Project Report on

CHARACTERIZATION AND CLASSIFICATION OF STRESS USING PPG SIGNAL GUIDED BY GSR

Project Report Submitted for Partial Fulfilment of the
Requirement for B.Tech Degree in Instrumentation Engineering

From the

Department of Applied Physics
University of Calcutta

Under the guidance of:

Dr. Saurabh Pal

Submitted by:

Suparno Banerjee,
Instrumentation Engineering,
4year B. Tech, 8th Semester,
Roll- T91/IE/194100,
Registration No: D01-1111-0194-19

Department of Applied Physics, University of Calcutta,
92, Acharya Prafulla Chandra Road, Rajabazar,
Kolkata-700092, West Bengal.
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AIM OF THE PROJECT:

The aim of the project is to develop a Machine Learning based system to detect different stress generating events such as solving arithmetic problems, listening to music, reading from computer screen etc. with respect to a threshold resting condition using physiological signals like PPG (Photoplethysmogram) and GSR (Galvanic Skin Response). The proposed algorithm uses GSR as event marker and different events are classified from PPG based features. The developed method can be used in a mental stress detection and analysis system to identify the events that can cause stress.

DEPARTMENT OF APPLIED PHYSICS
UNIVERSITY COLLEGE OF TECHNOLOGY
UNIVERSITY OF CALCUTTA
92, Acharya Prafulla Chandra Road, Kolkata - 700 009, West Bengal, India
ফলিত পদার্থবিদ্যা বিভাগ, কলিকাতা বিশ্ববিদ্যালয়

CERTIFICATE OF APPROVAL

The project report titled “Characterization and Classification Of Stress Using PPG Signal Guided By GSR”, submitted by **Suparno Banerjee (Roll No- T91/IE/194100), 8th semester, B.Tech, Instrumentation Engineering**, is hereby approved and certified as a creditable study in technological studies, performed in a way sufficient for its acceptance for particular fulfilment of the degree for which submitted. It is to be understood by this approval, the undersigned does not, necessarily endorse or approve any statement made, opinion expressed or, conclusion drawn therein, but approved for the purpose for which it is submitted.

Signature of Project Supervisor

Dr.Saurabh Pal, Associate Professor, Instrumentation Engineering, Department of Applied Physics, University of Calcutta

Head of the Department, Dept. of Applied Physics, University of Calcutta

External Examiners

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Submitted by,
Suparno Banerjee
Roll No.- T91/IE/194100
4Yr. B.Tech 8th Semester
Instrumentation Engineering
University of Calcutta

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Chapter 1: Introduction to Stress

Stress is a response to particular events. It is the way our body prepares itself to face a difficult situation with focus, strength and heightened alertness. Therefore, it is necessary to build a device to detect stress. It is a feeling that people have when they are struggling to cope with challenges related to finances, work, relationships, environment, and other situations. Moreover, stress is felt when an individual perceives a real or imagined challenge or threat to their well-being. People often use the word stress interchangeably with anxiety, feeling anxious, fearful, nervous, overwhelmed, panic, or stressed out is the body's natural defence against real or imagined danger. It flushes the body with hormones to prepare systems to evade or confront danger. When we perceive a threat, our nervous system responds by releasing a flood of stress hormones, including adrenaline and cortisol. These hormones rouse the body for emergency action. In some cases, it is necessary to collect feedback in order to control this symptom because it can become dangerous in certain situations.

Stress is crucial in our community nowadays. There are many people who are suffering from stress and unfortunately it has already become part of our life. This problem usually happens to adult because of their high workloads, commitment in life, and also time pressure. Stress is a huge problem in today's society. Being able to measure stress, therefore, may help to address this problem.

1.1 Identifying Stress:

Several techniques are currently used to assess stress levels, although these are limited to intermittent measurements often requiring a skilled operator, rather than being suitable for continuous monitoring. For instance, cortisol hormone levels, which increase during stress, can be measured from samples of saliva, blood or urine. Stress can also be assessed from cardiovascular parameters such as blood pressure (BP), heart rate (HR), and heart rate variability; respiratory parameters; galvanic skin response; and biofeedback systems used to train athletes. However, changes in these parameters are not specific to stress. Therefore, there is a need to develop techniques for continuously monitoring stress levels. It has recently been proposed that stress could be assessed from the photoplethysmogram (PPG), a non-invasive signal which captures changes in blood volume over time in a bed of tissue.

Stress is not always easy to recognize, but there are some ways to identify some signs that you might be experiencing too much pressure. Sometimes stress can come from an obvious source, but sometimes even small daily stresses from work, school, family, and friends can take a toll on your mind and body.

If you think stress might be affecting you, there are a few things you can watch for:

- **Psychological signs** such as difficulty concentrating, worrying, anxiety, and trouble remembering
- **Emotional signs** such as being angry, irritated, moody, or frustrated
- **Physical signs** such as high blood pressure, changes in weight, frequent colds or infections, and changes in the menstrual cycle and libido
- **Behavioural signs** such as poor self-care, not having time for the things you enjoy, or relying on drugs and alcohol to cope.

1.2 Stress and Physiology:

Stress is not a situation or a condition during an adverse condition, as it is generally assumed. In fact, it is a way by which the body overcomes a demanding or undesirable situation. Whenever we are in some unfavourable condition (whether it is physical or mental) our body tries to maintain the homeostasis (internal milieu) and protect itself from such events adopting some ‘changes’. Stress is a series of events our body follows to cope with such situations. Selye (Hans Selye) used the term ‘stress’ to represent the effects of anything that seriously threatens homeostasis of the body. Both external and internal factors affect the homeostasis of the body.

1.3 The Physiology of Stress:

Physiological stress can be defined as any external or internal condition that challenges the homeostasis of a cell or an organism.

The body’s stress response is governed by the sympathetic nervous system. When faced with acute danger, your body responds with a cascade of physical and hormonal changes that prepare you to respond. Some of these changes include:

- Increased blood pressure and heart rate
- A surge of the hormone's epinephrine, norepinephrine and cortisol
- Reduced blood flow to visceral organs and increased blood flow to musculoskeletal system
- Heightened muscle tension
- Inhibition of immunity, digestion and reproductive functions (Sapolsky, 1994)

When confronting immediate, life-threatening danger, these physiological responses are protective. They help mobilize the body’s available resources to increase the chance for survival. Anything not immediately necessary, such as growth, digestion and reproduction, gets downregulated. Unfortunately, when the perceived threat is no longer acute, but stems from constant daily pressures, these responses can threaten your well-being. Eventually, the body’s stress response may wreak more havoc than the stressor itself, impacting numerous health outcomes (American Psychological Association, 2019).

1.4 Effect of Stress on Autonomic Nervous System

The autonomic nervous system (ANS) regulates the body's major physiological activities, including the heart's electrical activity, gland secretion, blood pressure, and respiration. The ANS has two branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS mobilizes the body's resources for action under stressful conditions. In contrast to the SNS, the PNS relaxes the body and stabilizes the body into steady state.

1.5 Types of Stress:

Stress are two types a) Physical Stress and b) Mental Stress

1.5.1 Physical stress

- **Walk:** Research has shown that walking promotes the release of brain chemicals called endorphins that stimulate relaxation and improve our mood.
- **Run:** Running reduces anxiety and depression. When you run, blood circulation to the brain is increased and the part of your brain that responds to stress and improves your mood is affected. This causes a change that temporarily improves your reaction to stressful situations.
- **Sit:** Sitting stress is a modifiable lifestyle behaviour. Generally speaking, it can result in two separate patterns affecting our health. One is associated with more metabolic problems. This means more body fat, higher blood pressure, blood sugar problems, and even cancer, heart disease and diabetes.

- **Brisk walk:** Brisk walking can boost your level of endorphins, the result of which can reduce your stress hormones and benefit those with mild depression. The production of these endorphins may diminish the perception of pain and reduce anxiety and improve self-esteem.
- **Excessive treadmill walks:** Excessive treadmill walking, regardless of holding on or not, can result in stress reactions and stress fractures in the feet.

1.5.2 Mental Stress

- **Listening to Soothing Music:** Music can have a profound effect on both emotions and the body. Faster music can make you feel more alert and concentrate better. Upbeat music can make you feel more optimistic and positive about life. A slower tempo can quiet your mind and relax your muscles, making you feel soothed while releasing the stress of the day. Music is effective for relaxation and stress management. Research confirms these personal experiences with music.
- **Involving in Arithmetic Calculation Task:** Mental Arithmetic, the mental arithmetic test evaluates the sympathetic vasoconstriction related to central nervous system activation following a mental stressor.
- **Studying for Long:** The stress of over-studying can show real physical signs— headaches or digestive issues and can lead to long-term health issues. Physical health concerns can be a sign of advanced stress from over-studying. If the concerns causing them to continue, it can lead to long-term physical (and mental) issues.
- **Playing video game:** Some research studies have found that video games induce mental stress.

1.6 Stress Related to Mental and Health Hazard:

Mental stress is a harmful psychological reaction to an increased level of demand placed on a person. It is a common health issue, associated with increased cardiovascular mortality and morbidity. It also has a great impact on both professional and private lives. Stress also affects individuals, being associated with negative mood, immunosuppression, impacts on physical and mental health and increased occurrence of illnesses. Several stress management interventions have been shown to be effective in both the workplace and personal settings. This provides great incentive for developing techniques to recognise elevated stress levels, prompting interventions to reduce stress levels, and potentially improve health.

Unfortunately, many of the stressors in modern life are ongoing. Chronic stress can be detrimental to both physical and mental health. Long-term stress increases the risk of mental health problems such as anxiety and depression, substance use problems, sleep problems, pain and bodily complaints such as muscle tension. It is a risk factor for hypertension and coronary artery disease. Other physical disorders, including irritable bowel syndrome (IBS), gastroesophageal reflux disease (GERD), and back pain, may be caused or exacerbated by stress. Chronic stress also plays a role in mental illnesses, such as generalized anxiety disorder and depression.

Health Hazards:

Sometimes stress will give a positive impact to some people. However, continuous stress can lead to negative impact especially on health such as hypertension, musculoskeletal disorders, depression, insomnia and heart disease.

Diabetes: Stress alone doesn't cause diabetes. But there is some evidence that there may be a link between stress and the risk of type 2 diabetes. Our researchers think that high levels of stress hormones might stop insulin-producing cells in the pancreas from working properly and reduce the amount of insulin they make.

Skin Conditions: For example, stress can aggravate psoriasis, rosacea, and eczema. It can also cause hives and other types of skin rashes and trigger a flare-up of fever blisters. Interfere with daily skin care. If you're stressed, you might skimp on this part of your routine, which can aggravate skin issues.

Asthma: Stress contributes to depression, anxiety and heart problems. Stress can also trigger an asthma attack. You cannot avoid stress; it is part of daily life. However, developing effective ways to manage stress and learning to relax can help you prevent shortness of breath and avoid panic.

Arthritis: The longer you're exposed to stress, the more destructive the inflammation can become. In a PLOS One study, people with RA identified stress as a trigger for disease flare-ups. Arthritis symptoms contribute to stress, especially when they're unrelenting. Constant pain, fatigue, and poor sleep create a vicious cycle.

Hypertension: Hypertension is a chronic medical condition in which the blood pressure is elevated. Persistent hypertension is one of the risk factors for strokes, heart attacks, heart failure and arterial aneurysm, and is a leading cause of chronic renal failure. Even moderate elevation of BP leads to shortened life expectancy.

Musculoskeletal disorders: Some physical stress triggers that can cause musculoskeletal disorders, The risk factors for work-related musculoskeletal disorders

- Work postures and movements
- Repetitiveness and pace of work
- Force of movements
- Vibration
- Temperature
- Lack of influence or control over one's job
- Increase pressure (e.g., to produce more)
- Lack of or poor communication

Depression: The effects of chronic, or long-term, stress can be harmful on their own, but **they also can contribute to depression**, a mood disorder that makes you feel sad and disinterested in things you usually enjoy. Depression can affect your appetite, your sleep habits, and your ability to concentrate.

Insomnia and Heart Disease: Once chronic insomnia takes hold, people often feel anxious about sleeping and other aspects of their lives. This increases day-to-day stress, which in turn exacerbates insomnia symptoms. Insomnia is linked to high blood pressure and heart disease. Over time, poor sleep can also lead to unhealthy habits that can hurt your heart, including higher stress levels, less motivation to be physically active, and unhealthy food choices. For better sleep, get enough natural light, especially earlier in the day.

The Occupational Safety and Health Administration (OSHA) declared stress a hazard of the workplace.

Chapter 2: Photoplethysmogram (PPG) Signal and Electrodermal Activity (EDA) Signal

2.A Photoplethysmogram (PPG) Signal

2.A.1 Introduction:

The photoplethysmogram (PPG) signal is widely used in clinical and consumer devices due to its non-invasive nature and cost-effectiveness. Traditionally, it has been primarily used to measure blood oxygen saturation and to monitor heart rate in patients at rest. Despite its use in clinical settings for several decades, PPG signal processing has now emerged as a large and growing field of research. This research has been prompted by the widespread use of PPG sensors in consumer wearables. This setting poses several challenges to the design of signal processing algorithms, not least that of handling motion artifact. In addition, the PPG signal contains valuable information on the cardiovascular, respiratory and autonomic nervous systems which is not yet routinely exploited. Together, these factors give opportunity to use the PPG to provide detailed health information, unobtrusively, in daily life. A key step in realising this opportunity is the development of robust PPG signal processing algorithms.

2.A.2 PPG Signal Generation:

Photoplethysmography measures changes in the blood volume of a vascular tissue bed. Optical radiation is used to illuminate peripheral tissue, where it is scattered and absorbed as it travels through different tissue layers before being transmitted through or reflected from the tissue surface. This attenuated light intensity is detected by an optical sensor and is recorded as a voltage signal known as the photoplethysmogram (PPG). A raw PPG waveform reflects the variations in attenuation of incident optical radiation by different tissue components within the tissue volume, as illustrated in Figure2.1. High frequency variations (the 'AC' part) are caused by changes in arterial blood volume with each heartbeat, and lower frequency variations (the 'DC' part) are caused by changes in other tissue components such as venous and capillary blood, bloodless tissue, etc. The attenuation of light in tissue can be described as a function of the optical path-length and the attenuation coefficient of the medium, based on the modified Beer-Lambert law. The origins of the PPG waveform have also been attributed to red blood cell orientation, the mechanical movement of cellular components, and a combination of factors.

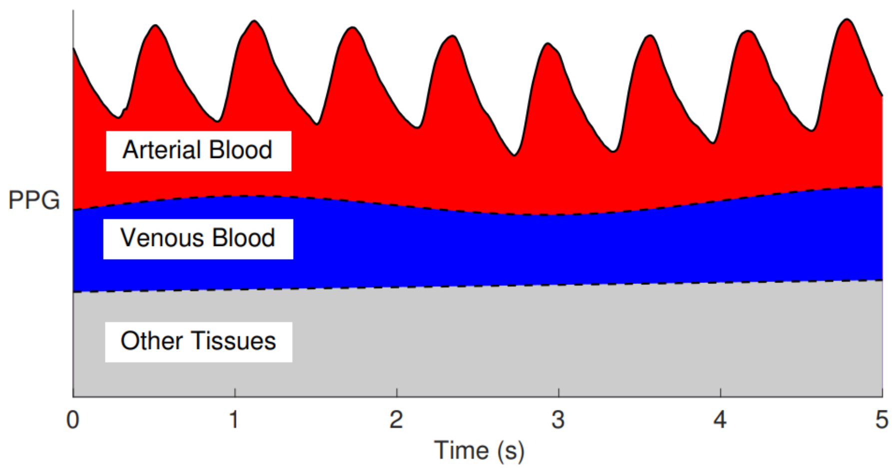


Figure 2.1 The simplified origins of the photoplethysmogram (PPG) signal

Presentation Of the Photoplethysmogram Signal:

The PPG signal exhibits a quasi-periodic pattern consisting of an arterial pulse wave for each heartbeat. The pulse wave resembles an arterial blood pressure pulse wave, although there are important differences in the waveform contour. Each PPG pulse wave consists of two distinct phases, as shown in Figure 2.2: the anacrotic and catacrotic phases, corresponding to the rising and falling limbs respectively. The morphology of the PPG pulse wave is influenced by the heart (characteristics of cardiac ejection including heart rate, heart rhythm, and stroke volume); the circulation (including cardiovascular properties such as arterial stiffness and blood pressure); additional physiological processes including respiration and the autonomic nervous system (which can be affected by stress); and disease. Figure 2.3 shows the changes in PPG pulse wave shape which occur in healthy ageing, for example.

A typical photoplethysmogram (PPG) pulse waveform can be separated into anacrotic and catacrotic phases, which are dominated by systolic ejection and wave reflections from the periphery respectively. The systolic rising edge in the anacrotic phase is caused by the expansion of the arterial system due to inflow of blood. The rate of expansion is linked to the contractility of the heart, and the amplitude of the systolic peak is linked to the stroke volume. The dicrotic notch and diastolic peak are caused by wave reflections, with their location and timing influenced by arterial stiffness. The diastolic decay is determined by the exponential contraction of the arterial system due to the outflow of blood and is influenced by the vascular resistance and compliance. The PPG pulse wave often exhibits a diastolic peak in young subjects (class 1) which diminishes with age (higher classes).

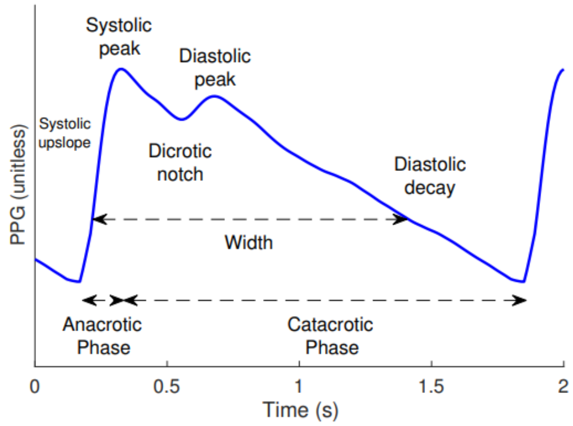


Figure 2.2 A typical photoplethysmogram (PPG) pulse wave

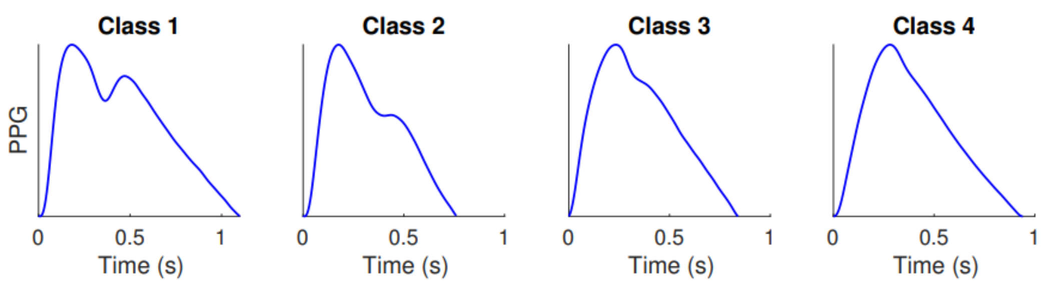


Figure 2.3 Classes of photoplethysmogram (PPG) pulse wave shape

2.A.3 Acquisition Of PPG:

Photoplethysmography sensors measure the amount of infrared light absorbed or reflected by blood. Volume changes are caused by pressure changes in blood vessels, which occur throughout the cardiac cycle. There are two types of functioning principles for photoplethysmography sensors: the *transmission or reflection* of light through or by a certain part of the body. The schematic representation of the PPG sensor is shown in Figure 2.4**:** the transmission operation, in which the emission module and the photodetector are located on diametrically opposite sides; and by reflection, in which the emission module is located on the same side as the photodetector.

With a PPG sensor in transmission mode, the LED light passes through absorbent substances, such as the skin pigmentation, bone and arterial and venous blood, and is then received by the detector and quantified by filters and converter.

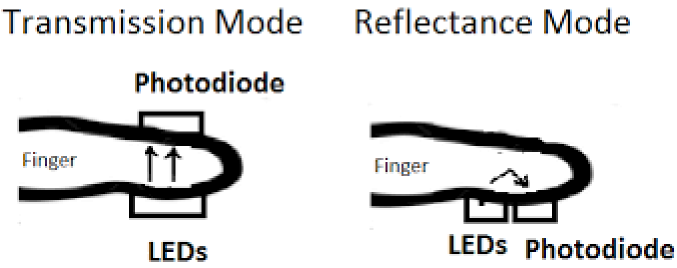


Figure 2.4 Position of photodiode and LEDs in different modes

In contrast, a PPG sensor in reflection mode reflects the LED light on the skin, which is received by the detector, and quantified in a similar fashion through the use of filters and converters. Nonetheless, this mode is applied mainly in the body parts too thick to allow the transmission of light (for example, wrist and forehead). Therefore, the PPG sensors can assume varied shapes, for example, a band, a wristwatch, or a patch. Additionally, some PPG sensors already make use of wearable technology, monitoring the heart rate in real time.

The working principle of the PPG sensor is based on the emission of infrared light by an LED which penetrates the skin and blood vessels. This light is captured by the detector to measure the blood stream, as can be observed in Figure 2.5. The results of the PPG signal depend primarily on the flow of blood and oxygen to the capillary vessels in each heartbeat.

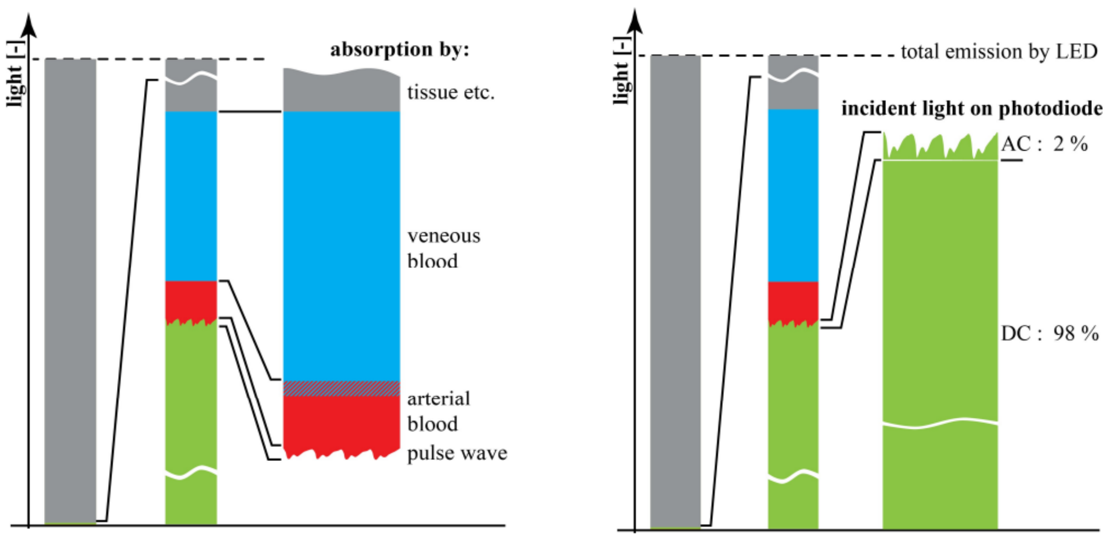


Figure 1 Graph of amount of light sent and received by ppg sensor

There are several challenges to PPG signal analysis, rendering the extraction of reliable information from the PPG is a complex task. The PPG signal exhibits several physiological variations, only one or some of which are relevant to any particular analysis. It is also susceptible to several types of noise as motion artifact and probe-tissue interface disturbance, power line interference, low- and high-frequency noise. In addition, technical aspects such as the type of sensor used and the location of the measurement site affect the waveform. The range of influences on the PPG adds complexity to its analysis.

Other factors influencing PPG reading accuracy include other anatomical or physiological differences such as skin colour and amount of fluid retained by the tissues. Because of these various limitations of different PPG sensors at various anatomical locations, many studies have been conducted exploring their accuracy under different conditions. Other studies have collectively compared PPG at the finger, forearm, earlobe, ear canal, wrist, shoulder, forehead, chest, temple, neck, rib cage, wrist, lower back,

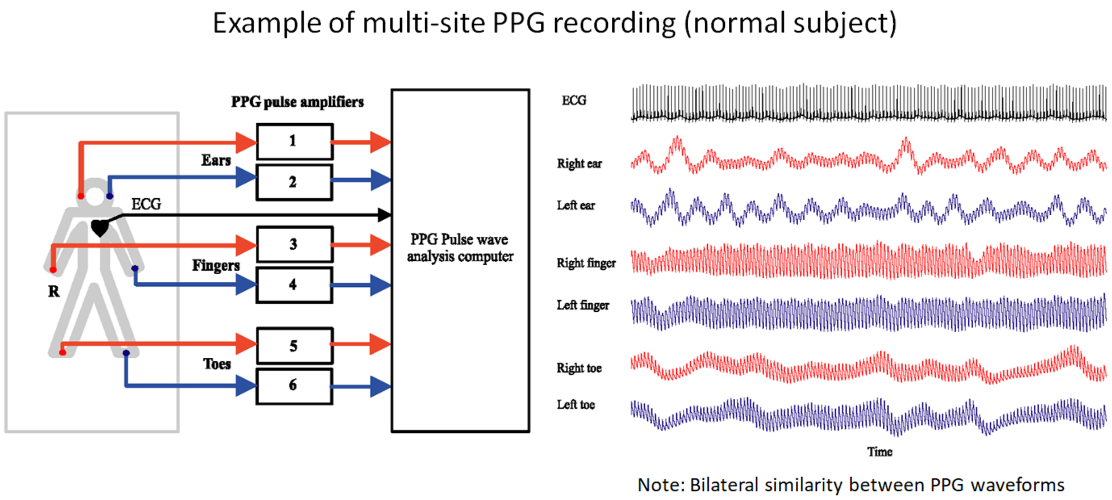


Figure 2.6 PPG signals acquired at different parts of body

and tibia. The consensus was that the forehead and finger locations provide the most accurate Pulse rate, SpO_2 and PPG measurements in static conditions, although both were found to be susceptible to deleterious effects from varying dynamic conditions, especially movement and desaturation events. While in a number of cases, the finger location was found to produce the most accurate results.

2.A.4 Features:

Heart rate variability (HRV):

Heart rate variability (HRV) describes the variations between consecutive heartbeats. The rhythm of the heart is controlled by the sinoatrial (SA) node, which is modulated by both the sympathetic and parasympathetic branches of the autonomic nervous system. Sympathetic activity tends to increase heart rate (HR↑) and its response is slow (few seconds). Parasympathetic activity, on the other hand, tends to decrease heart rate (HR↓) and mediates faster (0.2–0.6seconds). The continuous modulation of the sympathetic and parasym-pathetic innervations results in variations in heart rate. HRV has been found to correlate with, e.g., age, mental and physical stress, and attention.
Pulse Transit Time (PTT): Pulse transit time (PTT) refers to the time it takes a pulse wave to travel between two arterial sites.

RR interval: RR interval is the time elapsed between two successive R-waves of the QRS signal on the electrocardiogram (and its reciprocal, the HR) is a function of intrinsic properties of the sinus node as well as autonomic influences. The time-domain methods are the simplest to perform since they are applied straight to the series of successive RR interval values. The most evident such measure is the mean value of RR intervals ($\overline{RR}$).

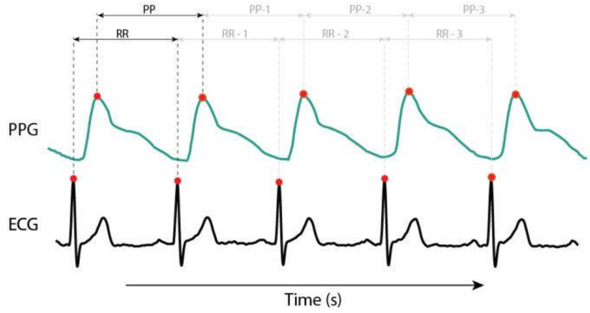


Figure 2.7 Correlation between RR interval and PP interval

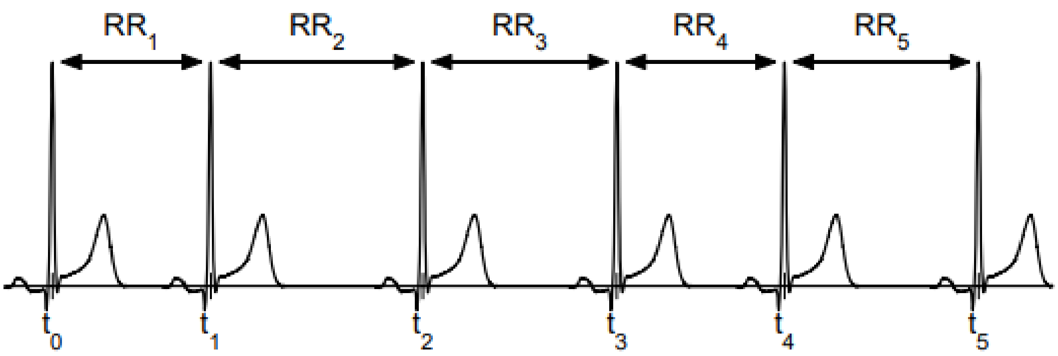


Figure 2.8 RR interval from ECG Signal

Box Plot: In biomedical research, it is often necessary to compare multiple data sets with different distributions. The box plot, also known as the box-and-whisker plot, represents both the summary statistics and the distribution of the primary data. The box plot thus enables visualization of the minimum, lower quartile, median, upper quartile and maximum of any data set.

A box is used to indicate the positions of the upper and lower quartiles; the interior of this box indicates the inner-quartile range, which is the area between the upper and lower quartiles and consists of 50% of the distribution. Lines (sometimes referred to as whiskers) are extended to the extrema of the distribution, either minimum or maximum values in the dataset.

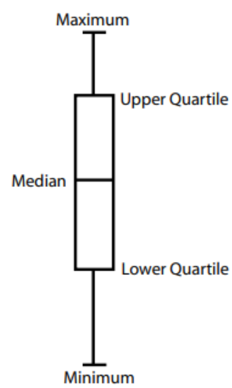


Figure 2.9 Anatomy of a Box Plot

Fast Fourier Transform (FFT):

Fast Fourier transform (FFT) is one of the most useful tools and is widely used in digital signal processing. The Fast Fourier Transform (FFT) is commonly used for frequency analysis. FFT analysis converts the time domain of a signal into the frequency domain. It is a faster version of the Discrete Fourier Transform (DFT) that can be applied when the number of samples in the signal is a power of two. The N-point DFT can be computed using.

$$x[k] = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2\pi kn}{N}} \qquad \text{.................. (1)}$$

Where x[n] is the discrete-time signal with a period of N. In order to determine the frequency of the PPG signal, FFT was computed and analysed.

Power Spectral Density (PSD):

PSD stands for power spectral density, which is a measure of the distribution of power over different frequencies in a signal. In the case of a PPG signal, the PSD can provide valuable information about the heart rate and other characteristics of the cardiovascular system.

The PSD of a PPG signal will typically have a peak at the frequency of the heart rate (also known as the fundamental frequency), as well as other peaks at harmonics of the fundamental frequency. The height and width of these peaks can provide important information about the health of the cardiovascular system. For example, a narrow peak at the fundamental frequency may indicate a healthy heart, while a broad peak may indicate the presence of arrhythmias or other abnormalities.

In summary, the PSD of a PPG signal can provide valuable information about the heart rate and other characteristics of the cardiovascular system and can be calculated using Fourier analysis.

The power spectral density (PSD) is then defined as the magnitude squared of the Fourier transform, so the formula for the PSD is:

PSD = |X(f)|^2, ... (2)

Where X(f) is the Fourier transform of a continuous-time signal X(t)

2A.5 PPG SIGNAL UNDER DIFFERENT STRESS CONDITIONS:

We examined the PPG signal under different stress conditions. We've collected PPG signals from six different conditions: resting before reading, reading, resting before music, music, resting before arithmetic, and arithmetic. The 16-minute recording was divided into six different conditions, including three resting conditions and three non-resting conditions. Before every non-resting condition, there was a resting condition. The non-resting conditions consisted of reading a book, listening to music, and verbal arithmetic problem-solving. We analysed the PPG signal to investigate changes in heart rate, and other relevant features under different stress conditions. The results of this study can be used to develop effective stress detection and management strategies, as well as to improve our understanding of the physiological changes that occur under different stress conditions.

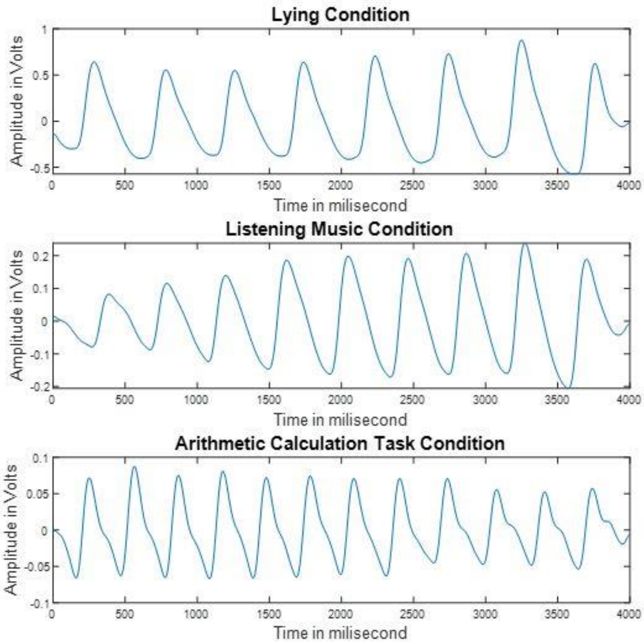


Figure 2.9: PPG signal under different stress condition

2A.6 Acquisition Device:

Biopac MP160:

The BIOPAC MP160 system is a flexible, proven modular data acquisition & analysis system for life science research. This is a 16-channel system with Acknowledge software with specialized analysis capabilities. The MP160 offers multiple configurations to suit individual research and teaching needs and records multiple channels with differing sample rates at speeds up to 400 kHz (aggregate). MP160 systems are Ethernet-ready and compatible with BIOPAC system components as well as many leading equipment brands and support a wide range of wireless & wired signal-specific amplifiers. Used in conjunction with Acknowledge software and BIOPAC electrodes, amplifiers, transducers and other system components, the MP160 is part of a complete data acquisition & analysis system.

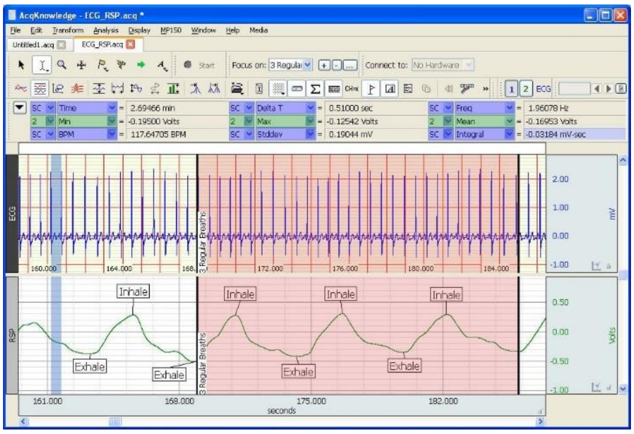


Figure2.10: Acqknowledge software which is used during data acquisition

Figure 2.11: Biopac MP160 hardware device

Pulse Bionomadix Transducer BN-PULSE-XDCR Emitter/Detector:

The Wireless Photo Plethysmogram (PPG) and Electro dermal Activity (EDA/GSR) Bio Nomadix module pair consists of a matched transmitter and receiver. The module combines these two measurements because they are typically performed on the same part of the body and they are often recorded in parallel for a variety of studies. Record one or both signals.

- The PPG channel measures Blood Volume Pulse (BVP) via optical plethysmography methods and provides for heart rate, inter-beat interval and vasodilation/constriction data. The PPG channel measures Blood Volume Pulse (BVP) via optical plethysmography methods and provides for heart rate, inter-beat interval and vasodilation/constriction data.
- The EDA/GSR channel—also known as Electro dermal Response, Skin Conductance Activity/Response or Galvanic Skin Response (GSR)—provides for indication of eccrine (skin sweating) activity.

Figure 2.12: BN-PULSE-XDCR Emitter/Detector

Table 1 Specification of Acquisition Device

Signal type:	PPG plus EDA
BandlimitsMax:	Both: DC to 10 Hz:
Factory pre-set:	PPG: 0.5 Hz to 3 Hz EDA: DC to 3 Hz
Filter Options:	Both: DC, 0.5 Hz HP, 3 or 10 Hz LP EDA: 1 Hz LP
Resolution:	PPG: FSR/4096; (4.88 mV) EDA: 0.012 µS (min step)
Signal range:	PPG: ±10 V (at output) EDA: 0 to 50 µS; excitation: 0.5 V constant V

Table 2 PPG Sensor Specification

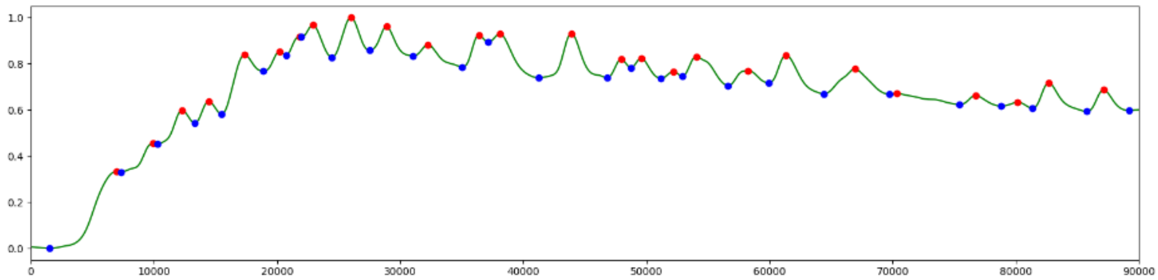
Wavelength:		860 nm ± 60 nm Optical LP Filter
Cut-off:		800 nm The operational range of the emitter and detector falls within the wavelength range of 800 nm to 920 nm. The filter is placed over the receiver; the filter of 800 nm is an optical low pass, so wavelengths longer than 800 nm will pass thru.
Nominal Output:		20 mV (peak-peak)
Power:		10 mA drive current
Sterilisable:		Yes

The optoelectronics of the PPG sensor and their tissue attachment mechanism are fundamental building blocks in a PPG measurement system. Their design will impact on signal quality, subsequent pulse wave analysis techniques, and the need for skilful de-noising. Probe-tissue interface pressure should be sufficient so that the PPG probe is held securely in place to minimise probe-tissue movement artefact and the associated signal noise, but not so high as to distort the main features of the pulse wave.

Figure 2.13: PPG sensor used on finger

2.B Electrodermal Activity (EDA)

Electrodermal Activity (EDA), also known as Galvanic Skin Response (GSR), is a measure of the changes in the electrical properties of the skin that occur in response to sweat secretion. The sympathetic nervous system, responsible for the fight-or-flight response and emotional arousal, controls sweat secretion. EDA is widely used as an indicator of psycho-logical or physiological arousal in response to stimuli such as images, sounds, words, emotions, etc. EDA has been used since the early 1900s in psychological research to study various topics such as emotion regulation, stress, anxiety, attention, memory, learning, decision making, deception, and more. It is also used in applied fields such as biofeedback, neurofeedback, marketing, entertainment, gaming, education, and health care.



2.2B. 1 GSR signal when subject is in stress

EDA has many advantages over other methods of measuring arousal. It is relatively easy to record and analyze, non-invasive, and inexpensive. EDA can capture subtle and rapid changes in arousal that may not be observable by other means, and it can also be combined with other modalities to provide a more comprehensive picture of human behaviour and experience.

Despite its advantages, EDA research also faces challenges and limitations. EDA is a nonspecific measure of arousal and cannot differentiate between different types of emotions or stimuli that cause arousal. EDA is also influenced by many factors other than arousal, such as skin temperature, humidity, movement artifacts, electrode placement, and more. Therefore, EDA data must be carefully controlled and interpreted in the context of the research question.

Recent advancements in technology, methodology, and reporting have improved the use of EDA in psychological science. These advancements have led to further refinements in analysis techniques and methods for handling EDA data. However, controversies still exist regarding how EDA should be analyzed in specific circumstances.

EDA research has a long history and a promising future. As technology advances and new applications emerge, EDA research will continue to contribute to our understanding of human psychology and physiology. It offers a unique and valuable way to explore how humans react to various aspects of their environment and themselves.

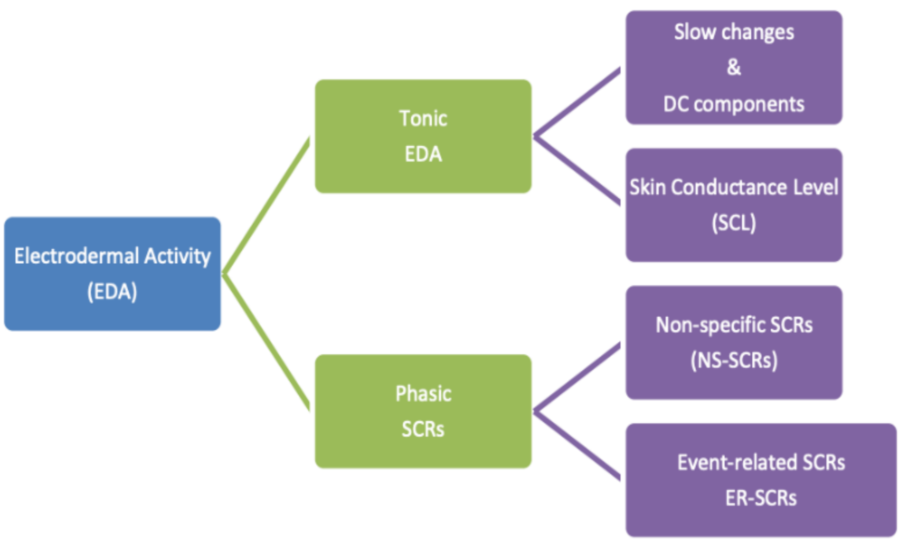
2.B.1 General Introduction:

Electrodermal activity (EDA), also known as Galvanic Skin Response (GSR), is a psychophysiological measure that reflects the activity of the sweat glands in the skin. When a person experiences emotional arousal, such as stress, anxiety, or excitement, the sympathetic nervous system activates and increases the activity of sweat glands in the skin. This leads to an increase in the electrical conductance of the skin, which can be measured using electrodes placed on the skin surface.

The most commonly measured property of EDA is the skin conductance level (SCL), which reflects the overall level of tonic activity in the sweat glands. This can be measured by applying a small electrical potential between two points of skin contact and measuring the resulting current flow. Changes in the SCL are thought to reflect changes in general autonomic arousal.
The other component of EDA is the skin conductance response (SCR), which reflects the rapid changes in sweat gland activity that occur in response to emotional or cognitive stimuli. SCRs are often elicited by sudden, novel, or salient stimuli, and are thought to reflect the phasic activity of the sympathetic nervous system.

Recent research suggests that both the tonic and phasic components of EDA are important, and may rely on different neural mechanisms. For example, some studies have found that the tonic component of EDA is related to activity in the insula, while the phasic component is related to activity in the amygdala. EDA has been used extensively in research on emotion, attention, and cognitive processing. It has been used as an objective measure of emotional states, as well as to examine implicit emotional responses that may occur without conscious awareness. EDA has also been used to investigate a wide range of topics, including psychopathology, personality disorders, conditioning, and neuropsychology.

EDA has two main components, the tonic-level SCL and the phasic SCR, which reflect different aspects of sweat gland activity. Both components are important and may rely on different neural mechanisms. EDA has been used extensively in research on emotion, attention, and cognitive processing, and has broad implications for understanding a wide range of psychological phenomena.



2.2B. 2 Components of EDA

2.B.2 Physiological Origin:

The physiological origin of EDA or GSR is not fully understood, but there are three main theories that attempt to explain it:

1. **<u>Muscular Activity Theory</u>:**
   The Muscular Activity Theory suggests that the EDA signal is produced due to changes in the tension of the muscles that surround the sweat glands. This theory was first proposed by Cannon in 1929 and supported by the work of both Vint and Hammond in 1933. They found that the EDA response could be blocked by paralyzing the muscles that control the sweat glands, suggesting that muscular activity was indeed responsible for the EDA response.
2. **<u>Vascular Activity Theory</u>:**
   The Vascular Activity Theory suggests that changes in the blood flow to the sweat glands are responsible for the EDA signal. This theory was first proposed by Holmes in 1928, who found that changes in blood flow could alter the EDA response. This theory was supported by the work of Wallin in 1977, who found that changes in blood flow to the sweat glands could affect the EDA response.
3. **<u>Secretory Activity Theory:</u>**
   The Secretory Activity Theory suggests that the EDA signal is produced due to changes in the secretion of sweat by the sweat glands. This theory was first proposed by Fowles in 1980, who found that changes in sweat gland activity could produce the EDA response. This theory was further supported by the work of Critchley and colleagues in 2002, who found that the EDA response was related to the amount of sweat produced by the sweat glands.

While each theory has its own evidence and supporters, it is likely that all three factors contribute to the EDA signal. The specific contribution of each factor may depend on the individual and the circumstances of the emotional or cognitive experience being studied.

For our project we are using the secretory activity method as it provides a direct measure of sweat gland activity, which is known to increase during emotional arousal. The method allows for a real-time measurement of stress levels, as changes in the GSR signal can be detected within seconds of exposure to the stimuli.

Furthermore, the secretory activity theory has been widely used in studies related to stress and emotional processing. It is also considered to be one of the most reliable and valid methods for measuring sympathetic arousal. Therefore, by using this theory or method, you may be able to provide valuable insights into the physiological mechanisms underlying stress and its relationship with different stimuli.

2.B.3 GSR Signal Generation:

1. **<u>Preparation of the subject:</u>**

The first step in generating a GSR signal is to prepare the subject for the recording process. The subject is asked to relax and sit comfortably. The recording environment should be free of any sources of interference that could affect the GSR signal, such as movements, loud noises, or bright lights. The subject should also avoid consuming any stimulants, such as caffeine or nicotine, prior to the recording session, as these can affect the GSR signal.

2. **<u>Sensor placement:</u>**

Once the subject is prepared, electrodes or sensors are attached to the subject's skin in a location that is known to produce a strong GSR signal. The most common location for GSR electrode placement is on the fingers or palms of the hands. The electrodes are typically attached using an adhesive or conductive gel to ensure a good connection between the electrode and the skin.

3. **<u>Signal recording:</u>**

Once the electrodes are in place, the GSR signal is recorded using a specialized device, such as a skin conductance monitor. The monitor measures the electrical conductivity of the skin, which varies as a result of changes in sweat gland activity. The GSR signal is typically recorded for a period of time ranging from a few minutes to an hour, depending on the study design and research question.

4. **<u>Signal processing:</u>**

The recorded GSR signal is then processed to remove any noise or artifacts that could interfere with the analysis. This may involve filtering the signal to remove high-frequency noise or baseline drift, or removing any segments of the signal that are affected by movement or other sources of interference. Signal processing techniques may also be used to normalize the signal or adjust for individual differences in skin conductivity.

5. **<u>Signal analysis:</u>**

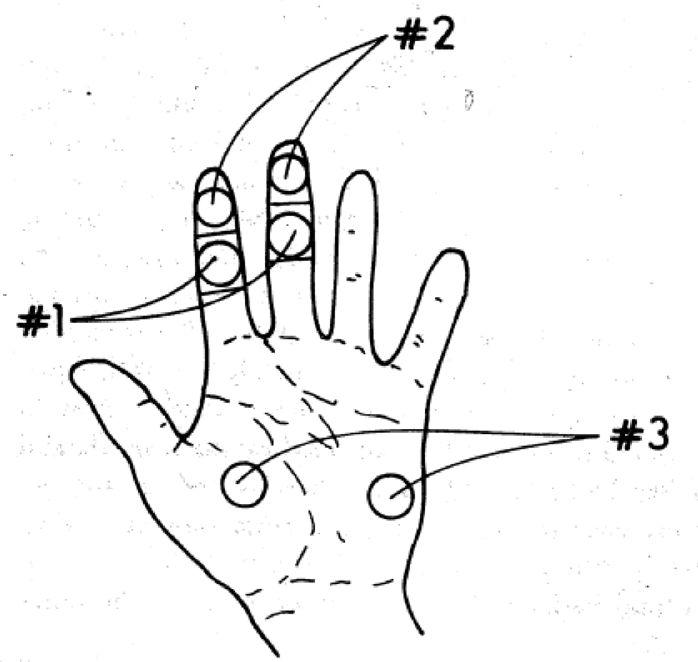
Finally, the processed GSR signal is analysed to identify patterns or changes that may be indicative of stress. This may involve looking for changes in the baseline level of the signal, changes in the frequency or amplitude of the signal, or changes in the shape or waveform of the signal. Signal analysis may also involve comparing the GSR signal across different conditions or experimental manipulations to identify any differences or similarities.

2.B.4 GSR Electrode and Data Acquisition System:

- **Precaution mentioned in previous works:**

Special consideration must be given to the choice of recording electrodes, electrode paste, and electrode placement. Silver-silver chloride cup electrodes are the type most typically used in skin conductance recording because they minimize the development of bias potentials and polarization. The electrode paste is the conductive medium between electrode and skin. Probably the most important concern in choosing an electrode paste is that it preserve the electrical properties of the bioelectrical signals of the response system of interest. Since the measurement of GSR involves a small current passed through the skin, the electrode paste interacts with the tissue over which it is placed. Commercial ECG or EEG gels should not be used because they usually contain near-saturation levels of sodium chloride and have been shown to significantly inflate measures of skin conductance level (Grey & Smith 1984).

Skin conductance is recorded with both electrodes on active sites (bipolar recording); hence it does not matter in which direction the current flows between the two electrodes. Skin conductance recordings are typically taken from locations on the palms of the hands, with several acceptable placements. The most common electrode placements are the thenar eminences of the palms and the volar surface of the medial or distal phalanges of the fingers (see Figure 1). It should be noted that, although electrodermal activity can be measured from any of these sites, the values obtained are not necessarily comparable. Scerbo and colleagues (1992) made a direct comparison of GSR recorded from the distal and medial phalange sites simultaneously and found that both the elicited SCR amplitude and SCL were significantly higher from the distal recording site.



2.2B. 3 Three electrode placements for recording electrodermal activity. Placement #1 involves volar surfaces on medial phalanges, placement #2 involves volar surfaces of distal phalanges, and placement #3 involves thenar and hypothenar eminences of palms.

Another recording issue concerns the hand from which to record. Many laboratories use the non-dominant hand for GSR measurements because it is less likely to have cuts or calluses and because it leaves the dominant hand free to perform a manual task. Although differences between left and right-hand GSR recordings have been reported, the differences reported by different studies are often in opposite directions and the interpretations have been ambiguous (see a review of early literature by Hugdahl 1984).

2.B.5 Features of GSR:

GSR (Galvanic Skin Response) signals are a measure of the electrical conductance of the skin, which can be influenced by a variety of factors, including emotional arousal, stress, and other physiological processes. The features of GSR signals are of interest to researchers and clinicians because they can provide insights into the psychological and physiological processes that underlie emotional arousal and stress.

Features of GSR signals include:

Baseline level: The baseline level of the GSR signal represents the average level of skin conductance when the subject is in a relaxed state. Changes in the baseline level can indicate changes in overall arousal or emotional state.

Amplitude: The amplitude of the GSR signal refers to the height of the signal waveform, or the difference between the baseline level and the peak of the signal. Larger amplitudes are generally associated with greater emotional arousal.

Rise time: The rise time of the GSR signal is the time it takes for the signal to reach its peak amplitude from the baseline level. A faster rise time is generally associated with more intense emotional arousal.

Recovery time: The recovery time of the GSR signal is the time it takes for the signal to return to the baseline level after a peak response. Longer recovery times may indicate sustained emotional arousal.

Frequency: The frequency of the GSR signal refers to the number of peaks in the signal waveform per unit of time. Changes in frequency can indicate changes in emotional arousal or other physiological processes.

Skin conductance level (SCL): SCL is a measure of the overall level of skin conductance, which considers both the baseline level and any peaks in the signal. SCL can be used as an overall measure of emotional arousal.

Skin conductance response (SCR): SCR refers to the peaks in the GSR signal that are associated with specific stimuli or events. SCR can be used to measure the intensity and timing of emotional responses to specific stimuli.

Number of peaks: The number of peaks in the GSR signal can provide information about the number and intensity of emotional responses to different stimuli. More peaks can indicate a greater number of emotional responses, while fewer peaks can indicate a lower number of emotional responses.

Latency: The latency of the GSR signal is the time it takes for the signal to begin to rise after the onset of a stimulus or event. Shorter latencies may indicate a more rapid and intense emotional response.

Recovery slope: The recovery slope of the GSR signal is the rate at which the signal returns to the baseline level after a peak response. Steeper recovery slopes may indicate a more rapid and complete recovery from emotional arousal.

Area under the curve: The area under the curve of the GSR signal represents the total amount of electrical conductance observed during a particular time period. The area under the curve can provide an overall measure of the intensity and duration of emotional arousal.

Phasic and tonic components: Galvanic skin response (GSR) signals are typically composed of two components: a tonic component and a phasic component.

The tonic component represents the baseline conductance level of the skin, which is affected by factors such as skin temperature, hydration level, and electrode placement. The tonic component is relatively stable over time and reflects the overall level of sympathetic nervous system activity.

The phasic component on the other hand, reflects the rapid changes in skin conductance that occur in response to specific stimuli, such as emotional or cognitive events. The phasic component is typically characterized by brief bursts of activity, known as skin conductance responses (SCRs), that last for several seconds. Accurate detection of phasic and tonic components from GSR signals is crucial for understanding emotional and physiological responses, and can have diverse applications such as stress monitoring, biofeedback therapy, and emotion recognition.

2.B.6 GSR Signal at Different Activities:

GSR signal can provide valuable insights into the physiological and emotional responses to different activities. By analysing changes in the GSR signal in response to various stimuli and interventions, researchers and clinicians can gain a better understanding of the effects of different activities on the body's stress response and develop more effective strategies for managing stress and other emotional states. Here’s how GSR signals can vary in response to different activities:

1. **Resting state**: During a resting state, the GSR signal will typically have a low baseline level with occasional small peaks. This indicates a low level of emotional arousal and physiological activity.
2. **Cognitive tasks:** During cognitive tasks, such as solving puzzles or completing mental arithmetic, the GSR signal may show an increase in amplitude, frequency, and number of peaks, indicating increased emotional arousal and physiological activity.
3. **Emotional tasks:** During emotional tasks, such as watching a sad or scary movie, the GSR signal may show a more pronounced increase in amplitude, frequency, and number of peaks, indicating a higher level of emotional arousal and physiological activity.
4. **Physical activity:** During physical activity, such as exercise or sports, the GSR signal may show an increase in amplitude, frequency, and number of peaks, indicating increased physiological activity and arousal. This response can be due to factors such as increased heart rate, sweating, and breathing.
5. **Relaxation techniques:** During relaxation techniques, such as deep breathing or meditation, the GSR signal may show a decrease in amplitude, frequency, and number of peaks, indicating a lower level of emotional arousal and physiological activity. This response can be due to factors such as decreased muscle tension and stress hormone levels.

Chapter 3: Literature Review

Advancements in Analysing Stress through PPG & GSR Signals: A Review of Previous Studies

PPG and GSR signals are non-invasive methods that have shown potential in detecting stress. PPG measures blood flow using a pulse oximeter sensor, while GSR/EDA measures skin's electrical conductance. Both methods can reliably detect stress using techniques such as machine learning, signal processing, and feature extraction. PPG-based stress analysis can be used in healthcare and consumer devices, while GSR/EDA-based stress analysis can be used in wearable and ambient devices. Previous studies have demonstrated the effectiveness and reliability of both methods in detecting stress in naturalistic and controlled settings.

[1] Ghaderyan et al. (2016) developed a reliable workload estimation model for stress analysis and other applications using decomposition and machine learning techniques on a group of 35 healthy participants with minimal psychophysiological signals.

[2] Abd Halim et al. (2017) developed a PPG-based stress analysis method using classification techniques to distinguish between normal and stress conditions. The method was effective and reliable in detecting stress conditions in healthy individuals, as shown in a study with five participants.

[3] Charlton et al. (2018) used a PPG signal numerical model to identify stress-related features. Results showed the features were effective for stress monitoring in healthcare and consumer devices.

[4] "First-Step PPG signal analysis for evaluation of stress induced during scanning in the open-air MRI device" by J.Pribil et al. (2020): This study used statistical analysis and signal processing techniques to detect and analyse the possible stress that has an impact on the speech signal recorded simultaneously for 3D modelling of the human vocal tract in lower field open-air MRI.

[5] Heo et al. (2021) used a two-step de-noising technique and lightweight classifiers to detect stress with a single PPG sensor. Results indicated their approach was more accurate than existing methods.

[6] Palanisamy et al. (2013) explore the use of multiple physiological signals, including GSR/EDA, to identify human stress. They compare various non-linear classifiers, including support vector machines, neural networks, and fuzzy logic systems, and assess their effectiveness on a dataset of 20 subjects exposed to various stress-inducing tasks.

[7] The paper by Greco et al. (2016) introduces a new method for processing EDA signals using convex optimization. It decomposes the signal into tonic, phasic, and noise components and is effective for noisy and non-stationary signals, with superior accuracy and computational efficiency compared to existing methods.

[8] Schmidt et al. (2018) introduces WESAD, a new dataset for wearable stress and affect detection. It includes GSR/EDA signals and other physiological signals like heart rate, respiration, and temperature. The paper also presents baseline results for stress and affect classification using various machine learning models.

[9] Aqajari et al. (2020) developed an open-source tool for GSR analysis using deep learning and statistical algorithms to detect stress. The tool was evaluated on the WESAD dataset, achieving 92% accuracy for stress detection with 10-fold cross-validation.

Table 3 Previous Studies on PPG and GSR

Work Summary	Year	Stressed Condition	Features	Classifier	Accuracy	Conclusion
[1]	2016	Solving arithmetic problems, performing a secondary task during user-system interaction	Statistical and entropic features that are sensitive to changes in time and frequency	SVM, PNN	90%	Provided effective, reliable, automatic, and real-time inference of psychological states
[2]	2017	Mental arithmetic task, cold pressor test	Difference in systolic peeks between stress and normal condition	SVM	85%	Systolic peeks of stress condition much higher than normal condition
[3]	2018	The paper used a numerical model of pulse wave propagation with varying input parameters to simulate different levels of stress	Thirty-two features were extracted out of which seventeen showed significant trend	SVM	Not Mentioned	Crest time and the duration of diastole were identified as suitable candidates for assessing stress
[4]	2020	Vibration, acoustic noise, arithmetic tasks,relaxation music.	Oliva–Roztocil index,instantaneous HR, BP variations	Not Mentioned	Not Mentioned	PPG signal could be used to evaluate the stress induced during scanning in the open-air MRI device
[5]	2021	Public speaking, mental arithmetic task, watching funny videos	HR, HRV, PTT, PAT	LR, KNN, SVM, RF	96.5%	Proposed method improved the stress-detection performance using a single PPG sensor, and can be used as a reliable indicator of stress

Work Summary	Year	Stressed Conditions	Features	Classifier	Accuracy	Conclusion
[6]	2013	Mental Arithmetic Task	Mean, standard deviation, power, energy, higher-order statistics	KNN, PNN	93.75%	Multiple physiological signal-based subject-independent analyses incorporated and its algorithm gives the reasonably improved detection rate.
[7]	2016	Not Mentioned	SCR, SCL, and noise (prediction and measurement errors).	Not Mentioned	Not Mentioned	It is a novel algorithm for the analysis of EDA using methods of convex optimization.
[8]	2018	Mental Arithmetic Task, Public Speaking Task, Watching Funny Videos	HR, Skin Conductance, RR, body temperature and acceleration	SVM, RF, KNN, DT, LR	Baseline vs stress vs amusement ~ 80% and stress vs non-stress ~ 90%	The paper introduced a new dataset (WESAD) for detecting stress and amusement from wearable devices and showed its usefulness and challenges using machine learning methods
[9]	2020	Mental Arithmetic Task, Public Speaking Task, Watching Funny Videos	Statistical features and deep learning features	SVM, RF, KNN, LR	92%	The paper proposes an open-source tool for GSR analysis that can extract features for stress detection

Chapter 4: Methodology

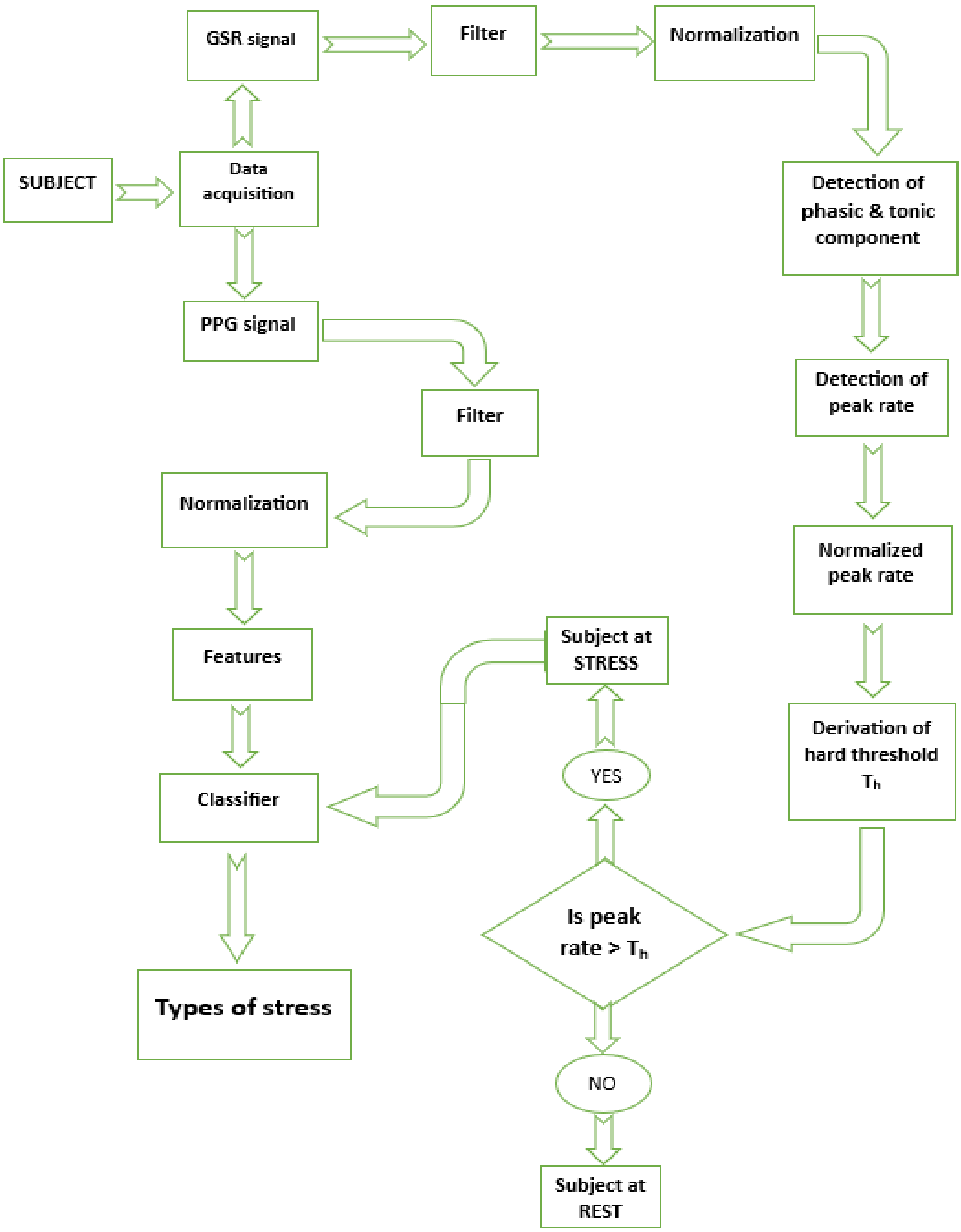
4.1 Introduction:

The plan of work for a stress analysis method using both PPG and GSR signals involves several steps. First, PPG and GSR signals are acquired using appropriate sensors such as photodiodes and electrodes, respectively. These signals are then pre-processed to remove noise and artefacts using techniques such as filtering, signal averaging, and baseline correction. Next, various features are extracted from the signals using methods such as first and second-order derivatives, spectral analysis, and entropy analysis, which are relevant for stress assessment. These features can include HR, HRV, GSR amplitude, and other physiological parameters.

The extracted features are then used as inputs to a machine learning algorithm, which is trained to classify individuals as either being stressed or not stressed based on the patterns in the features. Once the machine learning model has been trained, it can be used to make predictions on new PPG and GSR data. This allows for stress assessment which can be useful in a variety of applications such as monitoring patients with cardiovascular disease or in wearable fitness devices.

The inclusion of GSR signals in the stress analysis method enhances the accuracy of stress assessment as it provides additional information on the sympathetic nervous system's response to stress. The integration of PPG and GSR signals in a machine learning model provides a more comprehensive and accurate picture of an individual's stress level, which can inform appropriate interventions to manage stress.

4.2. Flow Chart:



4.3. Data Acquisition:

In this study, a total of 12 subjects were acquired with the age range of 22-30 years old. Here a Wireless Photo Plethysmogram (PPG) Bio Nomadix module pair consists of a matched transmitter and receiver is used for data acquisition and PPG probe which is attached with one fingertip at one side and other side connected with transmitter with a single wire which is tightened over the wrist, transmitting signals to receiver.

The recorded data is obtained continuously in such a way that is shown in below in the table:

Table 4 Data Acquisition

No. of subject	Resting before Reading (min)	Reading (min)	Resting before Listening Music (min)	Listening Music (min)	Resting before Arithmetic Calculation Task(min)	Arithmetic Calculation Task (min)
12	3	3	2	3	2	3

The experiments were carried out at the Bio-medical Laboratory, University of Calcutta, under controlled room temperature between 25±2°C. During experiment PPG signal was recorded for each individual in three Physical Condition; resting, reading a book, listening Music and verbal arithmetic Calculation Task. 12 university students of age range 20-30years were asked to volunteer the experiment. The subjects were rested 10-15 min before the start of the study, to acclimatize to the room temperature and also for restraining them from doing physical activity. The volunteers were asked to keep their movement to a minimum (specially, left hand in which the sensor is used) during the study to avoid motion artifacts on the acquired signals. Some protocols which were maintained during each physical condition.

4. 1 Silver-silver chloride cup electrodes

Volunteers have been properly rested for 2min before data acquisition started. They all had been instructed not to smoke from 2 hours before of data acquisition and also not to make much muscle movement during data acquisition specially the hand in which sensors are attached as this could introduce EMG noise.

4. 2 Subject wearing PPG, GSR, ECG, RSP sensors

For GSR acquisition we've used Silver-silver chloride cup electrodes as mentioned by Grey & Smith (1984). We've used the non-dominant hand (left) on middle and ring finger for GSR recording. Electrodes are used on volar surfaces of distal phalanges (like #2 condition in fig.1), for better accuracy but we've used the electrodes on different fingers because we used PPG sensor on index fingers as seen in fig 3.

In Fig 3 one of our subjects have worn PPG, GSR, ECG, RSP sensors and their respective transmitters. We had used his non-dominant left hand for PPG and GSR sensor; and the BN-PULSE-XDCR the emitter/detector for PPG & GSR on the left arm.

At first the sensors PPG&GSR senses the stimuli and then sends it to the BN-PULSE-XDCR, then the transmitter transmits it to the receiver.

During this we also recorded ECG and Respiration but as we had a limited we couldn't process these signals during our project but it might help for better detections of work based stress. Here, we've used 3leads ECG system and a strain gauge based RSP sensor which measures the movement of Diaphragm. RSP sensor is on the top of his chest (fig.3) and below it there is emitter/detector for ECG & RSP.

After the sensor attachments, a chair is used as a stable and comfortable sitting arrangement. After sitting we rested him and we let him stable his movements for 2min and then started data recording.

Data is taken continuously for 16min in different stress conditions to accurately detect the difference between GSR reading under different stressed condition and understand if there is any chance of carry-forward the effect of previous stress condition to the next of it. We've divided the 16min into 6 different conditions including 3 resting condition and 3 non-resting condition, and before every non-resting condition there is a resting condition. Non-resting conditions includes reading a book, listening to music and verbal arithmetic problem solving. Details about the tasks are given below:

i. **Resting before Reading:** As it is the starting phase of data acquisition we rested the subject for 3min; so that, the next non-resting conditions can be distinguished and the subject doesn't take any other stress than the task they're about to be perform, as GSR is very sensitive that may deviate our actual purpose.
ii. **Reading a book:** For this task we've used a book by Sister Nivedita,The master as I saw him. And used a phone with stand so that, they don't have to make much muscle movement during turning page or lean towards the table for reading book. Data is taken for 3min after previous resting, and we used to use small commands to let them know they've to perform the next task.
iii. **Resting before music:** As at this point subjects gets comfortable with data acquisition so we let this phase for 2min and used this phase just to diminish the affects from previous stress condition, if any persist.
iv. **Listening to music:** A wireless Bluetooth earphone with some noise cancellation is used for playing music and to avoid disturbance we let the subjects use the earphone before starting the acquisition as it has some noise cancellation this also might helped us to avoid some noises which could've cause some disturbances. For this phase we didn't use any commands, just started playing the music when time arrives and recorded data for 3min. Now, as people can have different music taste & preferences, an instrumental music of Pakhwaj is being played to avoid such situations. But this also can be soothing to some and be irritating to some so it may differ the results for subject to subject; though we choose a music which is may not sound soothing to someone so that we can't distinguish between resting and listening to music; as both GSR signals are almost same and have a continuous negative sloping.
v. **Resting before arithmetic:** This phase is for 2min and reason is same as previous resting.
vi. **Arithmetic problem solving:** We used a list of arithmetic problems, prepared before and used the same list for all subjects and also maintained the sequence of problems in the list. Some basic to medium problems like addition, subtraction and multiplications are asked with a constant pace. Data is recorded for 3min.

4.4 PPG and GSR Signal Pre-processing:

Digital filtering is an important step to minimise the impact of noise on PPG and GSR signal analysis. The attenuation of noise from both the signals is a crucial step in extracting valuable information from it. Digital filtering can be used to attenuate noise within specific frequency ranges (e.g., low- and high-frequency noise), although additional processes are required to attenuate noise which occurs within the frequency range of interest (e.g., motion artefact due to walking, where the frequency of steps can be similar to the heart rate).

It consists of de-noising, characteristic features detection, and feature extraction. It finally measures the performance of stress detection by training seven lightweight machine-learning classifiers available on low power wearable devices.

4.5 De-noising the signals using the Butterworth filter:

To limit the impact of high-frequency noise on the signal, a low-pass Butterworth filter is used. This filter is well-suited for removing noise from PPG signals because it has a steep roll-off in the stopband, which allows it to effectively suppress noise outside of the passband. It can also be designed to have a specific cut-off frequency that is tailored to the application, which helps to preserve the important information in the signal. The rate of roll-off response depends on the order of the filter.

The design of Butterworth Low Pass Filter with the help of passive elements like R, L and C and the magnitude of transfer function is given as under

$$\left|H_b(jw)\right| = \frac{1}{\sqrt{1+\left(w/w_c\right)^{2N}}} \quad \text{.................. (3)}$$

“N” is the order of filter, and the subscript “b” denotes the Butterworth filter, w_c is is th w_c frequency of the filter.

4.6 Moving Average Filter:

A moving average filter is a type of digital filter that is commonly used in signal processing, particularly in the analysis of PPG signals. It is a simple yet effective method for smoothing out the noise or “random” variations in a PPG signal, while still preserving the underlying trend or signal. A moving average filter works by taking the average of a set of consecutive samples in the signal and using this average value as the output for that time point. The size of the set of samples used to calculate the average or “window” can be varied to control the amount of smoothing applied to the signal. For a L point moving average filter with input represented by the vector x and the difference equation for averaged output y, is

$$y[n] = \frac{1}{L}\sum_{k=0}^{L-1} x[n-k] \quad \text{.................. (4)}$$

4.7 Normalization:

Normalization is a data pre-processing technique used to transform the data into a common scale, which can improve the performance and accuracy of machine learning algorithms. In the context of the above project, normalization was used to transform the PPG and EDA signals into a common scale.

The normalization process involves scaling the data values to fall within a predefined range, typically between 0 and 1 or -1 and 1, depending on the specific use case. This is accomplished by subtracting the mean of the data and dividing it by the standard deviation, ensuring that the data is centred around zero and has a unit standard deviation.

Normalization plays a crucial role in the above project, as it helps to ensure that the PPG and EDA signals are on a common scale, which is important for the accurate classification of tasks based on stress levels. Without normalization, the signals may have different magnitudes and ranges, which could potentially lead to inaccurate results.

According to the standardization method, the equation for normalization is as follows:

$$Z = \frac{X - \mu}{\tilde{O}} \text{ .... } \mathbf{(5)}$$

Where,

- X: the original data point
- µ: the mean of the data
- σ: the standard deviation of the data
- Z: the standardized data point

4.8 Differentiation Stage:

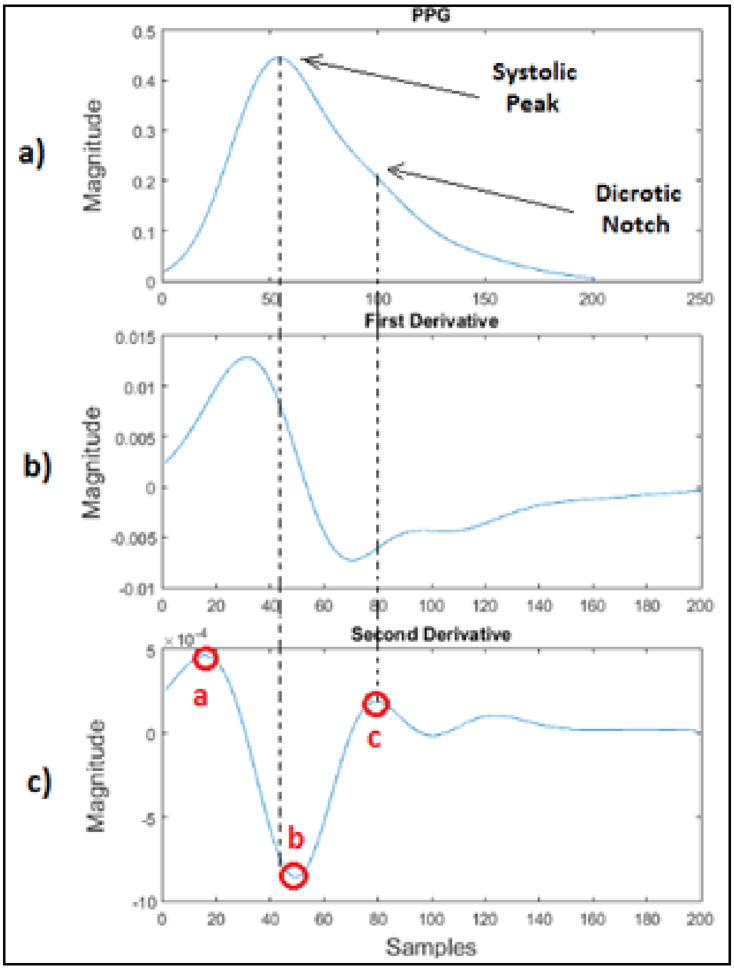
The second derivative wave of the original PPG signal is called the acceleration photoplethysmogram (APG), and it is more commonly used than the first derivative wave. APG is an indicator of the acceleration of the blood. Figure 4.1 shows the original PPG signal along with its first and second derivative waves.

There are a number of critical points that can be extracted from the second derivative wave of a PPG signal. These critical points can be used to detect and diagnose cardiac abnormalities. In clinical and research settings, there are still ongoing efforts to improve the current methods of obtaining critical points from the second derivative wave of the PPG signal.

Figure 4.1 shows only three critical points that were extracted by from the original PPG signal. Other articles such as investigated additional critical points of the second derivative wave. As demonstrated in, critical point a is the early systolic location. Point b is the lowest point in the early systolic wave. Point c is the resurgent of late systolic. Point d indicates the decreasing part of late systolic and point e represents the early diastolic wave. From the second derivative, we can compute the large artery stiffness index.

Additionally, the APG correlates with the distensibility of the carotid artery, age, blood pressure, risk of coronary heart disease, and the presence of the atherosclerotic disorders .PPG describes how fast blood moves within blood vessels.

After detection of those systolic and diastolic peak boxplot of those amplitude of the peaks and time interval of systolic peak to the next minima can be taken for various stress condition to extract some features for classification.

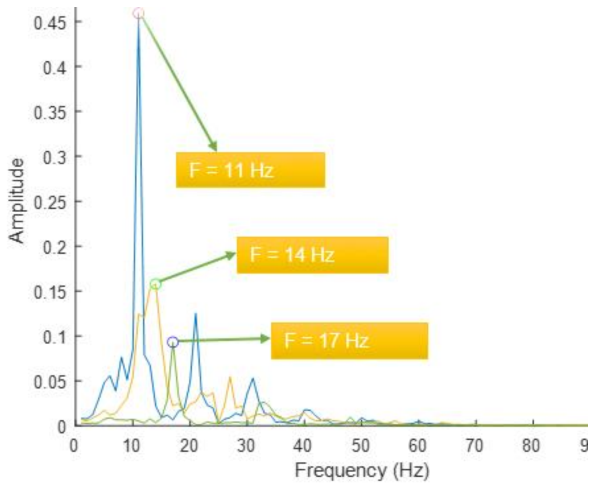


4. 3 Differentiation Stages of PPG Signal

4.9 Fast Fourier Transform of PPG Signals:

Fast Fourier Transform (FFT) is used for processing PPG signals because it is an efficient algorithm for calculating the frequency domain representation of a signal. This is useful for PPG signal processing because it allows the extraction of useful information, such as heart rate, from the signal. Additionally, FFT can be used to filter out noise and artefacts in the signal, which can improve the accuracy of the results.

To apply the FFT to a PPG signal, the first step is to pre-process the signal to remove any noise or artefacts. This can be done using various techniques such as filtering, smoothing, and detrending. Once the signal is pre-processed, the next step is to apply the FFT algorithm in accordance with equation (1) to compute the DFT of the signal. This can be done using a variety of software tools or libraries, such as MATLAB, Python, or R.



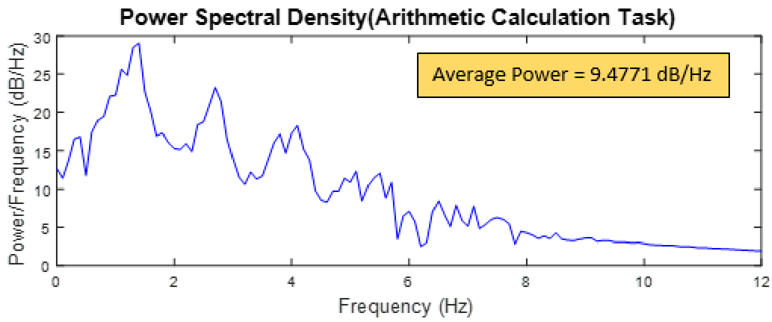
4. 4 FFT Plot

In our study, FFT is plotted for one person (subject 1) for different conditions to find most dominant frequency peaks for each condition and then overlapped those to get the deviation among maximum frequencies for each condition. Also, FFT has been used to find the power spectrum of the signal which can be used to calculate average power.

4.10 Power Spectrum Density (PSD) of PPG Signals:

PSD, or Power Spectral Density, is a common method used in signal analysis to assess the frequency components of a signal. In the context of PPG signal analysis, PSD can be used as an extraction feature to identify and analyse specific features of the PPG signal.

To extract relevant features from the PPG signal using PSD, the first step is to convert the time-domain signal into the frequency domain using a Fourier Transform. This process decomposes the signal into its constituent sinusoidal components, each with a unique amplitude and frequency. The resulting spectrum can then be plotted as a function of frequency, with the amplitude of each frequency component indicating its contribution to the overall signal.



4. 5 Power Spectral Density Plot

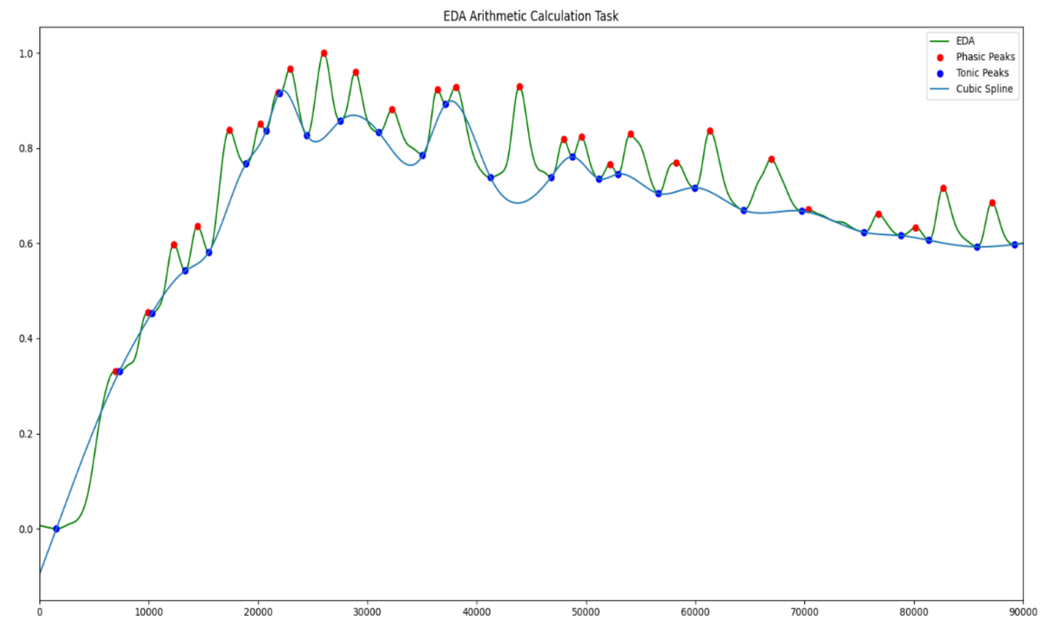
The PSD of a signal can be calculated by taking the square of the magnitude of the Fourier Transform of the signal in accordance with equation (2). This results in a plot of power (amplitude squared) versus frequency, which can be used to identify specific features of the PPG signal. For example, the dominant frequency of the PPG signal is typically in the range of 0.5-3 Hz, corresponding to the heart rate. The PSD can therefore be used to identify this frequency and extract it for further analysis. By analysing the frequency components of the PPG signal, PSD can provide valuable insights into the underlying physiological processes and help detect potential health issues.

4.11 Tonic and Phasic Component Detection from GSR Signal:

Phasic and Tonic components are two important aspects of the Galvanic Skin Response (GSR) signal, which provide insight into the autonomic nervous system's response to stress. The Phasic component refers to the rapid, short-term changes in the GSR signal that occur in response to stimuli, while the Tonic component refers to the baseline level of the GSR signal.

To detect the Phasic component of the GSR signal, interpolation can be used to fill in missing date points or smooth out noise in the signal. This is important as the Phasic component occurs in short bursts and may be missed if the signal is too noisy. Once the signal has been interpolated, peak detection algorithms can be applied to identify the peaks in the signal that correspond to the Phasic component. These peaks represent the skin's response to stimuli, which can be used to determine the intensity to stimuli and timing of the response.

To detect the tonic component of GSR signal, the baseline level of the signal can be determined using the cubic spline interpolation method. The tonic component represents the underlying activity of the autonomic nervous system, which is influenced by factors such as stress, arousal, and anxiety. By measuring changes in the Tonic component over time, it is possible to monitor an individual's overall level of stress and arousal.



4. 6 Detection of Phasic and Tonic Components in GSR Signal

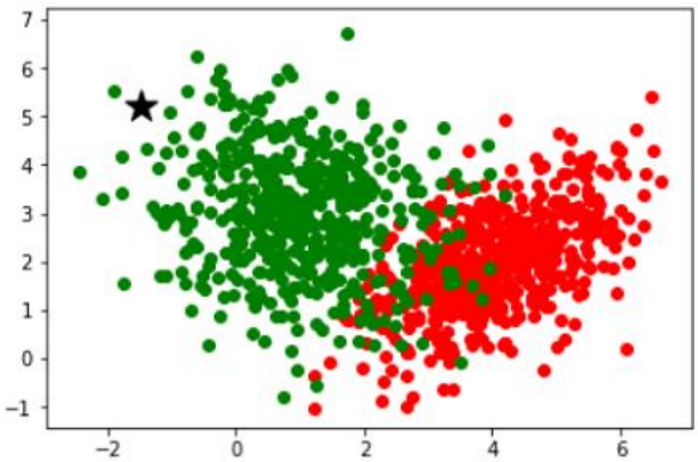
4.12 Classification under different stressed conditions:

There are various classification methods in PPG and GSR signal processing, such as Support Vector Machines (SVMs) and K-Nearest Neighbour (KNN) algorithms. SVMs and KNNs are important because they can be used for classification and regression tasks, such as identifying different types of cardiac events or predicting physiological parameters like heart rate or blood pressure.

K-Nearest Neighbour (KNN):

KNN is a supervised machine learning algorithm that works by finding the k nearest neighbours of a given data point and using their labels or values to predict the label or value of the given data point. In PPG signal processing, KNN algorithms can be used to classify different types of cardiac events or to predict physiological parameters. KNN is based on the assumption that data points that are close to each other belong to the same class.

For example, let us consider two classes, green and red, and a data point to be classified. The KNN algorithm decides the number k of nearest neighbours to the data point that are to be considered. If k=5, then the algorithm looks for the 5 nearest neighbours to that data point. If we assume k=4 in the given example, KNN finds out the 4 nearest neighbours. All the data points near the black data point belong to the green class, meaning all the neighbours belong to the green class. Therefore, according to the KNN algorithm, the black data point will belong to the green class only. The red class is not considered because the red class data points are nowhere close to the black data point.



4. 7 Showing a black data point which is classified as of green class

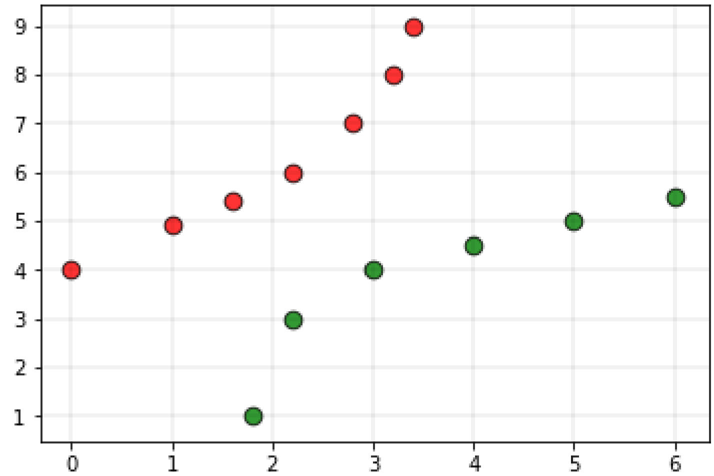
In this project, the Weighted KNN algorithm was used for the classification of stress based on PPG and GSR signals. Weighted KNN is similar to KNN but with the added feature of assigning weights to the nearest neighbours. The weights are assigned based on the distance between the data point to be classified and its neighbours. This helps in giving more importance to the nearest neighbours that are more relevant for classification. The Weighted KNN algorithm was trained on the features extracted from the PPG and GSR signals to classify stress into two categories - stressed and not stressed.

In machine Learning, Classification is the process of categorizing a given set of data into different categories. In Machine Learning, to measure the performance of the classification model we use the confusion matrix, Scatter Plot and Roc curve to present the classification result.

1. Scatter Plot:

Scatter plots are the graphs that present the relationship between two variables in a dataset. It represents data points on a two-dimensional plane or on a Cartesian system. The independent variable or attribute is plotted on the X-axis, while the dependent variable is plotted on the Y-axis.

Consider the following training set



4. 8 example of Scatter Plot

The red labels indicate the class 0 points and the green labels indicate class 1 points.

2. Confusion Matrix:

A confusion matrix is a matrix that summarizes the performance of a machine learning model on a set of test data. It is often used to measure the performance of classification models, which aim to predict a categorical label for each input instance. The matrix displays the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) produced by the model on the test data.

For binary classification, the matrix will be of a 2×2 table, for multi-class classification, the matrix shape will be equal to the number of classes i.e., for n classes it will be n×n.

A 2×2 Confusion matrix is shown below for the image recognition having a Subject 1 image or Subject 2 image.

Table 5 Confusion Matrix

		Actual	
Predicted		**Subject 1**	**Subject 2**
	Subject 1	True Positive (TP)	False Positive (FP)
	Subject 2	False Negative (FN)	True Negative (TN)

True Positive (TP): It is the total counts having both predicted and actual values are Subject 1.

True Negative (TN): It is the total counts having both predicted and actual values are Subject 2.

False Positive (FP): It is the total counts having prediction is Subject 1 while Subject 2.

False Negative (FN): It is the total counts having prediction is Subject 2 while actually, it is Subject 1.

Confusion Matrix is a classification performance indicator. Here Weighted KNN based confusion matrix is shown below. From that matrix different parameters like Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) can be found out through which classification result among classes will be more prominent, except those there are other parameter like F1, Recall, and Precision.

Classification / True class	Healthy	Disease
Healthy (121)	116 True Negetives	5 False positives
Disease (35)	12 False negetives	23 True positives

Accuracy=no of correct classification / total no of samples to classify= 0.891

Sensitivity: It is the number of disease cases that were correctly classified as such, divided by the total number of disease cases [(TP/ (TP+FN) = 0.657]

Specificity: It is the number of healthy cases that were correctly classified as such, divided by the total number of healthy cases [TN/ (TN+FP) =0.959]

Positive predictive value (PPV): It is the number of disease cases that actually classified as disease divided by the number of cases that the classifier classifies as having a disease [TP/ (TP+FP) =0.821]

Negative predictive value (NPV): It is the number of healthy cases that actually classified as healthy divided by the number of cases that the classifier classifies as being healthy [TN/ (TN+FN) =0.906].

3. ROC Curve:

An **ROC curve** (**receiver operating characteristic curve**) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

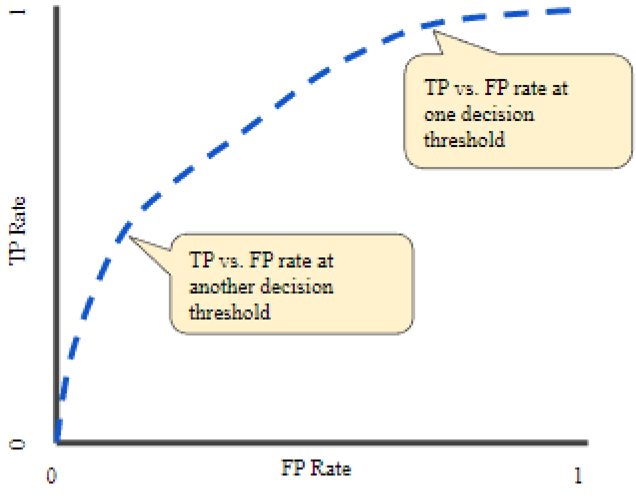
True Positive Rate (**TPR**) is a synonym for recall and is therefore defined as follows:

$$TPR = \frac{TP}{TP + FN} \quad \text{.......................... (6)}$$

False Positive Rate (**FPR**) is defined as follows:

$$FPR = \frac{FP}{FP + TN} \quad \text{..................... (7)}$$

An ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives. The following figure shows a typical ROC curve.



4. 9 TP vs. FP rate at different classification thresholds

To compute the points in an ROC curve, we could evaluate a logistic regression model many times with different classification thresholds, but this would be inefficient. Fortunately, there's an efficient, sorting-based algorithm that can provide this information for us, called AUC.

Chapter 5: Result and Discussion

5.A Result

5.A.1 De-noising PPG and GSR Signals:

Two step filtering process is used to de-noise PPG and GSR signals in our study

I. Filtering PPG and GSR Signals using Butterworth Filter.
II. Filtering the Signals using Moving Average.
III. Normalize both the signals.

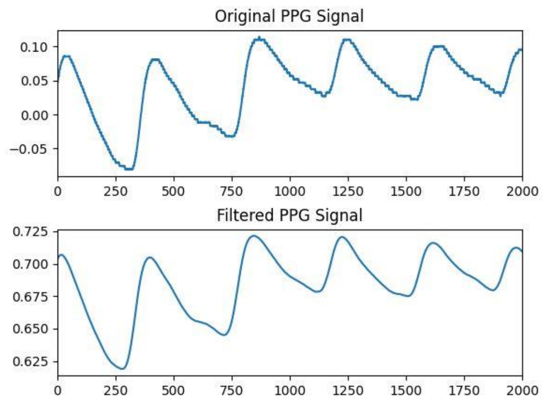
In order to debug the noises in the PPG signal as a pre-processing, a Butterworth band-pass filter with 0.1 to 30 Hertz stopband frequency range is utilized in which 0.3 to 10 Hertz passband frequency range, where passband ripple 15 dB and stopband ripple 50dB and sampling frequency is 500Hz.

In case of GSR signal, it is filtered with the same Butterworth band-pass filter with stopband frequency range 0.001 to 8 Hertz in which passband frequency range 0.003 to 3 Hertz, where passband ripple 3 dB and stopband ripple 15 dB and the sampling frequency is same as PPG signal.
In the noise filtering process, we use a band-pass filter to compensate the signals in terms of the frequency.

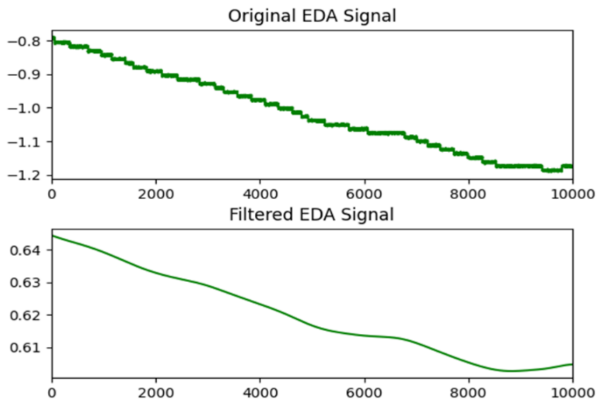
At the second step filtered signals are again filtered using moving average filter taking 50 set of consecutive points.

At the third step both signals are then normalized to basically kept amplitude of the signals in some predefined range between 0 to 1 by removing all negative values. Transforming all signals to such canonical form eases and robustifies the process of comparisons as well as serving too different needs such as visualization, and analysis.

The figures of both PPG and GSR Signal in original and filtered form is shown below:



5. 2 Original & Filtered PPG data



5. 1 Original & filtered GSR Signal

5.A.2 Detection of characteristic points of PPG Signals:

After removing noise, the signal some characteristic point is figured out from the De-noising PPG signal are:

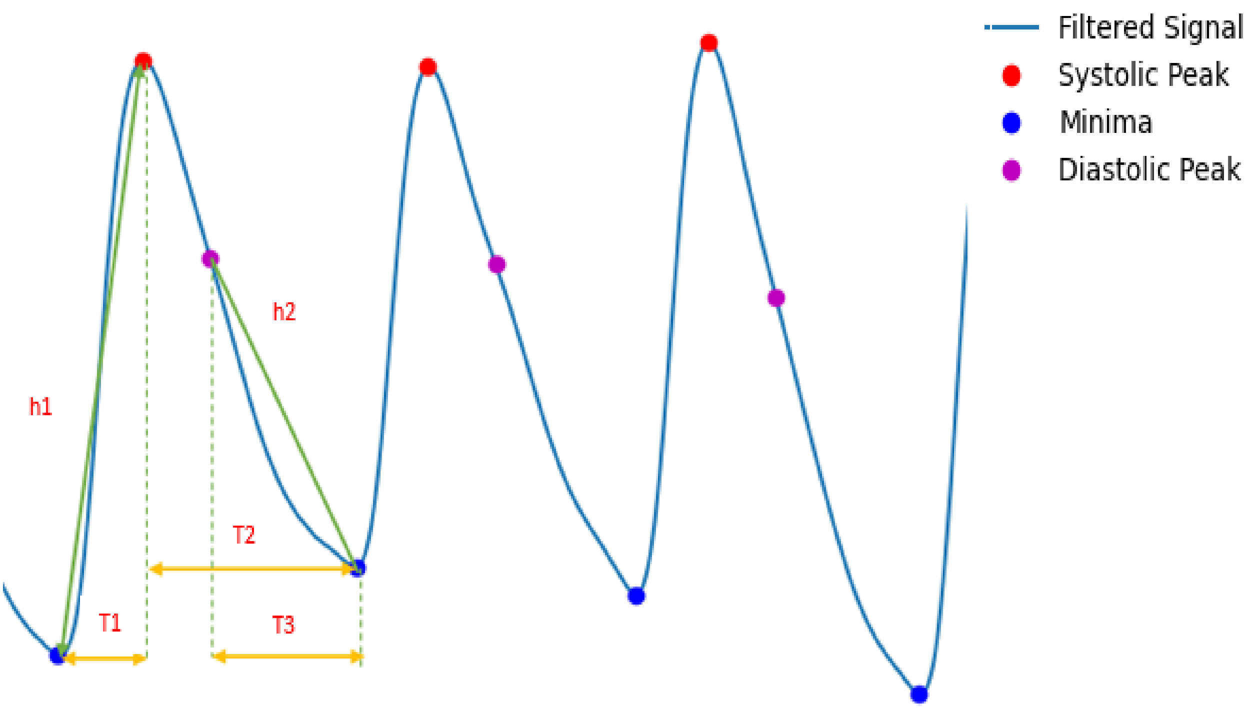
I. Amplitude difference of Systolic peak to previous minima(h1)
II. Time interval between previous minima to Systolic Peak(T1)
III. Time interval between Systolic Peak to next minima(T2)

Then, second derivative of de-noising signal is considered to extract the exact position of the Diastolic peak, where next minima of the minima is aligned with the Diastolic Peak of the PPG Signal.

Hence, two characteristic points are extracted with the above process given below:

I. Amplitude difference of Diastolic peak to next minima(h2)
II. Time interval between Diastolic Peak to next minima(T3)

<u>Now, figure of those characteristic points mentioned in the De-noising PPG Signal:</u>



5. 3 De-noising PPG Signal and its Second Order Derivative

The values of those characteristic points for various condition of one subject are mentioned in table below with their Boxplots:

As, we discussed in page 15, boxplot shows the distributions of the datasets given in the tables and in every boxplot, there are six stressed conditions given:

i. R1 ----> Resting before Reading
ii. NRe1 -----> Reading
iii. R2 ----> Resting before Listening Music
iv. NRe2 ----> Listening Music
v. R3 -----> Resting before Arithmetic Calculation Task
vi. NRe3 -----> Arithmetic Calculation Task

Table 6 Amplitude difference of Systolic peak to previous minima (h1) in millivolts

Amplitude difference of Systolic peak to previous minima(h1)					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
0.34	0.15	0.32	0.27	0.3	0.12
0.32	0.16	0.32	0.31	0.31	0.11
0.31	0.15	0.3	0.28	0.3	0.07
0.31	0.15	0.33	0.29	0.31	0.06
0.31	0.2	0.35	0.26	0.32	0.08
0.33	0.15	0.33	0.32	0.31	0.1
0.35	0.17	0.33	0.25	0.35	0.1
0.3	0.16	0.3	0.32	0.3	0.1
0.32	0.17	0.3	0.3	0.31	0.08
0.35	0.18	0.32	0.29	0.34	0.08
0.35	0.2	0.34	0.26	0.3	0.06
0.33	0.18	0.33	0.31	0.33	0.09

Table 7 Amplitude difference of Diastolic peak to next minima (h2) in millivolts

Amplitude difference of Diastolic peak to next minima(h2)					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
0.21	0.11	0.19	0.15	0.19	0.02
0.22	0.09	0.21	0.18	0.21	0.05
0.21	0.08	0.22	0.2	0.2	0.05
0.21	0.09	0.19	0.16	0.2	0.05
0.22	0.12	0.2	0.18	0.2	0.02
0.21	0.08	0.19	0.2	0.19	0.02
0.22	0.1	0.2	0.15	0.2	0.03
0.2	0.12	0.21	0.16	0.21	0.02
0.2	0.1	0.22	0.15	0.22	0.05
0.19	0.09	0.21	0.18	0.19	0.03
0.22	0.12	0.22	0.18	0.21	0.06
0.19	0.09	0.2	0.19	0.19	0.02

<u>Results:</u> When an individual is in a state of stress, their sympathetic nervous system is activated, which leads to an increase in heart rate and blood pressure. This is the body's natural response to stress, as it helps to prepare the individual for physical activity or a fight-or-flight response. This increase in heart rate and blood pressure can lead to a decrease in the amplitude of the PPG signal, as the systolic and diastolic peaks become more compressed. This can also be concluded by observing the two box plots of h1 and h2 on right.

Resting before reading: In this condition subject is under no stress so the amplitude of PPG signal is maximum i.e. the magnitude of h1, h2 (systolic & diastolic peak) is maximum. Shown as R1 in box plot.

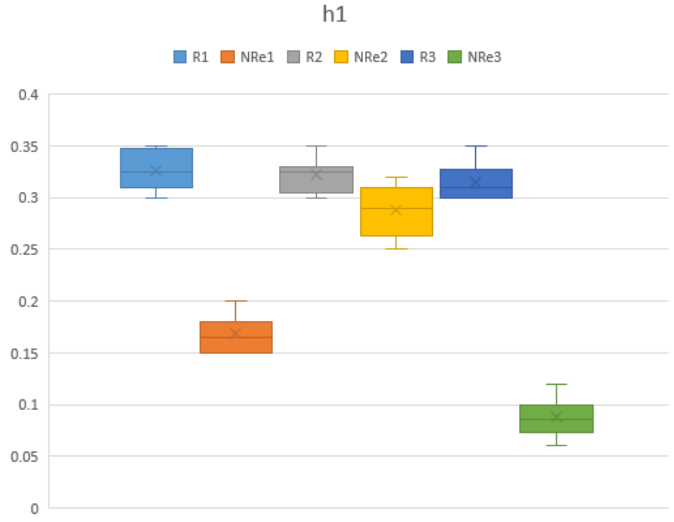
Reading: Now as reading introduces stress to the subject the amplitude gets compress and this can be distinguished by NRe1 (orange) in box plot.

Resting before music: In the next resting condition the subject was almost releases all the stress but some effect of reading remains so the amplitude is slightly less than first resting. We can conclude that by the R2 (grey) in box plot.

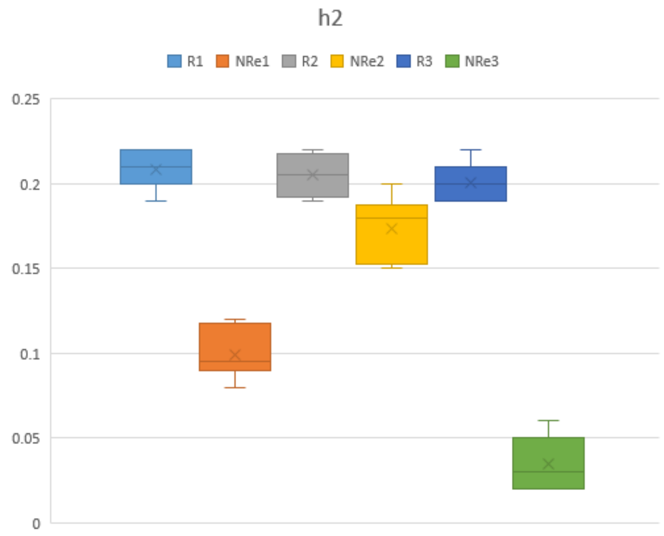
Music: As almost everyone liked the music (we asked them later) they doesn’t feel much stress other than while the pakhwaj (a musical instrument) was of slightly high bass. The magnitudes if h1, h2 are closer to resting but still lesser, shown as NRe2 (Yellow) in box plots.

Resting before arithmetic: As reading was more stressed than music so the effect of music after it would’ve been less stressed than resting before music but it slightly contradicts our assumptions, shown as R3 (in blue) in boxplots of h1, h2.

Arithmetic problem solving: Now, as problem solving can be stressed slightly much more than reading and listening to music, so the PPG signal will more compressed than reading and listening to music which shows the decrease in magnitude of h1, h2; shown as NRe3 (Green) in boxplots.



5. 4 Box plot of systolic peak amplitude(h1)



5. 5 Box plot of diastolic peak amplitude (h2)

Table 8 Time interval between previous minima to Systolic Peak (T1) in milliseconds

Time interval between previous minima to Systolic Peak(T1)					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
186.69	117.07	166.43	163.11	196.22	95.66
163.89	124.69	205.45	161.79	162.73	103.81
196.75	117.22	204.94	164.41	204.96	93.54
167.03	123.23	194.32	162.41	162.29	101.36
183.89	122.80	197.26	168.69	168.19	91.28
188.92	128.28	171.98	158.24	206.35	101.04
203.85	118.15	193.42	174.36	197.33	100.74
179.88	128.7	174.49	149.42	162.36	101.82
198.99	121.46	175.23	146.53	199.46	103.12
184.13	127.49	193.82	168.41	172.44	100.75
192.96	116.37	181.65	168.57	192.26	100.45
176.65	124.16	177.97	146.46	193.70	101.72

Table 9 Time interval between Systolic Peak to next minima (T2) in milliseconds

Time interval between Systolic Peak to next minima(T2)					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
316.29	240.52	292.36	292.25	291.82	202.93
291.15	246.57	319.92	273.32	306.79	189.82
327.14	228.17	303.93	296.81	298.74	184
299.85	229.67	315.55	274.10	298.65	208.33
319.41	244.83	301.69	280.37	292.45	210.19
307.14	240.39	317.93	278.66	307.61	184.50
297.77	226.83	318.94	292.70	316.47	186.06
309.51	224.98	324.97	284.99	319.09	200.93
324.7	226.90	302.85	283.01	327.05	196.42
310.05	246.71	315.23	296.57	297.59	187.21
308.01	238.17	290.76	291.12	299.44	200.30
299.75	250.21	325.75	284.08	318.80	186.10

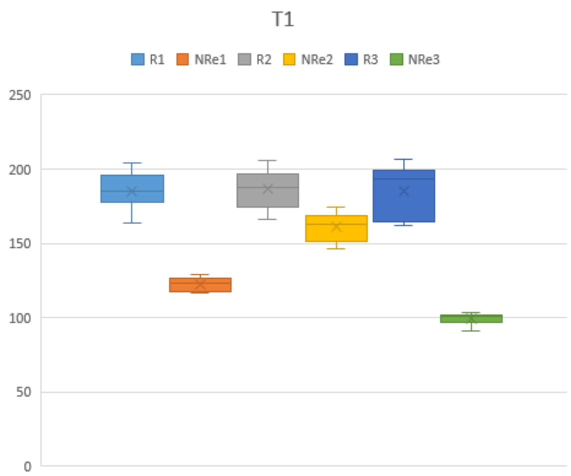
Table 10 Time interval between Diastolic Peak to next minima (T3) in milliseconds

Time interval between Diastolic Peak to next minima(T3)					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
218.64	171.94	211.56	183.45	221.04	111.63
223.98	179.04	220.69	180.85	222.88	114.22
221.85	173.34	223.40	185.80	222.99	107.86
223.85	171.96	208.08	184.17	223.15	113.50
200.59	164.85	221.12	198.97	210.40	107.34
212.08	179.04	203.96	185.79	224.62	121.91

224.95	169.57	215.71	185.91	198.86	119.40
209.67	179.32	216.82	180.61	196.56	117.76
198.77	180.42	222.46	208.79	215.52	113.17
211.10	168.03	219.56	199.31	206.12	110.64
199.42	165.25	223.27	198.44	216.52	106.78
200.69	160.99	225.21	195.73	211.52	109.07

Also, the time interval between the maxima and minima of a PPG signal is known as the pulse rate or heart rate. In general, the pulse rate is determined by the number of times the heart contracts and relaxes each minute. When an individual is in a state of stress, there is an increase in heart rate which in turn, can lead to a decrease in the time interval between the maxima and minima of the PPG signal, as shown in the box plot of T2 Time Interval as well as the boxplots of T1 and T3. Now, stress change with different work is described before and similarly T1, T2, T3 change with change in stress and this change can be seen in the box plot below.

5. 8 Box plot of T2



5. 6 Box plot of T1

5. 7 Box plot of T3

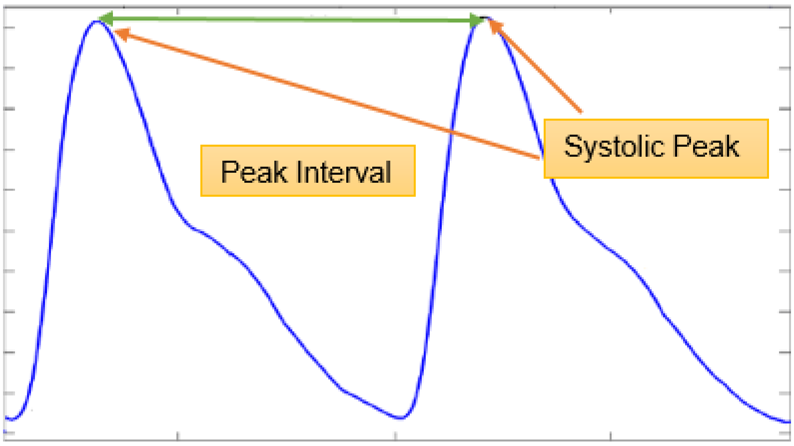
5.A.3 Extraction of Features:

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly i.e., to classify those PPG Signals for various conditions on the basis of different features from the raw data.

In this study one minute time frame is considered to extract those features as mentioned below:

- **Systolic Peak Interval of PPG Signals:**

Difference between the Systolic peak intervals for different stressed condition with resting is extracted as a feature for one minute data frame.



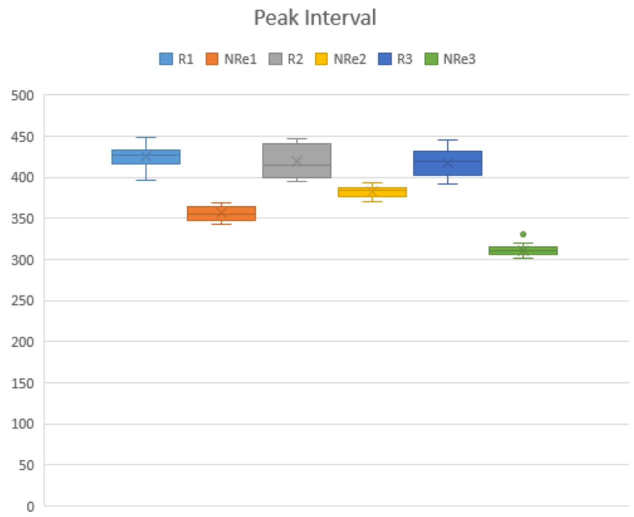
5. 9 Systolic Peak and Peak Interval of PPG Signal

A table of peak interval of different stressed condition of one subject is given below with its BoxPlot:

Table 11 Systolic Peak Interval in milliseconds

Systolic Peak Interval					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
427	355	447	370	401	315
428	354	395	384	435	320
428	369	427	394	434	303
434	363	401	374	445	312
434	352	442	381	420	301
411	365	397	384	412	314
415	366	446	389	392	305
418	346	438	372	425	308
427	343	431	392	419	308
433	363	403	384	404	312
448	347	399	383	426	307
397	347	400	384	401	330

A peak interval boxplot is used for analysing PPG signals to determine various intervals and durations of the cardiac cycle. To identify different stressed condition those data in the above table is represented in terms of boxplot. On the basis of the range of the values of peak interval, we can identify different stressed condition.



5. 10 Box plot of Peak Interval

Result: Now as we can see from the above boxplot the separation of peaks is found to be smaller under a relatively higher stress condition as Reading and Arithmetic calculation task compared to a relatively lower stress condition Resting before all stressed task as well as Listening Music which is higher. This could indicate that the heart is responding to the stress by increasing its rate or by changing its rhythm.

➢ Heart Rate from PPG Signals:

Heart Rate feature from PPG Signals is evaluated from that equation below:

$$Heart\ Rate(H.R.) = \frac{60F_S}{t_2 - t_1} \text{..................(8)}$$

Where, t_1 is time value of an arbitrary Systolic Peak, t_2 is time value of successive Systolic Peak.

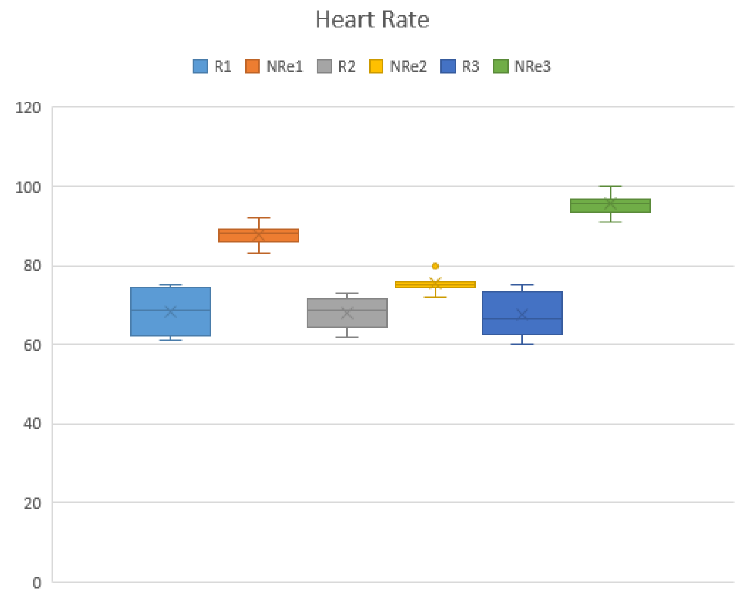
F_s is Sampling Frequency (i.e., 500 Hz)

Heart Rate of one subject is calculated from the given equation above and hence the values of different stressed condition of one minute data frame in form of table with its BoxPlots:

Table 12 Heart Rate

Heart Rate					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
72	83	64	74	61	100
70	88	62	75	69	93
71	92	65	75	60	96
62	86	72	80	66	95
63	89	70	76	71	93
61	89	69	76	74	100
67	88	73	75	62	95
75	85	72	80	75	95
67	86	68	75	66	96
75	86	65	76	64	96
75	89	64	72	75	97
62	92	70	74	67	91

Result: From the following Boxplot, we can observe how the average heart rate is varying with different stressed conditions. When the body is exposed to stress, the sympathetic nervous system is activated, which causes the heart rate to increase. This is a normal and healthy response to stress, and it is part of the body's stress response, also known as the "fight or flight" response. The exact effects of stress on the heart and the heart rate can vary depending on the individual and the specific stressor, and further analysis and interpretation of physiological measures such as heart rate and heart rate variability is needed to understand these effects.



5. 11 BoxPlot of Heart-rate

➢ Number of Peaks of PPG Signals:

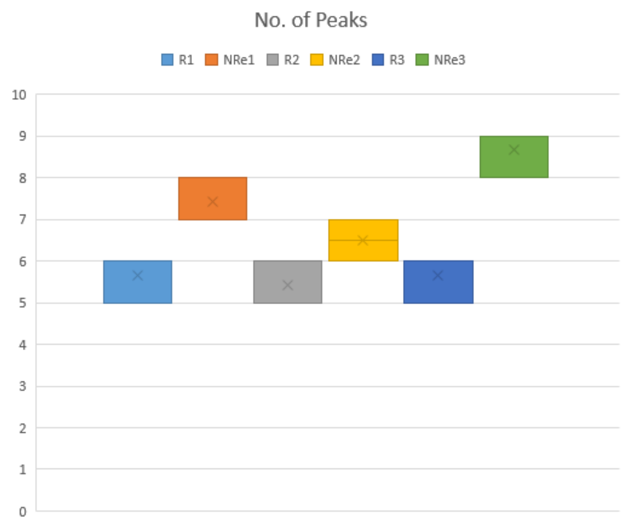
Number of Peaks of PPG Signal for one minute PPG data is extracted to identify the stressed condition individually. By the help of that feature, we can observe the in which condition Signal is more compressed and in which it is expanded i.e. means the frequency of PPG Signal of PPG Signal can also be assumed from that result. On the basis of the frequency, we can categorize the condition. A table of Number of Peaks of different stressed condition of one subject is given below with its BoxPlot:

Table 13 Number of Peaks per five seconds

Number of Peaks					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
5	8	6	6	6	9
6	8	5	7	6	8
6	8	5	6	6	9
5	7	6	6	6	8
6	7	5	6	6	8
6	7	6	7	6	9
6	7	6	6	5	9
6	7	5	6	6	9
5	8	5	7	6	9
6	7	6	7	5	8
6	7	5	7	5	9
5	8	5	7	5	9

Here each data on table is the 5 second peak count of PPG Signal and for each condition total 12 value is taken i.e., total one minute data is presented in the table for each condition.

Result: From that above boxplot, the Number of Peaks is varying under different stressed condition. As in tougher situation subject is taking more stress and as a result the frequency of PPG Signal is increased more than a resting condition as well as Listening Music. Hence, we can detect more peaks from Arithmetic Calculation Task and then Reading as the signal is more compressed than all Resting and Listening Music Condition, Peaks number is almost same.



5. 12 Boxplot of No. of Peaks

➢ Fast-Fourier Transform of PPG Signals:

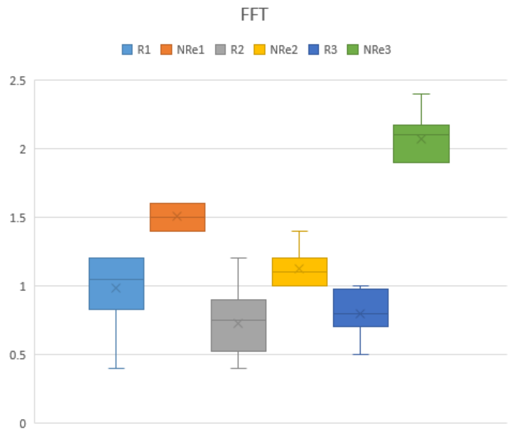
Introduction: FFT (more of this in pg. 16) is a mathematical algorithm that is often used to analyse PPG signals, in order to determine their frequency content. This can be useful for analysing stress in PPG signals, as changes in heart rate and blood pressure caused by stress can affect the frequency content of the signal. Here FFT has been used to determine the peaks of dominant frequencies and how it deviates under different stressed conditions. Samples are collected from one subject and the sampling frequency is taken as 500 Hz.

A table of Fast Fourier Transform of different stressed condition of one subject of one minute data frame and its Boxplot is given below:

Table 14 FFT of PPG Signals in Hertz

FFT					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
1	1.6	0.9	1.1	0.6	2.1
1	1.6	0.6	1.3	0.7	2.1
0.8	1.4	0.4	1.1	0.8	1.9
1.2	1.6	0.7	1	0.5	1.9
1.2	1.4	0.8	1	1	1.9
1.2	1.4	0.8	1.1	0.9	2.4
1.2	1.5	1.2	1.2	1	2.1
1.2	1.6	0.9	1.2	0.7	2.3
0.4	1.5	0.6	1.4	0.9	2.1
1.1	1.5	0.4	1	1	1.9
0.9	1.6	0.5	1	0.7	2
0.6	1.4	0.9	1.1	0.8	2.2

Result: From the above figure we can observe that if the dominant frequency of the FFT of PPG signal is increasing under different stressed conditions, it could indicate a change in the heart rate and blood pressure of the individual. The dominant frequency of a PPG signal is determined by the heart rate, so an increase in dominant frequency could indicate an increase in heart rate. Additionally, a decrease in amplitude could indicate a change in blood pressure. Increase in dominant frequency indicate subject is more stressed like Arithmetic Calculation Task and then Reading than all Resting as well as Listening Music.



5. 13 BoxPlot of FFT of PPG signal

➢ Power Spectral Density of PPG Signals:

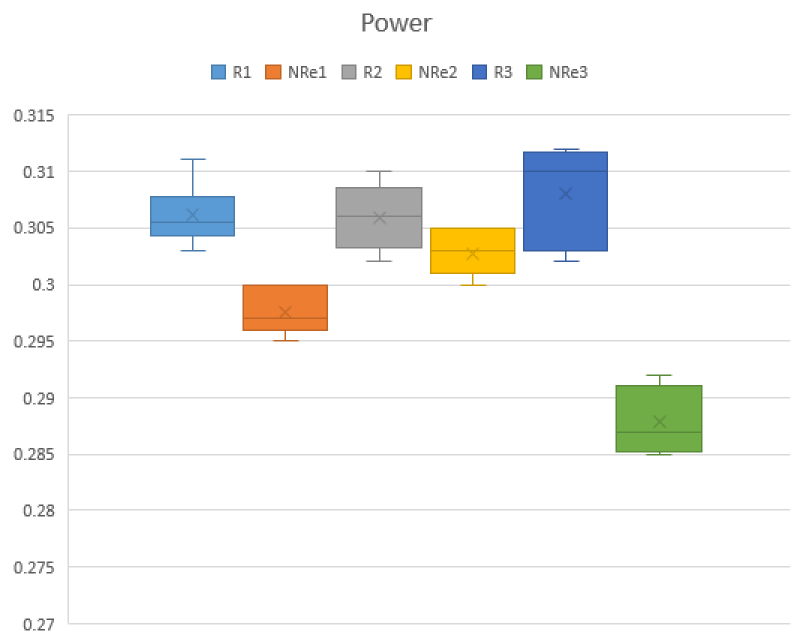
Introduction: Description of PSD is given in pg.16. In this case, we can use PSD of the PPG signal to calculate average power of the signal over a specific frequency range (0 Hz to 12 Hz). Calculating average power can be useful for analysis because it can provide information about the overall strength of the signal. This can be useful for identifying changes in the strength of the signal over time, which can be indicative of changes in heart rate, blood pressure, or other physiological parameters, additionally, the average power can be used to normalize the signal which can be useful for comparing PPG signals from different individuals or under different conditions.

A table of Average Power of different stressed condition of one subject of one minute data frame and its Boxplot is given below:

Table 15 Average Power in dB

Power					
R1	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
0.304	0.295	0.303	0.301	0.312	0.289
0.303	0.296	0.309	0.303	0.303	0.291
0.303	0.295	0.31	0.305	0.308	0.287
0.307	0.296	0.302	0.305	0.312	0.292
0.305	0.3	0.306	0.3	0.302	0.291
0.306	0.3	0.307	0.305	0.311	0.286
0.305	0.297	0.304	0.301	0.311	0.285
0.311	0.297	0.302	0.305	0.309	0.286
0.306	0.297	0.306	0.301	0.311	0.285
0.305	0.297	0.309	0.301	0.303	0.291
0.308	0.3	0.307	0.303	0.302	0.287
0.311	0.3	0.306	0.303	0.312	0.285

Result: As seen from the above boxplot when subject is more stressed than the average power is lesser than the resting conditions. Hence, we can conclude during a rough and tough situation the value of average power of PPG Signal is identified more accurately what is being shown in the above boxplot, in case of Arithmetic Calculation Task and then Reading. But though the Listening Music to a subject is also a stimulus to the subject but in the above plot it is observed that the range of values, we can't separate the Listening Music condition from the resting ones as those values belong to almost same region of values.



5. 14 BoxPlot of Power of PPG Signal

5.A.4 Result of GSR Based Indication of Stress Stimuli:

In this part, we extracted the feature of the number of peaks per 2 minutes from the GSR signal to identify whether the subject is in a resting or stressed condition. However, we observed that the peak rate varied from subject to subject. Therefore, we normalized the peak rate values between 0 and 1 within a predefined scale to obtain a consistent feature. To evaluate the peak rate below equation is obtained.

$$PR = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \textbf{(9)}$$

where, X_i is peak rate one of the condition of each subject.

X_{max} is maximum peak rate of each subject.

X_{min} is minimum peak rate of each subject.

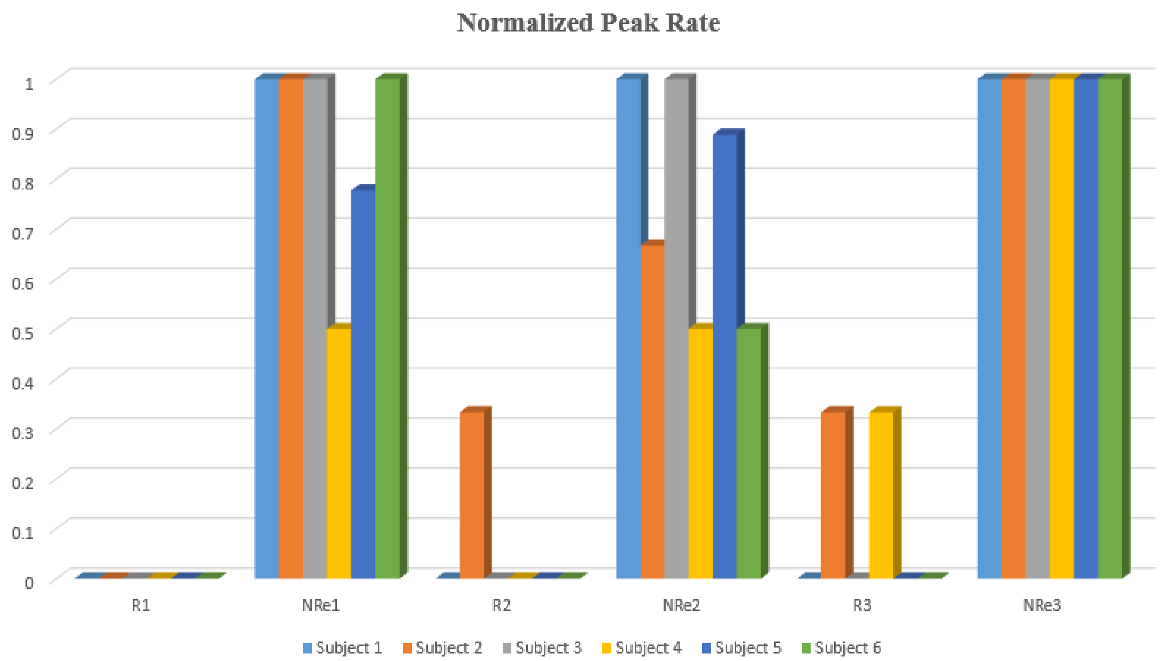
Initially, we applied the Weighted KNN classifier for classification, but we found that a clear threshold could be observed to distinguish between the resting and non-resting conditions. Hence, we decided to use a simple if-else statement instead of the Weighted KNN classifier. Specifically, we set a threshold value for the peak rate feature, and if the value was above the threshold, we classified the subject as non-resting; otherwise, we classified the subject as resting. This approach proved to be effective in accurately distinguishing between the two conditions.

Normalized Peak Rate estimated from GSR Signal is given below in the table.

Table 16 Normalized Peak Rate from GSR Signal

Normalized Peak Rate from GSR Signal						
Subject	**R1**	**NRe1**	**R2**	**NRe2**	**R3**	**NRe3**
1	0	1	0	1	0	1
2	0	1	0.33	0.67	0.33	1
3	0	1	0	1	0	1
4	0	0.5	0	0.5	0.33	1
5	0	0.77	0	0.89	0	1
6	0	1	0	0.5	0	1
7	0	1	0	0.67	0	0.67
8	0	1	0	1	0	1
9	0	1	0	1	0.17	1
10	0.22	1	0	0.44	0	1
11	0	1	0.33	1	0.17	1
12	0	1	0	1	0	1

Bar chart of the above table for six subjects is shown below:



5. 15 Bar chart of Normalised peak of different subject in different stress condition

From the above bar chart, we observe that the resting and non-resting condition can be easily separated using a threshold value around 0.38. Hence a simple logical binary classification will be sufficient to identify the deviation from resting condition, whatever be the new state of event (valid for present study) may be. Now to identification of individually stressed work we have to move forward to the second step i.e. PPG Signal based classification based on the 10 features mentioned in the 5.A.3 section.

5.A.5 Result of PPG based indication of stress stimuli:

This is a classification based on the 10 PPG features which is extracted to differentiate stressed condition individually.

To extract features of the PPG Signal of one minute PPG samples are taken for each stressed condition from middle of two or three minutes given signal. Therefore, signal is divided into twelve parts i.e. each five seconds data from one minute PPG signal is applied to get the features mentioned above in 5.A.3 section, and then the features value of the each five second is averaged. The reason behind to evaluate feature extraction in such a way to avoid more variability of features value. Hence, the twelve average feature value for each stressed condition is applied for the classification for all subjects in the part.

We have 12 features value for one condition out of six stressed condition and total 12 subjects. So, total 864 data is applied for classification for each feature.

Table 17 No. of dataset for classification

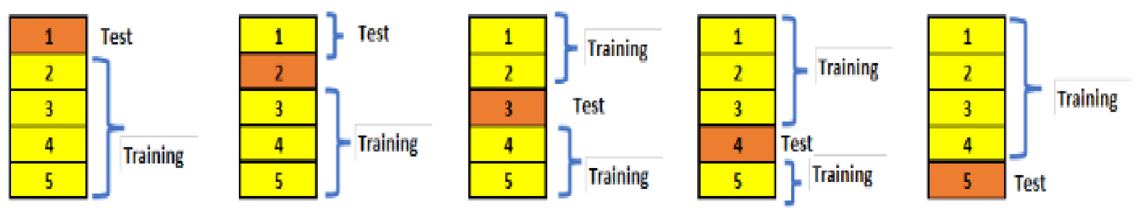
Total Number of occurrences of Resting events of same feature for all 12 subjects	432
Total Number of occurrences of Reading events of same feature for all 12 subjects	144
Total Number of occurrences of Listening Music events of same feature for all 12 subjects	144
Total Number of occurrences of Arithmetic Calculation Task events of same feature for all 12 subjects	144

In our study for classification Weighted KNN classifier is applied.

Weighted KNN is a modified version of k nearest neighbours. One many issue that affect the performance of the KNN algorithm is the choice of the hyper parameter k. If k is too small, the algorithm would be more sensitive to outliers. If k is too large, then the neighbourhood may include too many points from other classes.

Through this classification K-fold Cross Validation is obtained. In each set (fold) training and the test would be performed precisely once during this entire process. It helps us to avoid overfitting.

In the given dataset and we are splitting into 5 folds and running the Train and Test. During each run, one-fold is considered for testing and the rest will be for training and moving on with iterations, the below pictorial representation would give you an idea of the flow of the fold-defined size.



5.16 5 Crossfold Validation technique

In which each data point is used, once in the hold-out set and K-1 in Training. So, during the full iteration at least once, one fold will be used for testing and the rest for training.

In each iteration, we will get an accuracy score and have to sum them and find the mean accuracy.

We have four classes in this section:

I. Resting

II. Reading

III. Listening Music

IV. Arithmetic Calculation Task

First, we applied classification for resting class with other classes individually and then all classes together.

➢ Results of Classification:

A table for classification of four types given below:

Table 18 classification Table

.

Classification Type	No. of features	No. of Training Samples	No. of Testing Samples	TP	TN	FP	FN	Accuracy (%)	Sensitivity	Specificity	PPV	NPV
Resting vs Reading	10	230	58	142	130	14	2	94	0.98	0.90	0.98	0.98
Resting vs Listening Music	10	230	58	126	111	33	18	82	0.87	0.77	0.86	0.79
Resting vs Arithmetic Calculation Task	10	230	58	141	141	3	3	97	0.97	0.97	0.97	0.97
Resting vs All Condition	10	691	173	130	711	9	14	97	0.90	0.98	0.93	0.98

In the above table, where:

i. TP is True Positive
ii. TN is True Negative
iii. FP is False Positive
iv. FN is False Negative
v. PPV is Positive Predictive Value
vi. NPV is Negative Predictive Value

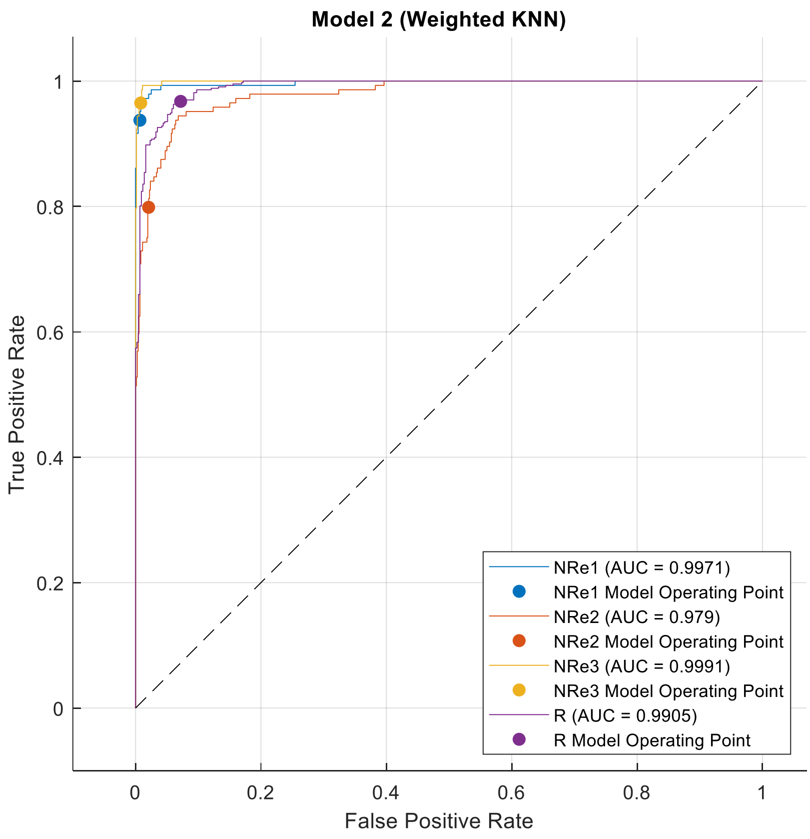
The accuracy of the classification of Resting vs Reading is 94.44%, which indicates a high level of performance. The sensitivity value of 0.9861 indicates that the model can correctly identify the positive cases, while the specificity value of 0.9021 indicates that it can correctly identify the negative cases but not as positive cases. The positive predictive value of 0.9848 indicates that the model can accurately predict the presence of stress, while the negative predictive value of 0.9861 indicates that it can accurately predict the absence of stress.

The accuracy of the classification is 82.29%, lower performance than any other stressed condition. The sensitivity value of 0.8750 indicates that the model is less effective at correctly identifying positive cases than in the first scenario, while the specificity value of 0.7708 indicates that it is also less effective at identifying negative cases leads to error more than other classification. The positive predictive value of 0.8605 indicates that the model is less accurate at predicting the presence of stress, while the negative predictive value of 0.7924 indicates that it is still less accurate at predicting the absence of stress.

The accuracy of the classification is 97.92%, which is again a high level of performance. The sensitivity value of 0.9791 indicates that the model can correctly identify the positive cases, while the specificity value of 0.9791 indicates that it can correctly identify the negative cases. The positive predictive value of 0.9791 indicates that the model can accurately predict the presence of stress, while the negative predictive value of 0.9791 indicates that it can accurately predict the absence of stress.

Overall it is considered that all types classification shows above 90% for accuracy and above 0.9 for rest of the classification parameter results that reflects high level of performance subjected a good classification except the Resting vs Listening Music classification where we assume that some of the data points are overlapping somehow for both conditions. As music itself non-stress releasing effect, after a longer period of subject is not aroused on impact of the music. Also condition of music to subject would not be the choice of it i.e. not comfortable with it. As a result this condition may vary subject to subject that is concluded from above classification result where all accuracy is 82.29% and other classification parameter is less than 0.9 leads to lower performance than all other types of classification. In general, Listening Music condition is less stressful or lesser stress impact and Continuous Arithmetic Calculation task is more stress impact than any other condition.

This is the ROC curve for Resting vs all condition.



5. 17 ROC Curve of Resting vs. All Condition

From above ROC curve it is observed the area under curve for all condition is almost 0.99 except Listening Music Condition which is around 0.97 a bit of less accurate among all kind of stressed condition. So, this result can be applied for Health Mentoring purposes and further future work over with more and more subjects to generalize the classification result for given condition.

5.B Discussion:

5.B.1 The Importance of The Work

Stress is a pervasive problem in modern society, and it affects millions of people worldwide. Managing stress is crucial to maintaining good physical and mental health. Therefore, there is a need for accurate and efficient methods for stress detection and management. One promising approach is to use physiological signals, such as PPG and GSR signals, to monitor stress levels in individuals.

In our project, we focused on developing a novel approach for stress monitoring that combines PPG and GSR signals, guided by machine learning algorithms for classification. We collected data from four different conditions, namely resting, reading a book, listening to soothing music, and performing verbal arithmetic tasks, to capture a range of stress levels in individuals.

The two-state classification approach we adopted, where we first classified whether the subject was at rest or in a non-rest state using GSR signals and then further classified the non-rest state using PPG signals, allowed us to develop a more targeted and effective approach for stress monitoring. By focusing on specific features of the signals that are indicative of stress, we were able to improve the accuracy and efficiency of stress monitoring using physiological signals.

Our work has several important implications. Firstly, it demonstrates the potential of using PPG and GSR signals for stress monitoring. By collecting data from multiple conditions, we were able to identify patterns in the signals that corresponded to different stress levels. This suggests that these signals could be used to monitor stress in real-world settings, such as in healthcare, workplaces, and personal stress management.

Secondly, our two-state classification approach has several advantages. By first classifying the subject as being in a resting or non-resting state, we were able to reduce the computational load and focus on specific features of the signals that are indicative of stress. This allowed us to develop a more targeted and efficient approach for stress monitoring, which could be particularly useful in real-time monitoring applications.

So, our project demonstrates the potential of machine learning algorithms for stress monitoring using physiological signals. By using these algorithms, we were able to identify patterns in the signals that are difficult for humans to detect. This suggests that machine learning algorithms could be used to develop more accurate and efficient methods for stress monitoring, which could have significant real-world applications.

In conclusion, our project represents an important contribution to the field of stress monitoring using physiological signals. By combining PPG and GSR signals with machine learning algorithms for classification, I have developed a more accurate, efficient, and targeted approach for stress monitoring. This has important implications for healthcare, workplaces, and personal stress management, and highlights the potential of machine learning algorithms for stress monitoring using physiological signals.

5.B.2 Advantages of Two State Classification

The two-state classification approach has several advantages:

Simplicity: The two-state classification approach is simple and easy to understand, which makes it a good starting point for more complex classification tasks. By breaking down the classification into two stages, it becomes easier to analyse and interpret the data.

Improved accuracy: By first classifying the subject into a resting or non-resting state, the two-state classification approach can improve the accuracy of the overall classification. This is because the resting state is a well-defined state and easier to classify accurately, which reduces the number of misclassifications in the non-resting state.

Reduced complexity: The two-state classification approach reduces the complexity of the classification task, which makes it easier to implement and faster to compute. This is especially important when dealing with large datasets or real-time applications where speed is critical.

The use of PPG data in the non-resting state classification stage also has several advantages:

High temporal resolution: PPG signals have a high temporal resolution, which makes it possible to capture changes in the physiological response in real-time. This is important for detecting changes in stress levels, which can occur rapidly and unpredictably.

Non-invasive: PPG signals are non-invasive and can be obtained using a simple device such as a finger clip or a wristband. This makes it a convenient and accessible method for monitoring stress levels in real-world settings.

Wide applicability: PPG signals can be used to detect changes in other physiological parameters such as heart rate, blood pressure, and oxygen saturation. This makes it a versatile tool for monitoring different aspects of physiological response.

Chapter 6: Conclusion and Future Scope

In this project, I have developed develop a Machine Learning based system to detect different stress generating events such as solving arithmetic problems, listening to music, reading from computer screen etc. with respect to a threshold resting condition using physiological signals like PPG (Photoplethysmogram) and GSR (Galvanic Skin Response). The algorithm we developed uses GSR as event marker and different events are classified from PPG based features. The developed method can be used in a mental stress detection and analysis system to identify the events that can cause stress. We can accurately distinguish whether the subject is at rest or in a non-resting state completely using GSR signal and later we can identify specific tasks with 97% accuracy using PPG signal.

FUTURE SCOPE OF THIS PROJECT:

The future scope of this project is significant, and there are several potential directions that could be pursued to extend the work further. Here are some possibilities:

- **Integration with wearable devices:** The use of physiological signals for stress monitoring is particularly suited to wearable devices such as smartwatches and fitness trackers. These devices can be used to continuously monitor physiological signals, providing real-time feedback on stress levels. Future work could focus on integrating our approach with wearable devices, allowing for more widespread and accessible stress monitoring.
- **Long-term monitoring:** While our project focused on short-term stress monitoring in response to specific tasks, stress is often a chronic condition that can have long-term health implications. Future work could explore the use of PPG and GSR signals for long-term stress monitoring, which could be particularly useful for individuals with chronic stress conditions.
- **Multi-modal approaches:** While our project focused on the use of PPG and GSR signals for stress monitoring, there are many other physiological signals that could be used to provide additional information on stress levels. Future work could explore the use of multi-modal approaches, combining signals from multiple physiological sensors, to develop more comprehensive and accurate methods for stress monitoring.
- **Validation on larger datasets:** Our project collected data from a small sample size of individuals, and future work could aim to validate our approach on larger datasets. This would provide more robust evidence for the effectiveness of our approach and could be used to develop more generalizable models for stress monitoring.
- **Clinical applications:** Stress is a significant health problem, and there is a need for effective interventions to manage stress. Our approach could be used as a screening tool to identify individuals who are at risk of developing stress-related conditions, allowing for early intervention and prevention. Future work could explore the use of our approach in clinical settings, such as in mental health clinics or primary care settings.

So, there are many exciting possibilities for future work in the area of stress monitoring using physiological signals, and our project provides a foundation for further research and development in this area.

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