Emotion Detection System using Skin Temperature and Heartbeat for Healthcare Applications

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***Abstract*—Mental health is a very important aspect of an individual's overall health scenario. Human beings are complex creatures that experience a large range of emotions, and when one is unable to express these emotions, it affects them both mentally and physically. Diseases or accidents could result in a medical condition called paralysis, which may render an individual incapable of doing mundane everyday activities, and even expressing themselves may become difficult. This emotion detection system uses a Raspberry Pi and two non-invasive sensors- Body Temperature and Electrocardiogram sensor- to collect data from a user and send it to the IoT analytics platform "Thingspeak". The initially generated data is used to train a machine learning model that uses the Random Forest Classifier predominantly and returns the emotion value of the user depending on his/her collected body temperature and ECG value. This result is displayed on an interactive dashboard.**

Keywords—Paralysis, Emotion Detection, Raspberry Pi, Body Temperature, Electrocardiogram, IoT, Machine Learning

I. INTRODUCTION

People connect and socialize with one another to convey their emotions. Technology is employed to complete the difficult work of studying how to understand them. Whether one is conscious of it or not, our emotions are always on display. Every time humans engage with each other, whether consciously or unconsciously, emotional states are interpreted. The topic of granting computers access to this kind of private and intimate information has become touchy in recent years, especially in light of the development of surveillance and facial recognition technologies. The technology that might make it possible for computerized human emotion identification has a good side, though. Recent technological breakthroughs have generated a lot of interest in the field of deep learning and machine learning for the purpose of recognizing the patient's emotions. Building intelligent healthcare facilities that can recognize depression and stress in patients and begin treatment early may benefit from automatically identifying the emotions. One of the most intriguing subjects is the use of cutting-edge technology to recognize emotions because it defines the interactions between people and robots. By using a variety of techniques, machines have learnt to anticipate emotions. IoT has played a significant role in a number of healthcare applications, including real-time health systems, smart care, smart medicines, and personal healthcare. There are no universally applicable criteria to identify mood swings because every person responds differently to various circumstances. Nonetheless, there are several distinctive characteristics that offer accuracy in regard to emotion identification. Emotional regulation is a crucial area of medicine. There has already been a great deal of study in this area that focuses on identifying emotions through physiological signals like the ECG, sweat, and skin conductance value, among others. Emotions and EEG: EEG signals are used to study the neurological system and provide data on various emotional states; Face expressions can convey a variety of emotions, and image processing techniques are employed to identify changes in facial expressions; Speech-based emotions: Voice recognition technologies track speech tonality and provide information about emotions; Text-based emotions: based on words and sentences spoken in conversation, for instance [2]. Deep learning is used in several scenarios for identifying various emotions in acoustic voice signals. Convolutional Neural Networks (CNN) are also thought to be a viable approach for categorizing speech emotions. The detection of various emotions using acoustic signals can be improved by paying closer attention to further study of sound properties including pitch, frequency, and Zero-crossing rate (ZCR) [3]. Many automatic emotion identification techniques have been developed as a result of years of scientific study. Using technology from various fields, including machine learning, signal processing, speech processing, and computer vision, researchers propose and assess various methodologies. In the past, algorithms for emotion recognition included Maximum Entropy, Support Vector Machine (SVM), and Naive Bayes. Modern cutting-edge algorithms are built on deep learning a few instances. Deep convolutional neural network (CNN) that lowers photos to 4848 pixels, applies two convolution-pooling layers, and identifies face landmarks from data [12]. In a study conducted on people with facial paralysis titled "Communicating without the Face: Holistic Perception of Emotions of People with Facial

Paralysis" by Kathleen Bogart, Linda Tickle-Degnen, and Nalini Ambady, [21], on examining the perceiver's emotion judgment of videos of people suffering from facial paralysis led to the conclusion that an inexpressive face with an expressive body has resulted in unfavorable perceptions of people experiencing significant facial paralysis. Although they suggest a holistic approach that relies on various other facial features excluding facial expression, it has to be noted that only a well-trained professional will be able to detect emotions of another individual in this manner. While these may be techniques that can help in treatment methods and implementation of mental health improvement strategies, when one's closest kin are unable to understand their emotional state due to any kind of health conditions, their mental and physical health may deteriorate. This is where an emotion detection system that uses non-invasive sensor values to detect an individual's emotion can contribute.
The aim of this study is to develop an emotion detection system that utilizes skin temperature and ECG (Electrocardiogram) values to accurately and non-invasively detect and classify human emotions. The system aims to leverage physiological changes in skin temperature and ECG signals that are known to be associated with different emotional states to provide a robust and reliable means of emotion detection. The primary objective is to design a system that can accurately classify emotions, such as happiness(excited), sadness, anger, and normal(relaxed) based on changes in skin temperature and ECG signals. Another objective is to evaluate the performance of the emotion detection system using statistical analysis, and comparison with existing emotion detection techniques. The system's accuracy, sensitivity, specificity, and overall performance will be thoroughly assessed to ensure its reliability and validity. The ultimate objective of this research is to contribute to the field of emotion detection by developing a reliable and non-invasive system that can accurately detect and classify human emotions using skin temperature and ECG values. The findings from this study may have potential applications in fields such as psychology, human-computer interaction, and healthcare, with implications for emotion recognition in various contexts, including virtual reality, affective computing, and mental health assessment

The remaining sections of the study have been organized as follows. Section 2 describes objective of this study. Section 3 describes motivation behind this study while section 4 showcases the Literature Survey. Section 5 describes Project Summary while Section 6 describes the Proposed System. Section 7 describes Implementation details while Section 8 Results and Discussion. Section 9 describes Conclusion and Future work.

II. LITERATURE SURVEY

Daniela Girardi et al, 2017 [1] conducted research with 19 participants and employed non-invasive, cost-effective EEG, EMG, and GSR sensors to evaluate valence and arousal in a cross-subject classification situation with outstanding results. This method for emotion recognition is effective and affordable since it does not require individual training and tuning of classification models. Kaur Guneet et al, 2018 [2] employed temperature and heart rate readings from sensors to train a machine learning algorithm. They used the Naive Bayes Classifier to detect patterns of body temperature and heart rate in various individuals. Additionally, they trained a KNN model for comparison and achieved 84% accuracy. Zeenat Tariq et al, 2019 [3] proposed a system for real-time emotion recognition that was unveiled by combining voice signals, deep learning technologies, and the Internet of Things (IoT). The system's goal is to help with the care of senior citizens residing in nursing homes. In order to record human speech and use deep learning to predict emotions, the researchers used audio IoT. Using the Speech Emotion Detection (SED) integrated deep learning model, they were able to achieve an accuracy of roughly 95%. Muhammad Tauseef Quazi, 2012 [4] developed a system that, with an accuracy rate of 86.25%, recognized emotions using physiological inputs from a skin temperature sensor, heart rate sensor, and skin conductance sensor. Fiona Victoria Stanley Jothiraj et al, 2022 [5] proposed a system specifically for people with autism spectrum disorder and devised a low-cost IoT device that records patients' emotion. The system makes use of cloud computing capabilities as well as sensors that track heart rate, perspiration, and heartbeats per minute. The device only managed to reach a 92% accuracy rate while at rest. Kahil Mustafa Jamal S et al 2019 [6] illustrated prospective techniques for emotion detection combining mobile computing and face skin temperature by conducting an experiment with 20 healthy participants. They employed an Artificial Neural Network (ANN), notably the Multilayer Perceptron (MLP), as a classifier and visual and audio inputs to elicit emotions. The group's accuracy rate was 88.75%. Christie et al, 2002 [7] used ECG signals to look at the locations of distinct emotions in a dimensional affective state space. They found that classic dimensional emotion models effectively captured the state space for self-reported emotion but needed adjustment for ANS activity. They did this by using pattern classification and discriminant function analysis. Andreas Haag et al, 2004 [8] used a technique for teaching computers to recognize emotions. It makes use of numerous inputs from several biosensors. They were able to identify emotion arousal and valence with high accuracy rates of 96.6% and 89.9%, respectively, using a neural net classifier. Ahsan Noor Khan et al, 2021 [9] collected pulse and breathing information via RF reflections off the body. They suggested a DNN architecture that included unprocessed and processed RF signals for emotion state categorization and applied unique noise filtering techniques. The accuracy of their approach was quite good (71.67%). Maria Egger et al, 2019 [10] found that accuracy of emotion detection varies depending on the quantity of emotions recognized, the features extracted, the classification method, and the caliber of the database utilized, according to comparison of multiple emotion recognition techniques. They found that electroencephalography had an accuracy of 88.86% for identifying four emotions, multimodal measurements had an accuracy of 79.3% for identifying four emotional states, facial recognition had an accuracy of 89% for identifying seven emotional states, and speech recognition had an accuracy of 80.46% for identifying joy and sadness. Raquel Tato et al, 2002 [11] used a technique to increase the precision of emotion identification by utilizing emotional space. Their strategy and experimental findings that show how the usage of emotional space might improve emotion detection are probably detailed in their publication. Ali Mollahosseini et al, 2016 [12] used a novel deep neural network model that integrated convolutional and fully connected layers to extract high-level information from face photos which was introduced in their study. They demonstrated that their strategy outperformed previous approaches by testing it on datasets of typical face expressions. Hafsa Mahin et al, 2020 [13] introduced a new technique for emotion identification that combines facial expressions with physiological markers such as the ECG, GSR, and temperature. The accuracy of emotion detection achieved by the authors ranged from 71% to 86%, depending on the kind of physiological input employed, and was accomplished using feature extraction techniques and machine learning algorithms, such as SVM, KNN, and MLP. In comparison to utilizing just facial expressions, they discovered that the combination of physiological signals with facial expressions increased the accuracy of emotion detection. Foteini Agrafioti et al, 2012 [14] suggested using ECG signals in emotion identification. They also did a thorough examination of the psychological characteristics of the signals. They stated that individualized emotion recognizers are necessary in order to capture the fleeting variations in ECG signals from their baseline. They recommended collecting information from each mode, such as local oscillations and instantaneous frequency, in order to detect dynamic emotion patterns in ECG. Kaushal Kanakia et al. (2018)[15] used Haar cascades for emotion detection from facial regions of interest (ROI), followed by feature extraction and processing using OpenCV and Python. They also used remote photoplethysmography for detecting heartbeat. Ch. Ravisankar et al 2019 [16] explored the use of skin temperature and heart rate values obtained from temperature and pulse sensors, respectively, to identify emotions using an AI algorithm. The study found that individuals respond differently in various situations, indicating that there are no generalized parameters for monitoring mood swings. The field of emotion detection has seen a lot of research focused on utilizing various physiological signals such as ECG, sweat, and facial expressions for accurate emotion recognition. Eiman Kanjo et al. (2019) [17] utilized a deep learning methodology to classify emotions, employing a repetitive process incorporating and excluding sensor signals from different sources. They gathered real-time data from smartphones and wearable devices and implemented Convolutional Neural Networks and Long Short-term Memory Recurrent Neural Network (CNN-LSTM) on unprocessed sensor data, eliminating the necessity for manually extracting data features. T Dissanayake et al. (2019) [18] used an ensemble learning technique for emotion recognition using ECG signals. The authors combined four ECG-based feature extraction methods, consisting of heart rate variability, empirical mode decomposition, within-beat analysis, and frequency spectrum analysis, to identify four major emotions: anger, sadness, joy, and pleasure. Zhongli Bai et al. (2023) [19] collected EEG signals from hearing-impaired subjects while they watched emotional video clips and converted frequency domain features into spatial domain using biharmonic spline interpolation. The classification accuracies using different features were improved compared to traditional methods. Dahua Li et al. (2022) [20] aimed to categorize expressions of emotions in individuals with impaired hearing based on facial expressions and signals generated by an EEG sensor. They generated EEG topographic maps (ETM) from differential entropy (DE) features of collected EEG signals. The average classification accuracy after multimodal fusion was higher compared to facial expressions or EEG signals alone.

III. PROPOSED SYSTEM

This emotion detection system aims to detect human emotions and analyze them in order to intervene at an early stage to prevent potential harm to an individual's health. The system utilizes sensors to continuously collect data on body temperature and heart rate, which is then sent to a Raspberry Pi. The data is further transmitted to a cloud-based gateway, where it is stored for analysis. The system employs a Random Forest classification algorithm for machine learning, using the collected data to train the algorithm to recognize four different emotions: happy (excited), normal (relaxed), sad, and anger. The data is collected from sensors such as temperature sensor and ECG sensor, and transmitted to ThingSpeak, an IoT cloud platform, through a Wi-Fi module in built in the Raspberry Pi using TCP/IP protocol. The communication follows a mesh network architecture. The data retrieved from ThingSpeak in CSV format is then subjected to the proposed machine learning algorithm for analysis. The system thus proposed can be further visualized through Figure 1.

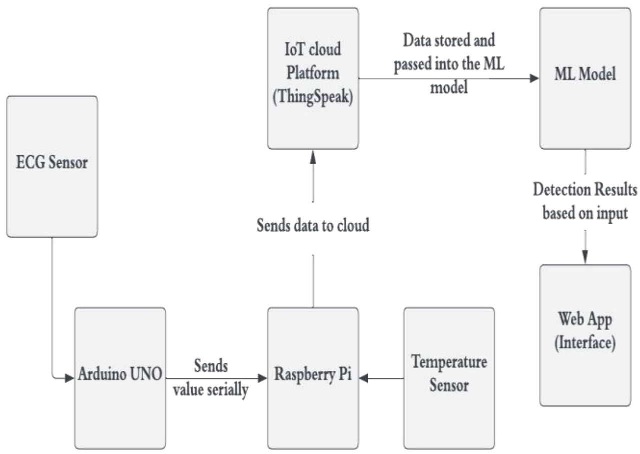

Fig 1: Block Diagram of the Emotion Detection System using Skin Temperature and Heartbeat for Healthcare Applications

IV. IMPLEMENTATION DETAILS

A. Hardware

This emotion detection system begins with data generation using sensors such as the ECG sensor (AD8232) and the temperature sensor (DS18B20). The AD8232 is a signal conditioning block specifically designed for biopotential measurements, including ECG, in noisy environments. It collects, amplifies, and filters small biopotential signals. The

DS18B20 is a temperature sensor that can measure temperatures from -55°C to +125°C with an accuracy of ±0.5°C within a range of -10°C to +85°C. These sensors are interfaced with the Raspberry Pi and Arduino.
The ECG sensor (AD8232) records heartbeat values and has pins for SDN, LO+, LO-, output, 3.3V, and GND connections. The ECG sensor is connected to the Raspberry Pi through the Arduino to convert analogue values to digital values. The LO+ pin indicates if only the left or right arm is disconnected, while the LO- pin indicates if the right arm is connected.
A temperature sensor (DSB1820) is used to record skin temperature, which has GND, VCC, and data pins. It can measure temperatures between -67oF and +257oF with 5% accuracy. The temperature sensor is directly connected to the Raspberry Pi, with the GND pin connected to the Raspberry Pi's GND, the 3.3V pin connected to the 3.3V pin of the Raspberry Pi, and the data pin connected to gpio 4 pin.

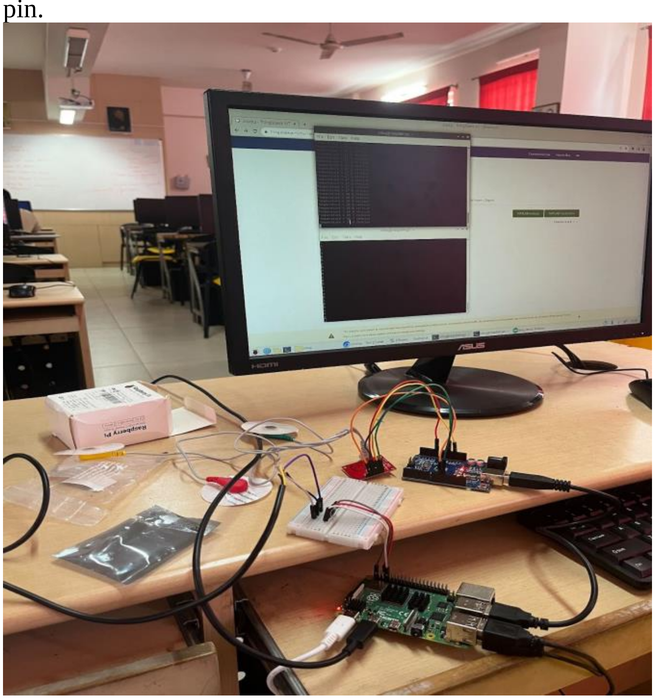

Fig 2: Hardware setup of Raspberry Pi with a Monitor and Sensors

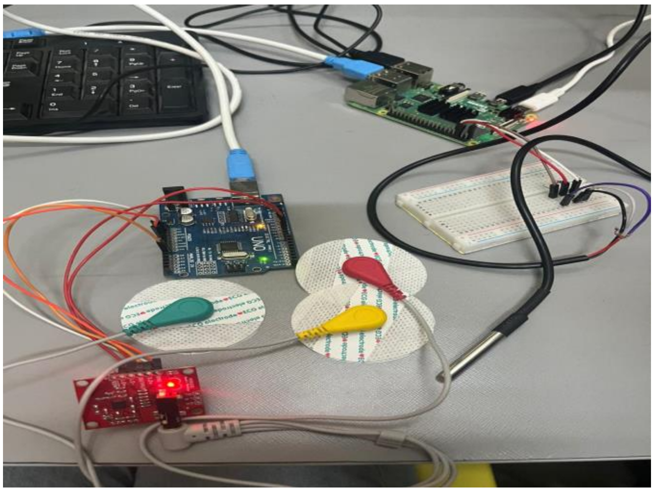

Fig 3: Raspberry Pi, Temperature sensor, ECG sensor connections.

Arduino interfacing is required for a sensor like ECG because it returns analogue output while the system requires digital and this is a method that can be used to convert said values to the required format
Figure 2 and 3 both show the overall hardware setup of the system. Figure 2, shows the Raspberry pi has been connected to a monitor and the used sensors, while figure 3 displays the sensor connections alone.

B. Software

1) Cloud Platform:

Data generated by the sensors is sent to the Thing Speak IoT cloud platform, where the recorded data values are converted to a csv file. This platform is used to store the data generated.

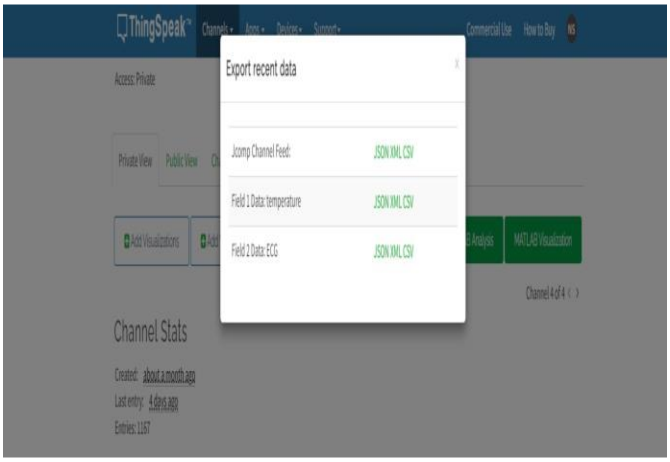

Fig 4: Interfacing with Thing speak

Figure 4 depicts the interface on ThingSpeak where the data collected from the sensors can be exported in various formats like json, xml or csv as required by the user.

2) Machine Learning Model:

For emotion classification, an ML model using the Random Forest algorithm has been implemented. It performs both regression and calculation, which classifies emotions more accurately and thus results in better output. It is an ensemble learning technique that combines several decision trees to provide predictions that are more precise than those produced by a single decision tree. The generated dataset was split in an 80-20 ratio for training and testing. The ML model is interfaced into a web application with the help of Python Streamlit.

The algorithm of the model selected:

RandomForestClassifier(n_trees, max_depth, n_features, n_samples, criterion)
Inputs:
n_trees: Number of trees in the forest
max_depth: Maximum depth of each decision tree
n_features: Number of features to consider at each split
n_samples: Number of samples in the bootstrapped sample for each tree
Criterion: Splitting criterion (e.g., Gini impurity or entropy)
Output:

A trained Random Forest classifier

Procedure Random Forest:

Input: Training data X, labels y

Output: Trained Random Forest classifier

Step 1: Initialize an empty list to store the decision trees

For i in range(n_trees):

Step 2: Bootstrapped Sampling

Randomly sample **n_samples** examples from X with replacement, along with their corresponding labels y

X_bootstrapped, y_bootstrapped = bootstrapped_sampling(X, y, n_samples)

Step 3: Decision Tree Construction

Create a decision tree using **X_bootstrapped, y_bootstrapped** with a maximum depth of max_depth, considering n_features features at each split, and using the specified splitting criterion

Step 4: Feature Randomness

Randomly select **n_features** features for the decision tree

selected_features = random_select_features(n_features, X_bootstrapped)

decision_tree.set_selected_features(selected_features)

Add the decision tree to the list of trees in the forest

add_to_forest(decision_tree)

Return the trained Random Forest classifier

Procedure Predict:

Input: Test data **X_test**

Output: Predicted class labels **y_pred**

Step 5: Initialize an empty array to store the predicted class labels y_pred

For each decision tree in the forest:

Step 6: Prediction

Predict the class labels for **X_test** using the decision tree

y_pred_tree = decision_tree.predict(X_test)

Add **y_pred_tree** to **y_pred**

Step 7: Ensemble Prediction

Compute the mode (most common) of the predicted class labels across all trees as the final predicted class labels

y_pred = mode(y_pred)

Return y_pred

V. RESULT AND DISCUSSION

On the basis of a person's temperature and heart rate, this system will be able to forecast his or her emotional states using the Random Forest Algorithm. As described in section V, the values generated from the sensors are then forwarded to the cloud platform- ThingSpeak, from where it is exported as a csv file, which is used for further analysis.

Figure 5 and 6 depict the real time temperature output received from the DS18B20 sensor. The commands required to open the temperature sensor directory followed by the raw temperature readings displayed on the terminal of the Raspberry Pi can be seen in the former. The values collected in real time with a delay of a few microseconds displayed in both Celsius and Fahrenheit is depicted in the latter.

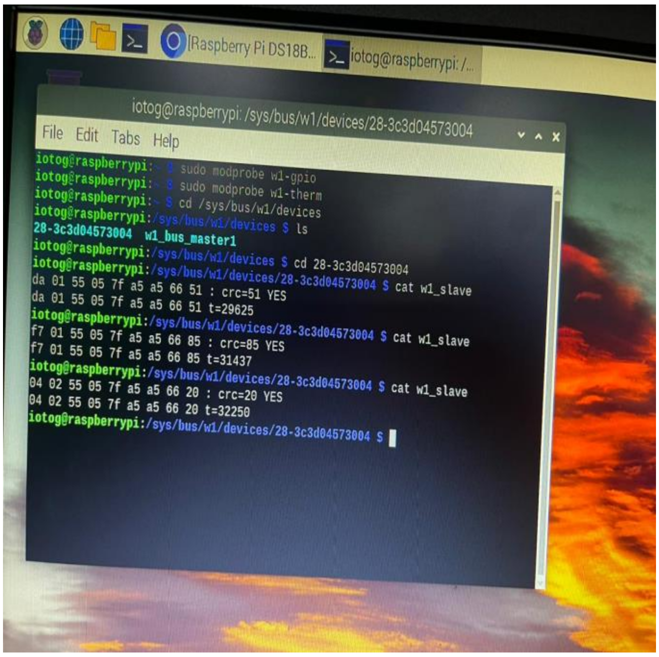

Fig 5: Serial Monitor Output for Temperature Sensor

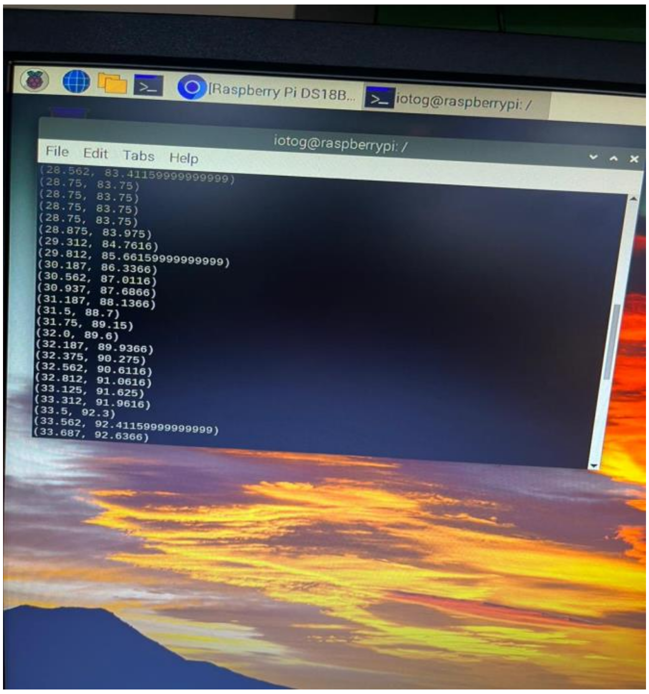

Fig 6: Real Time Temperature Outputs

In figure 7, the real time heart rate values returned by the ECG sensor displayed on the terminal of the Raspberry Pi can be seen.

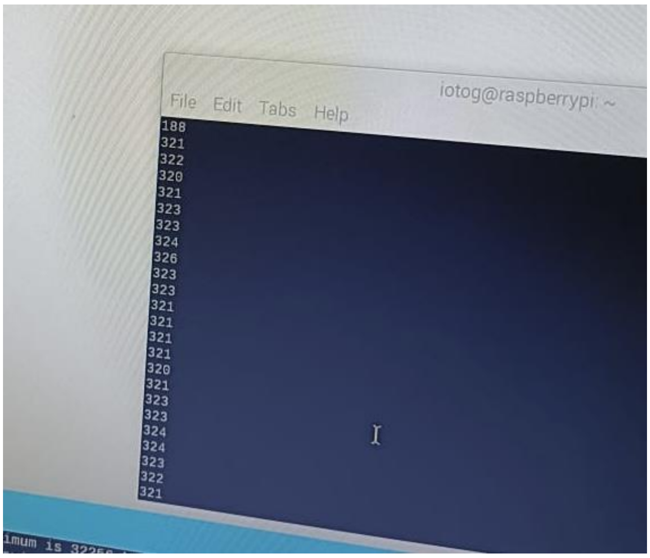

Fig 7: Serial Monitor Output Displaying ECG values

The system uses Random Forest algorithm to classify emotions using the generated dataset. It classifies data into 4 emotions: happy (excited), sad, normal (relaxed), and anger.

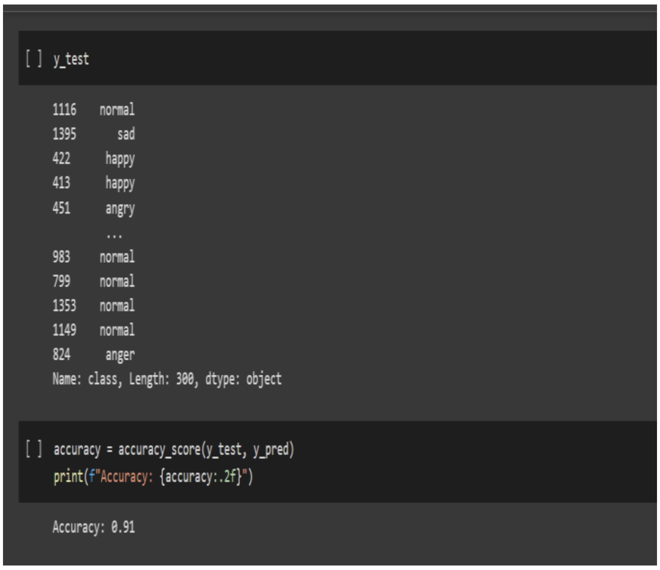

Fig 8: Accuracy depiction of the Random Forest model

As seem in figure 8, the application of Random Forest classifier returns an accuracy score of 91%. This model has been selected as an ideal classifier for this scenario as it performs both regression and classification. Regression is necessary in this scenario as prediction for given input parameters is also done, along with the classification of outliers with the general dataset. Another factor that contributed to selection of this model was the comparison results with other Machine learning models. Five multiple classification algorithms, namely Naïve Bayes, KNN, Decision Tree, LightGBM and Random Forest have been used for comparative study. These algorithms in particular have been opted for as they are multiple classification algorithms and are used to classify data into more than 2 classes. Following the implementation of emotion classification using the above 5 algorithms, it has been concluded that Random Forest will be the best suit for this system based on accuracy. Naïve Bayes algorithm returned an accuracy of 58%, KNN algorithm resulted in 86.33%, Decision Tree resulted in an accuracy of 69%, LightGBM algorithm resulted in an accuracy of 88.44% and Random Forest algorithm resulted in an accuracy of 91%. The accuracy of the compared models, which when compared to the 91% returned by the Random Forest Classifier, is not optimal

Figure 9 shows the bar graph representation of comparison of accuracies of all the models implemented. Accuracies of each model has been plotted, where the x-axis shows the model's name and y-axis contains the accuracy percentage of corresponding model.

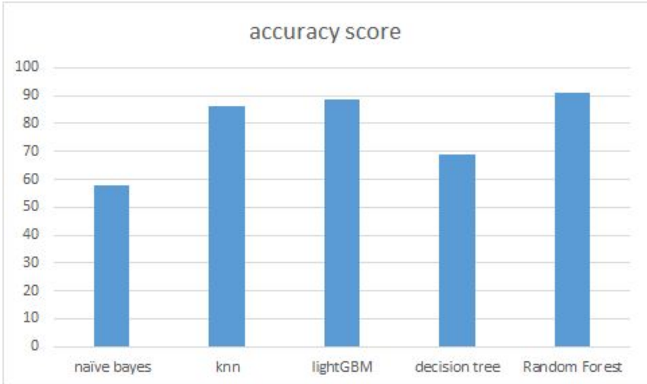

Fig 9: Accuracy Comparison of Different Models Considered

The system uses Streamlit framework for its web-based app interface. The data generation and ML modules of the system have been interfaced with a user-friendly web dashboard where the user may observe detected emotion value and the trends in temperature and heartbeat.

Figures 10,11 and 12 show the developed dashboard. Body temperature and heartbeat are taken as input to return the detected value as output to the user, which is displayed in figure 14. The historic temperature and ECG values recorded can be viewed and analysed by the user on scrolling further down on the application page. This is displayed in figures 11 and 12 respectively. The number of temperature and ECG values displayed can be varied according to user requirement.

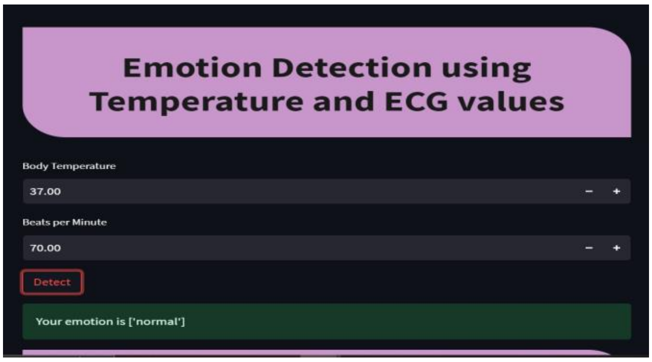

Fig 10: Dashboard reading input values

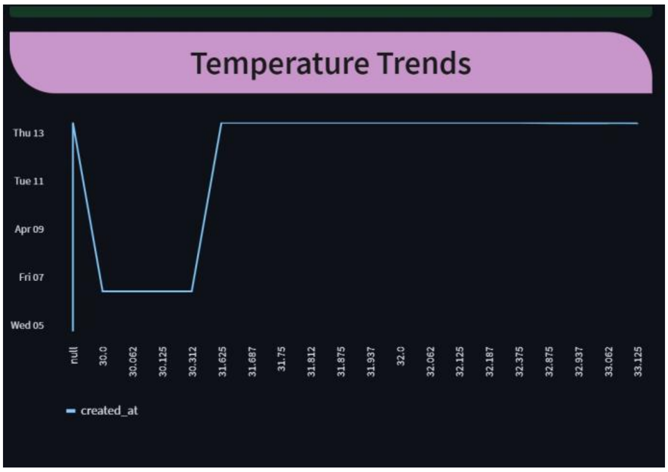

Fig 11: Temperature trends on the Dashboard

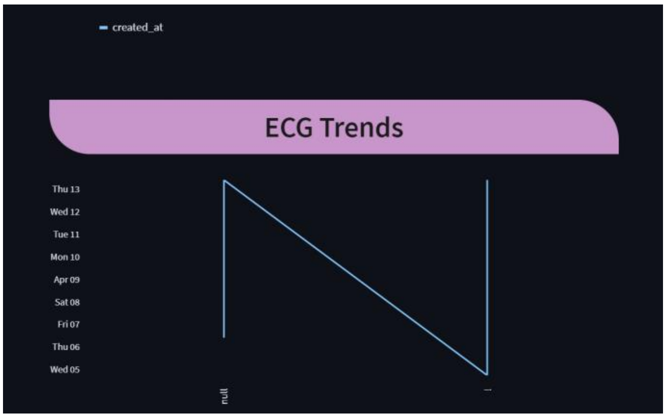

Fig 12: Heart Rate Trends on the Dashboard

The outcome of this study can be compared to the selected base paper [1] (see Table 1). The goal of authors of [1] were to use noninvasive and low-cost sensors in order to recognize various emotions. For this purpose, they used galvanic skin response (GSR), electroencephalography (EEG), and electromyography (EMG) sensors to find physiological signals associated with emotional states. They aimed to find the physiological measure that would be most suitable for a given emotion and this would be used to test their models and emphasize the importance of their goal in the healthcare domain. Out of all the algorithms they had used, they found out that SVM was the best machine learning algorithm for both arousal and valence detection.

For the given application, ECG sensors and temperature sensors are easier to use and are widely available. Temperature sensors provide information about the changes in the emotional arousal in the human body. It is known that temperature sensors and ECG sensors are portable and less expensive compared to EMG, GSR, and EEG sensors which makes the former a popular choice for projects. This emotion detection system uses ECG and temperature sensors in such a way that it could be applicable to a wider range of applications in healthcare which could lead to reduced cost and improved patient outcome. Furthermore, their work is more complex. This study got an accuracy of 91% using Random Forest algorithm but their work got F1-scores ranging from 0.563 to 0.638 depending on the sensor settings so this study has more accuracy compared to the base paper.

	Model	**Sensors Used**	**Accuracy**
[1]	SVM	EEG, EMG, GSR	56.3% - 63.8%
Proposed System	Random Forest	Temperature sensor, ECG	91%

Table 1: Comparison with the performance reported in the base paper [1]

VI. CONCLUSION AND FUTUREWORK

Emotion recognition using non-invasive sensors like a skin-temperature sensor and an ECG sensor finds its application in scenarios where any medical condition, disease, or accident may have rendered an individual paralyzed or in a situation where they may be unable to express their emotions freely using speech and expression. Therefore, as healthcare related technology evolves, a system that can help maintain the mental, and, in turn, physical health of any individual will prove to improve lives. The implemented system successfully takes temperature and ECG values as sensor inputs, stores this data on the cloud, displays it on an interactive dashboard, and returns the particular emotion value detected. The model, designed using the Random Forest Classifier algorithm, has an accuracy score of 0.91 after being trained and tested with data collected in real time by the sensor system. It is of utmost importance for any system that has applications in the healthcare industry to have quick response time and high accuracy. The accuracy of the system may be increased by including other non-invasive sensors like a GSR (Galvanic Skin Response) sensor or an EEG (electroencephalogram) sensor as these sensor values can also contribute to detection of emotion. The dashboard may be improved by modifying it to not just display sensor value trends but also to display real time emotions detected based on these sensor values.

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