

SUICIDE SAVING DEVICE

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

By

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**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

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

MARCH-2021



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **E. JANANI (37240029) and J. JAYASREE (37240032)** who carried out the project entitled "**SUICIDE SAVING DEVICE**" under our supervision from **September 2020 to April 2021**.

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Guide and supervisor

Dr. T. SUDHAKAR, M.Sc., Ph.D.,
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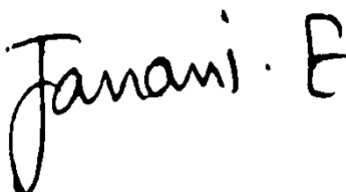
Submitted for Viva voce Examination held on – 10.04.2021

Internal Examiner

External Examiner

DECLARATION

We, **E. JANANI (37240029)** and **J. JAYASREE (37240032)** hereby declare that the Project Report entitled “**SUICIDE SAVING DEVICE**” done by us under the guidance of **Dr. ANIMA NANDA, Director, IQAC, Department of Biomedical Engineering** is submitted in partial fulfillment of the requirements for the award of **Bachelor of Technology** degree in **Biomedical Engineering**.

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DATE: 10.04.2021

PLACE: Chennai

SIGNATURE OF THE CANDIDATES

ACKNOWLEDGEMENT

We are pleased to acknowledge our sincere thanks to **Board of Management of SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. We are grateful to them.

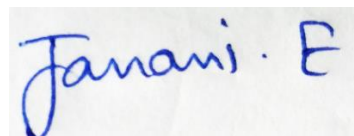
At first, we would like to express our prayer to the almighty for keeping us healthy in body and mind for successfully completing the project.

We express our sincere and heartfelt gratitude to our Project Guide **Dr. Anima Nanda, Ph.D, Director, IQAC, Department of Biomedical Engineering** for her valuable guidance, suggestions and constant encouragement which paved way for the successful completion of our project work.

We convey our sincere and deep sense thanks to **Dr. T. Sudhakar, M.Sc., Ph.D,** Head of the Department. We wish to express our thanks to all Teachers, **Dr. J. Prem Kumar, Ms. Bethanny Janney, Ms. Sindhu Divakaran, Dr. Krishna Kumar and Mr. G. Umashankar of Department of Biomedical Engineering** and the **Non-teaching staff** members for providing us necessary support and details at the right time during the progressive reviews in the entire duration of our project tenure.

Last but not least, we express our heartfelt gratitude to our beloved parents, family members and friends, who have played an instrumental role in finishing my project to receive the degree.

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ABSTRACT

Emotion is a common mental phenomenon that has a strong connection to our daily lives. Although it is simple for machines to detect other people emotions in human-human interactions, it is still difficult for machines to comprehend human feelings. Human emotion arises from a variety of brain cortex areas, including the orbital frontal cortex and the ventral medial cortex, according to neuroscience, human emotion is generated by a variety of brain cortex regions, including the orbital frontal cortex, ventral medial prefrontal cortex, and amygdala, providing us with a potential method for decoding emotion by recording continuous brain activity signals across these regions. We propose a technical solution using deep learning algorithms in this project. . We use a dataset of neural signals gathered from EEG electrodes to train a deep learning algorithm that predicts the type of emotion in this project. A hardware module is installed on the computer, and a neural signal is used as input to determine whether the patient is stressed. If the neural signal is negative, indicating that the patient is stressed, friendly music is played for the patient and a vibrato meter is used.

Keywords:- *Emotions, Decode emotion, brain activity signals, deep learning algorithms, EEG electrodes, hardware, negative, pleasant music, vibration*

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LIST OF ABBREVIATIONS

MATLAB	MATRIX LABORATORY
DWT	DISCRETE WAVELET TRANSFORM
SWT	STATIONARY WAVELET TRANSFORM
MODWT	MAXIMAL OVERLAP DISCRETE WAVELET TRANSFORM
PCA	PRINCPAL COMPONENT COEFFICIENT
DFA	DISCRIMINANT FUNCTION ANALYSIS
SVM	SUPPORT VECTOR MACHINES
KNN	K NEAREST NEIGHBOUR

CHAPTER - 1

INTRODUCTION

1.1 GENERAL:

Every year on October 10th, World Mental Health Day is commemorated with the goal of increasing global awareness of mental health issues and mobilising efforts in support of mental health. The Day allows all stakeholders involved in mental health issues to discuss their work and what more needs to be done to make mental health care a reality for people all over the world.

The theme for the day this year is 'mental health for all,' as it coincides with the worldwide COVID-19 pandemic, which has impacted the mental health of millions of people. As the world struggles to get COVID-19 under control, the levels of anxiety, fear, isolation, social distancing, and emotional distress associated with the virus have become pervasive.

However, the situation surrounding mental health has remained largely unchanged, particularly in India. Mental disorders continue to be stigmatized, and the number of psychiatrists and counsellors in the country is at an all-time low.

According to the WHO, India's mental health workforce is inadequate, with a significant shortage of psychiatrists and psychologists in comparison to the number of people suffering from mental illnesses. According to the WHO, there are 0.3 psychiatrists, 0.12 nurses, 0.07 psychologists, and 0.07 social workers per 100,000 people in India, while the desired number.

1.2 TECHNOLOGIES USED

1.2.1 Machine Learning

Machine learning is a branch of computer science that enables machines to learn without being specifically programmed. One of the most exciting technologies that one has ever encountered is machine learning. As the name suggests, it gives the machine the ability to learn, which makes it more human-like. The capacity for learning. Machine learning is currently in use, possibly in far more places than one would expect.

However, not all machine learning is statistical learning. A subset of machine learning is closely related to computational statistics, which focuses on making

predictions using computers. The field of machine learning benefits from the study of mathematical optimization because it provides approaches, theory, and application domains. Data mining is a related field of research that focuses on unsupervised learning for exploratory data analysis. Machine learning is also known as predictive analytics when it is used to solve business problems.

Machine learning is the process of computers figuring out how to do things without being specifically programmed to do so. It entails machines learning from data in order to perform specific tasks. It is possible to programme algorithms that tell the machine how to perform all steps necessary to solve the problem at hand for simple tasks assigned to computers; no learning is required on the computer's part. It can be difficult for a human to manually generate the algorithms required for more advanced tasks. In practise, assisting the machine in developing its own algorithm rather than having human programmers specify each required step will prove to be more efficient.

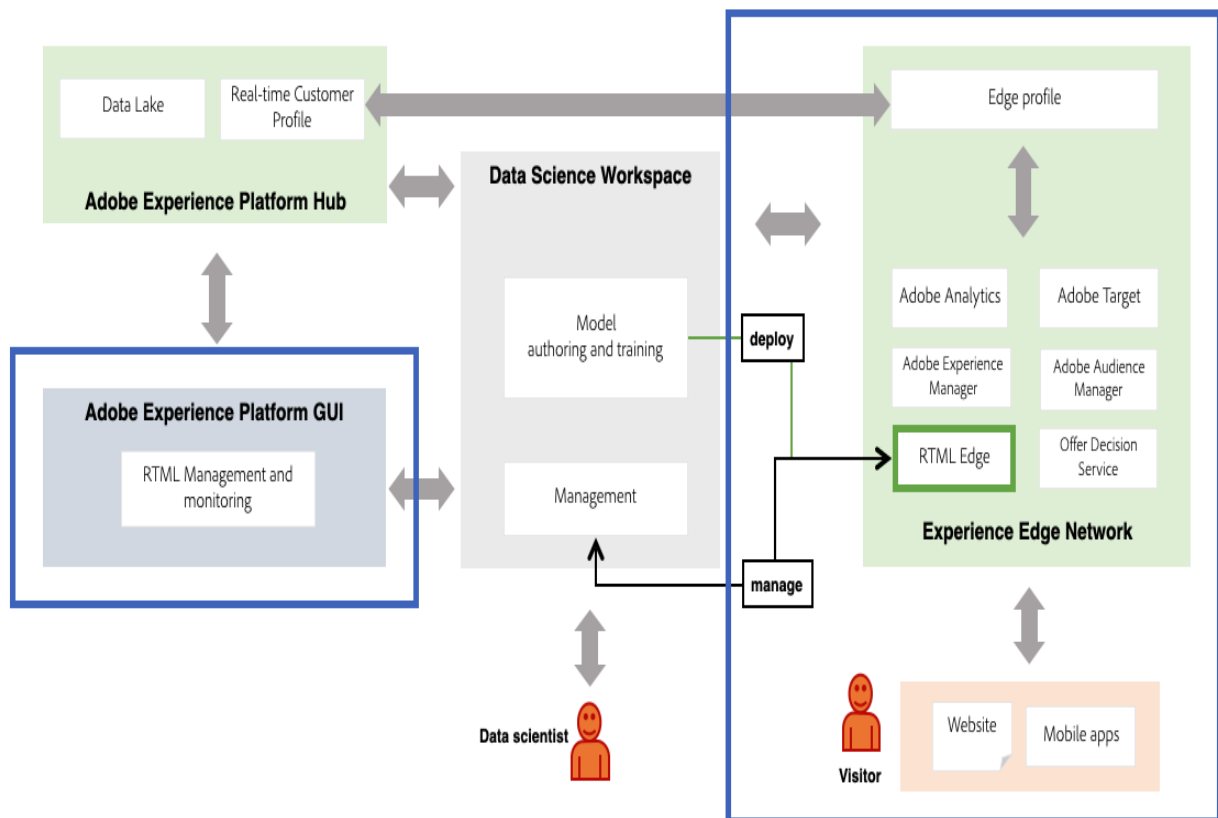


Fig:1.1 : End-State Architecture for Real-Time Machine Learning

1.2.1.1 Machine Learning approaches

Depending on the nature of the "signal" or "feedback" available to the learning system, machine learning methods are historically divided into three broad categories:

Supervised learning:

The term "supervised learning" refers to the presence of a supervisor who also serves as a teacher. Basically, supervised learning is when we teach or train a machine using well-labeled data, which means that some of the data has already been tagged with the correct response. The machine is then given a new set of examples (data) so that the supervised learning algorithm can analyse the training data (set of training examples) and generate a correct result from the labelled data.

There are input variables (x) and output variables (Y) in supervised learning, and an algorithm is used to learn the mapping function from the input to the output.

$$e = Y(X).$$

The aim is to approximate the mapping function well enough that the output variables (Y) for new input data (x) can be predicted with ease.

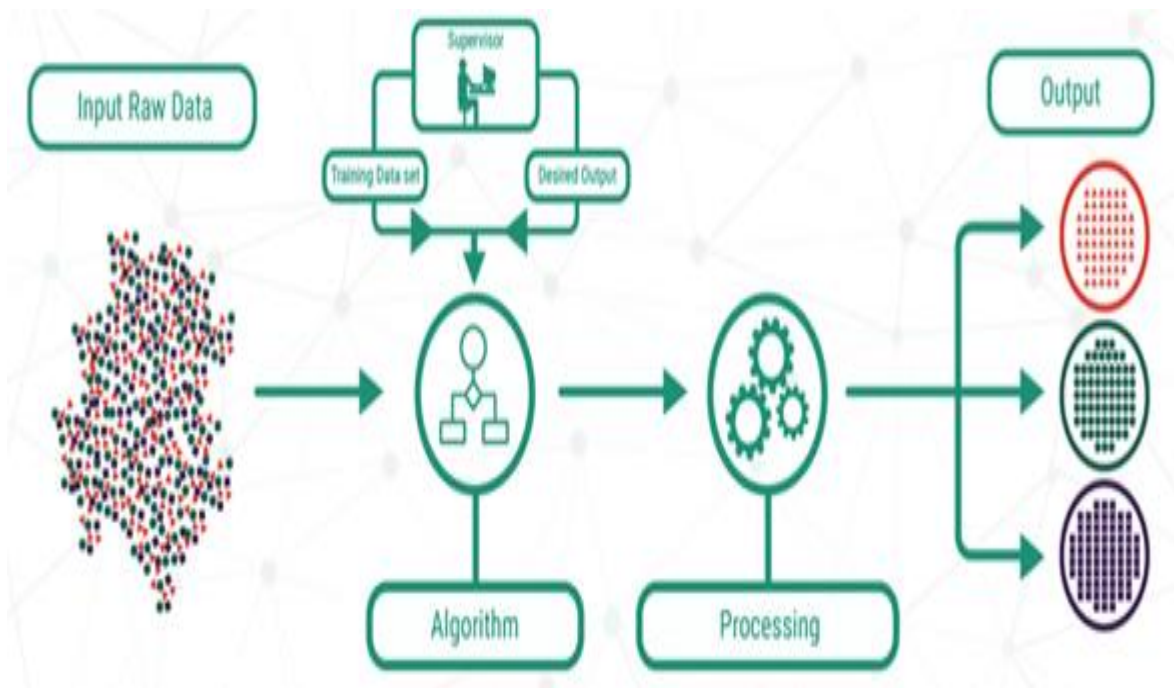


Fig:1.2 : Supervised learning flowchart

Unsupervised learning:

Unsupervised learning is the process of training a machine using data that hasn't been categorized or labelled, and then allowing the algorithm to act on that data without supervision. The machine's task here is to sort unsorted data into groups based on similarities, patterns, and differences without any previous data training.

Unlike supervised learning, there is no teacher present, which means the machine will not be trained. As a result, the machine is limited in its ability to discover hidden structure in unlabeled data on its own.

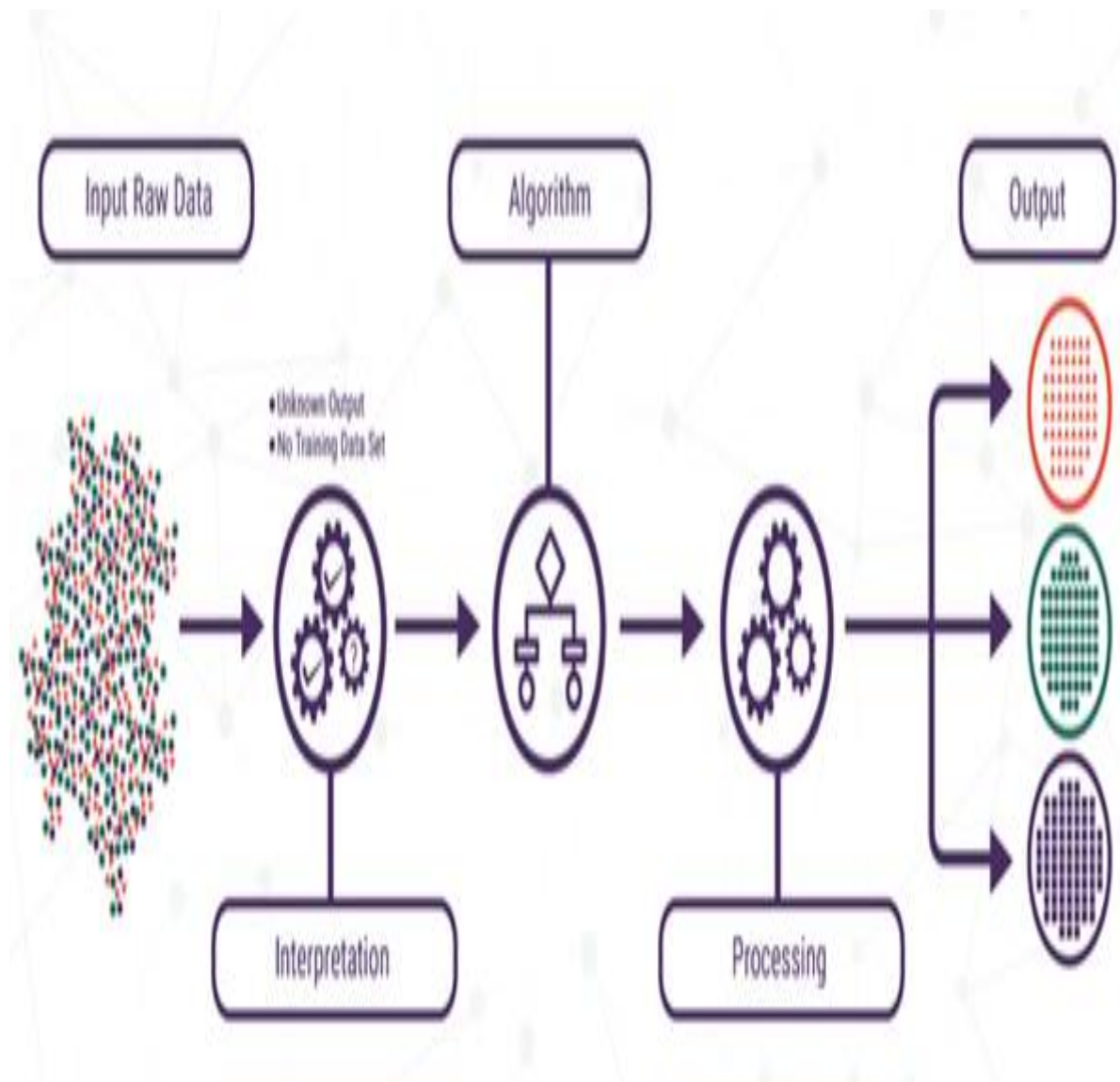


Fig:1.3 : Unsupervised learning flowchart

Reinforcement learning:

A computer programmer communicates with a dynamic environment in order to accomplish a specific task. The programmer receives feedback in the form of rewards as it navigates its problem space, which it attempts to maximize.

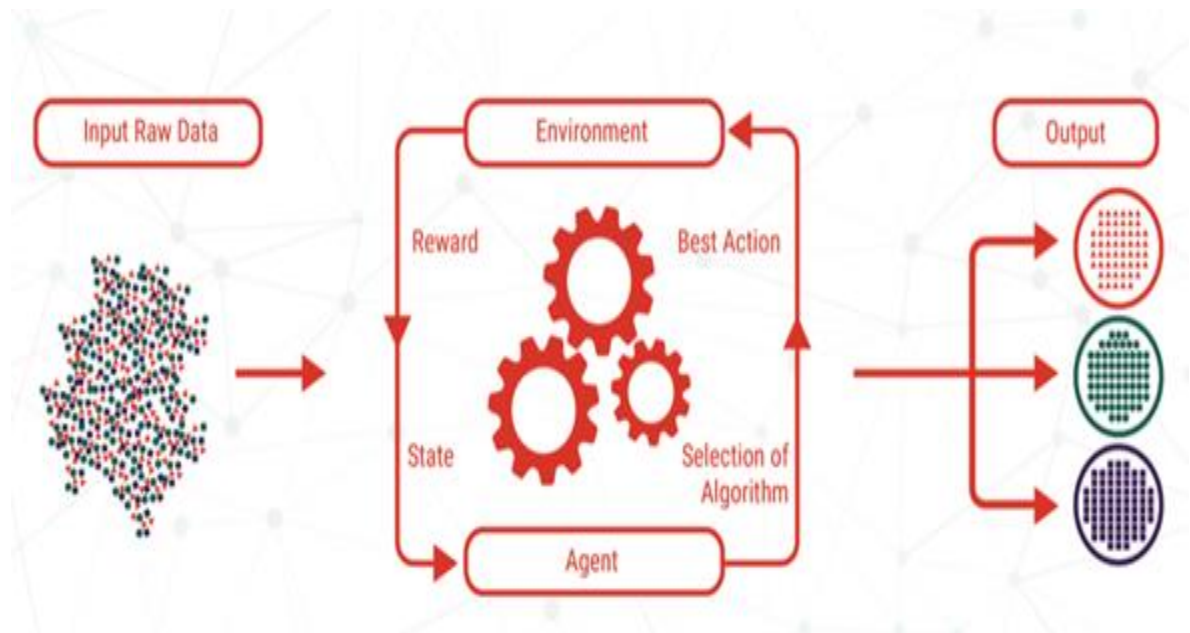


Fig:1.4 : Reinforcement learning flowchart

1.2.2 Embedded system

An embedded system is a microprocessor-based computer hardware system with software that is intended to perform a specific task, either independently or as part of a larger system. An integrated circuit is at the heart of the system, which performs computing for real-time operations.

From a single microcontroller to a suite of processors with connected peripherals and networks, and from no user interface to complex graphical user interfaces, there are many different levels of complexity. An embedded system's complexity varies greatly depending on the task for which it was created.

Digital clocks and microwaves are examples of embedded system applications, as are hybrid cars and avionics. Embedded systems consume up to 98 percent of all microprocessors produced.

Microcontrollers or digital signal processors (DSP), application-specific integrated circuits (ASIC), field-programmable gate arrays (FPGA), GPU technology,

and gate arrays are all used in embedded systems. These processing systems include components for dealing with electrical and/or mechanical interfacing.

Programming instructions for embedded systems, also known as firmware, are stored in read-only memory or flash memory chips and run on computers with limited hardware resources. Peripherals connect embedded systems to the outside world, connecting input and output devices.

1.2.2.1 Structure of embedded systems

The following components make up the underlying structure of an embedded system:

- **Sensor:** The sensor measures and converts the physical quantity to an electrical signal, which can then be read by an embedded systems engineer or any electronic instrument. A sensor stores the measured quantity to the memory.
- **An analog-to-digital converter (A-D converter):** It transforms an analogue signal to a digital signal.
- **Processors and ASICs:** Processors evaluate data in order to calculate output and store it in memory.
- **A digital-to-analog converter (D-A converter):** It converts digital data from the processor to analogue data.
- **Actuator:** An actuator compares the D-A Converter's output to the real output and stores the authorized output.

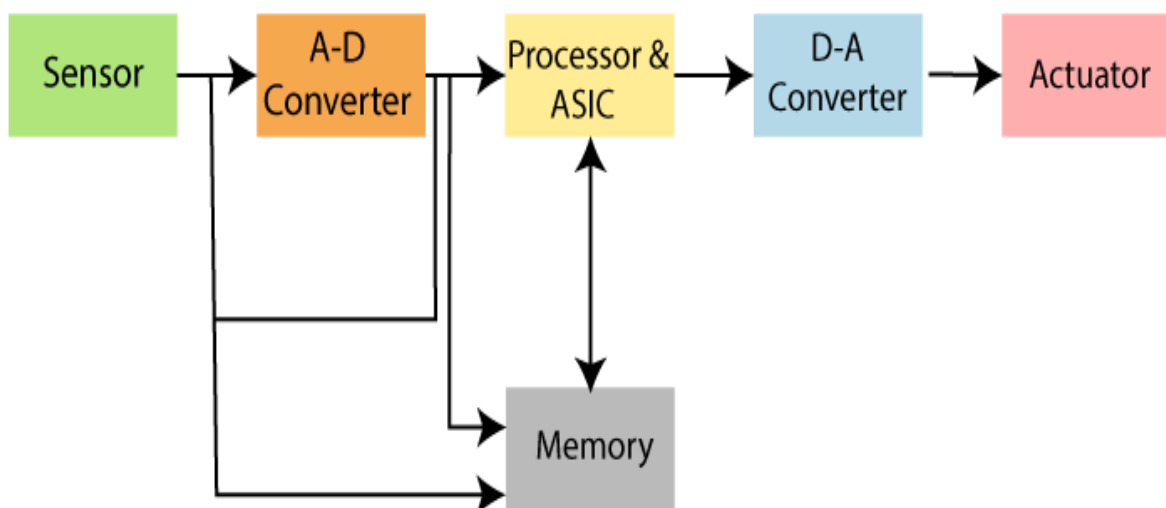


Fig:1.5 : Structure of embedded systems

1.2.2.2 Advantages of Embedded Systems

- Smaller and faster to load
- More specific to a single task
- Easy to manage
- Low cost
- Uses fewer resources
- Because this operating system is dedicated to a single device, it performs well and uses fewer resources such as memory and microprocessors.

CHAPTER - 2

LITERATURE SURVEY

Yang Li et al. (2020) Analysis in neuroscience have already shown inconsistency between emotion and right human brain hemispheres. In this paper, we propose a novel bi-hemispheric discrepancy model (BiHDM) to learn the discrepancy data between two hemispheres in order to improve electroencephalograph (EEG) emotion recognition. To proceed, we utilize four directed recurrent neural networks (RNNs) with two spatial orientations to traverse electrode signals on two different parts of the brain. This enables the proposed model to produce deep representations of all EEG electrode signals while retaining their innate spatial dependence. A subnetwork is intended to specifically record the discrepancies between the two hemispheres and to extract higher-level characteristics in order to achieve the final classification. We also integrate a domain discriminator which adversely leads to the general feature learning module creating emotionally related, but also domain invariant feature representation, in order to encourage further EEG emotional recognition, considering the existence of a domain shift between training and testing data. Experiments are conducted on three publicly available EEG emotional datasets, in which we assess the proposed BiHDM's performance as well as investigate the key brain regions in emotion expression and investigate how to obtain similar results with fewer electrodes. These experimental findings improve the superiority and advantage of the BiHDM model proposed in the solution of the EEG problem of emotional recognition.

Qianli Xu et al. (2020) Wearable sensors and semg processing have made it possible to detect human stress based on morphological characteristics. The intersubjective variation in stress responses, on the other hand, poses a significant challenge for reliable and precise stress estimation. This study suggests a new cluster-based analysis technique for assessing perceived stress from physiological signals that takes into account inter-subject differences. When human subjects go through a series of task-rest cycles with varying levels of stress, physiological data has been collected. An index of the State Trait Anxiety Inventory indicates stress. The physiological features are then analyzed in two steps to produce a quantitative stress measurement:

1) a k-means clustering process to split subjects into distinct categories (clusters), and 2) a cluster-wise stress assessment using a general regression neural network. When compared to conventional methods without clustering, the experimental results show a positive result in evaluation accuracy. The proposed method can be used to build effective, personalized goods for stress reduction in humans.

Yong-Jin Liu et al. (2017), is a converging technology for identifying, interpreting, and processing data that refers to, emerges from, or intentionally affects emotion or other attitudinal phenomena. Emotion recognition, which distinguishes human emotional states from behavioral and physiological signals, is one of the most important elements of affective computing. This data can be used to evaluate reasonable steps to express emotion and to design new ways for machine emotional intelligence and human-machine interaction, such as in a chatting robot or emotion-aware intelligent suggestion. Furthermore, our proposed system classifies three positive emotions (joy, amusement, and tenderness) with an average of 86.43 percent respectively and four negative emotions (anger, disgust, fear, and disgust) with an average of 86.43 percent accuracy. In this paper, we build a standardized database of 16 emotional film clips chosen from over a thousand different film excerpts. We propose a real-time movie-induced emotion recognition system based on emotional categories caused by these film clips for recognizing an individual's emotional states through brain wave analysis. Thirty people took part in this study, which involved them watching 16 consolidated film clips that represent real-life emotional experiences and target seven distinct emotions and neutrality. To segment the EEG signals, our system uses a 2-s window with a 50% overlap between two consecutive windows. In each window, emotional states are expected, including not only the valence and arousal dimensions, but also related discrete emotions in the valence-arousal coordinate space. Our real-time system determines high-arousal and balanced emotions from neutrality with an overall accuracy of 92.26 percent, and positive from negative emotions via an accuracy of 86.63 percent. sadness) with an average precision of 65.09 percent. These findings showed that EEG signals have an advantage over current state-of-the-art real-time emotion recognition systems in terms of classification accuracy and the ability to recognize similar discrete emotions in the valence-arousal coordinate space.

Habib ullah et al. (2018) proposed that emotions are an important aspect of human communication and decision-making. Different physiological signal measurement techniques such as Electromyography (EMG), Electrocardiography (ECG), respiration rate, galvanic skin response, and Electroencephalography (EEG) have been used for computer-based analysis of human emotions. EEG seems to be the most effective of these because it captures brain signals in a more convenient, non-intrusive, and precise manner. At a finer temporal resolution, multiple channel EEG signals encapsulate key emotional hints of human brain dynamics. Furthermore, techniques from the extensive signal processing literature can be easily applied to EEG brain signals for the development of novel computing approaches. For internal emotion recognition, we propose an ensemble learning algorithm for automatically computing the most discriminative subset of EEG channels. Our approach uses kernel-based representations computed from the training EEG recordings to describe an EEG channel. Using the kernel representations, we formulate a graph embedding linear discriminant objective function for ensemble learning. The objective function is efficiently solved using sparse non-negative PCA, and the final classifier is taught using the sparse projection coefficients. Our algorithm can help reduce the amount of data while also increasing computational efficiency and classification accuracy. Experiments on a publicly accessible EEG dataset show that the proposed algorithm outperforms the alternatives.

Vipin Gupta et al. (2018), Emotions play a key role in human life and are one of the most important characteristics of humans. Emotional behavior has a significant impact on daily activities such as communication, decision-making, and so on. For decades, brain-computer interfaces (BCI) have been one of the most exciting areas of biomedical engineering research, allowing people to control external devices with their thoughts. Computers and robots must be capable of processing emotions in order to achieve precise and natural interaction. Researchers from a variety of fields, including psychology, biomedical science, neuroscience, and others, have been drawn to the study of emotions. Emotion research is used in computer science to develop applications such as task workload assessment and operator vigilance. The computer interface becomes more user-friendly, efficient, and enjoyable with the addition of an

automated emotion recognition system. Emotion recognition using EEG signals is a difficult task that necessitates the use of advanced signal processing techniques to extract the emotions' hidden information. Cross-subject emotion recognition has been difficult due to the poor generalizability of EEG signal features across subjects. As a result, our goal is to explore the channel-specific nature of EEG signals in depth and develop an efficient method for emotion recognition based on the flexible analytic wavelet transform (FAWT). The EEG signal is decomposed into sub-band signals using FAWT. We also used information potential (IP) to extract features from the EEG signal's decomposed sub band signals. The extracted feature values were smoothed before being fed to classifiers that classified the emotions using random forest and support vector machine (SVM). SJTU emotion EEG dataset (SEED) and database for emotion analysis using physiological signal are two publicly accessible databases to which the proposed method is applied (DEAP). When compared to the current method, the proposed method performed better for human emotion classification. Furthermore, when exposed to the same stimuli, it produces channel specific subject classification of emotion EEG signals.

N. Beckmann et al. (2019) suggested that the automatic detection and classification of individual emotions be investigated. Data associated with emotional states is derived from a variety of signal sources. There are two types of data acquisition systems: stationary and non-stationary. Through installed cameras and microphones in a room, stationary systems may analyze, for example, facial expressions or individual speech. Wearable sensor systems may be used to analyze physiological parameters of non-stationary systems. Camera and microphone-based systems, on the other hand, can be non-stationary due to smartphones and smartwatches. Physiological parameters can also be collected wirelessly from stationary systems. Two photoplethysmography (PPG) sensors can be used to implement a method for measuring local PTT. This technique, however, is prone to errors. The physiological background that is thought to be responsible for erroneous PPG-based PTT measurements is discussed in this paper. To adapt to time-varying physiological effects, the algorithm analyses and compares the two PPG-signals. Calculating and analyzing the local PTT in the context of emotion recognition becomes

feasible with this algorithm. A 40-person study was conducted to test the algorithm and look into the utility of local PTT analysis for emotion recognition when combined with other physiological signals. If calculated using the established algorithm, PTT-based parameters obtained from the frequency domain of the signal revealed a statistically significant ($p < 0.05$) difference between induced emotional states. The results show that emotional stimuli have a significant impact on the parameters obtained by our approach. We believe that because this technique could be integrated into a single wearable device, it could be used to advance real-world emotion recognition research.

Amani Albraikan et al. (2018), the study of human behavior and cognition has begun to influence fields such as economics, finance, accounting, law, and marketing. When one has a cognitive awareness that emotions can influence decisions, they will make better decisions, which will result in less negative consequences. Human decision-making is often characterized by a tangle of emotions and rationalizations. According to the Gallup 2017 Global Feelings Report, emotions, not logic, account for 70% of human behavior. They present a stacking model-based hybrid sensor fusion approach that allows data from different sensors and emotion models to be collectively embedded within a user-independent model. As a base model, the WMD-DTW (weighted multidimensional DTW) and the k-nearest neighbors algorithm k-NN are used to classify feelings. On top of the two base models, ensemble techniques were used to learn a high-level classifier. On the dataset, we used a meta-learning approach and found that the ensemble approach outperforms any individual method. We also compared the outcomes using two different datasets. With the E4 dataset, our proposed system reached overall accuracies of 65.6 percent for all users, and 94.0 percent and 93.6 percent for identifying valence and arousal emotions with the MAHNOB dataset, respectively.

Ronak Kosti et al. (2019) The development of automatic systems for identifying emotional states has sparked a lot of interest in recent years. Several recent studies have demonstrated how emotions can be inferred from text, voice, or visual cues. In contexts where machines may communicate with or monitor humans, automatic emotion recognition has a wide range of applications. Automatic tutors in an online learning platform, for example, will give a student better feedback based on her

motivation or anger level. In addition, if a vehicle with driver assistance capabilities detects the driver is tired or anxious, it may interfere or sound an alarm. They present EMOTIC, a dataset of images of people in various settings annotated with their apparent emotion. The EMOTIC database combines two types of emotion representation: (1) discrete categories and (2) continuous dimensions of Valence, Arousal, and Dominance. We also present a statistical and algorithmic interpretation of the dataset, as well as an analysis of annotators' agreement. We train various CNN models for emotion recognition using the EMOTIC database, combining information from the person bounding box with information from the scene context. Our findings demonstrate how scene context contributes critical information to the automatic recognition of emotional states and encourage further research in this area.

Weihong Deng and Shan Li (2018) In the last two decades, automatic facial expression recognition has come a long way. Many established frameworks, on the other hand, have been used exclusively on data collected in controlled laboratory environments with frontal faces, uniform lighting, and posed expressions. Users from the real world, on the other hand, have captured a large number of photographs from various events and social gatherings in unrestricted environments. The development of systems capable of deducing a community's perception of emotional characteristics and affective displays from social images is gaining popularity. Unconstrained expression recognition has thankfully progressed to a new state-of-the-art thanks to emerging deep learning techniques. They present the Real-world Affective Face Database (RAF-DB), a new facial expression database that includes approximately 30,000 facial images with uncontrolled poses and lighting from thousands of people of various ages and races. Approximately 40 annotators label each image separately during the crowdsourcing annotation process. To accurately estimate the emotion labels, an expectation-maximization (EM) algorithm is developed, which reveals that real-world faces often express compound or even mixture emotions. The action units (AUs) of real-world emotions are far more varied than, or even deviate from, those of laboratory-controlled emotions, according to a cross-database study between the RAF-DB and the CK+ databases. theorization We propose a new deep locality-preserving convolutional neural network (DLP-CNN) technique for recognizing multi-modal

expressions in the wild, which aims to improve the discriminative power of deep features by preserving locality closeness while maximizing inter-class scatter. Benchmark tests on 7-class basic expressions and 11-class compound expressions, as well as additional experiments on the CK+, MMI, and SFEW 2.0 databases, show that the proposed DLP-CNN outperforms state-of-the-art handcrafted features and deep learning-based techniques in the wild. We made the RAF database, benchmarks, and descriptor encodings publicly accessible to the research community in order to encourage further investigation.

Emily Mower Provost and Yelin Kim (2019) Emotion is an important aspect of human communication because it has a significant impact on the overall quality and outcome of interactions. Because extracted affective information can be used to measure, convey, and intuit user needs, automatic emotion recognition can benefit human-centered and affective technology. However, designing such systems is difficult due to the complexity and dynamic nature of emotional expressions, especially in terms of the mixed factors of modulation that occur when a person speaks. To address this issue, the current research looks at how speech affects the dynamics of various facial regions during emotion expressions, and how this information can be used to design and create a new audio-visual emotion recognition system. The Informed Segmentation and Labeling Approach is a proposal for a new method of segmenting and labelling data (ISLA). Speech signals are used by ISLA to change the dynamics of the lower and upper face regions. We show how pitch can be used to increase upper-face emotion estimates, and how this estimate can be combined with lower-face and speech emotion estimates in a multimodal classification system. ISLA increases overall classification performance on the IEMOCAP and SAVEE datasets, according to the results.

Jose Rodriguez Borbon et al. (2018) Human action recognition (HAR) algorithms take one or more video sequences, usually a few hundred frames, as input and produce one or more output(s) categorizing the possible action(s) performed by the actor(s) within the video clip (s). Health care, assisted living, surveillance, automated video indexing, security, autonomous navigation, robotics, mobile computing, and other fields use HAR algorithms. Several challenges remain, despite recent significant progress in the design and implementation of HAR applications: higher throughput for handling

large video sequences, lower complexity for real-time applications, highly parallel implementations for faster response times, and energy efficient designs for embedded and mobile applications. For a video sequence lasting a few seconds, tasks like video pre-processing, feature extraction, feature quantization, and feature classification necessitate the execution of millions of arithmetic operations. To address these issues, we propose a heterogeneous approach based on a comprehensive algorithmic and experimental analysis of the HOG3D application. The application is divided into four stages, each of which is evaluated on CPU, GPU, and FPGA platforms. Our heterogeneous design combines the advantages of both FPGA and GPU platforms, achieving a 1.3X speedup over a state-of-the-art GPU while using 1.5X less energy than other homogeneous solutions, including FPGA-based designs. Furthermore, the accuracy of our heterogeneous HAR algorithm based on fixed-point arithmetic is similar to that of HAR algorithms based on single precision floating point arithmetic.

U. Sairam et. al., (2020) reported an answer utilizing the Internet of Things (IoT) worldview to give a medium between the visually impaired and the climate. A few sensors can be utilized to distinguish abnormalities like deterrents, flights of stairs and wet landscapes respectively. The model talked about here is a straightforward, complex and moderate keen visually impaired stick outfitted with different IoT sensors and modules. Additionally, this arrangement gives an approach to communicate something specific about the whereabouts of the client to the concerned individuals. Adding to the over, a product application is intended to help the colleagues of the oblivious in regards to deal with the stick's setup ex: add or erase telephone numbers to which ready messages must be sent. Losing the stick inside can likewise be a considerable issue. This arrangement likewise addresses this issue.

CHAPTER - 3

AIM AND SCOPE

3.1 AIM

- The main aim of the project is to develop a system that effectively monitor the emotional state of the patient.
- To provide relief to the patient if the patient is at stress by playing music and enabling vibration on the patient.

3.2 SCOPE

In the coming future, we review this application of power forecasting to predict the power generation nationwide with more accuracy and efficiency. The application has good use in the energy field. In the electricity department, they have more chance to develop or convert this project in many ways. Thus, this project has an efficient scope in coming future where manual predicting can be converted to computerized prediction in a cheap way.

3.3 EXISTING SYSTEM

Neuroscience study has revealed the discrepancy of emotion expression between the left and right hemispheres of human brain. Inspired by this study, in this paper, we propose a novel bi-hemispheric discrepancy model (BiHDM) to learn this discrepancy information between the two hemispheres to improve electroencephalograph (EEG) emotion recognition. Concretely, we first employ four directed recurrent neural networks (RNNs) based on two spatial orientations to traverse electrode signals on two separate brain regions. This enables the proposed model to obtain the deep representations of all the EEG electrodes' signals that keep their intrinsic spatial dependence. Upon this representation, a pairwise subnetwork is designed to explicitly capture the discrepancy information between the two hemispheres and extract higher-level features for final classification. Furthermore, considering the presence of the domain shift between training and testing data, we incorporate a domain discriminator that adversarial induces the overall feature learning module to generate emotion-related but domain invariant feature representation so as

to further promote EEG emotion recognition. Experiments are conducted on three public EEG emotional datasets, in which we evaluate the performance of the proposed BiHDM as well as investigated the important brain areas in emotion expression and explore to use less electrodes to achieve comparable results. These experimental results jointly demonstrate the effectiveness and advantage of the proposed BiHDM model in solving the EEG emotion recognition problem.

3.3.1 DISADVANTAGES OF EXISTING SYSTEM

- The existing system has focused on only identifying the type of emotions.
- No effective action is performed to provide relief to the patient.
- Cannot be used to develop real time applications.

3.4 PROPOSED SYSTEM

Emotion, as a common mental phenomenon, is closely related to our daily life. Although it is easy to sense other people's emotion in human-human interaction, it is still difficult for machines to understand the complicated emotions of human beings. from the viewpoint of neuroscience, human emotion originates from a variety of brain cortex regions, such as the orbital frontal cortex, ventral medial prefrontal cortex, and amygdala, which provides us a potential approach to decoding emotion by recording the continuous brain activity signals over these regions. In this project we propose a technological solution using deep learning algorithms. In this project we make use of a dataset of the neural signals collected from the EEG electrodes to train a deep learning algorithm to predict the type of emotion. A hardware module is setup on the A neural signal is given as input to check if the patient is in stress. If the neural signal is negative i.e, the patient is found to be in stress, pleasant music is played to the patient and a vibration is enabled to relieve the patient from the stress. Our project helps in preventing the patient from going into depression, thus saving lives.

3.4.1 ADVANTAGES OF PROPOSED SYSTEM

- Real time emotion recognition
- Performs effective actions to relieve the patient of stress

- Prevents the patient from going into depression

3.5 APPLICATIONS

- Applicable in psychological test.
- Applicable for psychiatry treatment.
- Emotion recognition.

CHAPTER - 4

MATERIALS AND METHODS

4.1 WORKING

We use a dataset of neural signals gathered from EEG electrodes to train a machine learning algorithm that predicts the type of emotion in this project. A hardware module is installed on the computer, and a neural signal is used as input to determine whether the patient is stressed. If the neural signal is negative, indicating that the patient is stressed, friendly music is played for the patient, and the vibration is activated to relieve the stress. Our project helps to keep patients from becoming depressed, which saves lives.

4.2 SYSTEM ARCHITECTURE

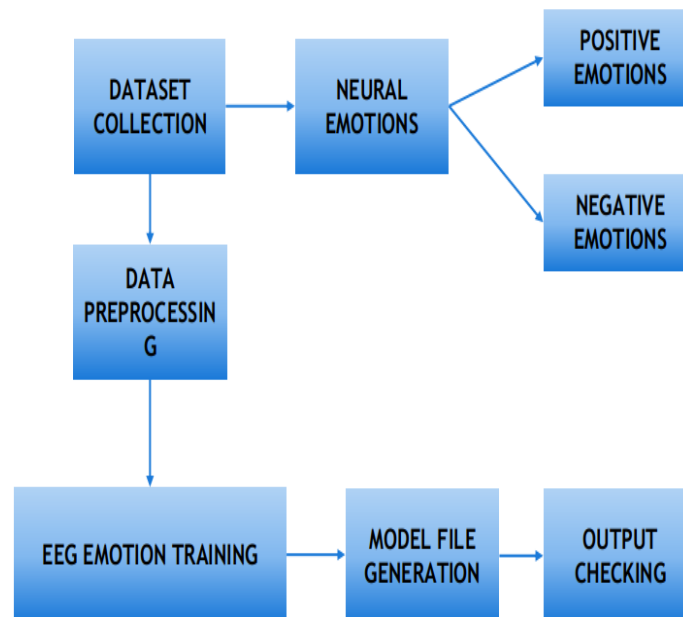


Fig: 4.1 : Emotion training

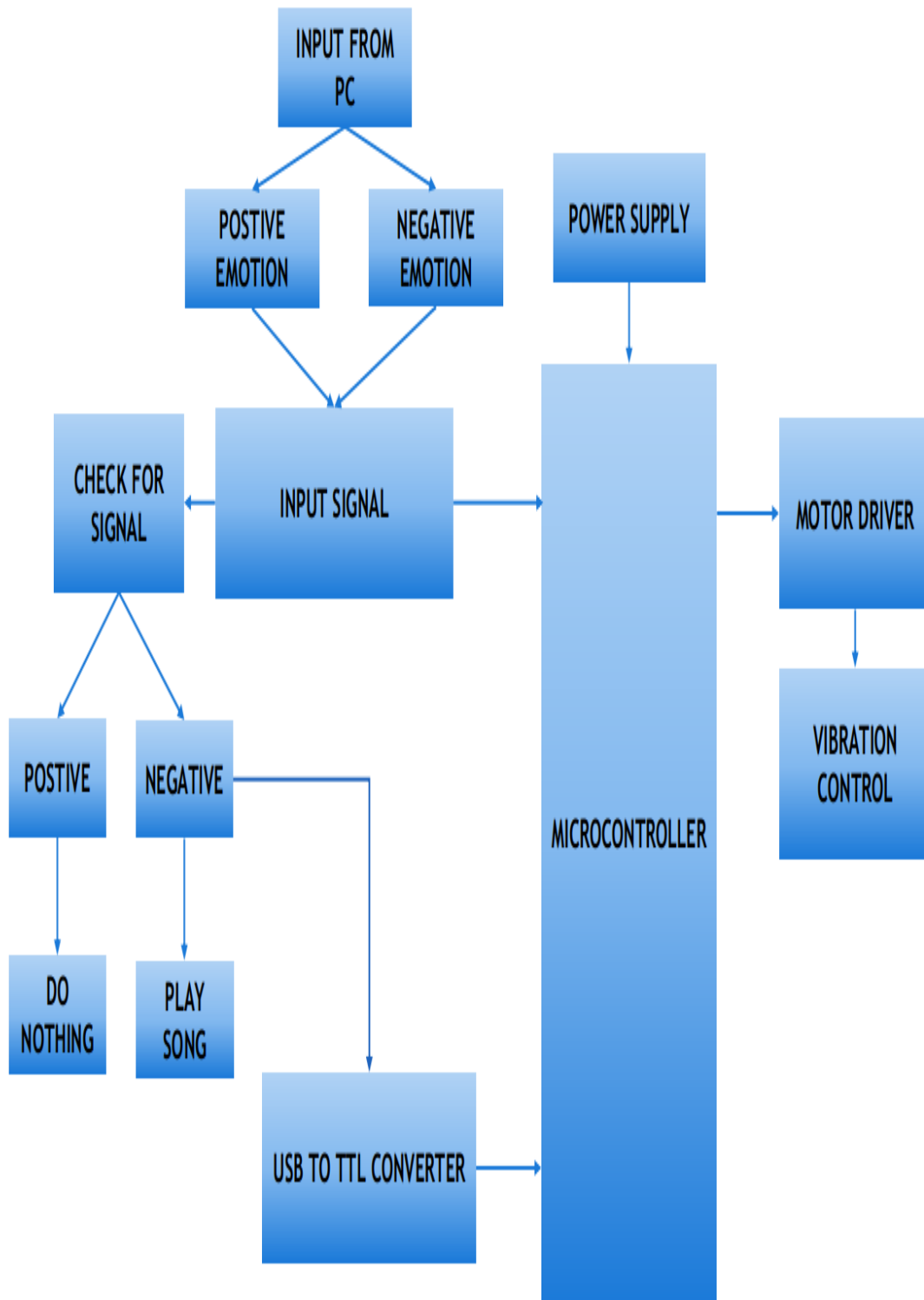


Fig: 4.2 : User training

4.3 HARDWARE SETUP

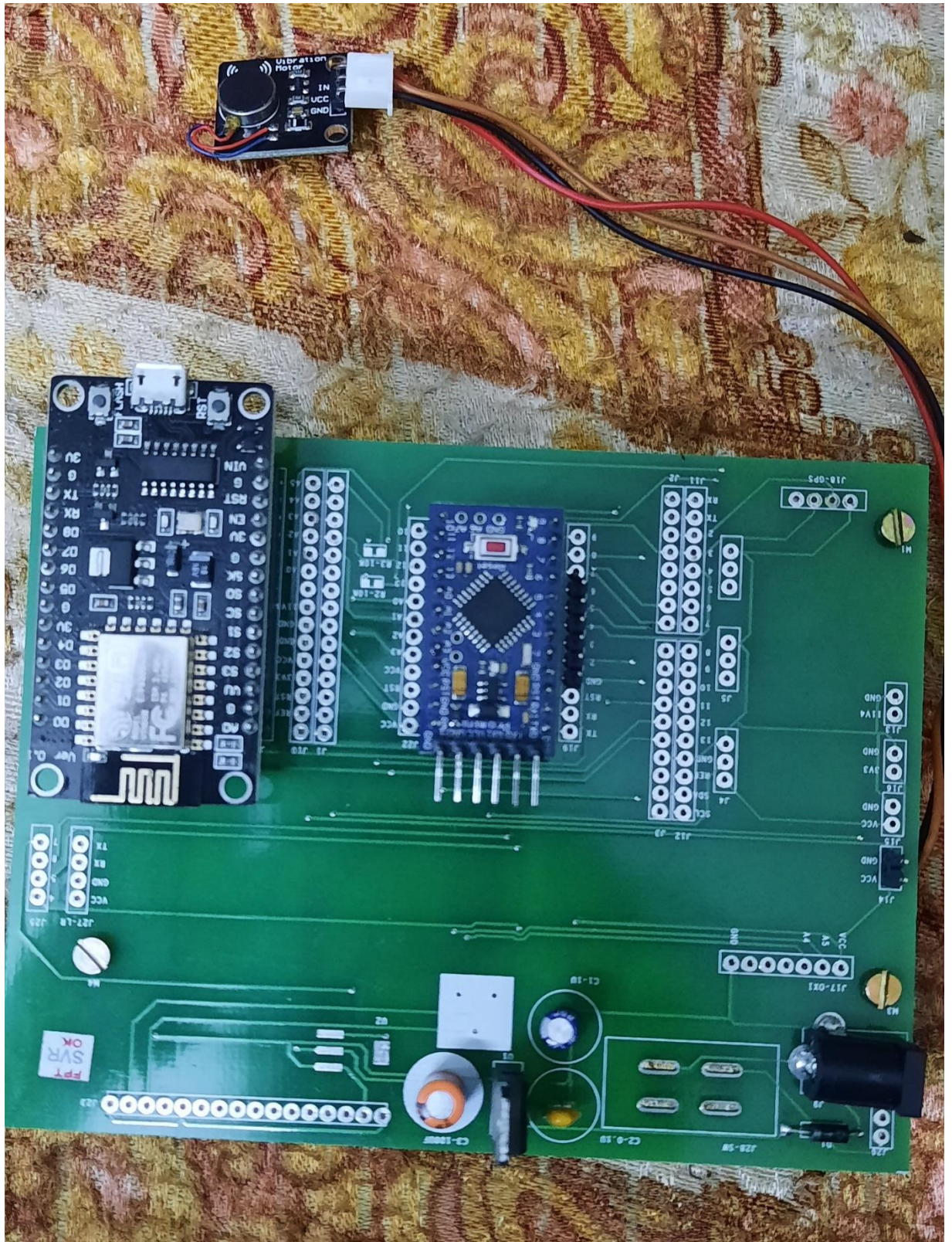


Fig: 4.3 : Hardware setup

4.4 MODULE DESCRIPTION

- COLLECTION OF EEG EMOTION DATASET
- EEG EMOTION TRAINING
- MICROCONTROLLER
- MOTOR DRIVER
- FRONT-END DEVELOPMENT

4.4.1 Collection of EEG emotion dataset

We will gather the dataset of signals obtained from EEG sensors in this project. The signals represent a person's neural emotions, which can be neutral, negative, or positive. The accuracy improves as the dataset size grows. A data set is a set of information. For many difficult real-world problems, machine learning has become the go-to technique. It is, without a doubt, the most effective technique for prediction tasks. These well-functioning machine learning machines need a lot of fuel, and that fuel is data. Our model performs better when there is more labeled data available. Google has even experimented with the idea of more data leading to better performance on a large scale, with a dataset of 300 million images. When using a machine learning model in a real-world application, it must be fed data regularly to improve its performance. Data is, without a doubt, the most precious resource in the machine learning era. The data collection process is broken down into three steps.

- **Classification:** When an algorithm is used to answer binary yes-or-no questions or to classify data into multiple categories (grass, trees, or bushes; cats, dogs, or birds, etc.)
- **Regression:** To get a numeric value from an algorithm. For example, if you spend too much time figuring out the right price for your product because it is dependent on so many variables, regression algorithms will help you estimate it.
- **Ranking:** Some machine learning algorithms simply rank objects based on a set of characteristics. The ranking is often used to suggest movies in video streaming

services or to display goods that a customer is likely to buy based on previous search and purchase activities.

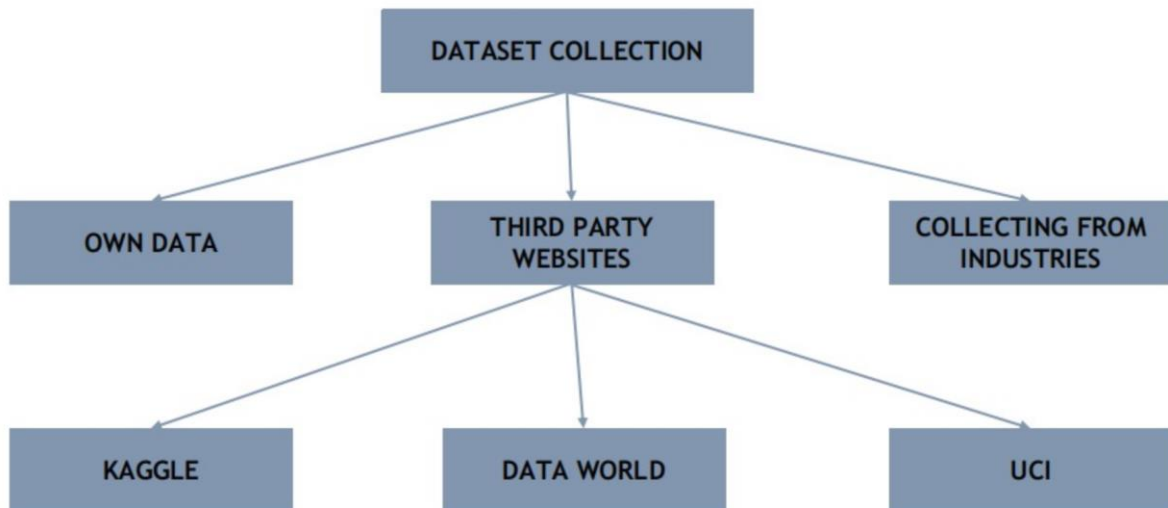


Fig:4.4 : Dataset collection

4.4.2 EEG Emotion Training

\In this project, we will use a machine learning algorithm called logistic regression to train the EEG emotion signal dataset to accurately predict a person's emotion.

The dataset is analyzed using the Logistic Regression statistical method, which yields a binary result. The dataset may have contained one or more autonomous variables. These factors, which are dichotomous in nature, determine the outcome. As a result, only two outcomes are possible. It's a type of regression that's used to predict binary and categorical outcomes in the most efficient way possible. The Logistical Regression technique is used to control the effect of a large number of independent variables that are presented at the same time. This approach can also predict any of the two categories of variables that are independent. To maximize the probability of classifying the identified data into the proper division, logistic regression uses the maximum likelihood approach to design the best-fitting function. Forecast market patterns discover success and failure rates in results, the true or false category in hiring

employees based on their performance in need of jobs in a company, image categorization, health care, and evaluate a group of people affected by Myocardial Infarction are just some of the applications of logistic regression.

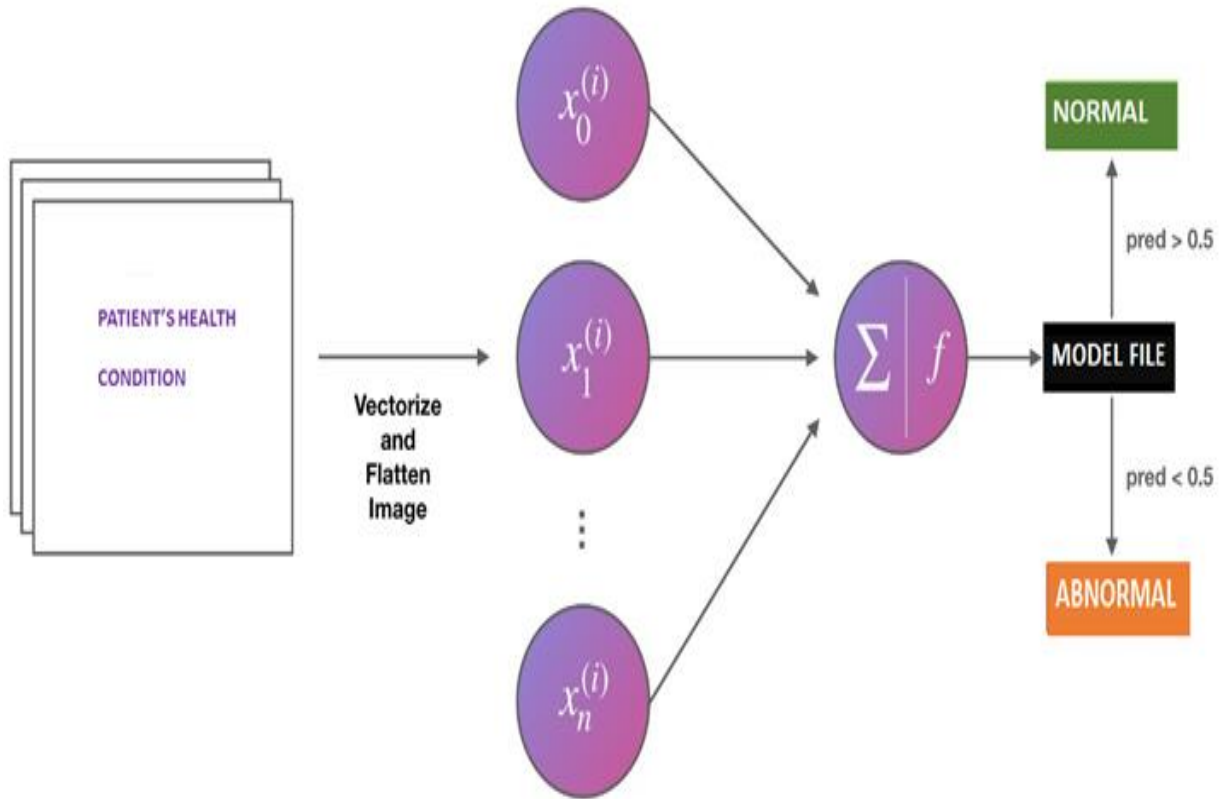


Fig:4.5 : Logistic regression

4.4.3 Microcontroller

The ATmega-328 is a microcontroller based on the Advanced Virtual RISC (AVR) architecture. It can handle data of up to eight (8) bits. The ATmega-328 has 32KB of internal memory. There are a lot of other features on this microcontroller. You should also read Introduction to PIC16F877a (a PIC Microcontroller) before comparing the two Microcontrollers' functions. Electrically Erasable Programmable Read-Only Memory (1KB) is available on the AT Mega 328. (EEPROM). This property indicates that even if the microcontroller's electric supply is removed, it can still store data and produce results after being reconnected to the power supply. Furthermore, the ATmega-328 has a 2KB Static Random Access Memory (SRAM) (SRAM). Other features will be discussed at a later time. The ATmega 328 has a variety of features that make it the most popular device on the market today. Advanced RISC

architecture, good performance, low power consumption, real timer counter with a separate oscillator, 6 PWM pins, programmable Serial USART, programming lock for software security, throughput up to 20 MIPS, and so on are some of the characteristics. The ATmega-328 is the most commonly used microcontroller in Arduino.

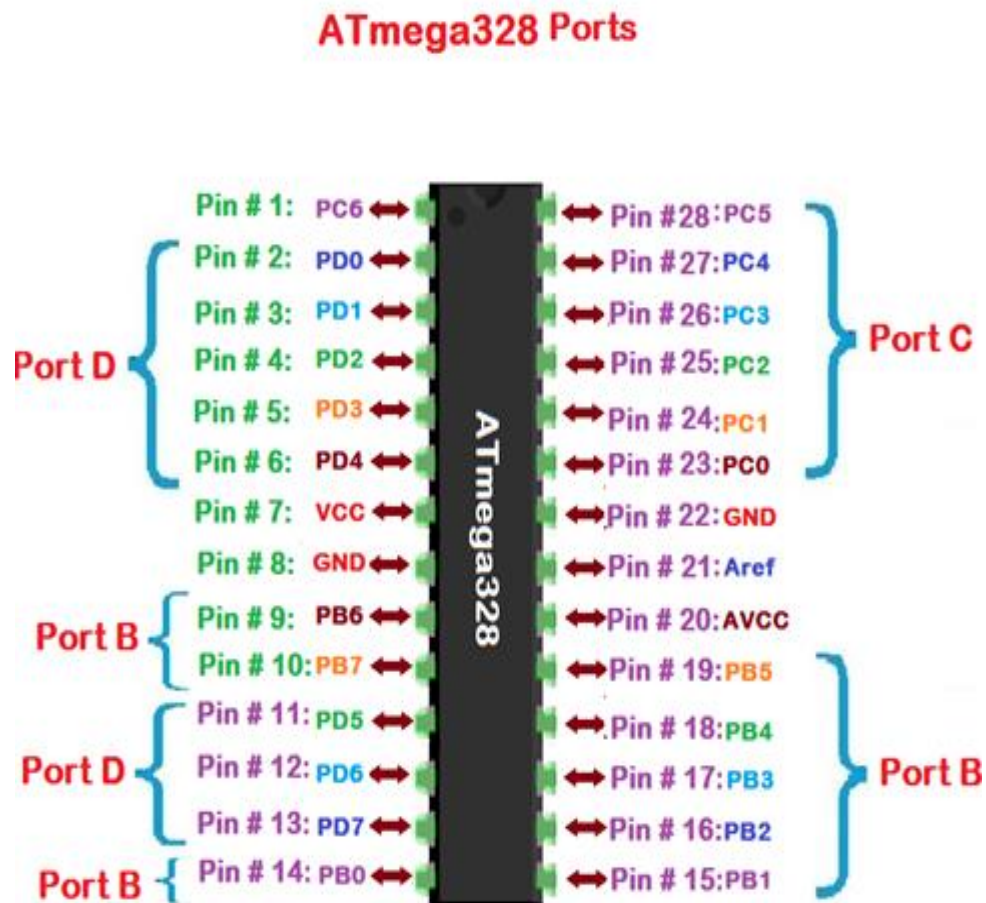


Fig:4.6 : Atmega 328

4.4.4 Motor Driver

The L298N 2A Based Motor Driver is a high-power motor driver that works well with DC and stepper engines (Now find out a wide range of motors at Robu. in).

It has an onboard 5V regulator that it can supply to an external circuit and uses the popular L298 motor driver IC. It can control up to four DC motors or two DC motors with speed and direction control.

This motor driver is ideal for robotics and mechatronics projects, as it allows microcontrollers, switches, and relays to control motors. Perfect for micro mouse, line-following robots, robot arms, and other DC and Stepper motor applications.

Pulse Width is a measurement of how wide a pulse is. Modulation is a method for adjusting the length of an electronic pulse. Consider the brush in an engine to be a water wheel, and the electrons to be water droplets flowing. Water flowing at a constant rate over the wheel would be the voltage; the more water flowing, the greater the voltage. Motors are rated at specific voltages, and if the voltage is applied too strongly or dropped too quickly to slow the motor down, it can cause harm.

As a result, PWM. Consider the water wheel analogy: the water is hitting it in pulses but at a constant rate. The water wheel will turn faster if the pulses are longer; if the pulses are shorter, the water wheel will turn slower. Motors will last much longer and be more reliable if controlled through PWM.

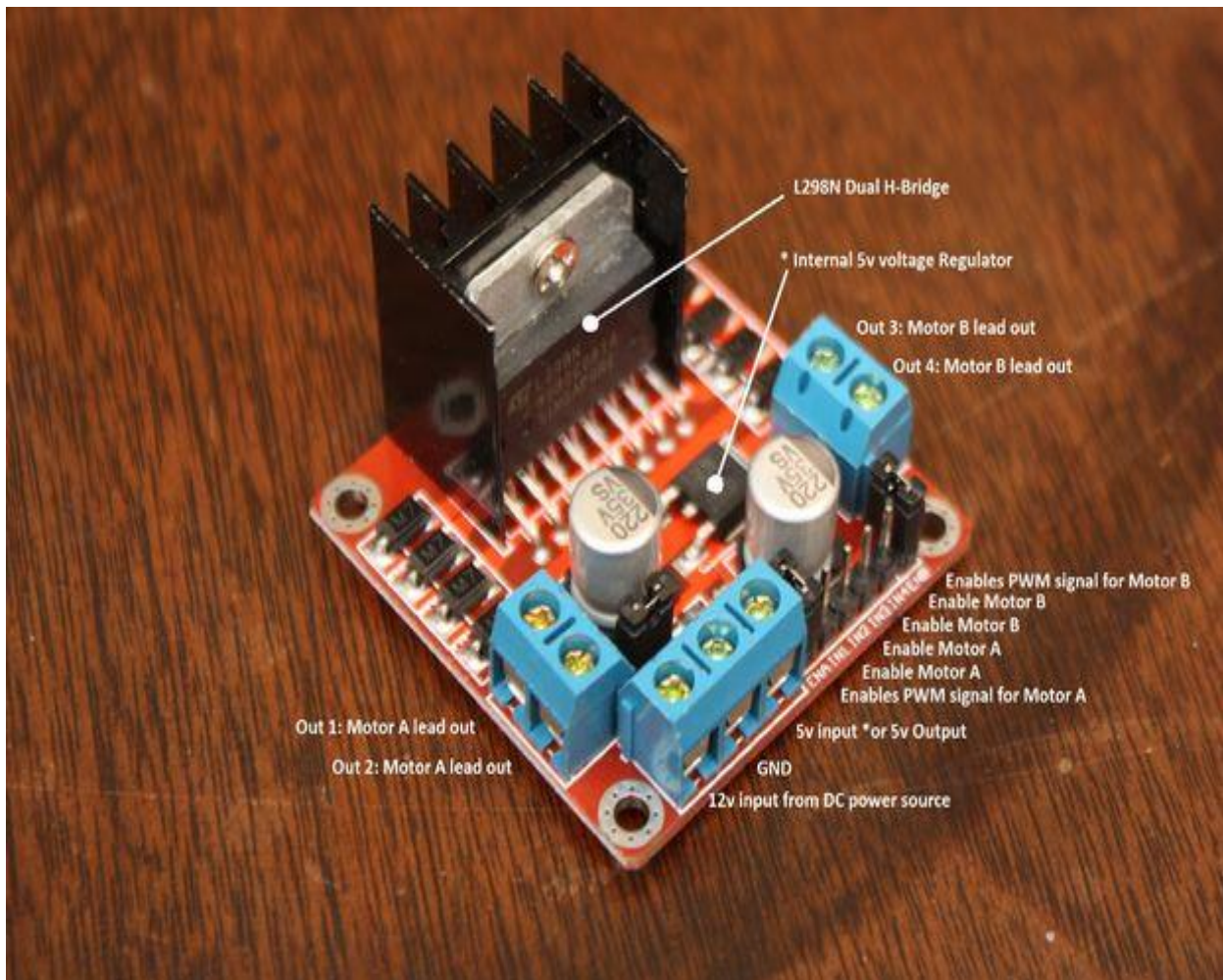


Fig:4.7 : Motor driver

4.4.5 Front-End Development

ReactJS is a JavaScript library that allows you to create reusable user interface components. The following is a definition from the official React documentation:

React is a library for creating composable user interfaces. It promotes the development of reusable user interface components that display data that changes over time. React is frequently used as the V in MVC. React abstracts the DOM from you, resulting in a more straightforward programming model and improved performance. React will also use Node to render on the server and React Native to power native apps. One-way reactive data flow is implemented in React, which reduces boilerplate and makes it easier to reason about than conventional data binding.

JSX:

- JavaScript XML is abbreviated as JSX. We can write HTML in React using JSX. In React, JSX makes it easier to write and add HTML.
- It is faster than standard JavaScript because it optimizes when converting to standard JavaScript. It facilitates the creation of templates for us. Rather than separating the markup and logic into separate files, React makes use of components. In subsequent articles, we will go over components in greater depth.

COMPONENTS:

- Components are self-contained, reusable code chunks. They perform the same functions as JavaScript functions, but they operate independently and return HTML via a render function.
- Class components and Function components are the two kinds of components; in this tutorial, we'll focus on Class components.
- React implements one-way data flow which makes it easy to reason about your app. Flux is a pattern that helps keeping your data unidirectional.

ADVANTAGES OF REACT JS:

- Uses virtual DOM which is a JavaScript object. This will improve apps

performance, since JavaScript virtual DOM is faster than the regular DOM.

- Can be used on client and server side as well as with other frameworks.
- Component and data patterns improve readability, which helps to maintain larger app.

4.5 SOFTWARE DESCRIPTION

4.5.1 Visual Studio

Microsoft Visual Studio is used as an IDE in this project.

Visual Studio Code combines the ease of use of a source code editor with advanced developer features such as IntelliSense code completion and debugging. It is, first and foremost, an editor who stays out of your way. Less time fiddling with your surroundings and more time executing on your ideas thanks to the delightfully frictionless edit-build-debug cycle.

Visual Studio Code is available for macOS, Linux, and Windows, so you can get started right away.

Visual Studio Code's core feature is a lightning-fast source code editor, which is ideal for day-to-day use. Syntax highlighting, bracket-matching, auto-indentation, box-selection, snippets, and more are all available in VS Code, which supports hundreds of languages. You can navigate your code with ease thanks to intuitive keyboard shortcuts, simple customization, and community-contributed keyboard shortcut mappings.

When it comes to serious coding, you'll often benefit from tools that interpret more code than just blocks of text. IntelliSense code completion, rich semantic code comprehension and navigation, and code refactoring are all built into Visual Studio Code.

When the coding becomes difficult, the tough turn to debugging. We made it happen because debugging is often the one feature that developers miss the most in a leaner coding experience. You can step through source code, inspect variables, view call stacks, and run commands in the console with Visual Studio Code's interactive debugger.

VS Code also integrates with build and scripting tools to help you complete common tasks faster. With Git support in VS Code, you can work with source control without having to leave the editor, including viewing pending changes diffs.

Customize every feature to your liking and add as many third-party extensions as you like. While most situations work right out of the box, VS Code grows with you, and we encourage you to customize your experience to meet your specific needs.

VS Code comes with enhanced built-in support for Node.js development, including JavaScript and TypeScript, and is powered by the same underlying technologies like Visual Studio. Web technologies such as JSX/React, HTML, CSS, SCSS, Less, and JSON are all well-represented in VS Code.

Visual Studio Code incorporates the best of mobile, native, and language-specific technologies in its architecture. VS Code uses Electron to combine web technologies like JavaScript and Node.js with native app speed and versatility. VS Code makes use of a newer, faster version of the same industrial-strength HTML-based editor that powers the “Monaco” cloud editor, Internet Explorer's F12 Tools, and a variety of other projects. VS Code also uses a tools service architecture that allows it to integrate with many of the same technologies that power Visual Studio, such as Roslyn for.NET, TypeScript, the Visual Studio debugging engine, and others.

4.5.2 Arduino

Beginners will find the Arduino software simple to use, but advanced users will find it versatile. It's compatible with Mac, Windows, and Linux. It is used by teachers and students to create low-cost scientific instruments, to demonstrate chemistry and physics principles, and to begin learning programming and robotics. Designers and architects create interactive prototypes, while musicians and artists use them to create installations and try out new instruments. Makers, for example, use it to build many of the projects on display at the Maker Faire. Arduino is a valuable tool for learning new skills. Children, hobbyists, artists, and programmers are all welcome.

For physical computing, there are a variety of other microcontrollers and microcontroller platforms to choose from. Similar functionality can be found in Parallax Basic Stamp, Net media's BX-24, Phidgets, MIT's Handy board, and many other

programs. All of these programs condense the complicated details of microcontroller programming into an easy-to-use package. Although Arduino simplifies the process of working with microcontrollers, it has some advantages over other systems for teachers, students, and interested amateurs:

- **Inexpensive:** In comparison to other microcontroller platforms, Arduino boards are relatively cheap. The Arduino module's cheapest version can be assembled by hand, and even pre-assembled Arduino modules cost less than \$50.
- **Cross-platform:** The Arduino Software (IDE) is available for Windows, Macintosh OSX, and Linux. The majority of microcontroller systems are only compatible with Windows.
- **Simple, clear programming environment:** The Arduino Software (IDE) is easy to use for beginners, but it's also versatile enough for advanced users. It's based on the Processing programming environment, which is handy for teachers because students learning to program in that environment will be familiar with how the ArduinoIDE works.
- **Open source and extensible software:** The Arduino software is available as open-source tools for experienced programmers to extend. People who want to learn more about the language can use C++ libraries, and those who want to learn more about the technical specifics should switch from Arduino to the AVR C programming language. Similarly, if you want to, you can include AVR-C code directly in your Arduino programs.
- **Open source and extensible hardware:** The Arduino board plans are made available under a Creative Commons license, allowing experienced circuit designers to create their version of the module, expanding and upgrading it. The breadboard version of the module can be built by even novice users to learn how it works and save money.

CHAPTER - 5

RESULTS AND DISCUSSION

5.1 RESULTS OBTAINED

To begin with, testing of the trained model, we can split our project into modules of implementation that is done.

Dataset collection involves the process of collecting the various emotions recorded from the humans

Various datasets were collected and one example among the collected dataset can be found below

The below screenshot shows a sample of dataset collected:

#	mean_0	mean_1	mean_2	mean_3	mean_4	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d	mean_d
1	4.62E+00	3.03E+01	#####	1.56E+01	2.63E+01	1.07E+00	4.11E-01	#####	2.06E+00	3.15E+00	2.15E+00	2.95E+01	#####	1.44E+01	2.15E+01	5.98E+00	3.07E+01	#####	1.47E+01
2	2.88E+01	3.31E+01	3.20E+01	2.58E+01	2.28E+01	6.55E+00	1.68E+00	2.88E+00	3.83E+00	#####	2.56E+01	3.28E+01	2.96E+01	2.15E+01	1.74E+01	2.55E+01	3.17E+01	3.15E+01	2.62E+01
3	8.90E+00	2.94E+01	#####	1.67E+01	2.37E+01	7.99E+01	3.36E+00	9.02E+01	8.99E+01	2.03E+00	7.75E+00	3.01E+01	#####	9.89E+00	2.53E+01	#####	2.53E+01	#####	#####
4	1.49E+01	3.16E+01	#####	1.98E+01	2.43E+01	-5.84E-01	-2.84E-01	8.82E+00	2.30E+00	#####	1.73E+01	3.20E+01	#####	2.04E+01	2.28E+01	1.32E+01	3.15E+01	#####	1.69E+01
5	2.83E+01	3.13E+01	4.52E+01	2.73E+01	2.45E+01	3.48E+01	#####	3.06E+00	4.14E+01	5.52E+00	2.61E+01	3.43E+01	4.37E+01	2.37E+01	2.06E+01	#####	3.41E+01	4.37E+01	#####
6	3.10E+01	3.09E+01	2.96E+01	2.85E+01	2.40E+01	1.65E+00	1.54E+00	3.83E+00	1.87E+00	#####	2.80E+01	3.17E+01	2.90E+01	2.51E+01	1.75E+01	3.23E+01	2.85E+01	2.64E+01	2.99E+01
7	1.08E+01	2.10E+01	4.47E+01	4.87E+00	2.81E+01	2.14E+00	1.02E+00	1.32E+01	1.16E+00	#####	1.07E+01	2.00E+01	2.47E+01	2.32E+00	3.33E+01	8.83E+00	2.10E+01	5.11E+01	6.19E+00
8	1.78E+01	2.78E+01	#####	1.69E+01	2.69E+01	#####	#####	9.80E+00	#####	-9.55E-01	1.96E+01	2.58E+01	#####	1.84E+01	3.20E+01	1.92E+01	3.16E+01	#####	1.88E+01
9	1.15E+01	2.97E+01	3.49E+01	1.02E+01	2.69E+01	#####	#####	3.89E+00	#####	#####	2.86E+01	2.86E+01	3.88E+01	2.69E+01	2.35E+01	3.24E+01	3.23E+01	2.73E+01	2.70E+01
10	8.91E+00	2.92E+01	#####	6.51E+00	3.09E+01	#####	1.90E+00	1.19E+01	#####	5.70E+00	9.85E+00	2.98E+01	#####	8.43E+00	2.93E+01	9.85E+00	2.67E+01	#####	8.20E+00
11	5.21E+00	2.84E+01	1.85E+01	3.66E+00	2.26E+01	-1.19E-01	#####	5.07E+00	4.61E-01	#####	6.18E+00	3.15E+01	1.52E+01	3.11E+00	1.98E+01	4.39E+00	2.78E+01	1.68E+01	3.74E+00
12	1.33E+01	3.04E+01	#####	1.18E+01	2.83E+01	3.03E+00	8.95E-01	#####	1.72E+00	-6.33E-01	1.14E+01	2.94E+01	#####	1.17E+01	2.78E+01	1.21E+01	3.06E+01	#####	1.03E+01
13	3.01E+01	3.27E+01	2.94E+01	2.83E+01	2.43E+01	#####	#####	1.69E+00	#####	6.02E+00	3.37E+01	3.51E+01	3.08E+01	3.03E+01	1.77E+01	3.26E+01	3.42E+01	2.64E+01	2.98E+01
14	1.93E+01	3.17E+01	#####	2.38E+01	3.29E+01	#####	6.77E-01	4.66E+01	6.80E+00	3.89E+00	8.92E+00	3.05E+01	#####	1.76E+01	2.60E+01	3.28E+01	3.21E+01	1.27E+01	2.31E+01
15	2.88E+01	3.18E+01	3.01E+01	2.69E+01	2.18E+01	-3.55E-01	4.65E-01	3.82E+00	4.42E-01	#####	2.64E+01	3.07E+01	3.05E+01	2.37E+01	2.10E+01	3.15E+01	3.25E+01	2.60E+01	2.95E+01
16	1.27E+01	2.38E+01	#####	1.11E+01	2.76E+01	#####	2.05E+00	1.98E+01	-8.04E-01	#####	1.49E+01	2.07E+01	#####	1.27E+01	2.56E+01	1.42E+01	2.48E+01	#####	1.03E+01
17	4.25E-01	3.49E+01	5.39E+01	#####	2.26E+01	1.24E+01	#####	#####	5.29E+00	#####	#####	3.86E+01	6.36E+01	#####	2.35E+01	1.07E+00	3.40E+01	4.93E+01	#####
18	2.89E+01	3.08E+01	2.94E+01	2.74E+01	2.51E+01	#####	1.02E+00	4.99E-01	#####	#####	3.31E+01	3.11E+01	2.96E+01	3.08E+01	3.23E+01	3.27E+01	2.94E+01	2.86E+01	3.24E+01
19	#####	2.19E+01	#####	8.93E+00	2.26E+01	2.89E-02	1.28E+00	1.64E+01	9.20E+00	4.26E+00	#####	2.16E+01	#####	3.29E+00	1.53E+01	#####	2.09E+01	#####	5.33E+00

Fig:5.1 : Data set collection

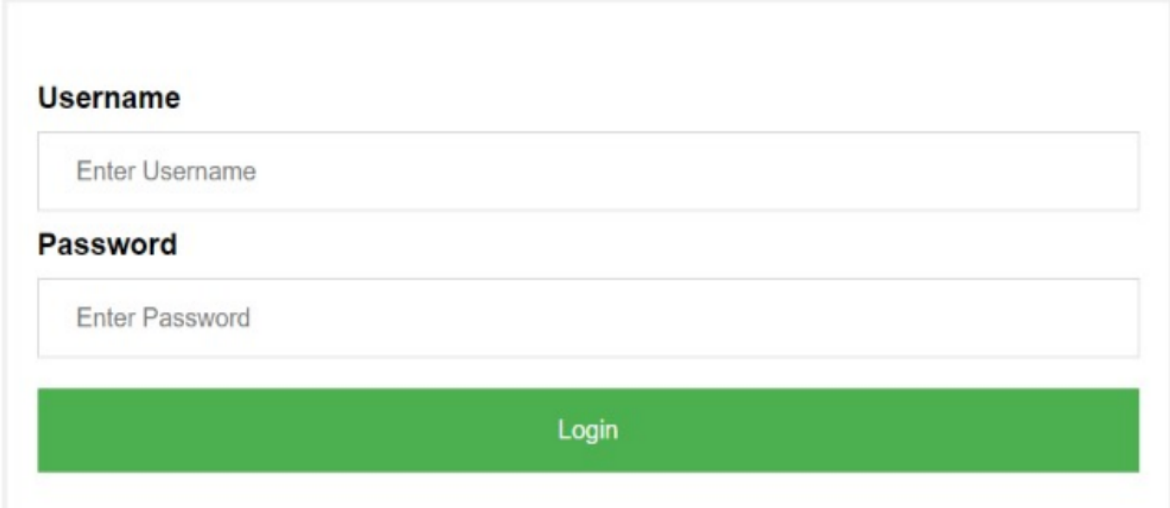
Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression (or logit regression) is estimating the parameters of a logistic model (a form of binary regression).

Table 5.1 :Training using different methods and its accuracy

TRANING METHOD	ACCURACY
Logistic regression	0.965625
Support Vector Machine	0.953437
Decision Tree with Gridseacrchcv	0.90555
Random Forest with Gridsearchcv	0.93055
Naive Bayes Bernoulli	0.93055
K-Nearest Neighbor	0.83333
XGboost Classifier	0.92777
Artificial Neural Network	0.898437

A web application using DJANGO framework is developed as an interface for the end user. The below image shows the login form of the web application:

Login Form

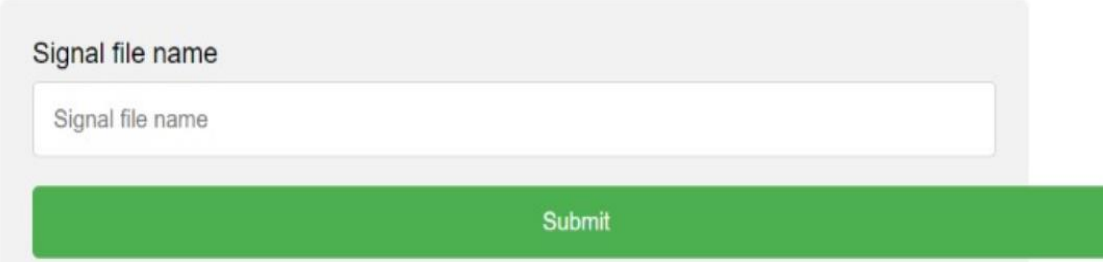


The login form is enclosed in a light gray border. It features two input fields: the first is labeled 'Username' and contains the placeholder text 'Enter Username'; the second is labeled 'Password' and contains the placeholder text 'Enter Password'. Below these fields is a prominent green button with the text 'Login' centered on it.

Fig:5.2 : Login form of the web application

The below image shows the home page of the web application on successful login:

Stress Control System



The home page has a light gray background. It includes a text input field labeled 'Signal file name' with the same placeholder text. Below the input field is a green button labeled 'Submit'.

Fig:5.3 : Home page of the web application

As seen in the above screenshot the user has to upload the EEG signal file for checking the emotion of the patient. The below image shows the user uploading the emotion file for testing:

Stress Control System

A screenshot of a web application interface titled "Stress Control System". It features a light gray background. At the top, the text "Signal file name" is displayed above a light blue rectangular input field containing the text "negative.csv". Below the input field is a wide, solid green button with the word "Submit" centered in white text.

Fig:5.4 : Uploading emotion file

Based on the emotion file uploaded the final results are displayed in the system:

Result



Fig:5.5 : Emotion response

Thus, from the above results and discussion we have successfully given a comparative study of the accuracies achieved from training using various other machine learning algorithms of accurately identifying the emotion of a person with a web application developed using the DJANGO framework.

CHAPTER - 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

In this project, we have successfully implemented a system of power forecasting in a city based on a dataset containing data of the power generation from various sources in a city. This dataset is trained using random forest regressor, a machine-learning algorithm. The present meteorological methods are inaccurate and inefficient. The system has provided an easy and efficient solution at very cost-effective approach.

6.2 CONCLUSION

In the coming future, we review this application of power forecasting to predict the power generation nationwide with more accuracy and efficiency. The application has good use in the energy field. In the electricity department, they have more chance to develop or convert this project in many ways. Thus, this project has an efficient scope in coming future where manual predicting can be converted to computerized prediction in a cheap way.

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APPENDIX

```
from django.shortcuts import render
from django.http import HttpResponse
from django.contrib import messages
from django.contrib.auth.models import User , auth
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_curve
from sklearn.svm import SVC
import requests
import sys
import os
import glob
from subprocess import run,PIPE
import pandas as pd
import json
#import matplotlib.pyplot as plt
import paho.mqtt.client as mqtt
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import warnings
import playsound
#from ubidots import ApiClient
import json
import urllib.request
import urllib.parse
```

```

broker_address="broker.hivemq.com"
client = mqtt.Client("PROJECT")
client.connect(broker_address)

# Create your views here.
def home(request):
    #return HttpResponse("Hello Worlds")
    return render(request,"login.html")

def view_patient_info(request):
    #print ("working")
    file_name=request.POST['file']
    print (file_name)
    f=open(file_name,"r")
    info=f.read()
    data_info=info.split('^')
    patient_info=data_info[0].split('~')
    result=data_info[1].split('~')

    return render(request,"patient_info.html",{
'patient_name':patient_info[0],
'patient_age':patient_info[1],
'Patient_temp':patient_info[2],
'Patient_vomit':patient_info[3],
'Patient_eye':patient_info[4],
'Patient_plates':patient_info[5],
'Patient_fatigue':patient_info[6],
'Patient_fever':patient_info[7],
'Patient_muscle':patient_info[8],
'Patient_skin':patient_info[9],
'status':result[0],
'file_name':file_name})

def login(request):
    user_id=request.POST.get('uname')
    password=request.POST.get('psw')
    page='dashboard.html'
    if(user_id=='abc@gmail.com' and password=='test'):

```

```

        page='dashboard.html'
        return render(request,page)
    elif (user_id=='abc@gmail.com' and password=='test'):
        if(len(os.listdir('static'))!=0):
            files=glob.glob('static/*')
            #print (files)
        page='doctor.html'
        return render(request,page,{'file_list':files})

def data_analysis(path):
    # Importing the csv file
    data = pd.read_csv('emotions.csv')

    # Encoding all the ordinal columns and creating a dummy variable for them to see if there are any effects on Performance Rating
    enc = LabelEncoder()
    # for i in (2,3,4,5,6,7,16,26):
    i=2549
    # data.head()
    # data.iloc[-1,:]= enc.fit_transform(data.iloc[-1,:])
    data.iloc[:,-1] = enc.fit_transform(data.iloc[:,-1])
    data.head()
    # Here we have selected only the important columns
    y = data.label
    #X = data.iloc[:,0:-
1] All predictors were selected it resulted in dropping of accuracy.
    X = data.iloc[:,:-
1] # Taking only variables with correlation coefficient greater than 0.1
    X.head()

```

```

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=1
0)

# Standardization technique is used
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Training the model
from sklearn.linear_model import LogisticRegression
model_logr = LogisticRegression()
model_logr.fit(X_train,y_train)

# Predicting the model
y_predict_log = model_logr.predict(X_test)
print("done")

from numpy import genfromtxt
my_data = genfromtxt(path, delimiter=',')
print(my_data)
# [30] is for 2(negative) [10] is for 0(neutral) [20] is for 1(positive)

a = my_data.reshape(-2548, 2548)
Y_pred = model_logr.predict(a)
#print(Y_pred)
if(Y_pred == [2]):
    print("negative")
    patient_condition = "negative"
    playsound.playsound('happy.mp3', True)
    client.publish("eeg_stress_vibratee","*")
    print("data published")

```

```

elif(Y_pred == [1]):
    print("neutral")
    patient_condition = "neutral"

elif(Y_pred == [0]):
    print("positive")
    patient_condition = "positive"

return patient_condition

def get_patient(request):

    #print(str(request.POST['age']))
    result = data_analysis(str(request.POST['age']))
    #result=api_client(str(request.POST['age']))
    # print(output_data)
    # # if output_data is not None:
    # result=output_data
    # print (file_path)
    # print(result)
    # style="style='color:red'"

    return render(request,'result.html',{ 'status':str(result)})

```