CHAPTER 1

INTRODUCTION

1.1 Overview

1.1.1The Prevalence of Mental Stress:

The youth of today face a unique set of challenges that contribute significantly to the rise in mental stress. Academic demands, competitive environments, social media scrutiny, and economic uncertainties collectively create a breeding ground for stressors. The constant pursuit of perfection, fueled by societal expectations and the fear of falling behind, has led to a surge in anxiety and depression among the youth.

1.1.2 Consequences of Mental Stress:

The consequences of mental stress among the youth are far-reaching and multifaceted. Physically, stress can manifest in ailments such as headaches, insomnia, and compromised immune function. Emotionally, it contributes to the development of anxiety disorders and depression, hindering one's ability to form healthy relationships and navigate the complexities of life. Moreover, the academic and professional aspirations of the youth often come at the cost of neglecting their mental well-being, leading to burnout and a diminished quality of life.

1.1.3 Importance of Prioritizing Mental Health:

Recognizing the importance of mental health is not merely a choice but a necessity for the overall well-being of the youth. A mentally healthy population is better equipped to face life's challenges, build resilience, and contribute positively to society. Prioritizing mental health promotes a culture of empathy, understanding, and support, fostering an environment in which individuals feel safe to seek help without fear of judgment.

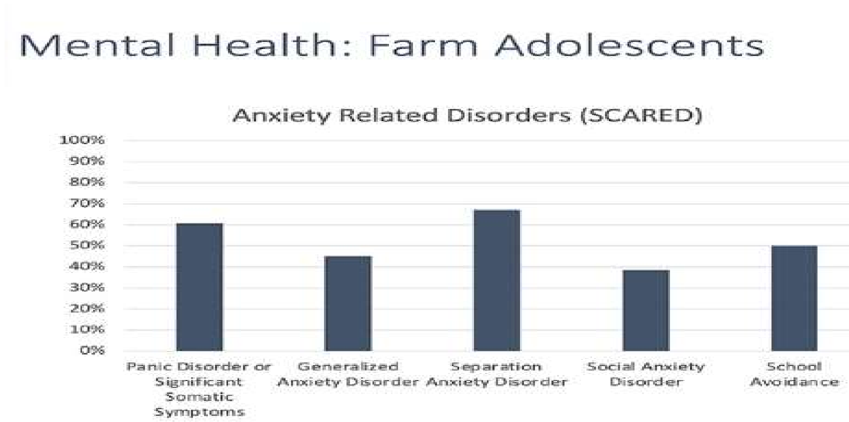


Figure 1.1 This table of statistics provide the suicide rate among the farmers [5]

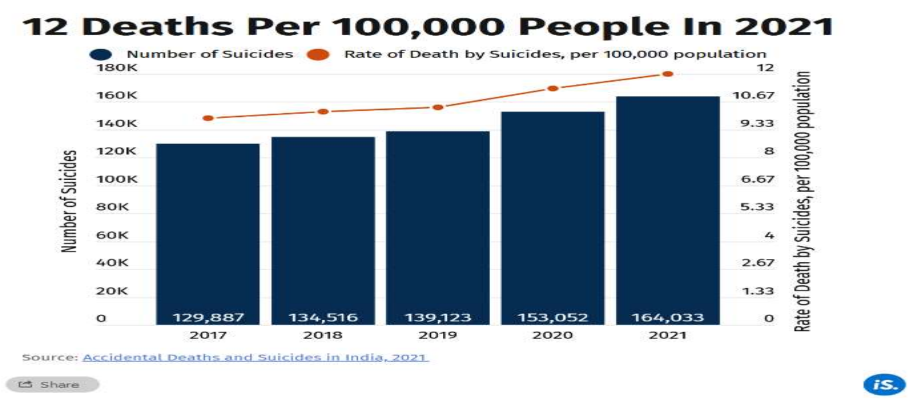


Figure 1.2 Number of suicides for each year[11]

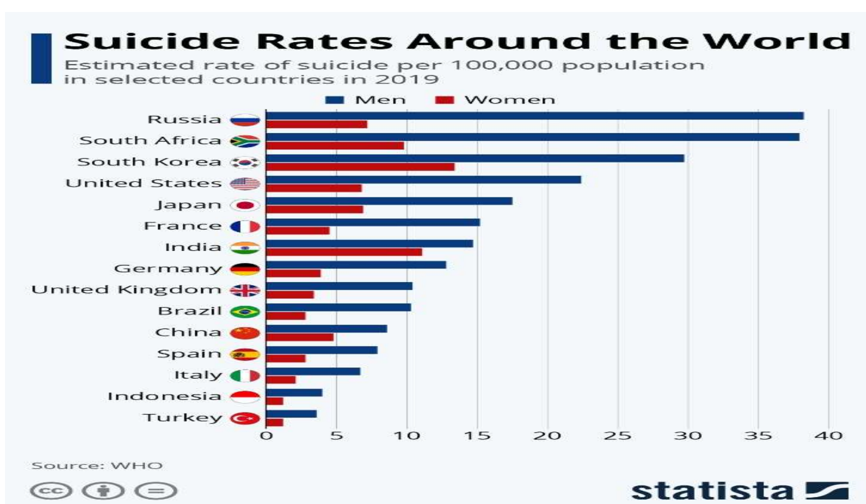


Figure 1.3 WHO report on suicide per 100000population[13]

1.2 Emotional State

Emotion is a subjective and conscious mental experience accompanied by particular biological responses or changes. Experts from different backgrounds have tried to uncover the universal definition of emotion; however, none of them have come to an agreement in establishing a single emotional model. Despite this, the two most widely accepted and used emotional models are discrete categories and the affective dimension. In addition, this paper also discusses another commonly used emotional model, the binary emotional model.

Arousal: Arousal refers to how "revved up" or stimulated an individual is feeling.

- **Low Arousal:** Low arousal states are associated with a sense of calm, relaxation, or even boredom.

  Examples: Feeling content, peaceful, or indifferent.
- **High Arousal:** High arousal states are characterized by a heightened sense of alertness, excitement, or even anxiety.

  Examples: Feeling thrilled, anxious, or extremely excited.

Valence: Valence is another crucial dimension in understanding emotional states, and it represents the positive or negative nature of an emotion. Valence provides information about whether an emotion is pleasant or unpleasant.

- **Positive Valence:** Positive valence refers to the pleasant or positive nature of an emotion.

  Examples: Feeling happy, joyful, or content.
- **Negative Valence:** Negative valence indicates the unpleasant or negative nature of an emotion.

  Examples: Feeling sad, angry, or fearful.

Combined Arousal and Valence:

- High Arousal, Positive Valence: Excitement, enthusiasm.
- High Arousal, Negative Valence: Fear, anxiety.
- Low Arousal, Positive Valence: Contentment, relaxation.
- Low Arousal, Negative Valence: Boredom, indifference.

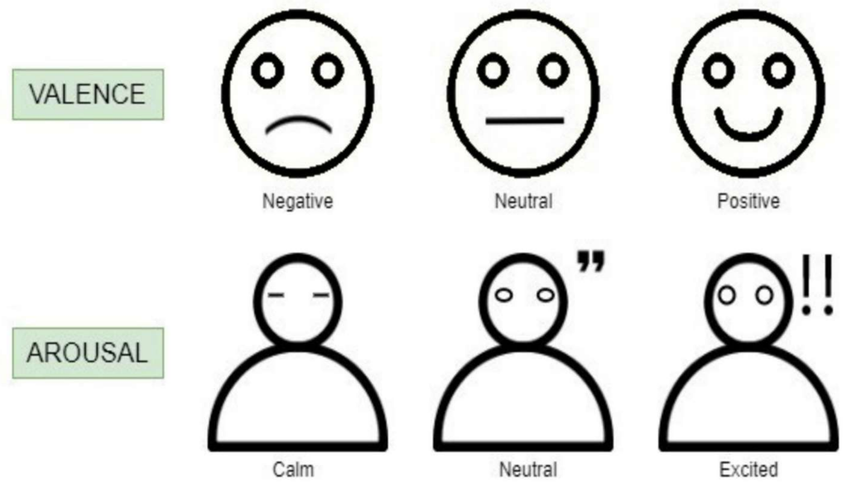


Figure 1.4 The graphical scheme provided to subjects to understand the ADM scales

The versatility of the ADM compared to the DEM is demonstrated in Figure.

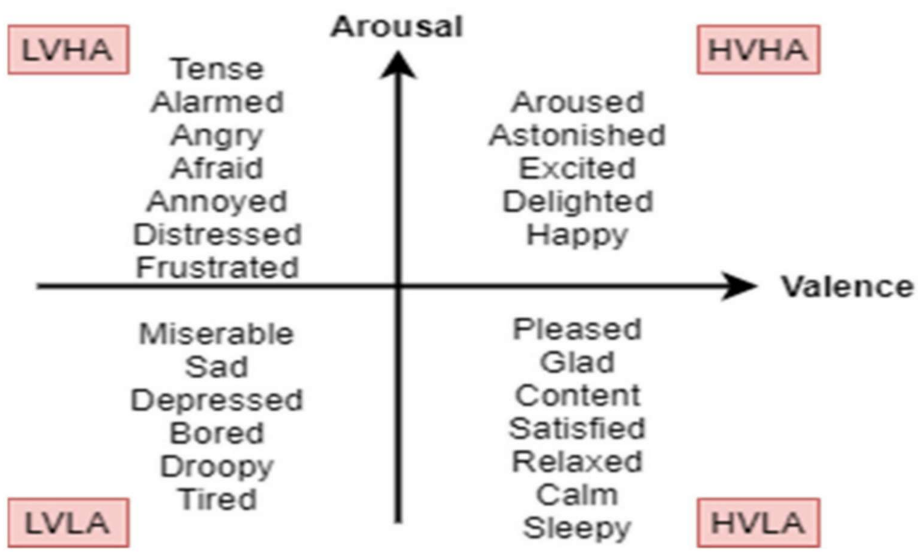


Figure 1.5 The mapping function between the Valence and Arousal

1.3 Traditional methods for finding emotional state

1.3.1 Cognitive Behaviour Analysis

The cognitive triangle model illustrates how thoughts, emotions, and actions are interconnected: Thoughts shape our feelings, which influence our behaviors. Emotional behaviors, like smiling or frowning, help regulate emotions based on individual and societal norms. For example, positive news might lead to a cheerful demeanor.a

Cognitive Behavioral Therapy (CBT) helps individuals challenge negative thought patterns and develop healthier cognitive habits. Effective for issues like anxiety and depression, CBT typically shows improvements within five to 20 sessions, offered in-person or online at a lower cost. Techniques include making lists, monitoring thoughts, cognitive restructuring, and exposure therapy.

1.3.2 Physiological Signal Based Emotion Recognition

Physiological signals, which are involuntary and continuous, are pivotal in analyzing six basic emotions: joy, sadness, fear, disgust, neutrality, and amusement. These emotions are induced using images from the International Affective Picture System (IAPS).

Signs of emotional arousal include heart rate changes, variations in skin blood flow causing blushing or paleness, piloerection, sweating, gastrointestinal activity shifts, altered respiration, and pupil dilation.

Ekman's theory suggests humans inherently possess emotions, expressed through universal facial expressions and physiological responses. Commonly used signals for emotion recognition include ECG for heart activity, EEG for brainwave patterns, and GSR for skin conductance changes, aiding researchers in understanding emotional mechanisms.

1.4 EEG Signal

1.4.1 Basic Introduction

EEG provides a collective view, reflecting synchronous activity from neurons with similar spatial orientations. This aspect contributes to its role in understanding overall brain function. Despite these strengths, detecting signals from deep sources, like subcortical areas, remains challenging due to signal interference and attenuation through brain layers.

1.4.2 Origin of EEG

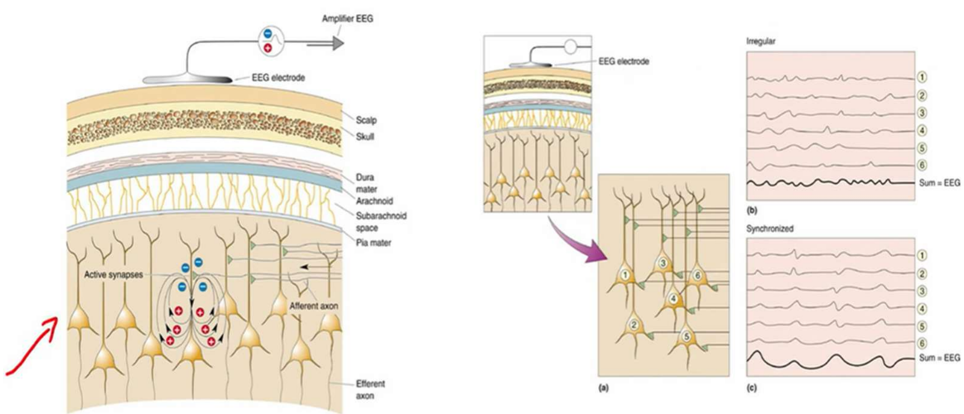


Figure 1.6: Origin of EEG

Many neurons need to sum their activity in order to detected by EEG electrodes. The timing of their activity is crucial. Synchronized neural activity produces larger signals.

1.4.3 Brain Waves

Brain waves are typically assessed by measuring the peak-to-peak voltage, with amplitudes ranging from 0.3 to 100 µV (~100 times lower than ECG signals). The raw EEG signal is obtained through Fourier transform power spectrum analysis.

The brain state of the individual may make certain frequencies more dominant. Brain waves have been categorized into four basic groups:

- Gamma (>30Hz): Usually associated with intense brain activity
- Beta (13-30 Hz): Awake, non-focused, relaxed, drowsy, or non-vigilant; low level of environmental stimulations

- Alpha (8-13 Hz): Awake, alert, focused attention and problem solving; dream/REM sleep; high level of environmental stimulation (e.g. eyes open)
- Theta (4-8 Hz): Visual imagery, hypnagogic/www hypnopompic imagery; light sleep
- Delta (0.3-4 Hz): Deep, restful sleep; vague dream states

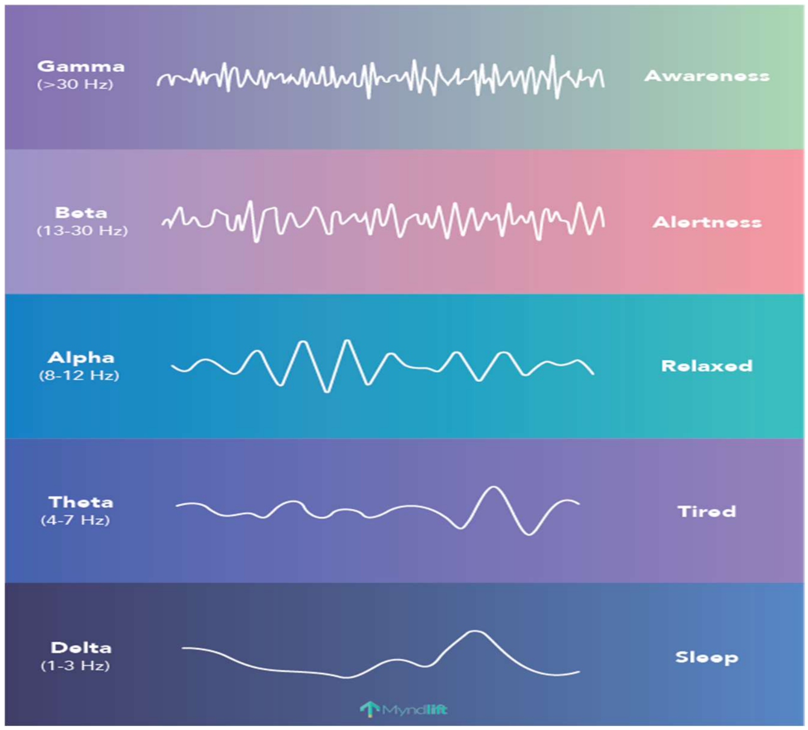


Figure 1.7: Human Brain Waves

1.4.4 Procedure of EEG Recording:

The 10/20 system is a widely used method for placing electrodes on the scalp during a standard Electroencephalogram (EEG). This system is named for the fact that electrode placements are determined by dividing the scalp into regions where the distance between adjacent electrodes is either 10% or 20% of the total front-to-back or right-to-left distance of the skull. This standardized placement ensures consistency across different individuals.

In this system, the 21 electrodes are strategically positioned based on the specific percentages, covering frontal, central, parietal, and occipital regions of the scalp. Each electrode placement is identified by a letter and number combination, reflecting the brain region and hemisphere it covers.

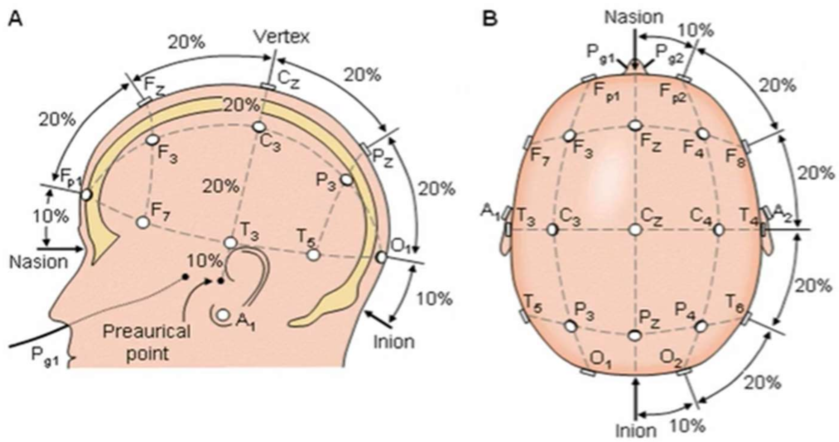


Figure 1.8: The 10-20 EEG electrode positioning System

1.4.5 Pros and Cons of EEG(Electroencephalography)

Pros of EEG:

Non-Invasiveness: EEG is a non-invasive technique, involving the placement of electrodes on the scalp without the need for surgery or penetration into the body.

High Temporal Resolution: EEG provides excellent temporal resolution, allowing the monitoring of rapid changes in brain activity in real-time.

Cost-Effective: Compared to some other neuroimaging techniques, EEG is relatively cost-effective, making it accessible for both research and clinical applications.

Cons of EEG:

Limited Spatial Resolution: EEG has limited spatial resolution compared to imaging techniques like fMRI. It provides information about the general location of brain activity but lacks precision in pinpointing specific brain regions.

Susceptibility to Artifacts: EEG signals can be affected by external factors such as muscle movements, eye blinks, and environmental noise, leading to potential artifacts that may complicate data interpretation.

Surface Signal: EEG measures electrical activity on the surface of the scalp, which may not accurately represent deeper brain structures. This limitation can impact the specificity of the recorded signals.

1.4.6 Potential Applications of EEG

Electroencephalogram (EEG) demonstrates a broad spectrum of applications across medical and research domains:

Monitoring Consciousness and Brain Death: EEG serves as a crucial tool to gauge alertness levels, assess coma states, and determine brain death by analyzing electrical brain activity.

Localization of Brain Damage: Following traumatic injuries, strokes, or tumors, EEG aids in precisely identifying damaged areas in the brain, facilitating diagnostic and treatment decisions.

Evaluation of Afferent Pathways: EEG-derived evoked potentials contribute to the assessment of sensory pathways, offering insights into the integrity of neural conduits.

Cognitive Engagement Monitoring: The alpha rhythm in EEG is harnessed to monitor cognitive engagement, providing valuable information about mental states and attention levels.

1.5 Literature Review

Understanding human mental states through electroencephalography (EEG) signals has gained significant attention due to its potential applications in various fields, including human-computer interaction and mental health. This literature review provides a comprehensive overview of research conducted in the past decade, focusing on advancements in EEG-based mental state classification.

[1] Reza Abiri et.al. (2019): Advances in brain science and computer technology in the past decade have led to exciting developments in brain–computer interface (BCI), thereby making BCI a top research area in applied science. The renaissance of BCI opens new methods of neurorehabilitation for physically disabled people (e.g. paralyzed patients and amputees) and patients with brain injuries (e.g. stroke patients). Recent technological advances such as wireless recording, machine learning analysis, and real-time temporal resolution have increased interest in electroencephalographic (EEG) based BCI approaches. Many BCI studies have focused on decoding EEG signals associated with wholebody kinematics/kinetics, motor imagery, and various senses. Thus, there is a need to understand the various experimental paradigms used in EEG-based BCI systems.

[2] Zehong Cao (2020): The advancement in neuroscience and computer science promotes the ability of the human brain to communicate and interact with the environment, making brain–computer interface (BCI) top interdisciplinary research. Furthermore, with the modern technology advancement in artificial intelligence (AI), including machine learning (ML) and deep learning (DL) methods, there is vast growing interest in the electroencephalogram (EEG)-based BCIs for AI-related visual, literal, and motion applications. In this review study, the literature on mainstreams of AI for the EEG-based BCI applications is investigated to fill gaps in the interdisciplinary BCI field. Specifically, the EEG signals and their main applications in BCI are first briefly introduced. Next, the latest AI technologies, including the ML and DL models, are presented to monitor and feedback human cognitive states. Finally, some BCI-inspired AI applications, including computer vision, natural language processing, and robotic control applications, are presented. The future research directions of the EEG-based BCI are highlighted in line with the AI technologies and applications.

[3] Mammur Rashid et.al. (2020): Brain-Computer Interface (BCI), in essence, aims at controlling different assistive devices through the utilization of brain waves. It is worth noting that the application of BCI is not limited to medical applications, and hence, the research in this field has gained due attention. Moreover, the significant number of related publications over the past two decades further indicates the consistent improvements and breakthroughs that have been made in this particular field. Nonetheless, it is also worth mentioning that with these improvements, new challenges are constantly discovered. This article provides a comprehensive review of the state-of-the-art of a complete BCI system.

[4] Naeem Ramzan et.al. (2015) In this work, we present DREAMER, a multi-modal database consisting of electroencephalogram (EEG) and electrocardiogram (ECG) signals recorded during affect elicitation by means of audio-visual stimuli. Signals from 23 participants were recorded along with the participants self-assessment of their affective state after each stimuli, in terms of valence, arousal, and dominance. All the signals were captured using portable, wearable, wireless, low-cost and off-the-shelf equipment that has the potential to allow the use of affective computing methods in everyday applications. A baseline for participant-wise affect recognition using EEG and ECG -based features, as well as their fusion, was established through supervised classification experiments using Support Vector Machines (SVMs). The self assessment of the participants was evaluated through comparison with the self-assessments from another study using the same audio-visual stimuli.

[5] XIANG LI et.al. (2022): Emotion recognition technology through analysing the EEG signal is currently an essential concept in Artificial Intelligence and holds great potential in emotional health care, human-computer interaction, multimedia content recommendation, etc. Though there have been several works devoted to reviewing EEG-based emotion recognition, the content of these reviews needs to be updated. In addition, those works are either fragmented in content or only focus on specific techniques adopted in this area but neglect the holistic perspective of the entire technical routes. Hence, in this paper, we review from the perspective of researchers who try to take the first step on this topic.

[6] Mei Wang et.al. (2022): Emotion is an indispensable part of human emotion, which affects human normal physiological activities and daily life decisions. Human emotion recognition is a critical technology in artificial intelligence, human-computer interaction, and other fields. The brain is the information processing and control centre of the human body. Electroencephalogram (EEG) physiological signals are generated directly by the central nervous system, closely related to human emotions. This paper summarizes the problems existing in current research methods. This paper discusses the research direction of emotion classification based on EEG information.

1.6Objectives

Emotion Classification: The primary goal is to develop machine learning models capable of accurately classifying emotional states based on EEG signals. Specifically, the project aims to classify emotions into different levels of valence (pleasantness) and arousal (intensity) using EEG data.

Model Evaluation: Another objective is to evaluate the performance of different machine learning algorithms, including Support Vector Machine (SVM), Random Forest, and Multilayer Perceptron (MLP), in classifying emotions from EEG signals. This evaluation involves training the models on a portion of the dataset and testing them on a separate portion to assess their accuracy, sensitivity, and overall performance.

CHAPTER 2

EEG DATA BASE

2.1 Dreamer Database

The DREAMER database is a collection of data from a study on emotions. It contains information from 23 volunteers who watched 18 different film clips each. This means there's a total of 414 physiological recordings in the database. For each clip, the volunteers watched, they were asked to report their emotional response on a scale of 1 to 5 for three emotions: arousal (how alert or energized they felt), valence (how positive or negative they felt), and dominance (how much control they felt). The researchers also recorded the volunteers' brain activity (EEG) and heart activity (ECG) while they watched the clips. Notably, the brain activity recordings captured electrical activity very frequently, at a rate of 280 times per second (280 Hz).

2.2 Experimental Summary:

Number of videos	: 18
Video content	: Audio-Video
Video duration	: 65 - 393 s (M=199 s)
Number of participants	: 25 (23)
Number of males	: 14 (14)
Number of females	: 11 (9)
Age of participants	: 22 - 33 (M=26.6, SD=2.7)
Rating scales	: Arousal, Valence, Dominance
Rating values	: 1 - 5
Recorded signals	: 14-channel 128Hz EEG, 256Hz ECG

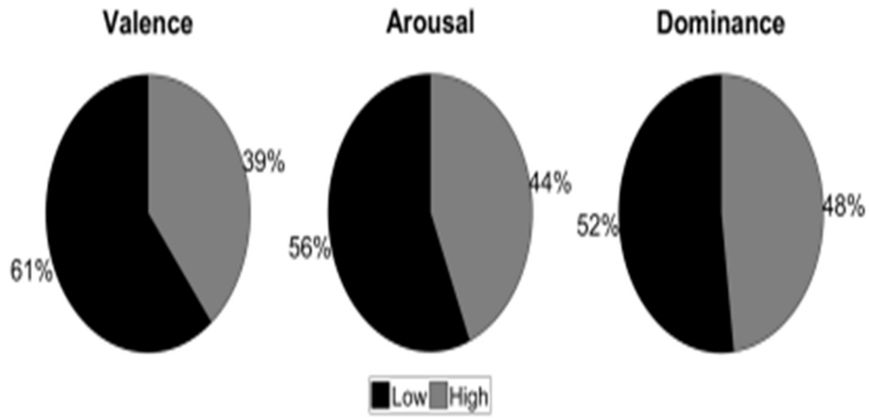
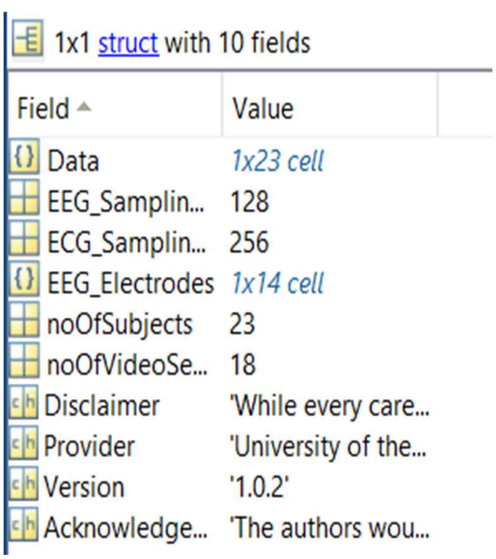


Figure 2.1 Overall class distribution across all participants after conversion to a two-class rating score.

2.3 Database File

The following figures shows how the data is stored in Dreamer database.



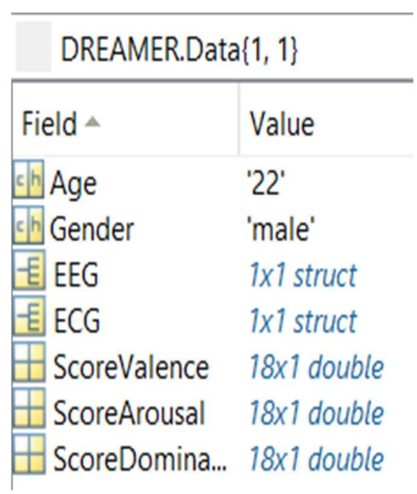


Figure 2.2

Figure 2.3

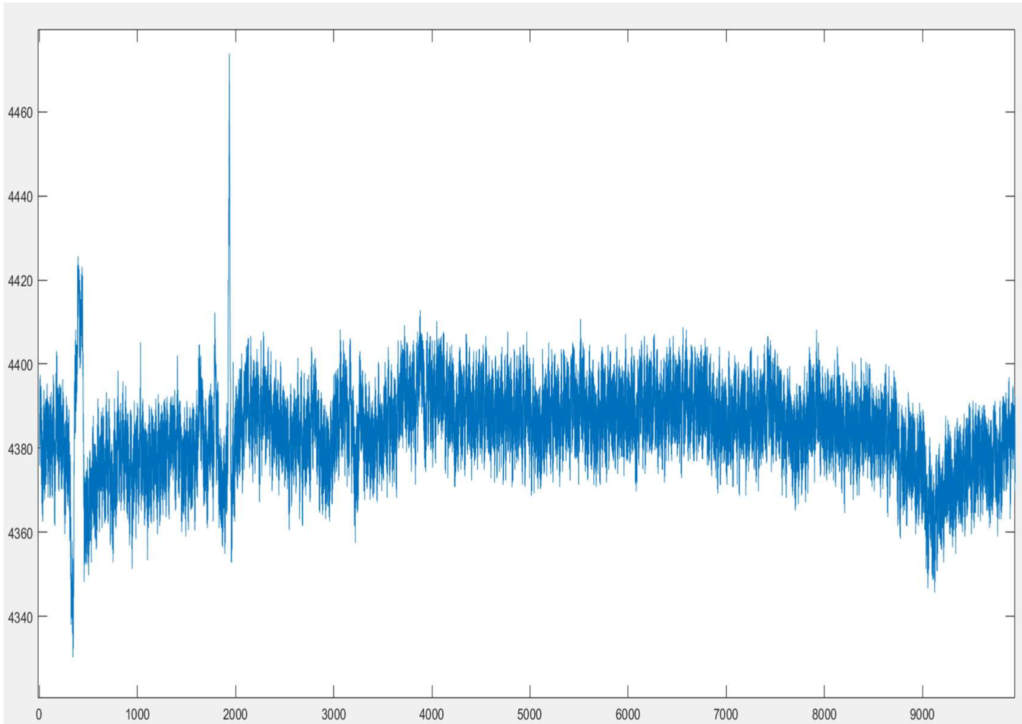


Figure 2.4: plot(DREAMER.Data{1, 1}.EEG.stimuli{1, 1}(:,1))

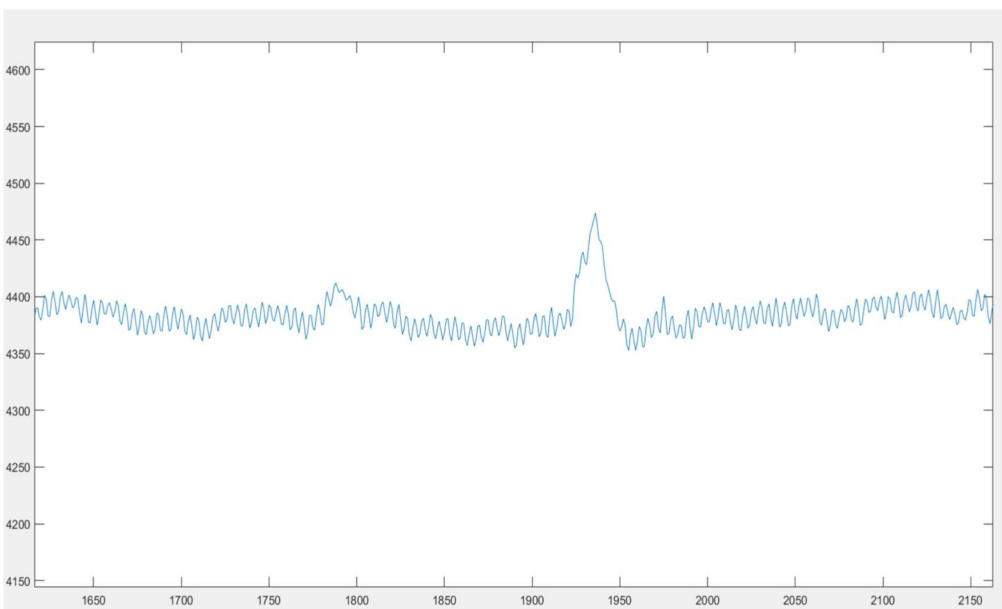


Figure 2.5: Low arousal EEG AF3 channel signal

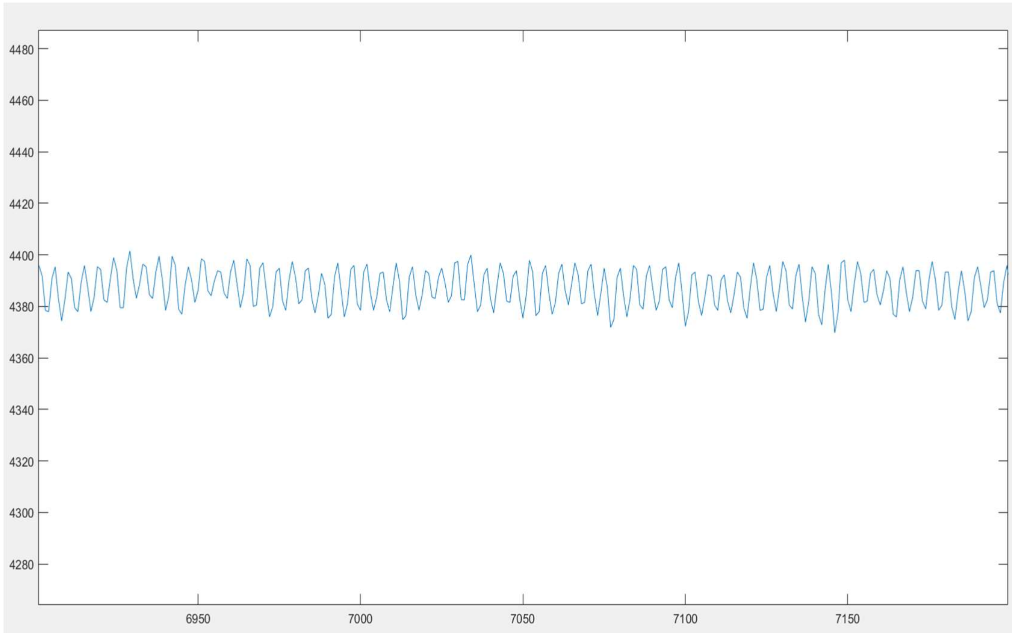


Figure 2.6: High arousal EEG AF3 channel signal

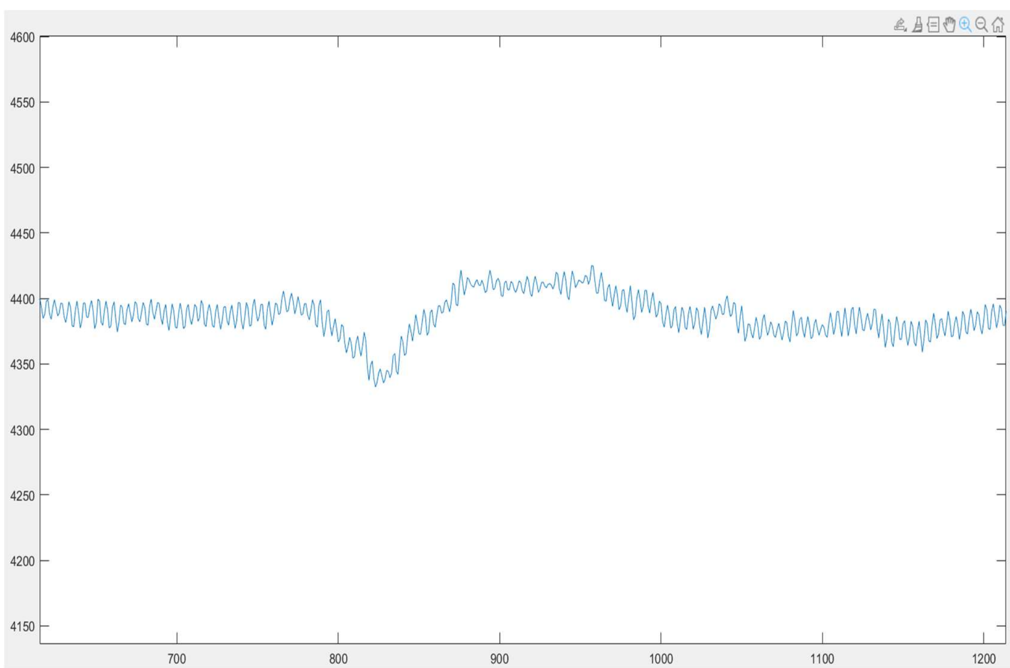


Figure 2.7: Low valence EEG AF3 channel signal

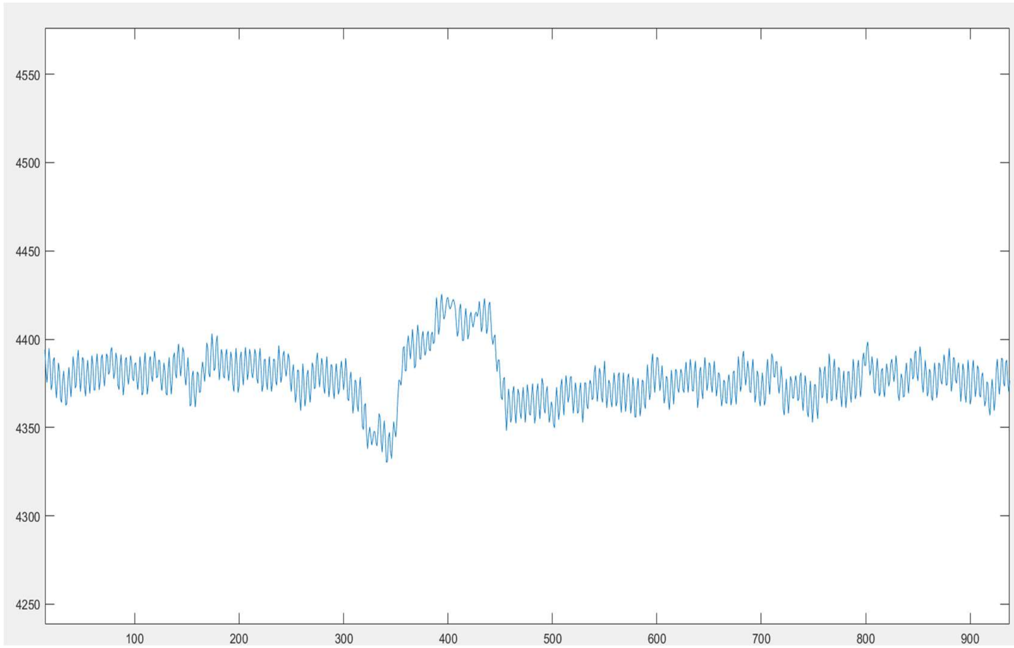


Figure 2.8: High valence EEG AF3 channel signal

CHAPTER 3

EEG SIGNAL PROCESSING BASED EMOTION RECOGNISATION

3.1 Arousal and Valence Classification

Classifying arousal (alertness) and valence (positivity/negativity) using EEG data offers a window into our emotional state. This can unlock a range of benefits. Researchers gain insights into the brain basis of emotions, while applications like affective computing (emotionally responsive computers) and neuromarketing (understanding emotional responses to products) become possible. However, challenges like accuracy limitations and privacy concerns need to be addressed as this technology matures.

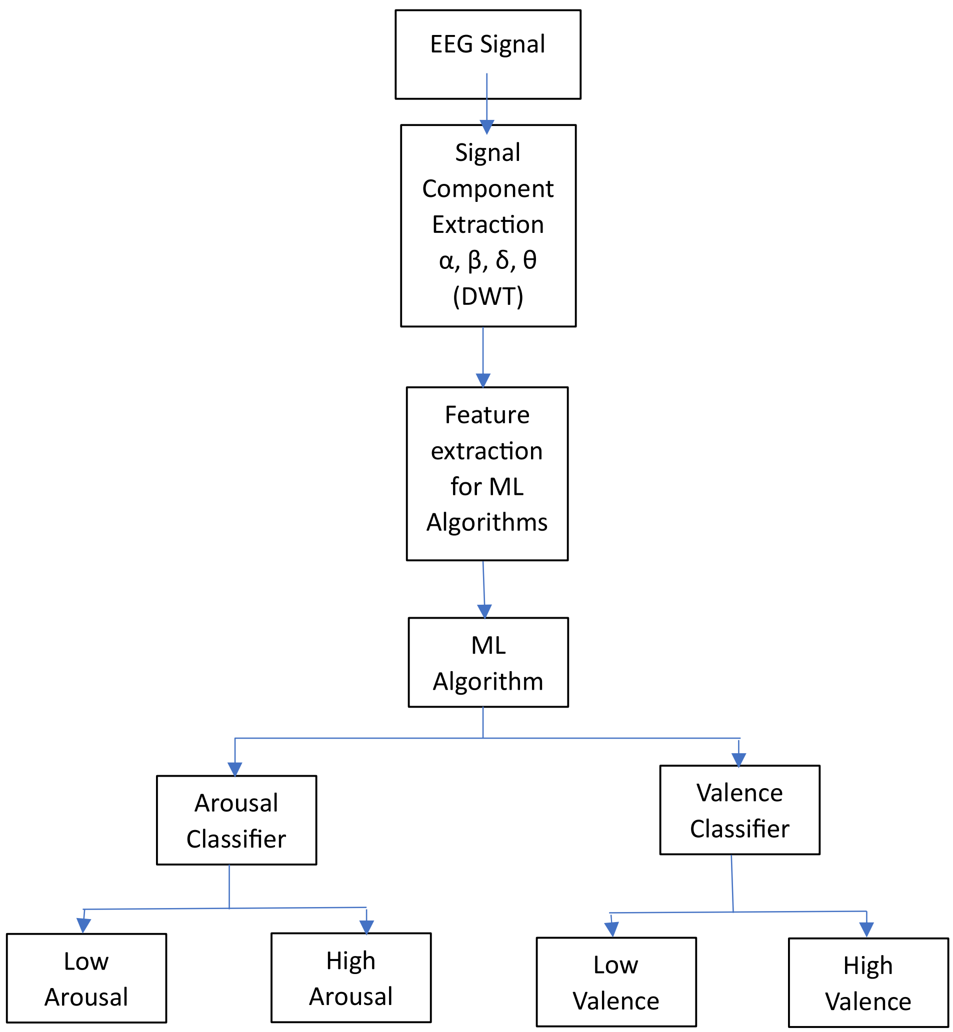


Figure 3.1: Flowchart of Arousal and Valance Classification

3.1.1 Data Loading and Preprocessing:

DREAMER.mat: This file likely stores the EEG data in a format (like MATLAB) suitable for analysis. It contain information about multiple participants, different stimuli they were presented with, and their corresponding EEG recordings.

Valence and Arousal Separation: These terms represent two fundamental dimensions of emotions. Valence reflects a positive-to-negative emotional spectrum (happy-sad), while Arousal reflects a calm-to-excited spectrum (sleepy-alert). Separating the data allows the code to build independent models for each dimension.

3.1.2 Wavelet Decomposition: This mathematical technique breaks down the EEG signal (a complex wave representing brain activity) into different frequency bands. Each band (delta, theta, alpha, beta) reflects specific brain processes. For example, the alpha band is associated with relaxation, while the beta band is associated with focused attention.

EEG Sampling Frequency: 128Hz

Maximum Frequency: 64Hz

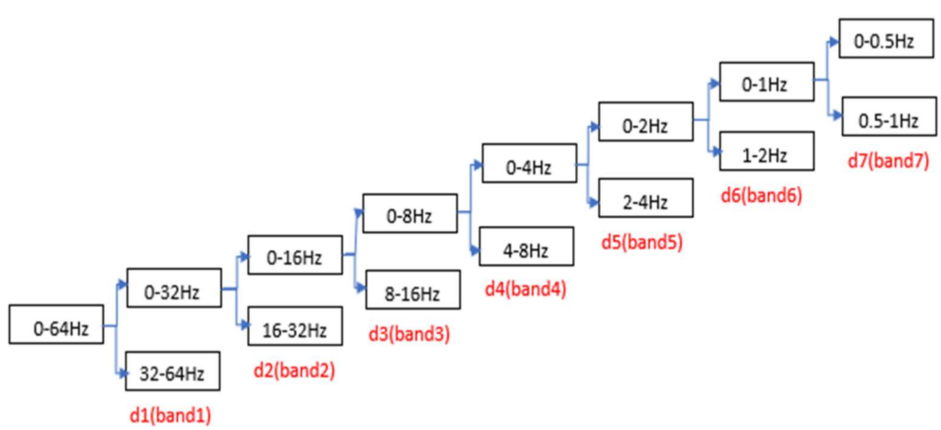


Figure 3.1: 7-level decomposition and corresponding frequency bands of EEG

3.1.2 Feature Calculation

After decomposition, we calculate various features within each band. These features quantify the characteristics of the brain wave activity, providing a window into the brain's state during the emotional response. Here are some commonly used features:

Mean

The mean, also known as the arithmetic average, represents the central tendency of a set of data. It's calculated by adding all the values in the data set and dividing by the total number of values. In the context of EEG, the mean would represent the average amplitude of the brain wave activity within a specific frequency band (delta, theta, alpha, beta) for a single data point (EEG recording).

- Mean: mean(signal);

Standard Deviation

Standard deviation tells us how spread out the data points are from the mean. A high standard deviation indicates that the data points are more dispersed, while a low standard deviation suggests the data points are clustered closer to the mean. In EEG analysis, standard deviation reflects the variability of the brain wave activity within a frequency band.

- Standard Deviation: std(signal);

Median

The median is the "middle" value in a sorted dataset. It's not as sensitive to outliers as the mean. For EEG data, the median represents the value that divides the data points within a frequency band into two halves (with an equal number of values on either side).

- Median: median(signal);

Skewness

Skewness describes the asymmetry of a data distribution. A positive skew indicates the distribution has a longer tail on the right, while a negative skew indicates a longer tail on the left. In EEG analysis, skewness tells us if the distribution of brain wave activity within a band leans more towards higher or lower values compared to a normal (symmetrical) distribution.

- Skewness: skewness(signal);

Kurtosis

Kurtosis describes the "peakedness" of a data distribution compared to a normal distribution. A positive kurtosis indicates a distribution with sharper peaks and heavier tails than normal, while a negative kurtosis indicates flatter peaks and lighter tails.

- Kurtosis: kurtosis(signal);

Entropy

Entropy measures the randomness or information content within a data set. Higher entropy indicates more randomness, while lower entropy suggests a more predictable pattern. In EEG analysis, entropy tells us how complex the brain wave activity within a frequency band is. More complex activity leads to higher entropy.

P=hist(signal,100);

P=p./sum(p);

- Entropy:-sum(p.*log2(p+eps));

Power

Power, in the context of EEG, represents the overall strength or intensity of the brain wave activity within a specific frequency band. It's often calculated by summing the squared values of the signal within the band after any necessary pre-processing. Higher power indicates stronger brain wave activity in that frequency range.

- Power: mean(signal.^2);

Normalized Power

Regular power can be influenced by individual differences in overall brainwave activity. Normalized power addresses this by dividing the power of each band by the total power across all bands. This provides a relative measure of the contribution of each frequency band to the overall EEG signal. It allows for a more standardized comparison between individuals.

- Normalizes Power: power/(Sum of all powers);

3.1.3 Classification: Building the Emotional Decoder

Once the features are extracted, we employs machine learning algorithms to classify the emotional states based on the extracted features:

Data Splitting: We randomly splits the data (with its extracted features) into two sets: training and testing. The training set is used to "train" the machine learning models. Imagine showing the model numerous examples of EEG data labeled as positive or negative emotions (for both Valence and Arousal). The model learns to identify patterns in the features that differentiate these emotional states. The testing set is then used to evaluate the model's performance on unseen data, mimicking real-world scenarios.

Machine Learning Algorithms

We employed three algorithms:

Support Vector Machine (SVM): This algorithm strives to find a hyperplane in the feature space that best separates the data points belonging to different classes (positive vs. negative emotion). It essentially draws a boundary between the two emotional states based on the extracted features.

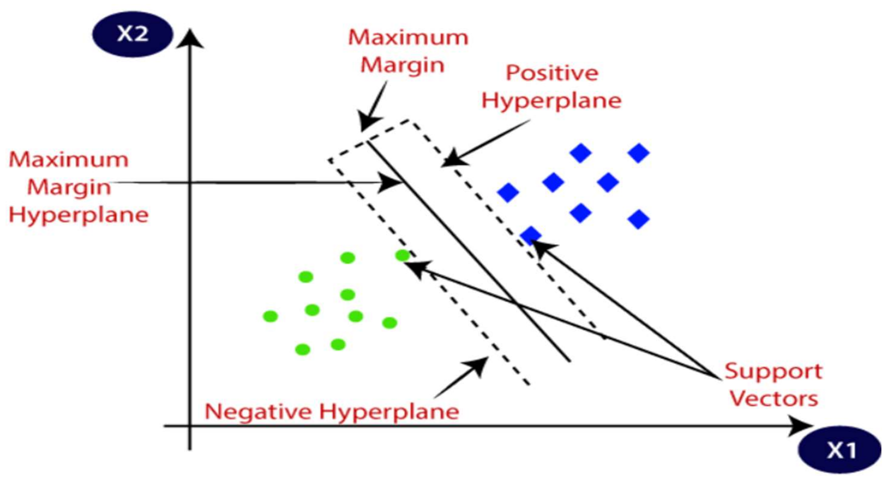


Figure 3.2: categories that are classified using a decision boundary or hyperplane

Random Forest: This algorithm builds a collection of decision trees. Each tree acts like a series of if-then-else rules based on the features. The final prediction is determined by a majority vote from all the trees in the forest, making it more robust to outliers and noise in the data.

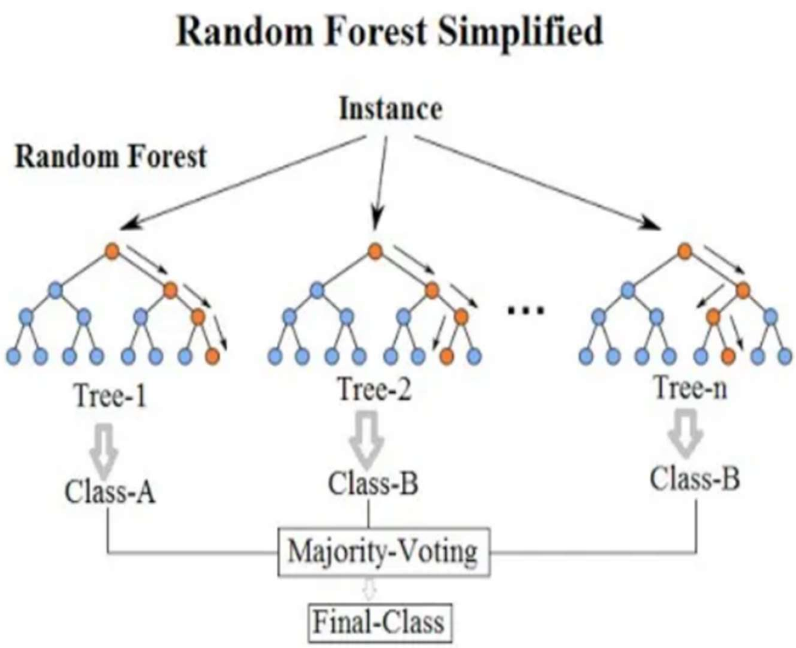


Figure 3.3: Random Forest Working Visualization

Multi-Layer Perceptron (MLP): This is a type of artificial neural network inspired by the structure of the brain. It consists of interconnected layers of processing units (neurons) that learn complex relationships between the features and the emotional states. By adjusting the connections between these neurons during training, the network learns to classify new data points.

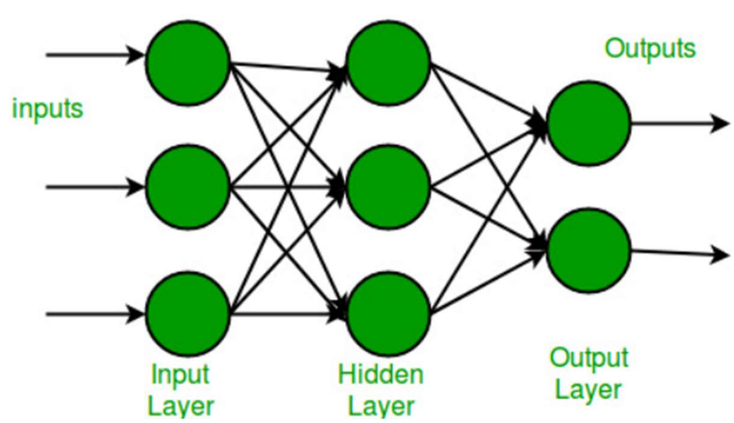


Figure 3.4: Multi-Layer Perceptron Working Visualization

3.2 Analysis

Here we have 14 channels AF3(1), F7(2), F3(3), FC5(4), T7(5), P7(6), O1(7), O2(8), P8(9), T8(10), FC6(11), F4(12), F8(13), AF4(14) in DREAMER database we need to analyse all the 14 channels with these three algorithms and we have to calculate the accurate one.

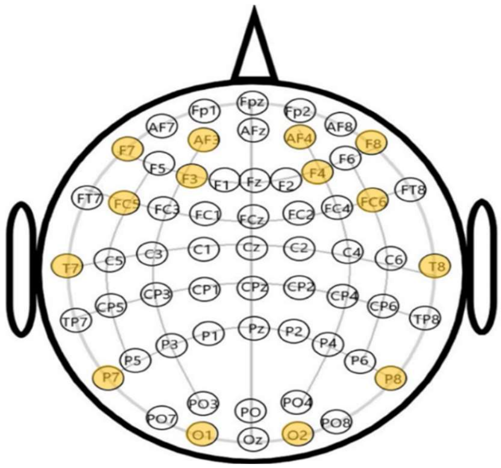


Figure 4.1: Channels Visualization

3.2.1Channels

AF3/AF4: These electrodes are positioned in the anterofrontal region, capturing activity from the anterior parts of the frontal lobes. They are important for detecting activity related to cognitive functions, including attention, memory, and emotional processing.

O1/O2: These electrodes are located over the occipital lobes, capturing activity from visual processing areas. They are crucial for detecting visual stimuli processing, spatial perception, and other visual-related cognitive processes.

F7/F8: Frontotemporal electrodes, capturing activity from the left and right frontal and temporal lobes. They play a role in detecting activity related to language processing, auditory perception, and aspects of executive functions.

F3/F4: Frontal electrodes, capturing activity from the left and right frontal lobes. These electrodes are involved in various cognitive functions, including motor planning, decision making, and emotional regulation.

FC5/FC6: These electrodes are typically positioned over the frontal cortex, specifically over the dorsolateral prefrontal cortex (DLPFC), which is involved in executive functions and working memory. They are essential for capturing activity from these regions.

P7/P8: These electrodes are positioned over the parietal cortex, capturing activity from the left and right parietal lobes. They are important for detecting parietal activity, including spatial processing and attentional processes.

T7/T8: T7 and T8 electrodes serve as vital channels for capturing neural activity from the temporal lobes, enabling researchers and clinicians to investigate a wide range of cognitive functions, clinical conditions, and brain-behavior relationships.

3.2.2 Confusion Matrix and its Features

Confusion Matrix : A **confusion matrix** is a matrix that summarizes the performance of a machine learning model on a set of test data. It is a means of displaying the number of accurate and inaccurate instances based on the model's predictions. It is often used to measure the performance of classification models, which aim to predict a categorical label for each input instance.

The matrix displays the number of instances produced by the model on the test data.

- **True positives (TP):** occur when the model accurately predicts a positive data point.
- **True negatives (TN)**: occur when the model accurately predicts a negative data point.
- **False positives (FP)**: occur when the model predicts a positive data point incorrectly.
- **False negatives (FN)**: occur when the model mispredicts a negative data point.

Accuracy

Accuracy is used to measure the performance of the model. It is the ratio of Total correct instances to the total instances.

- **Accuracy**: (TP+TN)/(TP+TN+FP+FN)

Sensitivity

Sensitivity or Recall measures the effectiveness of a classification model in identifying all relevant instances from a dataset. It is the ratio of the number of true positive (TP) instances to the sum of true positive and false negative (FN) instances.

- **Sensitivity**: (TP)/(TP+TN)

F1-Score

F1-Score is used to evaluate the overall performance of a classification model. It is the harmonic mean of precision and recall

- **F1-Score**: (2*Precision*Recall)/(Precision+Recall)

3.2.3 Performance Analysis of Described Method for Different channels of EEG Signal

AF3(1)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	60.2	1	0.75	60.1	0.91	0.73	53.0	0.87	0.67	60.2	0.88	0.72	46.9	0.55	0.52	57.8	0.65	0.62
30sec	60.2	1	0.75	61.4	0.97	0.75	51.8	0.91	0.68	50.6	0.95	0.67	49.3	0.48	0.51	48.1	0.47	0.49
60sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	48.1	0.88	0.64	50.6	1	0.67	53.0	1	0.69

Table 4.1: Performance analysis for EEG signal(Channel AF3)

F7(2)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	45.7	0.68	0.58	51.8	0.75	0.62
30sec	62.6	1	0.77	66.2	0.75	0.75	61.4	0.76	0.69	53.0	1	0.69	54.2	1	0.70	53.0	1	0.69
60sec	62.6	1	0.77	66.2	0.92	0.78	53.0	0.87	0.67	53.0	1	0.69	50.6	1	0.67	53.0	1	0.69

Table 4.2: Performance analysis for EEG signal(Channel F7)

F3(3)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	45.7	0.57	0.51	50.6	0.61	0.56
30sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	51.8	0.88	0.64	56.6	0.90	0.68
60sec	60.2	0.94	0.74	55.4	1	0.71	56.6	1	0.72	53.0	1	0.69	50.6	0.66	0.57	43.3	0.59	0.52

Table 4.3: Performance analysis for EEG signal(Channel F3)

FC5(4)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	53.0	0.95	0.68	54.2	0.93	0.69	53.0	1	0.69	50.6	1	0.67	53.0	1	0.69
30sec	66.2	0.94	0.77	61.4	1	0.76	56.6	1	0.72	48.1	0.86	0.63	44.5	0.47	0.46	49.3	0.52	0.52
60sec	59.0	0.88	0.72	56.6	1	0.72	56.6	1	0.72	53.0	1	0.69	49.3	0.97	0.66	51.8	0.97	0.68

Table 4.4: Performance analysis for EEG signal(Channel FC5)

T7(5)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	61.4	0.98	0.76	57.8	1	0.73	56.6	1	0.72	53.0	1	0.69	46.9	0.88	0.62	49.3	0.88	0.65
30sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	53.0	0.58	0.59	55.4	0.61	0.59
60sec	62.6	0.94	0.75	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	43.3	0.55	0.50	51.8	0.63	0.58

Table 4.5: Performance analysis for EEG signal(Channel T7)

P7(6)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	55.4	0.84	0.7	63.8	1	0.77	56.6	1	0.72	53.0	1	0.69	48.1	0.90	0.64	54.2	0.95	0.68
30sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	56.6	0.75	0.67	40.9	0.63	0.53
60sec	62.6	1	0.77	53.0	0.80	0.67	48.1	0.78	0.63	53.0	1	0.69	50.6	1	0.67	53.0	1	0.69

Table 4.6: Performance analysis for EEG signal(Channel P7)

O1(7)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	49.3	0.65	0.58	55.4	0.71	0.65	54.2	0.72	0.62
30sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	54.2	0.84	0.66	45.7	0.48	0.48	51.8	0.54	0.54
60sec	62.6	0.90	0.75	61.4	1	0.76	56.6	1	0.72	50.6	0.65	0.58	57.8	0.62	0.63	55.4	0.61	0.59

Table 4.7: Performance analysis for EEG signal(Channel O1)

O2(8)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	60.2	1	0.75	65.0	1	0.78	56.6	1	0.72	60.2	1	0.75	49.3	0.70	0.59	61.4	0.81	0.69
30sec	62.6	0.90	0.77	61.4	0.90	0.76	56.6	0.96	0.72	54.2	0.84	0.66	45.7	0.48	0.51	51.8	0.55	0.56
60sec	62.7	0.90	0.75	61.4	1	0.78	56.8	1	0.73	50.6	0.65	0.58	57.8	0.62	0.63	55.4	0.61	0.59

Table 4.8: Performance analysis for EEG signal(Channel O2)

P8(9)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	61.4	1	0.76	56.6	1	0.72	56.6	1	0.72	53.0	1	0.69	33.7	0.52	0.44	53.0	0.70	0.61
30sec	62.6	0.96	0.77	61.4	1	0.76	56.6	1	0.75	52.9	0.92	0.72	56.6	0.75	0.67	40.9	0.63	0.53
60sec	62.4	1	0.76	53.0	0.80	0.77	48.1	0.78	0.63	53.0	1	0.69	50.6	1	0.77	53.0	1	0.65

Table 4.9: Performance analysis for EEG signal(Channel P8)

T8(10)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	55.4	1	0.71	56.6	1	0.72	53.0	0.77	0.63	50.6	0.69	0.62	56.6	0.77	0.65
30sec	62.6	1	0.75	62.4	1	0.71	57.6	1	0.72	53.0	1	0.69	53.0	0.58	0.59	55.4	0.61	0.59
60sec	63.6	0.95	0.75	61.4	1	0.76	56.6	0.96	0.75	54.2	1	0.63	43.3	0.55	0.50	51.8	0.63	0.58

Table 4.10: Performance analysis for EEG signal(Channel T8)

FC6(11)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	57.8	0.94	0.73	55.4	0.95	0.70	53.0	1	0.69	46.9	0.57	0.52	49.3	0.59	0.55
30sec	66.2	0.96	0.72	60.4	1	0.72	56.6	1	0.72	48.1	0.86	0.63	44.5	0.47	0.46	49.3	0.52	0.52
60sec	59.0	0.88	0.72	56.6	1	0.72	56.6	1	0.74	53.0	1	0.69	49.3	0.97	0.66	50.8	0.97	0.58

Table 4.11: Performance analysis for EEG signal(Channel FC6)

F4(12)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	57.8	0.73	0.68	54.2	0.72	0.64	53.0	1	0.69	54.2	0.76	0.62	54.2	0.75	0.63
30sec	62.0	1	0.76	61.4	1	0.76	56.6	1	0.72	53.0	1	0.69	51.8	0.88	0.64	56.6	0.90	0.68
60sec	60.2	0.94	0.74	55.4	1	0.71	55.6	1	0.74	52.9	0.96	0.79	50.6	0.66	0.57	53.3	0.59	0.52

Table 4.12: Performance analysis for EEG signal(Channel F4)

F8(13)

	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	67.4	0.94	0.79	54.2	0.91	0.69	54.2	0.79	0.64	54.2	0.60	0.60	49.3	0.56	0.54
30sec	63.8	0.96	0.76	50.6	0.68	0.60	55.4	0.72	0.64	53.0	1	0.69	50.6	1	0.67	53.0	1	0.69
60sec	63.6	1	0.77	66.2	0.92	0.78	53.0	0.77	0.67	53.0	1	0.69	50.6	1	0.67	53.0	1	0.69

Table 4.13: Performance analysis for EEG signal(Channel F8)

AF4(14)

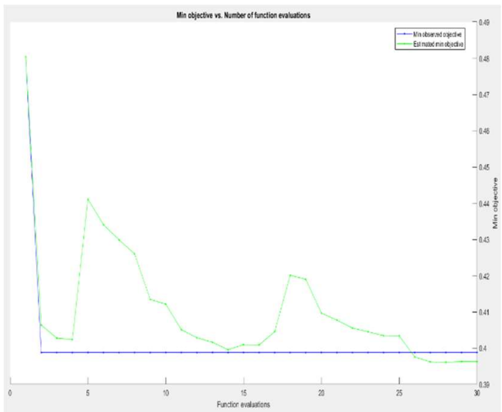
	VALENCE									AROUSAL								
Algo	SVM			Random Forest			MLP			SVM			Random Forest			MLP		
	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1	Accu	Sens	F1
10sec	62.6	1	0.77	57.8	0.97	0.73	55.4	0.97	0.71	53.0	1	0.69	45.7	0.40	0.43	53.0	0.47	0.51
30sec	62.6	1	0.77	49.3	1	0.66	56.6	1	0.72	54.2	0.77	0.64	51.8	1	0.68	53.0	1	0.69
60sec	62.6	1	0.77	61.4	1	0.76	56.6	1	0.72	48.1	0.88	0.64	50.6	1	0.67	53.0	0.96	0.70

Table 4.14: Performance analysis for EEG signal(Channel AF4)

3.2.4 Model Diagrams

Here we have taken an example of AF3 channel 10 sec EEG signal Valence feature matrix and performed these algorithms

Support Vector Machine (SVM):



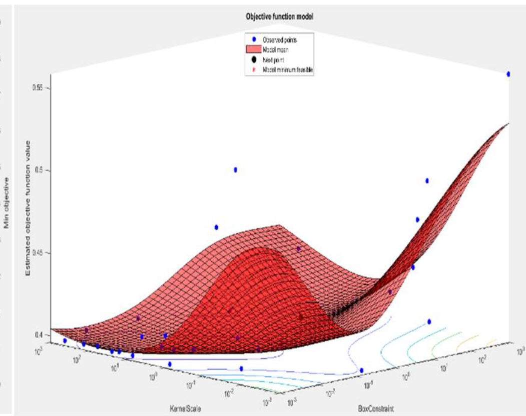


Figure 4.2: Min Objective vs Number of function evaluations

Figure 4.3: Objective Function Model

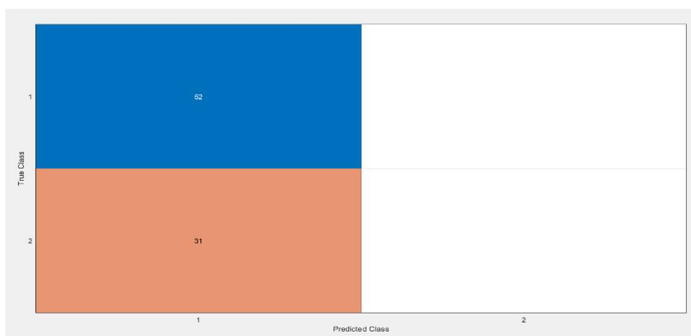
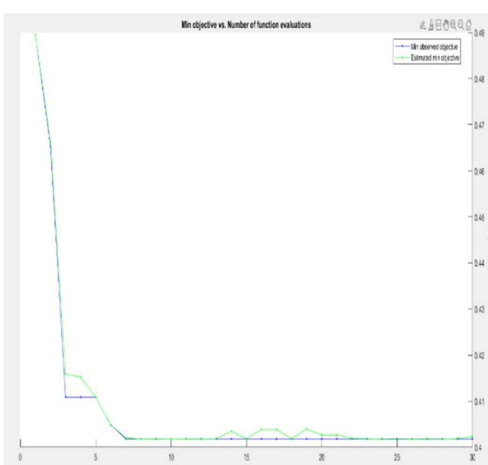


Figure 4.4: Confusion Matrix for SVM

Random Forest:



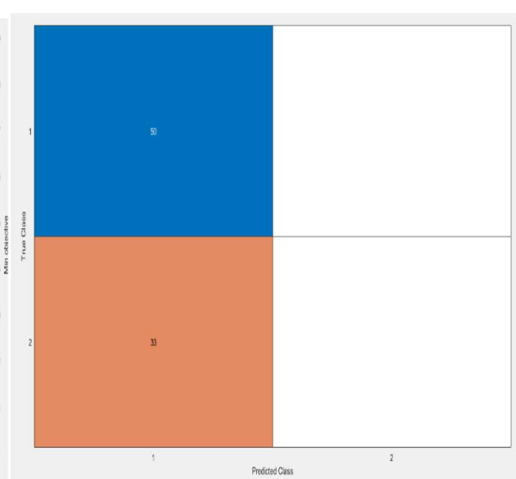


Figure 4.5: Min Objective vs Number function evaluations

Figure 4.6: Confusion Matrix for Random of Forest

Multi-Layer Perceptron (MLP):

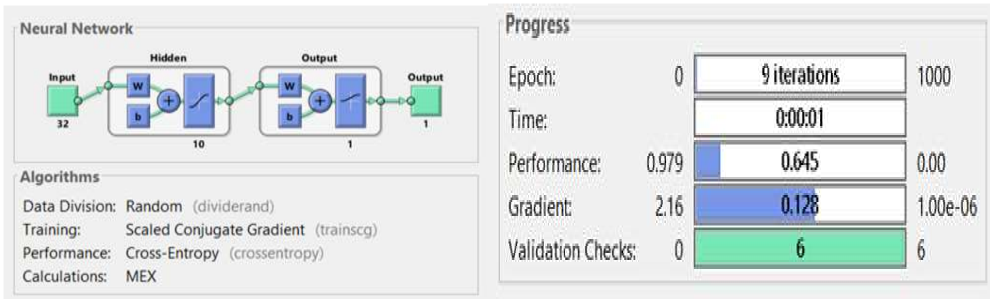
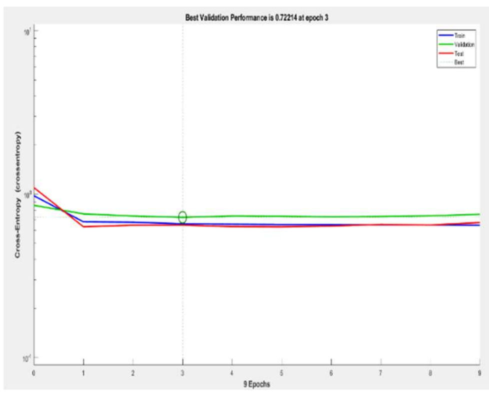


Figure 4.7: Performance and Progress of MLP



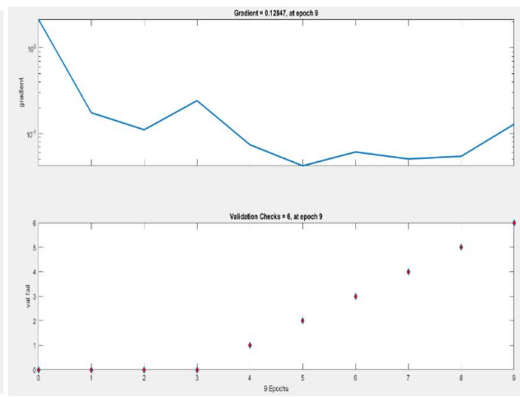
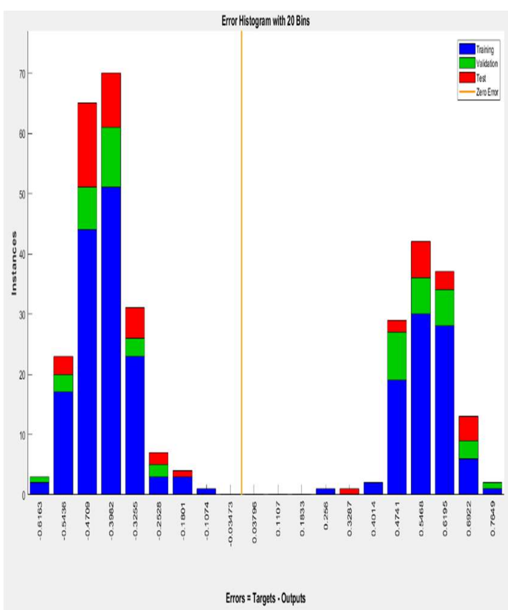


Figure 4.8: Performance plot of MLP **Figure 4.9**: Plot of Training State of MLP



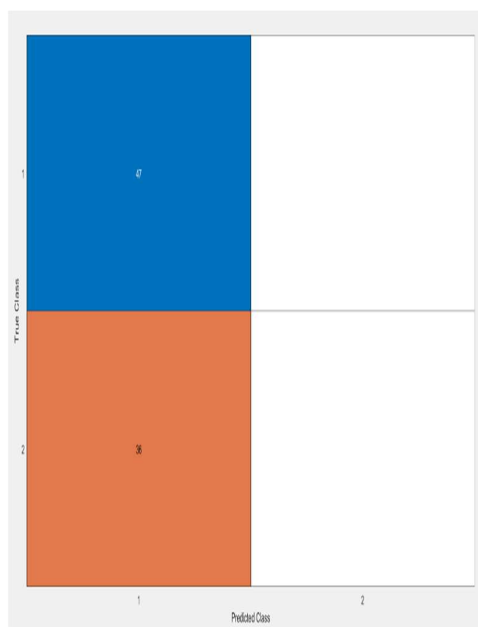


Figure 4.10: Error Histogram of MLP **Figure 4.11**: Confusion Matrix of MLP

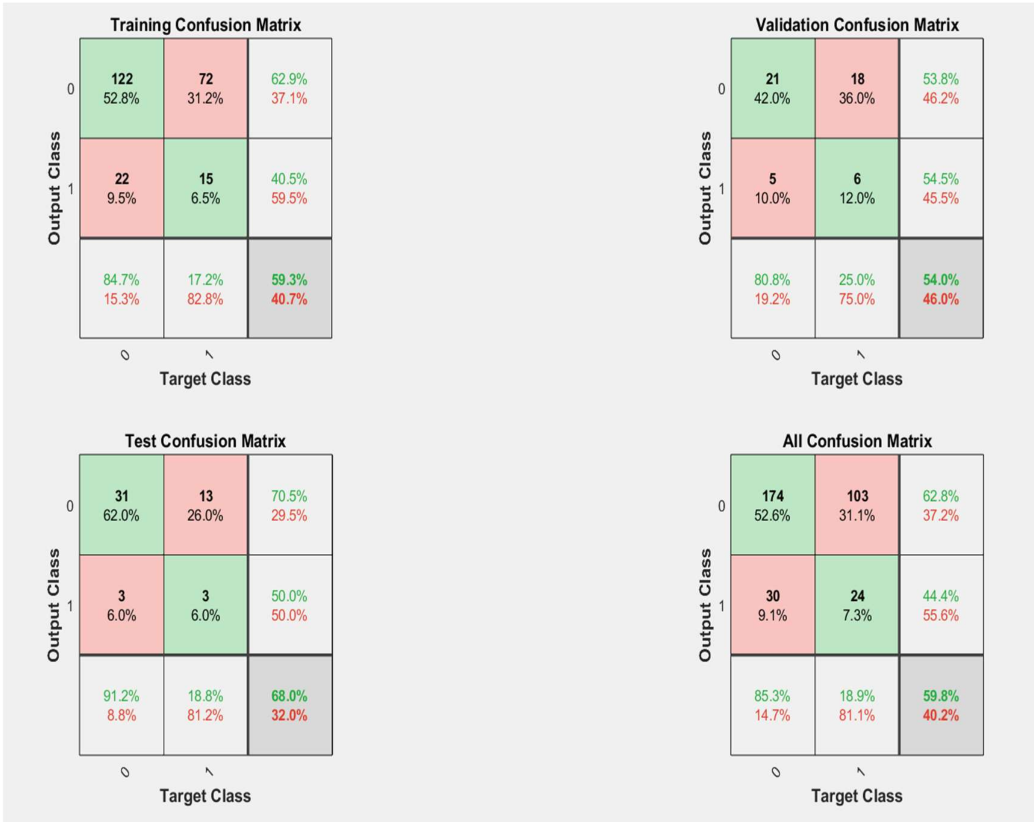


Figure 4.12: Training Confusion Matrix

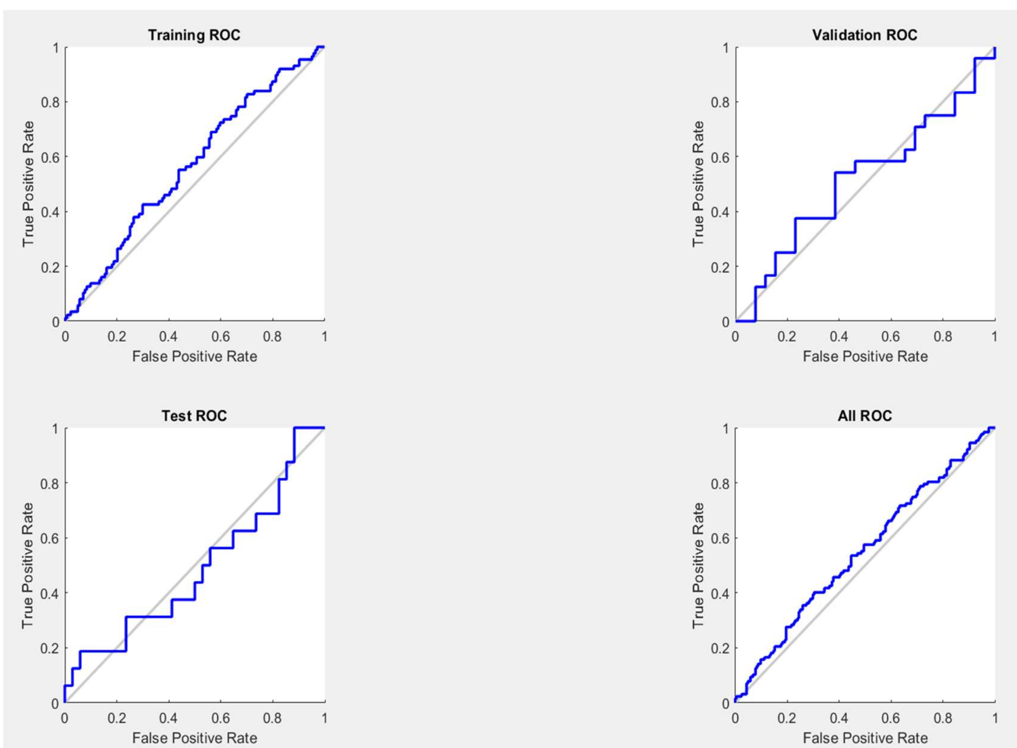


Figure 4.13: Receiver operating Characteristic

CHAPTER 4
CONCLUSION AND FUTURE SCOPE

4.1 Conclusion

4.1.1 SVM Reigns Supreme:

Our analysis identified Support Vector Machines (SVM) as the most effective classification algorithm for deciphering arousal and valence levels from EEG data in the DREAMER dataset. This suggests that SVM's ability to find hyperplanes effectively separates the data points representing different emotional states. Compared to Random Forest and Multi-Layer Perceptron, SVM might be better suited for this specific classification task due to its focus on maximizing the margin between classes.

4.1.2 Frontal Lobe Takes Center Stage:

Among the fourteen EEG channels analysed, F8, located in the frontal lobe, emerged as the most informative for classifying emotional states. This finding aligns with previous research suggesting the frontal lobe plays a crucial role in emotional processing. Brain activity in this region might be particularly sensitive to changes in arousal and valence levels associated with watching different film clips.

While F8 stood out, channels like T8, F7 and T7 (also located in the frontal and temporal lobes) also yielded good accuracy. This indicates that emotional processing likely involves a network of brain regions beyond just F8. These surrounding areas might provide complementary information that aids in accurate classification.

4.2 Future Scope

Frequency Band Significance: Our analysis focused on various features extracted from the EEG signal. To gain a deeper understanding of which brain wave frequencies contribute most to classification accuracy, future work could involve analyzing the significance of specific frequency bands (delta, theta, alpha, beta) within the EEG signal on channel F8 and other relevant channels. For instance, research suggests that alpha and beta bands might be particularly relevant for emotional processing.

Beyond the Film Clips: Our study focused on emotions triggered by film clips. But what about the real world? Future endeavors can explore integrating EEG data with other sources of information. Facial expressions, body signals (heart rate, sweat), or even how people describe their emotions could all be combined. This multi-layered approach can give us a richer picture of how emotions play out in the brain, body, and behaviour.

Going Global and Individual Differences: This project focused on a specific dataset. The next step is to see if these findings hold true across the board. Testing our models on different datasets with diverse populations will tell us how universal these brain-emotion links are. Since brains are like fingerprints, individual differences matter too. Future studies can explore how factors like age, gender, or personality might influence how our brains cook up emotions.

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