A project report on

IOT BASED FRAMEWORK DESIGN FOR AUTOMATED HUMAN EMOTION RECOGNITION

submitted in partial fulfillment of the requirements for the degree of

B. Tech
In
Electronics and Telecommunication Engineering

By

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CERTIFICATE

This is to certify that the project report entitled **"IOT BASED FRAMEWORK DESIGN FOR AUTOMATED HUMAN EMTION RECOGNITION"** submitted by

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in partial fulfilment of the requirements for the award of the **Degree of Bachelor of Technology** in **Electronics and Telecommunication Engineering** is a bonafide record of the work carried out under my (our) guidance and supervision at School of Electronics Engineering, KIIT (Deemed to be University).

Signature of Supervisor

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ABSTRACT

The most important aspect of a human being is their mental health yet it is also the biggest difficulty of our society to maintain it in such a fast pacing world which mostly leads to the state of mental stress, sadness, and anxiety, also they lead to be the root cause of several severe health problems such as high blood pressure, heart attacks, and even abrupt fatalities as well as self-destruction. Normally, counseling, questioning and close observation of a person can identify all of these issues. But, here in our project we will be concentrating on physical changes such as the capacitance of a stressed out person's sweat, heart rate of a depressed person, or the facial expressions of a person.While the existing works on real time emotion recognition mostly rely on facial data, there are a few works dealing with real time emotion recognition based on physiological data using pervasive devices. Our framework integrates most of the works which incorporates sensors which are cost efficient and simple in arrangement. The approach is implemented in an end-to-end soft real time emotion recognition system using smartphone and smartwatch devices, later sending the alert to medical professional and family.Based on the concept of IoMT and with the help of Machine language, we propose this model.This project not only just recognizes person's emotions but also with the data base maintained, it can predict if a person can be prone to depression in the long term.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Emotions play a critical role in human behavior, communication, and decision-making. By developing a system that can accurately detect emotions, we can gain a better understanding of the human emotional experience and how it affects various aspects of our lives.With the help of an emotion detection system, personalized experiences can be provided to the user based on their emotional state. For example, a music streaming service can play songs that match the user's mood or a virtual assistant can provide responses that are tailored to the user's emotional state.Emotion detection systems can help detect and monitor mental health conditions such as depression and anxiety. This can lead to early diagnosis and intervention, thereby improving treatment outcomes. Emotion detection systems can be used in educational and entertainment settings to personalize learning experiences or entertainment content based on the user's emotional state. This can lead to more engaging and effective learning or entertainment experiences.

1.2 Background Studies /Literature Survey

The recent models have the facility of detecting the mental health of an individual. We are going to detect different emotions by relying on different parameters like heart rate, and perspiration level and will keep all the data in the database of the patient. Further, we can classify these data from a database using machine learning to judge different physical fitness levels of the person. Simultaneously we will be using emotion detection algorithms for further classifications such as sad, happy, fearful, and angry. This will ease the doctor's work of following the patient's mental history.

1.3 Objectives

The objective of creating an emotion recognition system using ECG and GSR sensors is to create a precise and dependable system that can identify a person's emotional condition in real-time. The system should be able to recognise a variety of feelings, including joy, sorrow, anger, fear, and astonishment, and either give the user input or integrate with other systems to set off the proper reactions. While ensuring that the information gathered is trustworthy and can be used to create precise and applicable mood detection algorithms, the system should also be able to take into consideration individual differences, contextual variables, and private concerns. The ultimate goal is to create a system that can aid professionals in helping people better comprehend and control their emotions, as well as assist professionals in various fields such as mental health, education, and entertainment.

1.4 Literature Review

A. STRESS DETECTION USING WEARABLE SENSORS

In contemporary medical research and associated applications, sensors are crucial. They are frequently employed to gauge the degrees of various illnesses and diagnose them. In this subsection, devices that incorporate one or more sensors, such as B. HR, ST, GSR, RR, ACC, and BP sensors, are referred to as wearable sensors, and the relevant research is briefly discussed. If left untreated, stress is commonly regarded as one of the major contributors contributing to several serious health issues [12]. J. Ogorevc et al. [11] evaluated participants' physical and mental stress levels to look at how mental stress affected many psychophysiological indicators. When a person was under stress, their HR, GSR, and BP levels all went up. Psychological stress tests revealed a less significant impact.

B. STRESS DETECTION USING ECG

The electrical venture of the heart is measured by an Electrocardiogram. As a result, ECG data are typically used to determine HRV characteristics that are then separated into time and frequency domains for additional research [13], [14]. Time-domain techniques are more reliable than other techniques for detecting stress, according to earlier research [17]. As a result of its strong connection to the autonomic nervous system, HRV does a crucial role in the recognition of stress. Different combinations of HRV features can be utilized to differentiate between resting, physical, and psychological states since HRV is sensitive to changes in the mental or physical condition [15]. Additionally, her HRV measures associated *with the parasympathetic* activity are substantially connected with reactivity and recovery from psychological and physical stress [16].

Overview of emotion detection using wearable sensor studies in chronological order with their details.

[24] (2020), HR, Skin Conductance, ACC, ST, The WEKA toolkit was mainly used for the classification algorithm. The maximum classification accuracy for the three classes was 94.52% and the minimum accuracy was 91%. They created a session-based stress classifier that can classify stress levels with a maximum accuracy of 94.44 for HR signals and 100% for EDA signals.

[23] (2019), ST, GSR, HR, and Fuzzy logic were used to process the data from all the three sensors which are in use. This system can work with 85% accuracy.

[22] (2018), HR, Skin conductance, ST, A rule-based fuzzy logic algorithm was proposed to be used in stress level classification. Moreover, we compared the accuracy using decision trees, KNN, and naive Bayes algorithms.

[21] (2017), Numerous machine learning algorithms, including J48, naive Bayes, KNN, SVM, bagging, boosting, RF, and ensemble selection, have been tested with LOSO evaluation, including HR, EDA, BVP, ST, ACC, and many classifiers.

[20] (2016), HR, GSR, A fuzzy logic algorithm was developed and used by using the MATLAB's fuzzy logic toolbox. Data were processed with the help of adaptive neuro-fuzzy interface system, 'AVFIS'. It also supports sensing data from serial ports and uses the C# programming language used by Arduino boards.

[19] (2015), Body Temperature, The logistic regression was used to analyse the data. The accuracy of the training was 100% with regularisation and 91.66% without it.

[15] (2011), GSR, HR, Both human and automatic implementation of the suggested approach utilised a fuzzy decision algorithm.

[26] (2012), The logistic regression approach is used to discover the optimal collection of features for EDA, EMG, Respiration, HR, and Forward feature selection.

There can be many stressful events that may occur while driving like maintaining the speed limit, heavy traffic, and unsafe weather conditions, etc. Driving in such conditions may lead to violations of rules and possibly car accidents. Hence the identification of the stress level of a driver while driving is an important issue for safety, security, and health purpose. In such cases, wearable devices can be helpful by alerting the driver about the elevated stress levels and advising them to take necessary precautionary measures.

A dataset was available on the PHYSIONET website (http://www.physionet.org/) which was created by Jennifer Healey and Rosalind Picard , wherein they used four sensors namely electrocardiogram (EKG), EMG, skin conductivity, and respiration (through chest cavity expansion) for real-time physiological data collection during real-world driving situations under normal conditions. This database contains several signals from 24 healthy volunteers while driving on a route through open roads which identified city streets as high stress, highway as medium stress, and rest as low stress around Boston. This dataset was most commonly used in many studies. Hyun-Myung Cho et al. used the Physionet dataset and mental arithmetic data set to detect stress using row ECGs and a method for training a Deep Neural Network (DNN).

Some conventional machine learning classifiers namely decision tree, KNN, Logistic regression, RF, and SVM were tested. They used a transfer learning method to train a model with a small dataset which improved accuracy by 12.01% and 10.06% when 10s and 60s of ECG signal were used respectively in this model. This proposed method improved the accuracy of stress detection from 87.39% to 90.19% when compared with other DNN methods. In [25], a stress detection system was proposed where a professional dynamic driving simulator was used for an experiment. Three sensor devices were attached for recording the Skin Potential Response (SPR) from both the hands and ECG from the chest. The stressors included driving through a highway with some unforeseen events happening at some positions. SVM and ANN were used for classification, wherein ANN gave better results than SVM with a balanced accuracy of 77.59% for considered events.

CHAPTER 2

METHODOLOGY

2.1 Applied Techniques and Tools

Emotion detection using physiological signals such as Electrocardiogram (ECG) and Galvanic Skin Response (GSR) is an active area of research in machine learning (ML). The basic idea behind this approach is that different emotions are associated with different physiological responses, such as changes in heart rate and skin conductance.

Here are some applied techniques for emotion detection using ECG and GSR sensors:

Feature Extraction: In order to train a machine learning model for emotion detection, relevant features need to be extracted from the physiological signals. Some commonly used features for ECG analysis include R-R intervals, heart rate variability, and peak amplitudes. For GSR analysis, features such as skin conductance level and skin conductance response are commonly used.

Classification Models: Once the features are extracted, a classification model can be trained to identify different emotional states. Commonly used classification models include Support Vector Machines (SVM), Random Forest, and Deep Neural Networks.

Hybrid Approach: A combination of multiple physiological signals can be used to improve the accuracy of emotion detection. For example, ECG and GSR signals can be combined to develop a more robust emotion detection system.

Transfer Learning: Transfer learning can be used to improve the performance of emotion detection models by leveraging pre-trained models on large datasets. For example, models pre-trained on large datasets such as ImageNet can be fine-tuned for emotion detection tasks.

Overall, emotion detection using physiological signals such as ECG and GSR is an active area of research, and there are several applied techniques that can be used to develop robust emotion detection systems.

2.2 Technical Specifications

S. No.	**Equipments**	**Specifications**
1.	Raspberry pi Pico W	Microcontroller: RP2040, a dual-core ARM Cortex-M0+ processor, clocked at up to 133 MHz. Memory: 264 KB of SRAM and 2 MB of flash memory. GPIO: 26 multi-function

		General Purpose Input/Output (GPIO) pins. Analog Inputs: 3 x 12-bit ADC channels for analog inputs. Digital Interfaces: 2 x UART, 2 x SPI, 2 x I2C, 3 x 12-bit PWM channels, and 8 x Programmable I/O (PIO) state machines for custom peripheral support.
2.	Ecg Sensor AD8232	The AD8232 is a single-lead, heart rate monitor front-end integrated circuit (IC) designed for use in fitness and healthcare applications. The AD8232 can accept an input voltage range of ±300mV, making it compatible with most common ECG electrodes.The sensor consumes very low power, with a quiescent current of only 50 uA.
3.	Seeed Studio GSR Sensor MOA221027025	The GSR Sensor from Seeed Studio is designed to measure the skin conductance response of the human body, which is a measure of the electrical conductivity of the skin. The sensor comes with two stainless steel electrodes, and it can be connected to microcontrollers like Arduino and Raspberry Pi through a Grove connector. The operating voltage for the sensor is between 3.3V and 5V, and it has a measurement range of 0-4.096V with a resolution of 10-bit ADC.

2.3 Design Approach

Designing an emotion detection system using ECG and GSR sensors can involve the following approach:

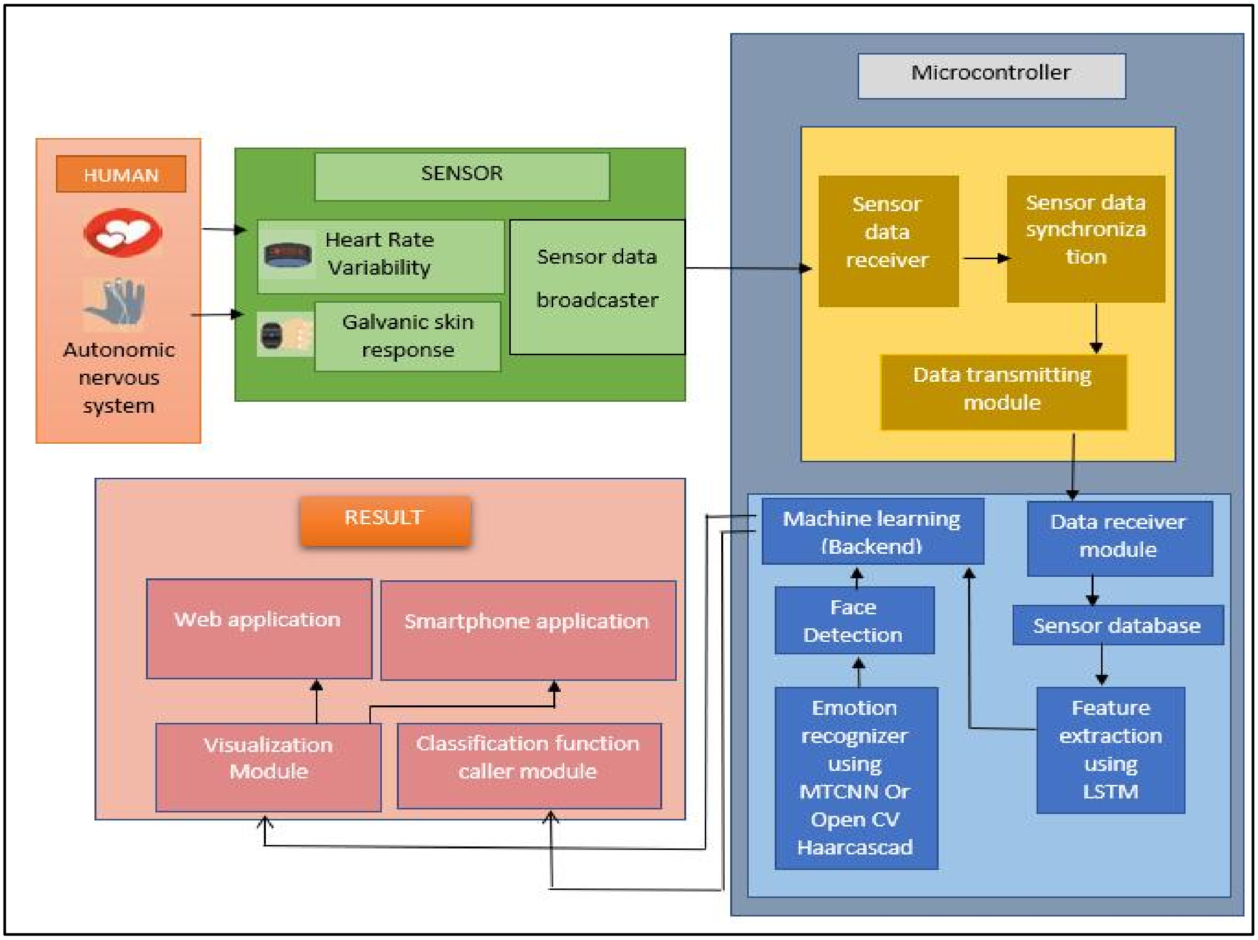


Fig 1. Flowchart of the proposed model

From the fig 1, the different steps involved in the design approach for an emotion detection system using GSR and HR sensors are

Sensor Selection: The first step in designing an emotion detection system using GSR and HR sensors is to select appropriate sensors for measuring these physiological signals. The selection of sensors will depend on several factors such as accuracy, reliability, and cost. GSR sensors measure the electrical conductivity of the skin, while HR sensors measure the heart rate variability. There are several types of sensors available on the market, such as dry and wet GSR sensors, and chest strap and wristband HR sensors. Choosing the right sensors is crucial to ensure accurate and reliable measurements of physiological signals.

Hardware Design: The next step is to design the hardware components of the emotion detection system. This will typically involve integrating the GSR and HR sensors into a wearable device or a module that can be attached to the body. The hardware design must also consider factors such as power consumption, data storage, and wireless connectivity. Wearable devices can include smartwatches, wristbands, or chest straps that can measure GSR and HR in real-time. These devices must be designed to be comfortable, unobtrusive, and easy to wear for extended periods.

Software Design: The software design component of the system will involve developing algorithms for data processing, analysis, and machine learning models for emotion classification. This may involve developing software applications for data visualization and user interaction. The software design must also consider factors such as compatibility, data security, and ease of use. Machine learning models can be developed using various algorithms such as support vector machines (SVM), neural networks, and decision trees. The software design must also ensure that the models are scalable, robust, and efficient.

Data Processing: Once the hardware and software components are in place, data processing can begin. This will involve collecting and analyzing physiological data from the GSR and HR sensors in response to various emotional stimuli. The data processing component of the system must be designed to ensure accurate and reliable measurement of physiological signals. This may involve filtering and preprocessing of the data, feature extraction, and normalization. The data processing component must also be designed to handle large volumes of data efficiently.

Machine Learning: The final step is to develop machine learning models that can classify the physiological signals into different emotional states. This will typically involve using supervised learning techniques to train the models using labeled data. The machine learning component must be designed to ensure that the models are accurate, reliable, and can generalize well to new data. This may involve cross-validation, hyperparameter tuning, and model selection. The machine learning component must also be designed to handle different types of data, such as time-series data from GSR and HR sensors, and to ensure that the models are interpretable and explainable.

CHAPTER 3

EXPERIMENTATION AND TESTS

3.1 Mathematical Modeling, Circuits etc.

GSR sensor mathematical model:

The electrical conductance of the skin, which varies in reaction to a person's changing emotional state, is measured by the Galvanic Skin Response (GSR) sensor. We can start with a simple circuit model that consists of a voltage source, a resistor, and a capacitor to simulate the circuit of a GSR sensor.The skin potential, which is the voltage differential between the skin and a reference electrode, is represented by the voltage source. The capacitor and resistor stand in for the skin's capacitance and resistance, respectively.The voltage across the capacitor (V_C) in this circuit model is proportional to the rate of change of the conductance, and the voltage across the resistor (V_R) is proportional to the conductance of the skin (G skin):

$$V\_R = G\_skin * I \qquad \text{……………….} \quad (I)$$

$$V\_C = (dG\_skin/dt) * C \qquad \text{……………….} \quad (II)$$

where I is the current flowing through the skin and C is the capacitance of the skin.

To measure the GSR, the skin is typically stimulated with a small electrical current, and the resulting voltage is measured across the skin and a reference electrode. The circuit model for this measurement can be represented as follows:

GSR Sensor Circuit Model:

In this circuit model, the voltage source (V_skin) represents the skin potential, the resistor (R_skin) represents the resistance of the skin, and the capacitor (C_skin) represents the capacitance of the skin. The current source (I_stim) represents the stimulus current, and the resistor (R_ref) represents the resistance of the reference electrode.

To measure the GSR, a small current is injected into the skin through the current source (I_stim), and the resulting voltage is measured across the skin and the reference electrode. The voltage across the skin (V_skin) is proportional to the conductance of the skin (G_skin):

$$V\_skin = G\_skin * I\_stim * R\_skin / (R\_skin + R\_ref) \qquad \text{……………….. (III)}$$

By measuring the voltage across the skin and the reference electrode, the conductance of the skin can be calculated using the following equation:

$$G\_skin = (V\_skin / I\_stim) * (R\_skin + R\_ref) / R\_skin \qquad \text{………. (IV)}$$

Overall, the circuit model for a GSR sensor is a simple yet powerful tool that can be used to understand the underlying principles of GSR measurement and to design and optimize GSR sensor circuits.

ECG sensor mathematical model:

An electronic device called an electrocardiogram (ECG) sensor detects the electrical activity of the heart and generates a graph known as an ECG or EKG (electrocardiogram). An accurate ECG signal is produced by the ECG sensor's electronic parts, which include electrodes, amplifiers, filters, and analog-to-digital converters (ADCs).

It's crucial to first comprehend the fundamental circuitry of an ECG sensor in order to comprehend the mathematical modeling of the sensor. Three electrodes are commonly used in an ECG sensor, and they are positioned on the chest, arms, and legs, respectively. The heart's tiny electrical signals are amplified by an instrumentation amplifier through which the electrodes are connected. The low-pass filter is used to filter out noise and high-frequency signals that are unrelated to the ECG signal after the signal has been amplified.

After being filtered, the signal is then transmitted via an ADC to transform it from analogue to digital. The ECG waveform is created by further processing and analysis of the digital signal.

The creation of equations that explain the behavior of the sensor's electronic parts is required for mathematical modeling of the ECG sensor. For instance, the operational amplifier (op-amp) circuit, which is characterized by a transfer function that connects the input signal to the output signal, can be used to simulate the amplifier. Using Kirchhoff's equations and Ohm's law, for example, circuit analysis techniques, it is possible to determine the transfer function of the op-amp circuit.A transfer function that outlines the low-pass filter's frequency response can also be used to represent it. Circuit analysis methods like Laplace transforms and Bode graphs can be used to determine the filter's transfer function.The resolution, precision, and sample rate of the ADC, as well as other input/output characteristics, can also be represented using mathematical formulae.

Once the mathematical representations for each part of the ECG sensor have been created, they may be merged to represent the sensor as a whole. The entire model can be used to replicate the sensor's behavior and improve the performance of its design parameters.

ECG Sensor Circuit Model:

The electrical activity of the heart is often measured by an ECG sensor, which is normally constructed from a variety of electronic parts. To measure the electrical activity of the heart and transform it into a signal that can be examined and understood, the sensor normally comprises of many circuit components.

Some of the main circuit components used in ECG sensors include:

1)Electrodes: The electrodes are typically placed on the skin and are responsible for detecting the electrical activity of the heart.

2)Amplifiers: The signal from the electrodes is typically very weak, so amplifiers are used to increase the amplitude of the signal.

3)Filters: The signal from the electrodes can be contaminated with noise, so filters are used to remove unwanted frequencies from the signal.

4)Analog-to-Digital Converters (ADCs): The amplified and filtered signal is then digitized using an ADC. The ADC converts the analog signal into a digital signal that can be processed by a computer or microcontroller.

5)Microcontrollers or Processors: The digitized signal is then processed by a microcontroller or processor to extract the relevant information about the heart's electrical activity. This information is then typically displayed on a screen or recorded for further analysis.

3.2 Experimental Setup/Design

GSR sensor:

We are connecting the GSR sensor to the Raspberry pi pico W through VCC(3.3V),GND and SIGNAL Pin.The finger gloves need to be wear by the patient .Then the raspberry pico W will be connected to the laptop.All the algorithms we are using are written and feed to the microcontroller through Thonny IDE.All codes are written in microPython programming language.

GSR Circuit:

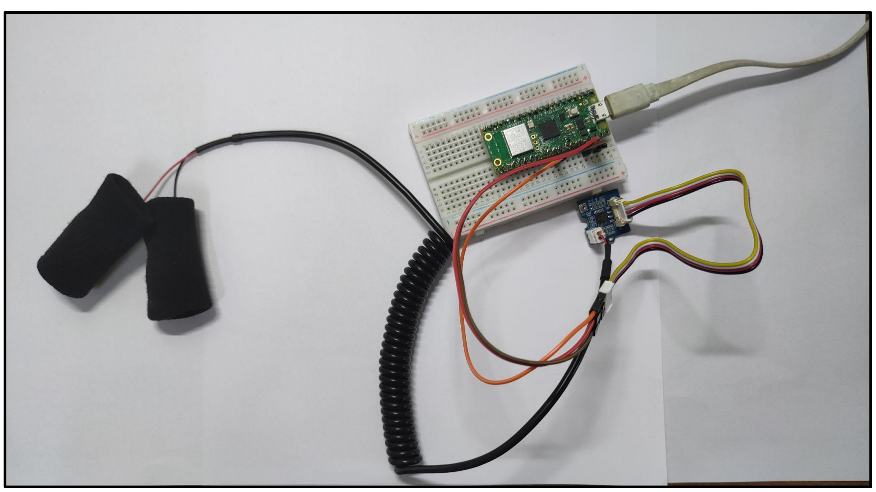


Fig 2. Connection of GSR module

Output:

GSR values(Kohm)				
Normal	Fear/Anxiety	Excitement/Arousal	Joy/Happines	Anger/Frustration
15.267	6.832001	5.151	5.320001	7.9773
15.187	6.112	5.663	4.919999	7.929299
14.755	5.903999	5.759001	5.016	8.1053
14.467	5.68	5.839001	4.776	8.0573
14.147	5.584	5.968	4.952001	8.1533
13.891	5.488001	5.936001	4.888	8.281301
14.051	5.327999	6.016001	5.112	8.297299
14.435	5.167999	5.968	5.112	8.4413
14.675	5.072001	6.208	5.176	8.4733
15.027	5.007999	5.855	5.320001	8.537301
15.251	4.912001	5.711	5.367999	8.4733
14.995	4.752001	5.551001	5.447999	8.6013
14.723	4.704	5.646999	5.56	8.585299
14.403	4.688	5.391	5.287999	8.617301
14.147	4.784	5.071	5.400001	8.569301
14.019	4.927999	4.927	5.495999	8.489301
14.355	4.944	4.799	5.512	8.377299

Fig 3. Dataset of different emotions for different GSR values

We are connecting the GSR sensor to the Raspberry pi pico W through VCC(3.3V),GND and OUTPUT Pin.The finger gloves need to be wear by the patient .Then the raspberry pico W will be connected to the laptop.All the algorithms we are using are written and feed to the microcontroller through Thonny IDE.All codes are written in microPython programming language.

ECG sensor:

We are connecting the ECG sensor to the Raspberry pi pico W through VCC(3.3V),GND and OUTPUT Pin.It has 3 electrodes which are needed to be placed on appropriate pulse position on the patient to get the proper pulse input.Then the raspberry pico W will be connected to the laptop.All the algorithms we are using are written and feed to the microcontroller through Thonny IDE.All codes are written in microPython programming language.

ECG circuit:

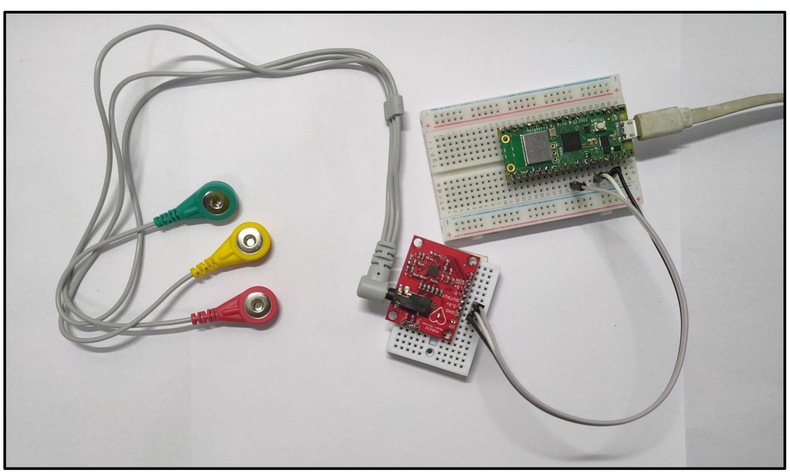


Fig 4. Connection of heart rate module (AD8232)

Output:

ECG VALUES (bpm)				
NORMAL	Fear/Anxiety	Excitement/Arousal	Joy/Happiness	Anger/Frustration
94.00961	125.3649	131.2607	98.04257	124.6635
92.79607	118.7583	142.943	91.27491	137.3127
92.47378	117.5498	143.0235	90.63037	136.4264
92.87663	116.7441	144.0709	91.11377	138.4456
90.62074	117.5498	142.943	90.3081	135.7819
93.2845	117.3081	142.7013	90.3081	136.2653
91.26528	117.3081	143.5875	90.87207	136.3459
92.23208	117.6304	142.7013	90.79149	136.2653
92.87663	117.5498	142.943	90.63037	135.2179
91.66811	117.7109	143.8292	90.3081	136.9098
93.2845	117.1469	142.5402	90.54979	135.7013
93.2845	117.4692	143.0235	90.63037	135.2179
94.49302	117.2275	143.3458	90.63037	136.2653
94.41245	117.5498	142.943	90.3081	136.0236
91.99039	117.5498	143.3458	90.38866	135.6207
93.5262	117.5498	142.8624	90.87207	135.0568
92.71549	117.3887	143.1041	90.63037	135.7013
92.87663	117.2275	142.5402	90.63037	135.7819
91.1847	117.6304	143.7487	90.87207	136.9904

Fig 5. Dataset of different emotions for different beats per minute values

3.3 Prototype Testing/Simulations

Using ECG sensor and GSR sensor we have gather 400 sample output of patient at different emotional states like anger,joy,anxiety, fear and frustration.The values of ECG sensor is in beats per minute and the values of GSR sensor is in Kilo-Ohms.

The code we are using for ECG sensor:

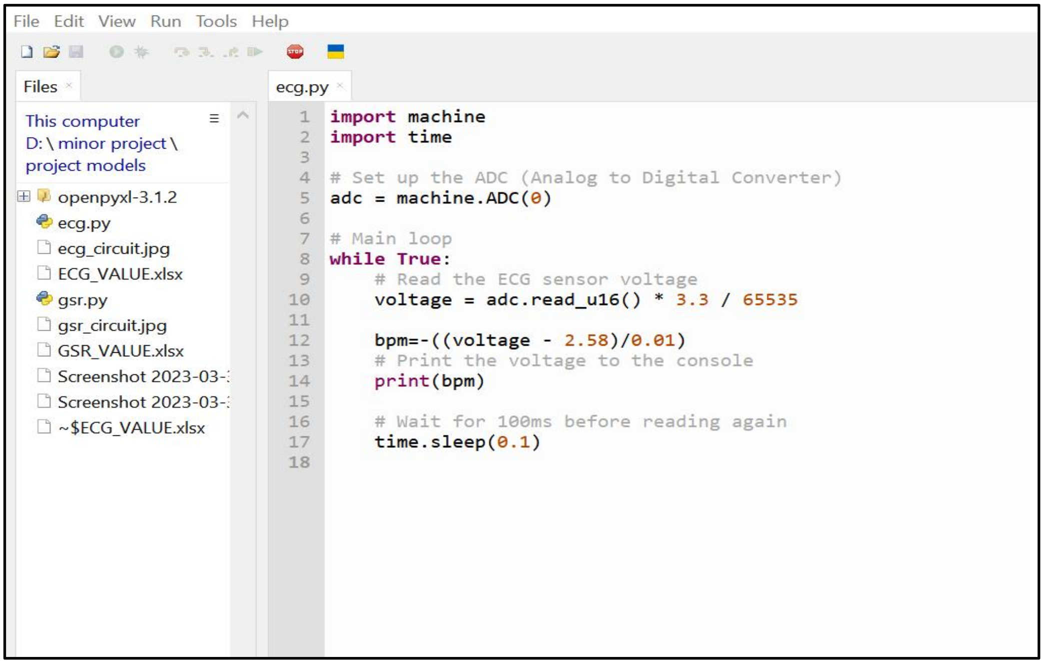


Fig 6. ECG sensor code in thonny IDE

In this code we are taking the ECG sensor value through the ADC(0) pin.Then first we are converting the ECG sensor value to the corresponding voltage using the given formula:

voltage = adc.read_u16() * 3.3 / 65535

Then, the voltage value is converted to the beats per minute value using the following formula:

bpm=-((voltage - 2.58)/0.01).

Then, we are putting all the ECG data for different emotions in the database for further Machine learning classification.

The code we are using for GSR sensor:

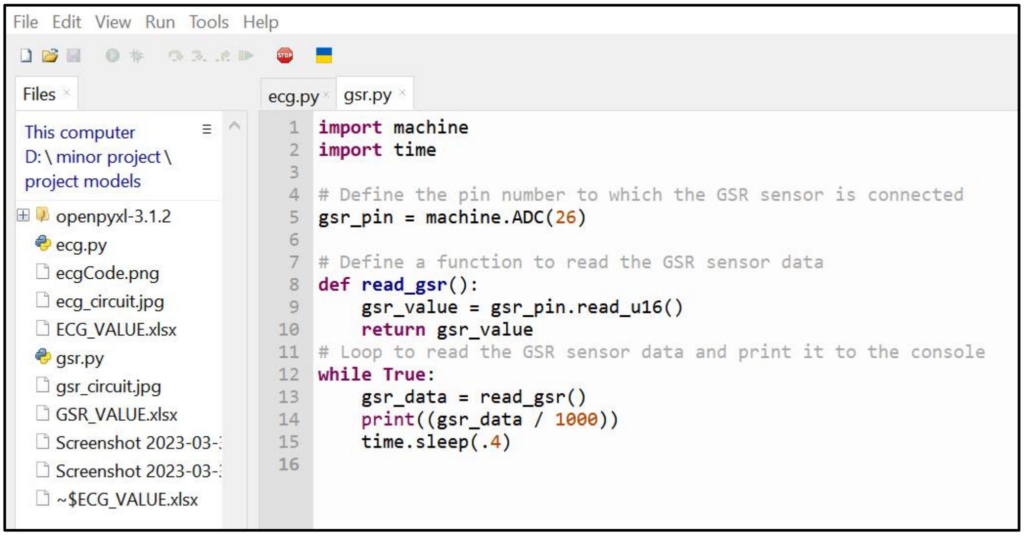


Fig 7. GSR sensor code in thonny IDE

In this code we are taking the GSR sensor value through the ADC(0) pin.Then we are converting the GSR sensor value which is by default in Ohms we are converting it to the corresponding Kilo-Ohms using the given code:

```
gsr_data = read_gsr()

print((gsr_data / 1000))
```

Then, we are putting all the GSR sensor conductivity data for different emotions in the database for further Machine learning classification.

<u>Classification using Machine learning algorithms:</u>

Database for the classification:

GSR Data	ECG Data	Predicted_Emotion
13.4	94	Normal
5.7	89.9	Normal
12.8	90.5	Normal
13.8	90.7	Normal
13.9	90.8	Normal
13.4	91.1	Normal
13.7	93.5	Normal
13.7	93.5	Normal
13.8	88	Normal
14.7	99	Normal
13.8	86	Normal
14.1	88	Normal
13.8	94.5	Normal
14.1	90.4	Normal
13.7	91.6	Normal
13.2	91.7	Normal
13.1	89.9	Normal
13.1	90	Normal
15.1	88.2	Normal
13.7	93.6	Joy
5.8	113.9	Joy
14.6	93.6	Joy
13.6	91.9	Joy
13.6	89	Joy
5.2	123	Joy
4.7	115.6	Joy
14.2	95	Joy
15	93	Joy
14.54	94	Joy
5.8	143	Anger
8.3	131.2	Anger
5.3	117.6	Anger
8.6	143.9	Anger
7.7	135.2	Anger
5.1	123	Anger
7.6	142.1	Anger
8.6	142.7	Anger
5.3	118	Anger
8.3	142	Anger
7.5	134	Anger
5.2	123	Anger
5.8	119	Fear
5.4	113.4	Fear
14.3	108	Fear
5.3	118.7	Fear
8.4	125.8	Fear
5.8	117.1	Fear
5.9	116.1	Fear
6	118.1	Fear
5.5	1141	Fear
5.8	113.1	Fear
5.1	117.1	Fear
5.38	115.1	Fear
5.7	113.1	Fear
13.238	89.34	Normal

The dataset contains 262 different values of heart rate sensor values and GSR values , with 4 different classes of emotion such as normal, fear, anger and joy. The database has been meticulously crafted to ensure the highest possible accuracy when used in conjunction with machine learning algorithms. It contains data gathered from GSR and ECG sensors for four different emotions: fear, normal, anger, and joy. The data has been carefully arranged in a linear order to facilitate easy processing and analysis.The use of GSR and ECG sensors allows for the collection of highly detailed physiological data, providing insights into how different emotions affect the body. By including data for a range of emotions, the database can be used to train machine learning algorithms to accurately identify and differentiate between different emotional states.The linear arrangement of the data ensures that it is easily accessible and can be processed efficiently by machine learning algorithms. This facilitates the development of highly accurate models that can be used to classify emotional states in real-world applications, such as mental health monitoring or emotion recognition in human-computer interactions.

In our project we have created a database file 'combined_data_csv.csv' and labeled the data with different emotional states to train the machine learning model.We have use colab platform to run the following algorithms :

1) Support Vector Machine algorithm:

Support Vector Machine (SVM) is a popular supervised machine learning algorithm used for classification and regression analysis. It finds the best separating hyperplane between different classes of data in a high-dimensional space. SVM maximizes the margin between the decision boundary and the closest data points, leading to better generalization and improved classification performance. It can also handle non-linearly separable data by mapping the input space to a higher dimensional space through a kernel function.

2) Decision tree classifier algorithm:

A decision tree classifier is a supervised learning algorithm used for classification tasks. It builds a tree-like model where each internal node represents a feature, each branch represents a decision rule based on that feature, and each leaf node represents a class label. The model is trained using labeled data and can be used to predict the class label of new data based on its features by traversing the decision tree.

3) Gaussian Naive Bayes algorithm:

Gaussian Naive Bayes is a probabilistic classification algorithm that assumes the features are independent and normally distributed. It calculates the conditional probabilities of each class given the features and selects the class with the highest probability. The algorithm is efficient and performs well in high-dimensional datasets. However, its assumption of independent features may not hold in some cases, leading to suboptimal performance.

I**4) Random forest algorithm:**

A random forest classifier is a type of machine learning algorithm that constructs multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. Each decision tree is trained on a randomly sampled subset of the training data, and a majority vote is used to determine the final prediction. This algorithm is commonly used for classification tasks, such as predicting whether an email is spam or not.

5) K-nearest Neighbour algorithm:

K-Nearest Neighbors (KNN) is a simple yet effective algorithm used for both regression and classification tasks in machine learning. It is a non-parametric algorithm that works by finding the K closest data points in the feature space to a new, unseen data point, and then using the majority class or average value of those K neighbors to predict the class or value of the new data point. The value of K is a hyperparameter that must be tuned to achieve the best performance. KNN is often used in applications where the decision boundary between classes is not well-defined, and where the underlying data distribution may be complex. KNN is easy to implement and interpret, making it a popular choice for both beginners and experts in machine learning. However, it can be computationally expensive for large datasets and may suffer from the curse of dimensionality.

CHAPTER 4

CHALLENGES AND REMEDY

4.1 Challenges Faced

Commonly used physiological signs for mood recognition include the electrocardiogram (ECG) and galvanic skin response (GSR). However, using these sensors for mood recognition comes with a number of difficulties:

Signal quality: A number of variables, including motion artifacts, electrode placement, and skin health, can influence the ECG and GSR devices' signal quality. These elements may result in signal noise, baseline drift, and other signal alterations, which may impair the precision of emotion recognition.

Individual variations: ECG and GSR readings can differ considerably between people depending on things like age, gender, physical condition, and mental state. This can make it challenging to generalize the mood recognition algorithm to various people.

Lack of standardization: The use of ECG and GSR instruments for mood recognition is not standardized. The precision and dependability of mood recognition algorithms may be impacted by variations in the gathering, processing, and analysis of data.

ECG and GSR sensors are frequently used in combination with other physiological sensors, such as face expression detection and EEG (electroencephalogram) sensors. Because there are variations in signal quality, data processing, and data fusion, integrating numerous sources can be difficult.

4.2 Remedial Strategies

To address the challenges of using ECG and GSR sensors for emotion detection, there are several remedial strategies that can be employed:

Signal processing techniques: To overcome signal quality issues, various signal processing techniques can be used, such as filtering, noise reduction, and artifact removal. These techniques can help to improve the accuracy of emotion detection algorithms by reducing signal noise and enhancing the quality of the physiological signals.

Personalization: To account for individual differences, personalized models can be developed that take into account the unique characteristics of an individual's ECG and GSR signals. This can help to improve the accuracy of emotion detection algorithms for specific individuals.

Context-awareness: To address the influence of contextual factors on ECG and GSR signals, context-aware emotion detection algorithms can be developed that take into account the environmental and social context in which the physiological signals are being measured. This can help to improve the accuracy of emotion detection by reducing false positives and false negatives.

Multimodal integration: To improve the accuracy of emotion detection, multiple physiological signals can be integrated, such as ECG, GSR, EEG, and facial expression recognition. Integrating multiple modalities can help to compensate for the limitations of individual sensors and enhance the overall accuracy of emotion detection.

Privacy protection: To address privacy concerns, it is important to ensure that the personal data collected through ECG and GSR sensors is secure and protected. Measures such as data encryption and anonymization can be employed to protect the privacy of the users.

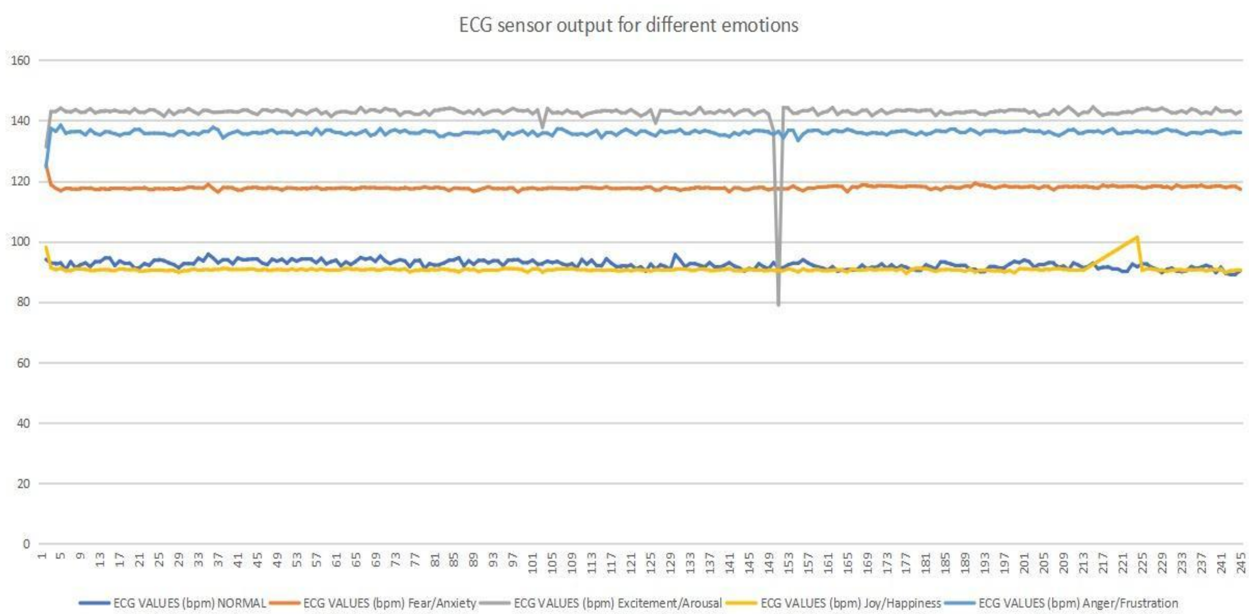
CHAPTER 5

RESULT AND DISCUSSION

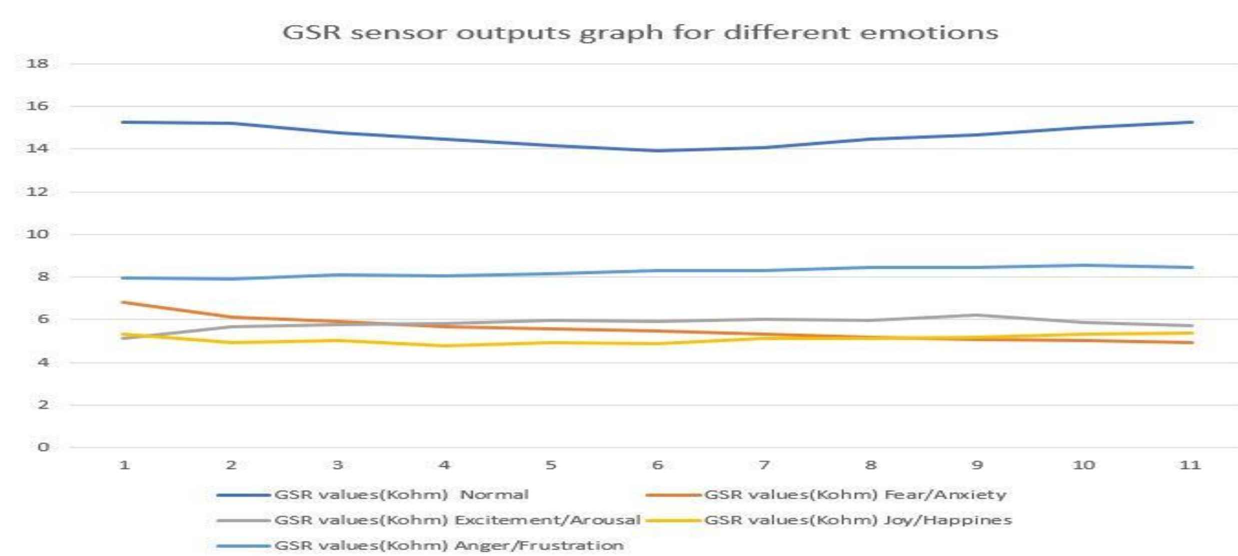
5.1 Results Obtained

Till now we have created hardware circuits with ECG sensor and GSR sensor.Then taken ECG and GSR sensor value from a from patients with different emotional states like happiness, fear, anxiety etc.All the gathered outputs of ECG and GSR sensor are then stored in a database for further classification.

ECG sensor output graph:



GSR sensor output graph:



Machine learning algorithms:

1)Support vector machine:

After feeding in the database in csv for in SVM algorithm we got the following results:

	Precision	recall	f1-score	support
Anger	1	0.53	0.69	17
Fear	0.63	1.00	0.77	17
Joy	0.86	0.83	0.84	23
Normal	0.90	0.86	0.88	22

We have received SVM accuracy approximately 81%.

2)Decision tree classifier:

After feeding in the database in csv for in decision tree classifier algorithm we got the following results:

	Precision	recall	f1-score	support
Anger	0.94	0.88	0.91	17
Fear	0.79	0.88	0.83	17
Joy	0.83	0.87	0.85	23
Normal	0.95	0.86	0.90	22

We have received Decision tree accuracy approximately 87.3%.

3)Gaussian Naive Bayes:

After feeding in the database in csv for in Gaussian Naive Bayes algorithm we got the following results:

	Precision	recall	f1-score	support
Anger	0.61	1.00	0.76	17
Fear	0.88	0.41	0.56	17
Joy	0.89	0.70	0.78	23
Normal	0.80	0.91	0.85	22

We have received Gaussian Naive Bayes accuracy approximately 80%.

4) Random forest classifier:

After feeding in the database in csv for in Random forest classifier algorithm we got the following results:

	Precision	recall	f1-score	support
Anger	1	0.88	0.94	17
Fear	0.81	1.00	0.89	17
Joy	0.90	0.78	0.84	23
Normal	0.87	0.91	0.89	22

We have received Random forest classifier accuracy approximately 89%.

5) K-Nearest Neighbour: After feeding in the database in csv for in K-Nearest Neighbour algorithm we got the following results:

	Precision	recall	f1-score	support
Anger	1	0.82	0.90	17
Fear	0.77	1.00	0.87	17
Joy	0.87	0.87	0.87	23
Normal	0.95	0.86	0.90	22

We have received K-Nearest Neighbour accuracy approximately 89%.

5.2 Analysis and Discussion

ECG sensor:

Successful Attempts:

1)Use of AD8232 ECG Sensor Module: The AD8232 ECG Sensor Module is a popular choice for measuring ECG signals. It has been successfully used with the Raspberry Pi Pico W, where the sensor was connected to the Pico W's analog input pins. A Python program was used to read the analog signals from the sensor, which were then processed and displayed on the Pico W's LCD screen.

2)Use of MAX30100 Pulse Oximeter and Heart-Rate Sensor Module: The MAX30100 module can also be used as an ECG sensor, as it can measure the heart rate and provide an estimate of the ECG waveform. This sensor has been successfully used with the Raspberry Pi Pico W, where the data was acquired using Python and displayed on the Pico W's OLED display.

Failed Attempts:

1)Use of ADS1292R ECG Analog Front End: The ADS1292R ECG Analog Front End is a high-precision ECG sensor that can be used for medical applications. However, it requires a more advanced microcontroller than the Raspberry Pi Pico W, as it has a high data rate and complex data processing requirements. Attempts to use this sensor with the Pico W have been unsuccessful, as the Pico W does not have the processing power to handle the data rate and signal processing requirements of the sensor.

2)Use of cheap, low-quality ECG sensors: Some attempts to use cheap, low-quality ECG sensors with the Raspberry Pi Pico W have been unsuccessful. These sensors may produce noisy or unreliable data, which can be difficult to process and analyze. Additionally, some of these sensors may not be compatible with the Pico W, which can result in errors or incorrect readings.

GSR sensor:

There have been both successful and failed attempts of using GSR sensors with Raspberry Pi Pico. Here are some of the key factors that contribute to the success or failure of such projects:

1)Sensor compatibility: The Raspberry Pi Pico does not support all GSR sensors. Certain voltage levels, interfaces, or library requirements for some sensors might not be supported by the Pico. It's crucial to pick a sensor that works with the Pico and has literature and code samples readily available.

2)Wiring and connections:GSR sensors often need precise wiring and connections in order to produce accurate data. Because there are a certain amount of GPIO pins on the Raspberry Pi Pico, it's critical to properly arrange the wiring to prevent conflicts or mistakes. Readings that are noisy or irregular can be caused by improper wiring.

3)Signal processing and filtering: When there is movement or sweat on the skin, noisy settings, or when GSR sensors are used, these signals can be noisy or inconsistent. To extract usable information from the raw data, appropriate signal processing and filtering techniques are required. It might be necessary for you to know a little bit about programming and signal processing.

4)Power management: GSR sensors can consume a lot of power, particularly if they need extra electronics or amplification. It's crucial to select a sensor that can function within the Raspberry Pi Pico's power constraints and to optimise the code and hardware to reduce power usage.

CHAPTER 6

CONCLUSIVE REMARKS

6.1 Overall Progress

The use of hardware and software for verifying emotions through physiological signals such as Galvanic Skin Response (GSR) and Heart Rate (HR) has shown promising results. The combination of hardware and software provides a more comprehensive approach to emotion detection, allowing for real-time monitoring and analysis of physiological signals.

The hardware component, which includes GSR and HR sensors, provides accurate and reliable measurements of physiological signals. These sensors capture changes in the electrical conductivity of the skin and heart rate variability, respectively, in response to emotional stimuli. The software component, which includes algorithms for data processing and machine learning models for emotion classification, allows for the analysis and interpretation of physiological signals.

The use of machine learning techniques for emotion classification has shown great potential in accurately detecting emotions from physiological signals. These techniques allow for the development of models that can learn to recognize patterns in the physiological signals associated with specific emotional states.

Overall, the combination of hardware and software for verifying emotions through physiological signals provides a powerful tool for various applications such as affective computing, human-computer interaction, and healthcare. With further advancements in technology, it is likely that we will see increased use and development of hardware and software-based emotion detection systems.

6.2 Further Plan of Action

Based on the progress we have made so far, here are some suggestions for further plans or improvements for your emotion detection system:

Increase the dataset size: Collecting more data can improve the performance of your machine learning models. We can try to obtain more samples for each emotional state to increase the dataset size and enhance the accuracy of your system.

Explore different feature extraction methods: There are several feature extraction methods available, and some may work better than others for your specific use case. We will try out various feature extraction techniques and compare their performance to determine the most suitable one for your system.

Optimize machine learning algorithms: The performance of your machine learning models depends on the selection of the appropriate algorithm and hyperparameters. Try different algorithms and tune the hyperparameters to optimize the performance of your models.

Evaluate the system in real-world scenarios: It is essential to evaluate the system's performance in real-world scenarios to determine its practicality and effectiveness.We have conduct user studies and experiments in different environments to evaluate the system's performance accurately.

We are thinking of integrating additional physiological signals: ECG and GSR are essential physiological signals for emotion detection. However, adding other signals such as facial expression, voice, and body movements can improve the accuracy of your system.

These are some suggestions for further plans or improvements for our emotion detection system. By implementing these improvements, you can create a more accurate and robust system that can effectively classify emotional states.

References

[1] Gunti Spandan, Tanveer Ahmed, Sangmeshwar and Rajesh S M “IoT Application: Human Emotions Management System” International Journal of Recent Technology and Engineering (IJRTE), Vol. 9, Issue-1, May 2020

[2] S. Lakudzode and S. Rajbhoj, “Review on human stress monitoring system using wearable sensors,” International Research Journal of Engineering and Technology (IRJET), vol. 3, no. 04, 2016.

[3] G. Giannakakis, D. Grigoriadis, and M. Tsiknakis, “Detection of stress/anxiety state from eeg features during video watching,” in the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 6034–6037,2015.

[4] A. Fernandes, R. Helawar, R. Lokesh, T. Tari, and A. V. Shahapurkar Determination of stress using blood pressure and galvanic skin response,” in 2014 International Conference on Communication and Network Technologies. IEEE, pp. 165–168,2014.

[5] T. Roh, S. Hong, and H.-J. Yoo, “Wearable depression monitoring system with heart-rate variability,” at 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2014, pp. 562–565,2014.

[6] S. Maestro, and M. A. Morales, “ECG and GSR measure and analysis using wearable systems: Application in anorexia nervosa adolescents,” in 2013 8th International Symposium on Image and Signal Processing and Analysis (ISPA). IEEE, pp. 499–504,2013.

[7] F.-T. Sun, C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, “Activity-aware mental stress detection using physiological sensors,” in International conference on Mobile computing, applications, and services. Springer, pp. 282–301, 2010.

[8] J. A. Healey and R. W. Picard, “Detecting stress during real-world driving tasks using physiological sensors,” IEEE Transactions on Intelligent transportation systems, vol. 6, no. 2, pp. 156–166, 2005.

[9] N. D. Ahuja, A. K. Agarwal, N. M. Mahajan, N. H. Mehta, and H. N. Kapadia, “GSR and HRV: its application in clinical diagnosis,” in 16th IEEE Symposium Computer-Based Medical Systems, 2003.Proceedings. IEEE, pp. 279–283,2003.

[10] T. Stamkopoulos, K. Diamantaras, N. Maglaveras, and M. Strintzis, “ECG analysis using nonlinear PCA neural networks for ischemia detection,” IEEE Transactions on Signal Processing, vol. 46, no. 11, pp. 3058– 3067, 1998.

[11] J. Ogorevc, A. Podlesek, G. Ger²ak, and J. Drnov²ek, ``The effect of mental stress on psychophysiological parameters," in Proc. IEEE Int. Symp. Med.Meas. Appl., Bari, Italy, May 2011, pp. 294-299.

[12] M. Koussai, C. Habib, and A. Makhoul, ``Real-time stress evaluation using wireless body sensor networks," in Proc. Wireless Days (WD), Apr. 2018, pp. 37-39.

[13] R. Costin, C. Rotariu, and A. Pasarica, ``Mental stress detection using heart rate variability and morphologic variability of EEG signals," in Proc. IEEE Int. Conf. Expo. Electr. Power Eng., Iasi, Romania, Oct. 2012, pp. 591-596.

[14] G. Giannakakis, K. Marias, and M. Tsiknakis, ``Astress recognition system using HRV parameters and machine learning techniques," in Proc. 8th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Cambridge, U.K., Sep. 2019, pp. 269-272.

[15] J. Taelman, S. Vandeput, I. Gligorijevic, A. Spaepen, and S. Van Huffel, ``Time-frequency heart rate variability characteristics of young adults during physical, mental and combined stress in the laboratory environment," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Boston, MA, USA, Aug. 2011, pp. 1973-1976.

[16] S.-Y. Dong, M. Lee, H. Park, and I. Youn, ``Stress resilience measurement with heart-rate variability during mental and physical stress," in Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2018, pp. 5290-5293.

[17] T. Pereira, P. R. Almeida, J. P. S. Cunha, and A. Aguiar, ``Heart rate variability metrics for ne-grained stress level assessment," Comput. Methods Programs Biomed., vol. 148, pp. 7180, Sep. 2017.

[18] A. Sano and R.W. Picard, ``Stress recognition using wearable sensors and mobile phones," in Proc. Humaine Assoc. Conf. Affect. Comput. Intell.Interact., Sep. 2013, pp. 671-676.

[19] M. Zubair, C. Yoon, H. Kim, J. Kim, and J. Kim, ``Smart wearable band for stress detection," in Proc. 5th Int. Conf. IT Converg. Secur. (ICITCS), Kuala Lumpur, Malaysia, Aug. 2015, pp. 14.

[20] A. Cantara and A. Ceniza, ``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," Int. J.Eng. Res. Technol., vol. 5, no. 3, pp. 2837, 2016.

[21] M. Gjoreski, M. Lu²trek, M. Gams, and H. Gjoreski, ``Monitoring stress with a wrist device using context," J. Biomed. Informat., vol. 73, pp. 159-170, Sep. 2017.

[22] A. G. Airij, R. Sudirman, and U. U. Sheikh, ``GSM and GPS based real-time remote physiological signals monitoring and stress levels classification,' in Proc. 2nd Int. Conf. BioSignal Anal., Process. Syst. (ICBAPS), Kuching, Malaysia, Jul. 2018, pp. 130-135.

[23] R. Setiawan, F. Budiman, and W. I. Basori, ``Stress diagnostic system and digital medical record based on Internet of Things," in Proc. Int. Seminar Intell. Technol. Appl. (ISITIA), Surabaya, Indonesia, Aug. 2019, pp. 348-353.

[24] Y. S. Can, N. Chalabianloo, D. Ekiz, J. Fernandez-Alvarez, G. Riva, and C. Ersoy, ``Personal stress-level clustering and decision-level smoothing to enhance the performance of ambulatory stress detection with smartwatches," IEEE Access, vol. 8, pp. 38146-38163, 2020.

[25] A. de Santos Sierra, C. S. Avila, J. G. Casanova, and G. B. del Pozo, ``A stress-detection system based on physiological signals and fuzzy logic," IEEE Trans. Ind. Electron., vol. 58, no. 10, pp. 4857-4865, Oct. 2011.

[26] J. Choi, B. Ahmed, and R. Gutierrez-Osuna, ``Development and evaluation of an ambulatory stress monitor based on wearable sensors," IEEE Trans. Inf. Technol. Biomed., vol. 16, no. 2, pp. 279-286, Mar. 2012.

Appendix A: Gantt Chart