DEPARTMENT OF INFORMATION ENGINEERING

MASTER’S DEGREE COURSE: BIOMEDICAL ENGINEERING

DETECTION AND MONITORING OF WORK-RELATED STRESS USING HEART RATE VARIABILITY

TYPE OF DISSERTATION: RESEARCH THESIS

STUDENT:
AFUA BOAKYEWAAH APPIAH

SUPERVISOR:
LORENZO PALMA

CO-SUPERVISOR:
ILARIA MARCANTONI

ACADEMIC YEAR 2020-2021

ABSTRACT

Stress, defined as a natural response by an organism to an intrinsic or extrinsic situation being positive, negative, physical, or mental (Unai Zalabarria et al., 2020) is undeniably one of the leading causes of physical and mental illnesses in humans (Felix Adochiei et al., 2019). It is reported to be the second most disease-causing factor in Europe and the United States. Out of four visits to the doctor, three are as a result of stress-related illnesses with some of these pathologies as serious as leading to death (Niraj K. Jha et al., 2017). A major source of stress in recent times is at the workplace, due to the intense mental and physical efforts that are required of workers and the needs of workers not being met as well as inadequate resources to promote work effectiveness and efficiency (Onur Parlak, 2021). Work-related stress has been shown to have several repercussions not only on the productivity of workers but also on the state at large. Approximately €617 billion is spent by the EU annually to cater for work-related stress depression, health costs and social welfare (Giorgia Acerbi et al., 2017). For this reason, work-related stress monitoring and management have recently become a fast-growing research field. This study aims to build on methods and algorithms for detecting and monitoring work-related stress using heart rate variability. The SWELL dataset, collected by researchers at the Institute of Computing and Information Sciences at Radboud University and the Delft University of Technology in The Netherlands was used for the implementation of the study. The dataset, consisting of a series of ECG signals were prepared for heart rate and heart rate variability feature extraction after which it was evident, significant differences between the heart rate and the heart rate variability values. The results showed an increase in the LF/LH and LF values and, a decrease in the frequency domain index HF and the time domain measurements particularly, RMSSD thus, indicating autonomic nervous system activity and hence detection of stress. A neural network was also created using machine learning techniques on MATLAB to implement the aim aforementioned using the heart rate variability features extracted from the data set. The model was also compared with other conventional models to determine which was best for the stress detection algorithm. Overall, the goal of this study was achieved, and the chosen classification model (Artificial Neural Network) proved to be the best for the detection and classification of stress with an accuracy and error rate of 78% and 22% respectively.

TABLE OF CONTENTS

ACKNOWLEDGEMENT

I take special pleasure in acknowledging the Almighty God for His guidance throughout this entire project.

Secondly, I am overly grateful to my supervisor, Lorenzo Palma, Department of Information Engineering, UNIVPM and my co-supervisor, Ilaria Marcantoni, Department of Information Engineering, UNIVPM for their invaluable guidance, consistent support, constructive comments, a sympathetic attitude which has sustained my efforts at all stages of this project.

I would also like to express immense gratitude towards my family and friends for their motivation and well-wishes which helped me in the completion of my project.

Finally, my appreciation to any individual who willingly helped me out and was instrumental to the progress of this project but was not mentioned.

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

Stress is undeniably one of the leading causes of physical and mental illnesses in humans (Felix Adochiei et al., 2019). It is reported to be the second most disease-causing factor in Europe and the United States, it is estimated that out of four visits to the doctor, three are as a result of stress-related pathologies or disorders (Niraj K. Jha et al., 2017). Stress is defined as a natural response by an organism to an intrinsic or extrinsic situation being it positive, negative, physical, or mental (Unai Zalabarria et al., 2020). It is the body's way of dealing with an overwhelming or unfavourable condition and always tries to bring the body to its normal balance (Sharma DK, 2018).

Stress is in stages and begins with the perturbation of an organism by a stimulus or event known as a stressor (Sharma DK, 2018). Stressors can be in so many forms but are generally grouped under two types; psychological which includes financial problems, loss of a relative, a job or even preparation towards an exam and physiological, with examples being hot temperature, lack of relaxation, infections etc. The responses to these stressors by the body may be short term or long term. Based on judgement by the body on a situation or an event as being stressful, the brain, specifically the hypothalamus activates and sends signals to the pituitary gland which in turn stimulates the adrenal gland to produce cortisol. The hormone produced stabilises the supply of blood sugar aiding in bringing back the body to normalcy. For short term stress responses, the hypothalamus stimulates the adrenal medulla which forms a part of the autonomic nervous system. During activation of the adrenal medulla, adrenaline is secreted. This hormone stimulates the sympathetic nervous system and produces the **fight or flight response**; this is the immediate response or reaction that is taken by an organism when it deems a situation as dangerous. The body goes back to normal after the stressor has been removed and the parasympathetic nervous system takes over (McLeod S. A., 2010; Sami Elzeiny et al., 2018).

Stress can be classified into three types and this classification is based on the time-lapse. There are specific symptoms, characteristics, duration, and management attributed to these three types. Acute stress; is the most common and frequent type of stress. It is brief and does not occur over a long period. It is caused by negative thoughts about certain events that may have occurred in the past, that may be currently present or yet to happen with an example being constant thinking about an upcoming assignment deadline. It may also be caused by daily demands and can lead to physical and emotional distress such as headaches, anxiety and anger but does not cause any significant damage to the body (Sami Elzeiny et al., 2018). The second type of stress is episodic stress, which occurs when acute stress is repetitive over a significant amount of time that it becomes habitual. It is very common in people who are short-tempered and overly competitive. Symptoms may include chest pains and migraine with treatment usually requiring the intervention of a professional. When stress occurs over a long period it becomes chronic and poses a lot of risks to the health of an individual. Chronic stress is characterised by unending miserable situations, unrelenting demands, and long-time pressures. It may be as a result of past traumatic events and early childhood experiences that become a part of one's life. Examples of situations or events that may lead to chronic stress include an unhappy marriage or career and poverty (Sami Elzeiny et al., 2018).

The implications of stress on the body are in connection with the type, timing and how severe the applied stimulus (stressor) is to the body. These implications can be instability or changes in homeostasis and can sometimes be worse as leading to the death of the individual (Yaribeygi H et al., 2017). Through the constant increase in blood pressure as a result of the constant release of hormones that cause the constriction of blood vessels, stress can play a part in the development of certain cardiovascular diseases such as hypertension (Kulkarni S. et al., 1998). While the effects of acute stress may be easily manageable and not damaging to the body, that of chronic stress is otherwise.

A major source of stress in recent times is at the workplace, due to the intense mental and physical efforts that are required of workers (Onur Parlak, 2021). It may also be as a result of the needs of workers not being met or resources needed by staff to work effectively being inadequate. Work-related stress has been shown to cause frequent absenteeism, accidents, and decreased productivity (Martin Gjoreski et al., 2017). It has been shown that approximately €617 billion is spent by the EU annually to cater for work-related stress depression, health costs and social welfare (Giorgia Acerbi et al., 2017). This shows that not only does work-related stress affect individuals and productivity, but it also affects the state at large. For this reason, work-related stress monitoring and management have recently become a fast-growing research field.

This study aims to build on methods and algorithms for detecting and monitoring work-related stress particularly, using heart rate variability to aid in combatting the adverse effects associated with the aforementioned.

1.1.1. THE ELECTRICAL ACTIVITY OF THE HEART

The muscle of the heart has its conduction system and does not rely on the central nervous system for its activation. This self-activation is made possible by a type of muscle cells known as the pacemaker cells (sinoatrial node and atrioventricular node) and conduction fibres (Cindy L. Stanfield). The heartbeat starts with the generation of an action potential by the pacemaker cells of the sinoatrial node (SN). This node can be found in the wall of the upper right atrium where it merges with the superior vena cava. The electrical impulse then spreads first through the right atrium via the internodal pathway and then through the left atrium via the interatrial pathway. The activation of the atria causes the atria to contract as a unit and then pump blood simultaneously, through the tricuspid and bicuspid valves of the right and left atria respectfully and then into the right and left ventricles. The electrical impulse spreads through the right atrium and propels towards the atrioventricular node (found near the tricuspid valve of the heart) and finally stimulates it. The activation of the atrioventricular node further causes the stimulus to travel through the bundle of His (a collection of muscle fibres located in the interventricular septum) which then branches, passing through the left and right bundle branches causing the activation and contraction of the left and right ventricles respectfully. This results in the pumping of blood from the ventricles through the pulmonary artery to the lungs and into the general circulation. From the left and right bundles, the signal is conducted through the Purkinje fibres (a network of fibres that run from the apex of the heart to the tricuspid and bicuspid valves) spreading through the ventricles after which it travels through the ventricular myocardial cells and collectively activating them (Goldberger et al., 2013). A pictorial representation of the phenomenon described above can be found in **Figure 1** below.

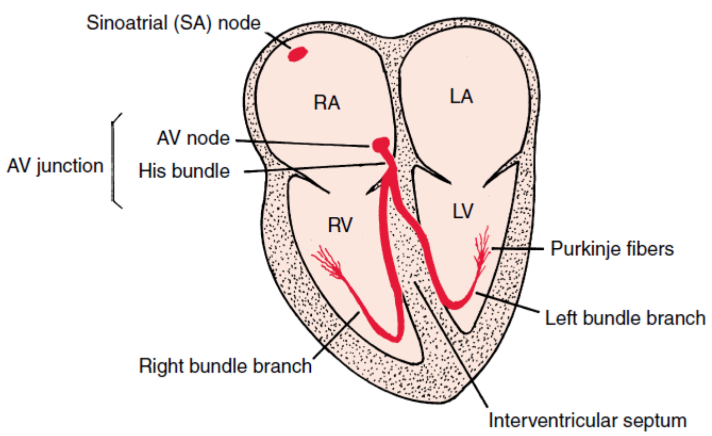

Figure 1. The diagram illustrates the pathway of the electrical impulse during a heartbeat. (Goldberger et al., 2013).

1.1.2. ELECTROCARDIOGRAPHY

Electrocardiography is the method of recording the electrical changes (electrical activity) obtained concerning the contraction and relaxation of the cardiac muscles during each heartbeat. These electrical changes are developed in sensors known as electrodes which are placed in a standard convention on the skin. Electrocardiography produces an electrocardiogram, a graph of voltage against the time of the electrical activity of the heart from an electrocardiogram (ECG). (David B. Geselowitz, 1989) (Leonard S. et al., 2016)

The electrocardiogram (ECG) is the most used tool for diagnosing pathologies related to cardiac electrophysiology (David B. Geselowitz, 1989) and it is used by physicians to determine and diagnose problems associated with the electrical activity of the heart (Cindy L. Stanfield). It is an all-around and relatively cheaper clinical test (Goldberger et al., 2013). The ECG is a graph of voltage against time and is made up of a series of waves, intervals and segments that depict the various stages of the electrical activity of the heart during a cardiac cycle. The following describes the various parts of ECG (Goldberger et al., 2013).

P Wave: It is the first wave of the ECG. It represents atrial depolarization, which is the activation or contraction of the right and left atria.

QRS Complex: The QRS complex follows the P wave, and it characterizes the depolarization of the right and left ventricles.

T Wave: This comes after the QRS complex and describes the repolarization or relaxation of the right and left ventricles.

U Wave: The U wave is the last and not usually seen. It also depicts ventricular repolarization.

P-R Interval: It occurs between the onset of the P wave and the beginning of the QRS complex. It represents the time of conduction through the AV node (electrode lead).

R-R Interval: The R-R interval is the period between two successive QRS complexes. It represents the time between heartbeats.

Q-T Interval: It is the time of the onset of the QRS complex to the end of the T wave. The Q-T interval describes the time for ventricular depolarization to begin to the end of ventricular repolarization.

P-R Segment: It is the period from the end of the P-wave to the beginning of the QRS complex. It characterizes the time between the end of atrial depolarization and the onset of ventricular depolarization.

S-T Segment: It is the period from the end of the QRS complex to the beginning of the T wave. This also describes the repolarization of the right and left ventricles.

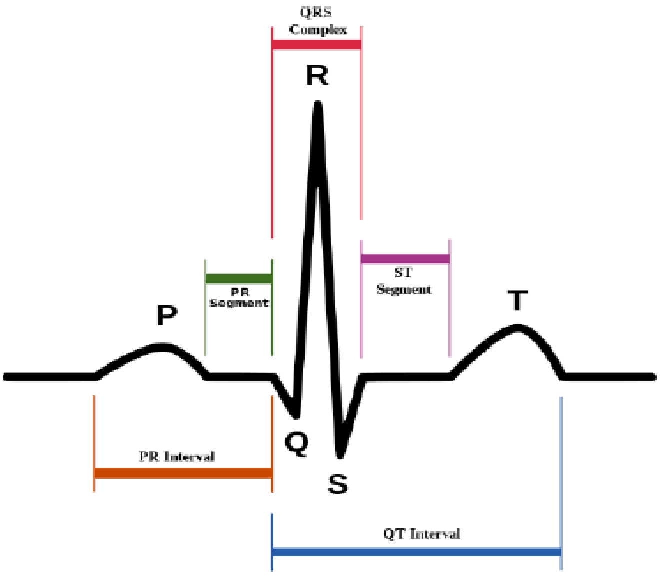

Figure 2. The figure illustrates the various waves that categorise the electrical activity of the heart (Atkielski, 2007).

1.2. HEART RATE VARIABILITY

It refers to the changes in the time intervals between consecutive heartbeats (RR Interval). HRV describes the neuro-cardiac function, and it is non-invasively obtained from the heart-brain interactions and dynamic non-linear autonomic nervous system (ANS) responses. HRV determines the regulation of autonomic balance, blood pressure, gas exchange, gut, heart, and vascular tone (Shaffer & Ginsberg, 2017) and can be measured or extracted from the R-R interval (heart rate) obtained from an Electrocardiogram (ECG) (gold standard) or a Photoplethysmogram (PPG) (Mejía-Mejía E. et al., 2020). HRV differs between people of different sex, age, mental and physical well-being (Shaffer & Ginsberg, 2017). (Hjortskov, et al., 2004) mentioned in his study that HRV decreases when one is mentally stressed, and this is due to an increase in the heart rate which is a result of the changes that occur in the autonomic nervous system function (increase in the sympathoadrenal activation). Changes in the HRV can thus be an indication of stress. The commonly used indices for stress detection are categorized into two groups, time domain and frequency domain. Time-domain indices are used to measure the differences in the inter-beat interval (period between consecutive heartbeats) measurements whereas frequency-domain indices distribute the HRV power spectrum into four frequency bands. Time-domain HRV indices decline with an increase in age and a decrease in fitness or physical well-being (Shaffer & Ginsberg, 2017).

The following table describes briefly the commonly used HRV indices and the type of activation they reflect. With the first four being the time domain indices and the rest, frequency domain indices.

HRV INDEX	DESCRIPTION	ACTIVATION TYPE
RMSSD	The square root of the mean of the sum of the squares of the difference between adjacent RR intervals	Parasympathetic
SDSD	The standard deviation of all intervals of differences between adjacent RR intervals	Sympathetic
pNN50	Percentage of adjacent RR intervals which differs by more than 50 ms	Parasympathetic
SDNN	The standard deviation of all N-N interval	Sympathetic
LF	The low-frequency band of the HRV power spectrum	Sympathetic
HF	The high-frequency band of the HRV power spectrum	Parasympathetic
LF/HF	The ratio of the LF to the HF	Parasympathetic
VLF	The very-low-frequency band of the HRV power spectrum with	Parasympathetic

Table 1. Heart Rate Variability Indices and their description (Nkurikiyeyezu, Shoji, Yokokubo, & Lopez, 2019).

CHAPTER 2: LITERATURE REVIEW

2.1. APPROACHES TO STRESS DETECTION AND MONITORING

The detection of stress first came about during a study to gather and assess the physiological data obtained while performing real-life driving tasks. The researchers utilized wires and electrodes that were intrusive in their methods and there was additionally the problem of a less intelligent and unresponsiveness of their method (Healey Jennifer, Picard Rosalind, 2005). The traditional method of stress detection also involved the use of psychometric instruments, scales, questionnaires, or surveys (Ulstein et al., 2007; David Carneiro et al., 2019). Questionnaires although inexpensive and easily used, have some demerits which makes them less effective to use for the aforementioned function. They are based on individual perceptions, participants may withhold needed information, researchers may assume what is important or not at the time of creation and some information that one would deem as important, if not present in the questionnaires, may be omitted (David Carneiro et al., 2019).

Aside from the traditional detection of stress through questionnaires and behavioural observations, studies have shown that it can also be obtained and quantified from physiological and psychological/neurological responses (Sami Elzeiny et al., 2018; Mengru Xue et al., 2019) due to its association with the autonomic nervous system with the indicative parameters being heart rate variability (HRV), galvanic skin response (GSR), respiratory rate, blood oxygen saturation, cortisol level, blood pressure (BP) and brain signals (Niraj K. Jha et al., 2017; David Carneiro et al., 2019). These parameters specifically HR, GSR and BP can be measured when the body activates the autonomic nervous system in response to the brain perceiving a situation as stressful (Mengru Xue et al., 2019).

2.1.1. PHYSIOLOGICAL MEASUREMENT OF STRESS

Cortisol level: This is produced as a response to the activation of the adrenal glands of the kidneys by the hormone adrenocorticotropic (ACTH) (produced by the pituitary gland). It aids the body in the metabolism of fats, glucose and also stress management and can be measured in the saliva and blood. Cortisol levels are affected in response to certain conditions such as physical and emotional stress. The constant release of cortisol into the bloodstream in response to stress can cause vasoconstriction which can lead to an elevation in blood pressure. The connection between stress and the release of cortisol into the bloodstream makes cortisol a biomarker for stress detection (David Carneiro et al., 2017).

Electrodermal Activity/Galvanic Skin Response: It is the measure of the changes in the skin's electrical activity or characteristics (Boucsein & Wolfram, 2012). It is due to changes in the autonomic nervous system (ANS) function caused by sympathetic activation due to changes in the emotional state of a person. The active state of sweat glands determines the variations in the skin's resistance. An increase in the sympathetic activity of the ANS increases sweat production and cutaneous blood flow which in turn causes a decrease in skin resistance leading to an increase in conductance. A decrease in the sympathetic activity of the ANS causes an increase in skin resistance and hence, a decrease in conductance. A common example of a situation that promotes sympathetic activation is stress. Skin conductance can be used as a basis for measuring stress. (A.N. Jayanthi, 2015).

2.1.2. RESEARCH BY OTHERS

Over the years, there has been a surge in the development of biomedical sensors and the Internet of Things. This has led to the significant improvement of stress detection questionnaires and intrusive methodology to non-invasive procedures, and easily require the use of sensors, machine learning and signal processing. These procedures are not complicated and do not require the need for skilled personnel. Below are some papers that summarise the recent trends in stress detection and monitoring.

With the negative impacts of stress on workers and productivity at the workplace becoming a concern, G. Niezen et al., (2016) designed a wearable stress monitoring system that uses a body sensor network, which can be used daily to help alleviate the adverse issues associated with occupational stress.

The monitor was designed using a microcontroller that received signals from three sensors in the form of voltages. An infrared photodiode and a photodetector were used to measure the heart rate, a GSR sensor was used to detect the galvanic skin response and a negative temperature coefficient resistor was used to measure the temperature. Because the galvanic skin response and temperature signals were in the resistance, a voltage source was connected to convert them into voltages. Using a serial communication, the output from the microcontroller was sent to a Bluetooth module which in turn relayed the output signal to a mobile phone. The mobile phone then used the measurements to plot graphs of the corresponding physiological signals via an application written using Java ME and then sent the data to a website via an SMS which was then stored in a database. Inferences are then made from the saved data to determine the stress levels of the user. Depending on the outcome that is, the stress level, an SMS was sent back to the mobile phone.

After setting up an experiment that involved subjecting participants to various stressful conditions, the output of the device was tested. It was seen that the outputs of the sensors varied in response to changes in the physiological signals of interest due to stress. High levels of stress corresponded to low voltages from the sensors and vice versa. The device was able to do that for which it was designed with a reasonable amount of accuracy.

Scaling down measurements to allow for the correct display of the graph and rounding off values to be able to satisfy the requirement of using integers for drawing graphs on the mobile phone was a limitation and resulted in inaccuracies. There was also the problem of loss of signal due to proximity while using Bluetooth for the communication between the sensor and the mobile phone. G. Niezen et al., (2016) recommended that other forms of communication be used to transmit information from the wearable sensor to the mobile phone.

To solve the problem of stress subjectivity when it comes to its detection and the direct monitoring of stress, Martin Gjoreski et al., (2017) proposed a method that can accurately, continuously, and unobtrusively detect and monitor psychological stress in real life. They explored the use of a wrist device as a source of physiological data, recognised user's activity by the assessment of the acceleration data obtained from the wrist device and used real-life contextual information. Stress detection using machine learning and signal processing techniques in laboratory conditions (constrained environment) was also explored using Empatica E3 and E4 and the extracted laboratory information was then applied to real-life data (unconstrained environment). Their proposal consisted of:

1. a laboratory stress detector that was trained on laboratory data and detected short-term stress every 2 min.
2. an activity recognizer that continuously recognized the user's activity and thus provided context information
3. a context-based stress detector that used the output of the laboratory stress detector, activity recognizer and other contexts to provide the final output.

Cognitive tasks and stressors from real life were analysed on 21 subjects to obtain input for the laboratory stress detector and 5 subjects for context-based stress detector. The collective data represented 55 days of real-life data. For the constrained environment data collection, subjects were made to solve mental arithmetic tasks under a varying time duration after which they provided answers verbally. The time to execute the task was shortened by 10% for every 2 consecutive answers and increased by 10% for each 2 consecutive wrong answers. Participants filled out a questionnaire after the sessions and the data was statistically analysed.

The data from the experiment showed that the proposed method detects 70% of the stressful events with a precision of 95% and therefore can be used in real life.

They were hurdled with the problem of sample size; a small population was used. Their method was tested only on a small and healthy population who had a mean age of 28 and a standard deviation of 4. They also mentioned that their proposed method was biased towards the device used for the physiological data collection.

For future work purposes, Martin Gjoreski et al., (2017) suggested an increase in sample size, the use of a population with a variety of ages, sex, and the use of their method on multiple/different devices to prevent biases.

In 2017, Giorgia Acerbi et al., (2017) proposed a method to illustrate the feasibility of mental stress detection and monitoring with the help of physiological data specifically, heart rate variability (HRV) and electrodermal activity (EDA)/galvanic skin response (GSR) collected by wearable sensors. According to them, HRV and EDA were used because of how they are the signals that have the most correlation with stress and can be obtained non-invasively.

To be able to measure the GSR/EDA and HRV respectively, two wearable sensors namely Shimmer GSR and Zephyr BioHarness™ were used because of their accuracy and unobtrusiveness. The former is composed of two electrodes worn around the finger that transmits the GSR using Bluetooth. The latter is a chest belt that uses Bluetooth to obtain the heart rate by measuring the R-R interval of the ECG. It has the capability of also measuring the breathing rate, temperature, and details about the posture.

12 participants with ages ranging from 21 to 30 years and no history of any neurological or cardiac disorder were made to undergo a series of tasks that put them in emotional and cognitive stress. The experiment consisted of a no activity, stressful and relaxing stage with the physiological parameters of interest being measured at each stage. Before and after each

stressful phase, a psychometric instrument (Questionnaires) was given to the participants to obtain a "subjective perception about the level of stress, anxiety and drowsiness." Another experiment was done to obtain a strong emotional response from the participants after being made to undergo neuropsychological tests with participants wearing the sensors throughout the tests. The emotional reactions as a response to stress were measured with psychometric instruments.

The output of the system was able to establish that through physiological data there is the possibility of differentiating stressed and non-stressed people. This could be indicated by the significant differences between the HRV and GSR/EDA parameters concerning the baseline and stressful phases of the experiment. The values of the psychometric analysis were also able to measure emotional state and the level of stress. It was concluded that the system will be able to detect and indicate stress levels of ageing workers helping to alleviate stress because of increased workload.

When the psychometric instruments (questionnaires) were used as a reference in determining the possibility of finding the stress levels from the physiological data, a low correlation was established.

They suggested that for future work, their feature extraction method used could be improved and a system that detects the stress level of the user in real-time could be obtained by the use of classification algorithms. Suggestions of ways of managing stress could also be incorporated into the system.

In 2018, Amudha et al. proposed a method that uses the Internet of Things to detect stress levels whilst providing management techniques to reduce the effects it has on the mental and physical health of an individual. The physiological parameters that were considered in their study were heart rate (HR) and galvanic skin response (GSR). The elements of the proposed system consisted of a Grove GSR sensor (a two-electrode sensor that measures and converts electrical resistance into voltages) embedded in a wearable wristband, a chest band with a 3-Lead ECG electrode, an Arduino Lilypad microcontroller and an ESP8266 Wi-Fi device. To establish the relationship between the galvanic skin resistance obtained and the heart rate variation in response to stress, two hypotheses were formulated. They state that

1. The mean of the galvanic skin response during stressful and non-stressful situations has no significant differences.

2. The mean of the heart rate variation during stressful conditions and non-stressful conditions has no significant differences.

A 30-minute experiment was conducted on 10 subjects with good vision during which videos of non-stressful scenes (baseline phase) were played for 5 minutes followed by stressful scenes for 10 minutes after which another non-stressful video was played for another 5 minutes. This was done to induce stress whilst the sensors measured the needed input. The signals obtained from the sensors were then processed by the microcontroller and the output was transmitted by the communication device to "ThingSpeak", an open IoT platform where data is stored for analysis. To classify the stressful and non-stressful events, MATLAB Analytics was used, and the outcome was plotted into a graph.

After a statistical analysis was performed, it was shown that the value of the GSR during a stressful event and that during a non-stressful event differ significantly. The same could be said about HR and therefore the hypotheses were rejected. A correlation test is done between the two physiological parameters also showed that they are negatively correlated. As the value of the HR increases during a stressful event, that of the GSR decreases and vice versa during a non-stressful event.

They proposed that in the future, more physiological parameters, an activity recognition system, and a machine learning technique should be added.

Kriti Sethi et al. in 2019 developed a model that uses physiological parameters measured from sensors incorporated in a cap to detect stress levels of an individual during his daily routine or at his/her workplace. They additionally explored the possibility of monitoring the stress levels of users telemetrically via an IoT network and where levels are beyond normal, an alert is sent to a medical practitioner or caregiver for immediate action.

Input signals in the form of heart rate and brainwave signals were measured by a cap that contained PPG and Electroencephalogram sensors. The measured input is then transmitted to an Arduino mega 2560 REV 3 where it is processed. The microcontroller unit uses an algorithm to determine whether the user is stressed or not by comparing and finding deviations from predefined real-time values. When the user is found to be stressed, the output is transmitted to coin vibration motors located at strategic points in the cap to alleviate stress by massaging. The output is additionally sent to a media player containing saved binaural beat music. The media player plays the music stored on its SD card when it receives a signal to cause auditory stimulation. The output can also be displayed on a screen or sent to the IoT platform for storage and analysis via a Wi-Fi module included in the microcontroller.

They recommended that as the elements of the device use low power due to optimised data collection, the device could be powered using solar energy. Furthermore, they proposed some elements of the device could be miniaturised to allow the user to be more comfortable with just the cap on the head without all the wires. Since stress is experienced by many people, the device in future works should be cost-effective and more sensitive than specific.

To monitor the mental health of robot operators in factories of the future to ensure a healthy-life-promoting work environment, Alessandro Leone et al., (2020) proposed a system that can determine excessive stress or cognitive load from physiological values specifically heart rate (HR), galvanic skin response (GSR) and electrooculogram (EOG) signals.

Five volunteers with ages ranging from 24 to 34 and of both genders participated in five cognitive tasks; assembling and manual handling (simulated using Legos) which were separated by a 2-minute resting period. During these tasks, two wearable devices (Empatica E4 and J!NS MEME) were worn. The physiological parameters were first recorded using the sensors before the tasks were initiated. The mistakes made by each participant after the task was recorded and the one with the most mistakes were considered to be more stressed than the others. The wearable sensors were used to measure the HR, GSR and EOG while performing the tasks after which the data were sent through a low energy Bluetooth to a PC for signal processing and analysis.

They concluded that the proposed method had a 93.6% ability to detect stress and an accuracy of 92.7%. The use of a few subjects for their experiment was a limitation to their work and affected the generalization capability of their classification method.

They suggested that future works should involve the development of a real-time stress identifier. Additionally, to improve the classification between stressful and non-stressful conditions and also to be able to identify different levels of stress, more feature extraction procedures and machine learning classifiers should be explored.

Jerry Chen et al. had a review in 2021 on techniques for detecting modern physiological and behavioural related pain and stress detection as well as an investigation into the demands for a monitoring system that uses wearables and the possibilities of using these wearables to solve pain and stress management issues. They made mention of several sensors that uses physiological parameters such as heart rate, electro-dermal activity and others in assessing stress with examples being the Empatica E4 wristband (a wearable wristband that allows the collection, streaming and visualization of multiple physiological data in real-time), Autosense (a wireless sensor that measures cardiovascular, respiratory and thermoregulatory signals through radio transmission), Sleepsense (a piezoelectric film sensor that detects respiration waveforms), BioHarness 3, BN-PPGED, Q-Sensor, Shimmer sensor, Wahoo chest belt, Mind wave mobile EEG headset, DataLog and Cardiosport TP3.

They concluded that for future works, wearables for pain and stress detection and monitoring should be lightweight and miniaturised for user comfortability and should dissipate low heat and radiation to ensure safety. Also, there should be the use of a good security system to protect the privacy of users during data transmission. They further discussed that to be able to reduce a large amount of money used in stress management and to make it affordable for all to use, low-cost stress monitors with easy-to-use features must be employed.

CHAPTER 3: MATERIALS AND METHODS

This section presents an overview of the materials and methods used in implementing the objective of this study. To develop an algorithm used in detecting, quantifying, and monitoring work-related stress, data are known as the SWELL-KW dataset was used. All the details about the dataset were obtained from (Koldijk et al., 2014). The project was fully written using functions and toolkits in MATLAB.

3.1. DATA SOURCE

The SWELL dataset was used for the implementation of the study. This dataset was collected by researchers at the Institute of Computing and Information Sciences at Radboud University and the Delft University of Technology in The Netherlands, as part of the Smart Reasoning Systems for Well-being at Work and Home (SWELL) project, an initiative supported by the Dutch national program, COMMIT. This project aimed to develop "user-centric sensing and reasoning techniques that help to improve physical well-being (mostly in a private context) and to improve well-working (in a work context)".

3.2. SUBJECT AND EXPERIMENT DESIGN

The dataset was collected on 25 healthy subjects which no record of heart diseases of which 17 were male and 8 were female. The subjects had a mean age of 25 years. Most of them were of Dutch origin and were university students who were already familiar with the use of computers, report writing, presentations and had experience with the handling of huge amounts of information.

They were each made to undergo a series of knowledge worker tasks such as report writing and presentations on predetermined topics, on a computer in a controlled lab setting where the conditions under which they worked were manipulated. Everything done was to emulate the knowledge work setting. The conditions under which they worked were three: neutral, stressor 'time pressure' and stressor 'interruption'. Under the neutral condition, the subjects were made to work for a maximum of 45 minutes on their tasks under no pressure and with no interruptions. Under the stressor 'time pressure' condition, participants worked on their tasks within a limited amount of time and the stressor 'interruptions' condition involved the participants being interrupted with emails as they worked on their tasks. Some of the emails that were sent during the tasks were essential to the work that was being done and required a response, others were of no importance and therefore did not require a response but were sent as a means of inducing stress. A block diagram of the three conditions under which the participants worked is shown in **Figure 2** below.

To eliminate influences on the data, the subjects were asked not to smoke or drink caffeine or alcohol 3 hours before the experiment. The participants worked under the neutral condition first followed by either the stressor ‘time pressure’ or the stressor ‘interruption’. The last two were always interchanged. There was an 8-minute period of rest after working under each condition. They were made to answer questionnaires after working under each condition. The subjects wore body sensors (Mobi TMSI) throughout their tasks to record the ECG and skin conductance in response to stress. Video recordings were also made with a high-resolution camera to capture the facial expressions of the participants as they worked. A Kinect 3D depth camera was used to record the posture features of the participants such as leaning back and sitting upright whilst performing the tasks.

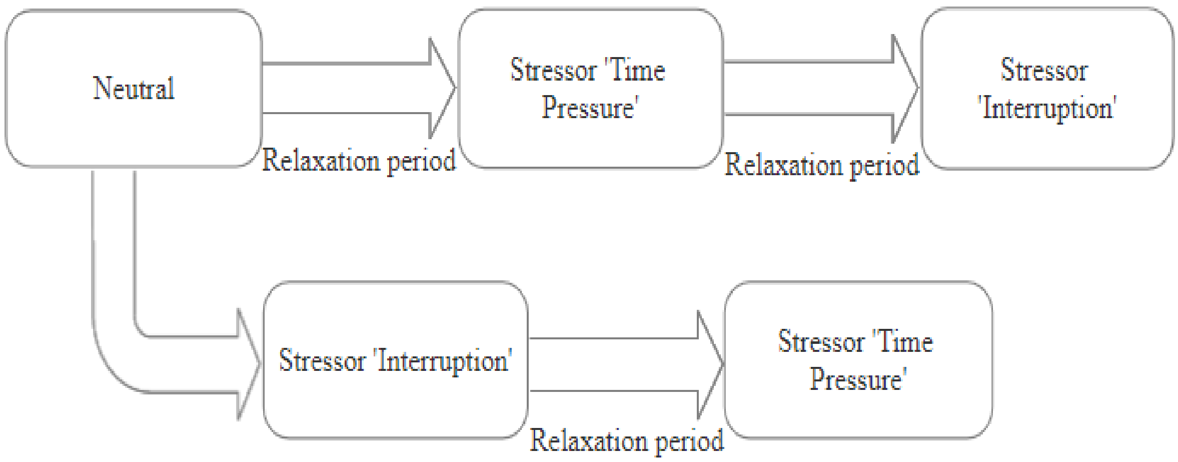

Figure 3. This figure shows the experiment design emphasizing the three conditions (Neutral, Time pressure and Interruption) under which the tasks were performed. The relaxation period refers to the 8 minutes resting period.

3.3. PRE-PROCESSING OF DATA

For this study, only the ECG data obtained from the body sensors will be used.

The originators of the data set used a TMSI Mobi device with 8 channels in obtaining the physiological signal of their experiment. The ECG signal used in this study was then taken from the 6th channel of the body sensor device and has a sampling frequency of 2048Hz.

It was then filtered with a 6th order Butterworth bandpass filter with a bandwidth of 0.4Hz - 45Hz to attenuate the low and high fluctuations below and above the bandwidth frequency of the filter such as common ECG noise; baseline wandering (caused by respiration) and powerline interference. The baseline wandering usually has a frequency between 0.15Hz – 0.3Hz and the powerline interference 50Hz or around 60Hz.

The resulting signal as shown in **Figure 4** below, was then detrended with a 6th order polynomial filter to remove the mean/DC components of the signal. This allows the visibility of the actual amplitudes of the peaks. This can be seen in **Figure 5**.

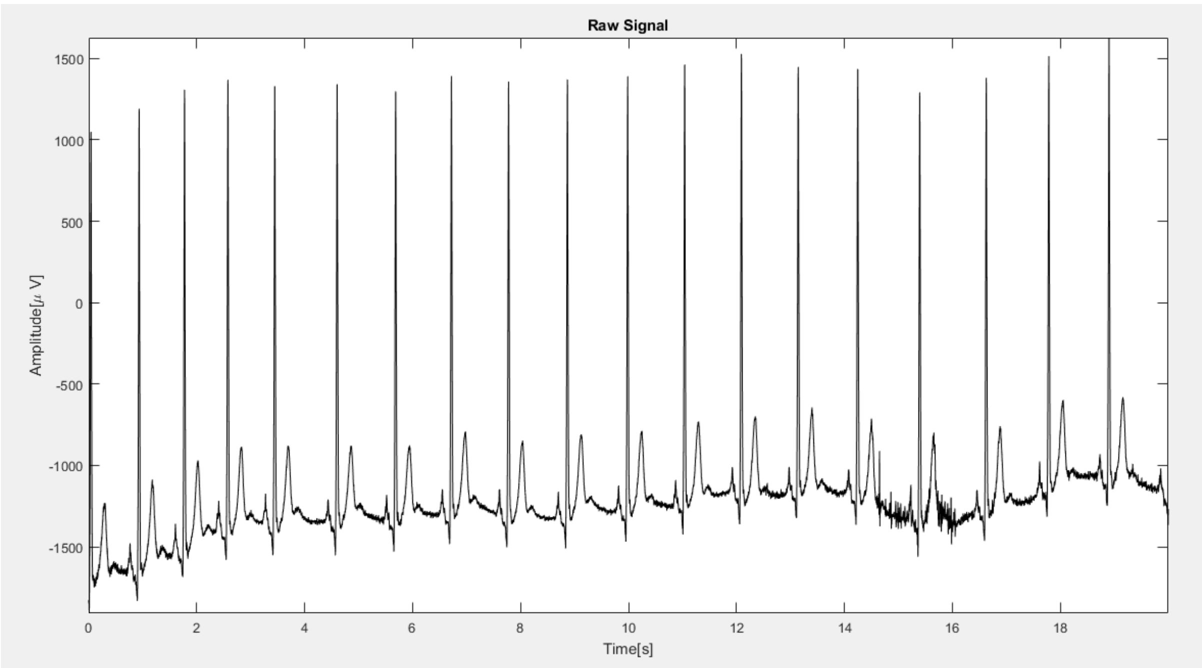

Figure 4. A 20s sampled raw ECG signal with trends, belonging to participant 1 under the neutral condition.

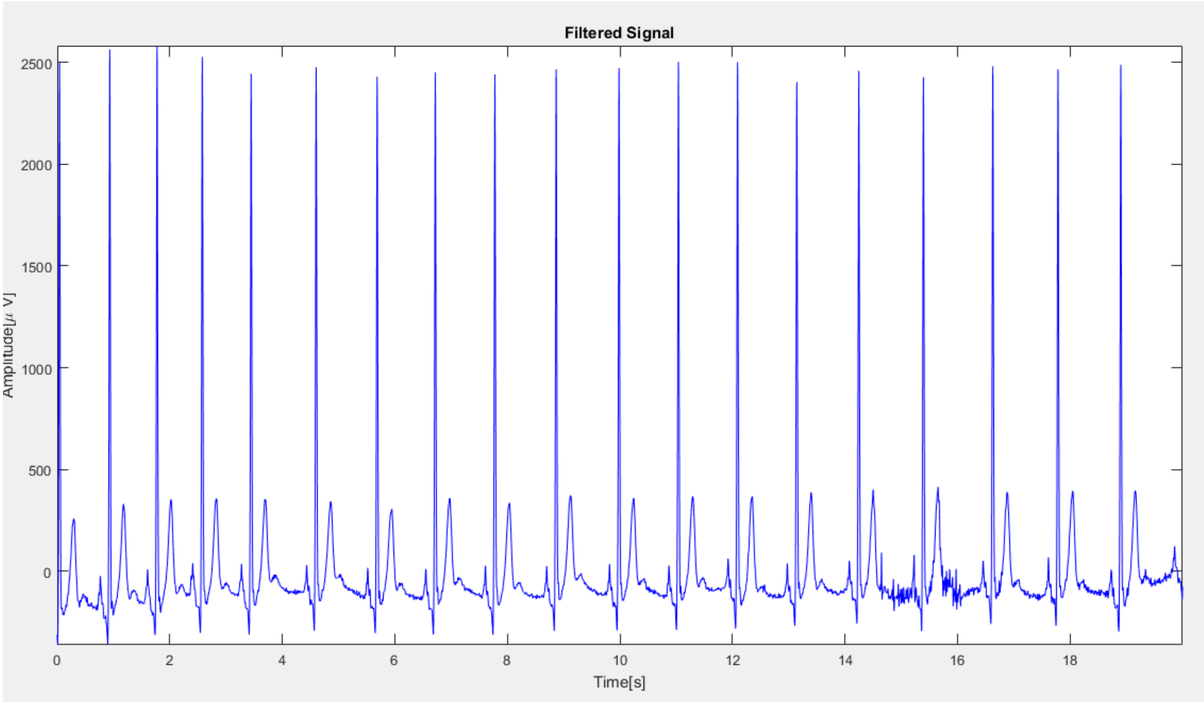

Figure 5. A 20s sampled filtered ECG signal belonging to participant 1 under the neutral condition.

3.4. EXTRACTION OF HEART RATE.

The position of the peaks corresponding to the R-waves of the filtered ECG signal was located using the Pan-Tompkins algorithm toolbox written by (Sedghamiz. H, 2014) made available on MATLAB file exchange (**Figure 6**). Using a 6^{th} order polynomial filter, all other peaks other than the R-peaks were removed or made zero to allow for the prominence of the R-peaks since those are the important part of the signal that is going to be used (**Figure 7**). R peak positions for every 5 minutes of the ECG signal up until the last minute was generated. The time intervals between successive R peaks (R-R interval) were then found by finding the difference between adjacent R peak positions. The computed R-R intervals were filtered to remove intervals with missed peaks and ectopic (premature) heartbeats which could cause errors in the heart rate computation. The filtering was done using the "RRfilter" function in the HRV toolbox written by (Marcus Vollmer, 2019) available on MATLAB file exchange. All the R-R interval values below 0.5s and above 1.2s which would have computed heart rates below 60bpm and above 120bpm were removed and replaced with the median of the previous R-R intervals after which the heart rates were computed using the heart rate function in the HRV toolbox.

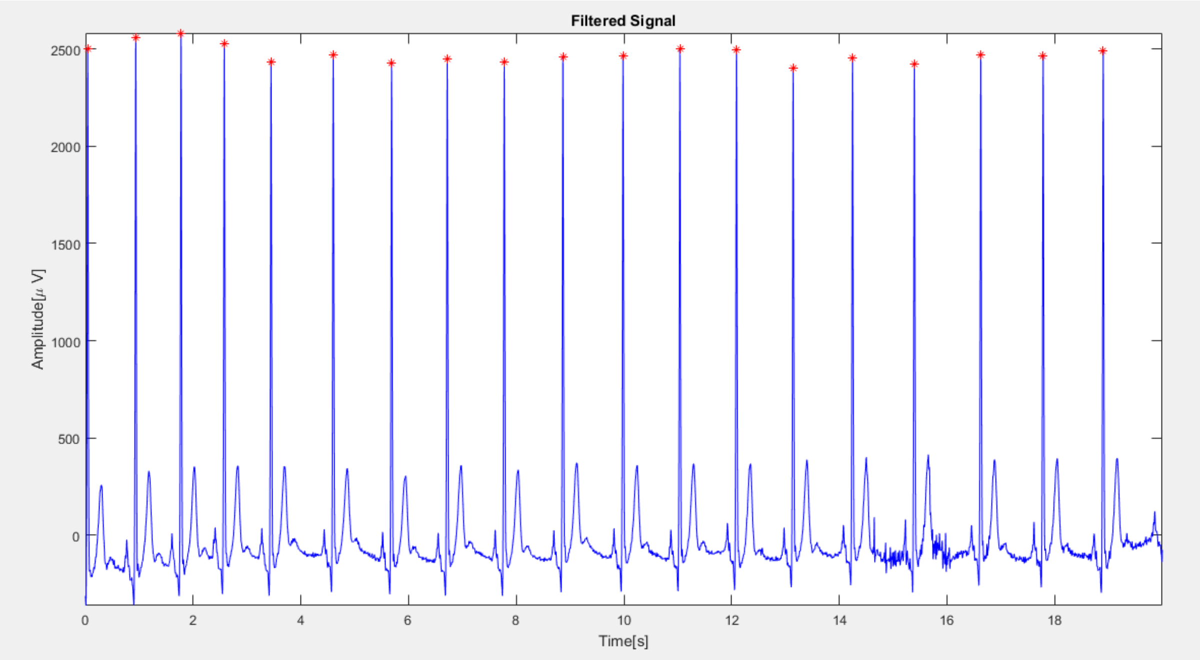

Figure 6. 20s sampled filtered ECG signal showing the located R-peaks. Data belongs to participant 1 under the neutral condition.

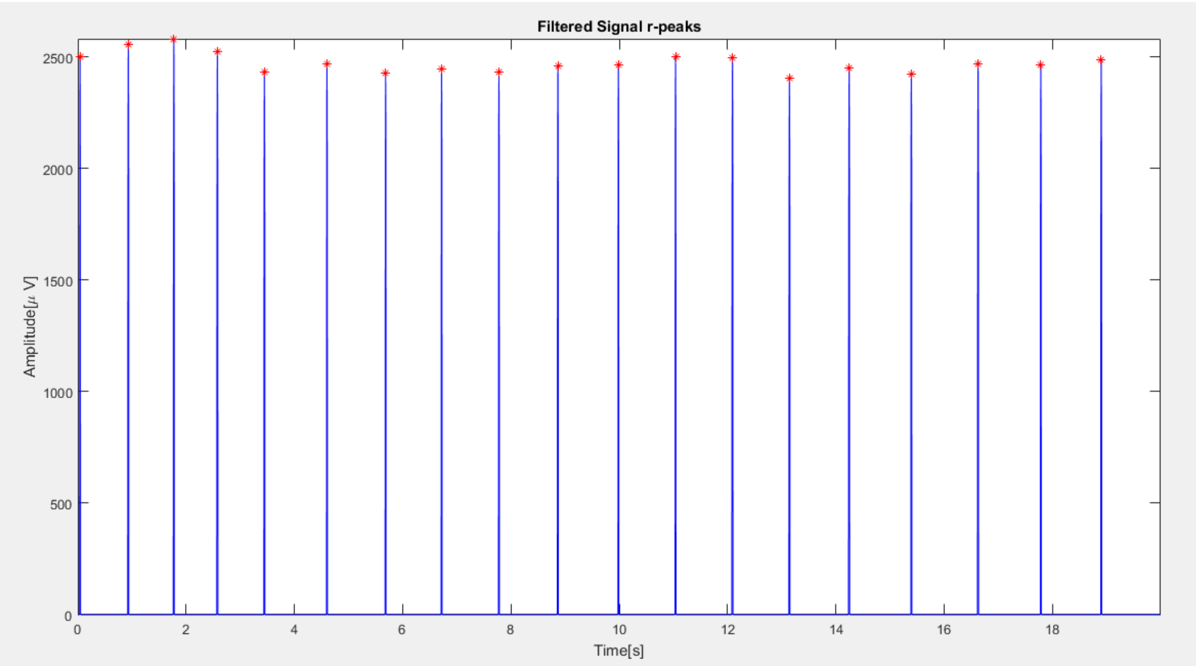

Figure 7. 20s sampled filtered ECG signal showing the located R-peaks excluding all other peaks. Data belongs to participant 1 under the neutral condition.

3.5. EXTRACTION OF HEART RATE VARIABILITY

Using the HRV toolbox, the following HRV indices were computed: RMSSD, PNN50, SDSD, SDNN, LF, HF, LF/HF, and VLF. They were then written into an excel spreadsheet to be used as the input data for the machine learning classifier. To obtain the target and response for the classification, the input data was annotated. Stressful conditions (Stressor "Time Pressure" and "Stressor Interruption") were labelled as 1 and neutral conditions as 0 and these were written on a separate spreadsheet.

3.6. MACHINE LEARNING MODELLING

Artificial Neural network (ANN) was chosen to fulfil the task of detecting and classifying the input data into two classes: stress and no stress. This is because of its ability to model high dimensional signals of a non-linear nature, higher classification accuracy and its multiclass classification function as opposed to other conventional methods such as logistic regression (Renganathan V, 2019). The ANN was implemented using the neural network toolbox in MATLAB. "Patternet", a variation of the feedforward approach was used. In this method, the product of each input and their corresponding weights are taken, fed into the first hidden layer, each multiplied by a bias and then fed into the next layer as its input. The procedure goes on until it reaches the output layer where it is then passed through an activation signal (sigmoid in this study) and the output retrieved with no information being fed back to the input layer.

The HRV features extracted from the ECG signal were organized into a table and used as the input data. The spreadsheet containing the labelled values corresponding to the classes of the individual HRV values were also organised into a table to be used as the target data. The target data consists of 2 columns each representing a class (stress and no stress). Each value of the HRV belonging to the class "stress" (that is those belonging to the time pressure and interruption conditions) has a value of 1 and for those who do not belong to this class (values belonging to the neural condition), a value of 0. A similar approach was taken for the column of the class "no stress". Before modelling, the data for participant 8 was removed as it consisted of invalid heat rates and HRV values and could have altered the accuracy of the classifiers.

The ANN was created to have 3 hidden layers with the first layer having 500 neurons, the second 400 neurons and the last also having 400 neurons. The conjugate gradient algorithm, trainscg was used as the network's training function as it is the fastest for function approximation problems and consumes less memory and mean square error was used to analyse the network's performance. The network was modelled to divide the input data into 3 subsets to prevent over-training of the input and for robust performance. 70% of the input data was used for training and 15% each was used for validation and testing of the network. The network was given a learning rate of 0.15 (default) and a maximum number of epochs of 60 to prevent overtraining. The trained network was afterwards, used on the whole input data to obtain an output after which it was used together with the target data to derive a confusion matrix and a receiver operating characteristics plot. A visual representation of the network architecture has been illustrated in **Figure 8** below.

The input data was also used in other classification models to allow for comparisons, and this was made possible using the classification learner app on MATLAB. The other models in which the data was tested were logistic regression and support vector machine (SVM) models. The features, in this case, the HRV values, were used as predictors and the target data as a response for the models with five-fold cross-validation. The flow chart of the algorithm used for the stress detection has been highlighted in **Figure 9**.

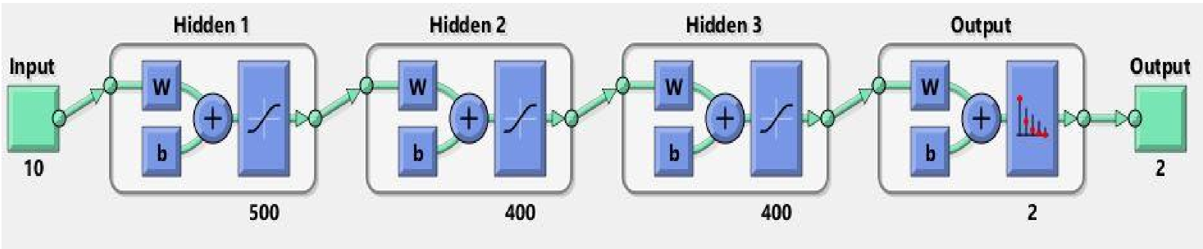

Figure 8. This figure illustrates the artificial neural network architecture used to implement the classification.

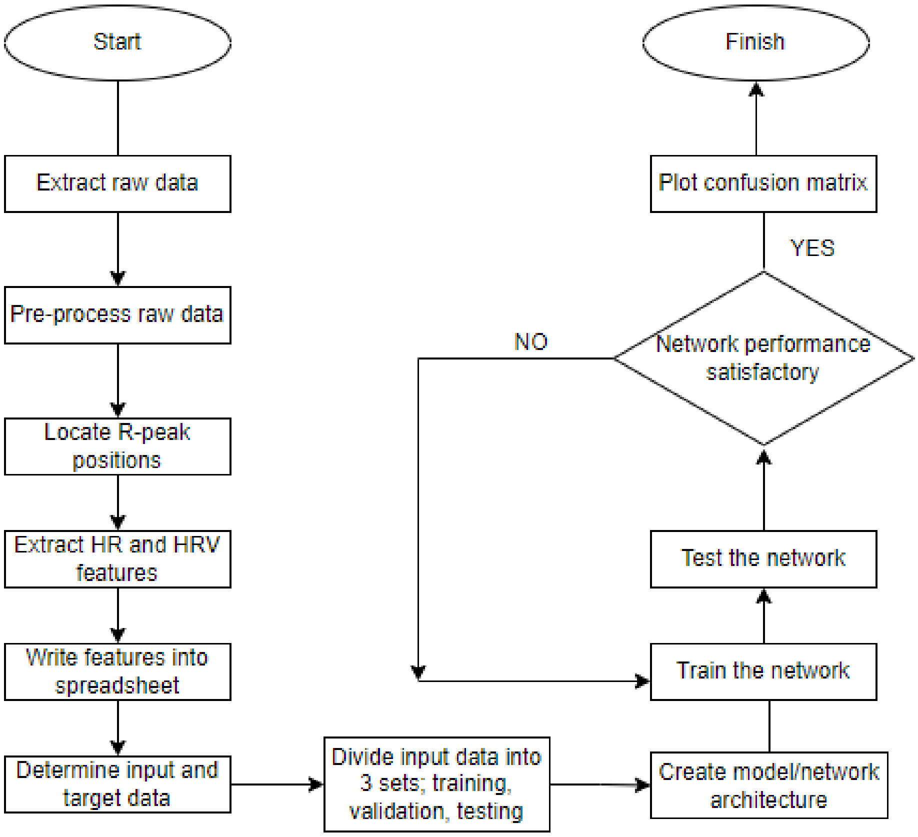

Figure 9. This figure gives an overall summary of the methods used in stress detection. It represents the stress detection algorithm used in this study.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. RESULTS

This section describes the results obtained after implementing the features extracted on the machine learning classifier. The HRV computations together with the heart rate computations of participant 1 during each of the three conditions (Neutral, Stressor 'Time-pressure' and Stressor 'Interruption') after the feature extraction can be found in **Table 2.** The metrics used in the performance evaluation were accuracy, positive predictive value (PPV) also known as precision and true positive rate (TPR) also known as sensitivity. These evaluation metrics were obtained from the confusion matrices plots (as shown in Figures **10, 11, 12, 13, 14, 15** and **16)** and can also be computed from the equations listed below.

1. TPR (No Stress) = TP/ (TP + FN) *100
2. TPR (Stress) = TN/ (TN + FP) *100
3. PPV (No Stress) = TP/ (TP + FP) *100
4. PPV (Stress) = TN/ (TN + FN) *100
5. Accuracy = (TP + TN)/ (TP + TN+ FP + FN) *100

Where TPR = true positive rate (percentage of all actual true positive predictions), PPV = positive predictive value (the number of all positive predictions), TP = true positive (actual true observations), FP= false positive (observations that were not true but predicted as true), TN = true negative (actual negative predictions) and, FN = false negative (observations that were true but predicted as false)

PARTICIPANT/CONDITION	HR (bpm)	RR (s)	SDSD (s)	SDNN (s)	RMSSD (s)	pNN50 (%)	LF/HF	VLF (s^2/Hz)	LF (s^2/Hz)	HF (s^2/Hz)
P1N	65.9260	5.4922	0.0824	0.1497	0.0826	0.3058	1.2817	2.0341	0.5729	0.4470
P1N	66.6806	4.7504	0.0397	0.1096	0.0398	0.1752	2.1176	2.4424	0.4266	0.2015
P1N	68.9365	4.9164	0.0482	0.0917	0.0483	0.2229	3.7077	1.5432	1.1159	0.3010
P1N	68.0470	5.5566	0.0479	0.0834	0.0480	0.2456	4.5603	1.0851	1.5720	0.3447
P1N	66.3969	5.1938	0.0483	0.0744	0.0484	0.2492	5.1047	0.4525	2.1886	0.4287
P1N	68.3719	4.7048	0.0399	0.0637	0.0400	0.2035	7.3724	0.3947	2.2790	0.3091
P1N	67.8413	4.8472	0.0400	0.0682	0.0400	0.2090	6.1604	0.9439	1.7840	0.2896
P1N	69.3285	4.6509	0.0434	0.0603	0.0435	0.2274	3.4833	0.5473	1.8370	0.5274
P1N	68.1645	4.6819	0.0482	0.0809	0.0483	0.2202	5.8003	0.9582	1.7528	0.3022
P1N	67.1395	3.7220	0.0326	0.0795	0.0327	0.1021	3.4361	2.0611	0.7636	0.2222
P1N	65.5927	4.5845	0.0430	0.0673	0.0431	0.2074	3.7162	0.8976	1.7546	0.4721
P1IN	68.0050	3.9211	0.3412	0.2950	0.3418	0.5541	1.6677	0.6583	1.4068	0.8435
P1IN	63.9965	4.2700	0.1241	0.1070	0.1243	0.3115	1.1202	0.7090	1.1643	1.0394
P1IN	65.0219	3.7520	0.0354	0.0633	0.0355	0.1429	4.4746	1.3296	1.4828	0.3314
P1IN	63.7699	5.0026	0.0529	0.0757	0.0530	0.2278	3.5499	0.6799	1.9740	0.5561
P1IN	62.9018	4.4911	0.0413	0.0663	0.0414	0.2244	4.2119	0.9449	1.8560	0.4407
P1IN	64.8597	4.7065	0.0427	0.0748	0.0428	0.1957	3.6380	1.3188	1.4301	0.3931
P1IN	64.6680	4.8913	0.1057	0.1195	0.1059	0.2862	2.0471	1.1253	1.3084	0.6392
P1T	56.8679	6.2223	0.0898	0.1464	0.0900	0.3915	1.9120	2.1172	0.9452	0.4944
P1T	57.0368	4.7758	0.0475	0.0753	0.0476	0.2562	3.0759	1.6148	1.5024	0.4885
P1T	59.9897	3.8969	0.0652	0.0813	0.0653	0.2034	1.7841	1.5705	1.1472	0.6430
P1T	62.2720	3.9967	0.0540	0.0830	0.0541	0.2138	2.7737	1.6119	1.2475	0.4498
P1T	59.6774	5.0371	0.0830	0.0802	0.0831	0.2804	1.4320	0.5852	1.5913	1.1112
P1T	63.5241	4.8228	0.0913	0.0964	0.0915	0.3226	1.6683	0.9189	1.3357	0.8006
P1T	62.3939	4.9977	0.0772	0.0797	0.0774	0.2885	1.3035	0.4979	1.5517	1.1903
P1T	65.2812	4.9486	0.0424	0.0774	0.0424	0.2112	3.5448	1.4555	1.3196	0.3723
P1T	64.5332	5.0763	0.0475	0.0821	0.0476	0.2563	2.9400	1.4674	1.2543	0.4266
P1T	64.9516	6.1225	0.0533	0.0855	0.0534	0.3271	5.4354	0.7319	2.0516	0.3775
P1T	65.2784	4.6804	0.0508	0.1021	0.0509	0.2338	2.8450	1.9767	0.8301	0.2918

Table 2. This table shows the HR and HRV values for participant 1 under the 3 conditions. P = participant, N = neutral condition, IN = stressor 'interruption' and T = stressor 'time interruption'.

The confusion matrix of the ANN (**Figure 9**) shows the number and percentage of correct classifications by the trained ANN. The confusion matrix shows that 145 observations(features) are correctly classified as "No Stress" and this corresponds to 26.2% of all 554 observations. Comparably, 287 observations are correctly classified as "Stress", and this is congruous with 51.8% of all observations. 48 of the Stress observations are incorrectly classified as No Stress and this corresponds to 8.7% of all 544 feature values. Similarly, 74 of the No stress observations are incorrectly classified as Stress and this corresponds to 13.4% of the total data. The neural network is also able to precisely predict 75.1% of the 193 No stress observations correctly and 24.9% of the 193 No stress observations incorrectly. It is also able to precisely predict 79.5% of the 361 Stress observations correctly and 20.5% of the 361 Stress observations wrongly. Out of 219 No Stress cases, 66.2% are correctly predicted as No Stress and 33.8% are predicted as Stress. Out of the 335 Stress observations, 85.7% are correctly classified as Stress and 14.3% are classified as No Stress. The artificial neural network model has an overall accuracy of 78% with 22% incorrect predictions.

Figure 10. Illustrates the accuracy and precision of the ANN from a confusion matrix. Class 1 = No Stress, Class 2 = Stress. The values in the green boxes represent the true values (upper left, TP and lower right, TN) and the values in the green boxes represent the false values (upper right, FP and lower left FN). The values at the far-right column except the blue box represent the PPV values and those at the lower row represent the TPR values.

Furthermore, the logistic regression model **Figure 11**, was able to correctly classify 99 observations as No Stress and 120 of the Stress observations wrongly classified as No Stress. 271 Stress observations were correctly predicted as such and 64 of the No stress observations on the other hand were incorrectly predicted as Stress. The logistic regression model **Figure 13** has a No Stress precision of 61%. That is, out of the 219 No Stress observations, 61% of this figure were accurately classified as such. The model also recorded a Stress precision of 69% showing that out of the 335 observations classified as Stress, 69% of this number were correctly classified as Stress. The logistic regression model **Figure 12** recorded a 45% sensitivity to the class No Stress and an 81% sensitivity to the class Stress. The model was able to accurately classify the observations into their respective classes by a 66.8% rate with an error rate of 33.2%.

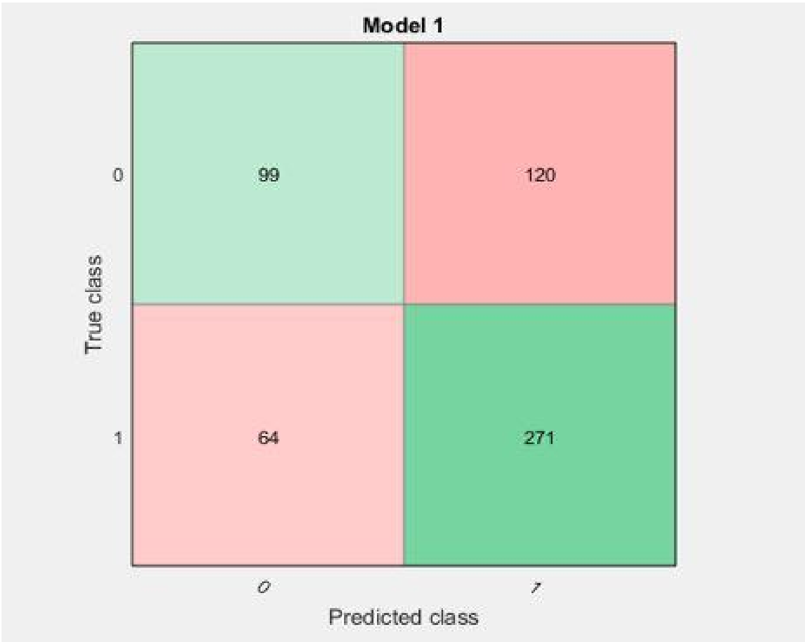

Figure 11. shows the number of observations predicted by the logistic regression model. Class 0 = No Stress and Class 1 = Stress. The values in the green boxes represent the true values (upper left, TP and lower right, TN) and the values in the green boxes represent the false values (upper right, FP and lower left FN).

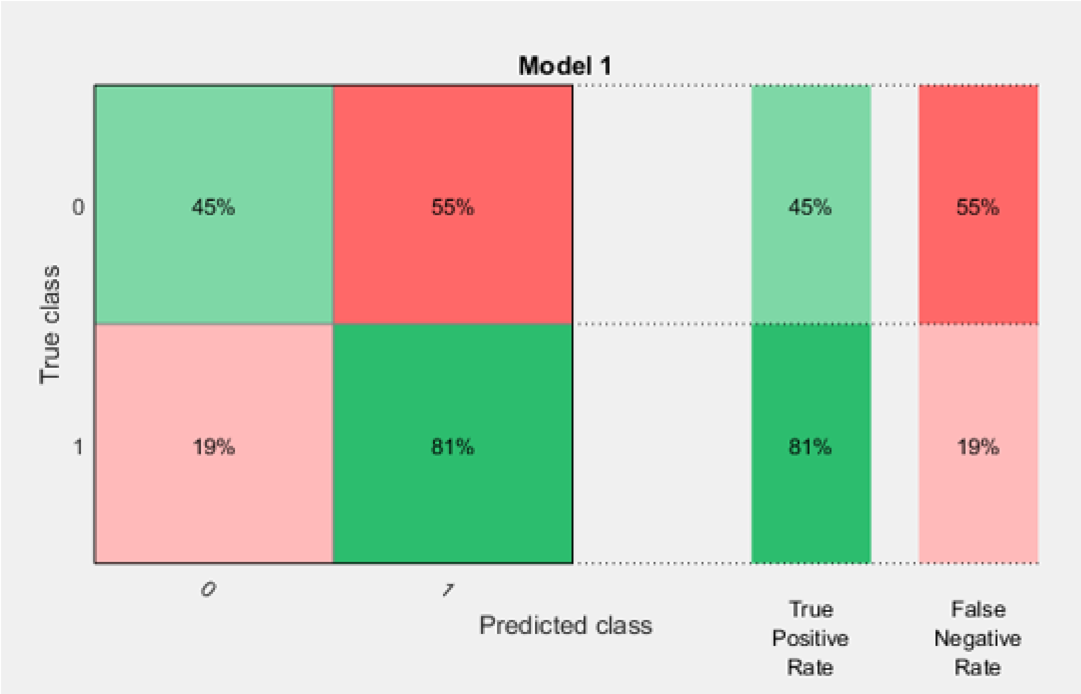

Figure 12. shows the TPR predicted by the logistic regression model. Class 0 = No Stress and Class 1 = Stress. Green boxes = TPR and red boxes = false negative rate

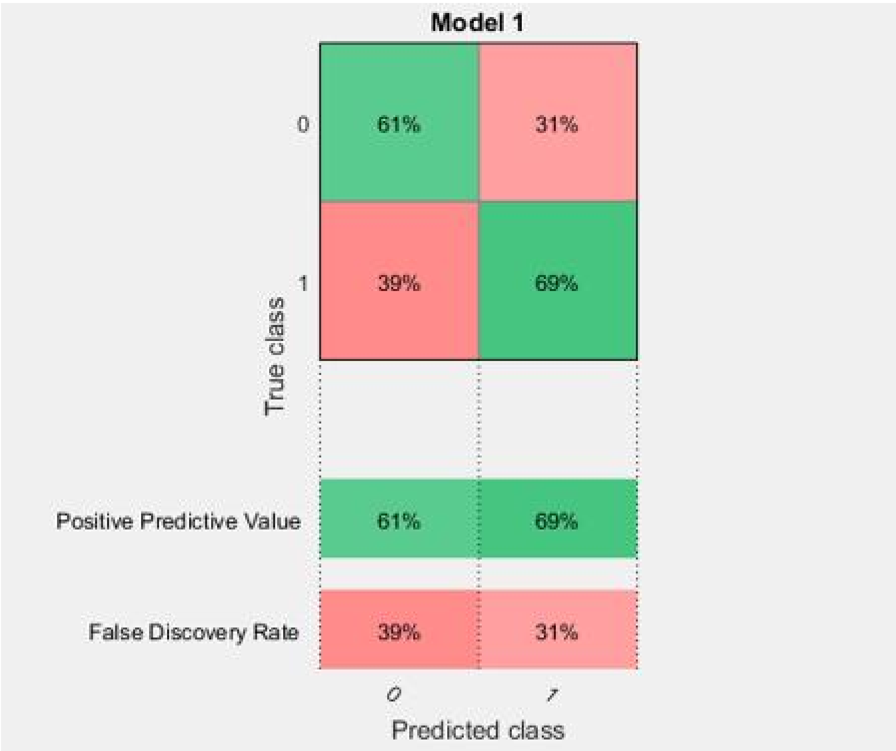

Figure 13. shows the PPV predicted by the logistic regression model. Class 0 = No Stress and Class 1 = Stress. Green boxes = PPV and red boxes = false discovery rate.

It can be seen from **Figure 14** that the SVM model was able to predict correctly 58 No Stress observations however 161 of the Stress observations were wrongly classified as No Stress. 298 Stress observations were correctly predicted whereas 37 of the No stress observations were incorrectly predicted as Stress. The SVM model **Figure 16** has a No Stress precision of 61%. That is, out of the 219 No Stress observations, 61% of this figure were accurately classified as such. The model also recorded a Stress precision of 65% showing that out of the 335 observations classified as Stress, 65% of this number were correctly classified as Stress. The SVM model **Figure 15** recorded an 89% sensitivity to the class Stress. The model however has poor sensitivity to the class No Stress as it recorded a low 26% rate. In all, the model was able to accurately classify the observations into their respective classes by a 64.3% rate with an error rate of 35.7%.

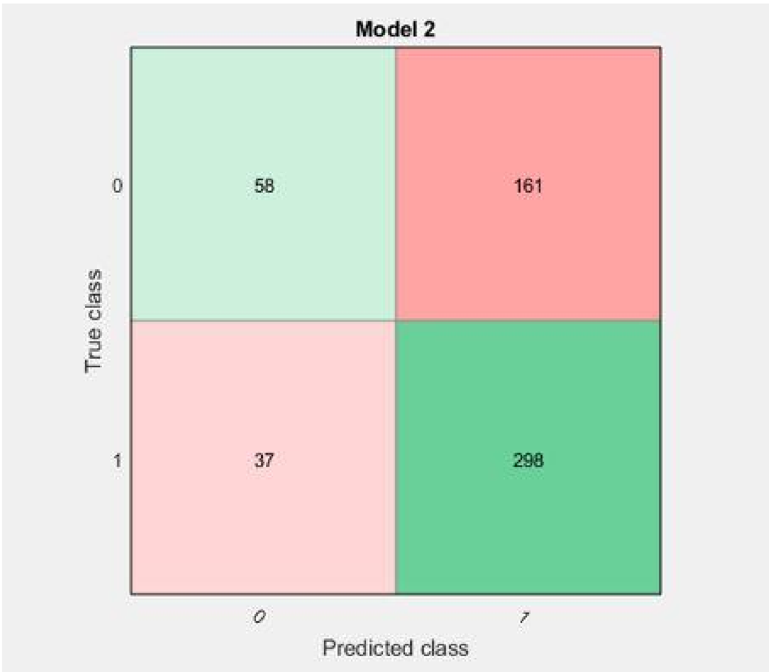

Figure 14. shows the number of observations predicted by the logistic regression model. Class 0 = No Stress and Class 1 = Stress. The values in the green boxes represent the true values (upper left, TP and lower right, TN) and the values in the green boxes represent the false values (upper right, FP and lower left FN).

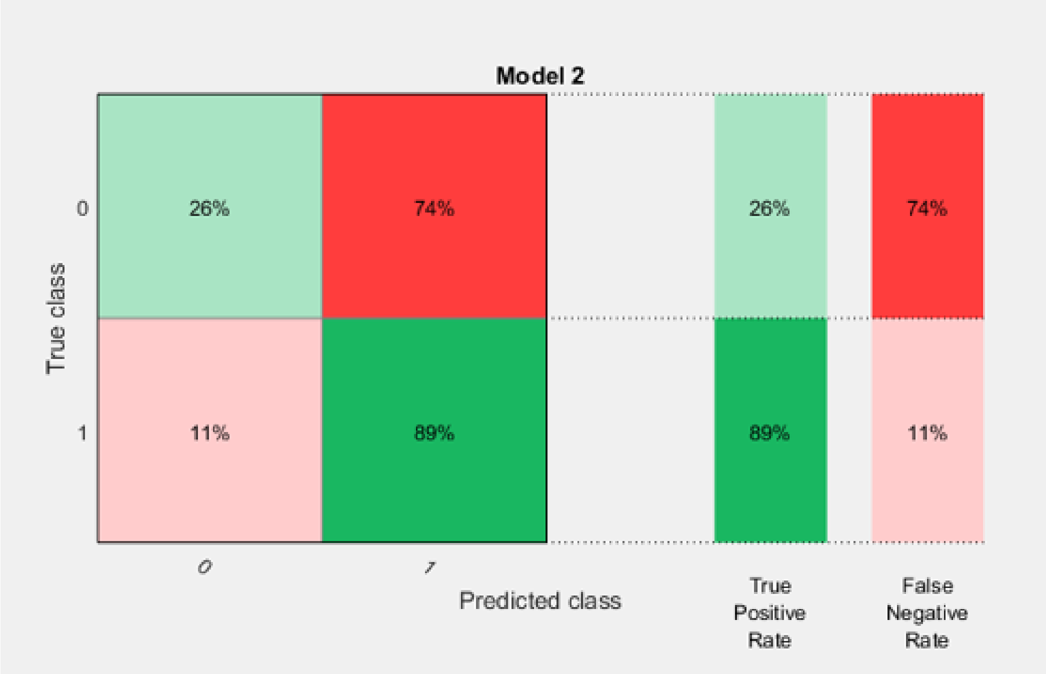

Figure 15. shows the TPR predicted by the SVM model. Class 0 = No Stress and Class 1 = Stress. Green boxes = TPR and red boxes = false negative rate

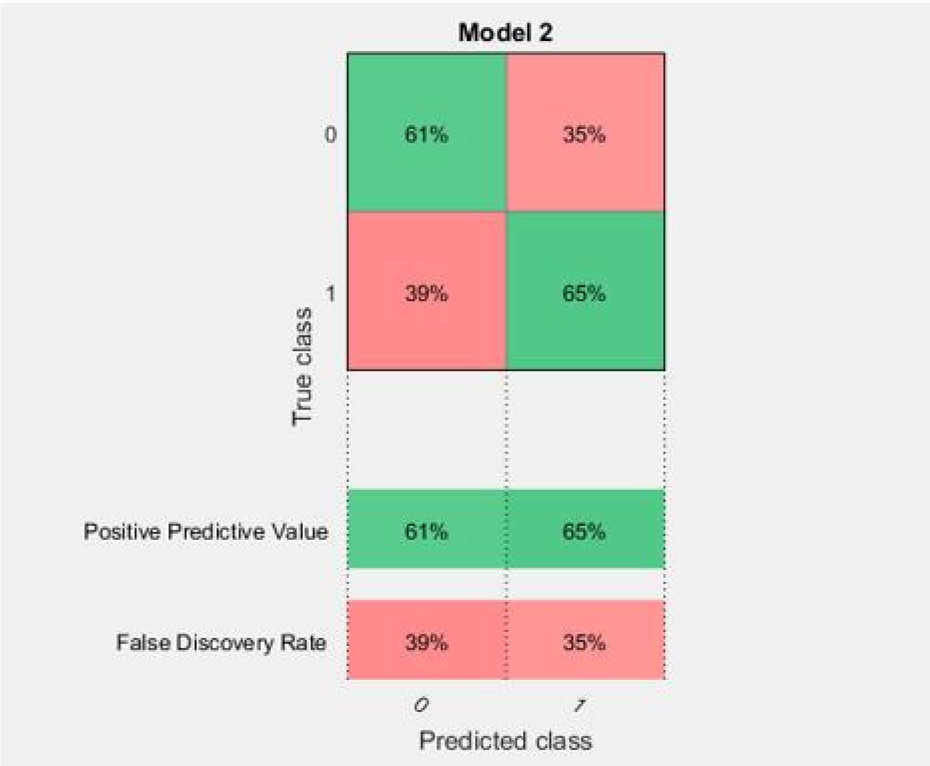

Figure 16. shows the PPV predicted by the SVM model. Class 0 = No Stress and Class 1 = Stress. Green boxes = PPV and red boxes = false discovery rate

The following table is a summary of the performance of the ANN, logistic regression and SVM models.

Model/Algorithm	**Accuracy (%)**	**PPV (No Stress) (%)**	**PPV (Stress) (%)**	**TPR (No Stress) (%)**	**TPR (Stress) (%)**
Neural Network	78.0	66.2	85.7	75.1	79.5
Logistic Regression	66.8	61.0	69.0	45.0	81.0
SVM	64.3	61.0	65.0	26.0	89.0

Table 3. Illustration of the performance of the machine learning classifiers.

4.2. DISCUSSION

It can be inferred from **Table 3**, that the neural network model with a positive predictive value of 66.2% and 85.7% in both the No Stress class and the Stress class observations respectively, is more precise in predicting positive observations than the Logistic regression and SVM models. Although the SVM model has the same positive predictive value in the No Stress class as the logistic regression model, it has the overall lowest precision. The same can be said about the sensitivity of the three models when they are compared. From these findings, it can be established that the ANN with an accuracy of 78% is more accurate and produces fewer errors as compared to the logistic regression and SVM models. This outcome buttresses the point made by (Renganathan V, 2019) that ANN has a higher classification accuracy and is better in modelling high dimensional signals of a non-linear nature like the data used in this study and as such the most useful in stress prediction.

Furthermore, it can be seen from **Table 2** the differences in HR and HRV in the different conditions. The HRV values are generally lower than the HR values during stressful conditions signifying changes in the autonomic nervous system function as a response to a stressor as stated by (Hjortskov, et al., 2004) in his study. The participants, under a lot of pressure to complete their tasks while working for a short period, and also being interrupted, recorded a higher heart rate and a lower HRV. There are also visible differences between the HRV values in the neutral condition and those in the stressor 'time pressure' and stressor 'interruption' conditions. The time-domain HRV and HF values are seen to decrease during the stressor ‘time pressure’ and stressor ‘interruption’ conditions and the frequency domain indices, particularly, the LF/HF and LF increase during the stressful conditions when compared to those of the neutral condition. This buttresses the point stated by (Shaffer & Ginsberg, 2017) that the time domain indices and the frequency domain index HF reflect parasympathetic activation and are therefore lower during stressful conditions and, the LF and LF/HF represent sympathetic activity and are therefore higher during stressful conditions. These HRV characteristics during stressful conditions that were shown are also similar to the findings of existing research by (Nkurikiyeyezu, Shoji, Yokokubo, & Lopez, 2019). These changes and differences in the HRV values show that indeed stress was detected. Although the obtained performance is not the highest as compared to the performance in other studies, for example (Nkurikiyeyezu, Shoji, Yokokubo, & Lopez, 2019), the goal of this study which is to detect stress using HRV was attained.

CHAPTER 5: CONCLUSION

The objective of this study is to write an algorithm to detect work-related stress. An overview and physiology of stress were elaborated and the approaches to which it can be measured was explained. The recent trends and similar works done by other researchers were summarized to give a perspective of the subject of interest. A data set was obtained, pre-processed, features were extracted, input and target data were determined, and the classification model architecture was created and implemented based on the data provided.

The results show that a non-invading system that can predict stress using heart rate variability is possible to design and that HRV is indeed an indicator of stress. Overall, the goal of this study was achieved, and the chosen classification model (ANN) was able to accurately implement this goal by a rate of 78%. Nonetheless, some limitations influenced the outcome of this study.

5.1. LIMITATIONS

The quality of the results obtained from a classification model depends on the quality of the dataset used in creating the model (Stephan Dreiseitl, Lucila Ohno-Machado, 2002). The dataset used had some inconsistencies and errors that could not be completely rectified without altering and making the ECG signals very synthetic. Some of the data particularly that of participant 8 generated invalid heart rate and heart rate variability computations and had to be removed. All of these contributed to the satisfactory results obtained.

5.2. RECOMMENDATIONS

For future works, a separate data set not used for model building should be used to test the efficacy of the algorithm to minimize generalisation error. An improved version of the algorithm should also be tested on a wearable device to capture its performance in real-time taking into consideration, fast communication and security systems and telemetry. Also, the other physiological parameters that are associated with stress detection should be explored.

REFERENCES

1. Symposium, I., Advanced, O. N., Engineering, T., Adochiei, F., Cepisca, C., Seri, G., … Academy, M. T. (2019). Complex Embedded System for Stress Quantification. 2019-2022.
2. Akmandor, A. O., & Jha, N. K. (2017). Keep the Stress Away with SoDA: Stress Detection and Alleviation System. IEEE Transactions on Multi-Scale Computing Systems, 3(4), 269–282. https://doi.org/10.1109/TMSCS.2017.2703613
3. Zalabarria, U., Irigoyen, E., Martinez, R., Larrea, M., & Salazar-Ramirez, A. (2020). A Low-Cost, Portable Solution for Stress and Relaxation Estimation Based on a Real-Time Fuzzy Algorithm. IEEE Access, 8, 74118–74128. https://doi.org/10.1109/ACCESS.2020.2988348
4. Sharma DK (2018) Physiology of Stress and its Management. J Med
5. McLeod, S. A. (2010). What is the stress response? Simply Psychology. https://www.simplypsychology.org/stress-biology.html
6. Elzeiny, S., & Qaraqe, M. (2018). Blueprint to Workplace Stress Detection Approaches. 2018 International Conference on Computer and Applications, ICCA 2018, 407–412. https://doi.org/10.1109/COMAPP.2018.8460293
7. Yaribeygi H, Panahi Y, Sahraei H, Johnston TP, Sahebkar A. The impact of stress on body function: A review. EXCLI J. 2017; 16:1057-1072. Published 2017 Jul 21. doi:10.17179/excli2017-480
8. Parlak, O. (2021). Portable and wearable real-time stress monitoring: A critical review. Sensors and Actuators Reports, 3(December 2020). https://doi.org/10.1016/j.snr.2021.100036
9. Gjoreski, M., Luštrek, M., Gams, M., & Gjoreski, H. (2017). Monitoring stress with a wrist device using context. Journal of Biomedical Informatics, 73, 159–170. https://doi.org/10.1016/j.jbi.2017.08.006
10. Acerbi, G., Rovini, E., Betti, S., Tirri, A., Rónai, J. F., Sirianni, A., … Cavallo, F. (2017). A wearable system for stress detection through physiological data analysis. Lecture Notes in Electrical Engineering, 426, 31–50. https://doi.org/10.1007/978-3-319-54283-6_3
11. Healey, J. A., & Picard, R. W. (2005). Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on Intelligent Transportation Systems, 6(2), 156–166. https://doi.org/10.1109/TITS.2005.848368

12. Ulstein, I., Wyller, T. B., & Engedal, K. (2007). A high score on the Relative Stress Scale, a marker of possible psychiatric disorder in family carers of patients with dementia. International journal of geriatric psychiatry, 22(3), 195-202.
13. Carneiro, D., Novais, P., Augusto, J. C., & Payne, N. (2019). New methods for stress assessment and monitoring at the workplace. IEEE Transactions on Affective Computing, 10(2), 237–254. https://doi.org/10.1109/TAFFC.2017.2699633
14. Xue, M., Liang, R. H., Yu, B., Funk, M., Hu, J., & Feijs, L. (2019). Affective wall: Designing collective stress-related physiological data visualization for reflection. IEEE Access, 7, 131289–131303. https://doi.org/10.1109/ACCESS.2019.2940866
15. Shaffer Fred, Ginsberg J. P., An Overview of Heart Rate Variability Metrics and Norms, Frontiers in Public Health, Volume 5, 2017, PAGE 258, URL=https://www.frontiersin.org/article/10.3389/fpubh.2017.00258, DOI=10.3389/fpubh.2017.00258, ISSN=2296-2565
16. Mejía-Mejía E, Budidha K, Abay TY, May JM and Kyriacou PA (2020) Heart Rate Variability (HRV) and Pulse Rate Variability (PRV) for the Assessment of Autonomic Responses. Front. Physiol. 11:779. Doi: 10.3389/fphys.2020.00779
17. Lebepe, F., Niezen, G., Hancke, G. P., & Ramotsoela, T. D. (2016). Wearable stress monitoring system using multiple sensors. IEEE International Conference on Industrial Informatics (INDIN), 0, 895–898. https://doi.org/10.1109/INDIN.2016.7819288
18. Uday, S., Jyotsna, C., & Amudha, J. (2018). Detection of Stress using Wearable Sensors in IoT Platform. Proceedings of the International Conference on Inventive Communication and Computational Technologies, ICICCT 2018, (Icicct), 492–498. https://doi.org/10.1109/ICICCT.2018.8473010
19. Sethi, K., Ramya, T., Singh, H. P., & Dutta, R. (2019). Stress detection and relief using wearable physiological sensors. Telkomnika (Telecommunication Computing Electronics and Control), 17(3), 1539–1546. https://doi.org/10.12928/TELKOMNIKA.V17I3.9719
20. Leone, A., Rescio, G., Siciliano, P., Papetti, A., Brunzini, A., & Germani, M. (2020). Multi sensors platform for stress monitoring of workers in a smart manufacturing context. I2MTC 2020 - International Instrumentation and Measurement Technology Conference, Proceedings, 3–7. https://doi.org/10.1109/I2MTC43012.2020.9129288
21. Chen, J., Abbod, M., & Shieh, J. S. (2021). Pain and stress detection using wearable sensors and devices—a review. Sensors (Switzerland), 21(4), 1–18. https://doi.org/10.3390/s21041030

22. Koldijk, S., Sappelli, M., Verberne, S., Neerincx, M., & Kraaij, W. (2014). The SWELL Knowledge Work Dataset for Stress and User Modelling Research. To appear in: Proceedings of the 16th ACM International Conference on Multimodal Interaction (ICMI 2014) (Istanbul, Turkey, 12-16 November 2014).
23. Sedghamiz. H, "MATLAB Implementation of Pan Tompkins ECG QRS detector." March2014.https://www.researchgate.net/publication/313673153_Matlab_Implementation_of_Pan_Tompkins_ECG_QRS_detect
24. Pan Tompkins. W.J, "A Real-Time QRS Detection Algorithm" IEEE Transactions on Biomedical Engineering, Vol. Bme-32, No. 3, March 1985.
25. Vollmer, Marcus. "HRVTool - an Open-Source MATLAB Toolbox for Analysing Heart Rate Variability." 2019 Computing in Cardiology Conference (CinC), Computing in Cardiology, 2019, doi:10.22489/cinc.2019.032.
26. Stephen (2022). Natural-Order Filename Sort (https://www.mathworks.com/matlabcentral/fileexchange/47434-natural-order-filename-sort), MATLAB Central File Exchange. Retrieved January 20, 2022.
27. Goldberger, A., Goldberger, Z. D. & Shvilkin, A., 2013. Goldberger's Clinical Electrocardiography a Simplified Approach. 8th Edition ed. Philadelphia: Elsevier Saunders
28. David B. Geselowitz. (1989). On the Theory of the Electrocardiogram. *Fortschritte Der Physik*, *77*(6), 857–876. https://doi.org/10.1002/prop.19640120702
29. Lilly, Leonard S, ed. (2016). Pathophysiology of Heart Disease: A Collaborative Project of Medical Students and Faculty (sixth ed.). Lippincott Williams & Wilkins. p. 74. ISBN 978-1451192759.
30. Atkielski, A., 2007. File:SinusRhythmLabels.png. https://commons.wikimedia.org/wiki/File:SinusRhythmLabels.svg. (Accessed on 22 01 2022).
31. Boucsein, Wolfram (2012). Electrodermal Activity. Springer Science & Business Media. p. 2. ISBN 978-1-461-41126-0
32. Hjortskov, N. et al., 2004. The effect of mental stress on heart rate variability and blood pressure during computer work. Eur J Appl Physiol , Volume 92, pp. 94-89.
33. Moore, J., 2017. Normative Elite HRV Scores by Age and Gender. https://elitehrv.com/normal-heart-rate-variability-age-gender.
34. A.N., Jayanthi. (2015). Galvanic Skin Response Measurement and Analysis. Galvanic Skin Response Measurement and Analysis. 10. 2015.

35. Kulkarni S, O'Farrell I, Erasi M, Kochar MS. Stress and hypertension. WMJ. 1998 Dec;97(11):34-8. PMID: 9894438.
36. Renganathan V (Skyline University College, University City, Sharjah, U. A. E. (2019). Overview of artificial neural network models in the biomedical domain. 120(7), 536–540. DOI: 10.4149/BLL_2019_087
37. Stephan Dreiseitl, Lucila Ohno-Machado, Logistic regression, and artificial neural network classification models: a methodology review, Journal of Biomedical Informatics, Volume 35, Issues 5–6, 2002, Pages 352-359, ISSN 1532-0464, https://doi.org/10.1016/S1532-0464(03)00034-0. (https://www.sciencedirect.com/science/article/pii/S1532046403000340)
38. Nkurikiyeyezu, K., Shoji, K., Yokokubo, A., & Lopez, G. (2019). Thermal comfort and stress recognition in an office environment. HEALTHINF 2019 - 12th International Conference on Health Informatics, Proceedings; Part of 12th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2019, 256–263. https://doi.org/10.5220/0007368802560263
39. Cindy L. Stanfield. Principles of Human Physiology. Fifth edition, 2013. Pages 357 - 369.