction that we will take into account as inspiration, based on the literature reviews.

However, we note that there are many other stress symptoms that have not been taken into account at all in our research. Due to the new nature of this topic, we cannot expect all symptoms have been taken into account thus far. Such namely stress symptoms are some of those mentioned above. One in particular that will be discussed later is one’s erratic movement, which can be detected using a phone’s accelerometer. Despite a lack of investigation in previous literature reviews, other sources indicate subconscious movement is a body’s way of minimising mental stress [1, 26]. This theoretical knowledge has resulted in a decision to investigate this symptom, which is viewed as a knowledge gap.

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.

[2]3. Own Work

Intro

## 3.1 Proposal

### 31.

[27][1, 28, 25]

[5][2]

[2]

### 3.1.

## 3.2 Specific Learning

### 3.2.1 Android API

Further research was conducted regarding elements of the Android API. To proceed, we investigate specifically how to utilise each hardware device. The accelerometer and hygrometer both utilise the SensorEvent class that comes standard in the Android libraries.

An accelerometer delivers three useful types of information, as presented below.

|  |  |  |  |
| --- | --- | --- | --- |
| Sensor | Sensor event data | Description | Units of measure |
| [TYPE\_ACCELEROMETER](http://developer.android.com/reference/android/hardware/Sensor.html" \l "TYPE_ACCELEROMETER) | SensorEvent.values[0] | Acceleration force along the x axis (including gravity). | m/s2 |
| SensorEvent.values[1] | Acceleration force along the y axis (including gravity). |
| SensorEvent.values[2] | Acceleration force along the z axis (including gravity). |

Table 1 Data collected from accelerometer\*\*\*INSERT REFERENCE\*\*\*

An hygrometer delivers information, as presented below. The percentage is a direct measure of the detected, relative humidity i.e. “the amount of water vapor in the air relative to what the air can hold.” [29].

|  |  |  |  |
| --- | --- | --- | --- |
| Sensor | Sensor event data | Units of measure | Data description |
| [TYPE\_RELATIVE\_HUMIDITY](http://developer.android.com/reference/android/hardware/Sensor.html" \l "TYPE_RELATIVE_HUMIDITY) | event.values[0] | % | Ambient relative humidity. |

Table 2 Data collected from hygrometer\*\*\*INSERT REFERENCE\*\*\*

We note that the sensor delivers values in our 2 other values in the presented array. These are ignored, and are of no use to us. However, for future progression, we will keep a log of them in the event they prove useful.

### 3.1.2 Machine learning algorithms

## 3.3 Process

### 3.3.1 Data Gathering

### 3.3.2 Manual Inferences

### 3.3.3 Machine learning

### 3.3.4 Refine Algorithm

## 3.4 Implementation

### 3.4.x <talk about each package> - half a page per class on average

# 4. Evaluation

Intro

## 4.1 Testing procedure

## 4.2 Method

## 4.3 Results

## 4.4 Discussion

# 5. Conclusion

Intro

## 5.x Future work

# 6. Bibliography

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1. A “turn” is a continuous speech segment where a person starts and ends her speech [4] [↑](#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 [31] [↑](#footnote-ref-3)
4. Written as of June 20th 2014. Future developments have occurred since this conclusion, to be discussed later. [↑](#footnote-ref-4)
5. A ‘hygrometer’ is defined as “a device for determining the humidity of the atmosphere” [30]. It can also be used to measure the moisture of one’s palms when holding the phone. [↑](#footnote-ref-5)