

EMOTION DETECTION USING HEART RATE AND RESPIRATION RATE

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in Biomedical Engineering.

By

ANTONY FATHIMA SHINY J (37240006)

MERCY GRACE M (37240052)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

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Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600 119

www.sathyabama.ac.in

DEPARTMENT OF BIOMEDICAL ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Antony Fathima Shiny J (37240006)**, **Mercy Grace M (37240052)** who have done the project work as a team who carried out the project entitled “**Emotion Detection using Heart rate and Respiration rate**” under our supervision from **October 2020 to March 2021**

Dr. **S. KRISHNAKUMAR**, M.Sc., Ph.D.,

Internal Guide

Dr. **P. GRACE KANMANI**, M.E., Ph.D.,

External Guide

Dr. **T. SUDHAKAR**, M.Sc., Ph.D.,

Head of the Department

Submitted for Viva voce Examination held on _____

Internal Examiner

External Examiner

DECLARATION

We, **ANTONY FATHIMA SHINY J (37240006)**, **MERCY GRACE M (37240052)** hereby declare that the Project Report entitled “**Emotion Detection using Heart rate and Respiration rate**” done by us under the guidance of **Dr. S. Krishnakumar**, Department of Biomedical Engineering **Dr. P. Grace Kanmani**, M.E., Ph.D., **Department of Electrical and Instrumentation Engineering** is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE: 09.04.2021.

PLACE: CHENNAI.

1. *J. Antony Fathima Shiny*
2. *M. Mercy Grace*

SIGNATURE OF THE CANDIDATES

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ABSTRACT

Emotions play a vital role in everyone's daily life and it is a mental state that does not arise through free will and is often accompanied by physiological changes. Therefore, monitoring these changes at an early stage before they become serious is important. Emotion recognition is an important subject when it comes to human-machine interaction. Various methods have been used in the past to examine human emotions. The most commonly used physiological signal is obtained from the textual information, facial expressions, speech, and body gesture. Here we have developed an emotion detection system based on information provided by physiological signals. The signals are obtained from a non-contact temperature sensor and heart rate sensor. The denoised and filtered signals from the sensor are input into the Machine learning where all the processing takes place. Data analyses take place in supervised machine learning and feature extraction for emotion recognition. The four basic emotions observed in this project are happy, surprise, calm, and anxious. The data has been collected from healthy individuals, including both male and female, with ages ranging from 18 to 62 years. The developed system has shown an overall emotion recognition rate of 91.5%.

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LIST OF ABBREVIATIONS

ALC	AMBIENT LIGHT CANCELLATION
ANN	ARTIFICIAL NEUTRAL NETWORK
ASSP	APPLICATIONS OF SIGNAL PROCESSING
CNN	CONVOLUTIONAL NEUTRAL NETWORK
DFA	DISCRIMINANT FEATURE ANALYSIS
DSP	DIGITAL SIGNAL PROCESSING
EEPROM	ELECTRONICALLY ERASABLE PROGRAMMABLE READ-ONLY MEMEORY
ELM	EXTREME LEARNING MACHINE
KNN	K-NEAREST NEIGHBORS
MuPAD	MULTIPROCESSING ALGEBRA DATA
PCA	PRINCIPAL COMPONENT ANALYSIS
PPQ	PHOTO PLETHYSMOGRAPHY
PVM	PARALLEL VIRTUAL MACHINE
SCL	SERIAL CLOCK
SDA	SERIAL DATA
SVM	SUPPORT VECTOR MACHINE
VDD	VOLTAGE DRAIN DRAIN
VSS	VOLTAGE SOURCE SOURCE

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CHAPTER 1

INTRODUCTION

1.1. OUTLINE OF THE PROJECT

Improving individual health has been the subject of many research investigations. Recent research studies have been focused on improving the quality of human life in terms of health by designing and fabricating sensors that are either in direct contact with the human body or indirectly. These sensor-based systems would have a positive impact on the medical cost and the health management system as they would allow for early detection of physiological and emotional changes. Emotions play a critical role in everyone's behavior which is a mental state that does not arise through free will and is often accompanied by physiological changes. These changes need to be monitored as they contain information about various emotions which will assist in understanding behaviors. The main objective is to design a real-time monitoring system, capable of evaluating four basic emotions i.e. happy, surprise, calm, and anxious, using low-cost and non-invasive physiological sensors. The system should be capable of monitoring data in a comfortable manner, with the ability to wireless communication. In order to achieve these objectives, a literature review was conducted to analyze the different types of emotion recognition techniques and methods that are available. The emotion detection systems researched are those that use text, facial expressions, speech, body gestures and movements, and physiological signals. Emotion is a critical parameter in everyday life making people themselves outside the realm of verbal (AlMejrad, et al., 2015) An overview of the steps involved in the transmission of physiological signal data from the sensors to the computer for data analysis and emotion recognition is then given. The physiological parameter chosen for this project is respiratory rate using a non-contact temperature sensor and heart rate sensor. Parameters for emotion detection are set based on data collected from healthy individuals. The results obtained.

1.2. EMOTIONS

Emotions may be a positive or negative experience with a particular pattern experience. Emotions produce various physiological and behavioral changes. The original role of emotions was to motivate behaviors that in the past would have contributed to the passing on of genes through reproduction, and kin selection. Research on hate that clearly shows that hate continues beyond this restoration target. Hatred's aim, on the other hand, is to harm and destroy the object of hatred (Fischer et al. 2018). Emotions are biological states associated with the nervous system brought on by neurophysiological changes variously associated with thoughts, feelings, behavioral responses, and a degree of pleasure or displeasure.

1.3. RESPIRATORY RATE

The number of breaths per minute or, the number of movements of inspiration and expiration per unit time is usually determined by counting the number of times the chest rises or falls per minute. One complete cycle comprises of one inhalation, when the chest rises, followed by one exhalation when the chest falls. To measure the respiratory rate, count the number of breaths for a minute or count for 30 seconds and multiply that number by two.

1.4. HEART RATE

The number of contractions (beats) of the heart per minute is used to determine the heart rate (beat per minute). The heart rate is modulated by a variety of factors, including biology, physical health, stress or psychological condition, diet, medications, hormonal status, climate, disease/illness, and the relationship between and among these factors. It is normally the same as or very similar to the pulse measured at any peripheral stage

1.5. RELATION BETWEEN EMOTIONS AND RESPIRATORY RATE

In the brainstem, breathing is normally performed for metabolic and homeostatic reasons, but breathing can also change in response to changes in emotions such as sorrow, happiness, anxiety, or fear. The final respiratory output is by a complex interaction between the brainstem and higher centers, including the limbic system and cortical structures. Respiration is important in maintaining physiological homeostasis with emotions. In the brain, complex neural networks produce motor instructions for the contraction of these muscles. To generate respiratory rhythm and tidal activity, various afferent inputs are combined, primarily in response to metabolic demands. Chemoreceptors, which form reflex feedback mechanisms for respiratory motor activities, are the most important inputs for breathing-control. Although some research distinguishes between the terms uncertainty, lability, and variability, others do not.(Natasha Bailen, et al., 2019).

1.6. RELATION BETWEEN EMOTIONS AND HEART RATE

Symptoms such as palpitations and hyperventilation are examples of how emotions affect the autonomic nervous system. Emotional processes are known to cause changes in heart rate (HR), heart rate variability (HRV), and contractility. The following bodily organs had higher TF-IDF values: indignation with the liver, satisfaction with the heart, thoughtfulness with the heart and spleen, sorrow with the heart and lungs, apprehension with the kidneys and heart, surprise with the heart and gallbladder, and anxiety with the heart and lungs. Based on the emotion corpus, an emotion dictionary was created that contains details about eight basic emotions.(Li, et al., 2009).

CHAPTER 2

LITERATURE REVIEW

Al Mejrads (2015) reported that emotions play critical roles in rational and intelligent behavior. When people are happy, their attitude is skewed against happy activities, and the same is true when they are sad. Similarly, users' affective states are also a factor in their decision-making. Emotions can be categorized into various types. He found six basic emotions i.e. happiness, sadness, fear, surprise, anger, and disgust. These six basic emotions have been widely accepted and used to date. He later expanded his list and included amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame. Recently, studied human emotions using brain wave signals and classified human emotions into three types, i.e. motivational, basic, and self-conscious or social. The motivational type consists of thirst, hunger, pain, and mood; basic type consists of happy, sad, fear, disgust, rage, and surprise; self-conscious or social type consists of shame, embarrassment, pride, and guilt; and self-conscious or social type consists of shame, embarrassment, pride, and guilt. Based on his theory of emotional coherence, he built a computational model to integrate both emotion-based and deliberative decision-making processes. The key benefit of emotion-based decision-making, according to him, is pace and performance, as emotion helps to frame the choices for action to be assessed. De Sousa (1987) reported that emotions fall somewhere in between clear cases of activity (intentional actions), and clear cases of passivity (involuntary physiological processes). Emotions might not be the same as actions but that does not imply that emotions can be separated from our understanding of the nature of action. He called emotions an integral part of the process of reasoning and decision making. He found that some patients with neurological damage in specific sites of their brains who lost their ability to process emotion normally also lost their ability to make rational decisions in everyday life.

To find the negative implications of negative terms in Chinese sentences, Wu and Ren (2008) used a pattern matching tool. To create a corpus, they gathered sentences from the web that contained negative words and emotional information. For the matching method, they summarized and organized negative auxiliary modifiers vocabulary, degree adverbs vocabulary, and causative verbs vocabulary. This approach introduced a new way of thinking about how to deal with the issue of emotion recognition in negative sentences, and it achieved a high level of precision.

Wang et al. (2007) created an emotional chatting device that took personality into account. The participants were instructed to converse with the emotional Chabot. The chat's reported results were then read by a computer that followed simple emotion reasoning laws. The accuracy of both devices was tested by the participants at the end. They demonstrated Text Tone, a method for expressing explicit emotion in online textual communication. It took into account the tastes of individuals.

Li and Ren (2009) created a three-dimensional (3D) emotion space to visually and intuitively describe the text's emotional orientation. Based on the emotion corpus, they produced an emotion dictionary with details on eight basic emotions. The emotion keywords were projected into the emotion space as 3D structure distributions.

Matsumoto and Minato (2005) devised an emotion estimation method in order to develop an effective robot that can interpret emotion based on language knowledge gleaned from spoken words. The method estimates a speaker's or writer's emotion by extracting emotion event conditions from emotions found in terms and sentence definitions.

Zhang et. al., (2005) developed emotion recognition using text has become popular these days, especially when it comes to human-machine interaction. Textual information is not only an important communication medium that exists in books, newspapers, websites, emails, etc; but a rich source of emotion. Different approaches have taken place in order to recognize and evaluate these emotions. The most common approach uses natural language processing Emotion techniques, which extract emotions and sentiments by analyzing the input text. He devised a semi-automated method for obtaining emotional knowledge from a sentence or text. They constructed a Chinese language emotion thesaurus in which words had their own

classification (such as commendatory, derogatory) and the corresponding emotion information. Their emotion recognition system was able to interpret textual input, such as sentences and paragraphs, to extract emotion information such as emotion category.

Calix et al. (2010) used automated emotion detection in descriptive sentences to fine-tune facial expression parameters for 3-D character generation. They used support vector machines to compare manual and automated word feature selection approaches to see how word features affected classification accuracy (SVM).

Boucouvalas (2003) created a real-time communication interface that improved text communication by detecting typed text in real time. On the projector, the interacting subjects' extracted emotions were shown as facial expression images or sketches. The interface made use of a text-based emotion extraction engine that was built in real time.

Danisman et. al., (2008) studied the automatic classification of anger, disgust, fear, joy, and sad emotions in the text on the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset. They used Vector Space Model for the classification of emotions and valences in text. When the findings were compared to those of other strong text-based classifiers, it was discovered that the results performed better for detecting emotion in sentences.

Chakraborty et al. (2009) proposed a fuzzy relational approach to human emotion recognition and regulation based on facial expressions. Their proposed method involved using an external stimulus to elicit particular emotions in human subjects, whose facial expressions were studied by segmenting and localizing individual frames into regions of interest. Using Mamdani-type relational models, selected facial features such as eye-opening, mouth opening, and the length of brow constriction are extracted from localized regions and mapped onto an emotion domain.

An emotion avatar image (EAI) was developed by Yang and Bhanu (2011) as a single representation for video or image sequences for emotion recognition. To align the face images, they used the scale-invariant feature transform (SIFT) flow algorithm,

which can compensate for broad global motion while preserving facial feature motion detail. They then used an iterative algorithm to create an avatar reference face model, which and face image is aligned against. They used both local binary pattern (LBP) and local step quantization to extract features (LPQ).

Valstar and Pantic (2006) developed a fully automated framework for accurately recognizing facial expressions from the video. By understanding facial muscle action units, they were able to analyze subtle changes in facial expression and their temporal behavior. These action units aided in the identification of emotional, attitude, and mood expressions in a face video using facial signals. In the first frame of an input face video, a fully automatic facial localization system is used to detect 20 points of interest. For the identification of temporal segments and muscle action units, a support vector machine is used, which is trained on a subset of the most informative Spatio-temporal features.

Matsumoto and Willingham (2009), on the other hand, compared the expressions of congenitally and non-congenitally blind athletes at the 2004 Paralympic Games to those created by sighted athletes at the 2004 Olympic Games. They also looked at how facial expressions shift from one situation to the next and found no distinctions between congenitally blind, non-congenitally blind, and sighted athletes on the level of individual facial movements or facial emotion configurations. While blind athletes had more overall facial activity, it was limited to head and eye movements.

Koolagudi and Rao (2010) proposed a method for extracting epoch parameters from speech using linear prediction (LP) residuals and zero frequency filtered speech signals. They describe an epoch as the point at which the glottis closes within the pitch time of an LP residual. According to them, major vocal tract excitation normally occurs at the time of glottal closure. They classified emotions based on the intensity of epoch, instantaneous frequency, sharpness of epochs, and slope of the strength of epochs, which were derived from the glottal closure area of the LP residual.

Pao et al. (2010) used a whole sentence segmentation approach to study emotion recognition and found the emotion transfer point in the continuous expression. They looked at five emotions: indignation, happiness, sorrow, boredom, and neutral and used two classification algorithms in the recognition phase: the traditional K-nearest

neighbor (KNN) and the weighted discrete-KNN (WD-KNN). The used research sentence had an average recognition rate of 73 percent, according to their findings.

Kamaruddin and Wahab (2011) looked for a connection between the driver behavior state (DBS) and speech emotion states (angry, happy, sad, and neutral). They used three different classifiers, including the Multi-Layer Perceptron, the Adaptive Neuro-Fuzzy Inference scheme, and the Generic Self-organizing Fuzzy Neural Network, along with the Mel Frequency Cepstral coefficient features extraction process, to achieve a 70% accuracy. They discovered that sleep DBS was reliably recognized as sad emotion, which was attributed to the fact that both emotions in the affective state model shared the same negative meaning of the activation axis.

Tokuno et al. (2011) looked at emotions based on voice data obtained from military medical corps staff that was on a special stressful assignment. They used sensibility technology for an emotion voice analysis device that can detect rage, joy, sorrow, calmness, and excitement among other emotions. The results suggested that using proper emotion recognition techniques could help with mental health screening in military situations.

Camurri et al., (2003) investigated and classified expressive gestures in human full-body movement, especially dance performances. The aim of their study was to identify motion cues that were primarily responsible for communicating the dancer's expressive intentions to the audience during a dance performance. Using a series of established models and algorithms, these movements were calculated and analyzed in order to identify dance gestures in terms of basic emotions. The results of audience reviews for the same dance fragments were compared. Observers were able to detect the expected feelings, according to their findings. Fear-based performances had a lower recognition rate than other types of performances. They also looked at children and adults' general ability to decode happiness, sorrow, rage, and fear in dance types of expressive body movement. They discovered that four-year-old children decoded sad expressions better than chance, while five-year-old children could tell the difference between happiness, sorrow, and fear.

On a corpus of theatre movies, Kipp and Martin (2009) investigated the relationship between emotion and gestural features. They coded emotions according to the

enjoyment, arousal, and domination (PAD) dimensions. They looked at handedness, hand shape, palm orientation, and motion direction for gestural features. They compared the material of two different actors playing the same role and discovered that handedness and emotion had important associations. They discovered that the right hand was used more when both actors were in a pessimistic and hostile mood, while the left hand was used more when they were calm and positive.

Kapur et al., (2005) used full-body skeletal movements recorded using Vicon Motion Systems' video-based sensor technology to train a computer to recognize various human emotions. Lightweight markers were mounted on different points of the body in 3D space, and movement was digitized into x, y, and z displacement data using a series of six cameras. Four emotions were represented by the gestural data obtained from five subjects.

Based on physiological signals tracked by non-invasive and non-intrusive sensors, Zhai and Baretto (2006) developed a stress detection system. They analyzed the collected data to discern affective states in a computer consumer by monitoring four signals: galvanic skin reaction, blood volume pulse, pupil diameter, and skin temperature. They used a support vector machine to classify different states and discovered that when stress stimuli were applied, the controlled physiological signals had a strong correlation with changes in an emotional state, with pupil diameter having the most important effect relative to the other signals.

Sierra et al. (2011) have suggested a physiological signal-based stress detection method. The physiological knowledge of a person was obtained using the galvanic skin response and heart rate. They created a database for teaching, validating, and evaluating the proposed method by designing complex psychological tests to cause stress in individuals. In terms of HR and GSR, fuzzy logic was used to explain an individual's actions under stressful stimuli.

According to Natasha, et al., (2018) adolescence is a period of transition from childhood to adulthood where major changes occur in a variety of areas, including emotional experience. This article explores the research on the adolescent perception of four distinct emotional dimensions: emotional frequency, strength, volatility, and clarity. 10 to 19, and equate adolescent emotional functioning to adult emotional functioning. We also look at whether and how gender and puberty play a role in age-related variations in emotional experience. Finally, we examine how these results could guide future research on the typical course of emotional experience as well as the development of psychopathology.

CHAPTER 3

AIM AND SCOPE

3.1. AIM

We propose emotion detection using a breath rate and a heart rate sensor in this project. Machine learning is used to verify the performance of the labeled input readings. To create a non-contact emotion detection device that can help brain dead patients sense their emotions and to develop a device that aids in the identification of a criminal's emotions in forensic cases.

3.2. SCOPE

Different architectures of Artificial Neural Network (ANN) such as Convolutional Neural Network (CNN), Long-short term Memory, and Extreme Learning Machine are well-known deep learning algorithms for future growth (ELM). Emotion recognition based on body movements and gestures.(Kipp et al., 2009)Deep learning approaches' success in the domain of emotion detection can largely be due to this. Hybrid approaches to emotion detection are basically a mix of knowledge-based techniques and computational methods that take advantage of both techniques' strengths. Sentic computing and I feel, both of which use the concept-level knowledge-based resource Sentic Net, are examples of works that use an ensemble of knowledge-driven linguistic elements and statistical methods. In the emotion classification method, the role of such knowledge-based tools in the implementation of hybrid approaches is critical. Reformulated our original skill model here, led by a few rules, clarified some of the model's earlier claims that were vague, and updated some of it in light of new research.(John. et al., 2016) Since hybrid techniques gain from the benefits offered by both knowledge-based and statistical approaches, they tend to have better classification performance as opposed to employing knowledge-based or statistical methods independently. From the recording of a physiological dataset to a feature-based multiclass classification, the critical stages of an automatic recognition system are discussed.(Kim, et al., 2008).

CHAPTER 4

MATERIALS AND METHODS

4.1. ARDUINO UNO

Arduino-cc created the Arduino UNO, an open-source microcontroller board based on the Microchip ATmega328 microcontroller. The board has a number of digital and analog input/output (I/O) pins that can be used to connect to different expansion boards (shields) and other circuits. The board has 14 digital I/O pins (six of which can be used for PWM output) and 6 analog I/O pins, and it can be programmed using the Arduino IDE (Integrated Development Environment) and a USB type B cable. It can be powered by a USB cable or an external 9-volt battery, with voltages ranging from 7 to 20 volts.



Fig: 4.1. Arduino Uno

4.1.1. General Pin Function

- LED: A built-in LED is powered by digital pin 13. The LED is turned on when the pin has a high value, and it is turned off when the pin has a low value.
- VIN: When using an external power source, VIN is the input voltage to the

Arduino board (as opposed to 5 volts from the USB connection or other regulated power source). This pin may be used to supply voltage or to access voltage if it is supplied through the power jack.

- 5V: This pin receives a controlled 5V from the board's regulator. The DC power jack (7 - 20V), the USB connector (5V), or the board's VIN pin can all be used to power the board (7-20V). Using the 5V or 3.3V pins to supply voltage bypasses the regulator and may harm the board.
- 3V3: The on-board regulator generates a 3.3volt supply. The maximum current draw is 50 mA, and the GND pins are used to connect to the ground.
- IOREF: The voltage reference with which the microcontroller operates is provided by this pin on the Arduino board. The IOREF pin voltage can be read by a properly calibrated shield, which can then pick the appropriate power source or allow voltage translators on the outputs to operate with 5V or 3.3V.
- Reset: Added a reset button to shields that block the board's reset button.

4.1.2. Special Pin Function

Under software control (using pin Mode(), digital Write(), and digital Read() functions), each of Uno's 14 digital pins and 6 analog pins may be used as an input or output. They are powered by 5 volts. Each pin has a 20-50K ohm internal pull-up resistor (disconnected by default) and can provide or receive 20 mA as the recommended operating condition. To prevent permanent damage to the microcontroller, a limit of 40mA on any I/O pin must not be exceeded. The Uno has six analog inputs, numbered A0 through A5, each with a resolution of 10 bits (i.e. 1024 different values). They measure from ground to 5 volts by default, but the AREF pin and the analog feature can be used to adjust the upper end of the range.

4.2. MLX90614 SENSOR

The MLX90614 is an infrared thermometer that measures temperature without touching it. It's a low-noise amplifier with a powerful 17-bit ADC and DSP unit that achieves high precision and thermometer resolution. The thermometer has a digital

PWM and SMB (System Management Bus) output and is factory calibrated. As is customary, the 10bit PWM is configuration to continuously transmit the measured temperature in the range of -20 to 120 degrees Celsius with an output resolution of 0.14 degrees Celsius.

4.2.1. Signal Processing Principle

The MLX90614's operation is managed by an internal state machine, which monitors the object and ambient temperature measurements and calculations, as well as post-processing the temperatures for output through the PWM output or the SMB compatible interface.

Two infrared sensors can be used with the ASSP. The IR sensors' output is amplified by low noise, low offset chopper amplifier with programmable gain, converted to a single bit stream by a Sigma Delta modulator, and fed to a powerful DSP for processing. For further reduction of the bandwidth of the input signal, programmable (via EEPROM contend) FIR and IIR low pass filters are used to achieve the desired noise performance and refresh rate. The measurement result is the IIR filter's output, which is stored in the internal RAM. There are three separate cells: one for the on-board temperature sensor and two for the infrared sensors.

The corresponding ambient temperature T_a and object temperatures T_o are determined based on the effects of the above measurements. The resolution of both measured temperatures is 0.01 C. Data for T_a and T_o can be read in two ways: via the 2-wire interface (0.02°C resolution, fixed ranges) or via the PWM digital output (10-bit resolution, configurable range).

The measured T_a and T_o are rescaled to the PWM's desired output resolution in the final stage of the measurement cycle, and the recalculated data is loaded into the registers of the PWM state machine, which generates a constant frequency with a duty cycle representing the measured data. The argument is that material generated by actors for such studies implies that gesture handedness may have a universal connection with the emotional dimensions of pleasure.(Kipp,et al., 2009)

4.2.2. Pin Definition and Description

Table 4.1. Pin Definition and Description

SCL / Vz	For the two-wire communications protocol, a serial clock input is needed. This pin has a 5.7V Zener for connecting an external bipolar transistor to the MLX90614Axx in order to supply the system from an external 8...16V source.
SDA / PWM	Input and output are both digital. The calculated object temperature is available at this pin Pulse Width Modulated in normal mode. The pin is automatically configuration as open drain NMOS in SMB compatible mode.
VDD	External supply voltage.
VSS	Ground. The metal can is also connected to this pin.

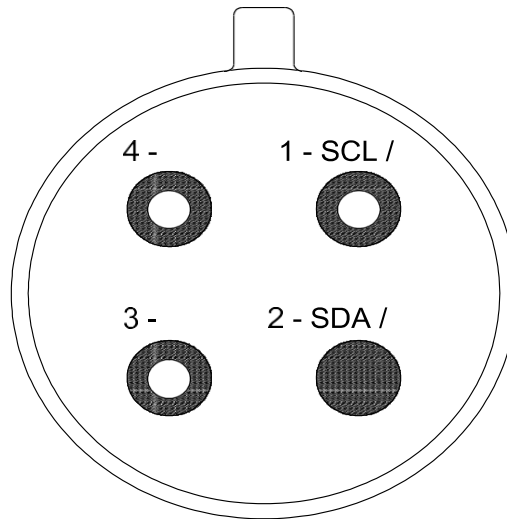


Fig: 4.2. Sensor Model

4.3. MAX30102/100 SENSOR

The MAX30102 is a PPG (pulse oximetry and heart rate monitor biosensor module with integrated pulse oximetry and heart rate monitor (PhotoPlethysmoGraphy). It's so lightweight that it can be worn on your finger or wrist to collect data. The sensor has an internal 18-bit ADC and can output I2C data, which is compatible with most controllers.

4.3.1. General Description

The MAX30102 is a pulse oximetry and heart rate monitor module that works together. The kit includes internal LEDs, photo detectors, optical components, and low-noise electronics with ambient light rejection. The MAX30102 is a full system solution that makes design-in for mobile and wearable devices much easier. The MAX30102 is powered by a single 1.8V supply as well as a separate 3.3V supply for the internal LEDs. Communication is through a standard I2C-compatible interface. The module can be turned off with zero standby current via software, leaving the power rails powered at all times. This works on the theory of PhotoPlethysmoGraphy, which states that changes in the amount of blood in an organ are determined by changes in the intensity of light flowing through that organ. As a result, the emitted light from the LED can only be received by the photo sensor when there is blood in the vein, resulting in the pulse being measured. The final output is conditioned and filtered from the output signal.

MAX30102 is a sensor that combines pulse oximetry and a heart rate monitor. It detects pulse oximetry and heart rate signals using two LEDs (IR and Red), a photo detector (visible + IR), calibrated optics, and low-noise analog signal processing. The digital output data is stored in a 32-deep FIFO within the computer, and it is completely configurable via software registers. It communicates with a host microcontroller through an I2C digital interface. Ambient light cancellation (ALC), an 18-bit sigma-delta ADC, and a patented discrete-time filter make up the pulse oximetry subsystem in the MAX30100. It operates at ultra-low voltage, making it suitable for battery-powered applications.

It has an integrated temperature sensor for calibrating the temperature dependence of the pulse oximetry system. It also has a proximity detection function to reduce power consumption and visible light emission when the user's finger is not on the sensor.

4.3.2. MAX30102 Pin Diagram

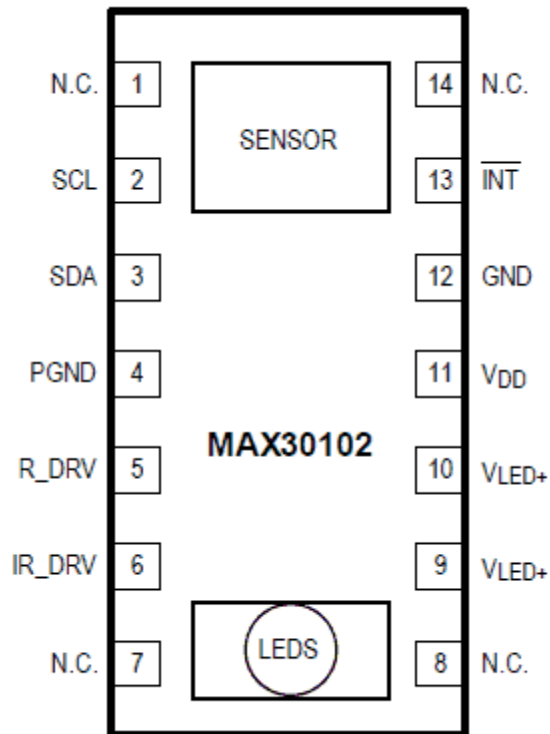


Fig: 4.3. Pin Diagram

4.4. MATLAB

MATLAB is a fourth-generation programming language and numerical computing environment. Matrix manipulations, plotting of functions and data, implementation of algorithms, design of user interfaces, and interfacing with programs written in other languages, such as C, C++, Java, and Fortran, are all possible with MATLAB, which was developed by Math Works.

While MATLAB is primarily designed for numerical computations, an optional toolbox that uses the MuPAD symbolic engine provides symbolic computing capabilities. Simulink, a separate kit for dynamic and embedded systems, adds graphical multi-domain simulation and Model-Based Design.

Little's specialty, control engineering, was the first to introduce MATLAB, but it soon spread to a variety of other fields. It is now widely used in education, especially in the teaching of linear algebra and numerical analysis, and among image and signal processing scientists. The MATLAB framework is based on the MATLAB

programming language. The most straightforward way to run MATLAB code is to type it into the command window, which is one of the MATLAB Desktop's features. MATLAB can be used as an interactive mathematical shell when code is inserted in the command window. The MATLAB Editor is usually used to save command sequences in a text file. MATLAB provides a number of features for documenting and sharing your work

- Linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration are all mathematical functions.
- Data visualization using 2-D and 3-D graphics features.
- Tools for creating personalized graphical user interfaces
- External applications and languages, such as C, C++, Fortran, Java, COM, and Microsoft Excel, can use these functions to integrate MATLAB-based algorithms.

Signal and image processing, communication, control design test and calculation, financial modeling and analysis, and computational all use MATLAB. Add-on toolboxes (groups of MATLAB functions with a specific purpose) extend the MATLAB environment to solve specific types of problems in these application areas. MATLAB is a programming language that can be used on both personal computers and powerful server systems.

4.4.1. The MATLAB Language

Vector and matrix operations are central to engineering and science issues, and the MATLAB language supports them. It allows for quick development and implementation. Since you don't have to perform low-level administrative tasks like declaring variables, identifying data types, or allocating memory, the MATLAB language allows you to program and build algorithms faster than traditional languages. MATLAB removes the need for 'for' loops in certain situations. As a consequence, a single line of MATLAB code will frequently be used to substitute multiple lines of C or C++ code.

4.4.2. Signal Processing

Signal Processing Toolbox includes functions and applications for analyzing, pre-

processing, and extracting features from signals that are sampled uniformly or non-uniformly. Filter configuration and analysis, resampling, smoothing, detrending, and power spectrum estimation are all included in the toolbox. Extracting features such as change points and envelopes, detecting peaks and signal patterns, quantifying signal similarities, and performing measurements such as SNR and distortion are all possible with the toolbox. Vibration signals may also be subjected to modal and order review.

Without writing code, Signal Analyzer allows you to pre-process and analyze several signals simultaneously in the time, frequency, and time-frequency domains; explore long signals, and extract regions of interest. Filter Designer allows you to build and analyze digital filters by selecting from a number of different algorithms and responses.

4.5. PRE PROCESSING

4.5.1. Principal Component Coefficient

The principal component coefficients, also known as loadings, for the n -by- p data matrix X are returned by PCA (x). Observations are represented by rows of X , while variables are represented by columns. It's a p -by- p coefficient matrix. The coefficients for each principal component are mentioned in descending order of component variance in each column of coefficients. By default, PCA uses the Singular Value Decomposition (SVD) algorithm to center the data.

A quantitatively rigorous method for achieving this simplification is principal component analysis. The principal components method creates a new set of variables. The original variables are linearly combined in each principal factor. There is no redundant knowledge since all of the principal components are orthogonal to one another. The principal components as a whole provide an orthogonal foundation for the data space.

An orthogonal basis for multiple columns of data can be constructed in an infinite number of ways.

A single axis in space is the first major part. The values that result from projecting

each observation on that axis form a new variable. And this variable's variance is the highest of all the options on the first axis.

The second main part is a perpendicular axis in space to the first. When you project the observations onto this axis, you get a new variable. This attribute has the highest variance out of all the options on the second axis. The proposed stress-detection system is ideal for real-time applications, according to the paper, since it only needs two physiological signals for accurate stress detection.(Sierra A. S, et al.,2011)

The total number of principal components is the same as the number of variables in the original package. The number of the variances of the first few principal components, on the other hand, is often greater than 80% of the total variance of the original results. Inter-channel connections in EEG signals are represented by an adjacency matrix in a graph neural network, with the adjacency matrix's correlation and sparseness inspired by neuroscience theories of human brain organization.(Peixiang Zhong,et al., 2019). The PCA function aids in the discovery of the primary components. The real calculated data had to be analyzed in order to use PCA.

4.5.2. xlsread

A = xlsread('filename') returns numeric data from the first sheet in the filename Microsoft Excel spreadsheet format in array A. Leading rows or columns of text are ignored by xlsread. If a cell in a leading row or column is empty or contains text, however, xlsread replaces it with a NaN.

4.5.3. Machine Learning

Machine learning teaches machines to learn from experience in the same way as humans do. Machine learning algorithms employ analytical methods to “learn” knowledge directly from data rather than relying on a model based on a predetermined equation. As the number of samples available for learning grows, the algorithms adapt their output.

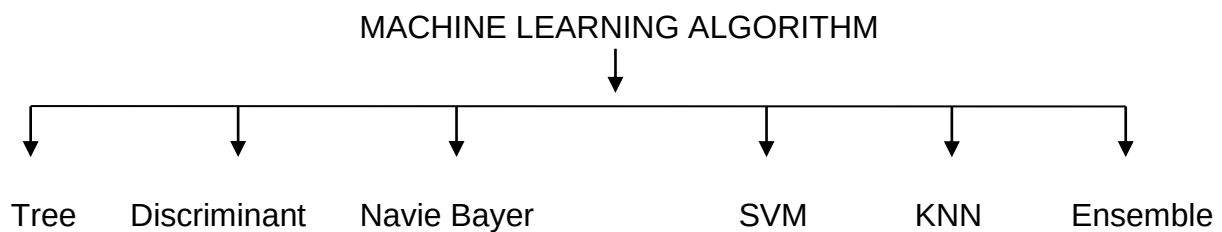
Machine Learning uses two ways of technique

- Supervised learning is a method of training a model using known input and

output data in order to predict potential outcomes.

- Unsupervised learning is the discovery of hidden patterns or intrinsic structures in data without the use of supervision.

In the face of uncertainty, the aim of supervised machine learning is to create a model that can make predictions based on data. A supervised learning algorithm uses a known collection of input data and known responses to the data (output) to train a model to make accurate predictions about how new data will react. To build predictive models, supervised learning employs classification and regression methods.



4.5.4. Classification Learner

Importing data, defining validation schemes, interactively exploring the data, selecting features, training models, and evaluating model efficiency are all possible with Classification Learner.

The Classification Learner app teaches data classification to models. It uses automatic training to find the best classification model sort, which can include decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naive Bayes, and ensemble classification.

Techniques for classifying data predict categorical responses, such as whether an email is real or spam, or whether a tumor is cancerous or benign. Input data is classified using classification models. Medical imaging, image and speech recognition, and credit scoring are examples of popular applications.

Train Classification Models with the Classification Learner App

The Classification Learner app allows you to use supervised machine learning to train models to classify data. Using different classifiers, the software allows you to

interactively explore supervised machine learning.

- Automatically train a number of models and assist you in selecting the right one. Decision trees, discriminant analysis, support vector machines, naive Bayes, and ensemble classification are some of the different types of models.
- Investigate your data, define validation schemes, choose features, and visualize the results. Cross-validation is used by default to defend against over fitting. The validation results will assist you in selecting the best model for your data which are reflected in the plots and performance indicators.
- To make predictions with new data, export models to the workspace. The app often trains a full model as well as a model with the required validation scheme, and the full model is the model you export.
- Build scripts, train with new data, work with large data sets, or change the code for further analysis using MATLAB code generated from the app.
- *Decision Tree*

Decision trees, also known as classification trees and regression trees, are used to forecast data responses. Follow the decisions in the tree from the root (beginning) node down to a leaf node to predict an answer. The answer is stored in the leaf node. Nominal answers, such as 'true' or 'false,' are given by classification trees.

➤ *Discriminant Analysis*

DFA (Discriminant Feature Analysis) is a mathematical method for classifying unknown persons and determining their likelihood of being classified into a specific category (such as sex or ancestry group). The presumption in discriminant analysis is that the sample is usually distributed for the trait.

Where the parameter or dependent variable is categorical and the indicator or independent variable is the interval in nature, discriminant analysis is a method used by the researcher to interpret the test results.

➤ *Support Vector Machine*

Support-Vector Machines (also known as support-vector networks) are supervised learning models with associated learning algorithms that analyze data for classification in machine learning.

An SVM model is a representation of the examples as points in space, mapped such that the examples of the different categories are separated by a large distance. New examples are then mapped into the same space and assigned to one of the categories depending on which side of the distance they fall on.

➤ *Naive Bayes*

The Naive Bayes classifier is a basic, but powerful, machine learning classifier. In a Bayesian context, it is a probabilistic classifier that makes classifications using the Maximum A Posteriori decision law. A very simple Bayesian network can also be used to describe it. A similar approach is used by Naive Bayes to estimate the likelihood of various classes based on various attributes. This algorithm is usually used for text classification and problems with multiple groups.

➤ *Ensemble Classification*

Since ensemble can be trained and then used to make predictions, an ensemble is a supervised learning algorithm. It has been shown that qualified ensembles have greater versatility in the roles they can serve. In theory, this versatility allows them to over-fit the training data rather than a single model, although some ensemble techniques have been shown to minimize problems associated with over-fitting the training data.

Where there is a lot of variety among the models, ensembles seem to produce better results. Many ensemble methods contribute to model diversity by combining several models. More random algorithms (such as random decision trees) may generate a stronger ensemble than very deliberate algorithms (such as entropy-reducing decision trees), which may seem counterintuitive.

➤ *KNN Classification*

Categorization KNN is a nearest-neighbor classification model in which the distance metric and the number of nearest neighbors can both be modified. You can use a Classification KNN classifier to compute substitution predictions because it stores training data. Alternatively, you can use the predicted approach to identify new findings using the model. The KNN binary (as a two-class system) provides a more reliable data classification, making it advantageous to use k as an odd number to avoid irregular data. In machine learning, the KNN procedure is used. It's an object that's been categorized using a mainstream set of its neighbors, with the determination to assign occurrence for the most common class of its k closest neighbors (k is a positive integer, classically small). The distance metric used in the past was Euclidean distance; however, this is only suitable for infinite variables. KNN is a modern method for delivering all available cases based on a quantity of assessment (e.g., distance functions). The KNN protocol is similarly straightforward. It regulates the K -nearest neighbors by requiring a minimum distance between the interrogation instance and the training samples.

4.5.5. Confusion Matrix

The rows correspond to the expected class (Output Class) and the columns to the true class on the confusion matrix map (Target Class). The diagonal cells refer to correctly identified observations. The off-diagonal cells refer to findings that were wrongly labeled. Each cell displays the number of observations as well as the percentage of the total number of observations.

The percentages of all the examples predicted to belong to each class that is correctly and incorrectly categorized are shown in the column on the far right of the map. The precision (or positive predictive value) and false discovery rate are two commonly used metrics. The percentages of all the examples belonging to each class that is correctly and incorrectly labeled are shown in the row at the bottom of the plot. The recall (or true positive rate) and false negative rate are two commonly used metrics.

➤ *Confusion Matrix for Binary Classification Metric*

Confusion Matrix is a square matrix where C_{ij} represents the number of data

instances that are known to be in group i (true label) and predicted to be in group j (predicted label).The predicted label for a machine learning algorithm is the predicted label, while the true label for a machine learning algorithm is the true label. The following Diagram represents the confusion matrix for binary classification.

		PREDICTED LABEL	
		NEGATIVE	POSITIVE
TRUE LABEL	NEGATIVE	TRUE NEGATIVE	FALSE POSITIVE
	POSITIVE	FALSE NEGATIVE	TRUE POSITIVE

Fig: 4.4. Binary Classification Metric

When a statement is actually positive and classified as positive, the statement is known as TRUE POSITIVE (TP). When a statement is actually negative and classified as negative, the statement is known as TRUE NEGATIVE (TN). When a statement is actually negative and classified as positive, the statement is known as FALSE POSITIVE (FP). When a statement is actually positive and classified as negative, the statement is known as FALSE NEGATIVE (FN). The Confusion Matrix, which is required to calculate the machine learning algorithm's accuracy in classifying data into its labels.

➤ *Accuracy*

The number of correctly identified data instances divided by the total number of data instances is known as accuracy. If the set of data's is not balanced, accuracy may not be in good measures.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{TP} + \text{FN}}.$$

➤ *Precision*

A successful classifier should have a precision of 1 (high). Only when the numerator and denominator are equal, i.e. $\text{TP} = \text{TP} + \text{FP}$, does precision become 1. This also

implies that FP is zero. The value of the denominator becomes greater than the numerator as FP increases, and the precision value decreases (which we don't want).

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}).$$

➤ *Recall*

A successful classifier should have a recall of 1 (high). Only when the numerator and denominator are equal, i.e. $\text{TP} = \text{TP} + \text{FN}$, does recall become 1. This also implies that FN is zero. The value of the denominator becomes greater than the numerator as FN increases, and the recall value decreases (which we don't want).

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}).$$

➤ *F1 Score*

Only when precision and recall are both 1 does the F1 Score become 1. Only when both precision and recall are high does the F1 score rise. The F1 score is a better metric than accuracy since it is the harmonic mean of precision and recall.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}).$$

➤ *Binary Classification Metric for Various Emotions*

Happy

Table 4.2. Binary Classification Metric for happy

TRUE NEGATIVE 50	FALSE POSITIVE 0
FALSE NEGATIVE 2	TRUE POSITIVE 48

$$\text{ACCURACY: } = \text{TN} + \text{TP} / (\text{TN} + \text{FP} + \text{TP} + \text{FN})$$

$$= 48 + 50 / (50 + 0 + 48 + 2)$$

$$= 0.98$$

$$= 98\%$$

$$\text{PRECISION: } = \text{TP} / (\text{TP} + \text{FP})$$

$$= 48 / 48$$

$$= 1$$

$$\text{RECALL: } = \text{TP} / (\text{TP} + \text{FN})$$

$$= 48 / 50$$

$$= 0.96$$

$$\begin{aligned}
 \text{F1 SCORE:} &= 2 * ((\text{Precision} * \text{recall}) / (\text{Precision} + \text{Recall})) \\
 &= 2 * (0.96 / 1.96) \\
 &= 0.98
 \end{aligned}$$

Surprise

Table 4.3. Binary Classification Metric for surprise

TRUE NEGATIVE 40	FALSE POSITIVE 10
FALSE NEGATIVE 7	TRUE POSITIVE 43

$$\begin{aligned}
 \text{ACCURACY:} &= \text{TN} + \text{TP} / (\text{TN} + \text{FP} + \text{TP} + \text{FN}) \\
 &= 40 + 43 / (40 + 10 + 43 + 7) \\
 &= 0.83 \\
 &= 83\%
 \end{aligned}$$

$$\begin{aligned}
 \text{PRECISION:} &= \text{TP} / (\text{TP} + \text{FP}) \\
 &= 43 / 53 \\
 &= 0.81
 \end{aligned}$$

$$\begin{aligned}
 \text{RECALL:} &= \text{TP} / (\text{TP} + \text{FN}) \\
 &= 43 / 50 \\
 &= 0.86
 \end{aligned}$$

$$\begin{aligned}
 \text{F1 SCORE:} &= 2 * ((\text{Precision} * \text{recall}) / (\text{Precision} + \text{Recall})) \\
 &= 2 * (0.69 / 1.67) \\
 &= 0.83
 \end{aligned}$$

Calm

Table 4.4. Binary Classification Metric for calm

TRUE NEGATIVE 41	FALSE POSITIVE 9
FALSE NEGATIVE 9	TRUE POSITIVE 41

$$\begin{aligned}
 \text{ACCURACY:} &= \text{TN} + \text{TP} / (\text{TN} + \text{FP} + \text{TP} + \text{FN}) \\
 &= 41 + 41 / (41 + 9 + 41 + 9) \\
 &= 0.82
 \end{aligned}$$

$$=82\%$$

$$\text{PRECISION:} = \text{TP} / (\text{TP} + \text{FP})$$

$$=41 / 50$$

$$=0.82$$

$$\text{RECALL:} = \text{TP} / (\text{TP} + \text{FN})$$

$$= 41 / 50$$

$$=0.82$$

$$\text{F1 SCORE:} = 2 * ((\text{Precision} * \text{recall}) / (\text{Precision} + \text{Recall}))$$

$$=2 * (0.67 / 1.62)$$

$$=0.83$$

Anxious

Table 4.5. Binary Classification Metric for anxious

TRUE NEGATIVE 49	FALSE POSITIVE 1
FALSE NEGATIVE 2	TRUE POSITIVE 48

$$\text{ACCURACY:} = \text{TN} + \text{TP} / (\text{TN} + \text{FP} + \text{TP} + \text{FN})$$

$$= 49 + 48 / (49 + 1 + 48 + 2)$$

$$=0.97$$

$$=97\%$$

$$\text{PRECISION:} = \text{TP} / (\text{TP} + \text{FP})$$

$$=48 / 49$$

$$=0.98$$

$$\text{RECALL:} = \text{TP} / (\text{TP} + \text{FN})$$

$$=48 / 50$$

$$=0.96$$

$$\text{F1 SCORE:} = 2 * ((\text{Precision} * \text{recall}) / (\text{Precision} + \text{Recall}))$$

$$= 2 * (0.94 / 1.94)$$

$$=0.97$$

From the above classification carried out emotion happy has the higher accuracy

compared to all other motions where set of data taken is in a balanced state and in good measures, also a successful classifier should have a precision of 1 (high). Only when the numerator and denominator are equal and this condition is satisfied by emotion happy in an accurate rate. Recall and F1 Score has a higher range in emotion happy and hence emotion happy is in good measures compared to all other emotions like surprise, calm, and anxious. These findings show that the development of spontaneous emotional facial expressions is not solely based on observational learning, but also that there is a learned dimension to the social management of expressions. (Matsumoto., et al., 2009).

CHAPTER 5

RESULTS AND DISCUSSION

5.1. RESULTS

A non-contact Infrared temperature sensor and a heart rate sensor and an Arduino were used to collect 200 readings of respiratory rate and heart rate. We used supervised machine learning to verify our reading efficiency percentage. The Arduino readings are transferred to Microsoft Excel. In machine learning, the filtered signals are then passed on to a classification learner. An ablation experiment to see how two different parameters influenced the prediction outcome as well as the computational training time of the proposed Delay Tolerant Mobile Network (Pao, et al., 2010) The parameters are evaluated and the efficiency is verified in the Confusion matrix which produces a precise result.

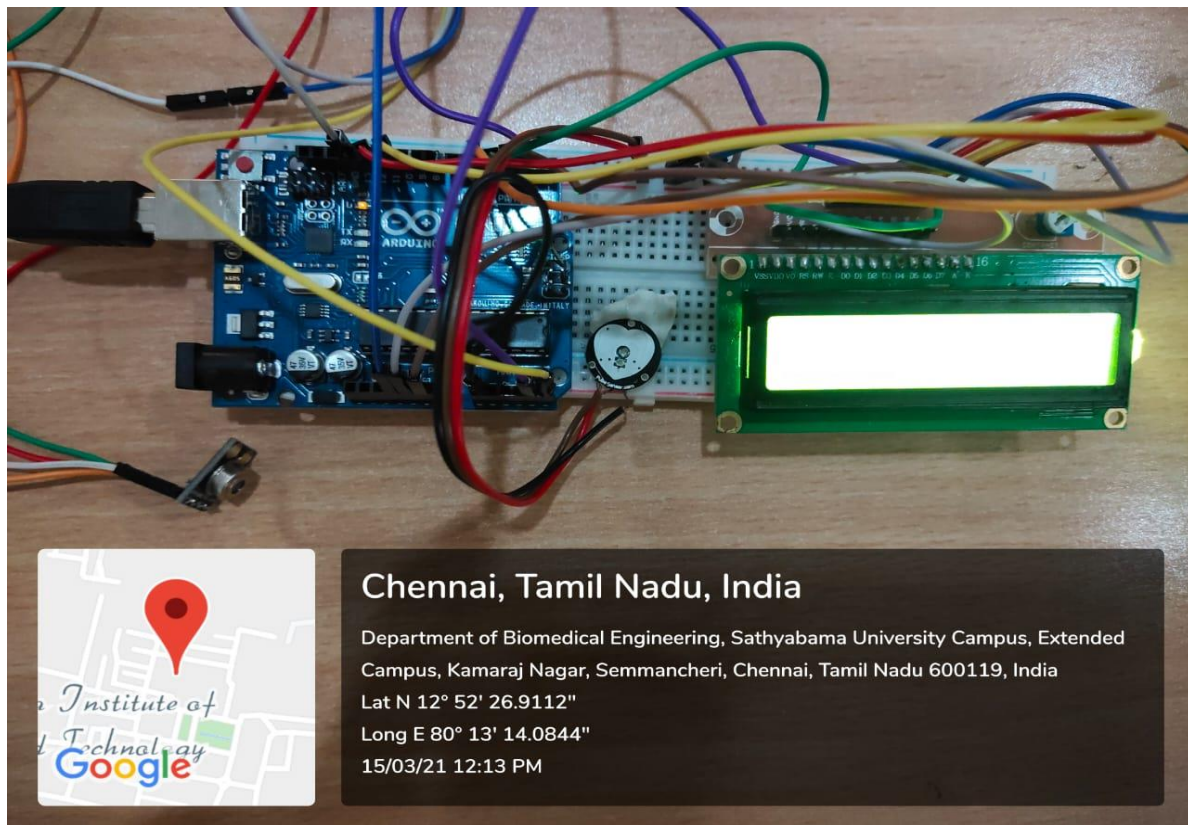


Fig: 5.1. Prototype of the Emotion Detection Device

Figure 5.1 represent the prototype of the Emotion Detection Device. The principle components of the system that is the Arduino Uno, the pulse sensor and the temperature sensor have been connected according to the block diagram. The inputs are obtained from the sensors and are sent to MATLAB where they are processed and the output is obtained.

5.1.1.1. CLASSIFICATION LEARNER OUTPUT

The Classification Learner is a program that teaches models how to classify data. In a CV unit, a VOP is an anchor point from which a vowel starts. These are calculated using the linear projection residual's energy levels, the short time continuum, and the modulation spectrum. (Koolagudi, et al., 2010) It uses automatic training to find the best classification model sort, which can include decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naive Bayes, and ensemble classification.

Table 5.1. Classification Learner Output

CLASSIFICATION	ACCURACY
Fine Tree	86.0%
Medium Tree	86.0%
Linear Discriminant	72.5%
Quadratic Discriminant	72.0%
Linear SVM	74.5%
Cubic SVM	81.0%
Fine Gaussian SVM	77.0%
Medium Gaussian SVM	75.0%
Fine KNN	78.5%
Weighted KNN	79.5%
Bagged Trees	91.5%
Subspace KNN	91.0%

The Classification Learner is a program that teaches models how to classify data. It aids in the exploration of supervised machine learning using various classifiers and data, as well as the selection of features, specification of validation schemes, training of models, and evaluation of performance.

➤ *Scatter Plot of Emotions for original set of data's*

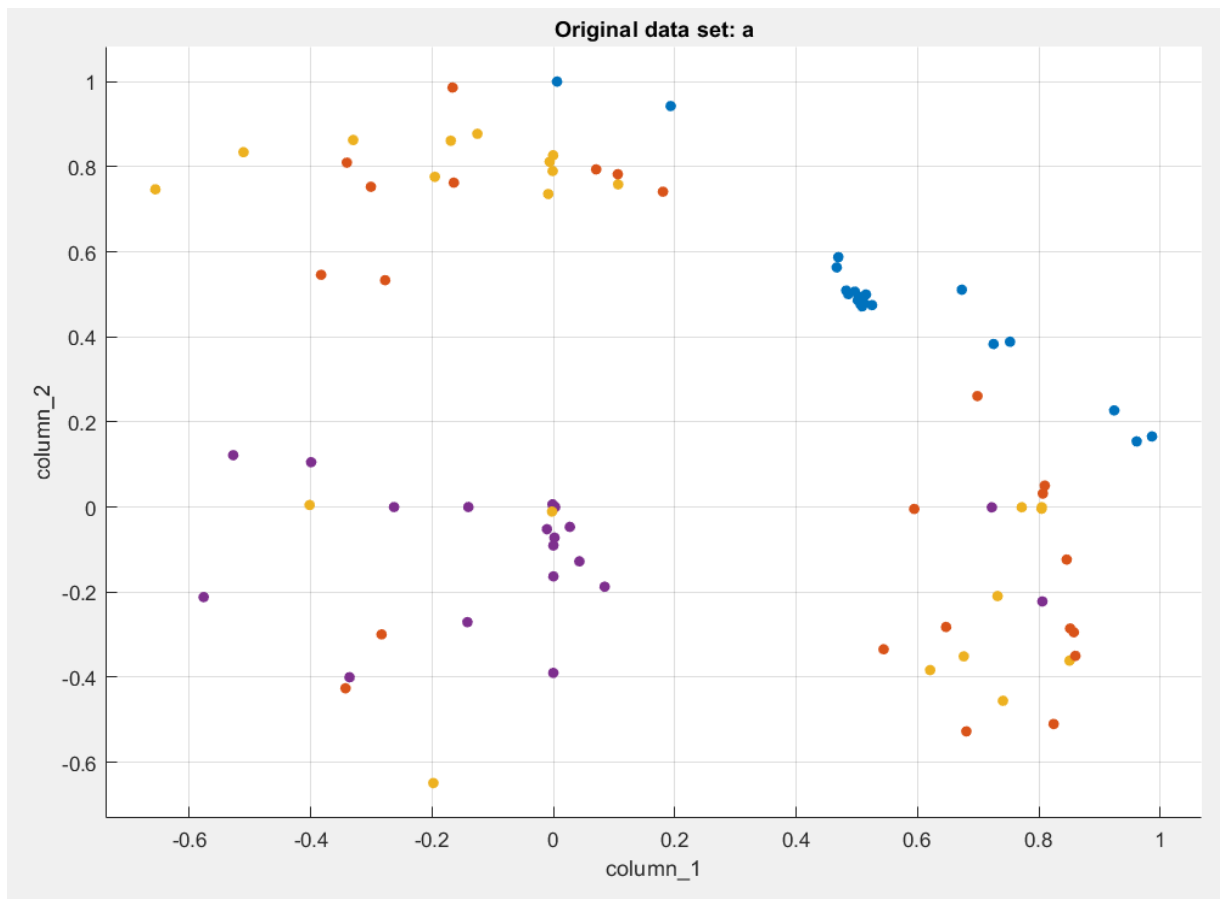


Fig: 5.2. Scatter Plot of Emotions for original set

in terms of knowing, controlling, and communicating emotions in order to adapt to our environments and maintain well-being (Petrides, et al., 2016). In scatter plot of emotion under data category the original set of data is obtained. The colors blue, red, yellow, and purple indicates emotions like happy, surprise, calm, and anxious. Emotion happy has the higher accuracy compared to all other emotions where set of data taken is in a balanced state.

➤ *Scatter Plot of Emotions for predicted set of data's*

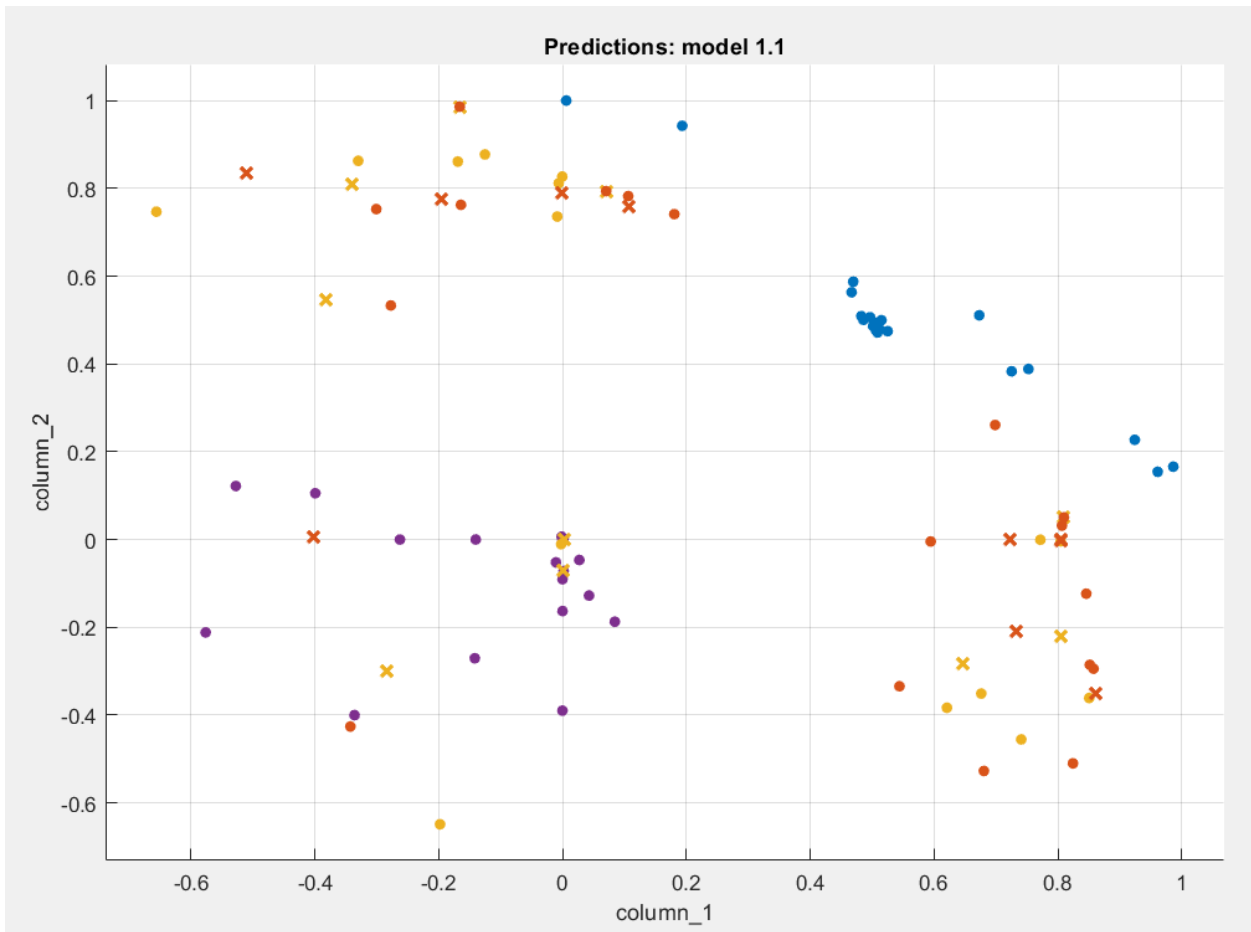


Fig: 5.3. Scatter Plot of Emotions for predicted set

In scatter plot of emotion under data category the model prediction, predicted set of data is obtained. The colors blue, red, yellow, and purple indicates emotions like happy, surprise, calm, and anxious. Emotion happy has the higher accuracy compared to all other emotions where set of data taken is in a balanced state.

5.1.2. CONFUSION MATRIX

The feature extraction process is seen in the final production. This process takes place in a matrix of uncertainty. K nearest classification is used in this method. KNN is a lazy learning algorithm that is non-parametric. Its aim is to predict the classification of a signal using a database with data points divided into several groups. Based on the existence of cavities on the input picture, it divides the signal into four categories: happy, sad, surprise, and angry dotted domains.

Table 5.2. Binary Classification Metric Rates

EMOTIONS CLASSIFICATION	HAPPY	SURPRISE	CALM	ANXIOUS
ACCURACY	98%	83%	82%	97%
PRECISION	1	0.81	0.82	0.98
RECALL	0.96	0.86	0.82	0.96
F1 SCORE	0.98	0.83	0.83	0.97

Emotion recognition based on facial expressions, which has a number of benefits, but we already know that facial expressions can be actively regulated (Chakraborty et al. 2009) From the above classification carried out emotion happy has the higher accuracy compared to all other motions where set of data taken is in a balanced state and in good measures, also a successful classifier should have a precision of 1 (high). Only when the numerator and denominator are equal and this condition is satisfied by emotion happy in an accurate rate. Recall and F1 Score has a higher range in emotion happy and hence emotion happy is in good measures compared to all other emotions like surprise, calm, and anxious. Basic emotions namely angry, disgust, fear, happy, sad and surprise along with neutral one are recognized.(Kharat, et al., 2008).

➤ *Confusion Matrix for original set of data's*

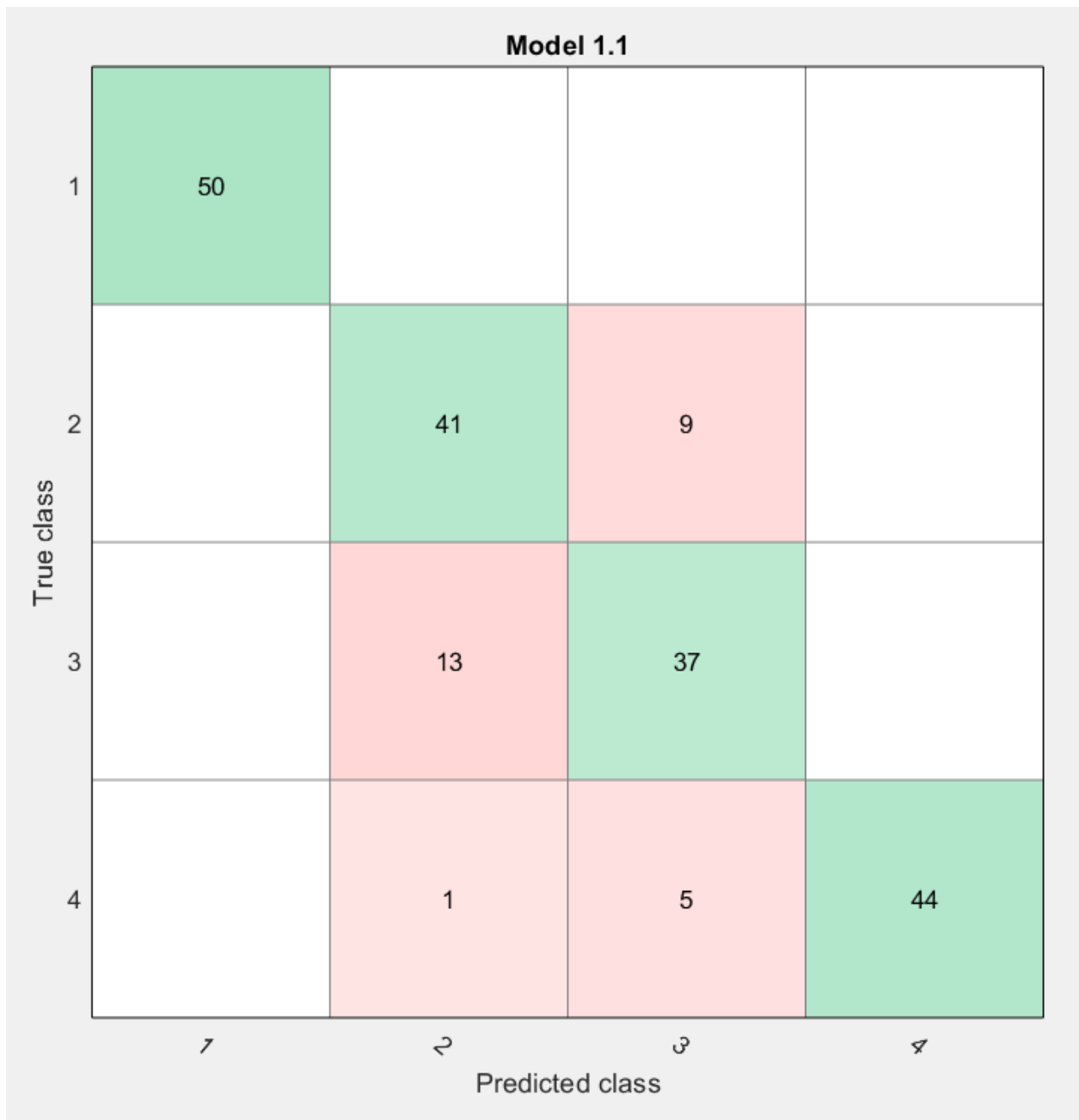


Fig: 5.4. Number of Observation.

In Confusion Matrix for original set of data's under Number of Observation category the set of data is obtained. The green box with the values indicates the true positive of various emotions like happy, surprise, calm, and anxious.

➤ *Confusion Matrix for True Positive and False Negative Rates*

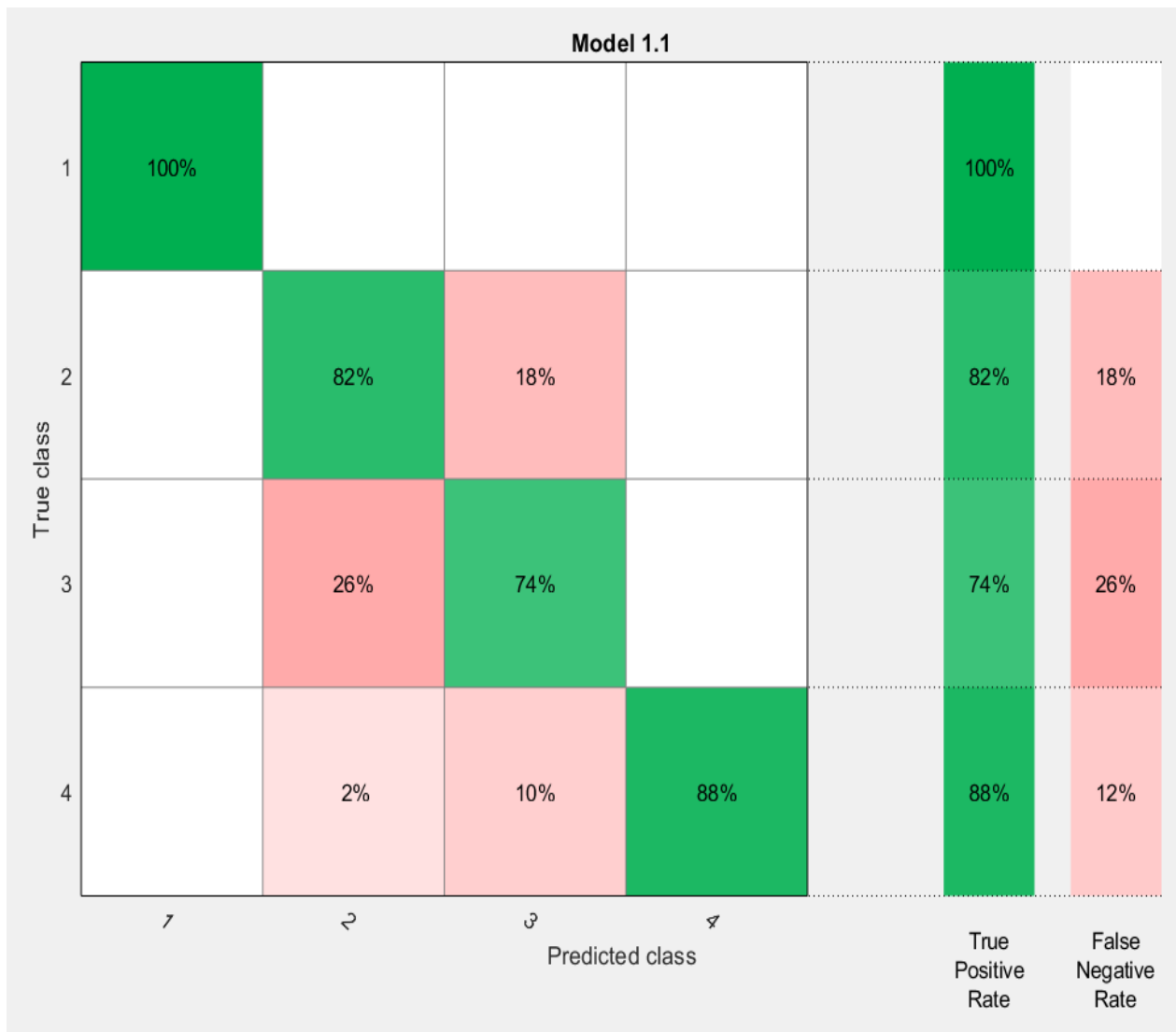


Fig: 5.5. True Positive Rate and False Negative Rate.

In Confusion Matrix for original set of data's under Positive Rate and False Negative Rate category the set of data is obtained. True Positive rates for emotion happy is 100 %, surprise is 82 %, calm is 74 %, anxious is 88 % and False Negative rates for emotion happy is nil, surprise is 18 %, calm is 26 %, and for anxious is 12 %. Hence True positive is has accuracy for emotion happy.

➤ *Confusion Matrix for Positive Predictive and False Discovery*



Fig: 5.6. Positive Predictive and False Discovery

In Confusion Matrix for original set of data's under Positive Predictive rate and False Discovery Rate category the set of data is obtained. True Predictive rates for emotion happy is 100 % and has accuracy compared to all other emotions. The aim of this paper is to assist and direct researchers by reviewing recent work and offering suggestions for how to develop this area.(Wafa Mellouk, et al., 2020).

5.2. DISCUSSION

Emotion recognition using text was introduced by Matsumoto et al. and applied to words or sentences in a specific language. When it comes to designing a universal scheme, this is a huge disadvantage. Chakraborty et al. (2009) suggested emotion recognition based on facial expressions, which has a number of benefits, but we already know that facial expressions can be actively regulated. This means that a happy person may demonstrate anger or any other emotion, demonstrating that facial expressions are not necessarily connected to inner emotions. Emotion recognition using voice, developed by Koolagudi et al. (2012), is a non-invasive and simple method of recognizing emotions based on the tone of speech signals. We know that different cultures have different tones of speech; a person from one culture or region speaking in a normal tone can appear angry to someone from another culture due to the pace and volume of conversation. As a result, emotion detection systems based on speech will be culturally or geographically specific rather than universal. The least common method of measuring emotions, according to Kipp et al., (2009) is emotion recognition based on body movements and gestures. One of the main disadvantages of this approach is that it measures emotions based on individual acts or dances that are delegated and naturally occurring. We addressed the importance of emotion recognition based on data from physiological sensors in this project, which has grown in popularity in comparison to other emotion recognition methods because it collects information from the body's physiological changes. Since physiological changes are governed by the autonomous nervous system, which is influenced by emotions, we chose this approach for this project because it offers details about a subject's internal emotions rather than just physical changes. Non-invasive, low-cost, accurate, and power-efficient physiological sensors were used in this project, with the ability to track data in a comfortable manner. Local Binary Pattern and Local Phase Quantization are used to extract features from the Emotion Avatar Image. The findings of both texture descriptors are then put to the test on samples. (Yang, et al., 2011).

CHAPTER 6

SUMMARY AND CONCLUSION

6.1. SUMMARY

In this project, we have developed a real-time emotion detection system, based on data provided by physiological sensors. The literature review enabled an appropriate method of selection for the sensor utilized in order to achieve emotion recognition. Physiological sensors have found to be the best approach to recognize emotional changes, as they provided information about changes that take place physiologically and are out of a person's control. Information and knowledge gained from other researches helped in providing information about the ranges of the physiological parameters and allowed in confirming results obtained from this study. The non-contact temperature sensor and heart rate sensor used in this project will track real-time breath rate and heart rate and provide accurate data output. The proposed approach was tested using MATLAB's machine learning and deep learning functions. New deep neural networks and related training strategies focused on both static and dynamic image sequences that are optimized for FER (Calix, et al., 2010) Preprocessing is a technique for reducing noise in sample reading input by using statistics coefficient parameters. Computer learning has been sent the filtered info. As compared to data collected from individuals in four emotional states, the KNN network algorithm used in this project for data clustering produced similar results.

6.2. CONCLUSION

Arduino software is used in this project to obtain sample readings of respiratory rate and heart rate using a non-contact Infrared temperature sensor and a heart rate sensor. The obtained signal readings are transferred to MATLAB through Microsoft Excel for processing and testing. We developed software that has a 91.5 percent recognition rate across all four emotions in MATLAB using multiple classification techniques and signal processing of sample readings using denoising filters, supervised machine learning, classification learner, and confusion matrix.

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APPENDICES

```
#include <LiquidCrystal.h>

#include <Adafruit_MLX90614.h>

#include <Wire.h>

Adafruit_MLX90614 mlx = Adafruit_MLX90614();

// initialize the library by associating any needed LCD interface pin
// with the arduino pin number it is connected to

const int rs = 12, en = 11, d4 = 5, d5 = 4, d6 = 3, d7 = 2;

LiquidCrystal lcd(rs, en, d4, d5, d6, d7);

#include "MAX30105.h"

#include "heartRate.h"

MAX30105 particleSensor;

const byte RATE_SIZE = 4; //Increase this for more averaging. 4 is good.

byte rates[RATE_SIZE]; //Array of heart rates

byte rateSpot = 0;

long lastBeat = 0; //Time at which the last beat occurred

float beatsPerMinute;

int beatAvg;

int count=0;

float temp = 0;

unsigned long int milli_time; //variable to hold the time

void setup()

{

    Serial.begin(9600);          //Fastest baudrate
```

```

Serial.println("CLEARDATA");    //This string is defined as a
                                // command for the Excel VBA s
                                // to clear all the rows and columns

Serial.println("LABEL,Computer    Time,Time    (Milli    Sec.),IR
VALUE,BPM,TEMPERATURE");

                                //LABEL command creates label for
                                // columns in the first row with bold font

mlx.begin();

// set up the LCD's number of columns and rows:
lcd.begin(16, 2);

// Initialize sensor

if (!particleSensor.begin(Wire, 200)) //Use default I2C port, 400kHz speed
{
    //Serial.println("MAX30105 was not found. Please check wiring/power. ");
    while (1);
}

//Serial.println("Place your index finger on the sensor with steady
pressure.");

particleSensor.setup(); //Configure sensor with default settings

particleSensor.setPulseAmplitudeRed(0x0A); //Turn Red LED to low to
indicate sensor is running

particleSensor.setPulseAmplitudeGreen(0); //Turn off Green LED
}

void loop()

{
    long irValue = particleSensor.getIR();

```

```

temp = mlx.readObjectTempC();
if (checkForBeat(irValue) == true)
{
    //We sensed a beat!
    long delta = millis() - lastBeat;
    lastBeat = millis();
    beatsPerMinute = 60 / (delta / 1000.0);
    if (beatsPerMinute < 255 && beatsPerMinute > 20)
    {
        rates[ratesSpot++] = (byte)beatsPerMinute;
        //Store this reading in the array
        ratesSpot %= RATE_SIZE; //Wrap variable
        //Take average of readings
        beatAvg = 0;
        for (byte x = 0 ; x < RATE_SIZE ; x++)
            beatAvg += rates[x];
        beatAvg /= RATE_SIZE;
    }
}
if(irValue < 1000)
{
    beatsPerMinute=0;
}
count=count+1;
if(count==50)s

```

```

{
    count=0;
    milli_time = millis();
    Serial.print("DATA,TIME,");
    Serial.print(milli_time);
    Serial.print(",");
    Serial.print(irValue);
    Serial.print(",");
    Serial.print(beatsPerMinute);
    Serial.print(",");
    Serial.println(temp);
    lcd.clear();
    lcd.print("Object : ");
    lcd.print(temp);
    lcd.setCursor(0, 1);
    // print the number of seconds since reset:
    lcd.print(beatsPerMinute);
    lcd.setCursor(8, 1);
    lcd.print("IR=");
    lcd.print(irValue);
}
}

```