An approach to detect stress using combination of physiological signals and facial expression

By

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In Guidance of

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Thesis Submitted to
Gujarat Technological University in Partial Fulfillment of the Requirements for the Master of Engineering Degree in Computer Software Engineering

May, 2021

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CERTIFICATE

This is to certify that the research work embodied in this report entitled **"An approach to detect stress using combination of physiological signals and facial expression"** has been carried out by **Ms. Drashti Shaileshkumar Patel [190420702006]** studying at **Sarvajanik College of Engineering & Technology, Surat (Institute Code - 042)** for partial fulfillment of Master of Engineering degree in Computer Engineering, 4th Semester to be awarded by Gujarat Technological University, Ahmedabad during the academic year 2020-21. This research work has been carried out under my guidance and supervision and it is up to my satisfaction.

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ACKNOWLEDGMENTS

I would like to express my special thanks to those who help me in dissertation work and showing valuable cooperation at various stages of dissertation work. Primarily, I would like to express my intense feeling of gratitude towards my Guide **Prof. (Dr.) Dipali Kasat** and **Prof. Fagun Vankawala** for her extremely good suggestions, guidance, and constant inspiration at every stage of my work.

I would also like to thank our Head of Department **Prof. (Dr.) Pariza Kamboj** for her cooperation and encouragement. I have to appreciate the guidance given by supervisors and panel members of my dissertation presentation for their guidance and suggestions. I also express a deep sense of gratitude towards my family and classmates who directly or indirectly helped me while preparing this report.

I would also thank **SWELL-KD** dataset community to provide me dataset acces for my research purpose.

Drashti Shaileshkumar Patel

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Abstract

Due to a rapidly changing lifestyle and an increasing workload, there is a need to develop new technology for stress management in working professionals. Daily stress management can allow users to better understand their levels of stress and provide doctors with more reliable data for treatments. Stress can be monitored by measuring physiological parameters like Electrocardiogram (ECG), Heart Rate (HR), and Galvanic Skin Response (GSR) continuously over a period of time. One of the traditional methods to detect stress is based on physiological signals including self-report questionnaires. As observed from a psychological point of view, a common problem with questionnaires may be the image of participants to respond truthfully without barriers of culture, society, or other such factors. Taking into consideration these factors we tend to replace the psychological part with facial expression. We propose a multi-modal stress recognition approach based on physiological signals and facial expression data streams and give 88.49% accuracy. The proposed model is applied to the standard SWELL dataset and the optimum results are obtained.

CHAPTER 1 INTRODUCTION

1.1 What is Stress?

Stress is a commonly used concept, but it is not easy to agree on the definition Because it is a subjective and complicated phenomenon to define. Merriam Webster's dictionary defines stress as a physical, chemical, or emotional factor which causes physical or mental stress and may be a cause of diseases [78]. Stress may be external (environment, psychological or social) or internal (illness or medical) circumstances. **In today's world one of the major leading factors to health problem is STRESS [49].**

1.2 Stress impact on society

Daily stress has been a major problem for modern society. Offices among other places contribute to the high stress most [44]. The mismatch in job requirements and abilities, time pressure and heavy workloads are the general causes of office stress. Family relationship problems, illnesses and chronic injuries and emotional problems may be described as reasons off-the-job stress. There are two different types of stress: acute and chronic [1]. Acute stress is more normal, because most people have experienced this type of stress. Potential causes of acute stress can be described as physical challenges, assessments or anxieties when meeting new people. Causes of chronic stress may be counted as long-standing pressures and demands related to socio-economic circumstances, problems in personal relationships, or dissatisfied careers.

As described above, stress has major effects on human health. In acute stress, possible signs can be identified as emotional distress, muscle aches and tension, stomach disorders, and over-arousal [77]. Minor health effects may include headaches, back pain, heartburn, stomach ache, high blood pressure, and rapid heartbeat.

1.3 Causes of Stress

Situations and pressures which trigger stress are known as stressors. We usually think of stressors as being negative, such as an exhausting work schedule or a relationship. However, anything that creates heavy demands on you can be stressful. This includes positive events such as getting married, buying a house, going to college, or receiving a promotion [78]. In addition, not all stress is due to external causes. Stress may also be internal or self-generated, whether you think too hard over anything that might or might not happen, or whether you have irrational, negative feelings over life.

Common **external** causes of stress include:

- Major life changes
- Work or school
- Relationship difficulties
- Financial problems
- Being too busy

- Children and family

Common **internal** causes of stress include:

- Pessimism
- Inability to accept uncertainty
- Rigid thinking, lack of flexibility
- Negative self-talk
- Unrealistic expectations / perfectionism
- All-or-nothing attitude

1.4 Sign and symptoms of stress overload

- Depression or general unhappiness
- Anxiety and agitation
- Moodiness, irritability, or anger
- Feeling overwhelmed
- Loneliness and isolation
- Other mental or emotional health problems
- Chest pain, rapid heart rate
- Frequent colds or flu
- Increase sweat

1.5 Stress Signals

We can measure stress symptoms in numerous ways. The Sympathetic Nervous System (SNS) ignites the stress reaction, resulting in psychological, physiological, and behavioral symptoms [41]. The psychological way of measuring stress can be self-report questionnaires or being interviewed by a psychologist [49].

The second way to detect stress is by evaluating physiological signals [81]. Signals of interest include different hormone levels, Electro Cardiogram (ECG), Electroencephalogram (EEG), Galvanic Skin Response, Blood Pressure (BP), Skin Temperature (ST), Electromyogram (EMG), Respiration, Blood Volume Pulse (BVP), Pupil Diameter (PD), Eye Gaze and Blinking, Thermal Imaging (TI) and functional Magnetic Resonance Imaging (fMRI). Stress affects in behaviors of individuals. Without invasive technique and a require for extra pieces of equipment can measure the behavioral changes. Behavioral responses provide keypad and mouse dynamics, posture, facial expressions, voice, smartphone use, walking pattern, and text messaging.

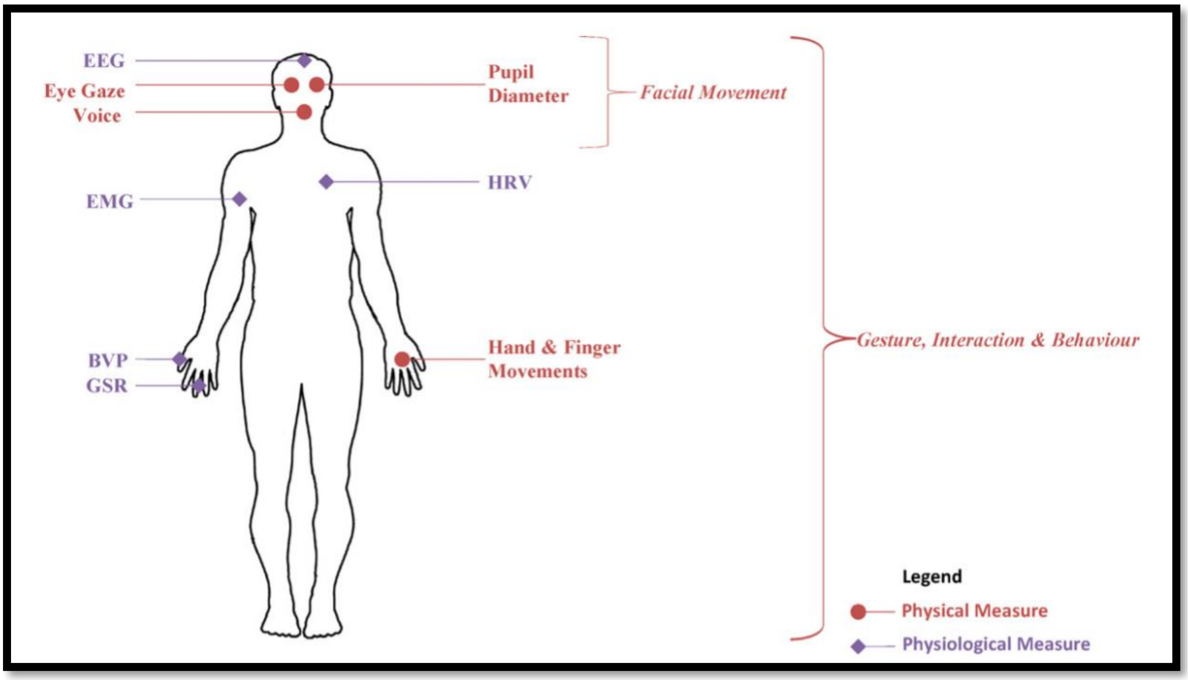


Figure 1: Common physical and physiological measures used to detect stress [72]

Figure1 shows the usual sources for the measures. Stress experiments that use various sensors to obtain objective measures of stress also use subjective assessment to verify measurements obtained from sensors [16].

1.5.1 Physiological signal

1. Heart activity:

One of the most common indicators of stress inequality is heart performance, since autonomic nervous system (ANS) directly affects the heart rate. The electrocardiogram (ECG) is used to measure the electrical activity of the heart by means of electrodes placed on the body, usually on the left arm, the right arm and the left leg. The normal heart beat has four basic elements, the P wave, the QRS complex and the T wave [8]. The most distinctive R peak is used for the extraction of features. Heart activity can be modelled with heart rate (HR), RR interval (IBI) and heart rate variability (HRV). The variability of the heart rate is the oscillation of time between consecutive beats. The IBI interval can be defined as the time between two consecutive R peaks. All of these can be inferred from R peaks [49].

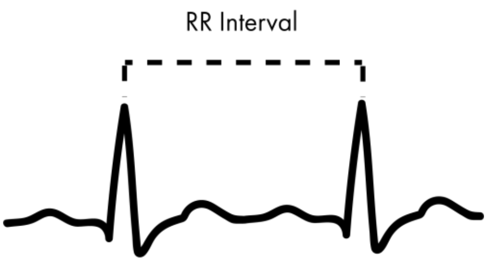


Figure 2: Heart rate RR interval [55]

2. Brain activity:

Brain activities are also affected by emotional changes and stress. The electroencephalogram (EEG) is used to measure brain activity by placing a collection of electrodes placed on the scalp of the subject. The EEG signal consists of four frequency bands: Alpha (8–13 Hz), Beta (13–30 Hz), Delta (0.1–4 Hz) and Theta (4–8 Hz) [49].

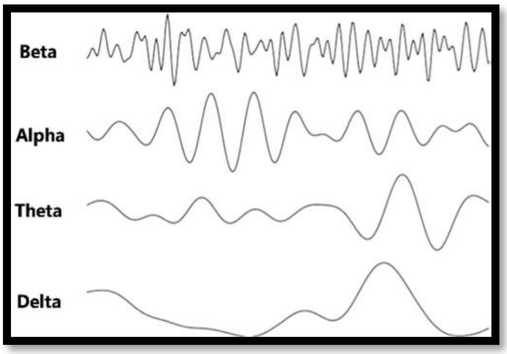


Figure 3: The waveforms of four typical EEG rhythms [72]

3. Muscle activity

The stress-related neurological activity also affects the muscles. The capacity for muscle activity is used to identify stress [3]. Electromyogram (EMG) tests the potential for muscle activity by placing electrodes on choosing muscles. Facial and Trapezius muscles are areas of interest for muscle function assessment. The mean, median, standard deviation, RMS, peak loads, and gaps per minute are widely used [49].

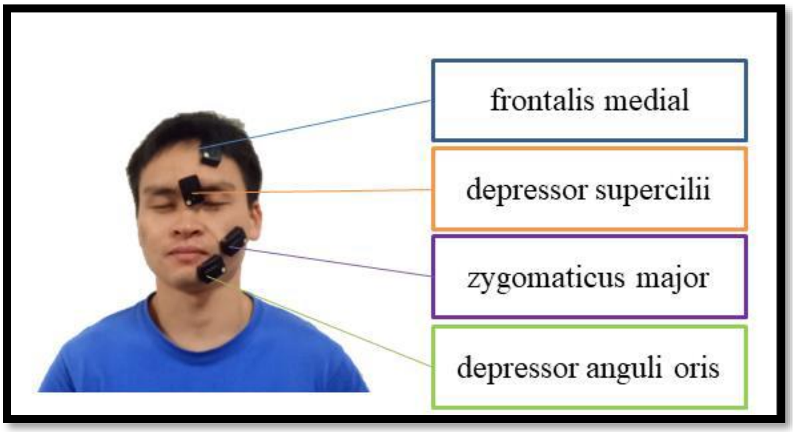


Figure 4: Locations of EMG sensors [3]

4. Electrodermal Activity (EDA)

EDA, also known as Galvanic Skin Reaction (GSR), is a variation in the electrical properties of the skin. Under emotional excitement and stress, body sweats and skin behavior increase. The EDA can be computed by adding a small current and by measuring the resistance of the skin between the two electrodes in place. The EDA signal consists of two parts. The first is the Skin Conductivity Level (SCL). It is a slowly changing part over the long term (Tonic). The second part is the Skin Conductance Response (SCR) which represents the faster and event-related part of the EDA (Phasic). The EDA is one of the best discriminatory signals along with the heart rate signal. ProComp Infiniti, Biopac MP150, Shimmer 3 GSR+, and Empatica E4 wristband are devices that are commonly used to evaluate EDA [49].

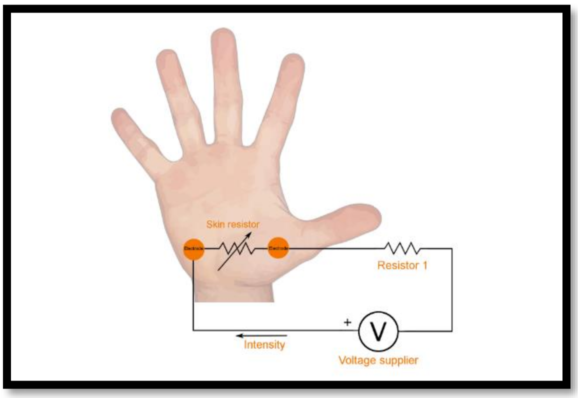


Figure 5: GSR sensor schematics [56]

The mean amplitude, standard deviation, minimum and maximum values, RMS, the delay between applied stimuli and response, number of peaks, peak height, rising time, recovery time, the position of maximum and minimum features are tried in the literature to determine stress of a user.

5. Blood volume pulse

As HR and HRV change with stressful events, blood volume and blood pressure may also change. Blood volume pulse (BVP) is a variation in the volume of the blood at each inter beat interval. Photoplethysmography (PPG) is a low-cost optical technique used to measure BVP. It makes use of the absorption of light by the blood. After light is emitted from a light source, different amounts of blood in the volume will absorb different amounts of light. In this method, the amount of blood will be evaluated. Although BVP features can be used directly, in major of the cases they are used to extract the heart rate variability or IBI features [49].

6. Skin temperature

The temperature of the skin may change due to various factors, including stress. Research has shown that arousal can cause a difference in temperature of 0.1 to 0.2 Celsius [10]. The key explanation for local temperature fluctuations is that the flow of blood is controlled by the SNS.

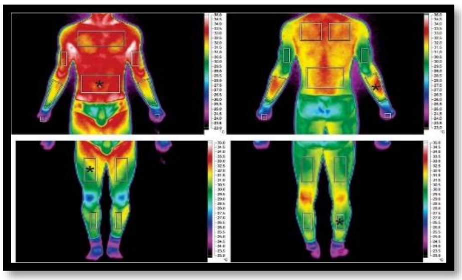


Figure 6: Daily oscillations of skin temperature [64]

The effect of stress on the skin temperature can be determined by monitoring several variables. In the literature, the mean, minimum, maximum and standard deviations of skin temperature characteristics were used to determine stress [49].

1.5.2 Behavioral Data

1. Speech

Stress causes changes to the human voice generation mechanism. Pitch, voice quality, energy and spectral properties are affected by stressful events. Speech is preferred by many researchers because it is non-invasive, and data gathering is simple in peaceful, controlled environments. Pitch (mean, standard deviation, range), higher frequency band ratio, voice modulation, voice intensity, smooth energy, voiceless speech ratio, Mel Frequency Cepstral Coefficients (MFCC) are features that are commonly used to identify stress levels [5].

2. Facial Expressions

Stress and emotional states are related to facial expression. It has been shown that facial expressions reflect emotions rather than self-reporting [18]. Facial EMG and camera image recognition were used to detect facial expressions in stressful situations. Mean smile frequency, eyebrow activity and activity of the mouth are the major facial features for stress detection [49].

3. Body gestures and moments

Individuals display behavior and gesture changes when getting stressed. These changes include, but are not limited to, clenching of the jaw, movement of the arm, self-touching, finger rubbing. The changing in posture is another indicator with stress. Stress in the sitting posture is examined by a variation in the pain center [47]. Subjects also demonstrated more changes through posture in stressful situations.

1.5.3 Questionnaires and surveys

Psychological stress assessments can be collected by asking participants to fill out questionnaires and evaluating people. There are two methods of data collection from subjects in daily life (or long laboratory experiments) that are instant reporting and day reporting (or cumulative reports). People need to understand about emotional peaks in 24 hours [1][50]. For this purpose, asking a question to subjects at the end of the day may cause incorrect readings. The alternative is to ask for stressful events to also be reported instantly. The difficulty with this way is that people will fail to record incidents. A combination of these methods is used in the literature to increase the accuracy of the reports [16].
E.g.

1. Age?
2. Height (cm)?
3. Weight (kg)?
4. Gender?

5. Dominant hand?
6. Did you drink coffee today?
7. Did you do any sports today?
8. Are you a smoker?
9. Do you feel ill today?
10. Did you drink tea today?

CHAPTER 2 LITRATURE REVIEW

2.1 Machine learning Techniques

Different machine learning (ML) techniques have been used in literature to predict mental stress based on physiology. Below the most frequently used techniques are described.

Table 1: Comparison Table of Existing Techniques

Sr No.	Techniques	Strengths	Weaknesses
1	Logistic Regression [75][73]	Calculates the strength of the relationships among elements and the result.	Underperforms where there are many non-linear decision boundaries; Only operates with numeric features; categorical data needs additional processing.
2	Support Vector Machine [74][76]	Not strongly impacted by noisy data and not sensitive to overfitting; Increasing in success as a result of its high precision and high-profile results in data mining competitions	Evaluating different combinations of kernels and parameter values is needed to identify the perfect model; Development may be time-consuming, particularly if the input dataset has a large number of features or samples; Produces a challenging black box prototype that is difficult, if not impossible, to understand.
3	Naive Bayes [75]	Simple to obtain the approximate likelihood for a measurement; Works well with noisy and missing data; Needs comparatively few observations for training but also works well with very large numbers of observations	Focuses on the sometimes incorrect statement that all features are equally important and independent; Not suitable for datasets with a large number of numerical features; Estimated chances are less trustworthy than expected classes.
4	DT [74]	Largely automated learning algorithm that can manage numeric or nominal attributes, incomplete data; Only uses the most relevant attributes; Can be used on data with a limited learning rate or a huge number of input samples; Produces a model that can be understood without a mathematical context (for relatively small trees)	DT models are often weighted against splits on features with a large number of levels; it is possible to overfit or underfit the model; small changes in the dataset may result in large changes in decision logic, and large trees may be challenging to evaluate, and their decisions can appear counterintuitive.
5	ANN [75]	One of the most precise modeling techniques; Makes few predictions based on the basic relationships of the data	Seems to have a history of computing complex and slow to learn, particularly when the network topology is complex; Is easy to overfit or underfit training data; and Produces a complex black-box model that is challenging, if not difficult, to understand.

Finally, the current overview has only focused on supervised stress detection techniques, where the model is developed based on a training set including examples of features (e.g. physiology) and output variable (e.g. stress). It could also be interesting to investigate supervised techniques to identify stress vs. normal.

2.2 Physiological signals and Sensors

A review of the physiological sensor of the literature survey. A list of different sensors, measure units, the equation is mention.

Table 2: Physiological signal sensor, measure unit, equations

Physiological signals	Sensors	Measure units	Equations
GSR	• E4 wristband • Shimmer 3+ GSR • Bio Harness 3.0	• 1 – 10 Hz –> Data Acquired • micro-Siemens (µS) –> measured unit	Conductance = 1 / Resistance Voltage = Intensity x Resistance = Intensity/Conductance
HRV	• E4 wristband • Bio Harness 3.0 • Vivo smart	• milliseconds (ms)	(RR Interval 1- RR Interval 2) ^2 + (RR Interval 2- RR Interval 3) ^2 + …..

2.3 Literature Survey

Related work consisting of various research papers for Stress detection, physiological signal, behavioral signal, etc.

Heart rate variability is one of the most recognizable signals to stress monitoring. Time-domain (mean RR, RR standard deviation), frequency domain (LF / HF, standardized LF HF difference), and nonlinear features were used in the literature [44]. Castaldo et al. [65] instead of short features of HRV(5 min), experimented with the ultra-short feature of HRV (2 min) and their effect on the accuracy of stress detection. They designed the SCWT, the daily life exam, and video game tested at the lab. By applying SVM (Support Vector Machine) over HRV features, the binary classification (stress vs. relax) achieved 70 % of total accuracy under laboratory conditions. These results are less than the findings of the literature.

Stress recognition using HR features has also been used to develop the system for the recognition of emotions. Tivatansakul et al. [66] designed a method that recognized negative facial emotions and provided hints about how to calm. However, they reported that the system had an uncertainty issue when differentiating positive and negative emotions and that the accuracy of the binary classification was 62.5 %. To improve the system, a stress monitoring scheme was introduced using the ECG signal and HRV features.

Akmandor et al. [62] developed a stress detection and relaxation method by collecting ECG, GSR, respiration, blood pressure, and blood oximeter in the lab environment. A memory game, a fly tone, an ice test was used to trigger stress. Classical music, warm stone, and positive news are used for alleviation. For a 2-class grouping, SVM and KNN were asked for. They achieved 95.8% accuracy. Results suggest that alleviation strategies make people return to a relaxed state faster.

Moses et al. [48] Also combined physiological and sociometric sensors to detect stress. EDA and PPG are used as physiological sensors. Sociometric sensors are microphones and accelerometers that are used in the schematic badge used to measure social activity. They took baseline measurements and used TSST to induce stress. Subjects are asked to prepare a presentation and to make a public speech. Personalized classifiers were used by individuals. A KNN, SVM, Adaboost have been applied as a classifier. They plan to extend this research into day-to-day life scenarios.

Zubaira et al. [44] proposed a scheme that would automatically measure the stress of graduate students. For around a year, they gathered data from 117 subjects. The features picked were mobile phone user behavior (call and SMS logs, Bluetooth proximity hits), weather conditions, personality traits. The environmental conditions were classified into six: mean temperature, pressure, total precipitation, humidity, visibility, and wind speed. They decided on personality by applying the Big Five questionnaire. The stress reference was estimated from a self-perceived stress level questionnaire performed at the end of the day.

The speech data may also be used to detect human stress levels. Kurniawan et al. [67] developed a combined method using both Galvanic Skin Response (GSR) signals and human speech. They created a benchmark data collection of 10 people recorded in a lab environment. K-means, GMM (Gaussian Mixture Model), SVM, and decision tree are used. Both sets of functions have been used individually and in a combined way. The SVM classifier works the best for every stress test.

Giannakakis et al. [75] developed a method for the determination of stress and anxiety from facial expressions. Face gestures, mouth activity, head-related gestures, and heart rate were measured from the camera. They used PPG-based sensors from the facial cues to estimate heart activity. They developed a laboratory experiment focusing on social exposure (foreign speaker), recall of emotions, stressful multimedia stages. KNN, SVM, Naive Bayes, and AdaBoost classifiers achieved 91% accuracy with three-class classification, i.e., neutral, relaxed, stressed.

Magnolia et al. [70] presented a stress detection method for drivers. They used the automobile driver Database (DRIVE DB) with ECG signals obtained from 16 separate persons traveling around Boston, Massachusetts. Data extracted time domain, frequency domain, nonlinear and time-frequency domain (such as wavelet and STFT) features. As classifiers, they used SVM-RBF, KNN, and RBF. They achieved 83% classification accuracy when discriminating between stress and no-stress conditions. They plan to extend their work into distinguishing more levels of stress.

Stress detection research has taken a step toward more unrestricted real life since the ultimate goal is to detect individual stress levels in their daily routines. However, researchers should come up with solutions to new problems that arise after taking a step outside the lab. Stress level identification of the performance of real-life schemes is lower than restricted environments and laboratory environments [16] (2016), ref. [45] (2015), ref. [42] (2020) and [38] (2018). The listed works have classification accuracies around 70% and 80%. The key factors may be the smaller storage of self-reported results, the unclear background of participants, and uncontrolled movement of subjects.

2.3.1 Comparison table

A comparison of the different techniques of the literature survey. List of different datasets, sensors, types of emotion detected is the main topic.

Table 3: Comparative Study of datasets and sensors used to detect/recognize the emotions

Papers	Summary	Inputs	Emotion Recognized/ Detected	Sensors	Datasets
Multilevel mental stress detection using ultra short pulse rate variability series, Elsevier, Muhammad Zubair, 2019 [44]	Experiment using mental arithmetic task for stress induction	PPG questionnaires	Stress or Normal	Pulse Sensor Amped	Self-Created (14 students Age:25-30)
Stress measurement from wearable photoplethysmography sensor using heart rate variability data, IEEE, P Madhan Mohan, 2016 [79]	Stress causes the development of an HRV signal and calculates the LF/HF ratio, which is a calculation of a human's stress		High level stress Low level stress	Shimmer3 GSR	DEAP
Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers, IEEE Trans., Stefano Betti, 2018 [40]	use of physiological wearable sensors and salivary cortisol analysis, which is considered a reliable biological marker of stress.	HRV, EDA, EEG	Stress or normal	Shimmer3 GSR	Self-Created (15 healthy participants, mean age: 40.8 ± 9.5 years)
Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers, Elsevier, Lan-lan Chen, 2017 [80]	Continuous stress examination was done during the entire driving experiment, due to a high relation with the true road situation, especially at the shifting variations of traffic conditions.			Own circuit	SUS
Stress detection using wearable physiological and sociometric sensor, IEEE, Oscar Martinez Mozos,2020 [48]	stress of people in a social situation by combining two sensor systems that capture physiological and social responses	GSR PPG questionnaires	Stress or normal	E4 Wristband	Self-Created (18-participant Age: 18-39)
Validating Physiological Stress Detection Model Using Cortisol as Stress Bio Marker, IEEE, Rajdeep Kumar Nath, 2020 [20]	Presented the validation of a generalized physiological stress detection model using as the bio marker for stress. It identify stressed			Shimmer3 GSR	Self Created (13 participants)

	states from non-stressed states.				
Stress detection in working people, Elsevier, S. Sriram prakash,2017 [16]	Development of intelligent stress detection algorithm and SVM, KNN are investigated to classify these extracted feature set.			Kinect3D	SWELL
Discriminating affective state intensity using physiological responses, Springer, Francesca Gasparini, 2020 [15]	sensitive measures for emotional arousal adopting a Sound 6D technology for audio reproduction.		Relaxation State, Stressful State	Shimmer3 GSR	DEAP
A machine learning model for emotion recognition from physiological signals, Elsevier, J.A. Domínguez Jiménez, 2020 [1]	Proposed two-dimensional model of emotions for effective emotion recognition	GSR PPG	Happiness, Sadness, Natural	Grove GSR	DEAP
Stress Sensor Prototype: Determining the Stress Level in using a Computer through Validated Self-Made Heart Rate (HR) and Galvanic Skin Response (GSR) Sensors and Fuzzy Logic Algorithm, IEEE, Anthonette Cantara, 2016 [81]	Generate a stress sensor prototype to evaluate stress level with a software using Validated Self-Made HR and GSR Sensors and a Fuzzy Logic Algorithm.		Stress, Normal	Pulse oximeters	WESAD
Towards Real Time Automatic Stress Detection for Office Workplaces, Springer, Franci Suni Lopez, 2019 [82]	The affect predictive method's stress detection mechanism is automated to detect stress in individuals in real-time.	EDA Questionnaires	Stress or Not stress	E4-wristband	Self Created (12-participant, age: 21-32)
Emotion recognition from galvanic skin response signal based on deep hybrid neural networks, ACM, Imam Yogie Susanto, 2020 [2]	A deep hybrid neural network-based emotion detection framework in which 1D CNN and Residual Bidirectional GRU are used for time	GSR	Anger, Disgust, Fear, Happy, Sad, Surprise	Raspberry Pi with robot	PMEMO

	series data evaluation.				
Smart wearable band for stress detection, IEEE, Muhammad Zubair, 2015 [83]	Help people in properly understanding their stress levels and still providing accurate evidence to physicians for much better care.		Stress or normal	shimmer	Self-crated (12 participant s Age: 23-56)
Automatic emotion detection model from facial expression IEEE, Debishree Dagar, 2016 [84]	To detect the emotion, facial features identified using principal component analysis and a clustering of various facial expressions with respective emotions are used.	Facial Images	anger, happy, sad, disgust, surprise	-	JAFFE (213 sample images)
Using Kinect for real-time emotion recognition via facial expressions, Springer, Qi-rong Mao, 2015 [85]	Approach to real-time emotion recognition based on 2D and 3D facial expression elements recorded by Kinect sensors		anger, disgust, fear, happiness, sadness, and surprise	Kinect sensors	RGB-D (1581 images)

2.3.2 Devices

Table 4: commonly available devices for real-time stress detection

Device	Signals Detected	Movable
E4 wristband	PPG, GSR, HR, ACC, ST	Yes
Vivo smart	HR, HRV, ACC	Yes
Bio Harness 3.0	HR, HRV, GSR, ACC, ST	Yes
Shimmer 3+ GSR	GSR, PPG	No
Mobita Wearable	ECG, EEG, EGG, EMG, and EOG	No

2.3.3 Dataset

Table 5: commonly available dataset

Dataset	No. of subjects	Physiological and behavioral modalities
DEAP	22	EEG, GSR
SWELL-KW	25	Physiological signals, computer logging, facial expressions, body postures
WESAD	15	ECG, EDA, EMG, BVP, body temperature, and acceleration
Drive dB	9	EMG, GSR, ECG, HR, and respiration
SUS	35	Speech
Distracted Driving Dataset	68	facial video, operational theater video, EDA (palm & perinasal), HR, RESP, driving performance

CHAPTER 3 PROPOSED WORK

3.1 Motivation

Health care is a crucial domain nowadays for research. Every disease is indirectly related to the patient's emotions. Emotion means intentional reactions or experiences.
Stress is one of the many causes that impact individual health in a variety of ways.Detection of stress or depression in time can help people to become more aware of their feelings, physical state of mind and to develop a more positive attitude towards life and healthy habits.

3.2 Problem Statement

An approach to detect stress in working professionals using a combination of facial expression and physiological signals galvanic skin response (GSR) and heart rate variability (HRV). The main objective is to build a combination model which is capable to analyze the stressed or normal state.

3.3 Challenges

- **Behavioral Data:** With the help of facial expression and speech recognition we don't get utmost accuracy in all the cases [6][9].
- **Limitations of using questionnaires for stress:** Not all individuals may be capable of reporting their mental states accurately [41][44][48][49].
- **Level of stress:** One of the major issues is to detect the level of stress. And the different levels of data can be acquired with wearable devices for the recognition of stress from physiological signals [4][7].
- **Real-time stress detection:** Real-time detection of stress or depression is useful in a human who suffers from environmental effects [50].
- **Detect emotion:** In physiological signal, only basic motion is detected so far, other emotions can also be recognized with the help of physiological signals [1].

3.4 Proposed work

As observed from the psychological point of view, self-reports relate more to the currently experienced emotions. But a common problem with questionnaires may be the image of participants to respond truthfully without barriers of culture, society, or other such factors. Taking into consideration these two factors we tend to replace the psychological part with facial expression. Facial images, GSR, HRV signal observations from the dataset are considered as input for the proposed stress detection model.

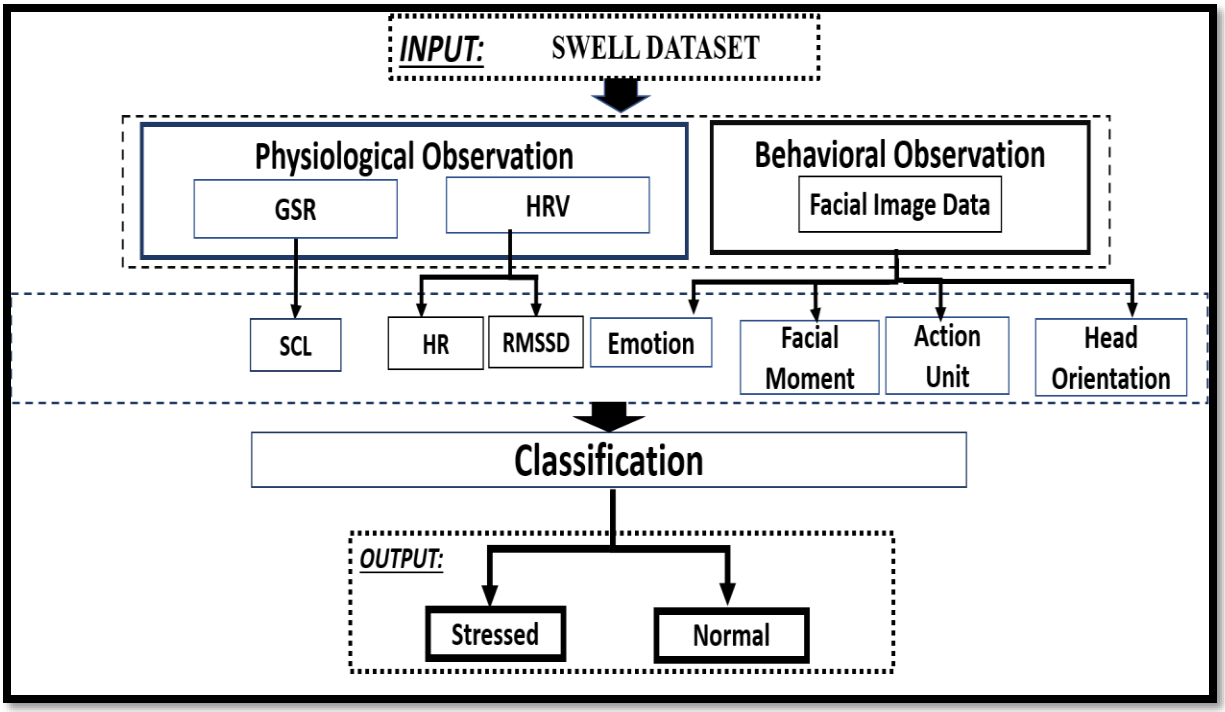


Figure 7: Human Stress Detection Model

- ## Data preprocessing:

Data preprocessing is the process of preparing data so it can be used by a machine learning model for further processing.

1. Data cleaning:

Data cleaning is the process of identifying and correcting incorrect information from a record collection, table, or database. It includes identifying incomplete or incorrect sections of the data and then replacing, updating, or removing the dirty data. The data can have many missing parts. To handle this part, data cleaning is done by deleting those records.

2. Type conversion:

The basic principle behind type conversion is to allow a variable of one type compatible with a variable of another type such that a procedure can be performed. So, the object type database is converted to float for further data processing operation.

3. Data visualization:

Data visualization helps clarify what the data represents by providing visual meaning in the form of charts or graphs. This validates the data for the visual system, making it much simpler to analyze and interpret, patterns, and outliers of large data sets.

For data visualization, we identify different ranges for GSR, HRV, and HR for stress or normal person through the graph.

- **Feature Selection:**

After the step of data pre-processing, the next step is to select an important feature from the facial image data. For feature selection having three methods filter-based, wrapper-based, and embedded feature selection method.

For feature selection we applied the ANOVA feature selection, correlation coefficient, univariant feature selection, decision tree, LASSO regression, minimum squared error model algorithm was analyzed and compare. Out of them, we finalize the embedded feature selection technique lasso regression model.

- **Classification:**

After the feature selection step, the next step is to classify it as stressed or normal. Classification is a supervised learning methodology in which a software program learns from inputs and then applies what it has learned to classify new observations.

For classification, we have applied the SVM, Random Forest, K-Nearest neighbor, Naive Bayes, and Binary tree were analyzed and compared. Out of them, the Random forest was finalized.

3.5 Tools & Technology

After describing the purpose flow work, an important task is to do the study tools and technology by our proposed work.

3.5.1 Python Tools

Python is an object-oriented, interactive, interpreted, and high-level scripting language. Python is to be highly readable. It uses English other language keywords frequently and it has fewer syntactical constructions than other scripting languages.

Python has other features include as follows:

- Functional and structured programming approaches are supported by the Python programming language.
- The Python language can be used as a scripting language.
- It supports garbage collection also.
- The python language can be easily integrated with C, C++, and Java

Tools: Following are the tools identified

- **Pandas**: A Python data processing library designed to enhance analytics and modeling.

- **Matplotlib**: For Quality Visualization
- **Jupyter Notebook**: collaborative work capabilities
- **NumPy**: Scientific computing with python
- **Scikit-learn**: machine learning framework

3.5.2 Database

SWELL Dataset [52]:

SWELL dataset contains data for 25 participants (3 hours each). It's collect data in 3 different working conditions time pressure, interruptions, and normal. Time pressure and interruptions state were used as stressors for an office work scenario. The initial results obtained on this dataset demonstrated the ability to distinguish stressful from normal work conditions. Its collecting data information about ECG, GSR, computer logging, facial expressions, body postures, and questionaries from the 3 different condition. We use this data to get an aggregation of facial expressions, physiological signal heart rates, and skin conductance levels (SCL).

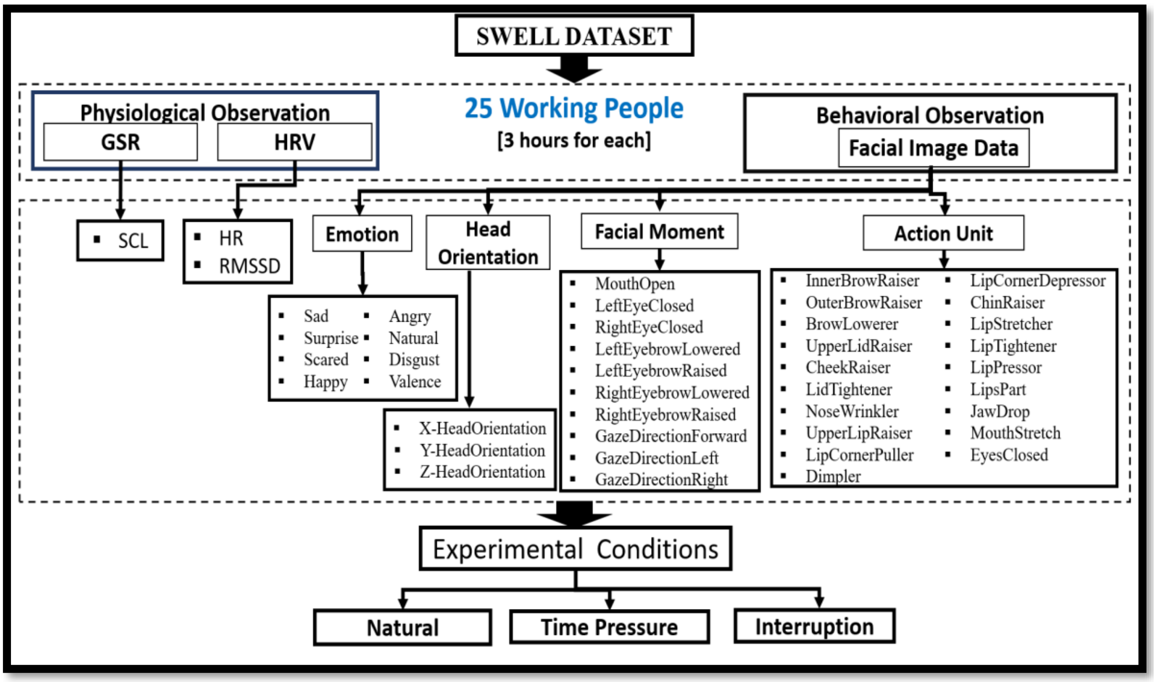


Figure 8: Dataset description

CHAPTER 4 IMPLEMENTATION

4.1 Data Preprocessing

1. Data cleaning:

The data can have many irrelevant and missing parts. To handle this part, data cleaning is done.

Table 6: Data cleaning

BEFORE CLEANING SHAPE OF DATA	AFTER CLEANING SHAPE OF DATA
3138, 49	2502, 49

2. Type conversion:

Our dataset having data value in object type so we converted it into a float for further processing data.

3. Data visualization:

A clear understanding of what the information signifies by providing visual context in the form of charts or graphs. So, we first show a number of stress or normal person data using a graph.

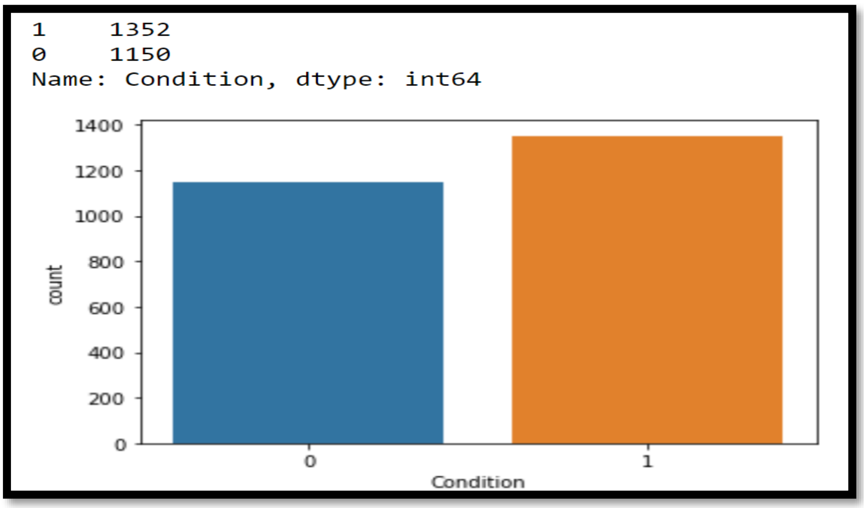


Figure 9: Stressed or normal person

Next, we try to identify the range of GSR, HRV, HR for stressed or normal state by using binning and graph method to show the approx range.

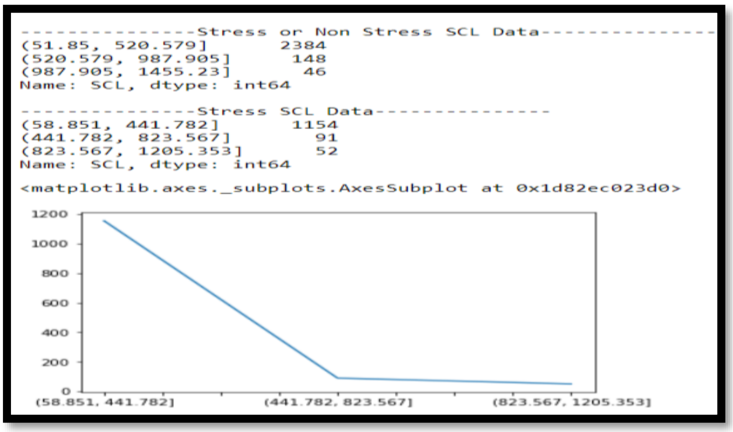


Figure 10: GSR Range

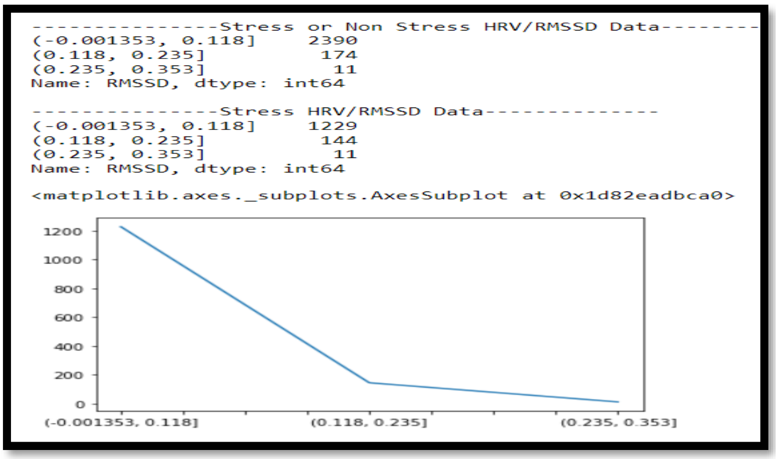


Figure 11: HRV/RMSSD

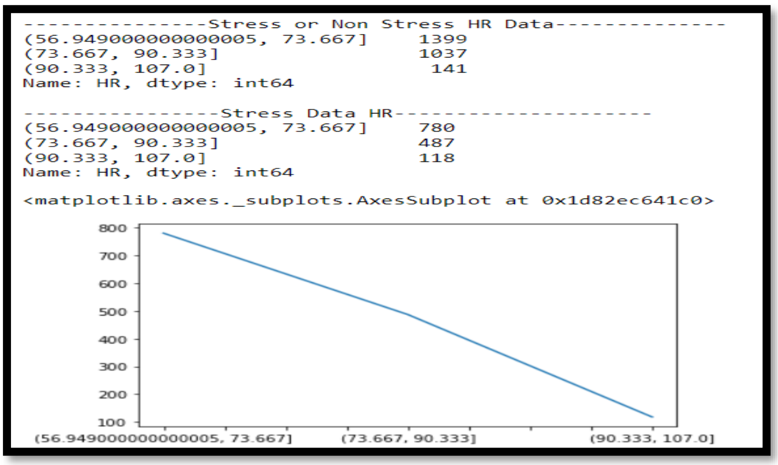


Figure 12: HR

4.2 Feature selection

- **Selecting features using Lasso regression Model**

- **To See the Selected set of features**

Facial expression having a total of 41 features so after applying the lasso regression model get 22 selected feature and 19 features are dropped.

```
In [6]: ##To See Selected set of features
        selected_feat = X_train.columns[(sel_.get_support())]
        print('total features: {}'.format((X_train.shape[1])))
        print('selected features: {}'.format(len(selected_feat)))
        print('features with coefficients rank to zero: {}'.format(
              np.sum(sel_.estimator_.coef_ == 0)))

        total features: 41
        selected features: 22
        features with coefficients rank to zero: 19
```

Figure 13: Feature selection using lasso regression

- **Identifying the selected features index**

```
Out[9]: Int64Index([ 1,  2,  9, 10, 11, 12, 13, 15, 17, 18, 19, 23, 25, 27, 31, 32, 33,
                     35, 36, 38, 39, 40],
                    dtype='int64')
```

Figure 14: Selected feature index

4.3 Pre-modelling task

- **Splitting the dataset**

Split our data into training and testing with an 80/20 ratio.

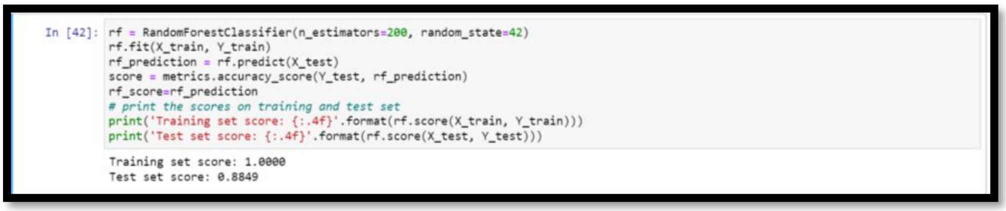
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.20, random_state = 42)
print("X_train",len(X_train))
print("X_test",len(X_test))
print("Y_train",len(Y_train))
print("Y_test",len(Y_test))

X_train 1909
X_test 478
Y_train 1909
Y_test 478
```

Figure 15: Splitting data

4.4 Classification model:

We finalize the random forest model to classify the stressed or normal state of the person. so we implemented a random forest classification model to train or test our data.



```
In [42]: rf = RandomForestClassifier(n_estimators=200, random_state=42)
         rf.fit(X_train, Y_train)
         rf_prediction = rf.predict(X_test)
         score = metrics.accuracy_score(Y_test, rf_prediction)
         rf_score=rf_prediction
         # print the scores on training and test set
         print('Training set score: {:.4f}'.format(rf.score(X_train, Y_train)))
         print('Test set score: {:.4f}'.format(rf.score(X_test, Y_test)))

         Training set score: 1.0000
         Test set score: 0.8849
```

Figure 16: Classification model

4.5 Model evaluation

- **K-Fold validation:** Cross-validation is a resampling used to evaluate our model on a limited data sample. It's having a single parameter called k that refers to the number of groups that a given data sample is to be split into. So, we try on different k values to evaluate our model.
  .

Table 7: k- Fold validation

Cross fold	RANDOM FOREST
K=5	87.22%
K=10	87.43%
K=20	87.95%
K=50	87.96%

- **Confusion matrix:** Technique for summarizing the performance of a classification algorithm. Confusion matrices are useful because they provide directly calculated values like True Positives, False Positives, True Negatives, and False Negatives for our model.

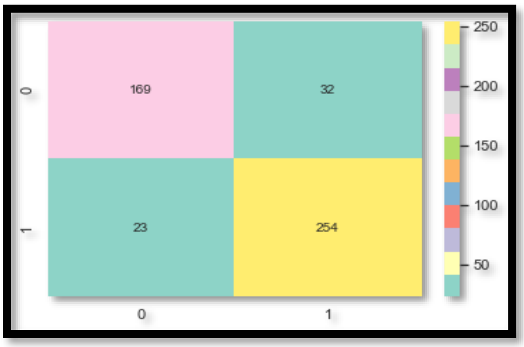


Figure 17: Confusion matrix

- **Accuracy score:** Number of correct predictions from the total number of predictions. It provides an 88.49% accuracy score in our case.

Accuracy_Score

```
In [24]: from sklearn.metrics import accuracy_score
         print(accuracy_score(Y_test, rf_prediction))

         0.8849372384937239
```

Figure 18: Accuracy score

- **Precision:** Number of positive class predictions that belong to the positive class. So, for our model 88.81% accuracy score.

Precision

```
In [25]: rf_pre=precision_score(Y_test, rf_prediction)
         rf_pre

Out[25]: 0.8881118881118881
```

Figure 19: Precision

- **Recall:** The number of positive class predictions made out of all positive examples in the dataset. For our model recall accuracy value is 91.69%.

Recall

```
In [27]: rf_recall=recall_score(Y_test, rf_prediction)
         rf_recall

Out[27]: 0.9169675090252708
```

Figure 20: Recall

- **Classification report:** A Classification report is to measure the quality of predictions from our classification model. How many predictions are True and how many are False in our case.

Classification Report

```
In [28]: from sklearn.metrics import classification_report
         print(classification_report(Y_test, rf_prediction))

                      precision    recall  f1-score   support

                 0.0       0.88      0.84      0.86       201
                 1.0       0.89      0.92      0.90       277

            accuracy                           0.88       478
           macro avg       0.88      0.88      0.88       478
        weighted avg       0.88      0.88      0.88       478
```

Figure 21: Classification Report

CHAPTER 5 CLASSIFICATION ANALYSIS

We applied a number of classifiers such as SVM, RF, K-Nearest neighbor, Naïve Bayes, and Binary tree and we compared. Out of them RF we finalized. RF has produced very good results comparing to other classifiers.

5.1 Classification on a single modality

First, we applied classification on single modality HRV, GSR, and facial so from that random forest give the highest accuracy so we finalize random forest classification model for further classification.

Table 8: Classification for single modality

	SVM	DECISION TREE	RANDOM FOREST	KNN
HRV	60.00%	67.37%	**77.86%**	74.36%
GSR	58.15%	66.22%	**68.20%**	67.22%
FACIAL	73.26%	65.14%	**77.66%**	73.27%

So, the random forest produces 77.86% accuracy for HRV, 68.20% accuracy for GSR, and 77.66% for facial expression.

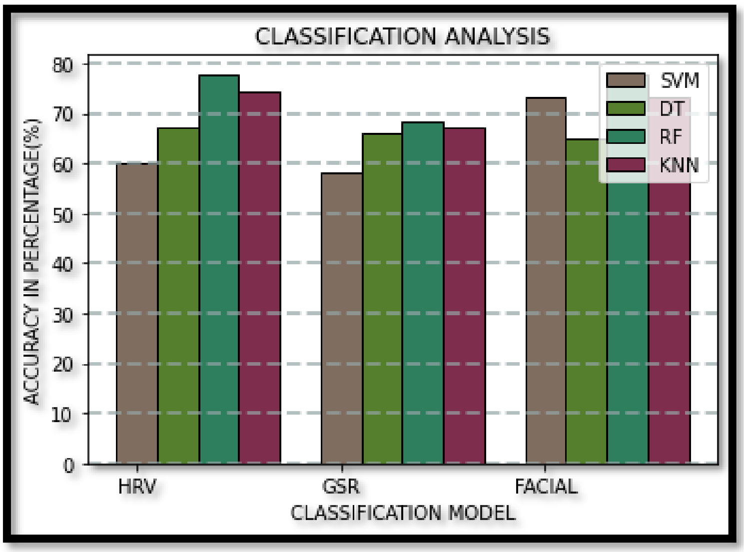


Figure 22: Graphical representation for single modality classification

5.2 Classification on multiple modalities

We applying an RF classifier with 200 trees and split points chosen from a random selection and the unlimited max depth of a single decision tree.

Now for classification on different combinations of all modalities like GSR and HRV, HRV and Facial, GSR and Facial. And then finally for all combinations of physiological signal (HRV and GSR) and facial expression with the help of a random forest classifier.

Table 9: classification model for different combination modality

	Random Forest Classification
HRV+GSR	82.21%
GSR+FACIAL	84.59%
HRV+FACIAL	85.77%
HRV+GSR+FACIAL	**88.49%**

So, for that classification result HRV and GSR accuracy is 82.21%, GSR and Facial accuracy is 84.59%, HRV and facial accuracy is 85.77, and finally HRV, GSR, and Facial expression fusion getting highest accuracy score of 88.49%.

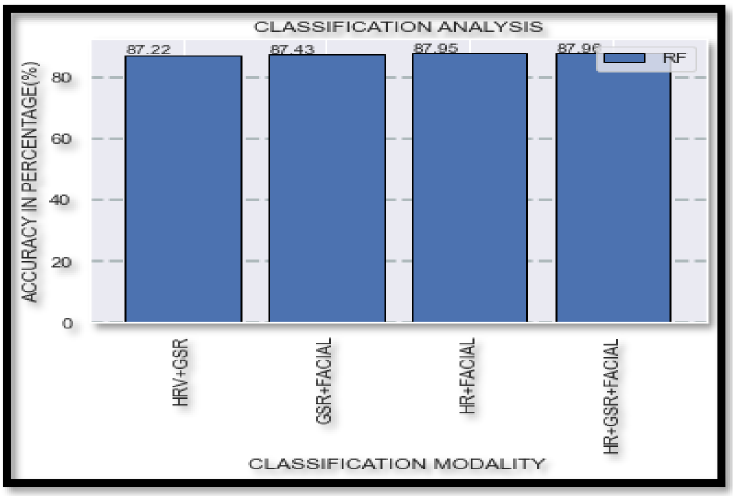


Figure 23: graphical representation for different combination modality

5.3 Cross model validation

Cross-validation is a resampling procedure used to evaluate our proposed models on a limited data sample. It is having one parameter called k that refers to the number of group fold that a given data sample is to be split into. As such, the process is often called k-fold cross-validation. When a particular value for k is chosen, it may be used in place of k in the reference to the proposed classification model, such as k=10 becoming 10-fold cross-validation.

RF has produced a very good result for our system compared to others, the result of 20-fold cross-validation applied on 478 data is shown in the Table.

Table 10: Cross fold validation accuracy

Cross fold	Random Forest Classification
K=5	87.22%
K=10	87.43%
K=20	87.95%
K=50	87.96%

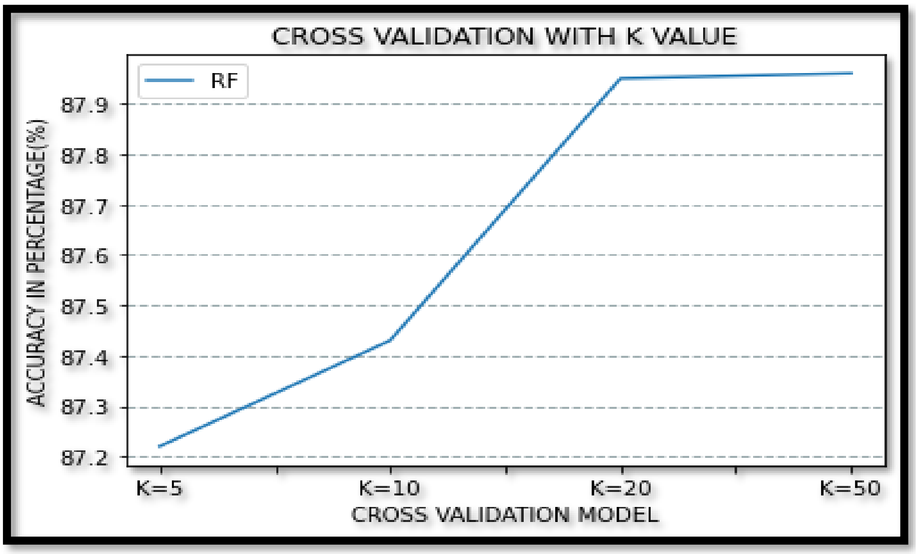


Figure 24: Graphical representation

Graphical representation of the overall accuracy of all the classifiers is described in Table 5.2 where RF has a maximum overall accuracy of 87.95%.

5.4 Overall classification analysis

A confusion matrix is a table often used to represent how well a classification model works on a variety of test data for which the actual value is calculated.

So, we generate a confusion matrix for our proposed modality to check correctly and miss classified data. The below table describes the confusion matrix.

Table 11: Overall classification confusion matrix

		Predicted	
		Normal	**Stressed**
Actual	**Normal**	169	32
	Stressed	23	254

From the confusion Metrix we get four Outcomes:
• True positives (TP): In the result, data labeled as positive and that data are actually positive
• False positives (FP): In the result, data labeled as positive but that data are actually negative
• True negatives (TN): In the result, data labeled as negative and that data are actually negative
• False negatives (FN): In the result, data points labeled as negative but that data are actually positive

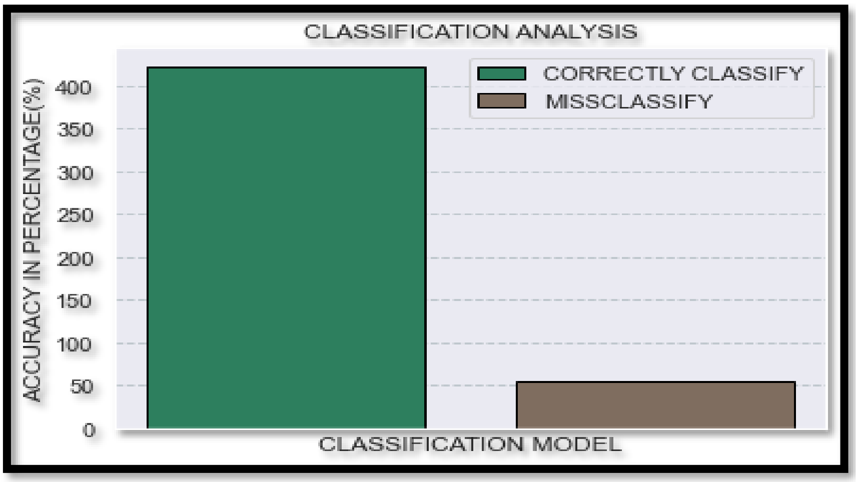


Figure 25: graphical representation of correctly and misclassified

Graphical representation of overall correctly classified and misclassified data. So, from 478 data 423 is correctly classified and 55 is miss classified.

5.5 Recall, Precision, and F- measure

Precision: Computes the number of positive class predictions that actually belong to the positive class.

Recall: Computes the number of positive class predictions builts out of all positive examples in the dataset.

F-Measure: Computes a single score that balances both precision and recall in one number.

From the confusion matrix, we calculated the True Positive Rate (TPR) as the recall and the False Positive Rate (FPR) as the precision. The equations:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positives + False Negatives}}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positives + False Positives}}$$

$$\text{F-Measure} = \frac{(2 * \text{Precision} * \text{Recall})}{(\text{Precision + Recall})}$$

So, from the confusion matrix, we finding recall and precision f measure respective values.

Table 12: Overall Accuracy

	Accuracy	Recall	Precision	F- measure
Random Forest Classifier	**88.49%**	**91.70%**	**88.81%**	**90.23%**

RF classifier is giving an overall accuracy of 88.49% and proved to be better among all of our model.

CHAPTER 6 RESULT ANALYSIS

In [16], present work on stress detection on working people take physiological signal (HRV, GSR) and questionaries as input and use SWELL dataset to recognize stressed or normal state by achieving 72.82% accuracy. Instead of taking questionary, we consider the facial expression

Our proposed model considers physiological signal (GSR, HRV) and facial expression as input and uses the SWELL dataset to recognize stressed or normal state by achieving 88.49%. so, by neglecting the psychological part we improve accuracy from 72.82% to 88.49%.

Table 13: Result Analysis

Paper	Input	Dataset	Emotion Recognized/ Detected	Accuracy
Stress Detection in Working People [16]	Physiological signal (GSR, HRV), Questionnaires	SWELL	Stressed, Normal	72.82%
PROPOSED WORK	Physiological signal (GSR, HRV), Facial expression			**88.49%**

CONCLUSION

Stress is the body's reaction to any modification that happens when a human being is going through any typical changes. During stressed state body responds physically, mentally, and emotionally. Due to stress, that is detriment happen the most significant damage is a hampered quality of life individual’s personal, professional and social life. The literature survey observed that physiological signals like GSR and HRV cannot be controlled by human beings; therefore, they can be useful in several applications such as Depression detection, Personal life coach, lie detector, healthcare, gaming, and sports, etc. However, one of the traditional methods to detect stress is based on physiological signals including self-report questionnaires, but one of the common problems which we can witness from the psychological point of view is that participants cannot respond truthfully owing to cultural barriers, community, and many more.

We have identified the issues/challenges in the detection of physiological, behavioral, and psychological stress signals. The proposed an approach to detect stress in working professionals based on the combination of facial expression and physiological signal. Our model tested in different fusion modality scenarios and is proven to be working well in combination with facial expression and physiological signals. Those provided 88.49% accurate results with the help of random forest models.

The model can be extended for stress detection on the real-time scenario and level of stress in the future.

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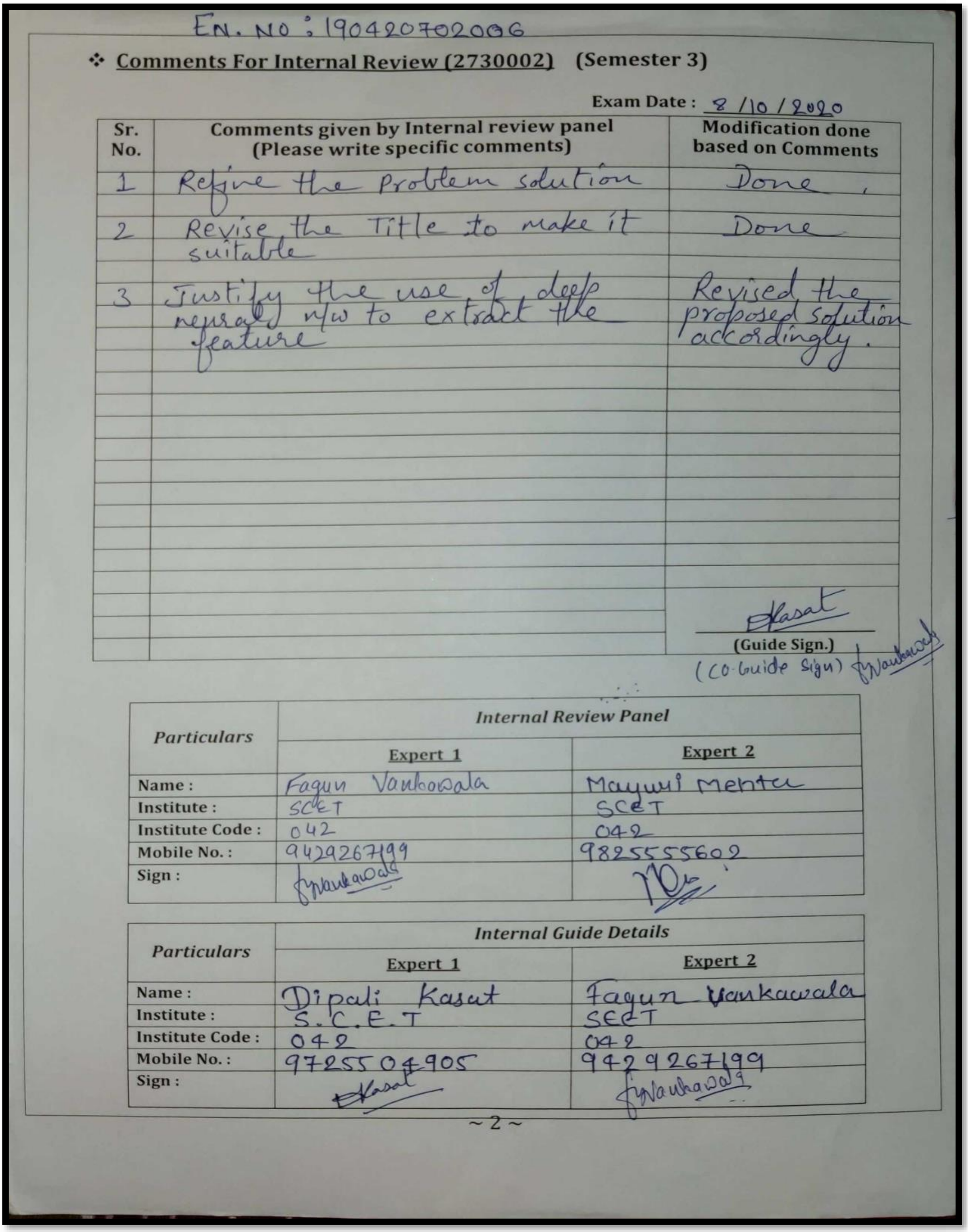
APPENDIX A

List of acronyms

GSR	Galvanic Skin Response
SCL	Skin Conductance Level
SCR	Skin Conductance Response
EDA	Electrodermal Activity
HR	Heart Rate
HRV	Heart Rate Variability
ECG	Electro Cardiogram
EEG	Electroencephalogram
EMG	Electromyogram
ST	Skin Temperature
SNS	Sympathetic Nervous System
ANS	Autonomic Nervous System
PD	Pupil Diameter
TI	Thermal Imaging
fMRI	functional Magnetic Resonance Imaging
PPG	Photoplethysmography
MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning
CART	Decision Tree
SVM	Support Vector Machine
RF	Random Forest
ANN	Artificial Neural Network
NB	Naive Bayes
LR	Logistic Regression
KNN	K- Nearest Neighbours

APPENDIX B

Review Card – IR-I



En. No : 190420702006

❖ Comments For Internal Review (2730002) (Semester 3)

Exam Date : 8/10/2020

Sr. No.	Comments given by Internal review panel (Please write specific comments)	Modification done based on Comments
1	Refine the Problem solution	Done.
2	Revise the Title to make it suitable	Done
3	Justify the use of deep neural n/w to extract the feature	Revised the proposed solution accordingly.

(Guide Sign.)

(Co-Guide Sign)

Particulars	Internal Review Panel	
	Expert 1	Expert 2
Name :	Fagun Vankawala	Mayuri Mehta
Institute :	SCET	SCET
Institute Code :	042	042
Mobile No. :	9429267199	9825555602
Sign :		

Particulars	Internal Guide Details	
	Expert 1	Expert 2
Name :	Dipali Kasat	Fagun Vankawala
Institute :	S.C.E.T	SCET
Institute Code :	042	042
Mobile No. :	9725504905	9429267199
Sign :		

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Review Card – DP-I

GUJARAT TECHNOLOGICAL UNIVERSITY
DISSERTATION EXAM
ME SEM:3 REVIEW SHEET(WINTER 2020)

Enrollment No:	190420702006	**Subject Code:**	3730003
Student Name:	PATEL DRASHTI SHAILESHKUMAR	**College Code:**	042
Date of Exam :	1/21/2021	**Hall No:**	08
College Name :	SARVAJANIK COLLEGE OF ENGINEERING & TECHNOLOGY, SURAT		
Title Name :	AN APPROACH TO DETECT STRESS USING COMBINATION OF PHYSIOLOGICAL SIGNALS AND FACIAL EXPRESSION		

OBSERVATION

1	Appropriateness of title with proposal(Yes/No)	yes
2	Weather the selected theme is appropriate according to the title ? (Yes/No)	yes
3	Justify rational of proposed research.(Yes/No)	yes
4	Clarify of objectives.(Yes/No)	yes

Comments given by Examiner
(Please write specific comments)
i)Main reasons for approving the work.
ii)Main reasons work is not approved.

• Feature extraction methods should be more clear. • Feature fusion methods should be explored in more detail.

Note *Above suggestion/modification/comments must be fulfil/accommodate by student in ir-2*	
Approved / Not Approved	Approved
Expert 1	**Expert 2**
Name : Prof. Safvan Vohra	Name : Prof. Kamal K. Sutaria
Mobile : 9033440930	Mobile : 9428232881
Mail Id:savahora@gecmodasa.org	Mail Id:kamal.sutaria@gmail.com
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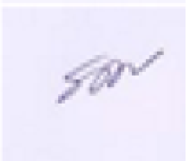	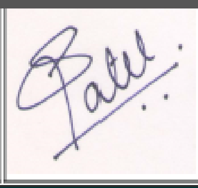

Review Card – IR-II

APPENDIX C

Plagiarism Report