AISSMS
INSTITUTE OF INFORMATION TECHNOLOGY
ADDING VALUE TO ENGINEERING

A

PROJECT REPORT ON

EMOTION RECOGNITION SYSTEM IN HEALTH CARE APPLICATION USING IOT

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE
IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE

OF

BACHELOR OF ENGINEERING

IN

(ELECTRONICS AND TELECOMMUNICATION)

BY

Revan Subhash Patil	**Exam No: 71708779E**
Omkar Satish Tingre	**Exam No: 71708903H**
Kaushal Shailendra Pathak	**Exam No: 71708773F**

UNDER THE GUIDANCE OF

Prof.Varsha Patil

Department of Electronics and Telecommunication

AISSMS INSTITUTE OF INFORMATION TECHNOLOGY,

[2019-2020]

CERTIFICATE

This is to certify that Project Entitled

" Emotion Recognition System in Healthcare Application Using IoT"

Submitted By

Revan Subhash Patil	**Exam No: 71708779E**
Omkar Satish Tingre	**Exam No: 71708903H**
Kaushal Shailendra Pathak	**Exam No: 71708773F**

is the record of bonafide work carried out by them in partial fulfillment of the requirement for the award of the Degree of **Bachelor of Engineering (Electronics and Telecommunication)**, as prescribed by the Savitribai Phule Pune University in the Academic Year 2019-2020

This project report has not been earlier submitted to any other Institute or University for the award of any degree or diploma.

(Prof.Varsha Patil)
Internal Guide
Department of E&TC Engg.

(Dr.M.P.Sardey)
Head
Department of E&TC Engg.

External Examiner
Date:

(Dr. P. B. Mane)
Principal,
AISSMS, Pune

Place: Pune.
Date: / /2020

Acknowledgment

It is my great pleasure in expressing sincere and deep gratitude towards my guide "**Prof.Varsha Patil**", Assistant Professor Electronics & Telecommunication Engineering Department for her valuable guidance and constant support throughout this work and help to peruse additional studies in machine learning using java

I take this opportunity to thank Head of the Department HOD **Dr.M.P.Sardey** and Project coordinator **Prof. Vineeta Phillip** and all staff members of department of Electronics &Telecommunication Engineering AISSMS IOIT, Pune, for cooperation provided by them in many ways.

The motivation factor for this work was the inspiration given by our honorable principal **Dr. P.B.Mane.**

Lastly I am thankful to those who have directly or indirectly supported for our work.

Revan Subhash Patil

Omkar Satish Tingre

Kaushal Shailendra Pathak

(B.E. E& Tc.)

Abstract

There is a growing interest and need for the detection of the emotion of a particular individual in various circumstances and locations such as Airport, Hotel Lobbies, Railway Stations, prison cells, etc. This is might be because of there is always a chance that someone with unhealthy motives would create some mishap. It is also useful in situations such as interrogations and lie detector tests to identify the emotion of the person being monitored. The recognition of the motion is highly difficult and requires the use of expertise and a human being utilized for the purpose of identifying the emotion is not always accurate and can be biased towards the individual. Most of the approaches that have been implementing various sensors and facial recognition have a lot of limitations along with lackluster performance that has left a lot to be desired from the conventional emotion recognition applications. Thus, the proposed system addresses these concerns by taking a step towards outlining a system that can automatically identify human emotions with the help of various parameters such as ECG signals, body temperature, and heart rate by using Dataset and Real-time Hardware Sensors. The proposed methodology implements K-means clustering, artificial neural networks, and Fuzzy classification to achieve highly accurate emotion classification.

Keywords: K-Means Clustering, Artificial Neural Network, Fuzzy Classification, Emotion Detection.

Contents

List of Figures

List of Tables

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Social Intelligence has been increasingly getting more attention nowadays as most of the communication is highly reliant on the social intelligence of an individual. It is a valuable addition that helps in decision making as well as understanding and responding to various human behaviors. Before communication who was done entirely through language, early humans developed these skills inherently. Early humans were very limited in their vocabulary since language was not as developed at an early age. The early humans were highly adept in understanding patterns and deciphering a lot of different gestures and actions. This allowed humans to interact with each other without having a structured language.

Basic human emotion recognition is built into humans. As humans have utilized emotion recognition for communication before the invention of spoken language. Language is being constantly evolved and developed through different ages and is becoming highly in highly complex as there are words needed that describe a particular expression or an event in their lives.

Every year more and more words are being added to dictionaries to keep up with our expanding vocabulary. Therefore, the primary forms of communication are heavily reliant on emotion recognition. This is also made worse with the fact that most of our communication even right now with highly diverse language is actually highly dependent on gestures.

Emotion recognition is highly necessary as it allows us to understand the inner intentions of a particular human being. As people can be highly deceiving by just concentrating on their verbal communication. Whereas the nonverbal form of communication is one of the most prominent that utilizes body postures gestures and facial expressions and various actions performed by the person and takes into consideration the emotional state of the person. This allows for much more accurate communication between two individuals. Therefore, it is imperative to understand the nonverbal part of the communication as an essential aspect of communication.

Facial expressions are an important mechanism that allows for the identification of an emotional state of a human being. Human being displays a varying degree of emotion to facial expressions in their everyday life. There are a plethora of different emotions that are expressed by a human being out of which certain emotions are highly important and are universal to all human beings, such as, anger discussed fear surprise sadness and happiness. These are the key emotions that Guide a particular human beings' life. One of the are the most important muscles are the facial muscles that help convey touch emotions with wearing facial expressions.

Automatic identification of facial expressions which can lead to recognition of human emotions is very difficult to be performed by computer whereas most of the humans can recognize facial expressions without any significant effort or delay. The facial expression system is a system that is utilized for the recognition of facial expression. For this application, one of the best techniques is to perform deep learning through various artificial intelligence methodologies. Image processing plays a vital role in the identification of facial expressions. The image processing paradigm has the ability to convert any image into the digital form and perform various operations that can extract valuable information from that image.

Artificial neural networks are one of the most accurate implementations for the purpose of prediction. These algorithms are highly tailored to provide efficient and Secure computation. Artificial neural networks are inspired by the various neural pathways that form the human brain. These characteristics make the artificial intelligence platform highly act for the purpose of facial expression and emotion recognition. Artificial neural networks require a lot of data to be able to function accurately and the amount of data can help increase the accuracy of the methodology. due to the fact, that is due to the fact that these artificial neural networks are designed according to the human brain to help provide an edge in emotion recognition.

Wireless sensors or wireless sensor networks are a highly useful branch of science that has been getting a lot of advancements lately. These have allowed the creation of an innovative new paradigm called the internet of things or IoT. BRT platform facilitates the use of various sensors that can acquire and collect the data and send it wirelessly for processing and storage. The increasing number of sensors such as temperature, pulse, and ECG allows for the monitoring of a variety of different parameters wirelessly. These parameters are highly crucial for the purpose of emotion recognition. This combined with the might of artificial neural networks and supplemented by the fuzzy classification platform can achieve very highly accurate emotion recognition.

1.1.1 Motivation

Human can recognize emotions without any significant delay and effort but recognition of facial expression by machine is a big challenge. The system which performs recognition of facial expression is called facial recognition system. Image processing is used for Facial expression recognition. With the help of image processing useful information from image can get extracted. Image processing converts image into digital form and perform some operations on it to extract useful information from image. Static image or image sequences are used for facial expression recognition.2-D gray scale facial image is most popular for facial image recognition although color images can convey more information about emotion such as blushing. In future color images will prefer for the same because of low cost availability of color image equipment's. For image acquisition Camera, Cell Phone or other digital devices are used.

1.1.2 Goals

- Accurate collection of data from sensors.
- Efficiently identify and categories human emotion.

1.1.3 Expected Outcome

Emotion Level Prediction.

1.2 Organizations of The Project

Following sections are dedicated as the further steps of the report

- Section 2: Literature Survey
- Section 3: Aim and Objectives
- Section 4: Block Diagram of The System and Its Explanation
- Section 4: Hardware Design
- Section 5: Software Design
- Section 6: Operating Instructions
- Section 7: Test Results
- Section 7: Conclusion and Future Work

CHAPTER 2

LITERATURE SURVEY

Aravind E Vijayan [1] proposed a novel approach towards emotion recognition based on EEG signals using statistical measures such as Shannon entropy and cross-correlation along with autoregressive modeling. The raw EEG signals are pre-processed to remove artifacts. The processed signal is bandpass filtered and the filtered signal is decomposed into the five bands of brain wave namely, alpha, beta, gamma, theta and delta using wavelet decomposition. The EEG epochs that strongly represent the particular emotion are then selected as features using Shannon Entropy and Cross-correlation between signals. The algorithm is implemented in MatLab and used offline EEG data provided in the DEAP dataset. Emotions like excitement, sadness, happiness, and hatred were categorized utilizing Multi-Class SVM and 94.097% accuracy was obtained.

AayushBhardwaj presented a model based on Independent Component Analysis, Support Vector Machine and Linear Discriminant Analysis. SVM and LDA are used to categorize emotions into seven classes namely happy, sad, anger, disgust, neutral, fear and surprised. Emotions were recalled in the subjects by showing them pictures and EEG signals corresponding to those events were recorded. These signals were then processed to extract relevant features and then fed to the two classifiers [2]. The features considered for this study are Energy and Power Spectral Density (PSD). From the class-wise accuracy analysis, it is observed that happy and sad emotions are recognized with the best accuracy. SVM can recognize happy and sad emotions with an accuracy of 87.5% and 92.5% respectively whereas the accuracy fell to 82.5% and 87.5% respectively in the case of LDA. Also, the SVM model is better as compared to LDA as a classifier.

Sananda Paul introduced a classifier named as SVM to distinct the EEG feature space related to numerous emotional states into their respective classes. They used audio stimuli to elicit positive emotions like (happy, romantic) and negative emotions like (disgust, sad). Here EEG signal is recorded from the subjects for each happy, sad, romantic and disgust type of audio tracks for 30 sec [3]. The features are derived for the frequency band of 8-30Hz of EEG signal using MultifractalDetrended Fluctuation Analysis (MFDFA) and extracted feature set is classified using the following classifiers: Support Vector Machine (SVM), Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA) and K Nearest Neighbor (KNN) from EEG signal. The experimental results showed that the performance of SVM is better than other classifiers such as QDA, LDA, and KNN.

Wei-Long Zheng [4] introduced deep learning technologies to deal with the problem of critical frequency bands and critical channels for effective EEG-based emotion recognition. The authors applied the DBN models to the construction of EEG based emotion recognition models for three distinct groups of emotions named as positive, neutral and negative.

The 62-channel EEG signals are recorded from 15 subjects while they are watching emotional film clips with a totally of 30 experiments. After training the DBN models with the DE characteristics from multichannel EEG data, the authors presented a DBN-based technique to choose meaningful critical channels and frequency bands through the weight distributions of the trained DBNs and have designed distinct profiles of electrode sets. The experimental outcome showed that the DBN models obtained larger accuracy and lower standard deviation than those of shallow models such as KNN, LR, and SVM methods.

Shiyu Chen proposed a new approach to classify emotions from peripheral signals with the help of EEG signals. The presented technique first extract features from peripheral signals and EEG signals. Then in the training phase, a new feature space is created for peripheral features using CCA with the help of EEG features and uses the new feature to train an SVM classifier [5]. In the test phase, the extracted peripheral features are mapped to the new feature space. Then, the emotional state is predicted for each sample based on the new features.

The EEG features are only available during training to help the peripheral features to construct a better feature space as privileged information. Experimental results on two benchmark databases show that the presented method can improve the recognition performance for each peripheral signals and their combination on both valence and arousal spaces.

Jason Teo[6] investigated the machine learning approaches to emotion detection in VR stimulus with the main goal of achieving this reliably and consistently using only wearable EEG, which are cheap, Commercial-Off-The-Shelf (COTS) Brain-Computer Interface (BCI) headsets that have limited recording channels and low signal resolution. The intent is that eventually such VR-based emotion recognition systems could be deployed in tandem with VR headsets in a user-friendly and convenient setup at affordable costs to support procedurally-generated VR entertainment and learning content.

Gang Li proposed a low-cost in-ear EEG device. The whole process of ear EEG based emotion recognition is divided into three stages: Stage I is data collection, Stage II feature extraction, and Stage III is feature classification. Stage I involve the setting up of the EEG device in-ear and the completion of emotion inducible experiment. Stage II includes WPT based signal decomposition and feature extraction. Stage III involves the feature classification using SVM classifier with different kernels [7].

MursideDegirmenci introduced a technique which used EMD-based features for emotion classifications from EEG signal to define the emotional state as pleasant (happy) or unpleasant (unhappy). The experiments were carried out on 26 (13 females, 13 males) volunteers and obtained Visual evoked potentials (VEPs). EEG signals are disintegrated by EMD, and removed IMFs are analyzed utilizing various signal processing techniques namely PSD, and first, second, third, fourth moment for feature extraction [8].

To improve the accuracy rate of emotion recognition, EEG signal oscillations are extracted on most of the IMFs. To classify extracted features, SVM, Naïve Bayes, LDA classifiers were used and the experimental outcome proved that SVM provides a better solution to emotion recognition from EEG signals by using EMD method and signal processing techniques.

Chunmei Qing proposed a coefficients-based method based on machine learning using EEG signals. This method not only outperformed the benchmark algorithms in terms of accuracy but also interpret the progress of emotion activation [9]. Firstly, the extracted features from EEG signals and classified emotions using machine learning techniques. It was found that the latter stage of EEG signals has better correlations with emotions, hence better classifier performance can be achieved if the second half of the trial is utilized for training. Secondly, depend on the classification outcome, the correlation curves and entropy curves of emotions are built, which to a certain extent indicate the emotional activation progression. It is found that emotion was progressively activated. Finally, the obtained correlation coefficients and entropy coefficients are used to construct weight coefficients to improve the classification accuracy compared to current benchmark algorithms.

Huimin Lu proposed a fusion algorithm of the anxiety level parameter to research the human anxiety level changes using BCI for a human smart helmet in the EEG cloud computing platform. Experiments demonstrate that the amplitudes of the $\ominus$ rhythm enhance most significantly in the negative emotional state. Additionally, the fusion algorithm of the anxiety level has an accurate subsequent function to the negative emotional change. This method quantitatively represents the anxiety level of a human. This approach can accordingly be used to improve operating safety and avoid improper miner operation [10].

Jeevan Reddy Koya [11] introduces deep convolution neural networks to proposed and design the EEG-based emotion recognizer primarily in three modes. Differential Entropy (DE) is obtained as characteristics at a certain time interval for each channel. From a basic one dimensional deep model, and an SVM and KNN model. The authors found that HCNN (86.2% $\pm$ 2.5%) is better than SAE (83.2% $\pm$ 6.9%), and deep neural models are more preferable in emotion classification and estimation Machine computer interface system that models brain signals for emotions.

PeixiangZhong proposed a regularized graph neural network (RGNN) model to recognize emotions based on EEG signals. The proposed model is supported and captures biologically both local and global inter-channel relations. The RGNN model extends the SGC (simple graph convolution network) and leverages the topological framework of EEG signals [12]. A biologically supported sparse adjacency matrix is presented to catch both local and global inter-channel relations. Local inter-channel relations connect nearby groups of neurons and may disclose anatomical connectivity at the macroscale.

Global inter-channel relations connect distant groups of neurons between the left and right hemispheres and may reveal emotion-related functional connectivity. A node-wise domain adversarial training (NodeDAT) to regularize the graph model is also presented for better generalization in subject-independent classification scenarios. An emotion-aware distribution learning (Emotion DL) technique is utilized to address the problem of noisy labels in the datasets.

CHAPTER 3

AIM AND OBJECTIVES

3.1 Aim

- Capturing of sensor data into the software model.
- To collect the sensor Data accurately.
- To scrutinize the data more deeply.
- Proper setup of hardware devices.
- To efficiently identify and categories human emotion.

3.2 Objectives

- To scrutinize the sensor data properly.
- Effectively identifying threshold of emotions.
- To deploy the whole system thoroughly.

3.3 Methodology

There is a growing interest and need for the detection of emotion of a particular individual in various circumstances and locations such as Airport, Hotel Lobbies, Railway Stations, prison cells etc. as there is always a chance that someone with unhealthy motives would create some mishap. It is also useful in situations such as interrogations and lie detector tests to identify the emotion of the person being monitored. And a human being utilized for the purpose of identifying the emotion is not always accurate and can be biased towards the individual. Thus, the proposed system addresses the concerns by taking a tiny step towards a system that can automatically identify human emotions with the help of various parameters such as ECG signals, body temperature and heart rate. The proposed methodology implements K-means clustering, Artificial neural networks and Fuzzy classification to achieve highly accurate emotion classification.

3.4 Specifications of the System

3.4.1 Software Specifications

1. Platform: JAVA
2. Technology : JDK 1.8 and Above
3. IDE: Netbeans 8.2

3.4.2 Hardware Specifications

Sr. No.	Parameter	Minimum Requirement	Justification
1	Processor	2.2 GHz	For Fast Processing
2	Hard Disk	200 GB	For Fast Processing
3	RAM	4 GB	For Fast Processing
4	Monitor, Keyboard and UPS	1 Quantity	None
5	Arduino Uno	1	None
6	ECG, Pulse Sensors	1	None

Table 3.1: Hardware Requirements

CHAPTER 4

BLOCK DIAGRAM OF THE SYSTEM AND ITS EXPLANATION

4.1 Block Diagrams

4.1.1 Application Design

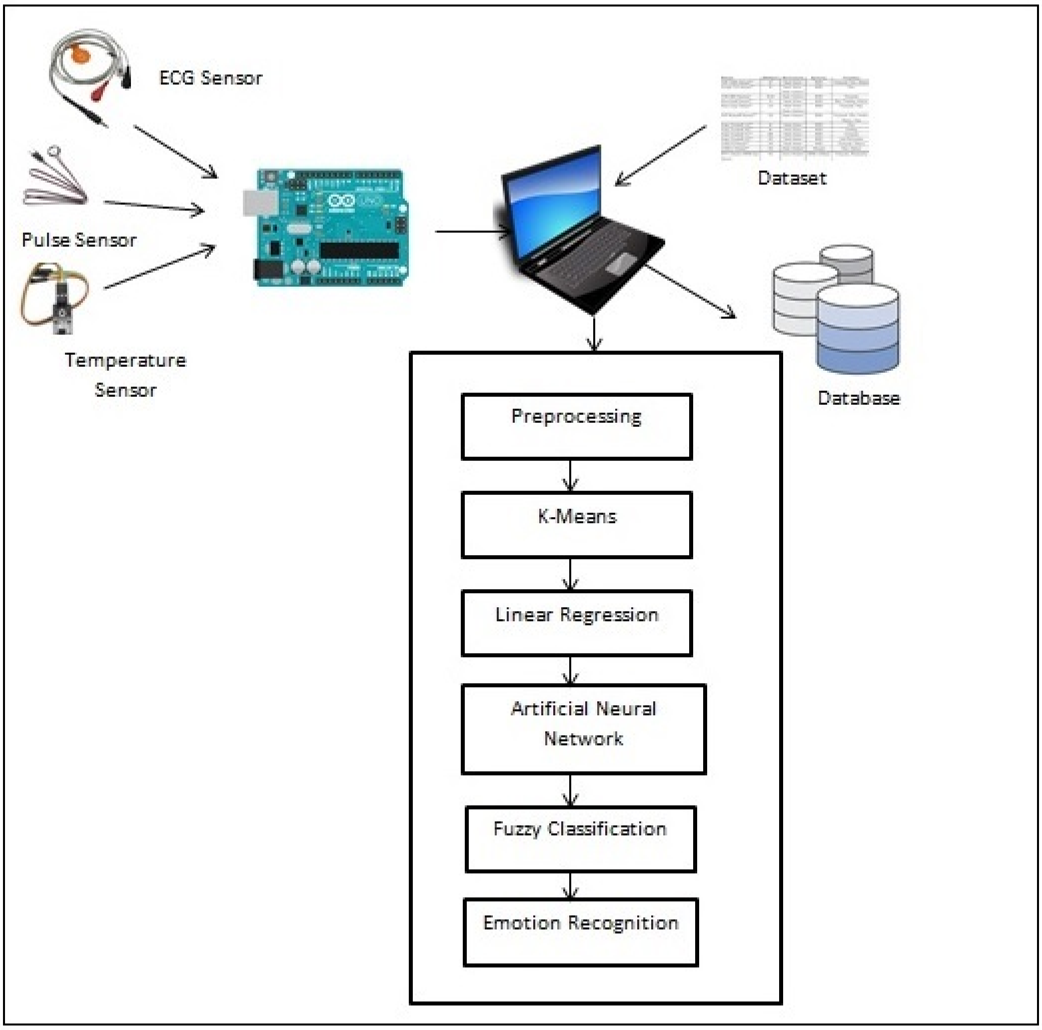

Figure 4.1: Application Design

4.2 Components and its Working

4.2.1 K- Means Clustering

Here in this process the preprocessed data is clustered using the K means clustering algorithm with the below mentioned steps like:

I. Distance Evaluation.

II. Distance Sorting.

III. Data Point Identification.

IV. Centroid Position Estimation.

V. Boundary Evaluation.

VI. Cluster Formation.

4.3 Linear Regression

This Regression analysis provides a prediction parameter for the important attributes of the clustered data. And these important attributes are segregated from each of the clusters to form a list which used in the next step of ANN.

4.4 Artificial neural Network

Once the regression list is received the neurons are created based on the hidden factors of the relationship attributes. These attributes are subjected for the cost estimation process of Artificial neural network that is further used by the Fuzzy Classification to yield the Classification factor list for the Emotion Recognition.

4.5 Fuzzy Classification

The formed neuron list from the past step is used forgeneration of classification labels based on the probabilistic conditions. Which are then segregated like VERY LOW, LOW, MEDIUM, HIGH AND VERY HIGH by using a Fuzzy Classification pattern. Based on these patterns the emotions are segregated.

4.6 Hardware Components

4.6.1 Arduino UNO

Arduino is a single-board microcontroller meant to make the application more accessible which are interactive objects and its surroundings. The hardware features with an open-source hardware board designed around an 8-bit Atmel AVR microcontroller or a 32-bit Atmel ARM. Current models consists a USB interface, 6 analog input pins and 14 digital I/O pins that allows the user to attach various extension boards.

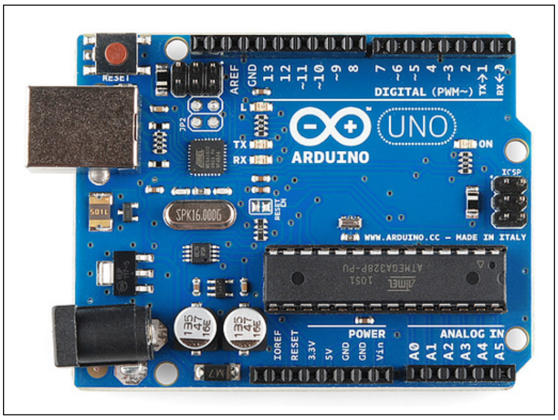

Figure 4.2: Arduino Uno

The Arduino Uno board is a microcontroller based on the ATmega328. It has 14 digital input/output pins in which 6 can be used as PWM outputs, a 16 MHz ceramic resonator, an ICSP header, a USB connection, 6 analog inputs, a power jack and a reset button. This contains all the required support needed for microcontroller. In order to get started, they are simply connected to a computer with a USB cable or with a AC-to-DC adapter or battery. Arduino Uno Board varies from all other boards and they will not use the FTDI USB-to-serial driver chip in them. It is featured by the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to-serial converter.

4.6.2 ECG Sensor

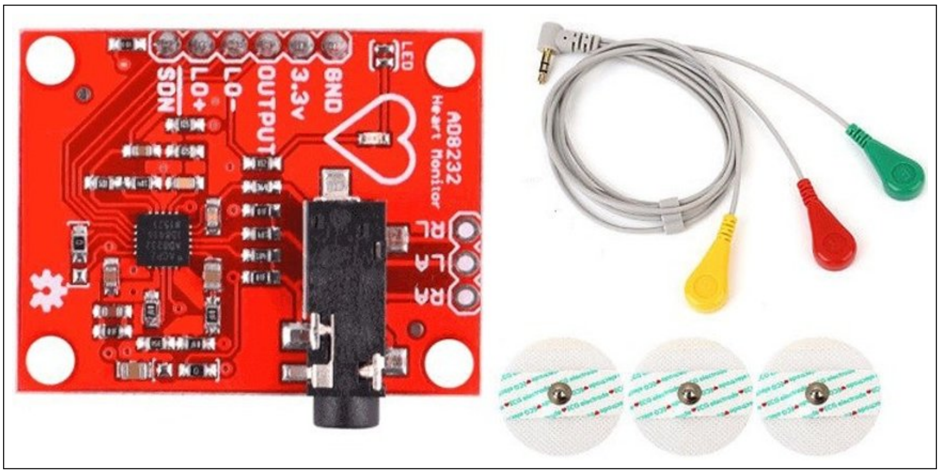

Figure 4.3: ECG Sensor

4.6.2.1 Description

- The length of the cable is 80 cm. The SHIELD-EKG-EMG-PRO unit does not include gel pads/gel electrodes. They have to be purchased separately. The Red header is left, the white header is right, the black header is DRL (feedback).

- Custom molded and labeled Cable for Gel ECG Electrodes for use with Olimex SHIELD-EKG-EMG.

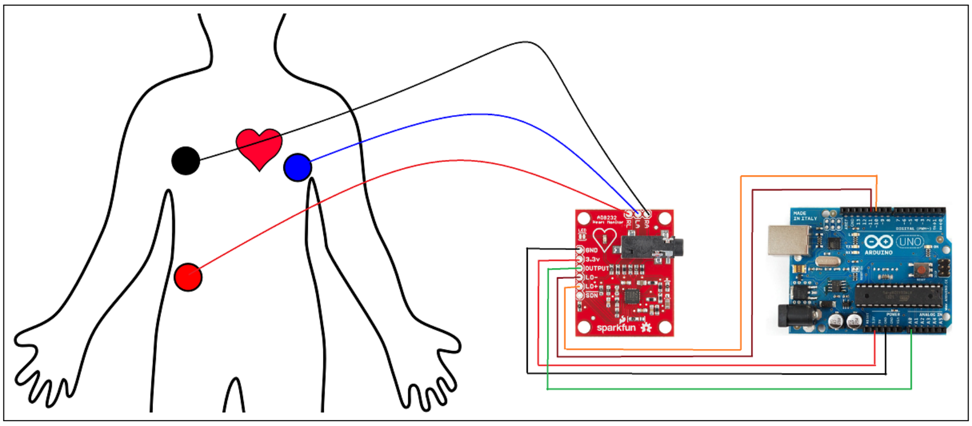

Figure 4.4: ECG Sensor Connection

4.6.2.2 Features

- AD8232 adopts an operational amplifier that is without using constraint to build a three pole low pass filter, eliminating extra noises.
- Rated temp range : 0—-70degree - Working temp range: -40——85degree.
- AD8232 adopts double poles high-pass filter to eliminate the motion artifacts and electrode half cell potential.

4.6.2.3 Specifications

Brand	Olimex
Shipment Weight	0.115 kg
Shipment Dimensions	7 x 7 x 3 cm

4.6.3 Pulse Sensor

Figure 4.5: Pulse Sensor

4.6.3.1 Description

- Heart Rate data can be used in many Electronic design and microcontroller projects. But the heart rate data is difficult to read, however, the Pulse

Sensor Amped help us to read heart rate. The Heart Beat Pulse Sensor Amped is a plug-and-play heart-rate sensor for Arduino.

- It can be used by students, artists, athletes, makers, and game & mobile developers who want to easily incorporate live heart-rate data into their projects.

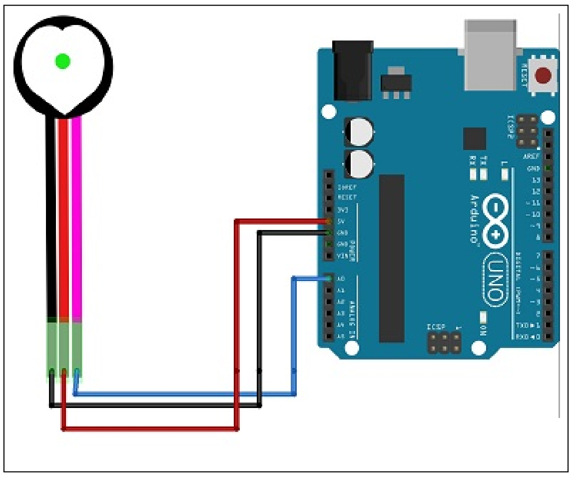

Figure 4.6: Pulse Sensor Connection

4.6.3.2 Features

- A Color-Coded Cable, with a standard male header connectors. Plug it straight into an Arduino or a Breadboard. No soldering is required.
- The Pulse Sensor has 3 holes around the outside edge which make it easy to sew it into almost anything.
- Visualization software (made in Processing) to instantly see the output of the sensor and for troubleshooting.

4.6.3.3 Specifications

PCB Diameter (mm)	15
PCB Thickness (mm)	1.5
Shipment Weight	0.085 kg
Shipment Dimensions	8 x 6 x 2 cm

4.6.4 Temperature Sensor

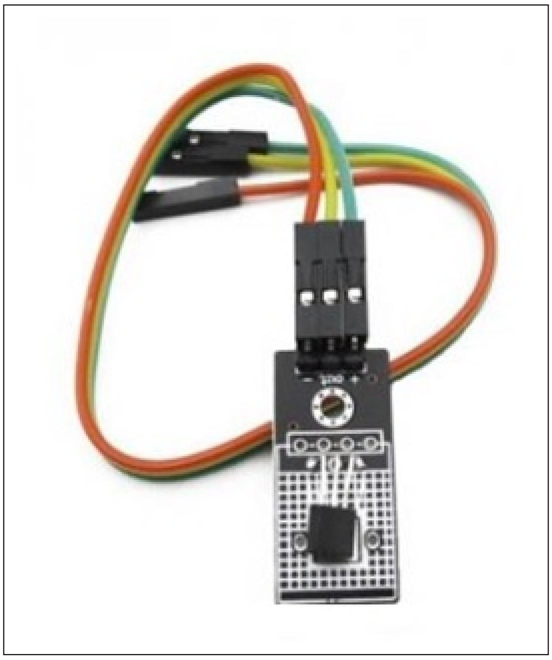

Figure 4.7: Temperature Sensor

4.6.4.1 Description

This LM35D Analog Temperature Sensor Module is based on the semiconductor LM35 temperature sensor. The LM35 Linear Temperature Sensor module is useful in detecting ambient air temperature. Sensitivity is 10mV per degree Celsius. The output voltage is proportional to the temperature.

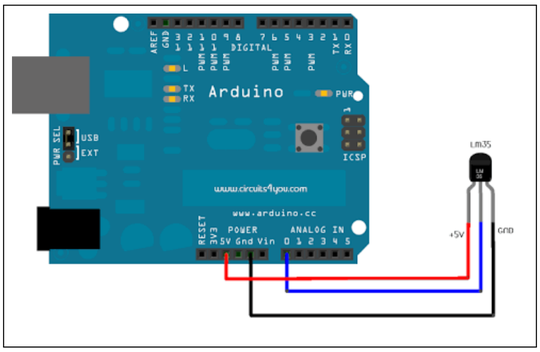

Figure 4.8: Temperature Sensor Connection

4.6.4.2 Features

- Based on the semiconductor LM35 temperature sensor
- Can be used to detect ambient air temperature
- Calibrated directly in °Celsius (Centigrade)
- Linear + 10 mV/°C Scale Factor
- 0.5°C Ensure accuracy (at +25°C)
- Low power consumption, less than 60uA
- Low output impedance, 1mA current through only 0.1Ω
- With screw holes for easy installation and fixed. Aperture 2.6mm

4.6.4.3 Specifications

Operating voltage (v)	4 ~ 30 V
Current Consumption (μA)	60
Scale Factor	+10 mV/°C
Measuring Accuracy	0.5°C
Operational Temperature (°C)	-55 ~ +150
Signal Output Type	Analog
Dupant Cable Length (cm)	20
Length (mm)	35
Width (mm)	13
Height (mm)	5
Weight (gm)	15
Shipment Weight	0.095 kg
Shipment Dimensions	8 x 5 x 2 cm

CHAPTER 5

HARDWARE DESIGN

5.1 Circuit Level Design

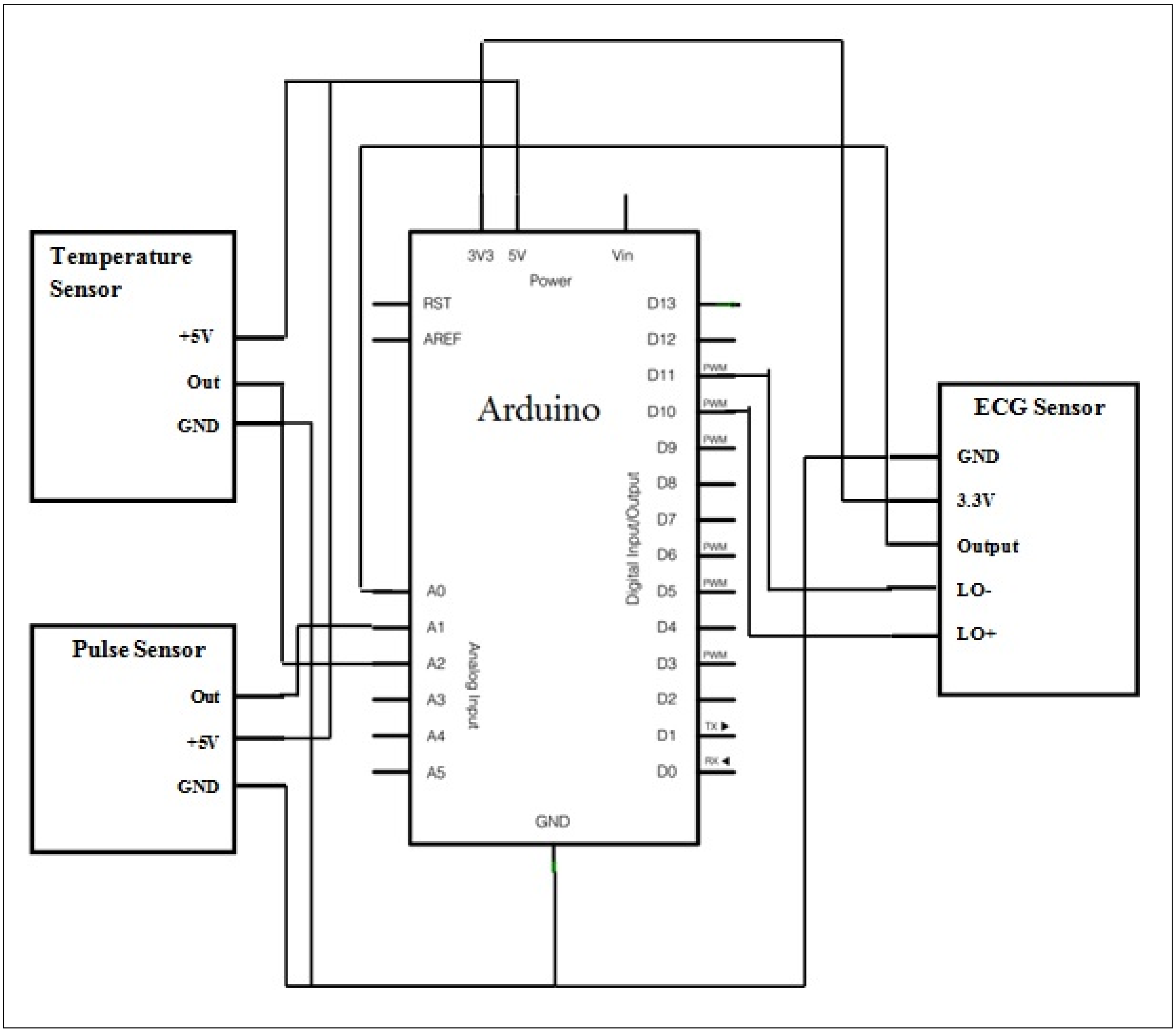

Figure 5.1: Circuit Design

5.2 Enclosure Design

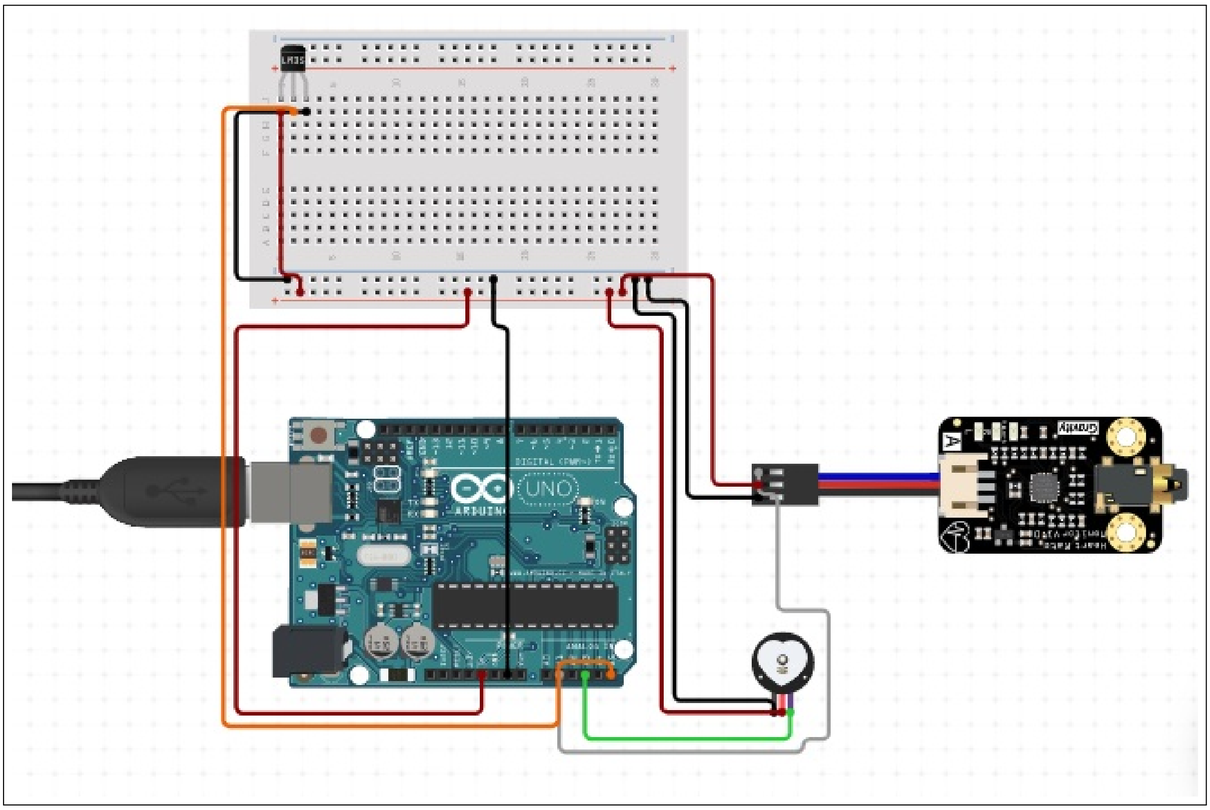

Figure 5.2: Enclosure Design

CHAPTER 6

SOFTWARE DESIGN

6.1 Flow Chart Diagram

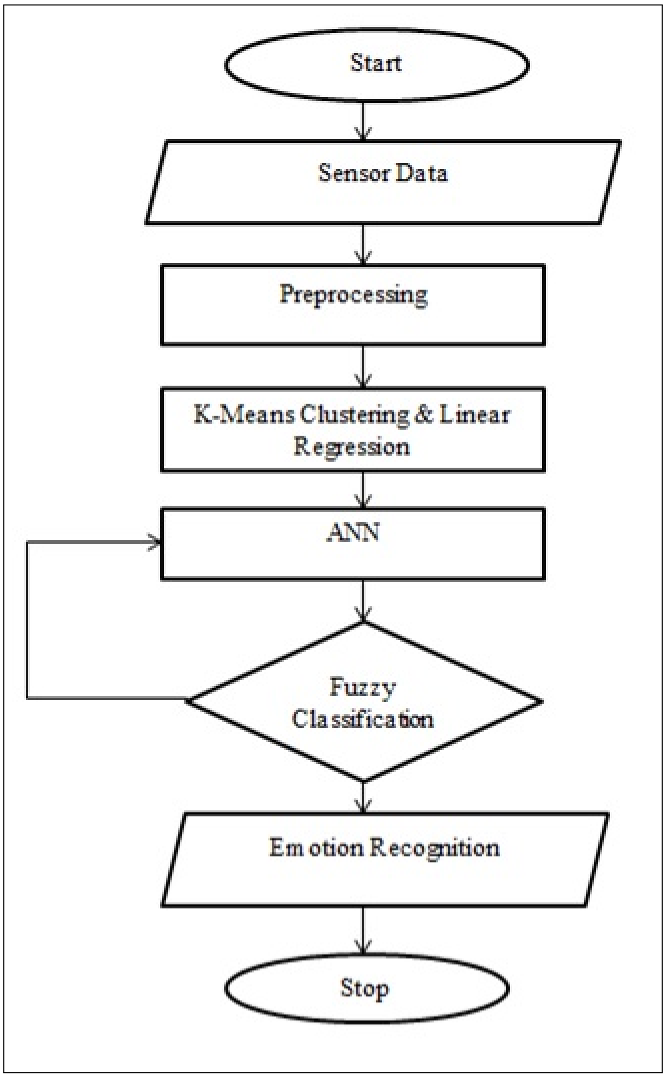

Figure 6.1: Flow Chart Diagram

6.2 Implementation Detail

The execution procedure of the proposed methodology has been detailed in the steps given below.

The proposed model for emotion recognition is designed using the both hardware and software based interfaces as depicted in the above Figure 1. The steps that are included in this process are broadly elaborate in the below mentioned steps.

Step1: Hardware Configuration and Dataset – This is a preliminary step of the proposed model, where a microcontroller called Arduino UNO is setup along with the sensors like ECG, Pulse and Temperature. The Connections are made with the microcontroller according to the established protocols. After this microcontroller is connected to the laptop using the USB Cables. Then the sensors are attached to the human body to measure the parameters of ECG, temperature and pulse rate efficiently. Once these parameters are collected at the laptop end, then using the proposed algorithms the coding is being done using Java programming language to estimate the emotion of the person.

On the other hand to verify the same model some authenticated dataset is being utilized by the proposed model to make sure the effectiveness of the obtained results. For this purpose a dataset is being downloaded from the URL https://rmc.dlr.de/download/CASE_dataset/CASE_dataset.zip.

This URL contains many attributes for the Electrocardiogram reading like ECG, BVP, GSR, RSP, SKT and many more. Where ECG indicates the electrocardiogram reading, BVP (Blood volume pulse), GSR (Galvic Skin response), RSP (Thoracic expansion and contraction while Respiration), SKT (Skin temperature), and all these attributes are having reading in real numbers. This collected dataset is stored in a spreadsheet which being fed to model of machine learning to estimate the emotion.

Step 2: Preprocessing- As the spreadsheet dataset is fed to system the complete dataset has been read in a double dimension list. This double dimension list is then subjected to select the most important attribute columns that eventually play best role in identifying the emotion. So for this purpose the proposed model selects the ECG and SKT readings, as they are more sensitive for the emotion of a person. These two attributes are collected in a double dimension list of n rows and two columns.

Step 3: K-Means Clustering – This step clusters the preprocessed list with two columns and n rows using the K-means clustering algorithm by following the below mentioned techniques. Distance Evaluation – The every row of the preprocessed list is subject to estimate the distance with all other rows for the attributes of ECG and SKT. The obtained row distance is appended at the end of each row to call as Row distance RDIST and the list is as the distance list. The average of this row distance yields the Mean Distance of the Dataset, as shown in the below mentioned equation 1 and 2.

$$R_{DIST} = \frac{\sqrt{(E1-E2)^2+(S1-S2)^2}}{n} \qquad \text{————-(1)}$$

$$\mu D = \textstyle\sum_{i=1}^{n}(RDIST)/n \qquad \text{————-(2)}$$

Where

RDIST- Row Distance

E1,E2 – Values of ECG Parameters

S1,s2- Values of Skin temperature

μ D- Mean Distance

n- Number of Rows

Sorting and Data point Selection- The obtained distance list is then sorted in ascending order using the bubble sort technique. And then a K number of random data points are selected and aggregated to 100

Centroid selection and boundary Estimation – The obtained data points are utilized to select that particular row distance to be called as centroids CD. Then the boundary of the clusters can be derived by adding and subtracting the mean distance of the dataset with the CD. This is depicted in the equation 3.

$$L_B = C_D - \mu D, U_B = C_D + \mu D \qquad \text{———————-(3)}$$

These lower and upper boundaries are then added into a list called boundary list to use in the cluster formation process.

Cluster Formation –The obtained boundary list is then used to evaluate the row distance of the each row. Then the matched row distance for the lower and upper boundary values are segregated as the clusters. This process is depicted in the algorithm.

Step 4: Linear Regression - The Obtained K-means clusters are subjected to estimate the regression rates using the Linear Regression. Here the two columns of the ECG and SKT values are stored in separate arrays like A and B. And these two arrays are used for the estimation of the gradient and y-intercept of the Linear Regression as m and b respectively. Then the obtained values of m and b are utilized for each of the instances of A array to call as x in the equation 4.

Y=mx+b ———————-(4)

Where

Y= Intercept

M= Gradient

B- Y Intercept

X-Instance of ECG.

Then the obtained Intercept value is measured for mid probability of the intercept values with each of the rows. Then the obtained rows are added into a list to call it as an ANN input list.

Step 5: Artificial Neural Network – The obtained ANN input list values are used to estimate the mean values of the ECG and SKT values for each and every row. Then from these mean values the maximum and the minimum values are being calculated to term them as the target1 and target2 variables of the ANN. After this process 10 random weights are bring estimated in the range of 0 to 1 to assign different variables like W1,W2,W3,W4,W5,W6,W7,W8,B1 and B2. Here B1 and B2 represent the values of bias.

Using these weights along with the ECG and SKT values hidden and Output layers are estimated using the equation 5 and Tanh function of ANN.

$$X1= AT1*W1 +AT2*W2 +B1 \qquad \text{———————-}(5)$$

Where AT1 and AT2 are the attributes like ECG, SKT or Hidden Layer outputs. The obtained output layer value is then measured for the minimum value to consider it as the Probability value of ANN to form ANN probability List.

Step 6: Emotion Classification through Fuzzy Logic- This is the last step of the proposed model, here based on the ECG values some emotion protocols are being classified in a list of Fuzzy crisp sets. This list contains some emotions like Good Mood, Sadness, Anger, Stress and Impatience. This fuzzy crisp set is used to classify the ANN probability list in the inference Engine segment. Once the classified values are being counted, then they are measured for their maximum value along with the attached mood. The obtained type of the mood is displayed to the user through an interactive user interface.

6.3 Algorithm

Algorithm 1 Cluster Formation

//Input: Sorted Distance List SD_L
//Input: Boundary List B_L
//Output: Cluster List C_L

Start
for i=0 to Size of B_L
$T_L = B_{L[i]}[T_L = TemporaryList]$
$L_B = T_{L[0]}, U_B = T_{L[1]}$
$S_{GL} = NULL$
for j=0 to Size of SD_L
$R = SD_{L[j]}$
$R_D = R[R_{SIZE} - 1]$
$IF(R_D >= L_B AND R_D <= U_B)$
$S_{GL} = S_{GL} + R$
End for
$C_L = C_L + S_{GL}$
End for
return C_L
Stop

6.4 Screen Shots

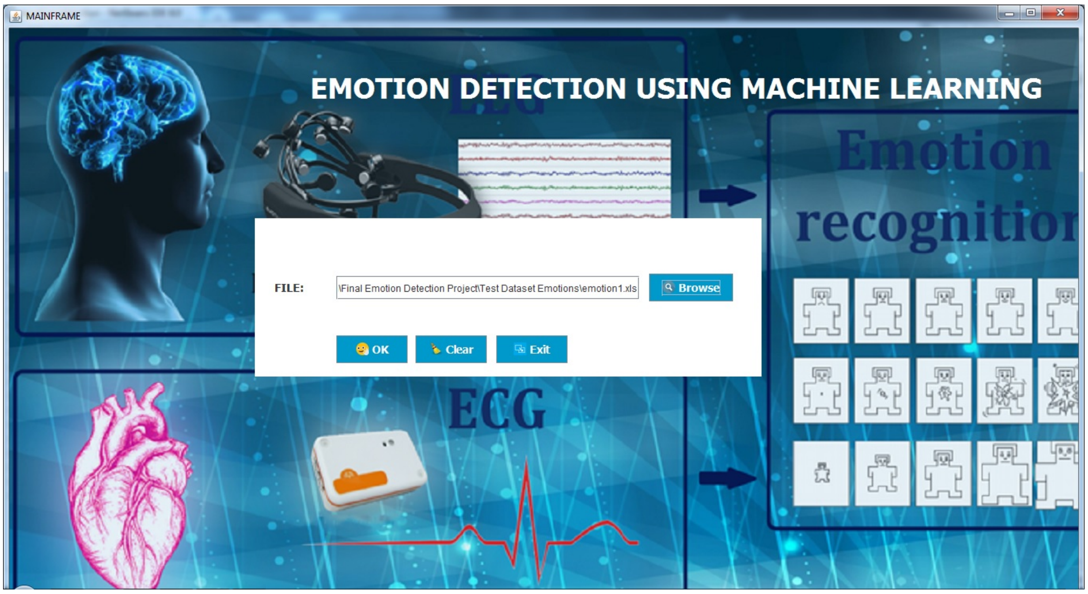

Figure 6.2: Main Frame

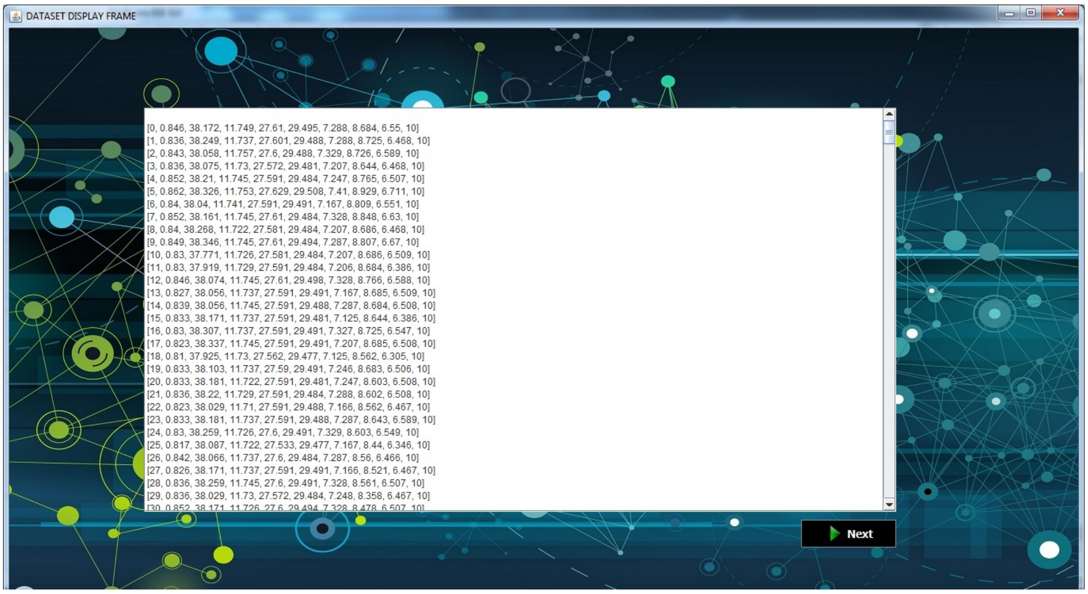

Figure 6.3: Dataset Frame

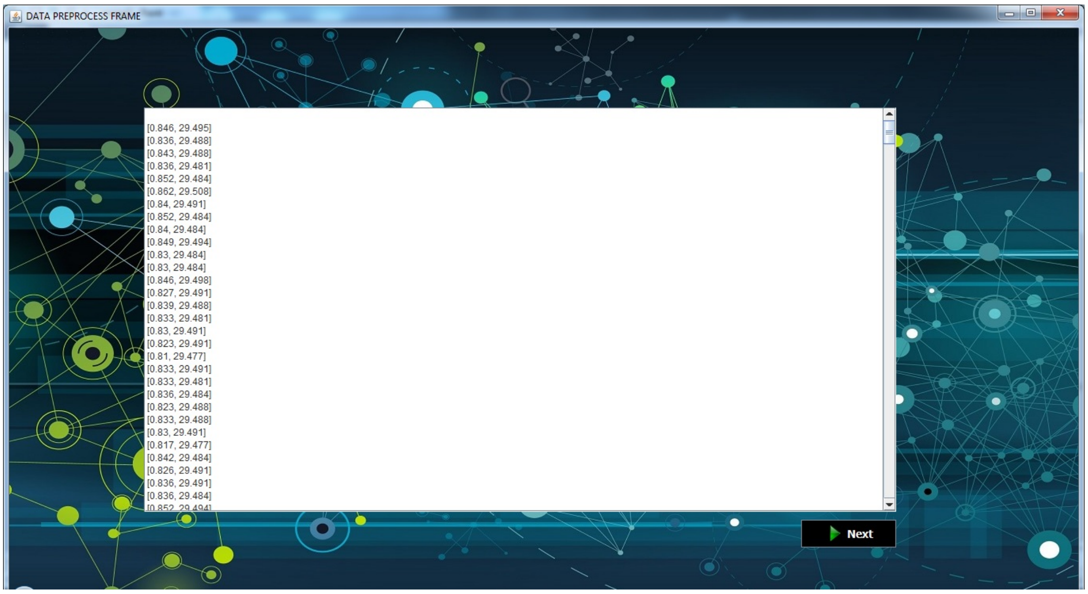

Figure 6.4: Data Preprocess Frame

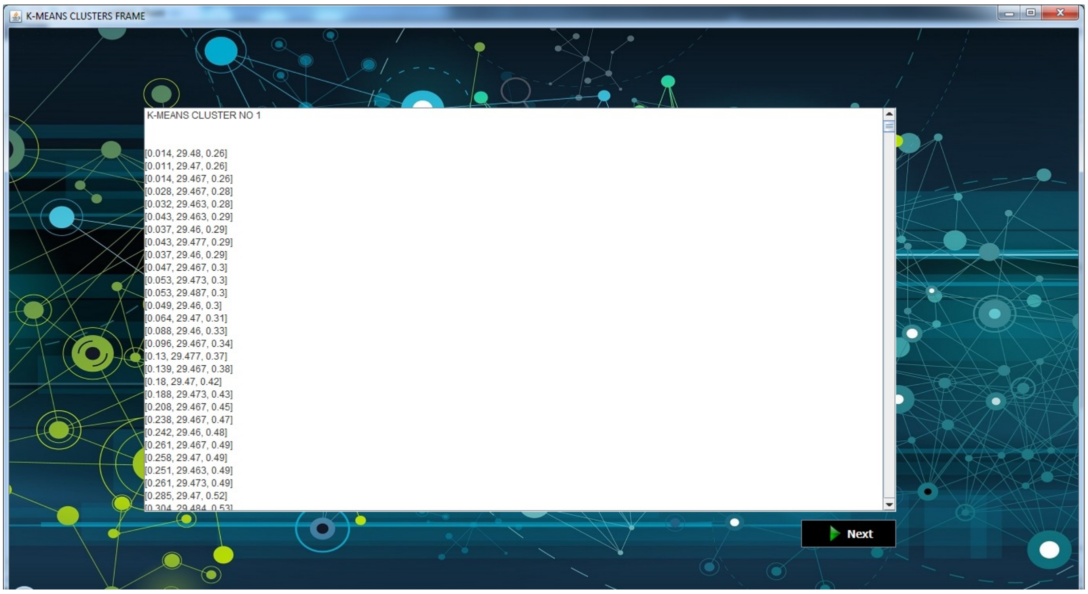

Figure 6.5: K-means Cluster Frame

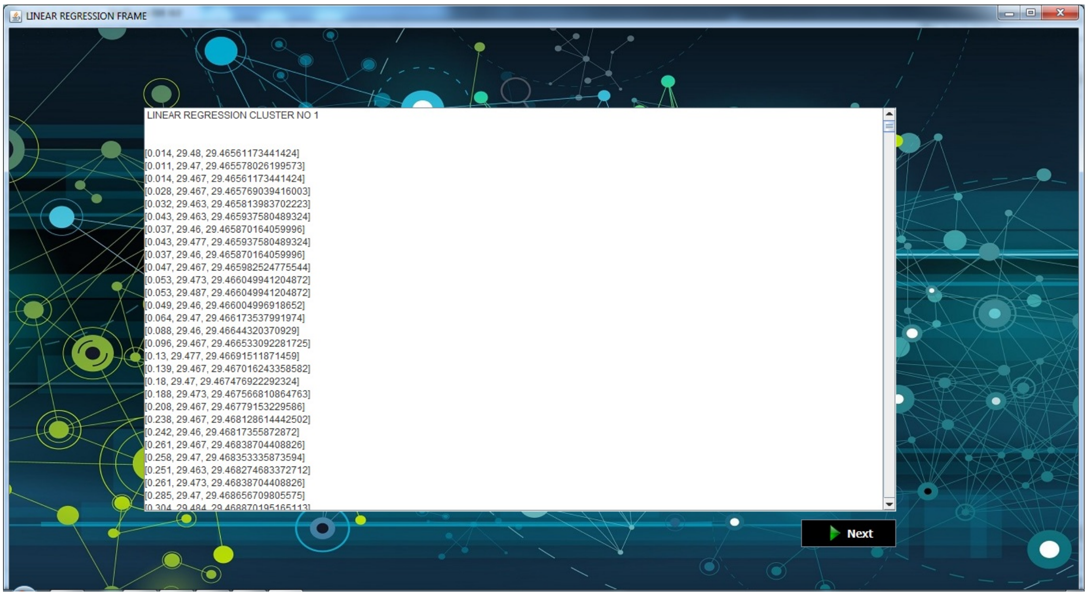

Figure 6.6: Linear Regression Frame

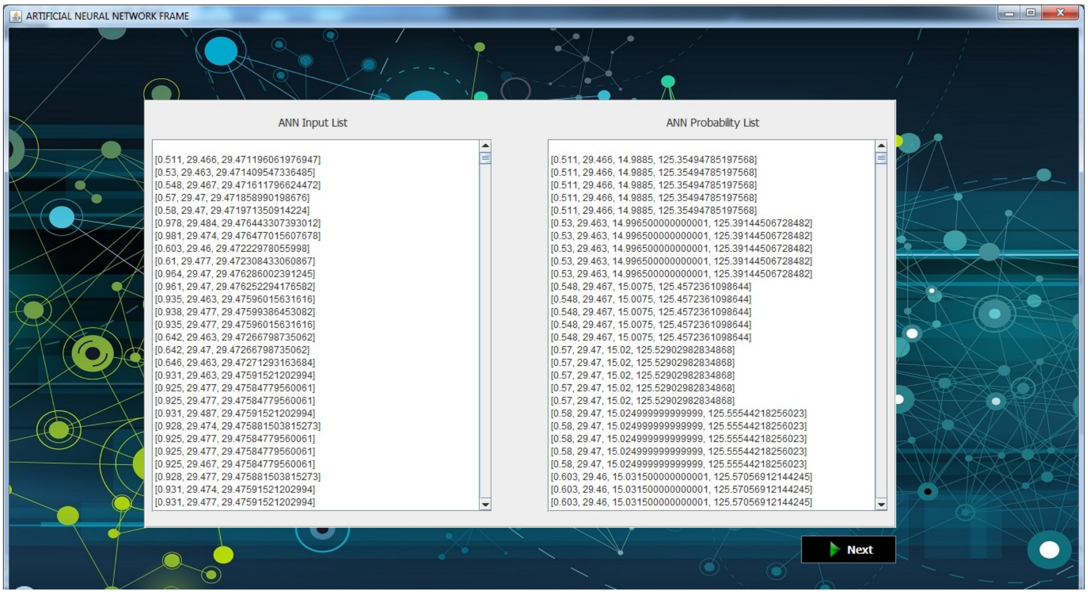

Figure 6.7: ANN Frame

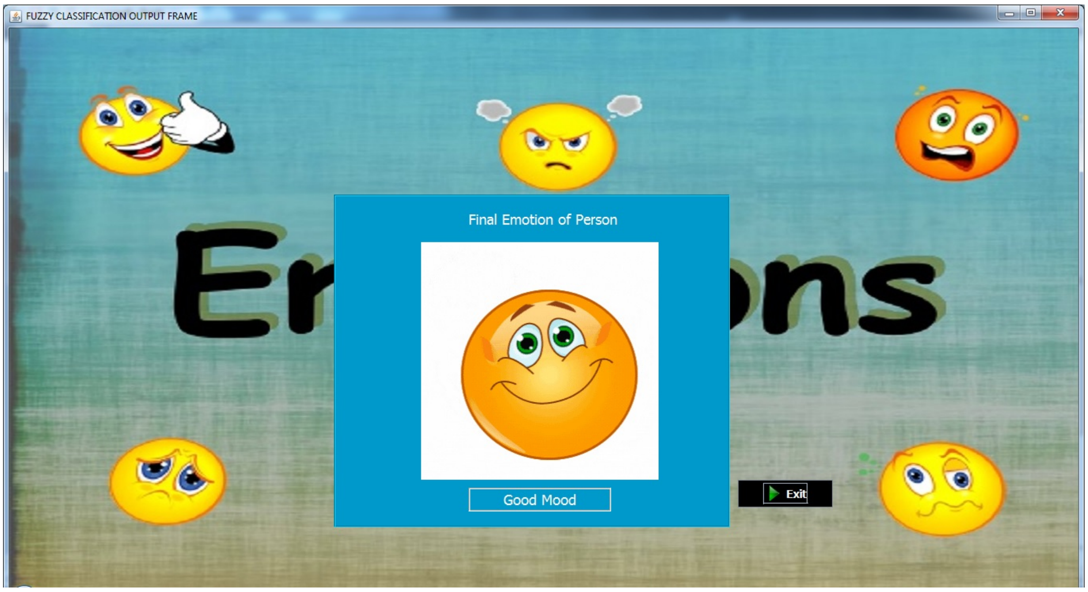

Figure 6.8: Output Frame

CHAPTER 7

OPERATING INSTRUCTIONS

The operating instructions has been detailed in the steps given below:

1. Connection: First connect ecg , pulse and temperature sensors with arduino uno as shown in below diagrams:

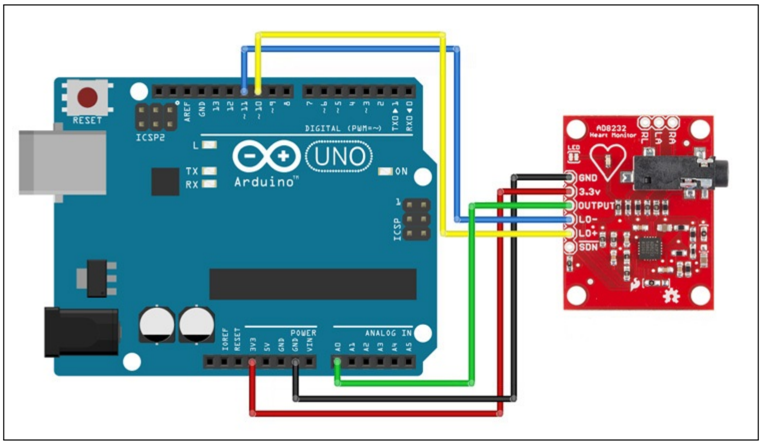

Figure 7.1: ECG Sensor Connection with Arduino Uno

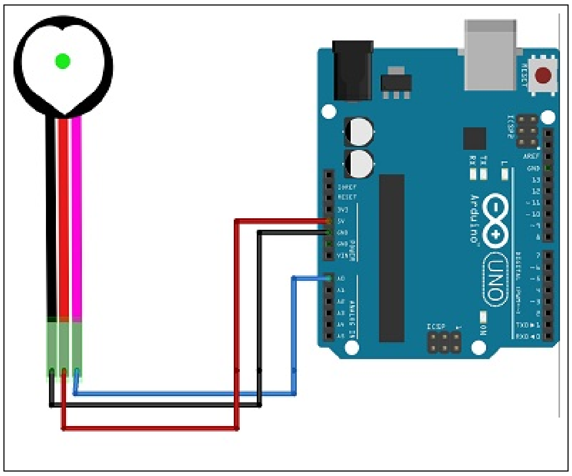

Figure 7.2: Pulse Sensor Connection with Arduino Uno

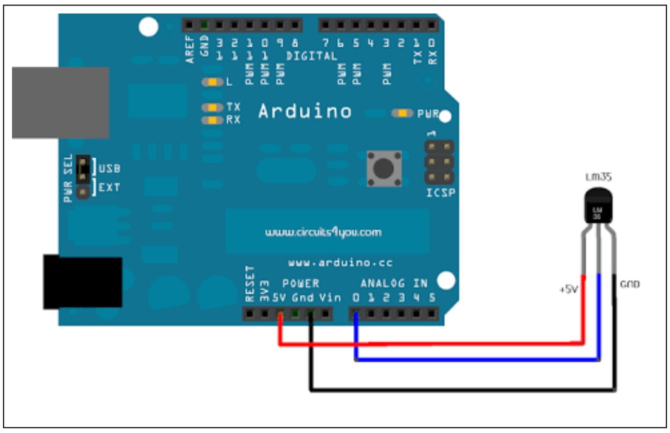

Figure 7.3: Temperature Sensor Connection with Arduino Uno

2. Then upload the arduino code in arduino uno.
3. Connect arduino uno with computer,
4. Start the application.

CHAPTER 8

TEST RESULTS

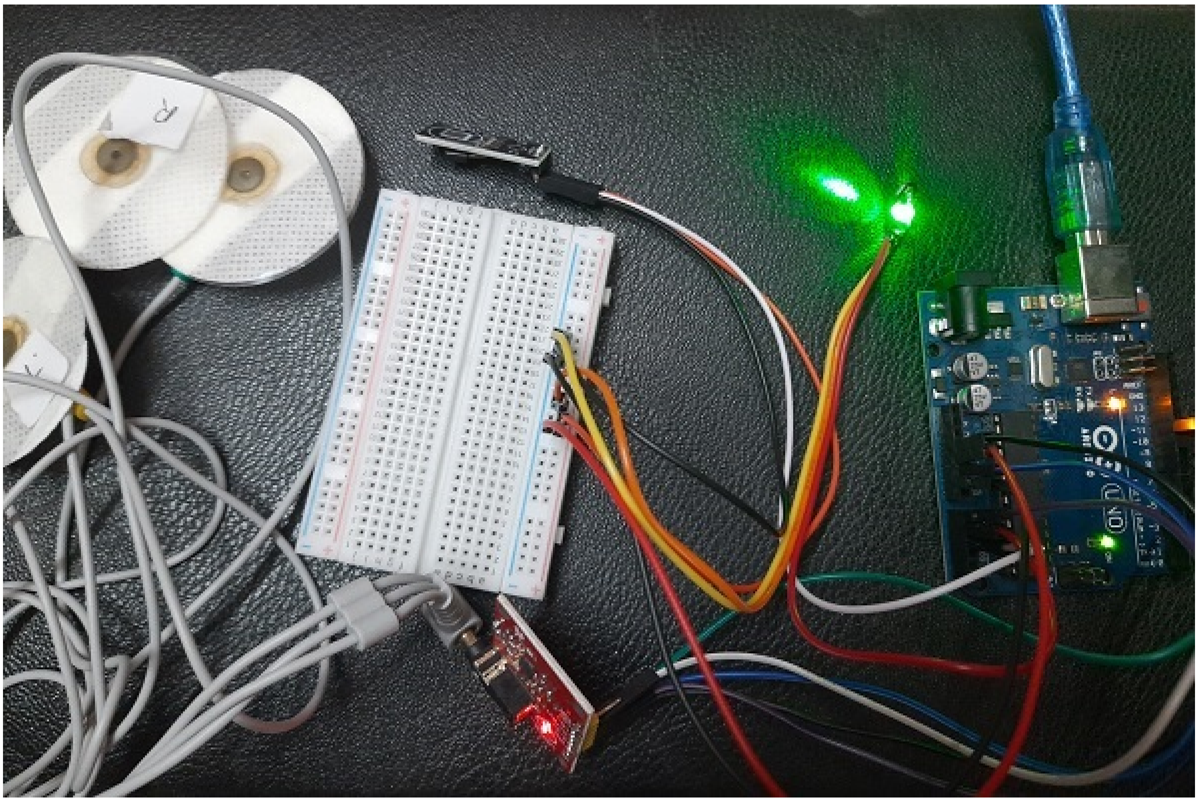

Figure 8.1: Circuit Connection

The presented technique for emotion recognition through the utilization of the IoT or Internet of Things platform is written in a java programming language by the utilization of the NetBeans Integrated Development Environment. The proposed methodology is implemented on a development machine that has a standard configuration such as an Intel Core i5 processor fulfilling the processing requirements augmented by the 500GB Hard drive and 4GB of RAM. The MySQL database server is utilized for database responsibilities and the D-Link WiFi router is used for networking capabilities. For the collection of the data 1 Arduino UNO microcontroller boards outfitted with the ECG sensor, Pulse sensors and is utilized along with the temperature sensor.

For gauging the accuracy of the presented Emotion recognition system, the RMSE or Root Mean Square Error is utilized. The RMSE approach is one of the most accurate performance metrics utilized for the purpose of estimating the error rate of the system. For this purpose, two continuous and correlated entities such as the actual emotion recognized and the expected emotion recognized are selected for the purpose of determining the error rate in the emotion recognition system. Equation 1 given below illustrates the RMSE approach mathematically.

$$RMSE = \sqrt{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2/n} \qquad \text{———}(1)$$

Where,

$\sum$ - Summation

$(x1–x2)^2$ - Differences Squared for the summation in between the actual emotion recognized and the expected emotion recognized

N - Number of samples or Trails

An intensive evaluation of the presented system is achieved using the RMSE technique, and the results obtained are tabulated in Table 8.1 given below.

Experiment Number(n)	Number of Actual Emotion Recognized	Number of Expected Emotion Recognized	MSE
1	9	8	1
2	10	8	4
3	6	5	1
4	7	6	1
5	5	4	1
5	10	8	4

Table 8.1: Mean Square Error measurement

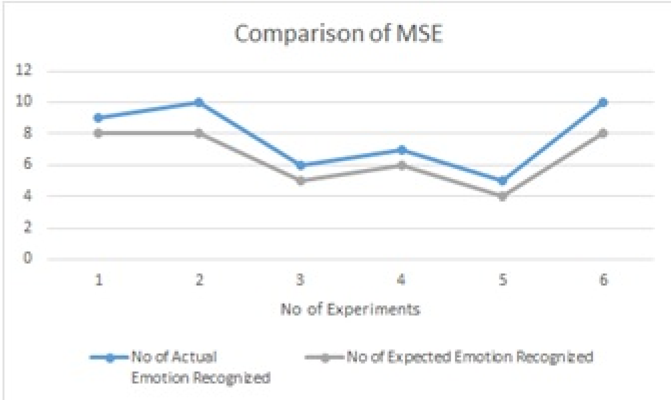

Figure 8.2: Comparison of MSE in between No of Actual Emotion Recognized Index V/s No of Expected Emotion Recognized

The graph plotted in figure 8.1 utilizes the data obtained in Table 1 given above which illustrates the experimental outcome of the presented technique. This is done by utilizing the mean square error rate between actual emotion recognized and the expected emotion recognized for detailed experimentation. Several trials are executed under each experiment. The outcomes of MSE and RMSE measured by the experimental results obtained are 2.0 and 1.41 respectively. The measured RMSE values are measured for the emotion recognition parameters such as Happy, sad and angry criteria. The RMSE value achieved depicts the efficiency and increased accuracy obtained by the presented system.

CHAPTER 9

CONCLUSION AND FUTURE WORK

9.1 Conclusion

The proposed methodology for Emotion recognition has been outlined in this publication requires the implementation of extensive hardware and software interfaces for achieving the goals of this research. There has been a myriad collection of technologies that have been dedicated to achieving the automatic emotion recognition system. But the majority of the approaches have been unable to achieve the high level of accuracy and reliability which is a problematic occurrence. Therefore, the presented technique in this report leverages the Internet of Things platform for facilitating highly accurate emotion recognition through the various sensor parameters such as temperature, ECG and pulse sensors. The presented technique integrates the K means clustering, linear regression along with Artificial Neural Networks and Fuzzy Classification paradigms to achieve emotion recognition through the Data collected by the IoT sensors and the Dataset. The extensive experimentation for the recognition of the errors in the methodology through the use of MSE and RMSE reveals that the methodology achieves significant improvements in accuracy and reliability in emotion recognition.

9.2 Future Scope

For Future Research prospects, the proposed methodology can be further extended by introducing more parameters by adding more sensors to the Arduino Microcontroller.

CHAPTER 10

REFERENCES

[1] Aravind E Vijayan, Deepak Sen and Sudheer A.P, "EEG-based Emotion Recognition Using Statistical Measures and Auto-regressive Modeling", 2015 IEEE International Conference on Computational Intelligence & Communication Technology, 02 April 2015.

[2] AayushBhardwaj, Ankit Gupta, Pallav Jain, Asha Rani, and JyotiYadav, "Classification of Human Emotions From EEG Signals Using SVM And LDA Classifiers", 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN), 27 April 2015.

[3] Sananda Paul, AnkitaMazumder, PoulamiGhosh, D.N. Tibarewala and G. Vimalarani, "EEG Based Emotion Recognition System Using MFDFA as Feature Extractor", 2015 International Conference on Robotics, Automation, Control and Embedded Systems (RACE), 30 April 2015.

[4] Wei-Long Zheng and Bao-Liang Lu, "Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks", IEEE Transactions on Autonomous Mental Development, Volume: 7, Issue: 3, Sept. 2015, 08 May 2015.

[5] Shiyu Chen, Zhen Gao and Shangfei Wang, "Emotion Recognition From Peripheral Physiological Signals Enhanced By EEG", 2016 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 19 May 2016.

[6] Jason Teo and JiaTian Chia, "Deep Neural Classifiers For EEG-Based Emotion Recognition In Immersive Environments", 2018 International Conference on

Smart Computing and Electronic Enterprise (ICSCEE), 19 November 2018.

[7] Gang Li, Zhe Zhang and Guoxing Wang, "Emotion Recognition Based on Low-Cost in-Ear EEG", 2017 IEEE Biomedical Circuits and Systems Conference (BioCAS), 29 March 2018.

[8] MursideDegirmenci, Mehmet AkifOzdemir, Reza Sadighzadeh and Aydin Akan, "Emotion Recognition from EEG Signals by Using Empirical Mode Decomposition", 2018 Medical Technologies National Congress (TIPTEKNO), 03 January 2019.

[9] Chunmei Qing, RuiQiao, XiangminXu, and Yongqiang Cheng, "Interpretable Emotion Recognition Using EEG Signals", IEEE Access, Vol: 7, 15 July 2019.

[10] Huimin Lu, Hyoungseop Kim, Yujie Li, and Yin Zhang, "BrainNets: Human Emotion Recognition Using an Internet of Brian Things Platform", 2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC), 30 August 2018.

[11] Reddy KoyaJeevan, VenuMadhavaRao S.P., Pothunoori Shiva Kumar and MalyalaSrivikas, "EEG-based Emotion Recognition Using LSTM-RNN Machine Learning Algorithm", 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT), 20 June 2019.

[12] Jia-Yi Zhu, Wei-Long Zheng, Yong Peng, Ruo-Nan Duan, and Bao-Liang Lu, "EEG-Based Emotion Recognition Using Discriminative Graph Regularized Extreme Learning Machine", 2014 International Joint Conference on Neural Networks (IJCNN), 04 September 2014.

APPENDIX A

Sr. No	Hardware Module	Quantity	Cost
1	Arduino Uno	1	450/-
2	ECG Sesnor	1	831.90/-
3	Pulse Sensor	1	230.10/-
4	Temperature Sensor	1	60/-
5	Jumper Wires	4	30/-
5	Breadboard	8	100/-
	Total		1802/-

Table A.1: Bill of Material

APPENDIX B

PAPER PUBLISHED/CERTIFICATES