Emotion Recognition Using (EEG) Signals

Capstone Project Report

MID SEMESTER EVALUATION

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ABSTRACT

The computer machinery needs to be empathic to the user which is one of the main aspects of affective computing. For the computer to look inside the user's head to observe its mental state we need EEG based emotion recognition. This project describes an ideology to recognize emotion from brain signals measured with the EEG device. Emotions play essential roles in decision making. They can be analysed in different ways. Compared with other emotion analysis, brainwave emotion analysis shows that the authenticity and non-immutable credibility of brain waves are high. BCI (Brain-Computer Interface) systems can be used to perceive our mental states and recognize them accurately using EEG. First, literature research has been performed to establish a methodological approach and determine statistics involved for emotion recognition using EEG. The second step will be putting all these statistics into practice with the EEG device during the experimental phase, which finally will be observed to analyze the final results.

DECLARATION

We hereby declare that the design principles and working prototype model of the project entitled **Emotion Recognition using EEG signals** is an authentic record of our own work carried out in the Computer Science and Engineering Department, TIET, Patiala, under the guidance of Dr. Ashima Singh and Dr. Vinay Kumar during the 6th semester (2021).

Date: 15th December 2021

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Lastly, we would also like to thank our families for their unyielding love and encouragement. They always wanted the best for us and we admire their determination and sacrifice.

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LIST OF ABBREVIATIONS

BCI	Brain-Computer Interaction
EEG	Electroencephalogram
DEAP	Database for Emotion Analysis Using Physiological Signals
SEED	SJTU Emotion EEG Dataset
IOT	Internet Of Things
MRI	Magnetic resonance imaging
fMRI	Functional magnetic resonance imaging
CPU	Central processing unit
NLP	Natural Language Processing
AI	Artificial Intelligence
FIR	Finite Impulse Response
FFT	Fast Fourier Transform
QOS	Quality Of Service
CNN	Convolutional Neural Network
CSV	Comma Separated Values
LSTM	Long Short-Term Memory
PReLU	Parametric rectified linear activation unit

GUI	Graphical user interface
SVM	Support Vector Machine
KNN	K Nearest Neighbor

INTRODUCTION

1.1 Project Overview

1.1.1 Technical Terminology

The techniques used in the project are as follows:

1. Google Colab: Colab notebooks allow you to combine executable code and rich text in a single document, along with images, HTML, LaTeX and more. When you create your own Colab notebooks, they are stored in your Google Drive account. You can easily share your Colab notebooks with co-workers or friends, allowing them to comment on your notebooks or even edit them.

2. Machine Learning: Machine learning is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead.

3. Deep Learning: Deep learning is a subset of machine learning in AI that has networks capable of learning unsupervised from data that is unstructured or unlabeled.

4. Data Analytics: Data analysis is a process of inspecting, cleansing, transforming and modelling data with the goal of discovering useful information, informing conclusions and supporting decision-making.

5. Arduino: It is an open-source hardware and software company, project, and user community that designs and manufactures single-board microcontrollers and microcontroller kits for building digital devices.

1.1.2 Problem statement

Emotions play essential roles in decision making. They can be analyzed in different ways. Compared with other emotion analysis, brainwave emotion analysis shows that the authenticity and non-immutable credibility of brain waves are high. BCI (Brain-Computer Interface) systems can be used to perceive our mental states and recognize them accurately using EEG.

1.1.3 Goal

To design and develop a machine/deep learning module for the classification of moods from EEG data and to design an IoT system for changes in lighting conditions based on perceived emotions.

1.1.4 Solution

For decades, BCI research has become one of the most exciting biomedical engineering research areas, and it has gotten much recognition in recent years. Most BCI applications are designed for noninvasive brain signal processing and are used in real-world scenarios.

Several EEG-based BCI applications have proven to be popular, such as word speller programmes and wheelchair controls. Not only can BCI be used to manipulate computers through our minds, but it can also be used to perceive our mental states. One of these implementations is emotion interpretation. Automatic emotion recognition algorithms can close the human-machine interface gap. The physiological and behavioural condition of being awake or reactive to stimuli, ranging from passive to aggressive, is arousal. The fluctuation of brain electric potentials caused by the ionic current flow between brain neurons is recorded as an EEG. The electrical processes at electrode locations on the scalp are measured to obtain EEG signals. Delta (1–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (31–50 Hz) are the five major frequency bands that make up the human brain wave. Every band's characteristics can be used to estimate a patient's cognition and emotional states.

Using machine learning/ deep learning and EEG signals, we propose a new interpretable emotion detection technique with an activation function in this project. We used machine learning/ deep learning methods to abstract features from EEG signals and classified emotions. This detected emotion can be used in several ways to monitor a patient's emotional state.

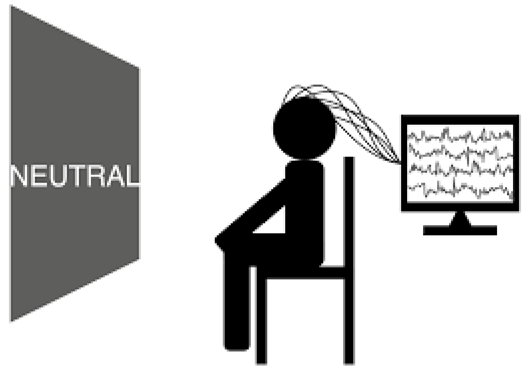


Figure 1: Using EEG for Emotion Analysis
(https://bcmi.sjtu.edu.cn/home/seed/img/index/neutral_sm.png)

Now there is an awareness of the current state of EEG based emotion recognition, and its use within human media interaction, it is time to move on to the primary goals of this research.

The main questions addressed in this research are:

1. Is the modality of the stimulus (visual, auditory, or audiovisual) recognizable from the recorded brain signals?

2. To what extent are emotions recognizable from an EEG?

3. What is the influence of the modality of the stimulus on the recognition rate?

4. When using only five electrodes, what would be good positions to place them for emotion recognition?

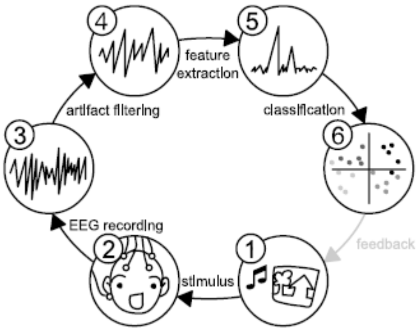
5. What features are interesting to extract from the recorded EEG signals for emotion recognition?

In 2000, Choppin analyzed EEG signals and used neural networks to classify them in six emotions based on emotional valence and arousal, with a 64% success rate. Important for our case, because of the limited number of available electrodes, are the influential EEG features detected during various emotional stimuli

• Valence: positive, happy emotions result in a higher frontal coherence in alpha, and higher right parietal beta power, compared to negative emotion.

• Arousal: excitation presented a higher beta power and coherence in the parietal lobe, plus lower alpha activity.

• Dominance: strength of emotion, which is generally expressed in the EEG as an increase in the beta/alpha activity ratio in the frontal lobe, plus an increase in beta activity at the parietal lobe.



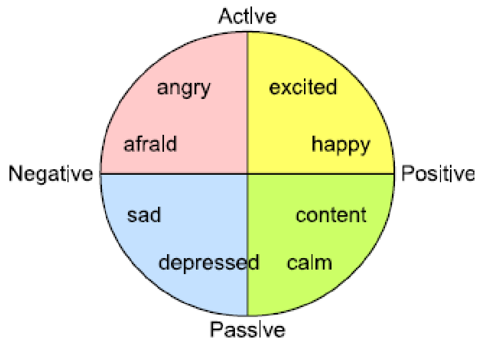


Figure 2: Brain-computer interface cycle Figure 3:Arousal - valence model

(https://www.researchgate.net/profile/Danny-Plass-Oude-Bos/publication/237777779/figure/fig1/AS:669556259446784@1536646060009/Brain-computer-interface-cycle.png)

(https://www.researchgate.net/profile/Danny-Plass-Oude-Bos/publication/237777779/figure/fig2/AS:669556259426304@1536646060022/Arousal-valence-model_W640.jpg)

1.2 Need Analysis

Emotions are a physiological state of mind. These are reactions to our internal stimuli or any physical experience. Emotions play essential roles in decision making. It is possible to hurt oneself by not being conscious of one's feelings or suppressing negative emotions. It's possible that we won't be able to access the crucial knowledge that feelings offer.

There have been different ways of classifying emotions into different categories. The primary classification system classifies emotions into six categories, i.e. fear, disgust, anger, surprise, happiness, and sadness. Using Emotion Based

Therapy, we can address many issues faced by many people and can help them :

1. The patient can become more aware of emotions.
2. Examine whether feelings are beneficial or harmful in a variety of cases.
3. Learn to use positive thoughts to motivate them to take action.
4. Develop safe coping mechanisms for circumstances that often evoke maladaptive emotions.

Our project uses the EEG signals obtained from the patient in different scenarios and tries to predict his/her actual emotions. This can provide an in-depth diagnosis.

The authors of the paper "Interpretable Emotion Recognition Using EEG Signals 2019" propose a new interpretable emotion recognition approach based on machine learning and EEG signals. The emotional activation curve is a novel concept proposed in this paper to explain emotions' activation mechanism.

Figure 4: Accessing brain signals using EEG
(http://www.eecs.qmul.ac.uk/mmv/datasets/deap/img/subject.jpg)

1.3 Research Gaps

In spite of the several distinct predictions/methodologies, there exist certain limitations, which must be addressed for attaining effective emotion recognition. The devised EEG is effective and gives results to great extent but to only be able to distinguish between happy and unhappy will often not provide sufficient granularity to be of much use for human-computer interaction. Therefore it is also necessary to derive a suitable method for representing and classifying emotions other than happiness like sadness, anger.

Emotion recognition is a challenging task as it requires deep insights into brain function and reactions to stimuli/events, analysis of data, and impact of news/ events on the human brain. The challenge is further exacerbated due to the insufficient human-computer interface. There is a lack of research concerning the prediction of further divided emotions. The authors of the paper "Interpretable Emotion Recognition Using EEG Signals 2019" propose a new interpretable emotion recognition approach based on machine learning and EEG signals. The emotional activation curve is a novel concept proposed in this paper to explain emotions' activation mechanism. From these findings, we created the foundation of our project and added our necessary features.

1.4 Problem Definition and Scope

Psycho-physiological research shows there is a direct link between the amount of action in the left frontal lobe and the right frontal lobe and the emotion shown as a resultant. A more active left frontal region indicates a positive reaction, and a more active right anterior lobe negative effect. This shows great potential for EEG-based emotion classification, but to only be able to distinguish between happy and unhappy will often not provide sufficient granularity to be of much use for human-computer interaction. Therefore it is also necessary to derive a suitable method for representing and classifying emotions other than happiness like sadness, anger.

Another element that can have much influence on the classification success rate is the way the emotions are elicited in the test subjects. For further research visual, auditory, and audiovisual stimuli can be compared all at once.

1.5. Assumption and Constraints

Table 1: Assumptions

S. No.	Assumptions
1	The experiments were conducted in a controlled environment. All the subjects of the dataset collection team were neutralized by exposure to the same videos so that there is no specific emotion output from them,

	Then they were shown a series of videos with specific expected emotion responses and the readings were recorded.
2	The size of the dataset is large. The dataset used is collected from 32 subjects where each one was shown 40 music videos and 40 channel data was collected.
3	It is assumed that all the sensors are of high sensitivity and give results with good accuracy. The EEG Headset used must contain 16 - 32 electrodes. This would ensure the availability of highly sensitive data.
4	We assume communication in our system is instant without any delay. When EEG signal scans are predicted into emotions, they are sent to an Arduino connected device which in turn changes the lights of the connected system. There should not be much delay for its smooth working.

Table 2: Constraints

S. No.	CONSTRAINTS
1	Patients' recordings are not always measured in a controlled environment. The emotions of the subject might fluctuate based on the surroundings and his/her personal life. This might result in unstable data collection and might affect results.
2	There might be noise interference with the Brain signals data received from the EEG Headset. Some electrodes might not be properly collected. Also, there might be some outside interference in the EEG signals from other devices nearby.

1.6 Standards

ISO/IEC 9126 This standard deals with the following aspects to determine the quality of a software application: Quality model, External metrics, Internal metrics, and Quality in use metrics.

This standard also presents some set of quality attributes for any software such as: Functionality, Reliability, Usability, Efficiency, Maintainability, and Portability.

830-1998 - IEEE Recommended Practice for Software Requirements

Specifications Replaced by ISO/IEC/IEEE 29148:2011. The content and qualities of a good software requirements specification (SRS) are described and several sample SRS outlines are presented. This recommended practice is aimed at specifying requirements of the software to be developed but also can be applied to assist in the selection of in-house and commercial software products. Guidelines for compliance with IEEE/ EIA 12207.1- 1997 are also provided.

To achieve harmonization of the content definition for software life cycle process results among the IEEE software engineering standards and with related international standards. This will help users to produce results consistent with the international standard for software life cycle processes,

ISO/IEC 12207

1.7 Approved Objectives

- To study existing tools and techniques available for EEG measurement
- With this objective, we aim to study the various impactful technologies that are already available and study the error statistics and try to improve that accuracy.
- To design and develop a machine/deep learning module for the classification of moods from EEG data
- The need for computer applications that can detect the current emotional state of the user is ever-growing. In an effort to copy human communication, research has already been done into recognizing emotion from face and voice. Humans can recognize emotions from these signals with a 70-98% accuracy, and computers are already pretty successful especially at classifying facial expressions (80-90%). Note that these high success rates are under very controlled circumstances, and will be lower in ordinary situations.
- To design an IoT system for changes in lighting condition based on

perceived emotions.

- The aim is to capture the emotion expressed by a person through EEG data that is generated. A light changing system is designed to capture human emotion through the data available.
- To implement all modules as an integrated system.
- Our final objective is to integrate all the modules created above into one single main module which is able to recognise emotion using EEG signals and help us change the light related to that emotion.

1.8 Methodology

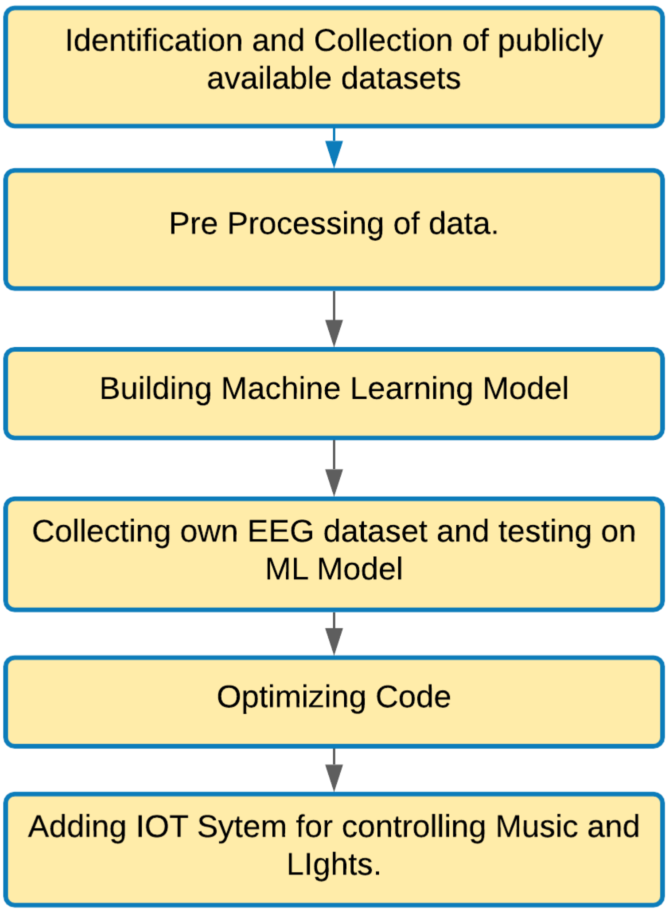


Figure 5: Project Execution Plan

1.9 Project Outcomes and Deliverables

- An accurate model which can detect the emotions of the user using EEG signals.

- An IoT based system that uses the results obtained from the above model to change the pattern lights based on it.

1.10 Novelty of Work

Earlier projects/research done on this field did not cover the aspect of using the emotion captured via EEG. We here use the emotion to a real-time application generating a change in lighting condition based on the current emotion. A direct feedback emotion recognition system.

Additional functionalities can be added to the project, like changing the ambience of the room by turning on/off the lights, or it can also be used in Lie-Detection or can be used by Psychiatrists in their therapy sessions.

We are trying to create here a general model which can impact every field which requires the art of emotions.

2.1 Literature Survey

2.1.1 Theory Associated With Problem Area

Researchers have concentrated on emotion recognition based on facial expressions, voice, body gestures, and image processing in recent decades. They have started to acknowledge brain impulses as a way of identifying an individual's "inner" emotional state in recent years. To get access to these brain signals, different neuro-imaging techniques can be used, which includes Functional Magnetic Resonance Imaging (fMRI), Magnetic Resonance Imaging (MRI), EEG.

According to author David G. Meyers, human emotion involves "...physiological arousal, expressive behaviours, and conscious experience." Emotion is an acute disturbance of the organism as a whole, psychological origin, including behavior, conscious experiences, and visceral functioning.

The primary emotion theories are grouped into three main categories: physiological, neurological, and cognitive. Physiological theories suggest that responses within the body are responsible for emotions. Neurological theories propose that activity within the brain leads to emotional responses. Finally, cognitive theories argue that thoughts and other mental activities play an essential role in forming emotions.

2.1.2 Existing Systems and Solutions

Compared with other emotion analysis, brainwave emotion analysis shows that the authenticity and non-immutable credibility of brain waves are high.

An EEG is a device that monitors and records brain wave patterns. Electrodes (small metal discs with thin wires) are placed on the scalp and transmit signals to a computer, which records the results. The brain's electrical activity follows a predictable pattern. Doctors might use an EEG to look for abnormal patterns that may suggest seizures or other issues.

The brain's response to different stimuli is usually measured by dividing the EEG signals into different frequency rhythms, namely, delta (0.5- 4Hz), theta (4 - 8Hz), beta (16 - 32Hz) and gamma (32Hz - above). These band waves are omnipresent in different parts of the brain.

- **The Delta** frequency band is linked with deep sleep.
- **Theta** is dominant during dream sleep, meditation, and creative inspiration.
- **Alpha** brainwave is linked with tranquility and relaxation.
- **Beta** frequency band is associated with an alert state of mind, concentration, and mental activity. They are divided into three sub-bands: **Beta1, Beta2, and Beta3.**

2.1.3 Research Findings for Existing Literature

Some of the most cited papers in the above fields are:

- **Interpretable Emotion Recognition Using EEG Signals** (BY CHUNMEI QING, RUI QIAO, XIANGMIN XU AND YONGQIANG CHENG)
- **Emotion Recognition from EEG Using Higher Order Crossings** (By Panagiotis C. Petrantonakis; Leontios J. Hadjileontiadis)

Public Dataset Available :

- **DEAP**[1] is a benchmark effective EEG database for emotion analysis. It includes a 32-channel electroencephalogram (EEG) and 8-channel peripheral physiological signals from 32 subjects.
- **SEED**[1] is a free and publicly accessible EEG dataset for emotional analysis. The SEED dataset included 62 EEG channels from 15 subjects for 15 experiments.

Table 3:Accuracy of Different Machine Learning algorithms

Algorithm	Accuracy %
KNN	51.3
SVM	60.8
ANN	60

2.1.4 Problem Identified

1. **Issues with EEG Headsets:** The EEG headset significantly impacts the quality of EEG data for BCI applications. There are a few challenges with EEG headsets that need to be addressed. First, most EEG headsets necessitate the use of gel or liquid on the electrodes, which is highly unpleasant. For practical applications, users prefer dry electrodes, as it is not mandatory to use any conductive gel between the scalp skin and electrode pad. However, it is a matter of open debate about whether this type of electrode offers identical signal properties.

2. **Lack of Ideal Data Analysis Methods:** EEG Data Pre-processing Strategies suffer from different limitations when utilized in a particular EEG-based application. Some methods are only focused on detecting and removing particular artefacts, while some methods need reference channels to enhance the accuracy of artefact removal, which is not feasible.

3. **Adopting a proper theoretical framework of emotion**[4]: The underlying theoretical challenge for all affective computing studies is to develop a proper emotion model. The categorical viewpoint and the dimensional perspective are two main meta-theoretical viewpoints for framing emotions. The former assumes that emotions are categorically discrete and that complex emotion is the result of combining many basic emotions. Contempt, for example, is made up of frustration and disgust. Although researchers disagree on the number of basic emotions and most agree that humans have at least six [5]: anger, disgust, fear, sadness, surprise, and

happiness. In contrast to the categorical view, the dimensional viewpoint holds that basic dimensions underpin emotions and that each emotion can be mapped into a particular position in the multi-dimensional emotion space.

4. **Understanding the EEG representation of affective states**[4]: The EEG-based affective computing rationale assumes that EEG signals can accurately and sensitively reflect human emotions. However, since the relationship between EEG signals and affective states can be complicated, this presumption cannot always be relied upon.

2.1.5 Survey of Tools and Technologies Used

Table 4: Literature Survey

S. No.	Roll Number	Name	Paper Title	Tools/ Technology	Findings	Citation
1	1018031225	Vishesh Gupta	An Evaluation of Feature Extraction in EEG-Based Emotion Prediction with Support Vector Machines	PCA AND SVM	The best feature extraction is "one-minute EEG data using a bandpower filter from 10-channel probes.	Itsara Wichakam and Peerapon Vateekul 2014
			Classification of Human Emotions using EEG Signals	Neural Network (NN); Wavelet transform	This study"s result gives a framework of methodology that can be used to elucidate the	Pravin Kshirsagar , Sudhir Akojwar July 2016

					dynamical mechanism for changing of human emotional underlying brain structure.	
			A Real-Time Model-Based Support Vector Machine for Emotion Recognition Through EEG	SVM Classifier	The model can recognize five basic human emotions in real time with average accuracy 70.5% from the experiment using SVM Classification Technique.	Viet Hoang Anh, Manh Ngo Van, Bang Ban Ha, Thang Huynh Quyet 2012
2	101803126	Prakhar Jindal	Classification of Emotional Signals from the DEAP Dataset	SVM Classification	The results showed that, being the classification accuracy is very high for most of the channels, the activation was not	Giuseppe Placidi, Paolo Di Giamberardino, Andrea Petracca, Matteo Spezialetti and

					differently distributed between hemispheres for different emotions.	Daniela Iacoviello 2016
			Compact Unsupervised EEG Response Representation for Emotion Recognition	Naive Bayes and RBF-SVM	Using compact EEG response representation modeled via unsupervised training they demonstrate competitive results in binary classification and regression tasks of emotion recognition on the DEAP dataset	Xiaodan Zhuang, Viktor Rozgi´c, Michael Crystal 2014
			Classification of EEG Signals using adaptive	Weighted adaptive nearest-neighbor	This WDNN could improve the generalizatio	E. Parvinnia , M. Sabeti , M.

			weighted distance nearest neighbor algorithm	classification	n accuracy for EEG signal Classification task	Zolghadri Jahromi , R. Boostani 2012
3	1018003128	Divyam Jain	DEEP LEARNING OF EEG SIGNALS FOR EMOTION RECOGNITION	KNN, SVM, ANN	Emotion recognition of EEG signal is subject dependent, and our subject tied implementation of deep learning achieves better recognition accuracy than conventional algorithms	Yongbin Gaol, Hyo Jong Lee , Raja Majid Mehmood, 30 July 2015
			Discrete Wavelet Transform Coefficients for Emotion Recognition from EEG Signal	Extreme Learning Machine, SVM Classifiers	The proposed method showed the best classification performance, reaching 84.00% (Fp2) and 89.33%	Rendi E. J. Yohanes, Guang-bin Huang 2012

					(Fp1), for happy and sad emotions, respectively. The proposed method also showed the best average performance of 84.67%. I	
			Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers	SVM AND Naive Bayes	Unlike other approaches, the approach uses the mRMR feature selection method as a signal preprocessing step so as to improve the predictive accuracy of an SVM emotion classifier based on a two-dimension emotions model.	John Atkinsona, Daniel Campos
4	101806169	Abhiraam	EG based Emotion	SVM and PSO	The core element of	Nivedha R, Brinda

		Khanna	Recognition using SVM and PSO		this paper is PSO which optimizes the classifier thus providing sufficiently higher classification accuracy. Also adding MSCE led to a better feature set as it estimates the coherence between various frequency domain signals	M, Devika Vasanth, Anvitha M and Suma K.V 2017
			Emotional state recognition using advanced machine learning techniques on EEG data	Machine learning	The analysis presented, showed that the best classification scheme achieved accuracies of 75.59%, 75.06% and	Katerina Giannakaki, Giorgos Giannakakis, Vangelis Sakkalis, Christina Farmaki

					75.12% for the three pairs of classes clam/exciting negative (C-EN), calm/exciting positive (CEP), exciting positive/exciting negative (EP-EN) respectively.	
5	101806189	Navia Sehgal	Using Deep and Convolutional Neural Networks for Accurate Emotion Classification on DEAP Dataset	Deep Neural Network (DNN), Convolutional Neural Network (CNN)	The CNN model, on the other hand, had classification accuracies of 81.41% and 73.35% for 2 classes on the Valence and Arousal Model respectively. While for our DNN model, the accuracy of all subjects	Samarth Tripathi, Shrinivas Acharya, Shrinivas Acharya, Sudhanshi Mittal, Samit Bhattacharya 2017

					but one were consistently over 70% which is a commendable achievement of our model. The highest classification accuracy for a single subject was as high as 82.5%.	
			Multimodal fusion framework: A multiresolution approach for emotion classification and recognition from physiological signals	SVM KNN	This study presents a multimodal fusion framework based on a multiresolution approach using Daubechies Wavelet Transform features for emotion recognition from physiological signals.	Gyanendra K. Verma, Uma Shanker Tiwary 2013
			Feature	Machine	Presented a	Robert

			Extraction and Selection for Emotion Recognition from EEG	Learning	systematic analysis and first qualitative insights comparing the wide range of available feature extraction methods using machine learning techniques for feature selection.	Jenke, Angelika Peer, and Martin Buss 2014

2.2 Software Requirement Specification

2.2.1 Introduction

2.2.1.1 Purpose

Emotions are a physiological state of mind. These are reactions to our internal stimuli or any physical experience. Emotions play essential roles in decision making. It is possible to hurt oneself by not being conscious of one's feelings or suppressing negative emotions. It's possible that we won't be able to access the crucial knowledge that feelings offer.

There have been different ways of classifying emotions into different categories. The primary classification system classifies emotions into six categories, i.e. fear, disgust, anger, surprise, happiness, and sadness.

Detecting human feelings via biological brain signals is becoming more appealing. Electroencephalography (EEG) is a cost-effective and dependable method of measuring brain activity.

2.2.1.2 Intended Audience and Reading Suggestions

The Intended audience is psychologists who can use it on their patients for Emotion-based Therapy.

It can also provide assistance, enhancement, monitoring, assessment, and diagnosis of neurological diseases.

This can also be used for patients who are in a state of paralysis or coma. Their emotional state can be perceived and can be easily treated.

2.2.1.3 Project Scope

Using EEG Emotion recognition for Emotion Based Therapy, we can address many issues faced by many people and can help them:

1. The patient can become more aware of emotions.
2. Examine whether feelings are beneficial or harmful in a variety of cases.
3. Learn to use positive thoughts to motivate them to take action.
4. Develop safe coping mechanisms for circumstances that often evoke maladaptive emotions.

2.2.2 Overall Description

2.2.2.1 Product Perspective

Emotions play essential roles in decision making. They can be analysed in different ways. Compared with other emotion analyses, brainwave emotion analysis shows that the authenticity and non-immutable credibility of brain waves are high. BCI (Brain-Computer Interface) systems can be used to perceive our mental states and recognize them accurately using EEG.

Our EEG Emotion Recognition system is a BCI that will help medical professionals to recognise the emotional state of their patients at different points of their therapy.

This can also help in manipulating the environments based on the perceived emotions to make them happy and joyful.

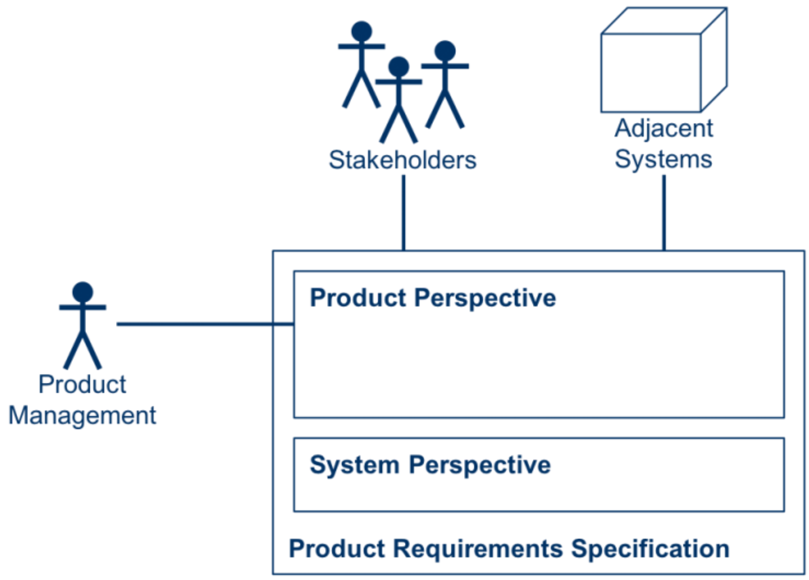


Figure 6: Product Perspective Diagram
(https://makingofsoftware.com/docs/Software_Product_Specification_200226_2.png)

Functional Requirements

1. Old EEG headset support.s
2. Accurate emotion Recognition
3. An IoT system for changing lighting conditions based on perceived emotions.
4. Get data from a database or collect data from patients in virtual environments.

USE CASE DIAGRAMS

Diagram 1

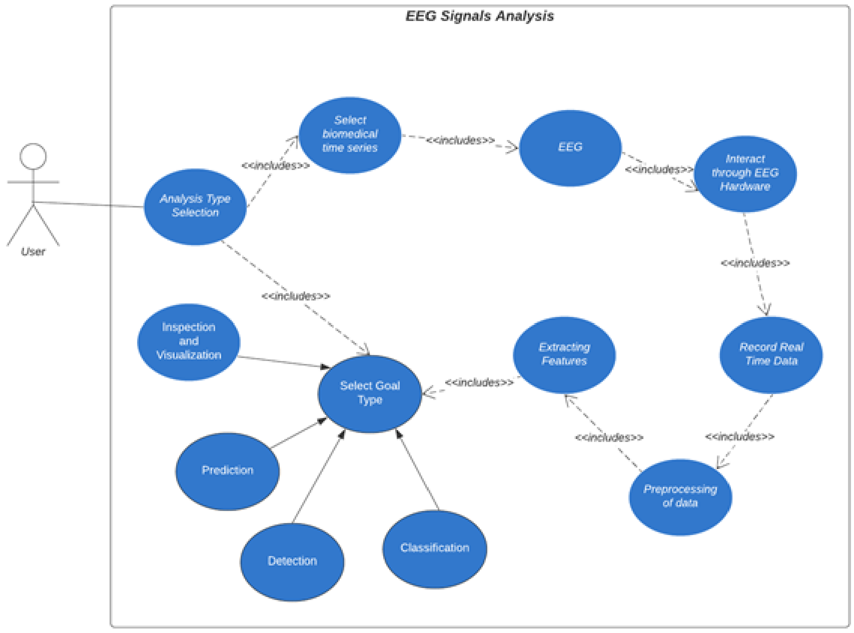


Figure 7: Use Case Diagram - EEG Signals Analysis

Table 5: Use Case Table - EEG Signals Analysis

Use Case Title: EEG Signals Analysis
Abbreviated Title: EEG Signals Analysis
Use Case id: 1
Actors: User
Description: With this analysis, the user can detect his/her emotions using EEG signals. The emotional state can be used to control lighting.
Pre Condition: 1. User must be equipped with EEG headgear.
Post Conditions: 1. User can view his desired results. 2. Users can go for another search.
Modification History: Date 21-May-2021

Author: Vishesh Gupta, Prakhar Jindal, Divyam Jain, Navia Sehgal, Abhiraam Khanna

Typical Course of Events/ Successful Scenario/ Normal Scenario

For EEG Signals Analysis:

1. User selects amongst the biomedical time-series selection.
2. User chooses the EEG time-series.
3. User wears the EEG headgear.
4. The signals are recorded.
5. Pre-processing of signals takes place.
6. Useful features are extracted.
7. The signals are recognized based on emotion using the ML model.
8. The output is presented on screen.
9. The signals are sent to Arduino.
10. There is a change in the light of the room.

Alternative Flow of Events:

For EEG Signals Analysis:

1. User wants a change in the light instead of music or vice-versa.

Exceptional Flow of Events:

For EEG Signals Analysis:

1. There is no required number of electrodes in EEG headgear.
2. Gel is not applied for smoothening of EEG signals.

3. The Arduino is out of power supply.

4. Integrating cognitive projects with existing hardware and systems.

Diagram 2

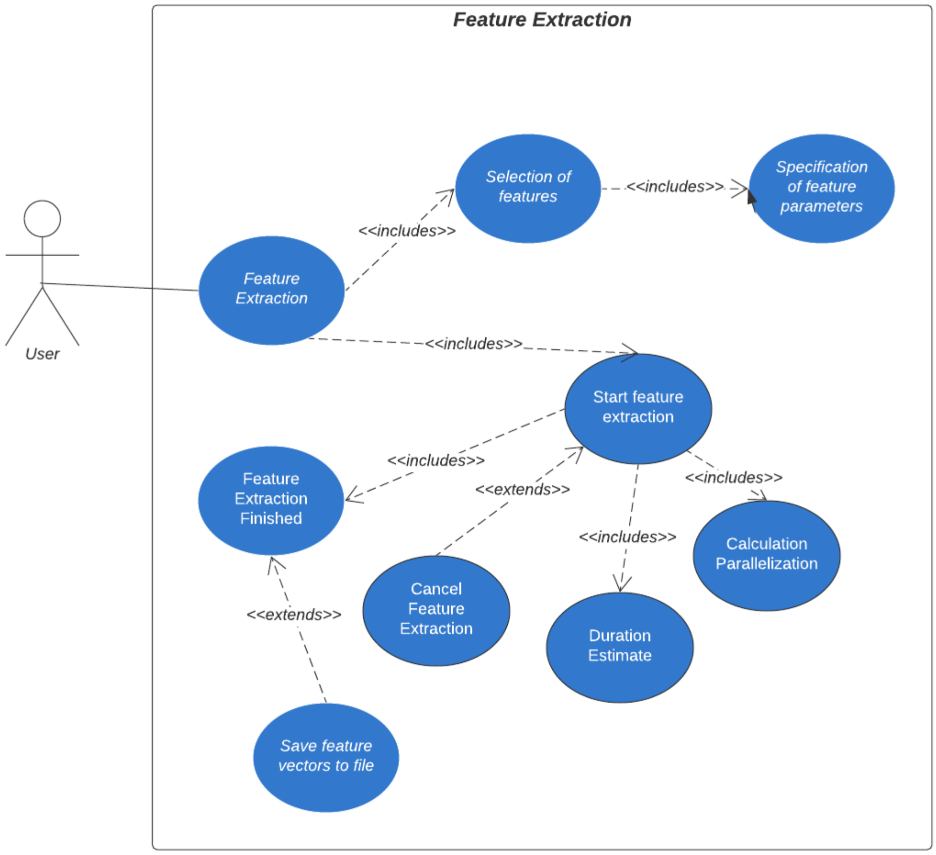


Figure 8: Use Case Diagram - Feature Extraction

Table 6: Use Case Table - Feature Extraction

Use Case Title: Feature Extraction
Abbreviated Title: Feature Extraction
Use Case id: 2
Actors: User
Description: With this analysis, the dimensionality of the raw data can be reduced and more informative, non-redundant features can be extracted.
Pre Condition:

1. Dataset must contain features.
Post Conditions: 1. Users can view and save the desired results. 2. Users can go for another feature extraction.
Modification History: Date 21-May-2021
Author: Vishesh Gupta, Prakhar Jindal, Divyam Jain, Navia Sehgal, Abhiraam Khanna

Typical Course of Events/ Successful Scenario/ Normal Scenario

For Feature Extraction:

1. Features are extracted from the dataset.
2. Relevant features are selected on the basis of feature parameters.
3. Inappropriate features are removed/reduced from the set.
4. There is a reduction in the dimensionality of the dataset.
5. The features are stored as vectors to the file which can be loaded later.

Alternative Flow of Events:

For Feature Extraction:

2. During feature extraction, the user has a change of mind and cancels the process.

3. User wants to add more features.

Exceptional Flow of Events:

For Feature Extraction:

1. Less amount of training data to extract relevant information.

2. Memory utilization of the CPU is 100%.

5. The saved feature vector file is empty i.e. the features are not saved correctly.

2.2.2.2 Product Features

Some of the features of our product are :

1. Emotion Recognition.
2. Update lighting condition output based on perceived emotion.

2.2.3 External Interface Requirements

2.2.3.1 User Interfaces

A graphical user interface (GUI) is a type of user interface through which users interact with electronic devices via visual indicator representations.

The user will be provided with a web app with access to EEG graphs on the screen. There will also be an option to manipulate the room lightning based on the emotion.

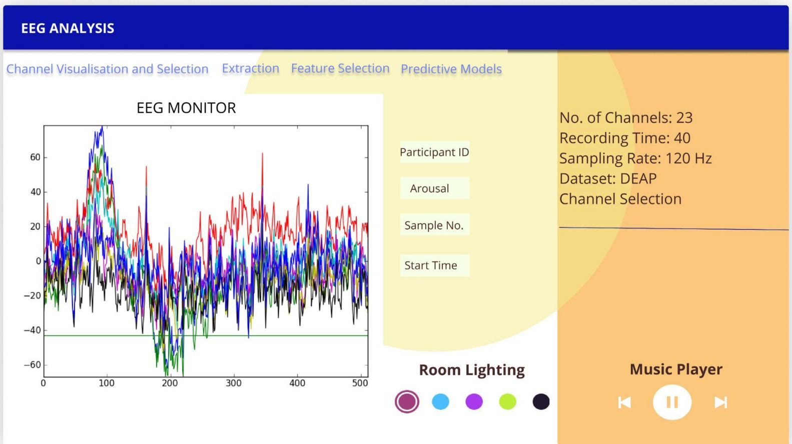


Figure 9: Sample GUI

2.2.3.2 Hardware Interfaces

Electroencephalography (EEG) is a monitoring method to record the electrical activity of the brain. Wearable EEG headsets position noninvasive electrodes along the scalp. The clinical definition of EEG is the recording of brain activity over a period of time.

EEG electrodes pick up on and record the electrical activity in your brain. The collected signals are amplified and digitized then sent to a computer or mobile device for storage and data processing.

Figure 10: EEG Headgear
(https://th.bing.com/th/id/OIP.dylPH9S5jMZJisB6tqHOHgHaFu?pid=ImgDet&w=208&h=161&c=7&dpr=1.25)

Arduino Uno is a microcontroller board based on the ATmega328P (datasheet). It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with an AC-to-DC adapter or battery to get started.

The Arduino will receive output from the website in terms of an integer value.

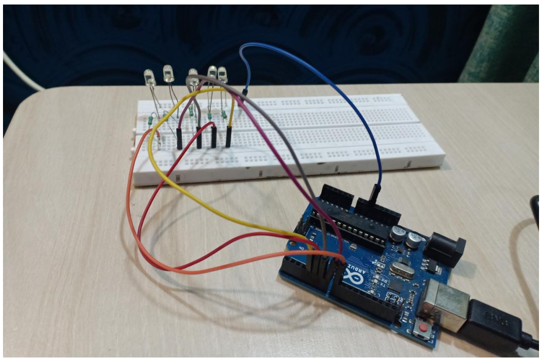


Figure 11: Arduino multiple light control

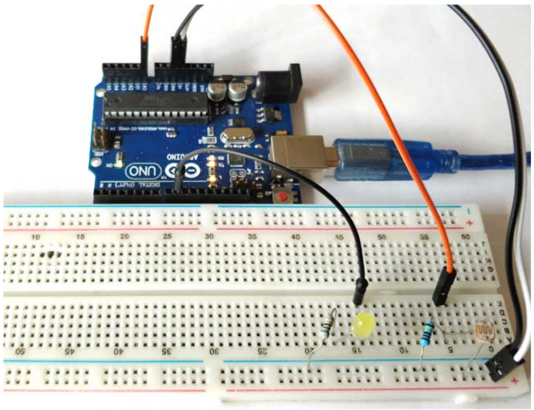


Figure 12: Arduino Light Control

[(https://circuitdigest.com/sites/default/files/projectimage_mic/Arduino-Light-Sensor-Circuit-using-LDR.jpg)](https://circuitdigest.com/sites/default/files/projectimage_mic/Arduino-Light-Sensor-Circuit-using-LDR.jpg)

2.2.3.3 Software Interfaces

Jupyter Notebook: The model is trained using jupyter notebooks running on the cloud i.e. COLAB. The programming language used is Python.

Arduino Uno IDE: The microcontroller Arduino is programmed using its own IDE and the code is written in the programming language C/C++.

2.2.4 Other Non-functional Requirements

2.2.4.1 Performance Requirements

1. Maximum Uptime
2. Better component design to get efficiency at peak time
3. Delivery, Deployment and Timing Requirements.
4. Flexible architecture to ensure backward compatibility

2.2.4.2 Safety Requirements

1. Safety of Subjects from the EEG Headgear

2.2.4.3 Security Requirements

1. Daily automated backup of data to prevent data loss.
2. Privacy of data collected and Physical security of the user.
3. Secure access of confidential data (Users and Recruiters data)
4. Privacy of data collected and Physical security of the user.

2.3 Cost Analysis

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Number of orders	5	5	8	10	15	11	13	8	10	13	15	15
Avg Price per Order	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00	₹ 25,000.00
Income	₹ 125,000.00	₹	₹	₹	₹	₹	₹	₹	₹	₹	₹	₹
Costs												
Software development	₹ 125,000.00	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -	₹ -
Software and server Maintenance	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00	₹ 5,000.00
Packaging and delivery	₹ 15,000.00	₹ 14,000.00	₹ 16,000.00	₹ 13,500.00	₹ 14,000.00	₹ 16,300.00	₹ 15,000.00	₹ 13,000.00	₹ 14,000.00	₹ 13,000.00	₹ 13,400.00	₹ 14,000.00
Marketing	₹ 13,000.00	₹ 11,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00	₹ 12,500.00
Hardware Research &	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00	₹ 10,000.00
Miscellaneous	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00	₹ 1,000.00
Licensing and Patent	₹ 68,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00	₹ 2,000.00
Total Costs	₹ 237,000.00	₹ 43,500.00	₹ 46,500.00	₹ 44,000.00	₹ 44,500.00	₹ 46,800.00	₹ 45,500.00	₹ 43,500.00	₹ 44,500.00	₹ 43,500.00	₹ 43,900.00	₹ 44,500.00
Net Profit/loss	₹ (112,000.00)	₹ 81,500.00	₹ 153,500.00	₹ 206,000.00	₹ 330,500.00	₹ 228,200.00	₹ 279,500.00	₹ 156,500.00	₹ 205,500.00	₹ 281,500.00	₹ 331,100.00	₹ 330,500.00
Income Tax	₹ -	₹ 14,670.00	₹ 27,630.00	₹ 37,080.00	₹ 59,490.00	₹ 41,076.00	₹ 50,310.00	₹ 28,170.00	₹ 36,990.00	₹ 50,670.00	₹ 59,598.00	₹ 59,490.00

Figure 13: Cost Analysis Diagram

2.4 Risk Analysis

1. Although EEG headsets are safe, they must be used in presence of a trained doctor.
2. There might be a chance of noise interference from external sources.

METHODOLOGY ACCEPTED

3.1 Investigative Techniques

Table 7: Investigation Techniques

Investigative Projects Techniques	**Investigative Techniques Description**	**Investigative Projects Examples**
Experimental	EEG is an efficient modality that helps to acquire brain signals corresponding to various states from the scalp surface area. Different emotions were added to the project. Contrasting lights were shown based on it. An IoT based deep learning system that uses the results obtained from the model to change lights based on emotions.	A Sad state of mind can be recognised using signals. Different emotion modalities based on different datasets results in distinct accuracies. Relaxed lighting if someone is in a bad state of mind.

3.2 Proposed Solutions

Using machine learning/deep learning and EEG signals, we propose a new interpretable emotion detection technique with an activation function in this project.

The fluctuation of brain electric potentials caused by the ionic current flow between brain neurons is recorded as an EEG.

We used machine learning/ deep learning methods to abstract features from EEG signals and classified emotions. This detected emotion can be used in several ways to monitor a patient's emotional state.

Our project uses the EEG signals obtained from the patient in different scenarios and tries to predict his/her actual emotions. This can provide an in-depth diagnosis.

After training for the other two emotion categories we will be able to integrate them with microprocessors and other systems like light systems.

3.3 Work Breakdown Structure

1. Project Proposal: -From 8th to 15th January, we discuss different types of research projects to make so that they will be beneficial to society. We as a group have discussed so many ideas and debated on them. After having a debate and long conversation we decided to go for Emotion Recognition using EEG signals.

2. Literature survey and study of Research Papers: -From 15th January to 25th January, we study research papers related to the project. We study all related details regarding our project. We also watch some of the YouTube videos about the project. During this time period, we also find the scope of our project to the society.

3. Designing Model: - From 25th January to 20th February, we design the basic architecture of our project. We designed Use case Diagrams, Activity Diagrams, Gantt Chart, etc.

4. Basic Implementation: - During this phase, we identified and collected required datasets and implemented some of our basic modules. We did coding for a dataset DEAP.

5. End Sem Presentation: - We have to give a presentation on a project in front of the capstone project evaluation team. We have to show them what we do in this regard.

6. Researching to expand the prototype: - In this phase, we have to research the framework to expand it and collect EEG recordings on our own.

7. Major implement: - We have to implement our code on the live dataset and generate a working code. We will also try implementing it on other publicly

available datasets. Other than this we will be implementing lighting scenarios which will change according to the emotions.

8. Testing and Debugging: -In this phase, we will be testing our project and will find the problems in it via feedback. We will test our project on our college students and professors.

9. Project Documentation: -In this section, we have to show the project flow chart and document everything about the project file. It would help people who want to know about our project in an effective and efficient way like function and non-functional requirements, the technology used in a project, various types of graphs, etc.

10. Final Project Presentation: - In last we have to pitch on our project and show the live working of our project in front of the capstone project evaluation team.

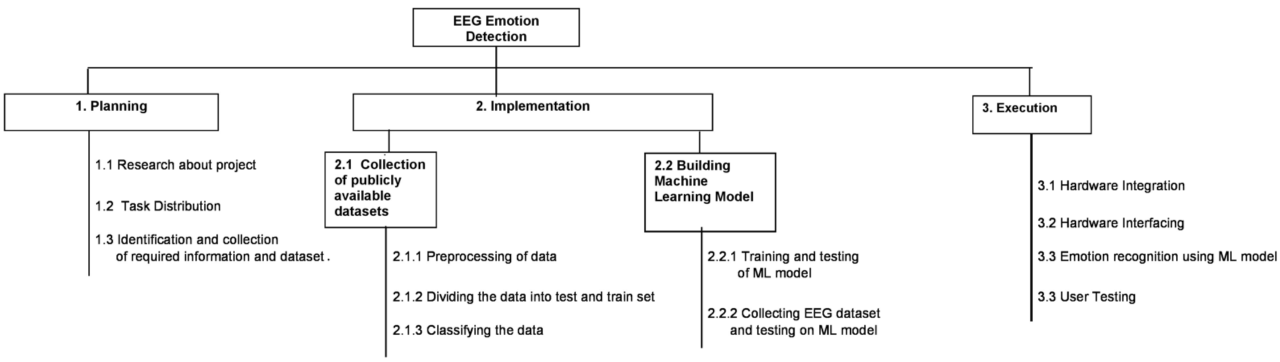


Figure 14: Work Breakdown Structure

3.4 Tools and Technology

UML tools and techniques: MS Visio, NetBeans, Open Office Draw, Star UML, draw.io, lucidchart

Programming languages: Python, HTML, JavaScript

Frameworks & Libraries: Keras, TensorFlow, Pytorch, Scikit-Learn, Matplotlib, NumPy

IDE: MS Visual Studio, Google Colab, Jupyter Notebooks

Versioning Control: Git

Hardware Used:

1. Arduino Board
2. Capacitors, Resistors
3. Voltage Regulators, Speaker
4. LEDs and Connecting Wires

Design Specifications

This section uses design specifications to be used in our Emotion Recognition Using EEG Signals.

4.1 Class Diagram

The logical structure of the project is shown using a class diagram. The following class diagram in Figure 14 is about the functionality of 'eeg headset' which is responsible for EEG data acquisition and real-time EEG visualization.

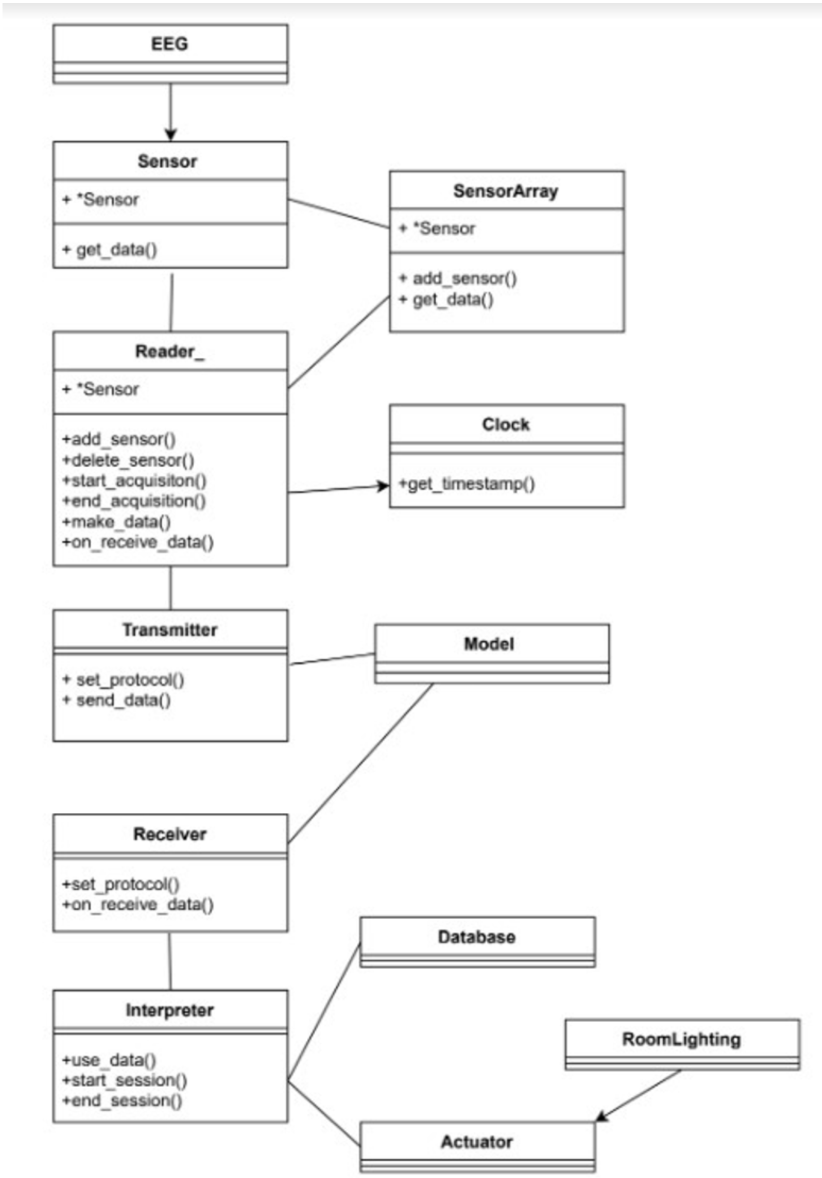


Figure 15: Class Diagram

4.2 Data Flow Diagram

The scope of the project is showcased using a context diagram in the following figures.

DFD Level 0 shows the concise form of the EEG project.

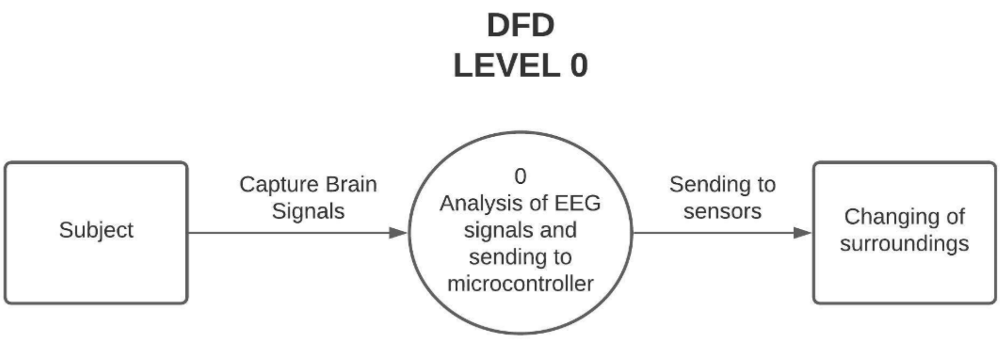


Figure 16: EEG DFD Level 0

DFD Level 1 describes the working flow of the complete project.

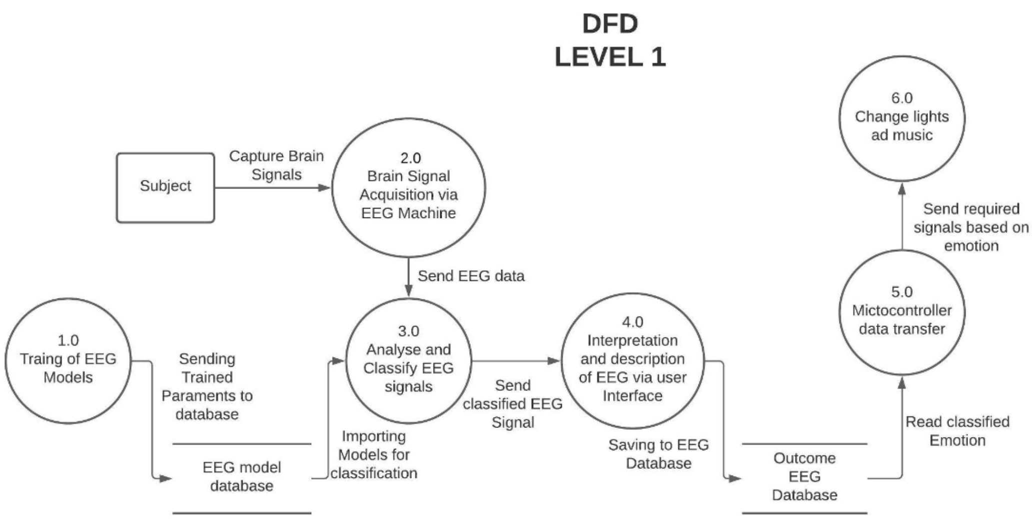


Figure 17: EEG DFD Level 1

DFD Level 2 diagrams describe the conversion of EEG signal to a usable format and machine learning flow respectively.

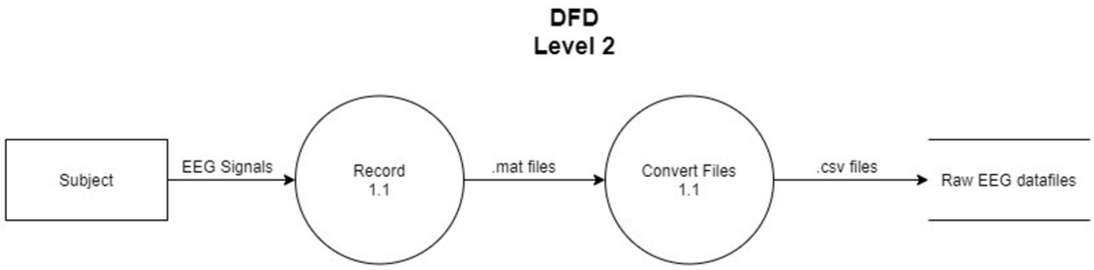


Figure 18: EEG DFD Level 2.1

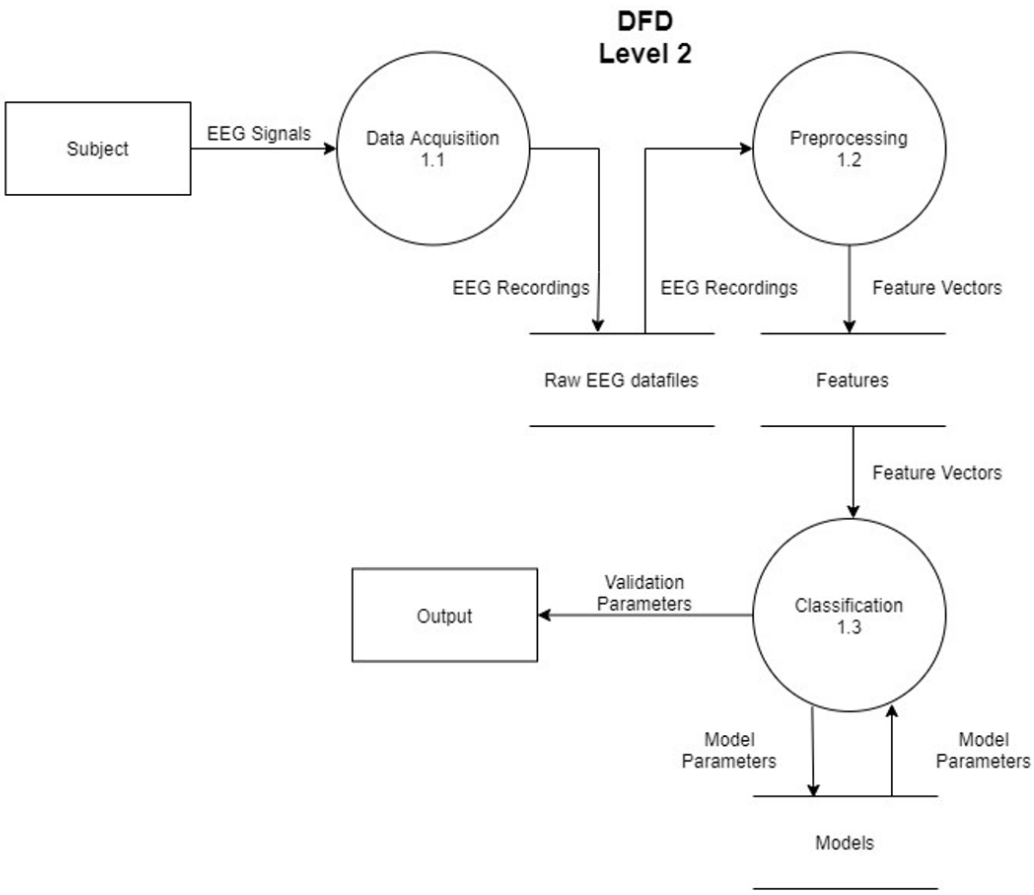


Figure 19: EEG DFD Level 2.2

4.3 Component Diagram

A component diagram describes different components of our diagrams and how they interact with each other.

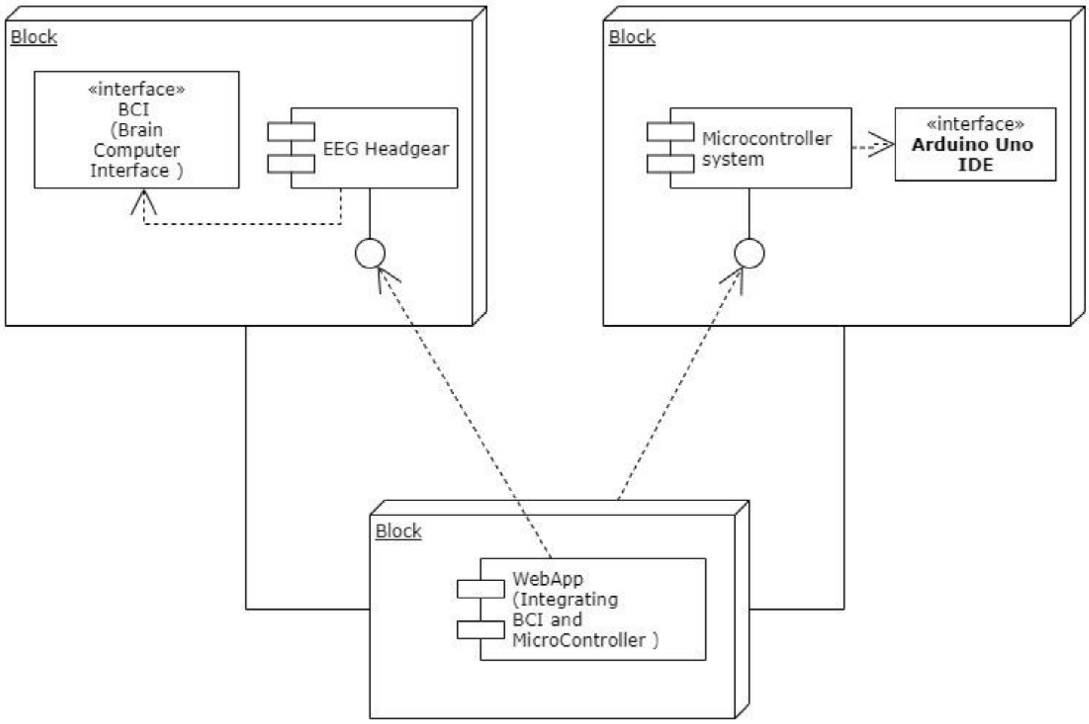


Figure 20: Component Diagram

4.4 MVC Diagram

Model View Controller is used to decouple the user interface (view), data (model), and application logic (controller) of our EEG project.

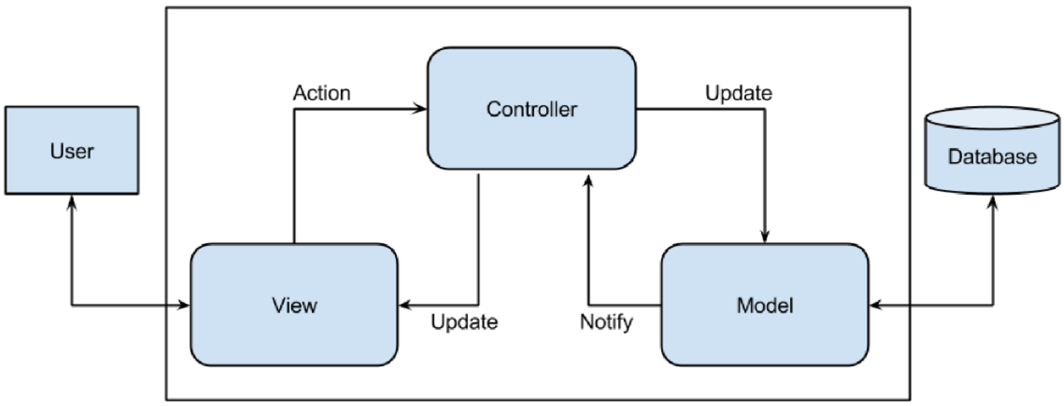


Figure 21: MVC Diagram

4.5 EEG GUI

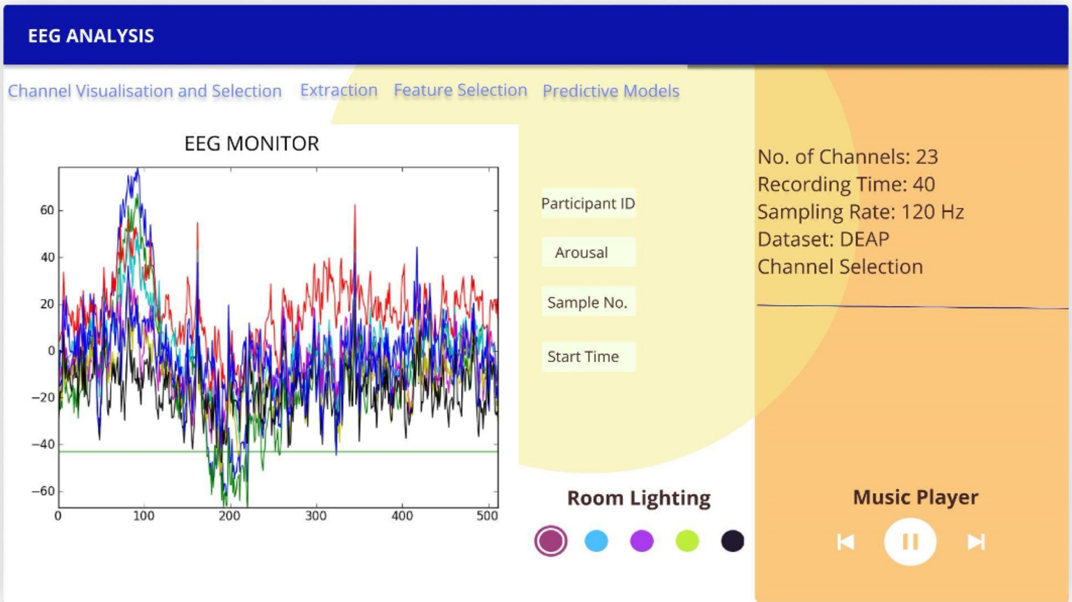


Figure 22: EEG Webapp UI

IMPLEMENTATION AND EXPERIMENTAL RESULTS

5.1 Experimental Setup (or simulation)

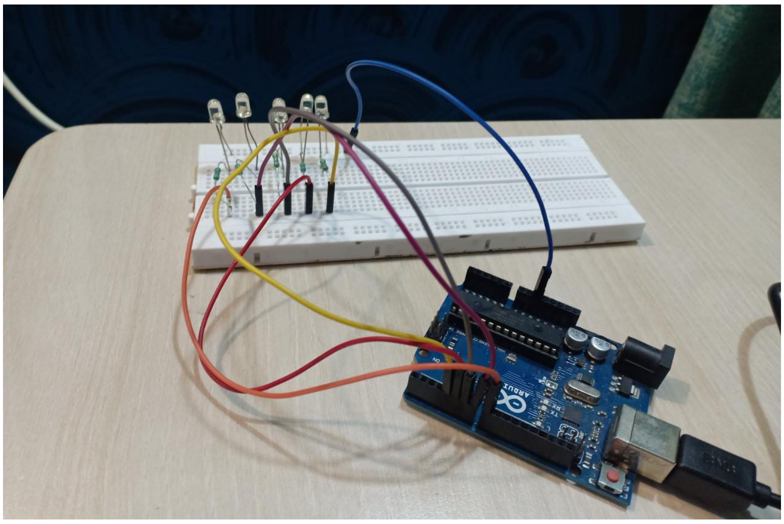


Figure 23: Arduino Setup

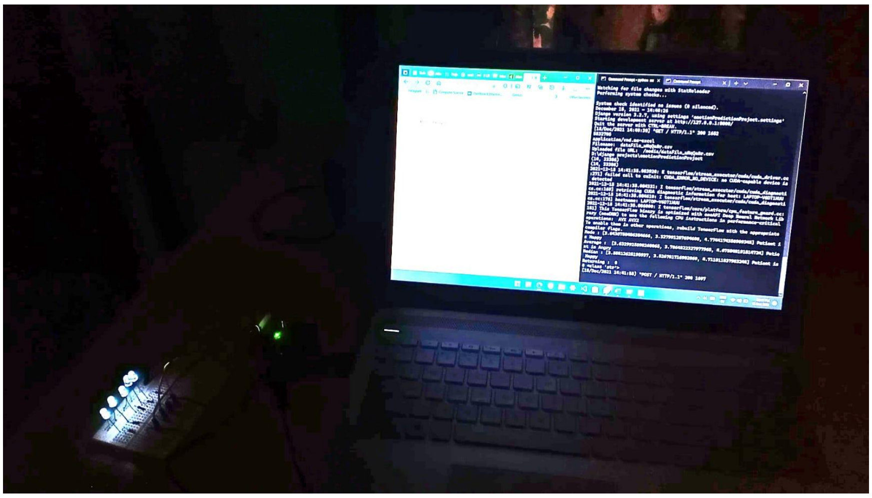


Figure 24: Lighting with website

5.2 Experimental Analysis

5.2.1 Data (Data Sources/Data Cleaning/Data Pruning/ Feature Extraction Workflow)

We have used the DEAP dataset for the emotion training of the model. The data set contains EEG recordings for 32 participants over four emotions which were recorded using 40 videos.

We have used 14 channels of the EEG data. The Emotive Epoch X headgear Contains 14 electrodes which means it collects 14 channel data.

The data collected has been preprocessed using the FIR and FFT filter with techniques. The FIR filter has a lower bandpass of 25 and an upper bandpass of 55. The frequency cutoff is 228. The data is filtered on a window size of 125.

The Processed data is divided into the ratio of 80:20 where 80% data is used for training and 20 % data is used for validation.

Value for each emotion for each EEG recording ranges from 1 - 9. Training for each emotion is done separately. The array of each emotion is converted into a categorical form.

5.2.2 Performance Parameters (Accuracy Type Measures/ QOS Parameters depending upon the type of project

The main parameter was calculating the validation accuracy. Each model was trained for about 50 epochs. A neural network model with multiple layers and fully connected layers was used. For the optimiser, we used the Adam optimiser with a learning rate of 0.01.

5.3 Working of the project

5.3.1 Procedural Workflow

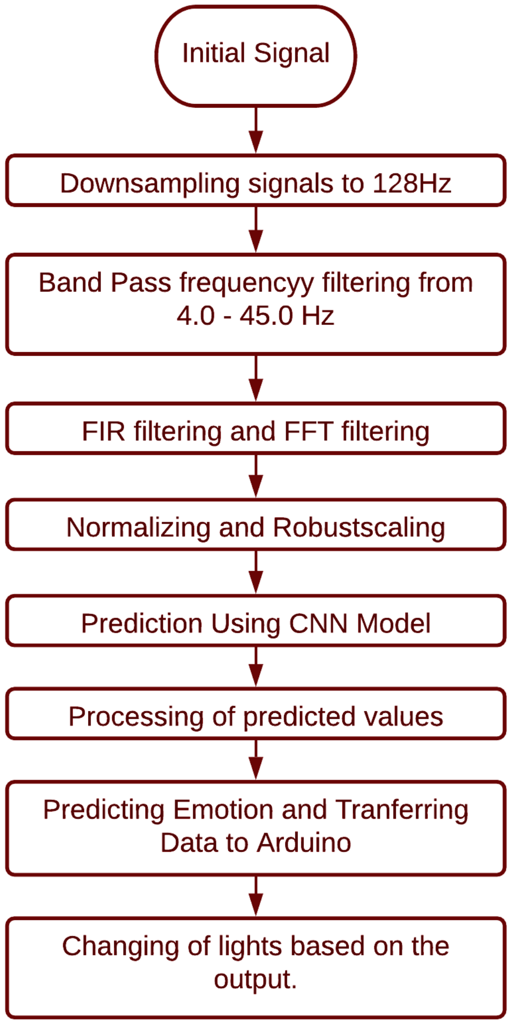


Figure 25: Procedural workflow

The process starts with a CSV file as an input to our website. The file contains EEG data collected from the user. The file should be in a specific format. It should have the column names as the EEG Channels and should have in total 14 channels as the model was trained on Emotive EpochX. This headset only has 14 electrode channel access.

The input data is then preprocessed. We first preprocess the data by applying a bandpass filter of 4-45 Hz and resampling it to a frequency of 128 Hz. Then the FIR and FFT filters are applied at multiple windows.

These combined data of multiple windows are then normalised and scaled using RobustScaler.

The Deep Learning models are loaded and used for prediction. The predicted values are converted into a 4 value of Valence, Domain, Arousal & Linking by taking the average. The emotion is predicted by calculating the distance of the predicted values to actual average values of the 4 categories for different emotions. The minimum distance emotion is the output.

The output is sent to the Arduino which based on the emotion makes specific patterns with lights.

5.3.2 Algorithmic Approaches Used

Pre Processing :

For Pre Processing of the data, we applied FIR and FFT filtering. The FIR filtering was applied on the frequency of 5 to 50 Hz. The Processing was applied on windows size of 255.

```
channel = [1, 2 , 3, 4, 7, 11, 13, 17, 19, 20,21, 25,
29, 31 ] band =
[32,33,34,35,36,37,38,39,40,41,42,43,44,46,48,50]
window_size = 255 #Averaging band power of 2 sec
step_size = 16 #Each 0.125 sec update once
sample_rate = 128 #Sampling rate of 128 Hz
subjectList = ['01', '02', '03', '04', '05', '06',
'07','08','09',] + [str(x) for x in range(10, 33)]
def butter_bandpass(lowcut, highcut, fs, order=5):
    nyq = 0.5 * fs
    low = lowcut / nyq
    high = highcut / nyq
    b, a = sg.butter(order, [low, high],
btype='band')
```

```
    return b, a

def butter_bandpass_2(lowcut, highcut, fs, order=5):
        nyq = 0.5 * fs
        low = lowcut / nyq
        high = highcut / nyq
        sos = butter(order, [low, high],
analog=False, btype='band', output='sos')
        return sos

def butter_bandpass_filter(data, lowcut, highcut, fs,
order=5):
        sos = butter_bandpass_2(lowcut, highcut, fs,
order=order)
        y = sg.sosfilt(sos, data)
        return y

def FFT_Processing (x, band, window_size, step_size,
sample_rate):
  meta = []
  data = []

  for i in range(14):
    data.append(butter_bandpass_filter(x[i], 4, 45,
128))
  data = np.array(data)

  start = 0;
  fs = 128
  lowcut = 25.0
  highcut = 45.0
  b, a = butter_bandpass(lowcut, highcut, fs,
order=3)

  while start + window_size < data.shape[1]:
    meta_array = []
    meta_data = [] #meta vector for analysis
    for j in range(14):
        X = data[j][start : start + window_size]
```

```
        Y_fir = sg.lfilter(b, a, X)
        Y = pe.bin_power(Y_fir, band, sample_rate)
        meta_data = meta_data + list(Y[0])
    meta_array.append(np.array(meta_data))
    meta.append(np.array(meta_array))
    start = start + step_size

  meta = np.array(meta)
  return meta
```

The output of the preprocessed array is normalized and scaled using Robust Scaler.

```
# Normalizing the data
X = normalize(X)

# Converting the data into a numpy array
x_test = np.array(X[:])

#  Scaling the data using RobustScaler
scaler = RobustScaler()
x_test = scaler.fit_transform(x_test)

# Reshaping the data
x_test       =       x_test.reshape(x_test.shape[0],
x_test.shape[1], 1)
```

Neural Network :

Initially, LSTM was used for making the neural network. It was giving a validation accuracy of about 65%. for each emotion.

Later CNN neural network was used. The model consisted of layers with filter sizes of **64, 128, 256, 512, 1024**. Activation function "**PReLU**" is used. Fully Connected layer comprises Dense and Dropout Layers.

Multiple Callbacks are also used to improve the performance of the model. For example The ReduceLROnPlateau helps in reducing the learning rate on successive failures in reduction of validation loss.

```python
from keras.layers import Dense, Dropout, Conv1D,
MaxPool1D, Flatten, LeakyReLU, PReLU
from keras.callbacks import ReduceLROnPlateau,
ModelCheckpoint, LearningRateScheduler,EarlyStopping

reduce_lr = ReduceLROnPlateau(monitor='val_loss',
patience=3,verbose=1, min_delta=0.000, min_lr=0.000)
earlystopping = EarlyStopping(monitor='val_loss',
min_delta=0, patience=4, verbose=1)

modelCheckpoint =
ModelCheckpoint("/content/drive/MyDrive/Deap
Dataset/emotiv/fft_fir_cnn_80_20_model_liking.h5",
    monitor="val_loss",
    verbose=1,
    save_best_only=True,
    mode="auto",
    save_freq="epoch",
)

# building a linear stack of layers with the
sequential model
model = Sequential()

# convolutional layer
model.add(Conv1D(64, kernel_size=3, strides=1,
padding='same', activation=PReLU(),
input_shape=input_shape))
model.add(MaxPool1D(pool_size=2))
model.add(Dropout(0.1))

# convolutional layer
model.add(Conv1D(128, kernel_size=3, strides=1,
padding='same', activation=PReLU()))
model.add(MaxPool1D(pool_size=2))
model.add(Dropout(0.1))
```

```
model.add(Conv1D(256, kernel_size=3, strides=1,
padding='same', activation=PReLU()))
model.add(MaxPool1D(pool_size=2))
model.add(Dropout(0.1))

model.add(Conv1D(512, kernel_size=3, strides=1,
padding='same', activation=PReLU()))
model.add(MaxPool1D(pool_size=2))
model.add(Dropout(0.1))

model.add(Conv1D(1024, kernel_size=3, strides=1,
padding='same', activation=PReLU()))
model.add(MaxPool1D(pool_size=2))
model.add(Dropout(0.1))

# flatten output of conv
model.add(Flatten())

# hidden layer
model.add(Dense(1024, activation=PReLU()))
model.add(Dropout(0.1))
model.add(Dense(526, activation=PReLU()))
model.add(Dropout(0.1))
model.add(Dense(325, activation=PReLU()))
model.add(Dropout(0.1))
model.add(Dense(50, activation=PReLU()))
model.add(Dropout(0.5))
# output layer
model.add(Dense(num_classes, activation='softmax'))

model.compile(optimizer ="adam",
loss=keras.losses.categorical_crossentropy,metrics=["
accuracy"])
model.summary()
print(epochs, batch_size)
m=model.fit(x_train,
y_train,epochs=epochs,batch_size=batch_size,verbose=1
,validation_data=(x_test, y_test),
callbacks=[reduce_lr,earlystopping,modelCheckpoint])
```

The data is sent to Arduino using the PySerial Library. The Arduino on reading input from the serial input makes patterns based on the predicted input. There are 2 different patterns for 3 different emotions.

```
int x;
int t = 40;
int rnd = 5;
int des1t = 75;

void setup()
{
  Serial.begin(115200);
  Serial.setTimeout(1);
  for (int i = 3; i <= 8; i++)
    pinMode(i, OUTPUT);
}

void loop() {

  while (!Serial.available());
  x = Serial.readString().toInt();

  if (x == 0) // User is angry
  {
    for (int i = 0; i <= rnd; i++) {
      des4();
    }
  }
  else if (x == 1) // User is happy
  {
    for (int i = 0; i <= rnd; i++) {
      des8();
    }
  }
  else if (x == 2) // User is sad
  {
    for (int i = 0; i <= rnd; i++) {
      des2();
    }
```

```
  }
}



void des2() {
  for (int i = 3; i <= 8; i++) {
    digitalWrite(i, HIGH);
    digitalWrite(i - 1, HIGH);
    digitalWrite(i + 1, HIGH);
    delay(100);
    digitalWrite(i, LOW);
    digitalWrite(i - 1, LOW);
    digitalWrite(i + 1, LOW);
  }

  for (int i = 7; i >= 4; i--) {
    digitalWrite(i, HIGH);
    digitalWrite(i - 1, HIGH);
    digitalWrite(i + 1, HIGH);
    delay(100);
    digitalWrite(i, LOW);
    digitalWrite(i - 1, LOW);
    digitalWrite(i + 1, LOW);
  }
}

void des4() {
  for (int i = 3; i <= 8; i++) {
    digitalWrite(i, HIGH);
    delay(100);
  }

  for (int i = 12; i >= 2; i--) {
    digitalWrite(i, HIGH);
    delay(100);
    digitalWrite(i, LOW);
  }
}
```

```
void des8() {
  digitalWrite(7, HIGH);
  digitalWrite(8, HIGH);
  delay(t);
  digitalWrite(7, LOW);
  digitalWrite(8, LOW);
  delay(t);
  digitalWrite(6, HIGH);
  digitalWrite(9, HIGH);
  delay(t);
  digitalWrite(6, LOW);
  digitalWrite(9, LOW);
  delay(t);
  digitalWrite(5, HIGH);
  digitalWrite(10, HIGH);
  delay(t);
  digitalWrite(5, LOW);
  digitalWrite(10, LOW);
  delay(t);
  digitalWrite(4, HIGH);
  digitalWrite(11, HIGH);
  delay(t);
  digitalWrite(4, LOW);
  digitalWrite(11, LOW);
  delay(t);
  digitalWrite(3, HIGH);
  digitalWrite(12, HIGH);
  delay(t);
  digitalWrite(3, LOW);
  digitalWrite(12, LOW);
  delay(t);
  digitalWrite(4, HIGH);
  digitalWrite(11, HIGH);
  delay(t);
  digitalWrite(4, LOW);
  digitalWrite(11, LOW);
  delay(t);
  digitalWrite(5, HIGH);
  digitalWrite(10, HIGH);
```

```
  delay(t);
  digitalWrite(5, LOW);
  digitalWrite(10, LOW);
  delay(t);
  digitalWrite(6, HIGH);
  digitalWrite(9, HIGH);
  delay(t);
  digitalWrite(6, LOW);
  digitalWrite(9, LOW);
  delay(t);
}
```

5.3.3 Project Deployment (Can be explained using Component and Deployment Diagrams)

Component Diagram :

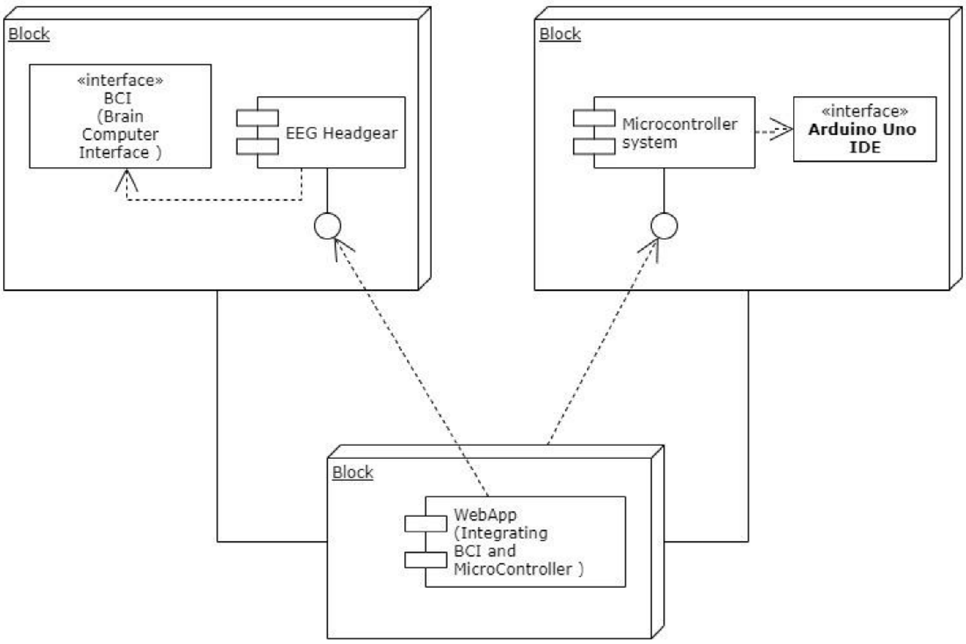


Figure 26: Component Diagram

Deployment Diagram

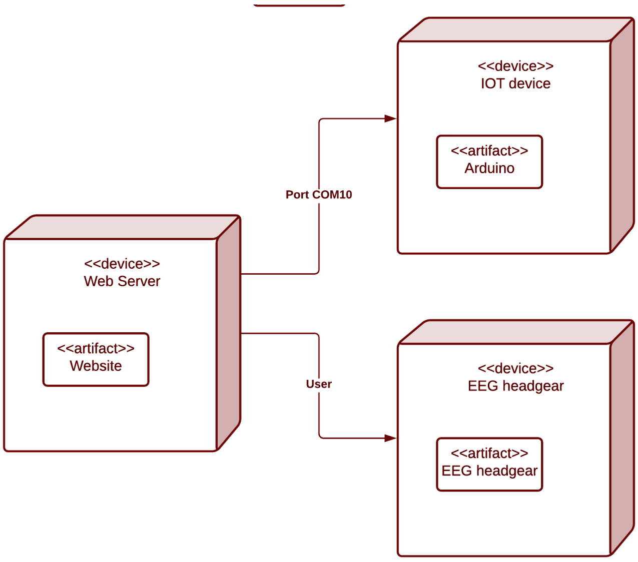


Figure 27: Deployment Diagram

5.3.4 System Screenshots

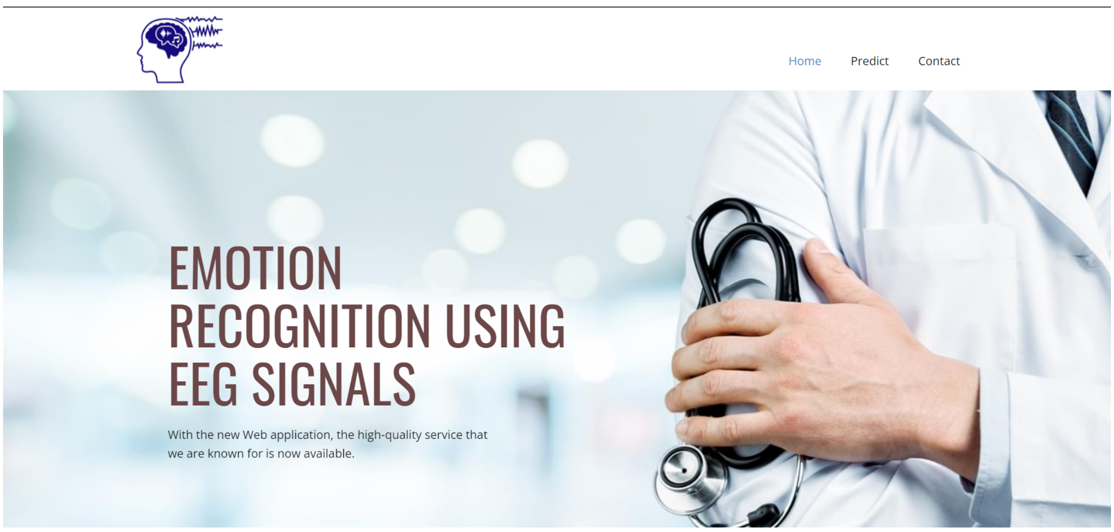


Figure 28: Website GUI

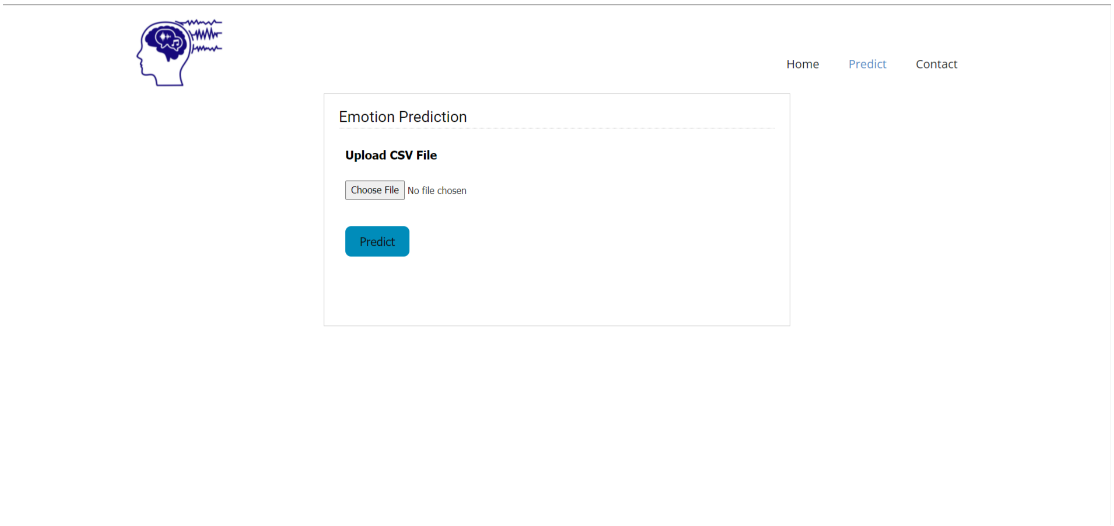


Figure 29: EEG signal upload page

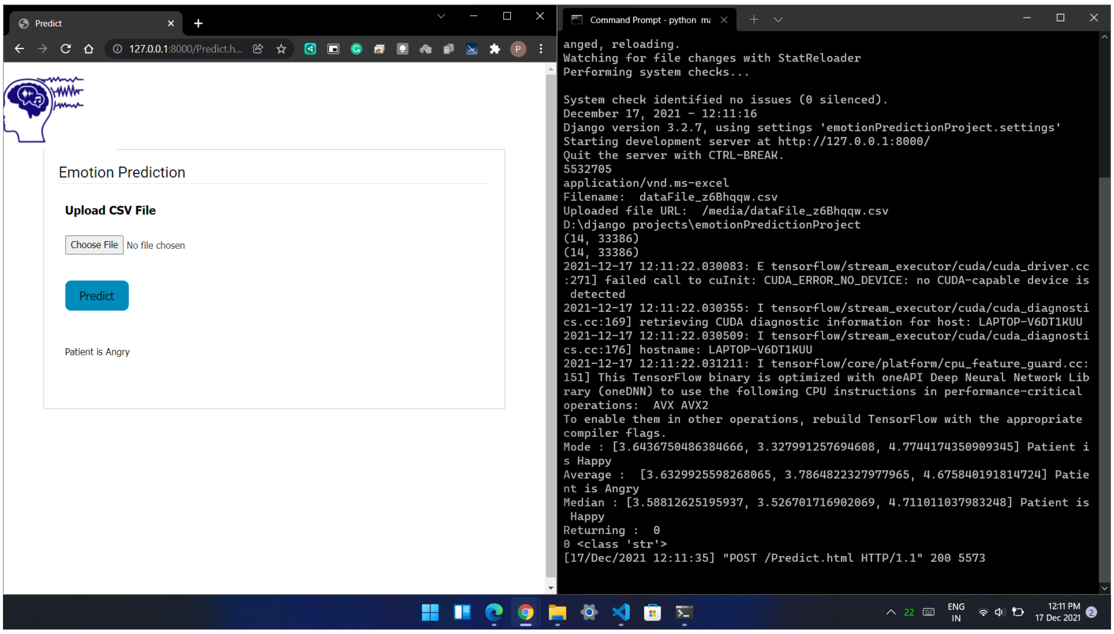


Figure 30: Website setup with Django backend

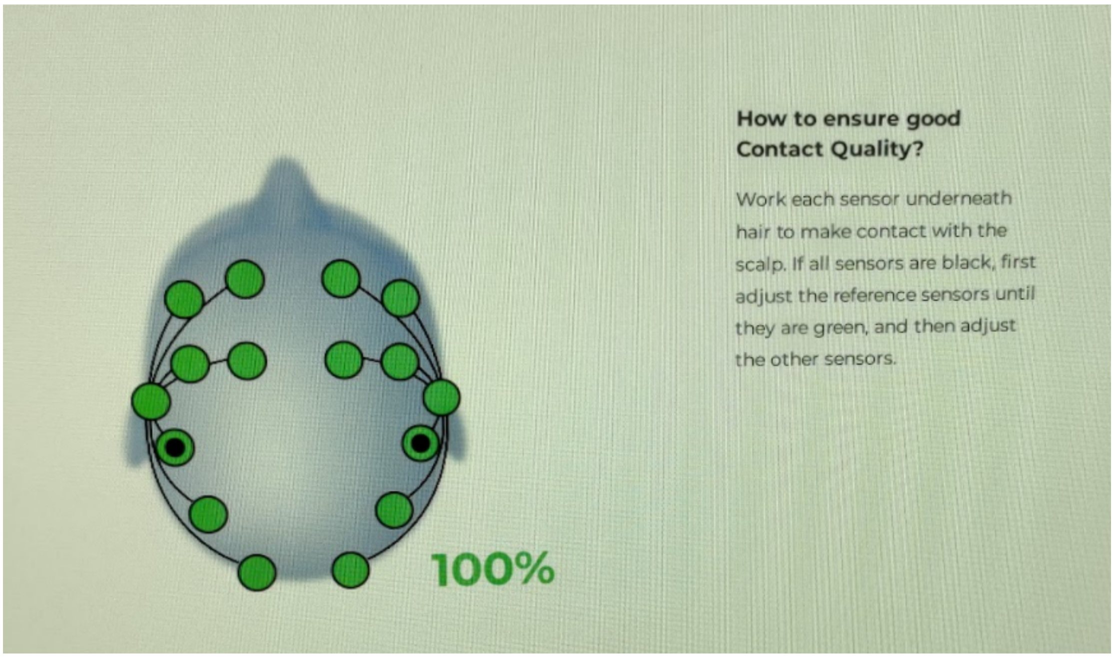


Figure 31: Setting up of Emotive EPOCH X headgear

Collecting data for testing of the project

5.4 Testing Process

5.4.1 Test Plan

Table 8: Test Plan

Test Case ID	Test Case Objectives	Pre Requisites	Steps	Input Data	Expected Output	Actual Output	Status
TC_1	The website is tested for accepting only CSV files.	The website is up and running on the localhost with a Django backend integrated with the DL model	1. Different formats of input files are added in the targeted folder. 2. Make them one of our input files	Input files with extensions of jpg, png, Xls, CSV.	The website accepts jpg or png files where CSV was expected	The website only gives access to CSV format files.	PASS
TC_2	Test the preprocessing of EEG Signals input	The website is up and running on the localhost with a Django backend integrated	1. Input an EEG signal file to the website. 2. Press the predict button 3. Check	A CSV input signal file with an appropriate format.	The preprocessing function fails to check for the given format.	The preprocessing function checks for the column headers and if	PASS

		with the DL model	the output of the website.			an incompatible file is found it returns an error	
TC_3	Test the Arduino connected to the website	The website is up and running on the localhost with a Django backend integrated with a DL model connected to the Arduino setup	1. Input an EEG file to the website. 2. Press the predict button. 3. Check the Arduino for the output on the lights connected and the pattern made.	Multiple outputs using multiple input signals.	The Arduino does not accept the output over localhost and does not send it to the lights connected.	The Arduino correctly accepts the output over localhost and sends it to the lights connected.	PASS

5.4.2 Features to be tested

1. Web GUI
2. Preprocessing of EEG Signals input.
3. Arduino connection to the website

5.4.3 Test Strategy

1. Web GUI: The website is tested for accepting only CSV files.
2. Preprocessing of EEG Signals: The Signal input to the website is tested if it is in the correct format with column headers as the 14 EEG channels required
3. Arduino Connection: The Arduino is tested for correct connection and output to the circuit connected.

5.4.4 Test Techniques

1. We tested the GUI by keeping different formats of files in the targeted folder and trying to make them one of our input files. If the website accepts the wrong file format it fails the test
2. We tested the backend by providing input files with different channels other than required.
3. We tested if Arduino is working for the given file and is giving the output as required by changing lights.

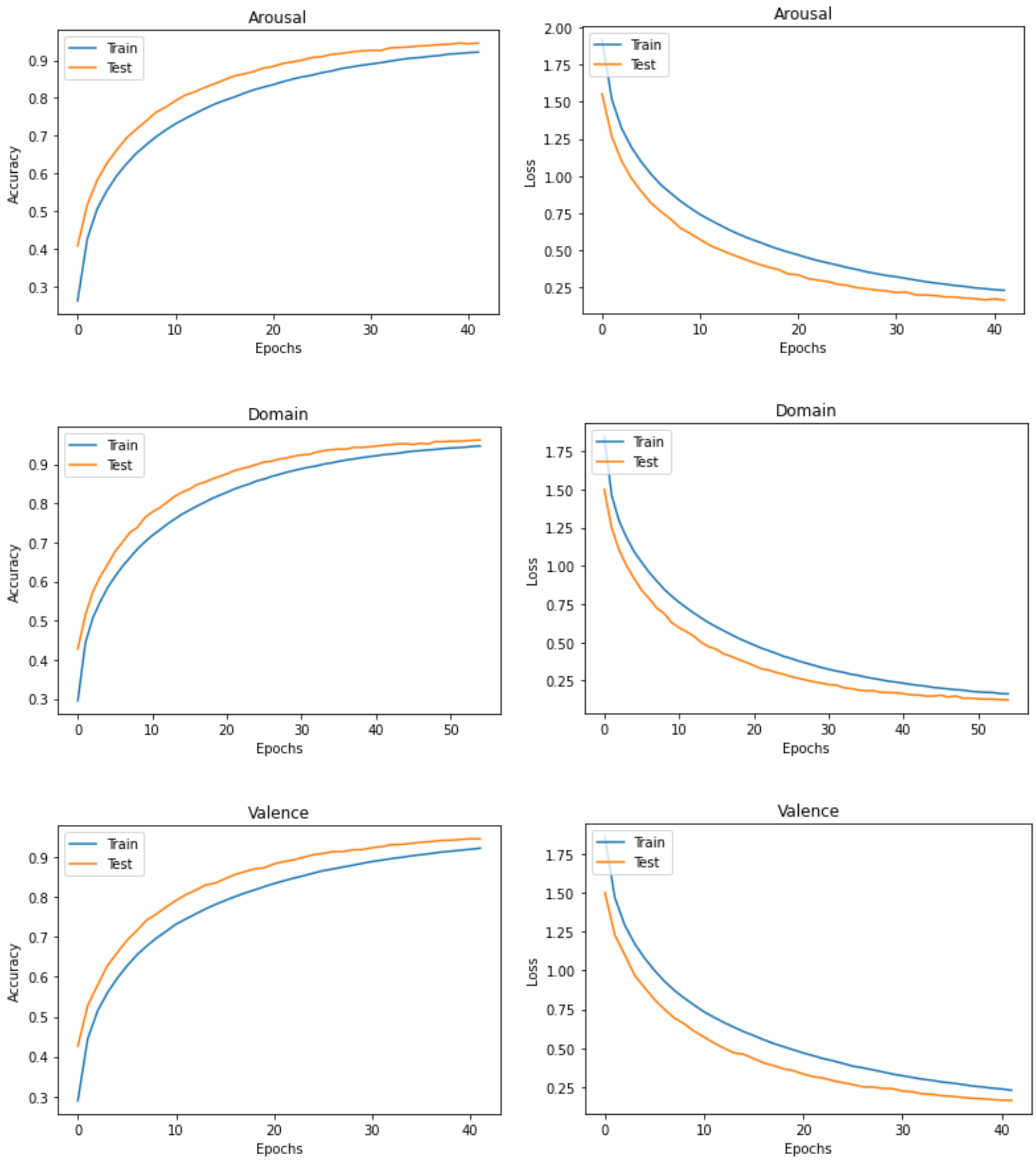
5.4.5 Test Cases

1. We tested the website user interface
2. We tested the preprocessing
3. We tested the working and connection of the Arduino to the website.

5.4.6 Test Results

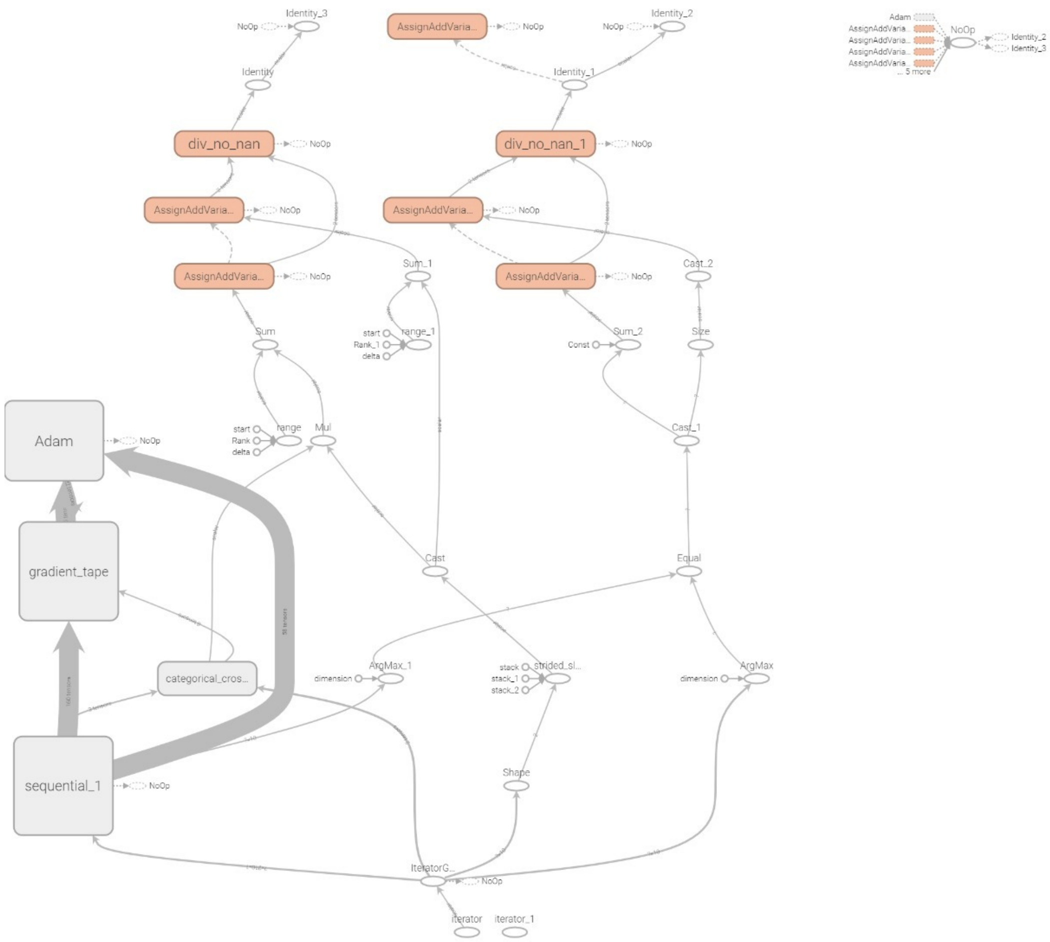
1. The website only allowed CSV files as input tag in the HTML file consisted of the allowed formats as ".csv" only
2. The preprocessing function checks for the column headers and if an incompatible file is found it returns an error.
3. The Arduino correctly accepts the output over localhost and sends it to the lights connected.

5.5 Results and Discussions (Visualization of results using graph plots and Comparison with related state of the artwork)



Emotions	Accuracy

Arousal	97.37
Domain	96.76
Liking	97.90
Valence	98.01



5.6 Inferences Drawn

The inferences drawn from the test results and by evaluating the performance parameters are:

1. The accuracy of the model increases with more no of subjects used for training.
2. The project is able to determine the value of valence, domain, arousal and liking for the given signals.
3. The greater the number of channels employed, the greater the model's

accuracy.

5.7 Validation of Objectives

Table 9: Validation of Objective

S. No.	Objective	Status
1	To study existing tools and techniques available for EEG measurement	Successful
2.	To design and develop a machine/deep learning module for the classification of moods from EEG data	Successful
3.	The aim is to capture the emotion expressed by a person through EEG data that is generated.	Successful
4.	To design an IoT system for lighting systems based on perceived emotions.	Successful
5.	To implement all modules as an integrated system.	Successful

CONCLUSIONS AND FUTURE SCOPE

6.1 Work Accomplish

Models have been generated for emotions like Arousal and Valence based on the Deap Dataset. We were able to achieve about **94% accuracy** for the emotion category **Liking** and also around **96% accuracy** for the **Arousal** category.

6.2 Conclusions

To conclude emotion and its recognition follows varied research and methodologies. Different approaches have been adopted by researchers categorizing emotions and their subparts.

The physiological and behavioural condition of being awake or reactive to stimuli, ranging from passive to aggressive, is arousal. The fluctuation of brain electric potentials caused by the ionic current flow between brain neurons is recorded as an EEG. Our project uses the EEG signals obtained from the patient in different scenarios and tries to predict his/her actual emotions. This can provide an in-depth diagnosis.

Using machine learning/ deep learning and EEG signals, we propose a new interpretable emotion detection technique with an activation function in this project. We used machine learning/ deep learning methods to abstract features from EEG signals and classified emotions. This detected emotion can be used in several ways to monitor a patient's emotional state. In the project, various high-level machine learning algorithms are implemented and integrated and the output is generated from the same making a user-visible with the outputs in the form of a graph which makes it easier for them to see and interpret their emotions.

The proposed software takes the raw set of data from the dataset and processes it. The cleaning and cleansing of data are done and then further processed to gain effective outcomes. After the computational means, the output is displayed on the screen in the form of a graph

6.3 Environmental Benefits

Emotions are a physiological state of mind. These are reactions to our internal stimuli or any physical experience. Emotions play essential roles in decision making. It is possible to hurt oneself by not being conscious of one's feelings or suppressing negative emotions. It's possible that we won't be able to access the crucial knowledge that feelings offer. Emotions have communicative signal value, they help solve social problems by evoking responses from others, signalling the nature of interpersonal relationships, and by providing incentives for desired social behaviour.

EEG is an integral part of the emotion detection and recognition system as it enables the identification of emotions or responses from brain functions and generates real-time results.

With our ML models and data collection, the result derived will help us to use our findings on users with the guarantee of proficient emotion detection.

It can be used to test the opposite person's intentions or behaviour. Additional functionalities can be added to the project, like changing the ambience of the room by turning on/off the lights, or it can also be used in Lie-Detection or can be used by Psychiatrists in their therapy sessions.

6.4 Future Work Plan

After training for the other two emotion categories we will be able to integrate them with microprocessors and other systems like light systems.

In future research, we plan to vary and select a suitable set of positions specifically for each emotional state.

The accuracy and the number of emotions are still small for real applications. Our model clearly needs to be improved. This is a purpose for future research.

Furthermore, the process of representing EEG data in a similar manner to that of an image, and consequently using the representation as images to feed our Convolutional Neural Model, exploiting the accuracy of CNN's on image classification to our advantage is a compelling technique for future research on this topic.

In the future, we will combine attention and meditation as emotion stress detection with other activities.

PROJECT METRICS

7.1 Challenges Faced

1. To learn different algorithms for improving the quality of signals.
2. Placement of electrodes in the best possible way to take the accurate EEG signals.
3. The signal transmitting quality of the headset should be very accurate.
4. Limited no of electrodes on the available headset. The greater the number of electrodes, the greater the model's accuracy.

7.2 Relevant Subjects

AI Applications - NLP, COMPUTER VISION, IOT(UCS655) is mainly used in this project. We learnt about various signal processing techniques such as signal enhancement, filter techniques and the algorithm to detect the emotion using EEG signals.

Software Engineering(UCS503) helped to analyze the needs and requirements to design, deploy and test new software.

Numerical Analysis (UMA007) was also very useful as we learnt about various MATLAB techniques to preprocess the signals.

7.3 Interdisciplinary Knowledge Sharing

1. Computer Science- The knowledge of this academic discipline has been used for understanding and deployment of the deep learning code.
2. Mathematics – The understanding of matrix representation and operations to perform on EEG signals during deep learning process.
3. Electronic – The knowledge of electronic devices and connections regarding their usage done for integrating, especially the coding of Arduino Uno board.

7.4 Peer Assessment Matrix

Table 10: Peer Assessment Matrix

		Evaluation of				
		S1	S2	S3	S4	S5
Evaluation by	S1					
	S2					
	S3					
	S4					
	S5					

S1- Vishesh Gupta

S2- Prakhar Jindal

S3- Divyam Jain

S4- Abhiraam Khanna

S5- Navia Sehgal

7.5 Role Playing and Work Schedule

1. Vishesh Gupta - Data set Collection and Documentation
2. Prakhar Jindal - Machine Learning model Designing
3. Divyam Jain - Machine Learning model and Data set Collection
4. Abhiraam Khanna - Hardware Integration and Documentation
5. Navia Sehgal - Hardware Integration and Documentation

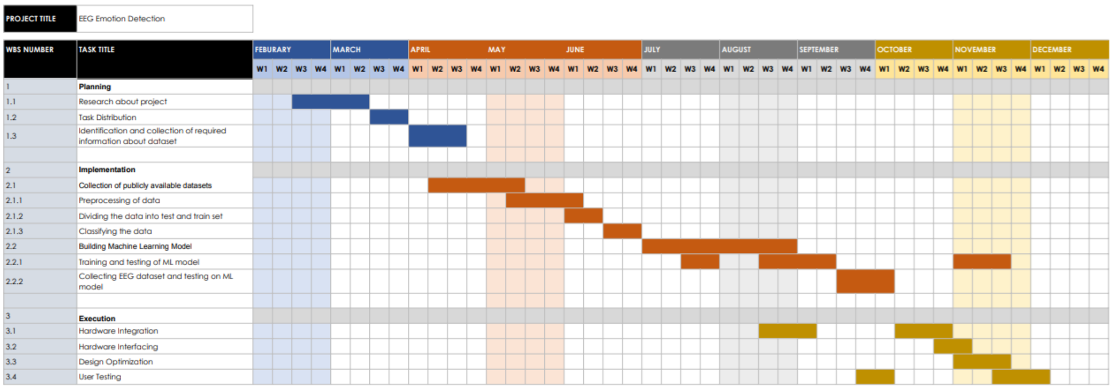


Figure 31: Work Schedule Diagram

7.6 Student Outcomes Description and Performance Indicators (A-K Mapping)

Table No. SO1-SO7 Mapping for the course 'UCS794- Capstone Project'

SO	SO Description	Outcome
1.1	Ability to identify and formulate problems related to the computational domain.	Researching different models and finding out the appropriate model for implementing our project.
1.2	Apply engineering, science, and mathematics body of knowledge to obtain analytical, numerical, and statistical solutions to solve engineering problems.	Used mathematical concepts like fir filter for smoothening process in signals. These concepts were also used to interpret and analyze the results.
2.1	Design computing system(s) to address needs in different problem domains and build prototypes, simulations, proof of concepts, wherever necessary, that meet design and implementation specifications.	We built efficient CNN architecture which is able to classify emotions and created a web portal using IOT technologies.
2.2	Ability to analyze the economic trade-offs in computing systems.	Developing the project with keeping the societal implementation and cost-effective mechanisms.

3.1	Prepare and present a variety of documents such as project or laboratory reports according to computing standards and protocols.	All of us prepared and presented the report according to the computing standards.
3.3	Able to communicate effectively with peers in a well organized and logical manner using adequate technical knowledge to solve computational domain problems and issues.	The team was regularly in touch with each other updating their peers about the progress and in working with one another. We tried our best to keep the work product up to the mark and present it well to the desired mentor or panel.
4.1	Aware of ethical and professional responsibilities while designing and implementing computing solutions and innovations.	This project will be able to understand emotions more precisely and be an aid as well as a learning tool for many. Apart from taking the responsibility as a team and interacting with others with the scope of implementation of our project in future.
4.3	Evaluate computational engineering solutions considering environmental, societal, and economic contexts.	By understanding the implications, we are building an easy to use economic product that does not require any extra work on the users end.
5.1	Participate in the development and selection of ideas to meet established objectives and goals.	Members were able to jump from one responsibility to another and also helped each other whenever it was needed.
5.2	Able to plan, share and execute task responsibilities to function effectively by creating a collaborative and inclusive environment in a team.	The work and roles were systematically divided among all five members to make use of their knowledge and skills effectively in a collaborative manner.
6.1	Ability to perform experimentations and further analyze the obtained results.	We performed various experiments by changing parameters in the model and analyzed based on the results obtained

		to get the best accuracy.
6.2	Ability to analyze and interpret data, make necessary judgement(s) and draw conclusion(s).	The members were able to express data using graphs and diagrams, make necessary judgement based on that and effectively present to the audience i.e. mentors.
7.1	Able to explore and utilize resources to enhance self-learning.	We studied various research papers, articles and blogs that helped us build this project.

7.7 Brief Analytical Assessment

Q1. What sources of information did your team explore to arrive at the list of possible Project Problems?

Ans: The group was aware of the project's requirements as well as the issues that needed to be addressed. We looked into the needed literature, which included several research articles published in various journals and magazines. After discussing with our mentor, we settled on the scope.

Q2. What analytical, computational and/or experimental methods did your project team use to obtain solutions to the problems in the project?

Ans: The first task was to work with an emotion recognition model that fits best based on our needs. We needed to find a dataset and retrain our model accordingly. Then we had to build a UI that would be user friendly and incorporate the electronics involved for the required output delivery.

Q3. Did the project demand demonstration of knowledge of fundamentals, scientific and/or engineering principles? If yes, how did you apply?

Ans: In this project, we used the principles of Deep Learning and Electronics.

We used application dev and software dev to create the UI and integrate the detection model with other features. Design, architecture and documentation principles were covered with the knowledge gained from the course of software engineering.

Q4. How did your team share responsibility and communicate the information of schedule with others in the team to coordinate design and manufacturing dependencies?

Ans: We're a three-person team, and we've been in constant contact throughout this process. We divided the project into sub-parts based on the requirements, with each individual in charge of one component and assisting one another. WhatsApp groups and Zoom calls were used to maintain effective communication.

Q5. What resources did you use to learn new materials not taught in class for the course of the project?

Ans: To learn new things, the group employed a variety of resources. The research papers we read to discover new strategies and comprehend how the model worked provided a large reservoir of information. For particular questions and lessons regarding subjects that weren't covered in class, we used YouTube and search engines like Google. We looked over the official documentation for Arduino, Tensorflow, and the other tools and approaches we utilised.

Q6. Does the project make you appreciate the need to solve problems in real life using engineering and could the project development make you proficient with software development tools and environments?

Ans: The project tackles a real-world issue and aims to help individuals understand emotions in a better way. Working on this project has helped us realise how important it is to tackle real-world problems, and it has inspired the team to take on new challenges in a variety of sectors.

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