EEG-BASED EMOTION ANALYSIS USING TEXT STIMULI

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Candidate of **Master of Science in Software Engineering (MSSE)** at the National University of Modern Languages do hereby declare that the thesis **EEG-Based Emotion Analysis Using Text Stimuli** submitted by me in partial fulfillment of MSSE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in the future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be canceled, and the degree revoked.

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ABSTRACT

EEG-BASED EMOTION ANALYSIS USING TEXT STIMULI

Emotions are fundamental to our daily lives, impacting our behavior, thoughts, and feelings. Accurately classifying emotions is of utmost importance in various fields, including psychology, psychiatry, and neuroscience, as it can aid in the development of effective diagnostic tools, and human-computer interaction systems. In this study, the aim was to classify emotions using Electroencephalogram (EEG) data, which provides a non-invasive and objective measure of brain activity. Data was collected from 25 participants using a 128-channel device and text stimuli. To achieve this goal, a comprehensive approach was adopted that integrates multiple feature extraction techniques, pre-processing techniques, and a Support Vector Machine (SVM) classifier. Four feature extraction techniques, Convolutional Neural Network (CNN), Wavelet Transform (WT), Power Spectral Density (PSD), and Raw data, are used to extract features from pre-processed EEG signals. The pre-processing techniques involved down sampling, re-referencing, and filtering the EEG signals to eliminate noise and artifacts. The Monte Carlo approach is applied to randomly selecting training and testing samples to ensure the reliability and validity of results of this study. Study focused on classifying emotions as positive and negative. T-tests were used to identify the most relevant features that contributed to the classification of emotions. The results show that the combination of CNN and SVM yields the highest average accuracy rate of 80%, followed by WT with 75%, PSD with 72%, and raw data with 65%. This suggests that the use of CNN, WT, and PSD as feature extraction techniques in combination with SVM as a classifier can significantly improve the classification of emotions based on EEG data. The proposed approach has significant implications for the development of more accurate and efficient methods for classifying emotions in various fields. For instance, in the field of human-computer interaction, accurate emotion recognition can be used to develop personalized interfaces that respond to the user's emotional state. In clinical settings, the accurate classification of emotions can aid in the diagnosis of psychiatric disorders and inform treatment strategies. Our findings highlight the potential of EEG data as a valuable source of information for emotion classification, with important applications in various domains.

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LIST OF ABBREVIATIONS

AgCl	Silver Chloride
BDI	Beck Depression Inventory
BDTs	Boosted Decision Trees
CNN	Convolutional Neural Network
C-SVC	C-Support Vector Classification
DEAP	Dataset For Emotion Analysis Using EEG, Physiological And Video Signal
DL	Deep Learning
DWT	Discrete WT
ECG	Electro-Cardiogarphy
EEG	Electroencephalogram
EGI	Electrical Geodesics Incorporated
EMD	Empirical Mode Decomposition
EMDB	Emotional Movie Database
EMG	Electro-Myography
EMG	Electromyography
EOG	Electro-Oculogram
ERP	Event-Related Potentials
FD	Fractal Dimension
FFT	Fast Fourier Transform
fMRI	Functional Magnetic Resonance Imaging
FP	False Positive
GSR	Galvanic Skin Response
HCI	Human Computer Interactions
HP	Hjorth Parameters
IADS	International Affective Digitized Sounds
IAPS	International Affective Picture System
IAPS	International Affective Picture System
ICA	Independent Component Analysis
ICA	Independent Component Analysis
IMFs	Intrinsic Mode Functions
IQ	Intelligence Quotient
KNN	K-Nearest Neighbour
ML	Machine Learning
MLP	Multi-Layer Perceptron’s
NB	Naïve Bayes
PCA	Principal Component Analysis
PSD	Power Spectral Density
PSD	Power Spectral Density
QDA	Quadratic Discriminant Analysis
RF	Random Forest
ROI	Region Of Interest
SEED	Sjtu Emotion Eeg Dataset
STAI	State-Trait Anxiety Inventory
STFT	Short-Time Fourier Transform

SVM	Support Vector Machine
TBI	Traumatic Brain Damage
TN	True Negative
TP	True Positive
WT	Wavelet Transform

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DEDICATION

This thesis work is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work hard for the things that I aspire to achieve.

CHAPTER 1

INTRODUCTION

1.1 Overview

Emotions are essential to human existence and have a big influence on a lot of cognitive functions such as reasoning, social interaction, Intelligence Quotient (IQ), perception. Affective computing, which integrates technology and emotions with Human Computer Interactions (HCI), seeks to close this gap by raising the emotional intelligence of computers [1].

To investigate how humans, interact with computer systems, the area of HCI incorporates elements of computer science, psychology, and otherrelated disciplines. Emotion recognition, which entails assessing a person's emotional state through observation of their interactions with a computer, is one of the main components of HCI. Numerous techniques, including the study of facial expressions, speech patterns, and physiological reactions, can be used to carry out this procedure [2].

Through the combination of information and methods from numerous disciplines like psychology, recent neuroscience, cognitive science, and computer science, the subject of emotion recognition has made significant strides in recent years. For instance, psychological theories of emotion have provided a framework for understanding how emotions are generated and how they are expressed. Modern neuroscience has provided insights into the neural mechanisms underlying emotions, while cognitive science has helped in understanding how emotions influence perception, memory, and decision-making. Computer science has provided the tools and methods to analyze, model and simulate emotions, allowing for the development of more advanced emotion recognition systems.

Computer systems that can recognize emotions aim to enhance human-machine interactions in different fields like gaming, industrial, military, and medical sectors [3].

These systems can be divided into two categories: those that use external signs of emotional expression like facial expressions, tone of voice, and body movements to identify emotions and those that use internal signals to determine emotions. The latter category uses non-invasive sensors to record physiological processes, such as electrical impulses, for example, electrocardiogram, EEG, and skin conductivity are some of the commonly used methods in these models [4].

Emotions can be evaluated using both objective and subjective methods. Questionnaires, checklists, and visual aids are called Subjective methods or self-reported measures. Measuring physiological signals such as blood pressure, skin reactions, pupillary responses, brain waves, and heart rate are called objective methods [5].

Both subjective and objective approaches can be used to evaluate emotions. Self-reported assessments using checklists, surveys, and visual aids are examples of subjective approaches. Measurements of physiological signals including blood pressure, pupillary responses, skin reactions brain waves, and heart rate are among the objective techniques.

For the classification of emotion Arousal and Valence and are commonly used. Valence refers to the level of pleasure or unpleasantness associated with a feeling, while arousal refers to the intensity of the emotion. From unpleasant to pleasant are the ranges of Valence, from passive to vigorous are the ranges of arousal. Additionally, another term that defines someone's level of emotional control is dominance. [6].

Three characteristics which are used to classify emotions are Arousal, Valence, and Dominance.

Valence: There is more frontal consistency in alpha signals in Positive emotions like joy have larger right parietal beta signals and more frontal consistency in alpha signals.

Arousal: Excitement is associated with a lower alpha signal activity and a stronger and more consistent beta signal in the parietal lobe.

Dominance: The intensity of the emotion is often shown in the EEG as an increase in the frontal lobes' alpha-beta activity proportion of signal and a rise in the beta activity of parietal lobe.

Acceptance, joy, rage, fear, grief, surprise disgust and anticipation are presented as Pluthick's theory of emotions [7]. The eight fundamental emotions as proposed by Plutchik [7] can be used to create other emotions through combination, such as disappointment. There are three categories of emotion: neutral, positive, and negative. To survival, evolution, and growth Positive emotions such as happiness and love are necessary, but negative emotions such as sorrow, rage, contempt, and fear serve an immediate and natural role. Neutral emotions, on the other hand, are more of a theoretical or descriptive model of emotions in negotiation and decision-makingand are not founded on scientific theory or study [8].

1.2 EEG SIGNALS AND EMOTIONS

The brain is the most complicated component of the human body, and the cerebral cortex is its most complex portion. Where bioelectric signals known as brain electrical signals are generated with amplitudes ranging from 10 to 100 volts [9] The cerebral cortex is divided into four sub-regions: the frontal lobe, which is responsible of intellectual thinking and psychological needs; the parietal lobe, which controls balance and coordination and processes tactile sensations; the temporal lobe, which is in charge of hearing, smell, emotional and mental processes; and the occipital, which is in responsible of visual information processing.

An EEG is a technique that monitors the brain's electrical activity of the brain using tiny metal discs connected to the scalp as electrodes. The electrodes are placed on the scalp in certain areas to capture the electrical activity that happens in the brain. Electrical activity is generally exhibited on a monitor as wavy lines known as EEG signals.

There are five different categories of EEG signals with different frequency bands. Those bands have significant roles with the brain activity of human.

Delta waves lie between the frequency range of 0.5 to 4 Hz and are typically associated with deep, dreamless sleep. They are characterized by slow, high-amplitude waves and are commonly found in the brain during non-REM sleep.

Theta waves lie between the frequency range of 4 to 8 Hz and are typically associated with light sleep or drowsiness. They are characterized by slower, lower-amplitude waves than alpha waves and are commonly found in the brain during non-REM sleep.

Alpha waves lie between the frequency range of 8 to 13 Hz and have a relationship with a relaxed, awake state of a person. They are characterized by slower, lower-amplitude waves than beta waves and are commonly found in the brain when a person is relaxed, and in awake state with eyes closed.

Beta waves lie between the frequency range of 13-30 Hz and are typically associated with an alert, awake state. They are characterized by faster, higher-amplitude waves than alpha waves and are commonly found when a person is engaged in cognitive activity.

The frequency range of Gamma is greater than 30 Hz and are typically associated with high-level cognitive processing and information processing. They are characterized by fast, high-amplitude waves and are commonly found in the brain when a person is engaged in complex cognitive tasks or during periods of heightened perception [10].

The brain's electrical activity, as measured by EEG, is associated with different states of consciousness and emotions. Theta waves are present during sleep, dreaming, and drowsiness and are linked to pleasant emotions.

The valence of emotions is reflected in the frontal lobe's asymmetrical alpha waves, and the midline sagittal channel is crucial for understanding EEG signals [11]. Alpha-waves are present when an individual is calm but awake, those are linked to neutral and negative emotions. Beta waves indicate emotional valence which are produced when the mind is focused.

and busy. Gamma waves are linked to increased brain activity. The power ratio of different waves can also serve as an indicator of the brain's level of activity [12, 13].

Identification of emotions can be improved using a combination of alpha, beta, and gamma waves in EEG. EEG signals have been found to have non-stationary features when it comes to emotions [14]. Studies have also found that the valence of emotions is asymmetrical in the forehead region, and that arousal is connected to activity in this region. Additionally, positive emotions are more evenly distributed and are less intense in the low-frequency band of EEG as compared to negative emotions, which are fully elicited in the higher frequency band [15].

EEG studies have shown that changes in emotional states, such as joy, sadness, or fear, are associated with changes in the strength of Theta, Alpha, and Beta waves on the midline of the brain. This suggests that the midline power spectrum of the EEG can be used as a feature for identifying emotions. Additionally, research has found that combining functional link network with local activation can help to understand how specific brain regions respond to emotions and how they are connected to other relevant areas, further aiding in the identification of emotions in EEG data [15].

1.3 EMOTIONS EVOKED

There are generally two methods used to evoke emotions in experiments: subject evocation and external event evocation. Subject evocation involves asking participants to recall specific emotional events or memories, but this method is not widely used due to its lack of control and uncertainty.

Dataset for Emotion Analysis dataset for emotion analysis using EEG, physiological and video signal (DEAP) database, the SJTU Emotion EEG Dataset (SEED), the International Affective Picture System (IAPS), the International Affective Digitized Sounds (IADS), Mahnob HCI, and personal experiments are some commonly used EEG datasets for emotion recognition.

To understand the brain's electrical activity EEG is a valuable tool during different events. Studies have shown that EEG can help identify brain wave activity associated with thoughts, feelings, and behavior [16, 17]. The use of datasets is also crucial for researchers Analyzing emotions [18]. Different studies have been conducted using various datasets to classify emotions, such as audio, video, and images. However, there is a lack of research on classifying emotions based on text stimuli. Further studies need to be conducted to better understand emotions based on different events and various stimuli, including text. The goal of such research is to classify emotions using EEG signals based on text stimuli.

1.4 PROBLEM STATEMENT

Different stimuli (such as audio, video, images) have been used to evoke and classify emotions based on EEG. Some studies also used text-based stimuli for discrimination of emotions [19, 20]. However, in these studies data was acquired from fewer subjects with lesser EEG channels. These studies have differentiated the positive and negative emotions with good accuracy rates (around 60-70%), which can further be improved by increasing the EEG channels and number of subjects.

1.5 RESEARCH QUESTIONS AND OBJECTIVES

The research questions and objectives of this study.

Research Questions

- RQ1: What is the relationship between the human brain and written text stimuli?
- RQ2: What techniques can be employed to improve the accuracy of emotionrecognition in written text stimuli?

Objectives

- To identify relationship of human brain with text stimuli
- To investigate and identify techniques that can be used to improve theaccuracy of emotion recognition against text stimuli.

1.6 SCOPE OF THE STUDY

The primary objective of this study is to classify emotions using emotional text stimuli as input. The study aimed to detect certain changes in the human brain using EEG to better understand the neural processes underlying emotional responses.

To achieve this goal, the study included the identification of a better feature extraction method for emotional text stimuli, which can improve the accuracy of the classification of emotion. The study also explored the use of deep learning and Machine Learning (ML) techniques for the analysis of emotion.

The goal of this study is to contribute to the field of mind-reading by providing a better understanding of how emotions are represented in the brain. The findings of this study can assist in the advancement of the knowledge about how the brain works and how emotions are processed.

1.7 CONTRIBUTION AND SIGNIFICANCE

The primary objective of this study is to investigate the development of an efficient emotion classification system using EEG signals. The study aims to use a combination of CNN layers along with SVM algorithm toextract features as well as to construct an efficient EEG emotion classifier.

The study focuses on identifying a framework that can effectively classify emotions against text stimuli and help us to understand human emotion in more detail. The study investigated the use of CNN layers to extract features and optimize their performance to improve the accuracy of emotion classification.

The study may contribute to the field of emotion recognition and may help in the development of assistive technologies for autistic people or mentally challenged people to express them

emotions. The study may also have potential applications in the field of mental health, providing a non-invasive way to monitor and understand emotional states.

1.8 OVERVIEW OF THESIS

The thesis is summarized in Chapter 1. It introduces the idea of BCI and previous EEG-based emotion recognition research. It describes how things evolved in the last few years of this technology. Additionally, the rationale for this thesis as well as its goals and scope have been discussed in this chapter.

Chapter 2 of the thesis provides an overview of the relevant background information and academic literature that informs the research. This chapter includes information on topics such as the human brain's anatomy, EEG signals, and theories of emotion, and draws on several academic papers to help understand the concepts used in the study.

Chapter 3 uses the literature and academic works introduced in this chapter to develop the thesis.

Chapter 4 describes the tests conducted on the installed system and provides an overview of the dataset and software programs used in the investigation.

Chapter 5 of the thesis provides a comprehensive examination of the results and analysis of the current study. It covers the data collected, the methods used to analyze it and the key findings and outcomes of the research. This chapter delves into the details of the study's methodology and results, providing readers with a thorough understanding of the research.

CHAPTER 2

BACKGROUND

2.1 Structure of Human Brain

Given how intriguing the brain is, neuroscience has been one of the most stimulating fields of study. A person's individuality and personality are determined by their brain, which is distinctive in every human being. The underlying emotions that participants were having at the time of the observations can be understood with the help of physiological signals coming from the brain [21].

EEG signals are electrical signals that are generated by the brain, and which are recorded using electrodes which are placed on the scalp or cortex. These signals reflect the activity of the neurons present in the brain and can provide insight into different states of consciousness and emotions. EEG signals are typically recorded along several channels, with each channel representing the activity of a specific region of the brain [22].

Prefrontal cortex and amygdala are the two main parts of the brain which are related to emotional activity [23]. Cognitive processes such as decision-making, planning, and social cognition have a relationship with prefrontal cortex. The amygdala is a small almond-shaped structure that is involved in the processing of emotions such as fear, anger, and pleasure. It is also involved in the processing of memories, particularly those with an emotional component. The temporal lobe includes the amygdala, and the frontal lobe of the brain consists of the prefrontal lobe. They are near the hippocampus, which is involved in the formation of new memories and spatial navigation.

Research suggests that the amygdala may be more active during stressful situations than during joyful ones, although its possible lateralization is not entirely clear [24]. Some studies have found that the left amygdala is more active in response to positive emotions, while the right amygdala is more active in response to negative emotions, while others have found that both amygdalae are activated in response to different emotions.

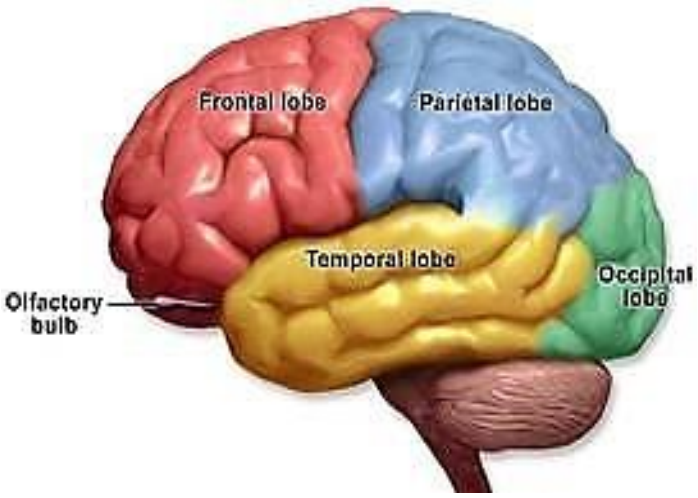

Figure 1 Human Brain

Adapted from: Blausen 0111 BrainLobes.png Blausen.com staff (2014).

The cerebrum, diencephalon, brain stem, and cerebellum are the four major components of the brain. The cerebrum, which is the largest component of the brain, is covered entirely by a layer of grey matter called as the cerebral cortex [25]. Cerebral cortex encircles the forebrain on both sides and is divided into two separate sections known as the right and left cerebral hemispheres [25]. There are four lobes that make up the hemisphere frontal, parietal, temporal, and occipital lobes and each has a specific function in the brain [25].

2.1.1 Temporal Lobe

The temporal lobe is responsible for speech, long-term memory, and auditory recognition. It is also where sensory input is processed, and memories are formed. The processing of emotional information, including arousal, occurs in this area of the brain [25]

2.1.2 Frontal Lobe

The frontal lobe is connected to the motor system and controls awareness, short-term memory, and cognition. This is the region of the brain where most cognitive processes begin, and positive emotions such as pleasure and contentment are associated with frontal lobe [25].

2.1.3 Parietal Lobe

The parietal lobe interprets haptic sensations such as touch, pressure, and pain, as well as proprioception (known as the sense of bodily position) and kinesthesia (also called as the sensation of movement) [25].

2.1.4 Occipital Lobe

Brain's visual processing, including visual object and information is done by occipital lobe.

Frontal and parietal lobes serve primarily as descriptive regions for cortical emotional activity. Nevertheless, gamma, beta, and alpha waves have a discriminatory function. According to some experts, gender influences how the brain absorbs emotional triggers. According to the generally accepted belief that women are more sensitive to their emotions than males.

2.2 Emotional Well Being

Emotional well-being, also known as emotional health, is a key component of overall well-being. It is typically defined as having pleasant sentiments, a high degree of life satisfaction, happiness, and the ability to control negative emotions [26]. Emotional well-being can be measured by means of six dimensions, which include the physical, social, mental, emotional, material, and professional according to Lovén et al. [27]. A balance of negative and positive emotions which can also be categorized, low levels of stress, and emotional resilience. Figure 2 illustrates the six aspects of well-being that are commonly used to describe emotional well-being.

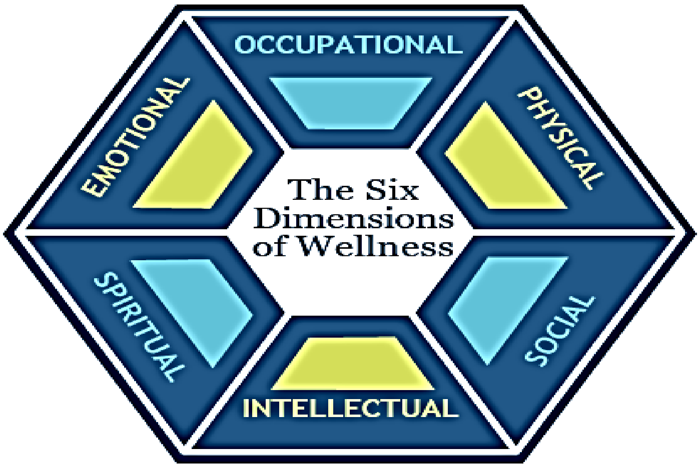

Figure 2 The six dimensions of well-being visual representation as described by

Emotional well-being is characterized by a balance of positive and negative emotions. It is typically defined as having pleasant sentiments and the ability to effectively manage negative feelings [27]. Emotional health is an essential component of overall well-being. It impacts our relationships with others on both a personal and professional level, enhances the enjoyment of life, and makes it easier to achieve our goals [27]. Maintaining good emotional health involves developing the ability to recognize, express and manage our emotions in a healthy way, and seeking help when necessary.

Advantages of emotional health

Paying attention to our emotional health is as important as it is to our physical and mental health.

Resilience: Emotional well-being plays a significant role in building resilience which enables individuals to bounce back from adversity and manage stress more effectively. Studies have shown that people with good emotional well-being have a stronger immune system, making them less vulnerable to physical illness [28].

Communication: Emotionally stable individuals tend to have great communication skills as well as responding to others in a better manner. They can express themselves effectively and actively listen to others.

Self-regulation: Emotionally healthy individuals possess self-regulation abilities, which enable them to manage difficult circumstances and carry out their tasks even under stress. They can control their emotions and reactions to situations, rather than allowing their emotions to control them.

Motivation: People with good emotional well-being have a positive outlook on life and are motivated to achieve their goals, even in the face of adversity.

Relationship building: People with good emotional well-being are better equipped to build and maintain positive relationships with others. They can understand and empathize with others' feelings and respond in a positive way.

Decision making: Emotionally stable individuals are better able to make sound decisions and think critically. They can weigh the pros and cons and make logical choices.

Stress management: Emotionally healthy individuals have better coping mechanisms to handle stress and bounce back from difficult situations. They can manage stress in a healthy way, rather than letting it take over their lives.

Mental health: Good emotional well-being is linked to better mental health and a lower risk of developing conditions such as depression and anxiety.

2.3 What Is Emotion

Emotions are affective states of mind that include feelings such as happiness, sorrow, worry, hate, etc. According to the book "Discovering Psychology" by Don Hockenbury and Sandra E. Hockenbury, emotions are made up of three components: subjective experience, physiological response, and behavioral or verbal response [29].

Conscious awareness of an emotion is called subjective experience. It is the individual's perception of their emotional state, and it can vary greatly depending on the person and the situation. For example, one person may experience fear while watching a horror movie, while another person may experience excitement.

Physiological response is the bodily changes that occur in response to an emotion. These changes can include changes in blood pressure, breathing rate, heart rate and muscle tension. For example, when a person is angry, they may have an increased heart rate, while when they are happy, they may have a decreased heart rate.

The way an individual behaves or speaks in response to an emotion is known as behavioral or verbal response. This can include things like facial expressions, body language, and tone of voice. For example, when a person is sad, they may cry, or when they are happy, they may smile.

Together, these three components work together to create the overall emotional experience. They are all essential for the expression of emotions and can be used to help understand and identify different emotions in ourselves and others.

2.3.1 Personal experiences

People of all backgrounds feel basic common emotions including happiness, sorrow, fear, and rage despite of their culture or place of birth [30].

2.3.2 Physiologic reaction

The autonomic nervous system's physiological condition, which is accompanied by emotions, causes physical symptoms such increased heart rate, perspiration, and sweating [31].

2.3.3 Behavioral reaction

The outward display of emotion is sometimes referred to as the behavioral reaction. Body language, posture, and facial expressions are a few examples of how people convey their emotions via their behavior [31].

2.3.4 Theories of Emotion

To characterize emotion, several theories have been put forward. We briefly touch on a few of them in this section.

2.3.4.1 The Emotion-Based James-Lange Hypothesis

The James-Lange hypothesis of emotion was put out by two renowned physiologists, William James, and Carl Lange. In their hypothesis, they claimed that people's emotional experiences are the result of physiological reactions to outside events [32]

2.3.4.2 The Emotional Cannon-Bard theory

The Cannon Bard theory of emotion suggests that emotional experiences and physiological responses occur simultaneously and independently of each other, this theory was proposed by Walter Cannon and Philip Bard in the 1920s. According to this theory, emotions are not caused by physiological responses, but instead, physiological responses and emotions are triggered by a stimulus at the same time.

The theory suggests that when a stimulus is encountered, it is processed by the thalamus, which sends signals to the sympathetic nervous system and the hypothalamus. The sympathetic nervous system then activates the physiological response, such as an increase in heart rate and blood pressure, while the hypothalamus is responsible for the emotional experience.

This theory differs from the James-Lange theory, which proposed that emotions are caused by physiological responses. The Cannon-Bard theory suggests that the emotional experience and physiological response are separate but occurring simultaneously.

Cannon-Bard theory also suggests that different emotions can be accompanied by the same physiological response. For instance, an increased heart rate and sweating could be associated with fear, anger, and surprise.

The Cannon-Bard theory has been criticized for its lack of empirical support and its inability to explain how emotions are differentiated from one another. However, it is still considered as an important contribution to the field of emotion studies.

For instance, exercise may cause a significant increase in heart rate, which is not always a sign of anxiety [33]

2.3.4.3 Valence Theory of Emotion

Silberman and Weingartner in the 1970s proposed valence theory of emotion which is also known as hemispheric valence theory [34]. This theory suggests that emotional valence, or the positive or negative nature of an emotion, is determined by the activation of specific brain regions and hemispheres.

According to this theory, the right hemisphere is primarily associated with negative emotions, such as fear, disgust, and anxiety while the left hemisphere is primarily associated with positive emotions, such as pleasure, happiness, and excitement [34]. This is based on the idea that the left hemisphere is dominant for language and logical processing, which is associated with positive emotions, while the right hemisphere is dominant for spatial processing and nonverbal communication, which is associated with negative emotions [34].

The left and right hemispheres play complementary role in emotional processing according to the valence theory of emotion [34]. The right hemisphere is responsible for the physiological response to an emotion as well as left hemisphere is responsible for the cognitive appraisal of emotion [34]. This theory also suggests that the balance of activity between the two hemispheres is important for the overall emotional experience [34].

The valence theory of emotion has been supported by some research, but it has also been criticized for its lack of empirical evidence and for oversimplifying the complexity of emotional processing. More recent research has shown that emotional processing is a complex and dynamic process that involves multiple brain regions and networks, rather than just specific hemispheres.

2.3.4.4 Emotional Theory of Approach-Withdrawal

The emotional theory of approach-withdrawal is a theoretical model that suggests that emotions are linked to a person's behaviors in their environment [35] According to this theory, emotions are evolutionary adaptations that serve to promote or inhibit approach or withdrawal behaviors in response to environmental stimuli [35]

The approach strategy promotes behavior associated with hunger and approach-related positive effects, such as pleasure and excitement, as a person approaches the desired objective [35]. This strategy is associated with positive emotions such as happiness, pleasure, and excitement [35].

On the other hand, the withdrawal strategy promotes behavior associated with avoiding or withdrawing from sources of unpleasant stimuli [35]. This strategy is associated with negative emotions such as fear, disgust, and anxiety [35].

It was suggested by the theory that anger is an approach emotion because it causes an individual by protecting themselves from sources of stimulation, which is why it is associated with happiness [35]. This is different from the valence theory of emotion that classifies anger as a negative emotion [35].

This approach-withdrawal theory is based on the idea that emotions are adaptive behaviors that evolved to help organisms survive and thrive in their environment [35]. It emphasizes the role of emotions in motivation and goal-directed behavior and suggests that emotions have a functional purpose in guiding behavior [35].

2.3.4.5 Circumplex Model of Emotion

The circumplex model of emotion, proposed by James A. Russell in 1980, is a two- dimensional emotional space that characterizes emotional states as a linear combination of valence (positive or negative) and arousal (High or low) [36].

This model aims to provide an experimental as well as a framework for understanding the neural basis of emotions, and it has been widely used to assess emotional responses to words, facial expressions, and cognitive reactions [36]. The center of the circumplex model represents a neutral emotional state with medium arousal, and the X-axis represents the valence dimension, ranging from positive to negative. The Y-axis represents the arousal dimension, ranging from low to high [36].

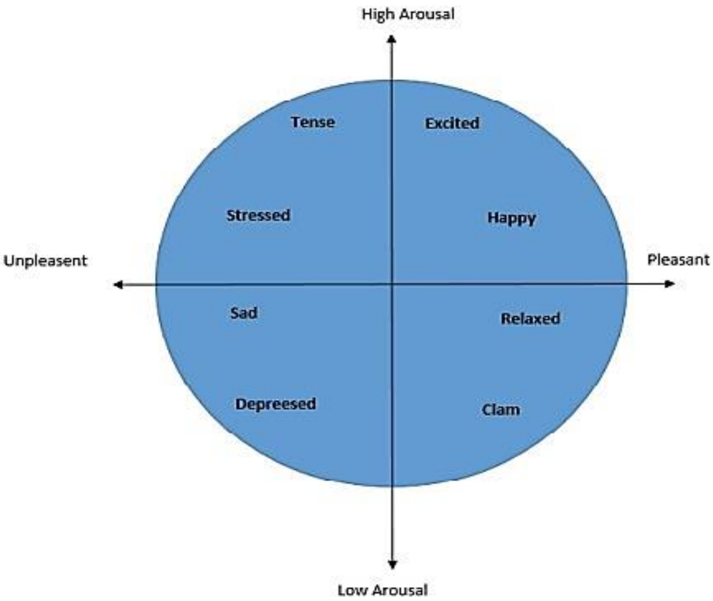

Figure 3 Circumplex model of emotion by Russell

The circumplex model of emotion has been widely used in research on emotion, as well as in clinicalpsychology, to understand and assess emotional disorders, such as depression and anxiety [36] Overall, the circumplex model of emotion is a widely accepted theory that provides a framework for understanding the neural basis of emotions, and it has been widely used in research on emotion and in clinical psychology to understand and assess emotional disorders. The circumflex approach is typically used to assess the emotional words, facial gestures, and cognitive reactions that are triggered [37].

The circumflex model of emotion is seen in Figure 2.3. A neutral valence and a medium degree of arousal is described by the model. The valence states are reflected by the x-axis; the arousal is specified by y-axis.

2.4 Electroencephalography

As this field was new for me so I went into details to gain a deeper understanding of

EEG.

Galvanic Skin Response (GSR) signals are a measure of physiological arousal produced by the human body, and these signals increase exponentially with increased activity in neurons. This increase in activity is caused by synaptic excitations that excite the dendrites of neurons, resulting in a difference in electrical potentials. According to sources [9, 38], EEG sensors need to activate a sizable number of neurons to detect these low-voltage occurrences.

The methods utilized to record the electrical activity of the brain which then can be divided into two categories: invasive and non-invasive approaches. [39] invasive treatments require surgical intervention to implant a device in the brain, while non-invasive techniques do not. One of the non-invasive methods is EEG for capturing brain waves [40].

An EEG is an equipment which is used to measure the electrical activity of brain waves [41]. Conductive gel is used to place electrodes on the scalp surface, amplifying and digitizing the impulses before measuring the electrical activity of the brain, as described in source [42]. Nowadays, there are portable, hassle-free EEG headsets available on the market, such as the "EMOTIV," which make it easy for individuals to use EEG technology.

2.4.1. EEG History

In the middle of the nineteenth century EEG technology was developed. As an English scientist, Richard Caton, examined the electrical activity in animal brains. Later in his studies, Ernst von Fleischl-Marxow found a relationship between muscular movements and brain activity. these two study directions led a German scientist to develop the EEG.Berger recorded the brain impulses silver foil electrodes were used by him as well as capillaryelectrometer, and a galvanometer. He was the first person to successfully record beta and alphabrain waves. "EEG." This name was given by Berger. It was realized that even electrical impulses this faint may be captured and amplified without requiring any type of surgery. The records were graphed on paper. It was proposed by him that it could be possible to distinguish between awareness and relaxation using the ongoing oscillations in EEG data [43].

It was shown in a study by Adrian and Matthews that "human brain waves" exist in a study it waspublished by them in 1934 [44]. Alpha-band was found to be oscillating between 10 and 12 Hzfrequency. The occipital lobes of the cerebral cortex are where the recordings were made. the rhythm disappeared when an individual got little more conscious or became concentrated.

Franklin Offner developed Concentric needle for use in EEG equipment. In 1935 when

Gibbs recognized the specific structure of spike waves when Clinical electroencephalography discipline was founded, [45] Later, researchers developed several techniques for identifying, sorting, and classifying brain signals, which gave them the ability for the identification of brainsignals that were malfunctioning.

The central reticular core of the brainstem triggers a response selection in the diffusely damaged brain, as scientists Moruzzi and Magoun found in 1949. With this approach, it is simple to prioritize some information while disregarding others [40]. To understand how the EEG signals were available throughout the surface of the brain William grey developed the EEG topography in 1950s. This idea was used in the research of neurophysiology for several decades after that. Several innovative EEG signal processing methods were developed and used in the years that followed.

2.4.2. Overview of EEG

Frequency bands are used to classify EEG signals. Several signal characteristics are taken into consideration when it comes to the analysis of EEG signals when it is carried out. Voltage is assessed in EEG tests as a function of time. The cerebral cortex's activity has a significant impact on EEG features [40, 46]. EEG signals often include a variety of waveforms and are sometimes classed initially by their frequency, such as alpha, beta, gamma, theta, and delta. The human brain emits these signals for various cognitive processes. Either of these frequency ranges will be more noticeable depending on the dominant task being performed by the brain. Second, the size of the waves is also considered. Another important factor in EEG analysis is the study or understanding of waveform.

A further consideration in the analysis of EEG data is spatial consideration. This depicts the analysis of EEG data by investigating of signal rhythmicity. One technique for analyzing the signal and removing artefacts is periodic waveform analysis, or PWA. These artefacts may include noise caused by the body moving or the eyes blinking while the signal is being captured. Particularly important for clinical applications is this element. Another factor is how sensitive the signals are. Reactivity is the change in an EEG signal's baseline activity brought on by external stimulus. This EEG component is used clinically to diagnose people with consciousness issues such coma and Traumatic Brain Damage (TBI).

2.4.3. Bands of EEG

The EEG method detects voltage variations brought on by ionic current and uses them to calculate the electrical activity of brain neurons. These five frequency bands—delta, theta, alpha, beta, and gamma—are categorized as brain waves and are frequently referred to as such.

Based on the frequency range that each of these bands corresponds to, they may be recognized.

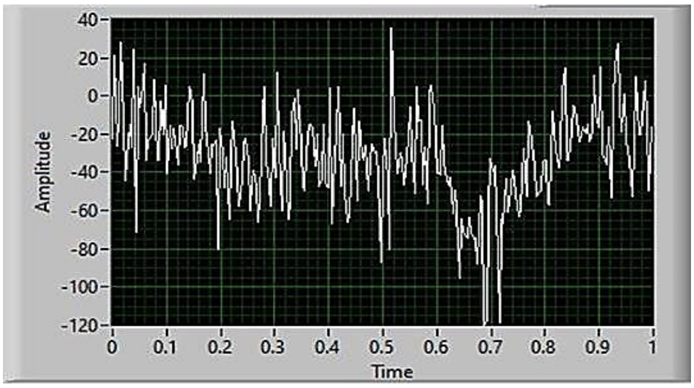

Figure 4 Raw EEG Signal [42]

2.4.3.1. Delta Waves

Delta brain waves often have amplitudes of more than 100 microvolts and range in frequency from 0 to 4 Hz. They frequently occur during sleep and are linked to produce growth hormones, which plays a vital role for self-healing [42].

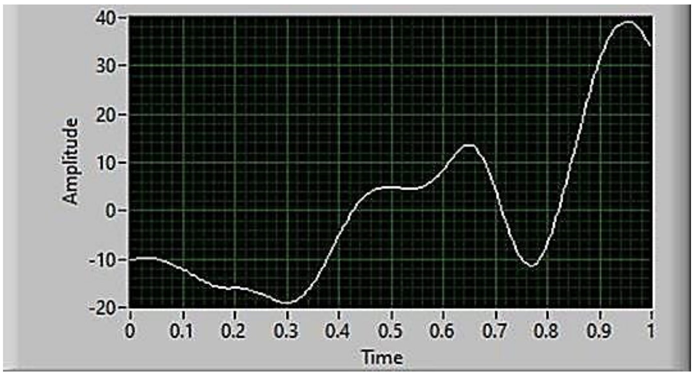

Figure 5 Delta waves [42]

2.4.3.2.Theta Waves

Theta brain waves, which vary in frequency from 4 to 8 Hz and are linked to creativity and task attention. Theta activity has been associated with difficulties making decisions, and an abundance of memories can reduce theta frequency [47].

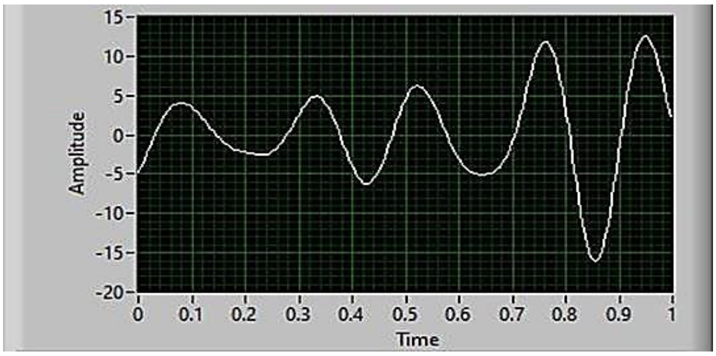

Figure 6 Theta waves [42]

2.3.3.3. Alpha Waves

Alpha brain waves are produced on the right hemisphere of the brain, having a frequency range of 8 to 13 Hz.

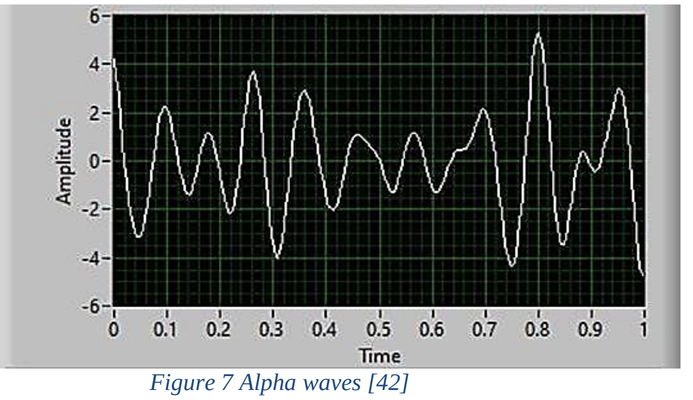

Figure 7 Alpha waves [42]

They are believed to enhance inner peace, lessen pain and cognitive stress, and are connected to abstract thinking and mental calmness [42]. It has also been discovered that alpha activity reflects visual processing [46].

2.3.3.4. Beta Waves

The left hemisphere of the brain produces beta brain waves, which have a frequency range of 13 to 30 Hz. They are associated to active task involvement, including decision-making, problem-solving, attentiveness, and other cognitive functions. Beta waves have the potential to stimulate the nervous system and speed up brain processing at high levels. Learning, information processing, and cognitive function are frequently linked to beta activity.

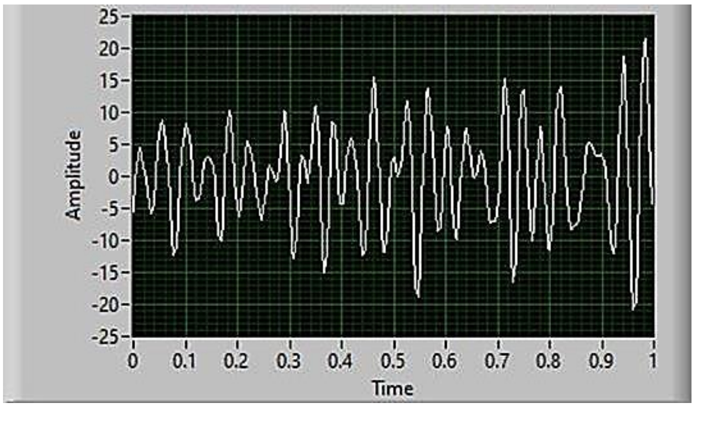

Figure 8 Beta waves

2.3.3.5. Gamma Waves

Gamma brain waves, which having a frequency range of 30-100 Hz, are linked to high levels of consciousness and rapid information processing. They are frequently absent from unprocessed EEG records.

High levels of gamma brain wave activity have been linked to improved cognitive processing, but they have also been linked to problems establishing new memories [42, 48].

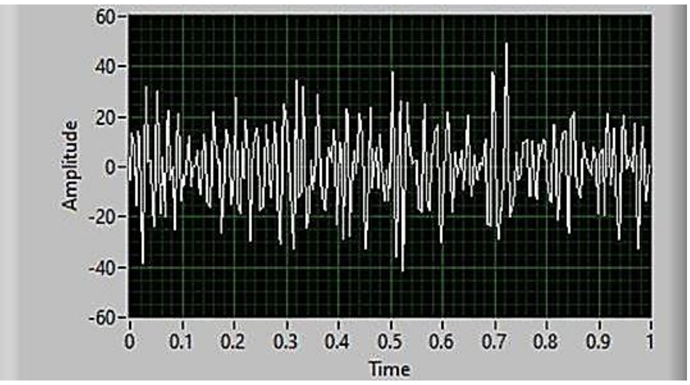

Figure 9 Gamma waves

2.3.4. Uses of EEG

The EEG has many uses since it is thought to be a secure and comfortable way to monitor the brain. This section has discussed a few of its applications.

Medical Innovation

EEG is increasingly used by biohackers and athletes to track their brain activity. This is used for assessing a person's cognitive capacities, including attention, distraction, and the stress of daily life. Using information from EEG data, they may create rational, scientific methods for reducing stress, improving concentration, or improving meditation [49].

Healthcare

There has been a significant increase in the use of healthcare EEG in the diagnosis of brain diseases such as brain dysfunction, head trauma, dementia, seizure disorders, sleep problems, memory problems, brain tumors, and stroke, [49].

Monitoring of sleep

EEG can be used for the evaluation of an individual's polysomnography, a method of diagnosing sleep issues. This method is frequently used to monitor nocturnal sleep patterns, oxygen saturation levels, heart rate and breathing [49].

Academic Research

To study cognitive psychology Researchers frequently utilize EEG, neurology, and other issues pertaining to mental impairments. Recent advancements in computer processing and hardware have given us the chance to learn more about the working of human brain also for the investigation of the basic neurological processes that underlie emotion regulation, perception, and behavior [50].

2.3.5. EEG Signal Acquisition

The following aspects are included in EEG signal recordings.

2.3.5.1. EEG Electrodes

For recording brain electrical activity, The EEG electrodes are one of the most crucial components. These are frequently metal discs or pellets made of stainless steel, tin, gold, or silver that are attached to the cranium using conductive paste, gel, or saline. The two types of commercially accessible EEG recording electrodes are wet and dry electrodes. The most common kind of wet electrode is Silver Chloride (AgCl), which consists of a layer of silver (Ag) and (AgCl). On the other hand, dry electrodes can be used to do the same task directly onthe skull without the need of electrode gel. [51]

2.3.5.2.Electrode Positioning

The 10/20 technique is most typically used to standardize the electrode placement system. The International Federation in Electroencephalography and Clinical Neurophysiology initially proposed this standardization in 1958 [52] It was based on the location of an electrode and the region of the cerebral cortex directly below it. The distance between electrodes from the tip of the nose, frontal regions, and inion, three landmarks on the skull, is represented by the numerals 10 and 20. According to this method, the inter-electrode distance would be 10% to 20% of the entire front-back or left-right distance [52]. The following electrodes are marked with the letters and numbers F (frontal), C (central), T (temporal), P (posterior), and O. (occipital). With the odd number designating the left hemisphere and the even number designating the right hemisphere, the electrodes are positioned across the midline core brain regions [51].

2.3.5.3.Number of Recording Electrodes

There is no predetermined ideal number of electrodes for EEG recording. The number of electrode channels in the experiment might range from 3 to more than 128, depending on the results and conclusions.

2.3.5.4.Electrode Impedance

Dead skin, scalp sweat, and greasy skin secretions can all hinder the transmission of brain electrical activity (sebum). Technically speaking, the resistance to this electrical activity is called the impedance, and it is measured in Ohm Ω units. To record high-quality EEG data, it is essential to keep electrode impedance as low as practical.

Impedance can be decreased by using the proper amount of electrode gel or saline and carefully cleaning all electrode areas with alcohol [51].

2.3.5.5.Signal Digitization, Amplification, and Transmission

In an active brain, the voltages created by an ionic current within the neurons are continually varying and changing [51]. The generated voltage is captured by the electrodes and is then sent to the amplifiers for amplification and digitization. The signal is subsequently transmitted wirelessly (through Bluetooth) or through a wired (like USB) connection to the recording computer [51].

2.3.5.6.International 10-20 EEG Placement System

The 10/20 system is a standardized method for positioning electrodes on the scalp during an EEG study. This system divides the scalp into a series of areas, with electrodes placed at specific points within each area. The goal of this system is to provide a consistent method for positioning electrodes that can be used across different studies and research projects. The 10/20 system uses a grid of electrodes placed at 10% and 20% intervals along the scalp, with the "C" electrode serving as a reference point. The American Electroencephalographic Society has also modified the 10/20 system to include intermediate 10% positions. In this modified version of the system, a total of 21 electrodes are used to capture EEG signals. The 10/20 system is commonly used in research and clinical settings to study brain activity and function.

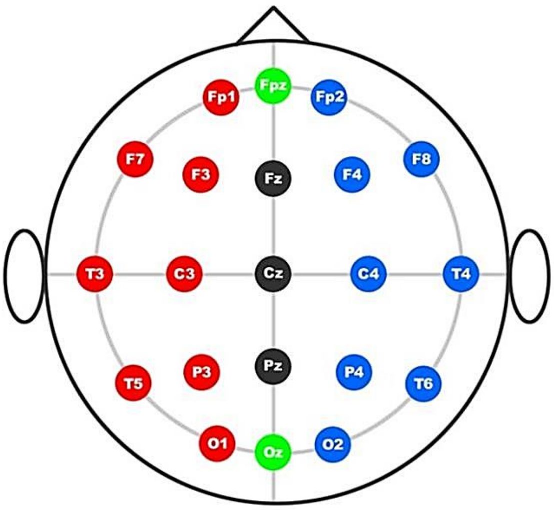

Figure 10 10/20 International positions of placement

TABLE 1 LETTERS TO IDENTIFY THE LODE POSITION

Electrodes	***Lobes***
P	Parietal Lobe
T	Temporal Lobe
F	Frontal Lobe
C	Central Lobe

Electrodes	*Lobes*
O	Occipital Lobe

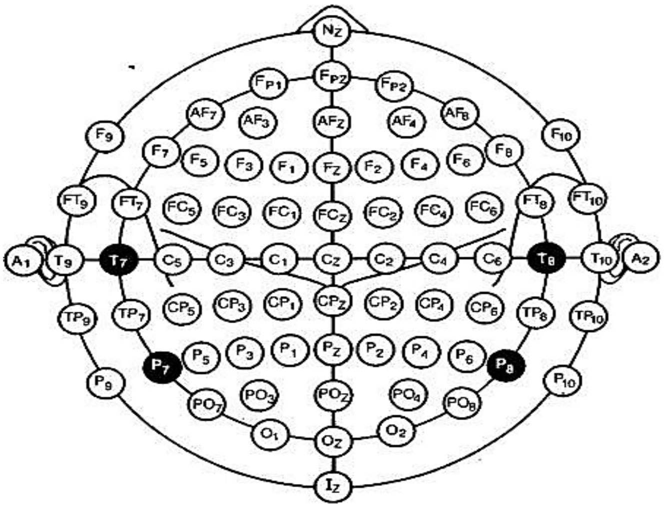

Figure 11 Modified 10/20 System source from [53]

2.3.5.7.ARTIFACTS

Artifacts or noise are unwanted signals that corrupt the brain waves during EEG signal monitoring. These items may be generally split into two groups.

a) Physiological Artifacts: These are the artefacts that the human body produces because of numerous biological functions including breathing, head, jaw, and tongue movement, eye movement, and blinking. Electro-oculograms, or EOGs, are artefacts that are produced by blinking and eye movement that occur below the frequency range of 4Hz. Another artefact brought on by heart rate is the ECG (electro-cardiogarphy), and the EMG (electro-myography), which is brought on by head and muscular movement, is often evident above the frequency of 30Hz.

For the HCI investigation, EMG and EOG artefacts are primarily considered among all these physiological artefacts [49, 54-56].

CHAPTER 3
LITERATURE REVIEW

3.1 Overview

Functional connection studies using EEG in the context of emotion recognition have gotten a lot of interest [52, 57, 58]. The brain regions engaged in a task are investigated using EEG-based functional connectivity. Functional connectivity is investigated using the similarities between activation maps or time series.

In several studies, EEG-based functional connectivity has been used to investigate brain regions engaged in emotion recognition tasks. In a study [52] participants watched video snippets to elicit neutral, positive, or negative emotions and the EEG signals were used to classify the emotions. The study aimed to explore the functional connection patterns in the brain using EEG-based functional connectivity and the results of the classification showed a high accuracy in identifying different emotional states.

IAPS dataset [58] was used for the evocation of happy, negative valence, and EEG signals were captured using electrode caps. A feature extraction algorithm was developed using Hjorth parameters (HP) and an SVM classifier was used for the classification of emotions. The results indicated that the HP and SVM classifier were able to accurately classify the emotions evoked by the IAPS images. Additionally, [59] created virtual settings using IAPS images to evoke positive or negative valence and a collection of characteristics derived from EEG data was fed into a SVM classifier. The study aimed to investigate the feasibility of using EEG signals to recognize emotions evoked by visual stimuli in virtual environments. The results mentioned that the classifier was good enough for accurate classification of emotions evoked by virtual environments.

A recent study [60] used Fredrickson's 10 positive emotion frameworks to recognize distinct positive emotions using EEG signals, using film clips to generate various happy feelings. The study aimed to explore the feasibility of using EEG signals to recognize different positive emotions. Based on subject judgements the emotions were divided into three groups based on the participants [61], “encouragement", "playfulness", and "harmony". However, the emotion recognition was limited to the video stimuli dataset.

IAPS images are used [62] for the elicitation of happy or sad emotions and the EEG signals were acquired through electrodes. Discrete WTs coefficients after which was then classifier was fed with those features, and the experiment was conducted on 22 subjects. The study aimed to investigate the feasibility of using EEG signals and discrete WTs to recognize emotions evoked by visual stimuli. The results showed that the classifier was able to accurately classify the emotions evoked by the IAPS images.

Using IAPS images happy or sad emotions were elicited [62] The EEG signals were acquired using EEG electrodes. A classifier was fed with discrete WTs coefficients. The experiment was conducted on 22 subjects. False memory the influence of positive and negative emotions was studied [63]. Twenty-eight participants were randomly divided into positive and negative groups and music was usedto induce corresponding emotions. The study aimed to investigate the impact of emotions on false memory and according to the results it was given that the brain of the positive group was more active as compared with the negative group and that positive emotions had a significant impact on false memory.

Most of the research on emotion recognition uses experimental data due to the nature of emotions. This information can be in the form of brain signals [64, 65] voice (audio) [66, 67] text [68, 69] facial expressions [64, 65] or a mix of various modalities [70, 71]. In some circumstances, information that was not developed expressly for emotion recognition is used to perform emotion recognition, such as video clips and audio recordings. Nevertheless, employing datasets designed expressly for emotion recognition is a more popular strategy. These datasets are produced by employing some sort of stimulation to elicit an emotional reaction. There are many datasets available for recognizing facial emotions. These datasets contain participant face expressions captured in still photos or short facial video clips. The stimuli utilized to elicit emotions for face emotion detection are frequently audio-visual (i.e., movie clips) [6, 72, 73] however still images [74] tasks based in a lab for producing emotions [75] or posed emotions [76] have also been used.

Three categories—induced, mimicked, and natural—can be distinguished among the datasets used for speech-based emotion identification. The most often used datasets are the simulated datasets, which frequently contain recordings of individuals. The recordings contain language that is linguistically neutral, but they are spoken to convey various emotions [77] Although there are many distinct simulated datasets (available in many languages) for many different emotions, and these datasets can typically be easily standardized, they don't always accurately reflect emotions experienced in the actual world. Compared to synthetic datasets, induced speech recognition datasets more closely mimic real-world emotions. These datasets are produced by listening to a participant and an anchor converse while the latter is guiding the dialogue to elicit an emotional reaction [78] The range of emotions might be confined.

Real-world speech may not exhibit the same level of emotion as simulated and induced emotion datasets, making it more challenging to identify. There are certain datasets that can be utilized for emotion identification that employ recordings taken in natural environments (such as call centers and cockpits). The natural data might not cover all the feelings, like generated emotion datasets. Additionally, emotion labels (or actual emotion labels) are not present in natural databases to evaluate the classification outcomes against.

The use of brain waves (signals) for emotion identification is very different from earlier techniques. Most individuals can instantly identify someone's emotions just by looking at them or hearing them. However, in a natural setting, people cannot decipher the brain messages. EEG recordings are used in most brain signal databases [6, 73] This is since EEG systems are less expensive and simpler to use than other brain signal recording equipment. To identify emotions and find brain regions associated with them, researchers have employed functional Magnetic Resonance Imaging (fMRI) [79] and MEG recordings [80] Typically, auditory (such as music) [81] visual (such as still pictures) [82] or audio- visual (such as movie clips, music videos) stimuli are utilized to identify emotions from brain signals. Participants must remain motionless for most brain signal recordings. Theoretically, brain signal recordings for emotion detection may be carried out in a natural environment using portable EEG sensors.

Additionally, some research has been done on classifying emotions using a variety of various modalities. For instance, [83] uses both facial expressions and EEG data, while [84, 85] uses both speech and facial films. Additionally, text may be used to recognize emotions. These datasets often include labels-annotated phrases (and/or brief paragraphs) (sometimes by third party). Since the way people react to stimuli varies greatly depending on the issue, selecting the right stimuli to trigger emotions can be challenging. For instance, although some people find images of cats to be appealing (related to positive feeling), others may find them indifferent or even repulsive. Due to the nature of the recordings, the options for stimuli for brain signal based emotion detection are likewise restricted to auditory, visual, and audio-visual stimuli. In general, video snippets are more effective in eliciting emotions. An Emotional Movie Database (EMDB) is described in [72] and includes labels (using the VDA scale) for the films as well as a collection of tested non-auditory clips that may be utilized for emotion identification. These classifications were determined by looking into the self-evaluations of 131 individuals [72] When one wants to capture feelings over a longer period, using video snippets might be helpful.

Less samples in an EEG-based emotion detection dataset are frequently associated with a longer time frame. The use of visuals as stimuli is common when a shorter time is preferred. The International Affective Picture System (IAPS) is a sample image-based emotioncollection that includes VDA labels [82].

3.2 Feature Extraction Methods

Extracting a specific feature from an EEG that is appropriate for the study is known as feature extraction. It is an essential component of emotion recognition using EEG; only extract the relevant characteristic that corresponds to the emotion to ensure the accuracy of the classification. A brief overview of the field of emotion identification via EEG was put out by Kim. [5] The reliable features reflect the relevant, practical data for the tasks' unique requirements. In general, having excellent features helps to identify emotional states effectively and practically, as it significantly determines a system's unique capacity to recognize objects via EEG [86]. Traditional approaches for extracting EEG features usually employ the time domain, frequency-domain, and time-frequency domain. [87, 88], respectively. Multiple novel types of EEG feature extraction methods have recently been presented as EEG-based research has grown. Deep neural networks and channels are used to produce significant improvements [2, 89, 90].

Despite the effectiveness of the new type of feature extraction techniques, conventional techniques also advance this field of study. Reviewing the contributions of various feature extraction techniques is important as a result. In the section that follows, I will describe a wide range of relevant feature extraction appropriate methodologies for EEG-based emotion identification in each domain independently. Qualities in time, frequency, time-frequency, and other new sorts of approaches are distinguished in general.

3.2.1. Time-Domain feature extraction

Time domain features refer to utilizing the EEG signal to extract time domain data or statistics to achieve a more advanced strategy [87].

EEG is a type of continuous time-series data that collects the most logical data to depict changes in human states. The comparatively easy, simple, and fundamental techniques for extracting time-domain characteristics are used in EEG-based research [87] Time-domain feature extraction techniques often use time-series EEG data that has already undergone artefact removal without any further manipulation, in contrast to other feature extraction techniques. As a result, ongoing time-domain-based EEG research representsthe core and most productive EEG processing technology. The text that follows will outline several excellent strategies.

The term "event-related potentials" (ERP) describes how the potentials in a particular area of the brain fluctuate in response to the delivery or cancellation of stimuli [91].

Typically, the ERP researcher would use images of various emotional face expressions or colors as stimuli, then identify various emotions by examining the evoked potentials in related brain areas. [92] used the amplitude and latency of ERPs (P100, N100, N200, P200, and P300) as features in their study. Eimer uses human face photographs with either neutral or terrified emotions as stimuli to discriminate between scary and neutral emotion [93].

According to their findings, when panic-related emotions are exhibited vertically, individuals generate a positive inherent frontal potential in 120 ms, however when the image is presented upside down, the corresponding potentials delay. Furthermore, they observed that emotional face photographs can improve ERP when compared to shots of emotionless faces. Furthermore, the N170 phenomenon reveals that the two parallel systems for information processing in the brain—emotional expression analysis and facial structure coding—do not change emotion identification. Because ERP is so simple to extract, there has been a lot of study on using it to achieve BCI [93, 94]

The probable issue is a weaker relationship between emotion and ERP data, which is caused by a lack of certain EEG-based emotion that relies on ERP. The most common and fundamental time domain feature strategy is the extraction of EEG signal statistics such as the standard deviation, mean, peak, absolute value, and other metrics [86]. Barr et al. [95] used the peak approach to compute and evaluate the registration of reduced activity traveling on EEG waves over the threshold of amplitude. As EEG characteristics, Khalili also proposed the first difference mean absolute value of the original data and the first difference mean absolute value of the normalized data [96]. Zhang proposed that the EEG feature be the time domain amplitude difference betweensymmetrical electrodes [97]. Yuen et al. [98] proposed the standard deviation, mean first difference, and second difference as inputs to the back-propagation neural network for emotion classification.

High-order-cross is a well-known approach for obtaining time-domain EEG characteristics (HOC). The zero-crossing counting filter [99] is applied to the sequence of time series EEG data. Petrantonak et al. used HOC to extract the feature from the intrinsic mode functions (IMFs) utilizing EMD to achieve the EEG-based emotion categorization. [100]. He proposed applying HOC to assess four distinct classifiers to get the maximum accuracy for emotion classification: discriminant analysis (QDA), KNN, SVM, and Mahalanobis distance, [101]. Liu [102] proposed that the features for emotion recognition tasks be a mix of statistics and HOC. I utilized HOC as a feature to recognize emotions in some of my earlier approaches, and I obtained extremely good results [103].

Mathematicians typically employ Fractal Dimension (FD) as an extraction method for determining time-series properties [104]. Because the EEG signal is chaotic and nonlinear, multiple studies show that FD is usefulfor EEG time domain feature extraction [105, 106]. The use of FD as an EEG features to differentiate between good and bad emotions wassuggested by Aftanas et al. [107] The study of Wang et al. [108] on EEG-based concentration detection included FD. When applying musical stimuli to an EEG, the author presented the FD as characteristics analyze emotion [109, 110]. To create real-time EEG emotion identification systems, FD was proposed as an onlinefeature extraction technique [111]

Despite the studies of EEG feature extraction of time-domain techniques which are mentioned, there are also exist several studies on time-based EEG processing. Three-time domain statistics Hjorth [87] offered where features were handed to the following researchers, who used this approach to produce varied results [86, 112, 113]. The non-stationary index (NSI), which Kroupi et al [114]. initially local average is used which are dependent to time to accomplish classification of emotion seldom employed in other EEG-based studies [115,116]. EEGLAB, which Delorme et al. [117] introduced, is a well-known EEG-processing program that offers one of the best for time dependent feature extraction and preprocessing. EEGLAB is commonly used as a support tool for EEG-based research.

3.2.2. Frequency-Domain feature extraction

By converting the EEG signal from the time domain to the frequency domain, frequency domain features which refer to the process of extracting the pertinent frequency characteristics as EEG features. The five mostly used EEG frequency bands are delta with the frequency of (1-4Hz), theta a frequency (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (36-44Hz) show correlations with all human physiological and psychological functions, according to earlier studies. The numerous EEG frequency bands, such as decision-making, mediation, emotion, memory, and other processes, represent the many brain functions by themselves or in combination with one another [118]

The initial step in frequency-based EEG research is transformation of time-series into the frequency domain. Various techniques, like DWT and (FFT) Fast Fourier transform (FFT) can be used [119-123].

Band power [124-126] power spectrum [127, 128] and power density spectrum [129, 130] are included as the frequency domain common features [86].

Extraction of frequency domain information is formed by the basis of PSD. For EEG data over a specific period PSD estimation is based on the FFT of time-seriesand is commonly used. PSD estimates the ratio of the mean of entire squared amplitude- frequency characteristic to time. The band power, power spectrum, and PSD frequency domain characteristics are reported based on Based on the PSD estimation [5, 86]. Frequency domain characteristics are often employed in EEG-based studies, particularly in the field of emotion identification. After using band pass filtering, band passes hypothesized that the raw EEG data may be divided into five frequency bands. It was estimated that the equivalent band power for these five bands to play an important role as the feature for emotion detection [131] it was recommended that for emotion features the EEG signals can be mapped as, theta, alpha, and betabands after applying FFT [107].

It was suggested by Kothe, a whole spectrum approach to examining the connection between EEG and cognition. To transfer the signal directly to another representation of signal, an adaptive mixed Independent Component Analysis (ICA) approach was employed. and then used a nonlinear or linear sparse learning algorithm for choosing several sparse features to produce the PSD as the feature for emotion classification [132].

EEG signals include various frequency bands, and researchers have focused their attention on the relationship between these bands and human emotions. In [133] suggested conducting study on the associations between two emotions and the EEG gamma band (happiness and sadness). The relationship between the theta and alpha EEG frequency band human emotional intelligence was populated [134].

For each of the five frequency bands individually, it was suggested [135] comparing the representation level using the features of the same frequency bands as well as the classification techniques. Graph theoretical study in the current paper showed that the gamma band exactly represents the patient with depression in a study of five frequency bands [136].

3.2.3. Time-Frequency Domain Features

It was stated that in case signal is non-stationary, time-frequency techniques can effectively result great information while taking the variations of dynamics into account [86].

Time-frequency domain studies on EEG have been conducted in recent years to determine which features can accurately capture the characteristics of both the time domain and the frequency domain, as EEG signals can be unstable. The dynamic shift in time-series data, a major problem in emotion research, is a key focus of the time-frequency domain. Emotions are time-dependent and, once formed, they continue for a while before returning to a settled state. This physiological interpretation of human emotions is an important factor in these studies. [137].

The time-frequency domain features are more competitive because of their ability to capture the dynamic shift in time-series data. The two most widely used techniques for this purpose are the DWT and the short-time Fourier transform (STFT) [138-140].

STFT is a variation of the conventional Fourier transform, which adds a window function with a continuously moving window to calculate the frequency and phase of the locally sine-wavelike signal [141].

Lin proposed using music as a stimulus and a 32-channel EEG electrode cap to gather participants' EEG signals. He suggested using the STFT to map EEG signals to five frequency bands, calculate the PSD associated with each electrode, and then combine features from four groups based on the symmetry between each electrode, such as the difference between symmetric electrodes, their ratio, the PSD without the central electrode, and their combined PSD. To identify emotions, group characteristics were used. The identification of emotions was accomplished using these group features [142]. Zhenget al. [4] also proposed using STFT to convert EEG to five different frequency bands before training a deep belief network to classify emotions.

For the identification of the essential frequency bands for EEG-based emotion detection, Zheng et al. [4] proposed using STFT for converting EEG to five different frequency bands before training a deep belief network for emotion classification., Lan et al. suggested using STFT to extract the band power and PSD features of five different frequency bands [143] for the testing of the stability of each feature. From there, it was proposed choosing the feature to develop real-time emotion recognition for the emotions of frightened, pleasant, happy, and angry.

DWT is another and effective technique for signal processing by preserving the signal's temporal information while decomposing the signal into many approximation and detail levels which correspond to different frequency ranges [86] Using films as the stimulus, Murugappan et al. [144] To show the wavelet coefficients study suggested applying DWT. The coefficients were allowed for the calculation of power of each wavelet. The root mean squared value of the alpha band wavelet coefficient, band power, and the rate were chosen as the features for the classification of emotion entire bands as well as the sub bands rate was considered. for the classification of emotion, a recorded 10-channel EEG-based device was employed, in a study.

[145] to address the EEG to matching frequency bands and extract features, it was suggested using DWT, followed by SVM as well as KNN. The DWT and deep neural networks were recently combined by Ang et al. [62] where DWT was initially used as a feature extraction technique for the classification of emotion, before utilizing an artificial neural network for this approach.

In the context of more EEG-based research, for signal processing empirical mode decomposition (EMD) is one of the most prominent methods [146-148]. EMD breaks down a non-stationary, non-linear signal into several intrinsic mode functions (IMFs) which operate at multiple frequency levels [149]. EEG signals are decomposed to IMFs first by using EMD, and after which DWT was used on those IMFs to provide wavelet coefficients as the features to perform classification of emotion, according to Shahnaz et al. [150]., Mert et al. [151] used multivariate EMD to break down multichannel EEG signals for the IMFs. They then examined the PSD, power ratio, HP, entropy, Hjorth as well as correlation as characteristics for the classification of emotions.

3.2.4. Overview of CNNs

Deep Learning (DL) has demonstrated near-human, and now super-human, abilities in a variety of applications, like, anomaly detection, object detection and recognition, voice-to-text translations and emotion recognition from audio or video recordings, among others in the most recent innovation of the ML era, this age was started before AlexNet wasintroduced, by the contribution of Hinton and Salakhutdinov [152]. significance of "the depth"of an ANN in ML and was clarified the and that was published in 2006 in the journal Science [152].

ANN has very strong learning capabilities having a lot of hidden layers, those layers can be enhanced and improved for better performance.

The term DL relates to a branch of ML which can handle complex patterns and objects in very huge number of datasets. The primary tools of deep learning (DL), the conventional (and deep) CNNs, while outlining their key characteristics and building components are discussed. The most current CNN design, the 1D CNNs, focusing entirely on data repositories and 1D signal, will be covered after a brief discussion of the most well-liked deep CNNs ever suggested. Compact and adaptable 1D CNN models will receive special attention since they can provide several benefits and advantages over the 2D CNN.

3.2.4.1. 2D-CNNs

Even though the initial CNN was developed about 30 years ago, contemporary CNN designs still share features like convolutional and pooling layers with the original. In addition to a few modifications, the Back-Propagation approach, a frequent training method since the 1990s, is another. The most essential concepts and historical cornerstone designs will be introduced while giving a quick review of the standard deep CNNs.

To begin with, the following benefits may be used to explain deep CNNs' popularity and broad variety of application domains:

1. Feature extraction as well as feature classification into one learning-body are combined in the operations of CNN. During the training phase, they may immediately learn how to optimize the features from the input data.

2. Compared to fully connected massive inputs with a great deal of computing efficiency are handled using Multi-Layer Perceptron’s (MLP) networks, CNNs. This is because CNN neurons relate to coupled weights.

3. CNNs are resistant to minor data modifications which includes scaling, skewing, translation, and distortion.

4. Various input size variations can be adjusted using CNNs.

In a traditional MLP, each hidden neuron has a single set of weights and processes a single input and output value. In contrast, CNN uses 2D kernels as weights and processes 2D input and output feature maps to classify images, as illustrated in Figure 12 for a 24x24 pixel image.

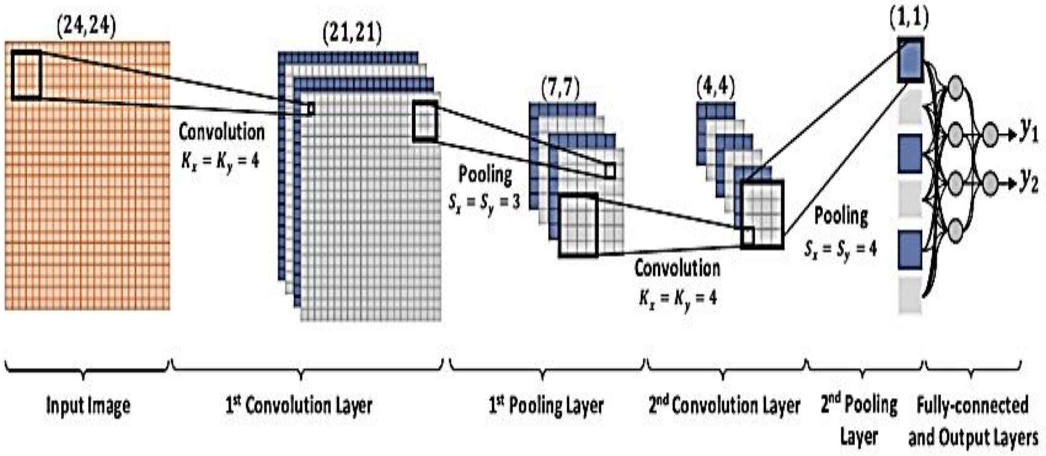

Figure 12 CNN with 2 convolutions as well as one fully connected layer

There are two convolutional as well as two pooling layers in the given network, each having four and six neurons. The classification output is generated by output layer which comes after processing the output of the final pooling layer by a single fully linked layer. Convolutional layer interconnections are determined using weighing filters with kernel sizes of K_x *and* K_y. Convolution occurs inside the bounds of the picture, K_x *and* K_y. pixels lower the width and height of the feature maps, respectively.

The subsampling factors s_x ; S_y are predetermined in the pooling layers. The two convolution layer kernel sizes in the sample illustration in the figure were set to $K_x\ {}^{1}/_{4}$, $K_y\ {}^{1}/_{4}\,4$ while the subsampling factors were set to $s_x\ {}^{1}/_{4}\,3$; $S_y\ {}^{1}/_{4}\,3$ for the first pooling layer and $s_x\ {}^{1}/_{4}$; $s_y\ {}^{1}/_{4}\,4$ for the second. For the assurance that the input for the fully connected layer as well as the output of the final pooling layer are both scalars (1x1), these numbers were chosen on purpose. The number of classes to which the picture is assigned is represented by two completely connected neurons in the output layer. In this sample CNN, a whole forward-propagation process is described by the steps below:

- A 24 by 24-pixel grayscale picture shows the input layer of CNN.
- A linear convolution is performed between the picture and the appropriate filter to create the inputs of the feature map.
- Activation function is applied to the input feature map of each neuron for the creation of the output feature map of the Convolutional neuron.
- The output feature map of the neuron that came before it in the convolution layer was decimated for building the feature map for each neuron in the pooling layer. In this

illustration,the first pooling layer produces 7x7 feature maps.

- The fully connected layers in a CNN are created by stacking multiple layers of convolution and pooling and using the output of the final pooling layer as input to these denselayers.
- The final output reflects the classification of the input image; the scalar outputs are forward propagated by the set next of fully connected output layers to create the output.

Although a significant amount of time has elapsed, there remain evident conceptual and architectural similarities. Notably, the design of AlexNet stands out due to its composition of millions of network features. Convolutional layers' two central traits, "weight sharing" and "restricted connectivity," distinguish CNNs from conventional MLPs. Despite these differences, both networks are homogeneous and employ the same linear neuron model.

3.2.4.2. 1-D CNNs

1D CNNs, a modified version of 2D CNNs, have been developed as an alternative for processing 1D signals such as audio and time series data. These networks have been shown to be more effective than 2D CNNs in certain applications due to factors such as lower computational complexity and better handling of temporal data. [45-54]. Research has shown that 1D CNNs have advantages over 2D CNNs when processing 1D signals for specific applications. These advantages include factors such as lower computational complexity and better handling of temporal data, which make 1D CNNs a preferred option in these cases:

The computational difficulty of 1D and 2D convolutions differs significantly; for example, an image with NxN dimensions convolved with a KxK kernel will have a computational cost of O(N2K2) $\sim O(N^2K^2)$, whereas this is O for the comparable 1D convolution with the same dimensions, N, and K ~O(NK). This indicates that the computational complexity of a 1D CNN is much lower than the 2D CNN under comparable circumstances (same configuration, network, and hyper parameters).

Recent studies have shown that 1D CNNs are typically used in more compact configurations, with fewer hidden layers and a smaller number of parameters (less than 10,000) compared to 2D CNNs, which are commonly used in deep architectures with more than 1 million (typically above 10 million) parameters. This is likely since 1D CNNs are simpler to train and use, as shallower architectures require less computational resources and less data to train.

Training in 2D-CNN typically requires specialized hardware (e.g., GPU farms or Cloud computing). On the other hand, training 1D CNNs with few neurons and few hidden layers over a conventional computer is achievable and rather quick to be implemented.

For real-time and low-cost applications 1-D CNN are highly suited, particularly on handheld devices and mobile, because of their minimal processing needs [158, 159-171].

Recent research has investigated that 1-D CNNs perform better on applications for example with less labelled data and strong signal fluctuations obtained from many means (i.e., EEG, patient, ECG, civil, mechanical, or aerospace structures, high-power circuitry, power engines ormotors, etc.). Two unique layer types are suggested for 1D CNNs.

1. The "CNN-layers," where 1- D convolutions, subsampling (pooling) and activation functions take place; and
2. Fully connected (dense), or "MLP-layers," layers that are like the layers of a normal Multi-Layer Perceptron (MLP).

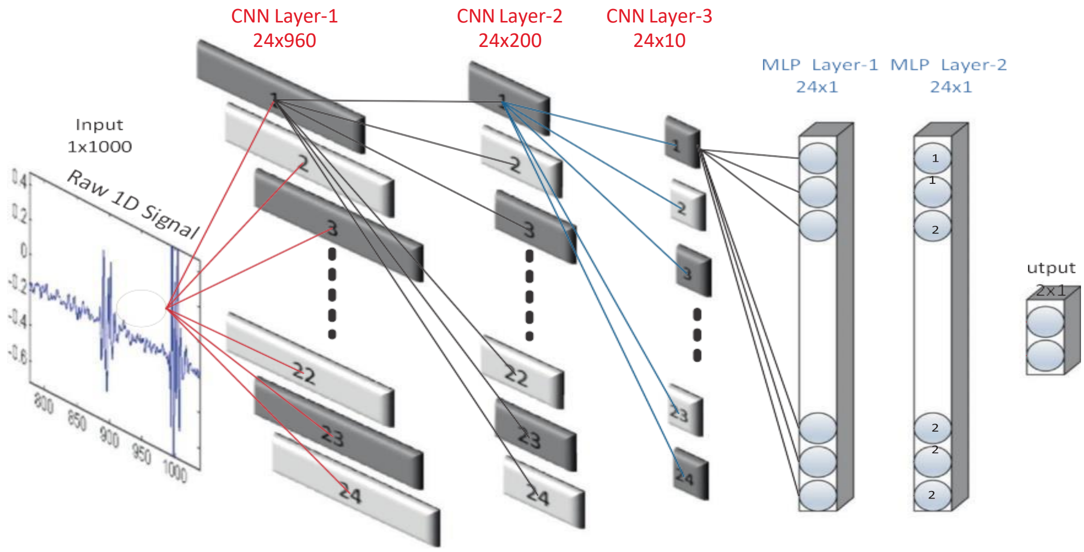

Figure 13 A 3 CNN and 2 MLP layers 1-D CNN

As an example, a 1D CNN is illustrated in Figure 13,

1. The filter size utilized in all the hiddenlayers of the CNN is 41.
2. The subsampling factor in each CNN layer in the sample 1D CNN is 4.

A 1D CNN has an output layer that is an MLP with many neurons equal to the number of classes, much like 2D CNNs. The input layer, which is passive, receives the unprocessed 1D signal. A 1D CNN with three succeeding CNN layers as an example is shown in Fig. 6.

Before the subsampling procedure is used, each neuron in the hidden CNN layer performs a sequence of convolutions that are then passed via an activation function. The subsampling factor is 2, and the filter kernels have a size of 3.

The primary distinction between 1D and 2D CNNs is the usage of 1D arrays as opposed to 2D matrices for both kernels and feature maps in 2D CNNs [168].

CHAPTER 4
METHODOLOGY

4.1. Overview

Experiment approach is used in this work. Experiment design, data collection, analysis, and outcomes are all parts of the process. The following sections provide a detailed explanation of each experimental module.

4.2. Experimental Procedure

The study recruited a total of 25 participants who met specific eligibility criteria, including having standard or corrected visual acuity, normal hearing, and no significant emotional or psychiatric issues as assessed using the Beck Depression Inventory (BDI) and State-Trait Anxiety Inventory (STAI). The STAI is a self-report measure used to assess an individual's level of state and trait anxiety, while the BDI is a self-report measure used to evaluate the severity of depression. Both measures were used to ensure that participants had no significant emotional or psychiatric issues that could impact the results of the study.

Additionally, it was a requirement that participants abstain from consuming any alcoholic beverages within 24 hours before the start of the experiment. This was to controlthe potential effects of alcohol on the participants' behavior and performance during the experiment. This requirement was also to ensure that the experiment results were not influenced by any alcohol-induced changes to the participant's cognitive or physiological state.

Before the formal experiment, all participants were introduced to the procedure and were required to sign an informed consent form. This introduction explained the nature and purpose of the study, the procedures that would be used, and the potential risks and benefits of participation. The informed consent form was designed for the assurance that participants fully got familiar with the nature of the current study also agreed to participate voluntarily. During the experiment, they had the freedom to terminate their participation at any time if they did not accept the content of the experiment. This was to ensure that the participants were comfortable throughout the experiment, and that the results were obtained from willing participants who were not under duress.

4.2.1. Conduction

In this experiment, each image appeared for 1-sec with a rest time of 1-sec as shown in Figure 15. Different emotional words are presented like angry, joyful, lost and many more. The subjects only saw those images and didn’t need to respond. All stimuli were in three different shades i.e., red, blue, and grey. All images are of equal size and have dimensions 960*720 as shown in Figure 16.

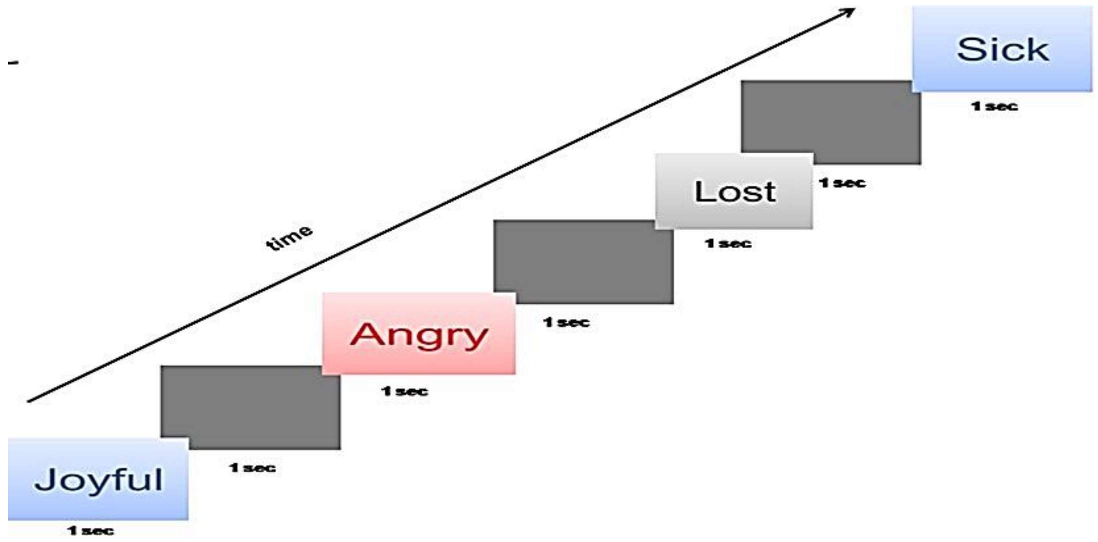

Figure 14 EEG experiment design to measure the response of different emotional words.

Figure 15 Stimuli presented to measure the response of different emotional words.

4.2.2. Dataset

The data for the experiment was collected from 25 subjects using the Electrical Geodesics Incorporated (EGI) system with 128 channels and a sampling frequency of 250 Hz. The data was recorded using Net Station software. The duration of the experiment was 5 minutes. In the following section A diagram of the EGI system and 128 channels used as provided.

Figure 16 EGI System used for recording.

Figure 17 128 Channel electrode used for recording.

4.3 Data analysis

After data collection Pre-processing is the initial stage, followed by feature extraction of the EEG data as well as feature selection, and finally classification processes. The step for the current study is mentioned below in Figure 19.

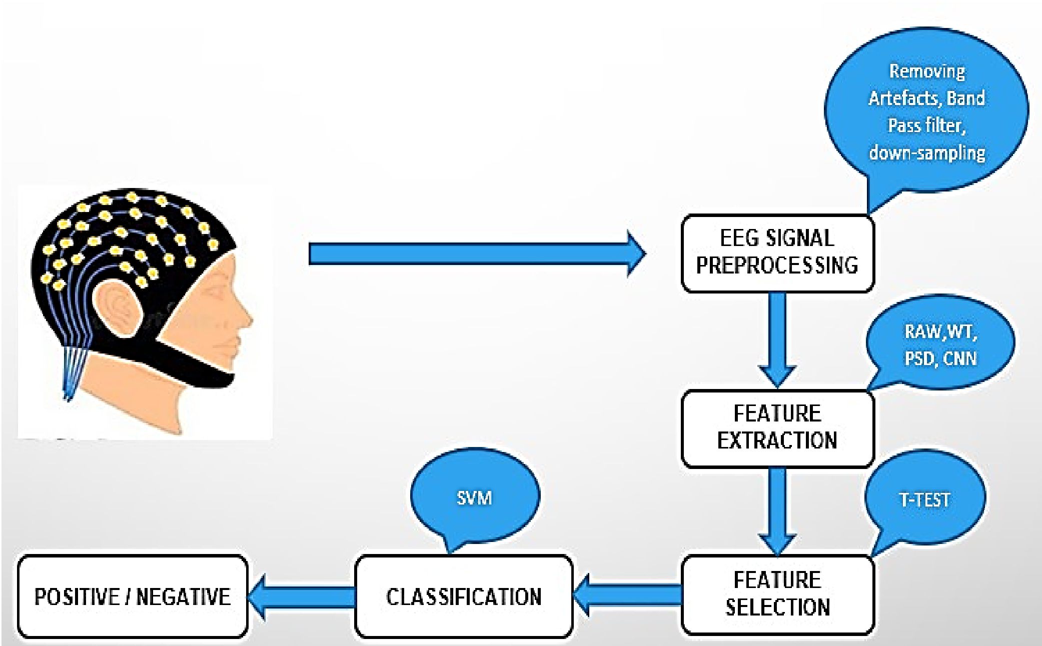

Figure 18 Steps of the study.

4.3.1. Preprocessing

The signals recorded from the scalp can be contaminated by various types of noise or artifacts, which can make it difficult to accurately interpret the data. Physiological and non-physiological are two types of Artefacts.

Artifacts from physiological are generated by human physical functions such as eye movement, blinking, heart rate, head and jaw movement, and respiration. These artifacts can have a significant impact on the EEG signals, as they can mimic or mask brain activity. Eye movement and blinking cause EOG (electro-oculogram) which are typically available in the frequency range of 4 Hz. These artifacts can be identified by their characteristic patterns in the EEG signals, such as a slow drift or a sharp deflection. Head and other muscular movements cause EMG (electromyography) and are found to be above the frequency range of 30 Hz. These artifacts can be identified by their high-frequency content and their temporal correlation with muscle activity.

Non-physiological artifacts, on the other hand, external sources introduce those artefacts such as electrode impedance, fluctuations, disturbances and power line interference from electrode position. These artifacts can have a significant impact on the quality of EEG signals, as they can introduce noise and distortion. For example, power line interference can produce a 50 or 60 Hz noise in the EEG signals, which can mask brain activity. Electrode impedance fluctuations can also produce noise and distortion, as they can change the sensitivity and stability of the electrodes. Disturbances in electrode position can also produce noise and distortion.

To improve reliability of EEG emotion recognition system, it is important to remove or reduce these artifacts. There are several methods that can be used for this purpose, such as digital band-pass filters, independent component analysis (ICA), and wavelet-based techniques. Digital band-pass filters can be used to remove or reduce the frequency components that correspond to the artifacts. Independent component analysis (ICA) can be used to separate the EEG signals into independent sources, based on their statistical properties. Wavelet-based techniques can be used to decompose the EEG signals into different frequency bands, and then remove or reduce the frequency bands that correspond to the artifacts.

However, these methods also have drawbacks, such as the potential to delete important frequency components or suppress real brain activity. For example, digital band-pass filters can remove or reduce the frequency components that correspond to the artifacts, but they can also remove or reduce the frequency components that correspond to brain activity. Independent component analysis (ICA) may be used to separate the EEG signals into independent sources, but it can also introduce errors and artifacts. Wavelet-based techniques can decompose the EEG signals into different frequency bands, but they can also introduce errors and artifacts.

In this case, the dataset was in raw condition and contained noise and unnecessary data, so preprocessing was an important step to be done. The preprocessing of raw data was done using a Matlab tool called EEGlab, which is an effective tool for EEG data processing. EEGlab is a powerful and flexible tool that can be used to filter, epoch, average, and visualize EEG data. It can also be used to remove or reduce artifacts by applying different methods, such as digital band-pass filters, independent component analysis (ICA), and wavelet-based techniques. EEGlab can also be used to perform other tasks, such as EEG source localization, coherence analysis, and event-related potential analysis.

4.3.1.1.Re reference

EEG data is a relative measure that compares the electrical activity at different recording sites with a reference site. To obtain pure measures, the reference electrode should be placed at a location that is not affected by brain activity. However, this ideal location does not exist. Common reference sites used in EEG include the mastoid bone behind the ear, the earlobe, and the nose-tip. However, since any reference electrode records some amount of brain activity, the EEG amplitude may be reduced in channels that are close to the reference.

4.3.1.1.1. Average re-referencing

One common method used in high-density EEG (with 64 or more channels), is average re-referencing. This method involves calculating the average of all electrodes to approximate an ideal reference. The principle behind this method is that the sum of potential fields (such as brain potentials) in a conductive sphere is zero when measured over the surface of the sphere (such as the head). However, this approximation to a zero (or inactive) reference is limited by the fact that EEG recordings can only cover 2/3 of the head.

4.3.1.2.Filtering the data

High-pass filtering is a technique that is used to remove linear trends from data. This is done by allowing high frequency components of the signal to pass through the filter while blocking or attenuating the low frequency components. The cutoff frequency, also known as the cutoff point or the corner frequency, is the point at which the filter starts to block or attenuate the low frequency components. The cutoff frequency is typically set at 1 Hz when high pass filtering data to obtain good quality ICA (Independent Component Analysis) decompositions.

ICA is a statistical technique that is used to separate a multivariate signal into independent non-Gaussian components. It is often used in the field of signal processing and neuroscience to analyze and interpret signals that are thought to be composed of multiple independent sources. By removing linear trends from the data before performing ICA decomposition, it is possible to obtain more accurate and meaningful results.

Low-pass filtering is another technique that is used in signal processing. It is used to remove high-frequency noise from a signal by allowing low frequency components to pass through the filter while blocking or attenuating the high frequency components. This is useful in situations where high-frequency noise is present in the signal and needs to be removed in order to obtain a clearer signal. This can be done by setting the cutoff frequency at a point that is higher than the frequency of the noise.

High pass filtering data at 1 Hz is recommended to obtain good EEG quality ICA decompositions. Low-pass filtering high-frequency noise is sometimes necessary to remove noise from the signal, and the cutoff frequency is set at a point that is higher than the frequency of the noise.

The data is filtered using high pass filter with 0.5 Hz and for low pass filter 50Hz frequency is used. To filter the data in eeglab tools> filter the data> basic FIR filter is used.

4.3.1.2.1. Applying Low and high pass filter

For high pass filter 0.5 Hz and for low pass filter 50 Hz frequency is used.

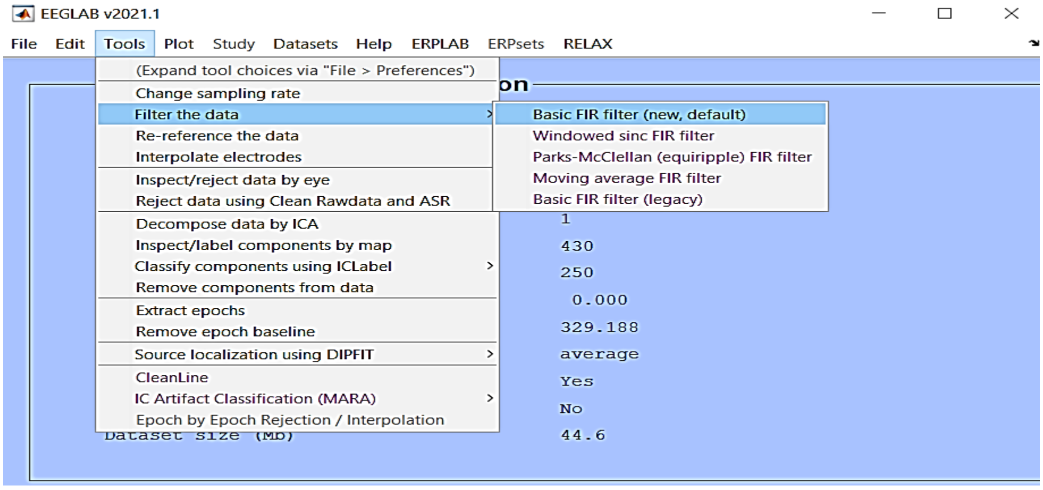

Figure 19 EEGlab tool for filtering

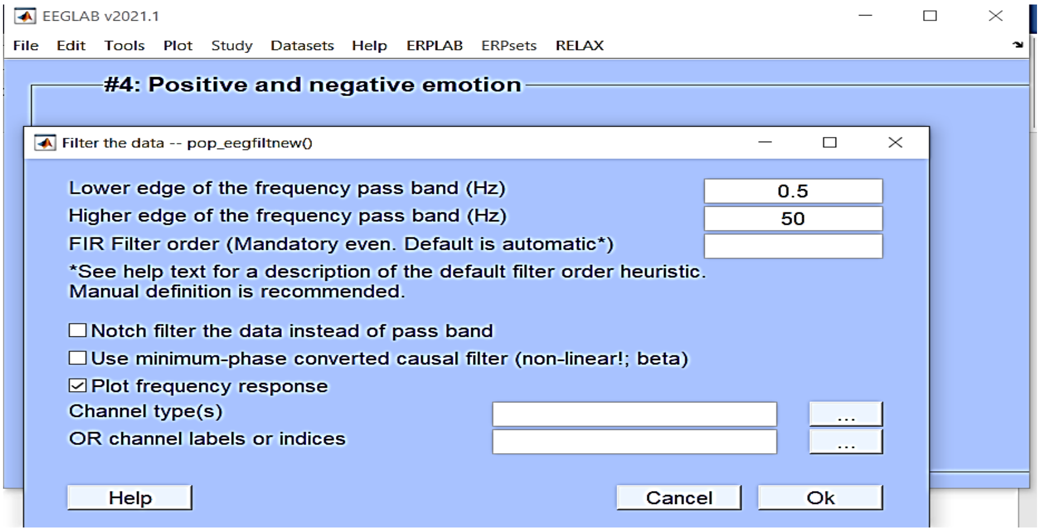

Figure 20 Applying low pass and high pass filter.

4.3.1.3. CleanLine

The CleanLine EEGLAB plugin is a tool that is used to remove line noise from EEG (electroencephalography) signals. It uses a combination of multi-taper and Thompson F-statistic method to adaptively estimate and remove line noise.

Multi-taper method is a technique that uses multiple Slepian sequences (also known as tapers) to estimate the PSD of a signal. This method is known for its ability to reduce the variance of the estimated PSD and improve the signal-to-noiseratio.

The Thompson F-statistic method is a statistical technique that is used to detect and quantify the presence of line noise in a signal. It uses the ratio of the variance of the signal to the variance of the line noise to calculate the F-statistic value. A higher F-statistic value indicates a higher level of line noise in the signal.

By using these two methods together, the CleanLine EEGLAB plugin can adaptively estimate and remove line noise from EEG signals. This can improve the quality of the EEG signals and make them more suitable for further analysis.

In order to clean line noise this tool is used and it effectively removes line noise in any channel in the data. in eeglab tool>cleanline is used to remove bad lines the data.

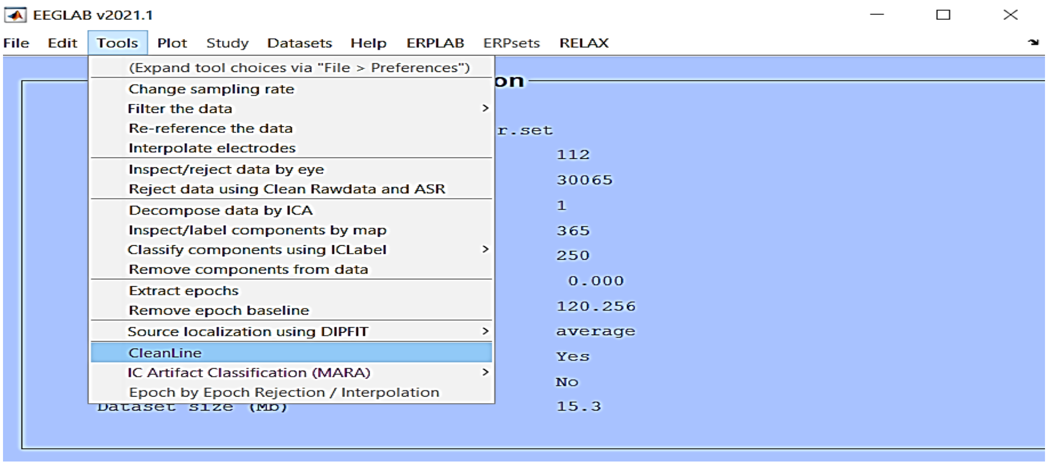

Figure 21 EEGlab cleanline tool

After selecting the cleanline tool the following options appeared and set then clicked okto start cleanline function.

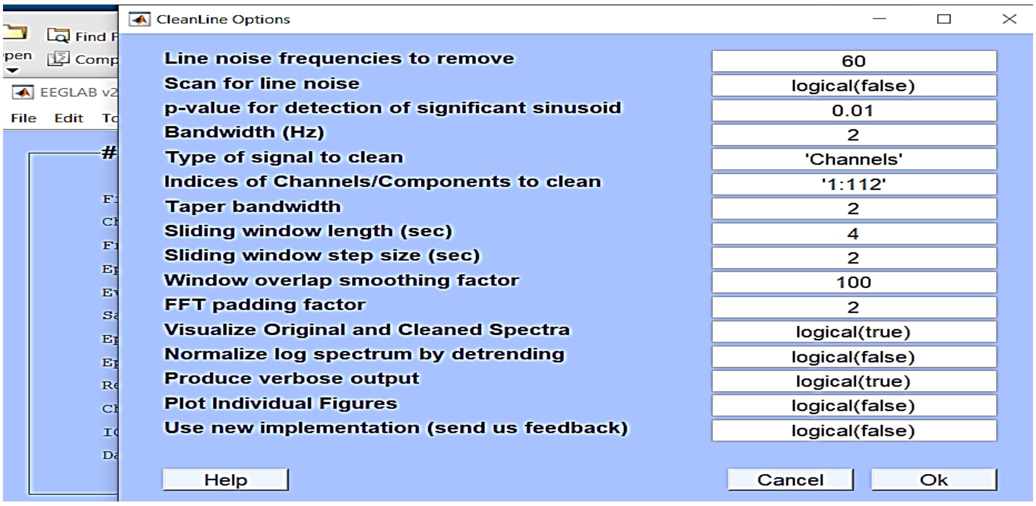

Figure 22 Cleanline function

After applying cleanline

The cleanline function removed the bad data and the result is shown in the figure below,

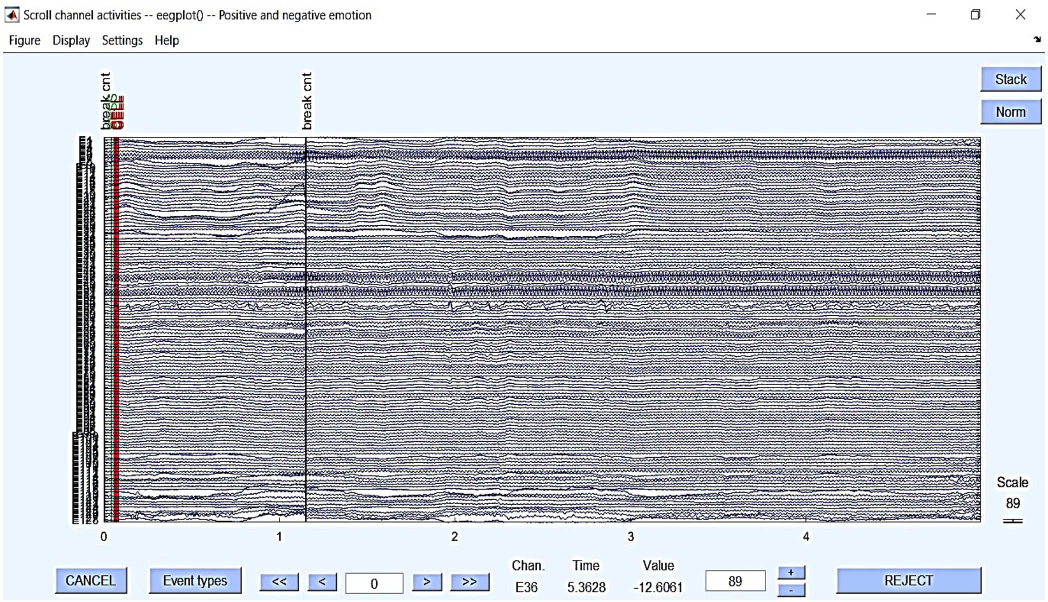

Figure 23 After applying cleanline.

4.3.1.4. Manually Select and Delete Bad Channels

Bad channels are a common issue when collecting EEG data. They can occur due to a variety of reasons, such as a loose or broken connection, poor contact between the electrodes and the scalp, or interference from other sources. Bad channels can result in poor quality data and can affect the results of any analysis that is performed on the data.

There are several ways to identify bad channels in EEG data. In some cases, the researcher may know in advance which channels are bad, for example, if the EEG equipment is known to have a problem with a specific channel or if the electrode was placed incorrectly. In other cases, the data must be inspected or scrolled manually to identify bad channels. This can be done by visual inspection of the data, which involves scrolling through the data and looking for any unusual or abnormal patterns, such as large amplitude noise or a complete absence of signals.

Once bad channels are identified, they should be removed from the data before any further analysis is performed. This can be done by using specialized software, such as EEGLAB, which has built-in tools for identifying and removing bad channels. It is also possible to use manual methods, such as removing the data from those channels and interpolating the missing data.

4.3.1.4.1. Scrolling channel data

To scroll through the channel data of the current dataset, Plot > Channel data (scroll) option is selected. Which popped up the scrolling data display window. The window has been magnified vertically.

Figure 24 EEGlab command to scroll through channels.

Before removing.

When the data is visualized the following window appeared with bad channels, which manually needed to be inspected and removed. The channels from 1 to 34 appear to be noisy from time 0 second to 3 for that those needed to be removed.

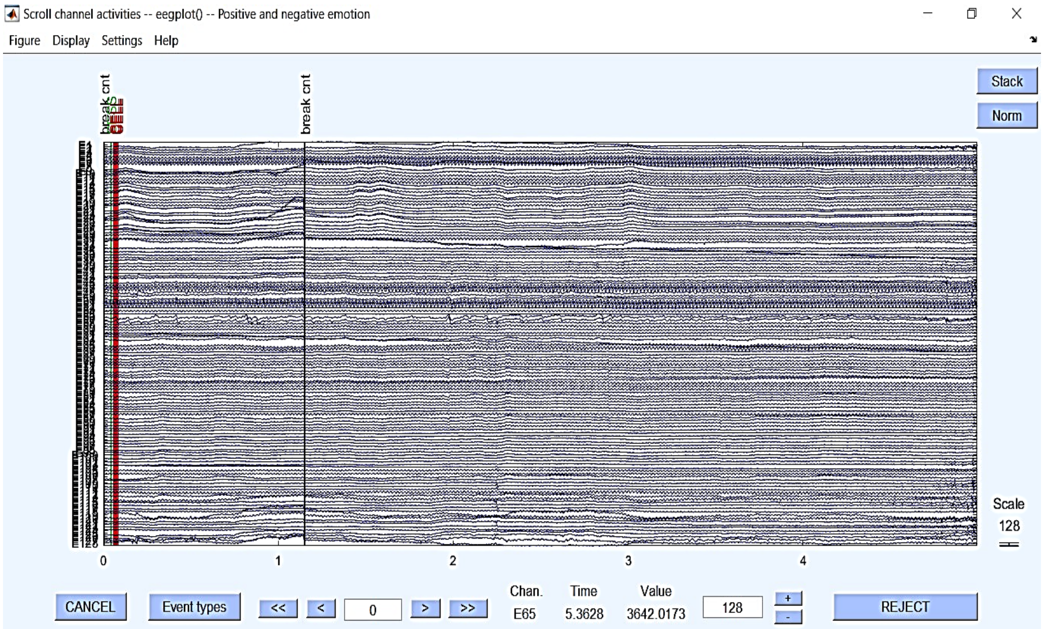

Figure 25 Visualization of channels before selecting bad channels.

4.3.1.4.2. Selecting the bad channels

After visualizing the data, the bad channels were removed using select data function in edit menu in EEGLAB.

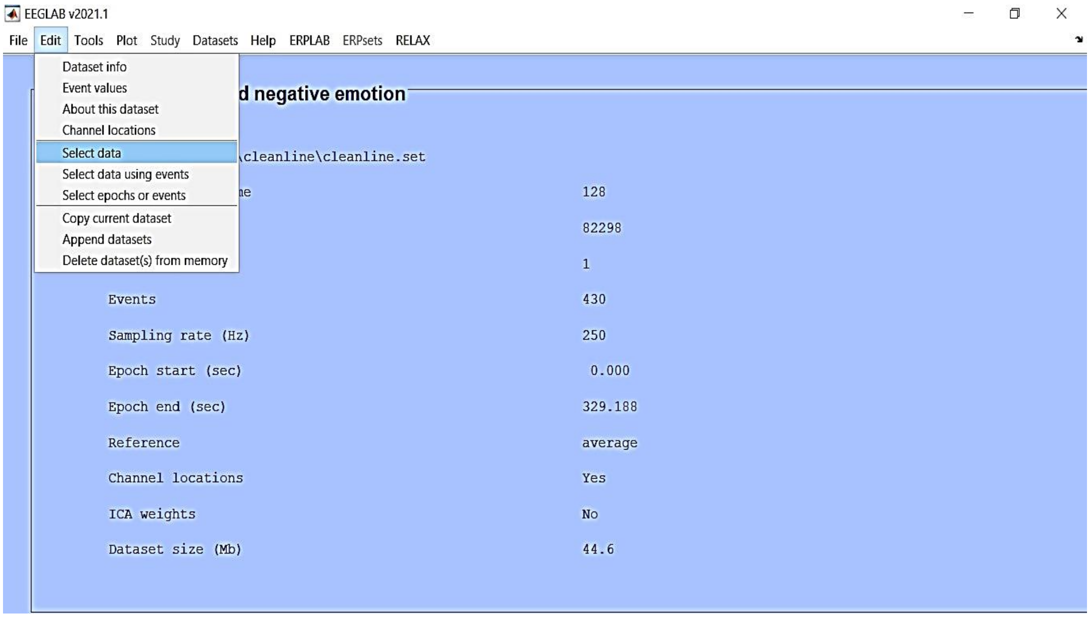

Figure 26 Selecting data.

After *SELECT DATA* the following window popped up where the channels which were bad are selected to be removed with their time limit.

Figure 27 Selecting the channel and time range of data.

After removing: -

The figure below shows the result of the removed data which appears to be clean as compared to the previous data.

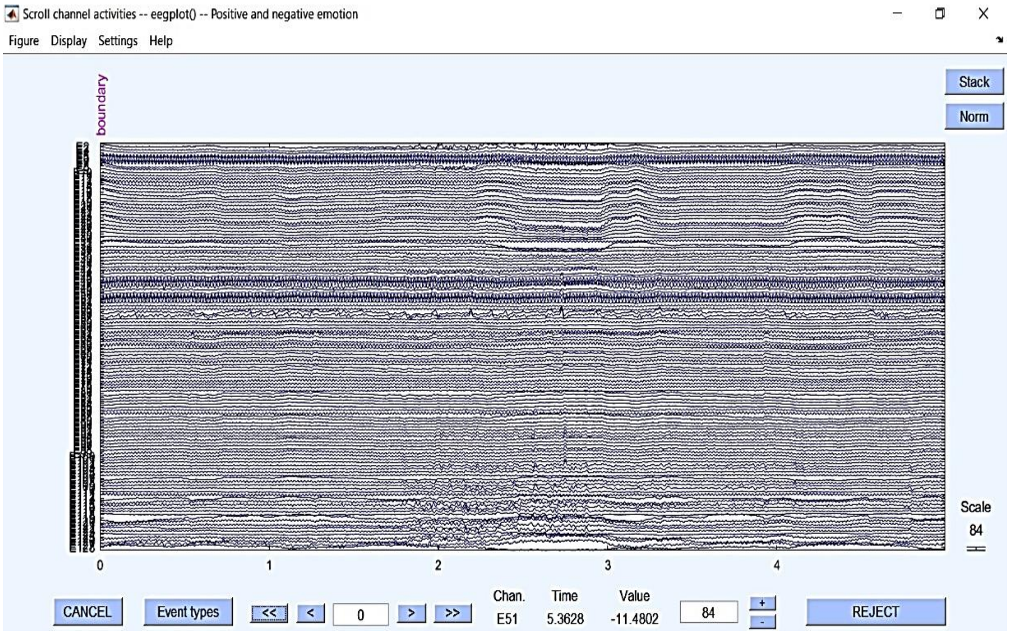

Figure 28 After removing bad channels.

4.3.1.5.Reject bad channels using Clean Raw data and ASR

The Clean Raw data and ASR plugin is utilized for additional preprocessing of data. It is used to eliminate poor data channels and segments by selecting the appropriate tools and selecting the "Reject data using Clean Raw data and ASR" option from the sub-menu.

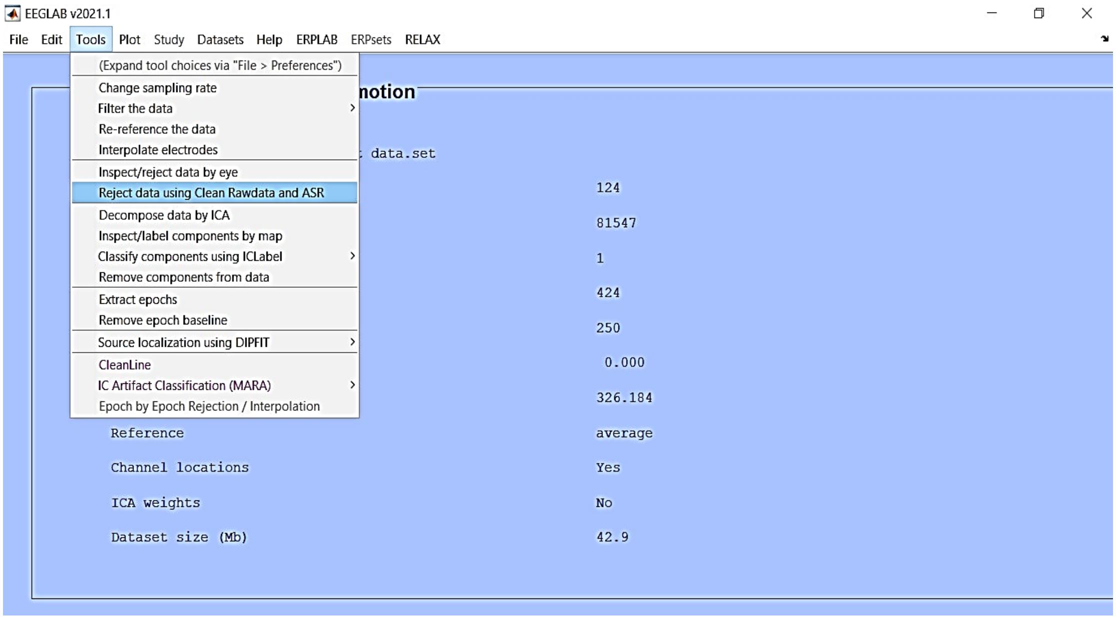

Figure 29 Reject bad channels using Clean Raw data and ASR.

After selecting the option for clean raw data and ASR, the following menu appeared.

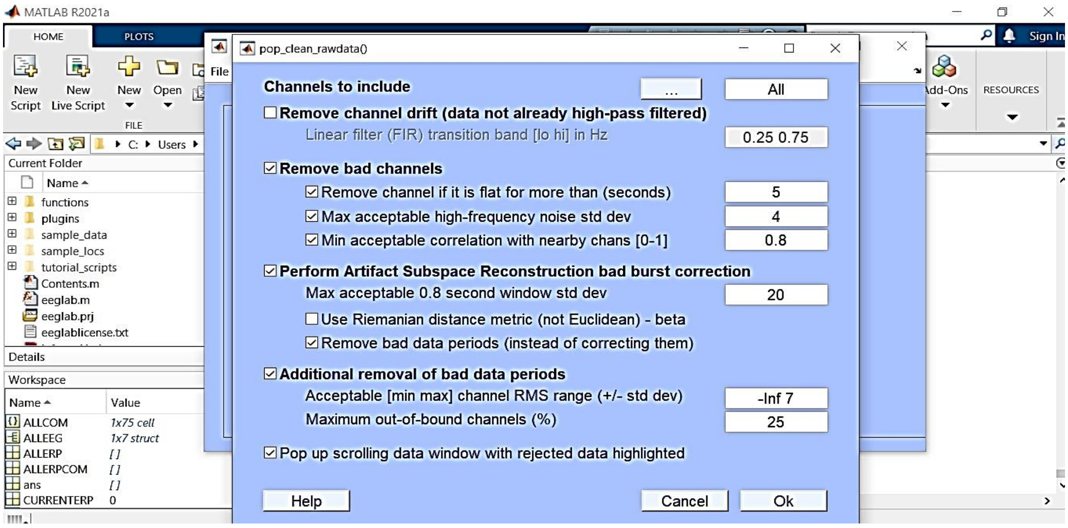

Figure 30 Reject bad channels using Clean Raw data and ASR

The result of rejecting of data in dataset are shown below.

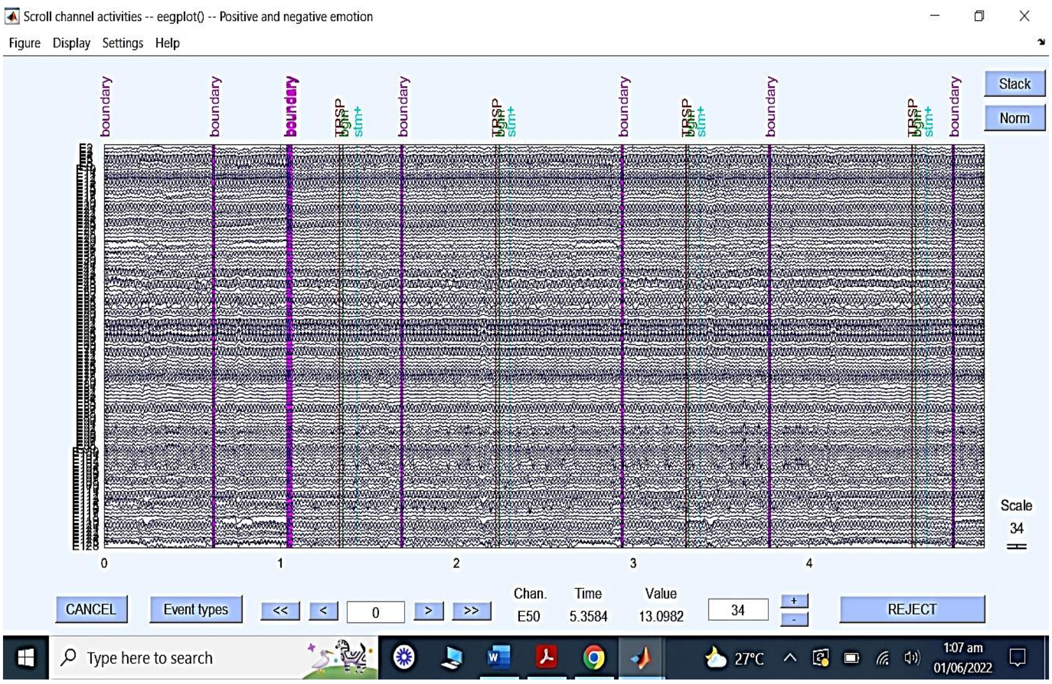

Figure 31 Result of rejected data.

4.3.1.6.Extracting data epochs

To analyze the EEG dynamics related to specific events in continuously recorded data, we need to extract segments of data (epochs) that are aligned with the timing of those events using tools such as the "Extract Epochs" feature in EEGLAB. The epochs were extracted by selecting Tools > Extract Epochs from the EEGLAB.

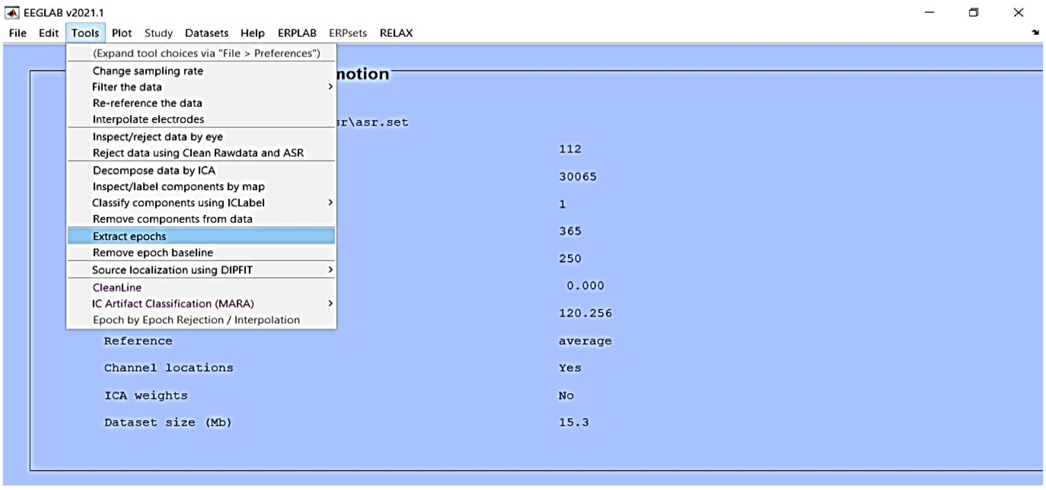

Figure 32 Tool for extracting data epochs.

4.3.1.7.Plotting Event Related Potential (ERP) images or Topo Maps

Plotting all-channel ERPs:

To visualize the average ERP across all data epochs and display scalp maps at specific latencies, one can use the "Plot" menu in EEGLAB and select "Channel ERPs" with the option to include scalp maps. The default settings in the pop-up window can be used, then the "Ok" button can be pressed to create the plots.

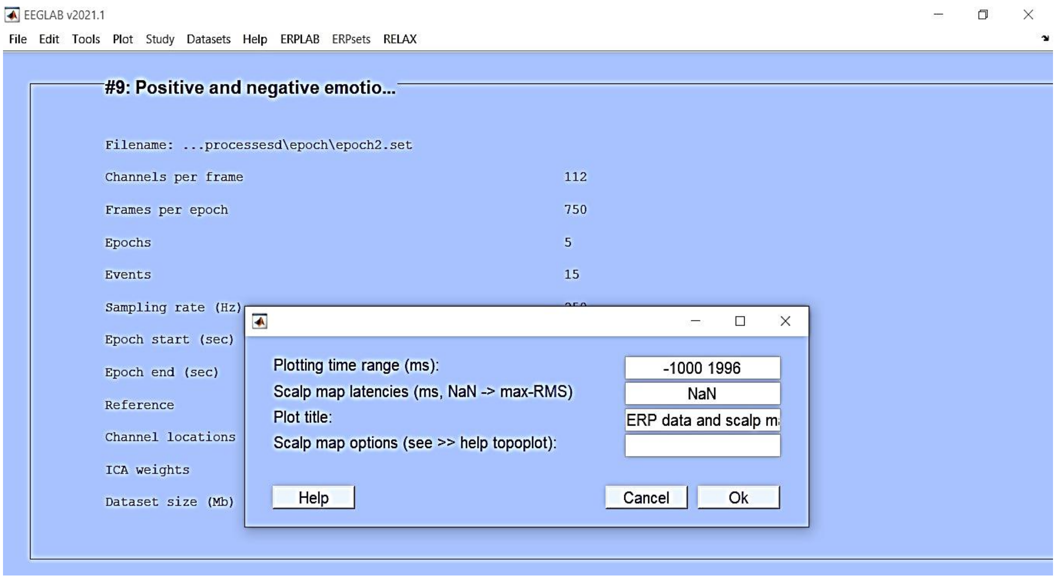

Figure 33 Plotting all channel ERP.

The figure generated by the timtopo() function in EEGLAB displays the average ERP at each channel as a separate trace. Additionally, it shows a scalp map of the average potential at a specific latency (in this case 424 ms) which corresponds to the time point where the ERP data variance is at its highest. This function allows to see the temporal evolution of the average ERP at all channels and the scalp potential distribution at different moments during the average

ERP time course.

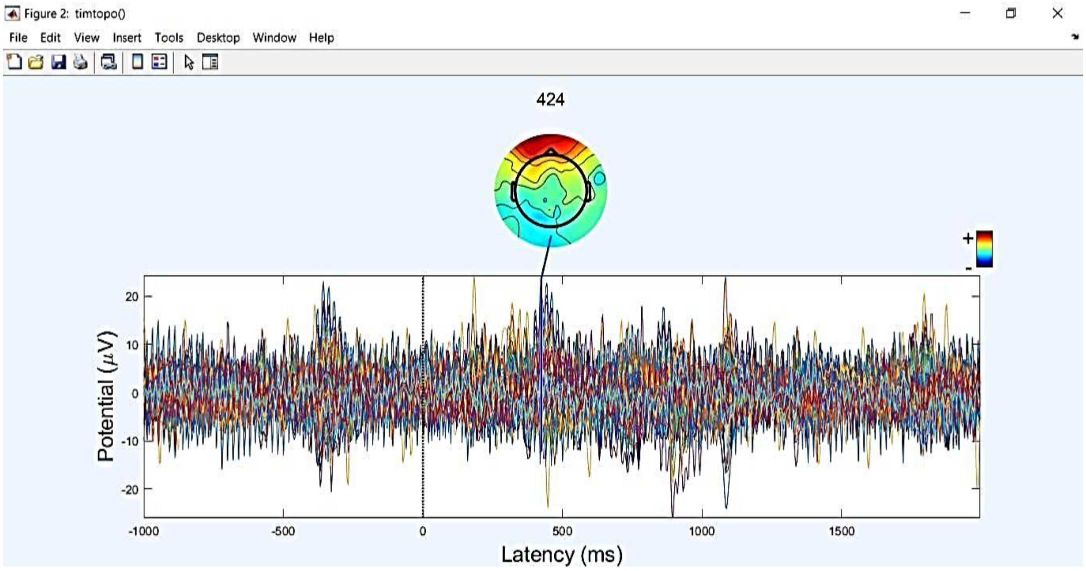

Figure 34 ERP at a given time.

4.3.1.7.1. Plotting ERPs in a Topographic Map

To view the ERPs of a dataset of epochs as single-channel traces arranged in a 2-D topographic layout, one can use the "Plot" menu in EEGLAB and select "Channel ERPs" with the option to display them in a "scalp array/rect. array". The default settings can be used in the pop-up window and then the "Ok" button can be pressed to generate the plot.

Figure 35 Procedure to plot ERP.

The following command produced the figure below,

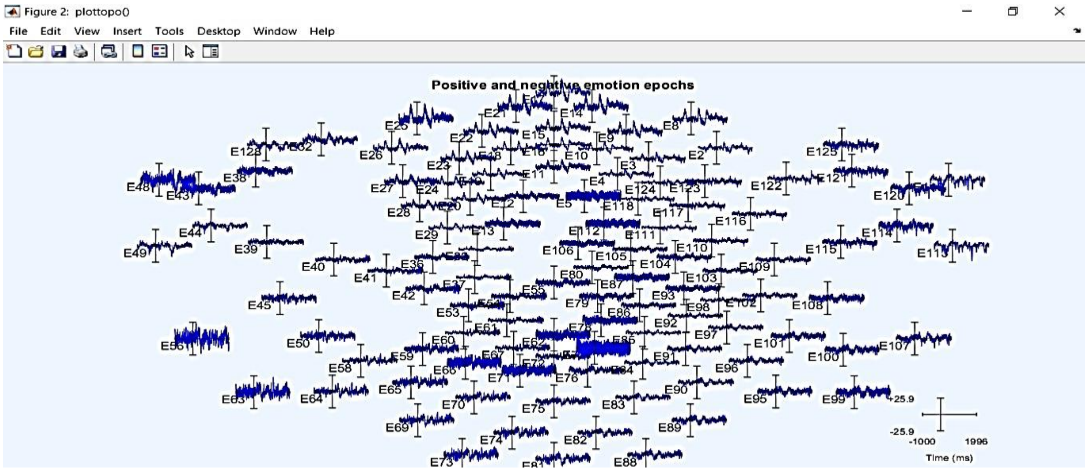

Figure 36 Topographic maps of all the channels.

The figure generated by the above steps allows to visualize the time course of a specific channel by clicking on its trace in the main plot. This will open a new window with a full-sized view of the selected channel's ERP trace, for example, if you click on the ERP trace labeled E56, it will show a full-sized view of that channel's ERP trace.

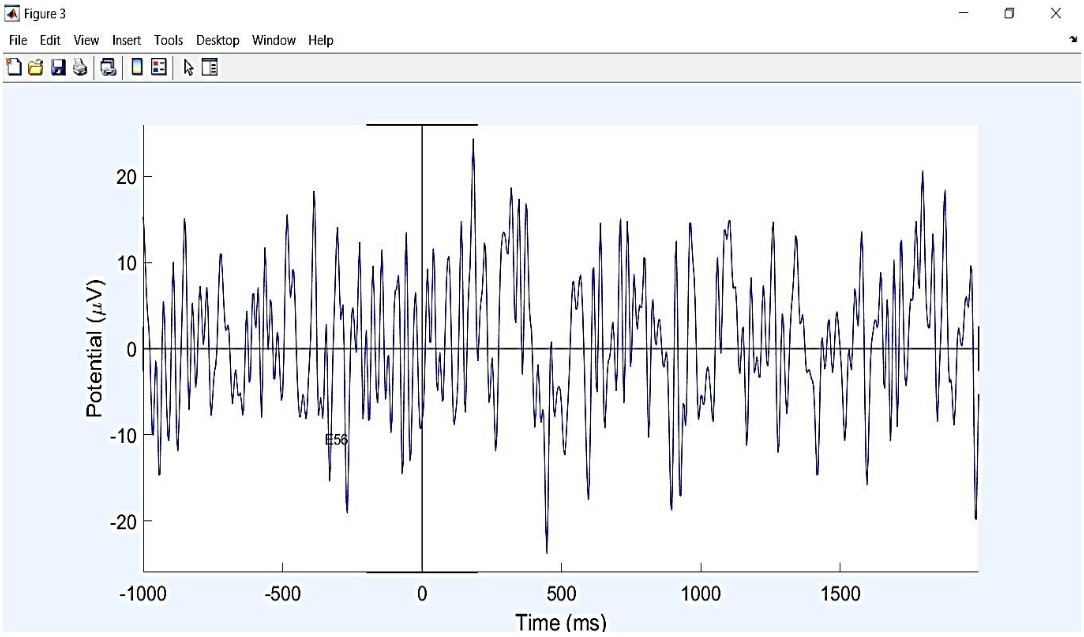

Figure 37 Topographic map of a single channel

4.3.1.7.2. Plotting ERPs in a Column Array

To plot one or more average ERP data traces in a two-column array, one can use the "Plot" menu in EEGLAB and select "Channel ERPs" with the option to display them in a "scalp/rect. array" This way it allows to view multiple ERP traces in a compact format.

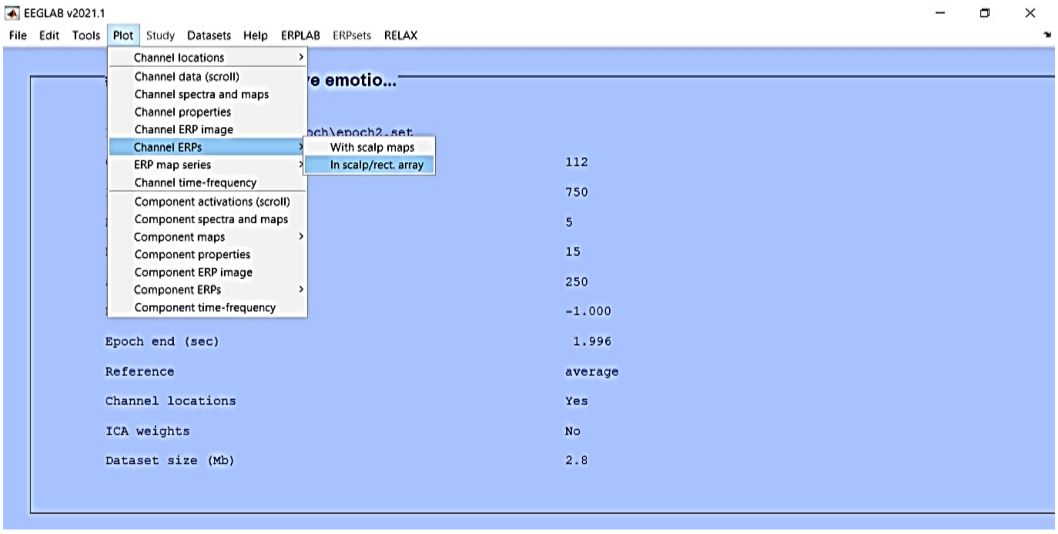

Figure 38 EEGlab command to plot ERPs in column arrays.

To use the default settings when plotting average ERP data traces in a two-column array, one can check the "Plot in rect. array" checkbox in the pop-up window that appears after selecting "Plot > Channel ERPs > In scalp/rect. array" in EEGLAB. Pressing "OK" will then generate the plot using the default settings.

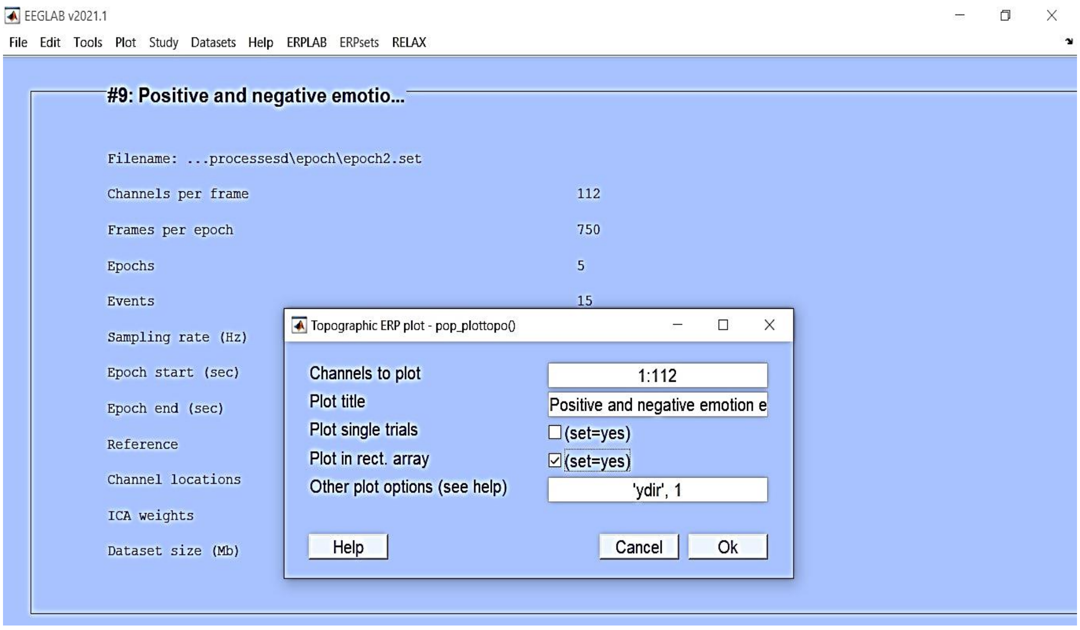

Figure 39 EEGlab command to plot ERPs in column arrays.

The resulting plottopo() figure (below) appeared.

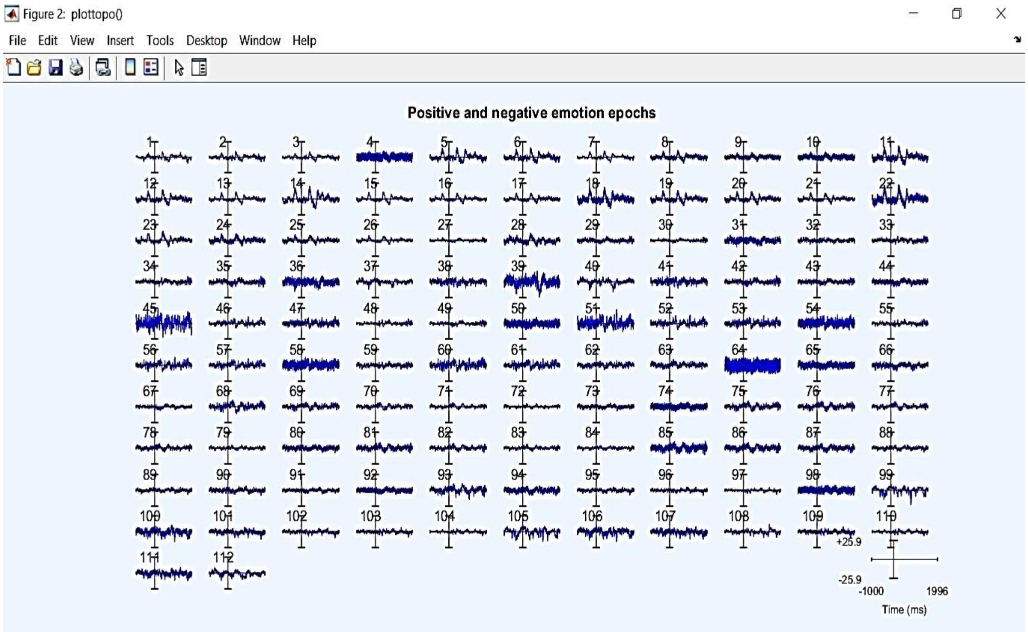

Figure 40 ERPs of different channels in column arrays.

4.3.1.7.3. Plotting a Series of 2-D ERP Scalp Maps

To plot ERP data as a series of 2-D scalp maps representing potential distributions at a selected series of trial latencies, one can use the "Plot" menu in EEGLAB and select "ERP map series" with the option to display them in "2-D". In the resulting pop_topoplot() window, you can type in the desired latencies of the ERP scalp maps in the top text box, this way it generates a series of 2-D scalp maps at those specific latencies.

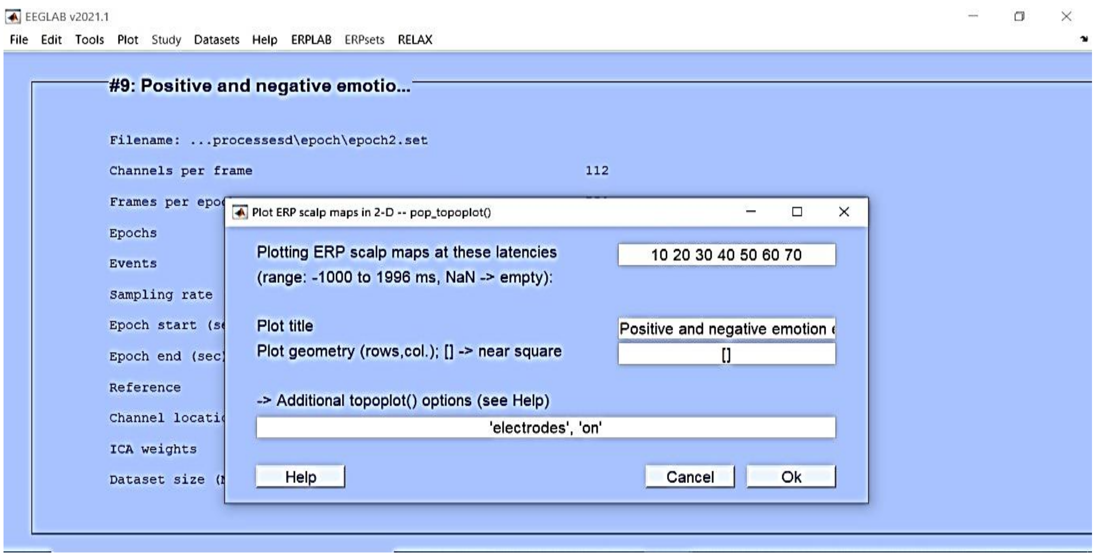

Figure 41 EEGlab command to plot ERPs of 2D scalp maps.

Once the latencies have been specified, the pop_topoplot() window will display the ERP scalp maps at those latencies. The layout of the plots can be configured with a grid.

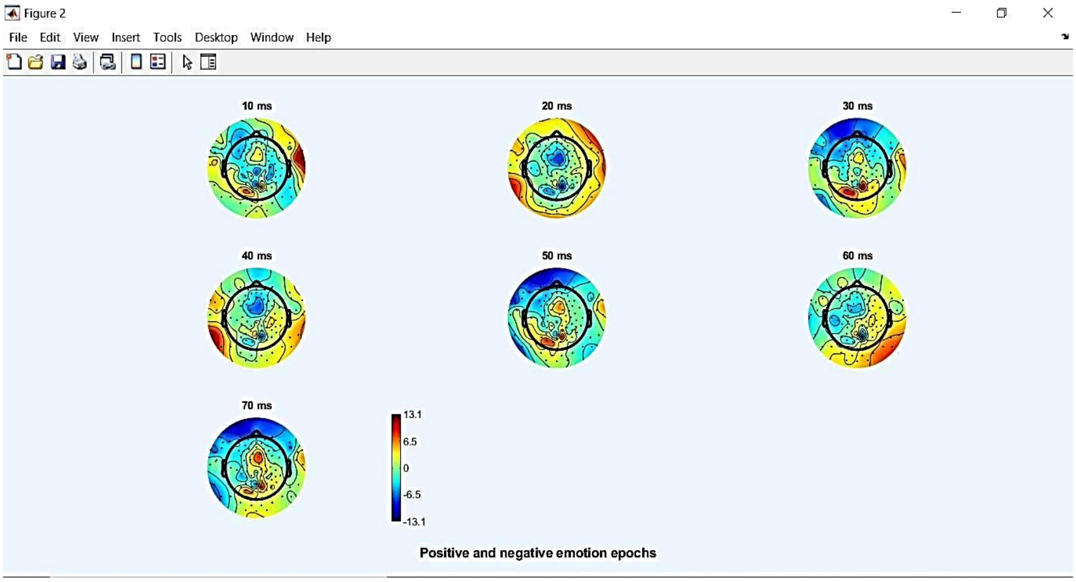

Figure 42 ERPs of 2D scalp maps.

4.3.1.7.4. Plotting a Series of 3-D ERP Scalp Maps

To create a series of 3-D scalp maps of ERP data, the option "Plot > ERP map series > In 3-D" was selected. A query window appeared, prompting to create and save a new 3-D head map spline file. This step only needs to be completed once for each montage, and by clicking "OK", the process begins.

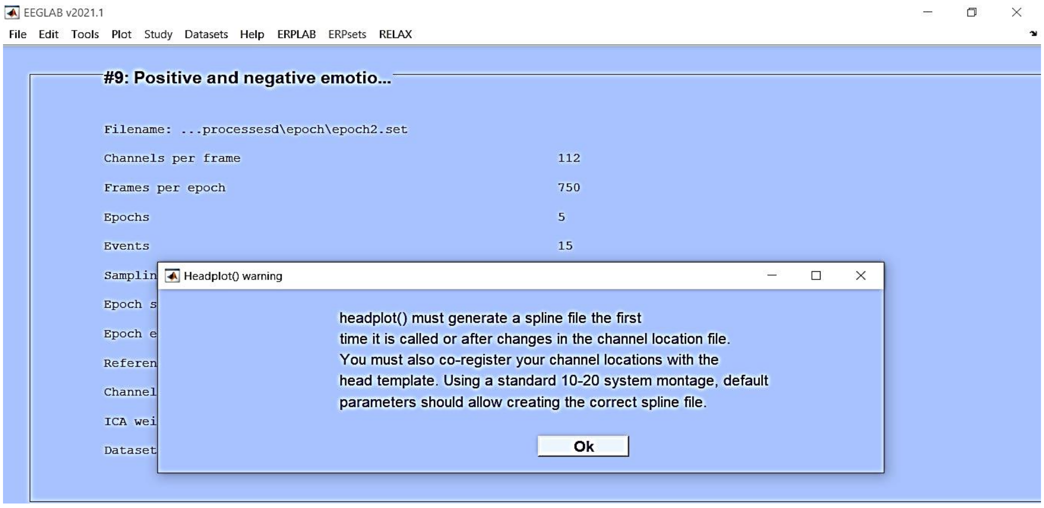

Figure 43 EEGlab command to plot ERPs of 3D scalp maps.

The following window appeared, where the trial latencies to be plotted were entered (i.e. 0:100:500, indicating latencies of 0, 100, 200, 300, 400, and 500 ms) and the "OK" button was pressed to continue.

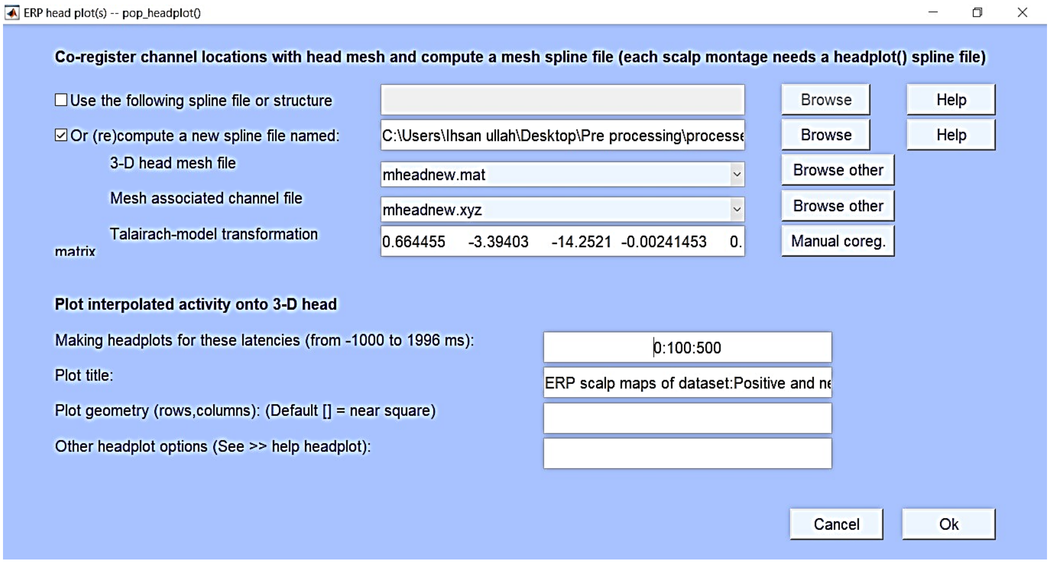

Figure 44 EEGlab command to plot ERPs of 3D scalp maps.

The function headplot() was used to create a 3-D channel locations spline file. A progress bar was displayed to indicate when the process had been completed. Once the 3-D spline file was generated, a plot of the data was displayed.

Figure 45 ERPs of 3D scalp maps.

By clicking on a head plot, it opened in a sub-axis window. The plot can then be rotated using the mouse for better visualization.

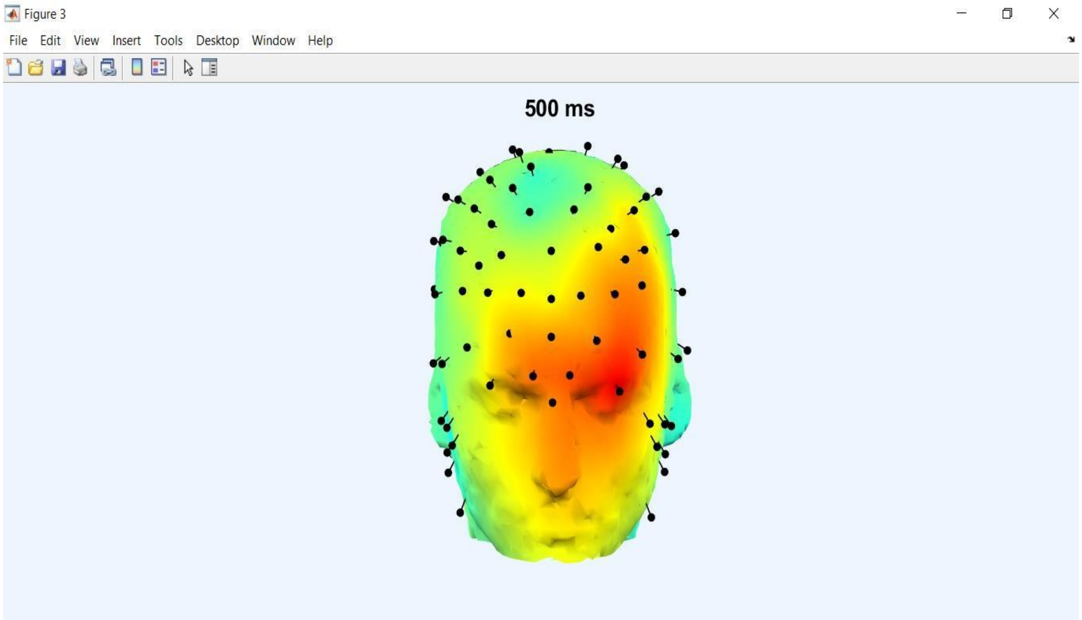

Figure 46 3D scalp map

4.3.2. Feature Extraction

Feature extraction is the process of identifying and extracting relevant patterns or features from EEG signals that are related to emotions. These features can be based on various properties of the EEG signals such as frequency, amplitude, power, and phase. The goal is to extract a set of features that can effectively differentiate between different emotions.

For example, studies have shown that the power in the alpha and beta frequency bands is related to emotional states, [42], so these features may be extracted from the EEG signals. Additionally, other features such as the mean, standard deviation, and skewness of the EEG signals can also be extracted and used for classification.

In this study three feature extraction methods are used, WT, CNN as a feature extraction Method, PSD as well as the raw features are extracted to classify emotions based on EEG, and MATLAB is used as a tool for the implementation of those methods.

4.3.2.1. Wavelet Transform (WT)

In WT, the signal is divided into its frequency components using the wavelet transform, which computes each one with its scale-dependent pattern resolution. As a result, it offers information in various resolutions. Wavelets are produced from mother wavelets at various sizes and translated by wavelet analysis. DWT employs those wavelets to define a function or picture as a linear combination of the wavelets and scaling function. In addition, wavelet variation is crucial for catching various scaled patterns. WT differs from Short Term Fourier Transforms (STFTs) in that they have windows with variable scales.

4.3.2.1.1. Daubechies 4 Wavelet

The Daubechies wavelet transforms compute running averages and differences through scalar products with scaling signals and wavelets.

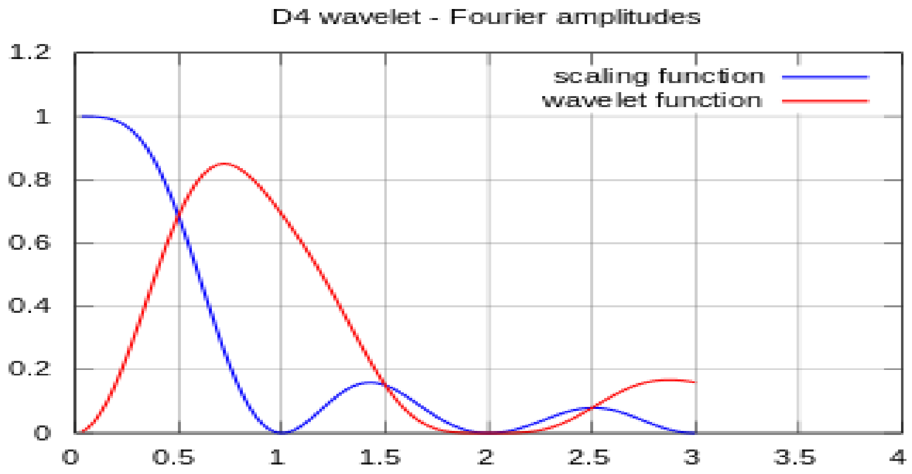

Figure 47 Daubechies Wavelet representing scaling and wavelet function.

The specific coefficients of the scaling function for the Daubechies D4 transform depend on the implementation and variant of the transform being used. The Daubechies D4 transform is known to have four wavelets and four scaling function coefficients. Which are:

$$\{h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}};\ h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}};\ h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}};\ h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

Equation 1

During each wavelet transform step, the scaling function is utilized to process the data input. If the initial dataset has N values, the scaling function will be implemented to generate smoothed values in the ordered wavelet transform. These smoothed values are then stored in the lower half of the N-element input vector. Additionally, the wavelet function coefficients are determined during this process.

$$\{g_0 = h_3;\ g_1 = -h_2; g_2 = h_1;\ g_3 = -h_0\}$$

Equation 2

The input data undergoes a wavelet transformation that utilizes the wavelet function, provided that the original dataset contains N values. The wavelet function is applied to compute N/2 differences based on the N values of the original dataset. The scaling and wavelet functions are determined by computing the inner product of the coefficients and four data values. The equations for the Daubechies D4 scaling function are as follows:

$$a_i = h_0 s_2 i + h_2 i + 2 + h_3 s_2 i + 3 \quad \textit{Equation 3}$$

$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3] \quad \textit{Equation 4}$$

Daubechies D4 Wavelet function:

$$c_i = g_0 s_2 i + g_1 s_2 i + 1 + g_2 s_2 i + 2 + g_3 s_2 i + 3 \quad \textit{Equation 5}$$

$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3] \quad \textit{Equation 6}$$

During each step of the wavelet transform, both a scaling function value and a wavelet function value are calculated.

4.3.2.1.2. Implementation

In the study “wavedec” function in MATLAB is used to perform a multi-level discrete wavelet decomposition of a signal represented by the variable r4. The decomposition is performed using the 'db4' wavelet and the decomposition level was 5.

The appcoef function is then used to extract the approximation coefficients at level 5 from the decomposition structure. The detcoef function is used to extract the detail coefficients for levels 5, 4, 3, 2, and 1 respectively.

Finally, the all the extracted coefficients are concatenated (cA5, cD5, cD4, cD3, cD2, cD1) into a single vector and assigned to the variable cp. The resulting vector contained the approximation coefficients at level 5 and the detailed coefficients for each level of the decomposition, in that order. This can be used to obtain the frequency information of the signal in different sub bands.

4.3.2.2. CNN

One of the most often used neural network methods today is CNNs. It was modelled after the human visual system. It is feasible to extract beneficial abstract properties. CNN lessens system complexity and enhances generalization. Convolutional layers, pooling layers, dropout layers, batch norm layers, fully connected layers, and SoftMax layers are all possible components of the CNN algorithm. The pooling layer follows the convolutional layer in the algorithm, which is where retrieved feature maps go following the convolution procedure. As the model continues to train, these features expand toencompass related patterns of the inputs at each stage of the training process since convolutionoperation is conducted with varied sized and different number kernels, providing filtering of the network's fed inputs.

On the image or feature map layer, the kernel consists of slides with predetermined intervals; these intervals are referred to as "strides." The convolution result on the feature map is represented as the weighted sum of the filtering operation for each stride step. The size of the features is reduced using this procedure. However, certain implementations might desire to safeguard the size of the fed input, in which case "padding" procedure is employed. The feature map matrices are surrounded by zeros in this procedure, and convolution is performed on this padded form. the end of the convolution operation result size can be stay same with the input. A sample convolution operation was given in Figure 49.

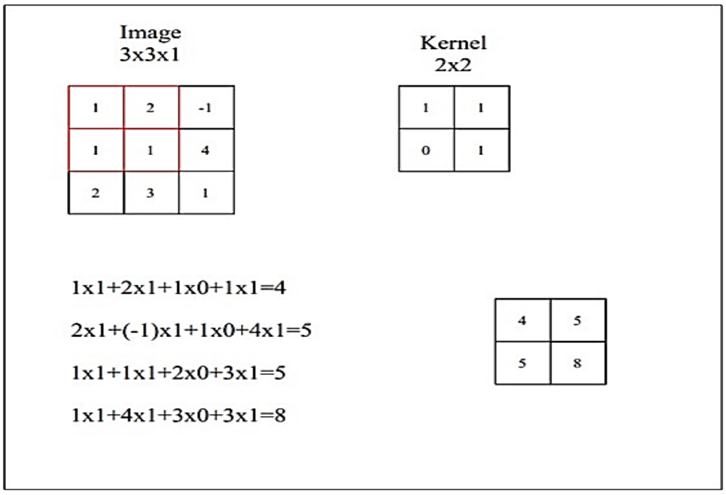

Figure 48 Convolution operation.

In this manner Feature maps are added to the Relu activation function after the convolution procedure. The use of this procedure is justified by the addition of nonlinearity to the model (Bengio, 2016) [172]. Feature maps were sent through the pooling layers after this layer. The width and height scales of the feature map are decreased by pooling layers. Since it shrinks the size of the feature maps, this method is used to lessen computational complexity and overfitting. The pooling operation's size and stride may be adjusted and run under different conditions. Figure 50 provided a max pooling operation example.

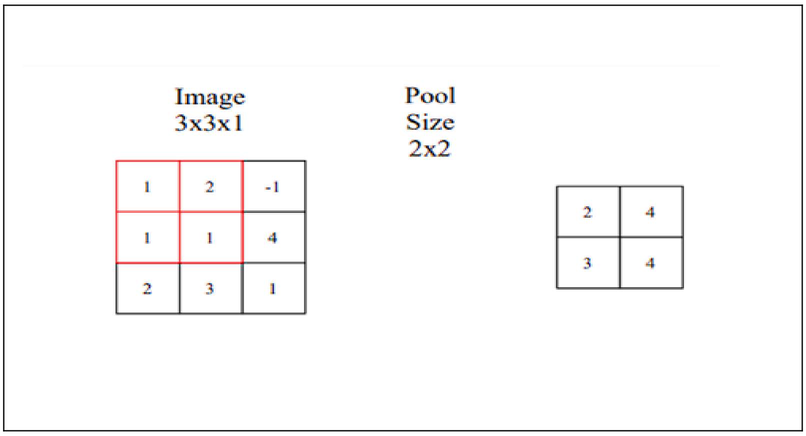

Figure 49 Max pooling operation.

Dropout layer is an additional CNN layer. Some neurons become inactive during training when dropout layers are used with certain probabilities. It stops a model from being overfit. Another CNN layer is the batch normalization layer. Input distributions shift as a model is being trained, necessitating adjustments. Batch normalization is a process that calibrates the inputs to each layer.

The output from the last pooling or convolutional layer is passed into the fully connected layer, where it is flattened before being applied. Finally, the softmax layer confines the outputs to a certain range by maintaining the total probability distribution summing at 1. (Liet al., 2016) [173].

4.3.2.2.1. Implementation

A 1-dimensional CNN is implemented in MATLAB. The input to the network is a set of 1-dimensional signals represented by the variable images, and the output is a set of features extracted from the input signals. Different vector filters were used to check the effectiveness of proposed model, but results were reported only for the filter size of (1 × 130).

The network architecture of our proposed CNN is defined by a set of parameters:

The dimension of the input images, in our case it was 1. The dimension of the filters used in the convolutional layer was 130. The number of filters (or feature maps) used in the convolutional layer was 100. The dimension of the pooling region used in the pooling layer; in this study it was 11. The details of layers and maps of every layer are shown in figure 51.

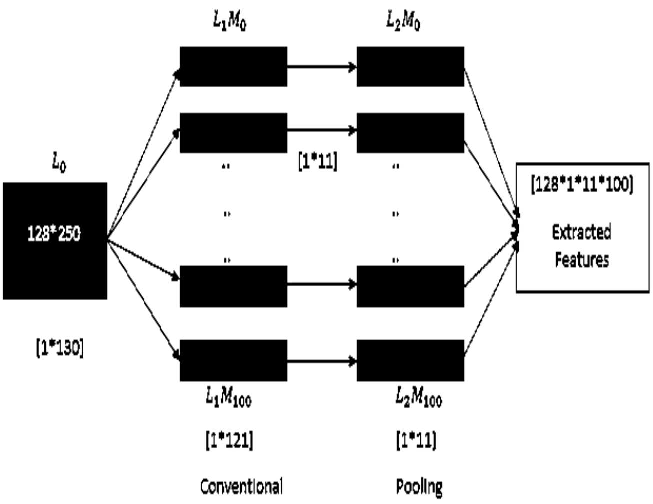

Figure 50 Proposed CNN model, where L indicates the layers and M defines the maps of convolutional layer.

The first step in the network was to initialize the weights W and biases b of the filters randomly using the randn and rand functions.

Then, the first 8 images are selected for testing and are stored in a variable.

After that the cnnConvolve_1D function is called to convolve the filters with the input images. This function took in the filter dimension, number of filters, input images and the filter weights and biases as input. The output of this function was the convolved features.

The next step was to perform pooling on the convolved features. The cnnPool_1D function was called to perform pooling on the convolved features. This function took in the pooling dimension and convolved features as input and returned the pooled features.

Finally, the pooled features were reshaped and concatenated to an existing feature vector and stored in a variable. This can be used as a feature representation of the input image.

4.3.2.3. PSD

PSD is used to illustrate frequency-dependent signal variations. It is used to distribute average power with respect to frequency. When calculating spectra with FFT, the spectra of the noise signal may be included; this may be eliminated by averaging. The spectra of the signal are averaged over windows using PSD using Welch. The input signal is first divided into tiny segments, and an average power spectrum of these segments is then calculated. Periodogram, a term used to describe the DFT evaluation of PSD, is easily determined using FFT. Using DFT, PSD may be computed as

$$P(x(t)) = \frac{1}{L}\left|X(e^{jw})\right|^2 \qquad \textit{Equation 7}$$

The periodogram's mean value will approach the genuine PSD when L is increased, but the variance won't disappear completely [174] A biassed estimator is the periodogram as a result. The use of ensemble averaging lowers the predicted periodogram's variance. The steps are as follows for Welch-based PSD calculation.

Split the input data up into L slots and Z samples. 2) Calculate the periodogram using the FFT for every slot.

$$P_j(w) = \frac{1}{KZ}\left|\sum_{z-1}^{n=0} X_j(n)w(n)e^{-jwn}\right|^2 \qquad \textit{Equation 8}$$

Where, k=1 $\sum_{z-1} w^2(n)$ is the average power of given window.

—

Theta band, Alpha band, and Beta band values of the Normalized PSD (NPSD) are computed. Equation 6.3's calculation of the NPSD is presented. Here, the PSD of one band is computed and divided by the total PSD of the other two bands.

$$\text{NPSD Band} = \frac{\text{PSD Band}}{\text{Total PSD Bands}} \qquad \textit{Equation 9}$$

4.3.2.3.1. Implementation

The pwelch function in MATLAB is used to determine a signal's PSD. The function employs the Welch's approach, which requires averaging many periodograms of overlapping input data segments. In addition to the input signal, the function also accepts optional inputs for the window function, the amount of overlap between segments, and the number of points employed in the FFT calculation.

4.3.3. Feature Selection

Feature selection is an important technique that can be used to improve the accuracy of ML models and reduce their training time. There are several different methods of feature selection that can be employed, including techniques like Region of Interest (ROI), Principal Component Analysis (PCA), Independent Component Analysis (ICA), t-test, and others. These methods are designed to identify and extract the most relevant features from a given dataset, which can help to improve the performance and efficiency of the model.

In the current study T-test is used as a feature selection method which is a useful tool for feature selection in EEG research as it allows researchers to identify the most informative features from a dataset and use them for classification or prediction task.

4.3.3.1. T- test Feature Selection

T-test can be used for feature selection, which is the process of identifying the most informative features from a dataset. A t-test can be used to compare the means of different EEG features, such as the power of different frequency bands or the amplitude of different electrodes, between two groups of subjects (e.g., healthy vs diseased, or with different cognitive states).

By comparing the means of different EEG features between two groups, researchers can identify which features are most different between the groups and thus most informative for differentiating between the groups. These features are considered as the most relevant and informative for classification or prediction tasks.

For example, a researcher may use a t-test to compare the power of the alpha frequency band (8-12 Hz) between a group of healthy subjects and a group of subjects with a specific disease. If the power of the alpha frequency band is significantly different between the two groups, this feature may be considered as an informative feature for differentiating between healthy and diseased subjects.

It's important to note that t-test is just one of the many statistical tests that can be used for feature selection, and it's not always the best choice, as it makes assumptions about the data such as normality and equal variances, other tests like Wilcoxon rank sum test, or non-parametric tests can be used as well.

T-test is a useful tool for feature selection in EEG research as it allows researchers to identify the most informative features from a dataset and use them for classification or prediction tasks.

4.3.3.1.1. Implementation

A t-test is performed to find the columns with p-values less than 0.05. This t-test is a two-sample test that compares the means of two samples and returns the p-value which is used to determine the significance of the difference between the means. The built-in function "ttest2" is used to perform the t-test with the option "Vartype" set to "unequal" which means that the variances of the two samples are different.

The columns with p-values less than 0.05 are then sorted in descending order based on their p-values and stored in the variable "zz1". The same process is then applied to the test data and stored in the variable "zztest1".

4.3.4. Model Validation

The process of model validation entails evaluating the performance of a ML model on a given task or problem using an independent dataset, with the aim of determining its ability to generalize to new, unseen data and identifying areas where it may be underperforming or overfitting. Various validation techniques exist, depending on the specific task or problem.

Below are some examples of such models,

Holdout validation: this method involves dividing the dataset into a training set and a validation set, with the model being trained on the former and evaluated on the latter.

Cross-validation: It is another technique, whereby the dataset is divided into k non-overlapping subsets or "folds", and the model is trained on k-1 of these folds and evaluated on the remaining fold. This process is repeated k times, with each fold serving as the evaluation set exactly once. Leave-one-out cross-validation is a special case of cross-validation where k is set to the number of samples in the dataset, and the model is trained on all but one sample and evaluated on the one left out.

Monte Carlo validation: is yet another technique that involves generating random samples from the dataset to train and evaluate the model. This technique is useful when data is limited or cannot be easily split into distinct subsets, such as when working with time-series data. Therefore, in this study, Monte Carlo validation was employed for this purpose.

4.3.4.1. Monte Carlo

Monte Carlo random sampling is a method used in statistics and computational science to generate random samples from a given distribution. The method is named after Monte Carlo, a city in Monaco known for its casinos and gambling. The basic idea behind Monte Carlo random sampling is to use random numbers to generate a set of samples that mimic the properties of the underlying distribution.

Monte Carlo random sampling is often used to simulate the effects of different experimental conditions on EEG data. For example, researchers may use Monte Carlo random sampling to simulate different types of brainactivity, such as different patterns of neural firing or different levels of synchronization. Researchers may also use the method to simulate different levels of noise in the EEG data, suchas measurement error or interference from other sources.

By simulating different conditions using Monte Carlo random sampling, researchers can gain a deeper understanding of the underlying mechanisms of EEG data and develop more robust and accurate methods for analyzing and interpreting EEG data. For example, researchers may use simulated data to test different analysis methods, such as signal processing algorithms or statistical models, to see which methods work best in different conditions.

Additionally, Monte Carlo random sampling can be used to estimate the uncertainty of the results obtained by a particular method, by simulating multiple sets of data and comparing the results. This can help researchers to determine how much the results may vary due to random factors such as measurement error or subject variability.

Overall, Monte Carlo random sampling is a powerful tool that can be used to gain a deeper understanding of EEG data and to develop more robust and accurate methods for analyzing and interpreting EEG data. It allows researchers to simulate different conditions, test different methods and estimate uncertainty, making it a useful technique for EEG research.

4.3.4.1.1. Implementation

In the current study MATLAB is used to implement the code of Monte Carlo where a loop from 50 to the length of the columns with p-values less than 0.05 (or a maximum of 5000) is implemented, in increments of 50, for the purpose of training and testing a classifier using the selected features. The selected features are stored in the variable "cc" and "b2" for the training and test data respectively.

4.3.5. Classification

Classification is a technique that allows us to predict the category or label of a given data point based on its features, using a set of labeled data as a reference. In EEG analysis, we can train a model to recognize specific patterns of brain activity associated with different cognitive states or emotions.

For example, by analyzing EEG signals, we can develop a classification model that distinguishes between signals that indicate a happy emotional state and those that indicate a happy or sad emotional state. There are many types of ML algorithms for classification i.e., SVM, Naïve Bayes (NB), Random Forest (RF). But in this study SVM is used as a classifier as it is found most effective for EEG classification

4.3.5.1. SVM

SVMs are a type of supervised ML algorithm that canbe used for classification and regression tasks. In the context of EEG SVMs can be used to classify different types of brain activity or different cognitive states based on EEG data.

Mathematically, an SVM can be represented as an optimization problem that aims to find the hyperplane that separates different classes of data with the largest margin. The margin is the distance between the closest data points of different classes and the hyperplane.

SVMs are a type of supervised ML algorithm that canbe used for classification and regression tasks. In the context of EEG, SVMs can be used to classify different types of brain activity or different cognitive states based on EEG data.

The basic idea behind an SVM is to find a "hyperplane" in a high-dimensional space that separates different classes of data. The hyperplane is chosen so that it maximizes the margin, or the distance, between the closest data points of different classes. The data points that are closest to the hyperplane are called "support vectors" and have the most influence in determining the position of the hyperplane.

An SVM can be trained on a dataset of EEG data from different subjects and different conditions, such as different types of brain activity or different cognitive states. The SVM can then be used to classify new EEG data based on the features that it has learned from the training data.

For example, a researcher may use an SVM to classify different types of brain activity, such as different patterns of neural firing or different levels of synchronization, based on the power of different frequency bands in the EEG data. The researcher can use different features such as the power of different frequency bands, the amplitude of different electrodes, or other derived features such as connectivity measures, coherence, etc.

It's important to note that as with any ML model, the performance of an SVM depends on the quality of the data, the choice of features, and the parameter tuning. Additionally, SVM is just one of the many ML models that can be used for EEG classification, other models such as Random Forest, Neural Networks, etc. can also be used andcompared with SVM.

SVMs are a powerful tool that can be used for EEG classification in research. They can be trained on a dataset of EEG data and then used to classify new EEG data based on the features that it has learned from the training data.

4.3.5.1.1. Implementation

To apply classification in the study, "svmtrain" function to train a SVM model on the provided "trainlabel" and "traindata" variables. The function took several parameters that are used to control the training process.

The "-s 0" parameter specified that the type of SVM model being used is a C-SVC (C-Support Vector Classification) type. This type of model is commonly used for classification tasks with a binary outcome.

The "-t 0" parameter specified that a linear kernel is being used. A kernel is a function that is used to transform the input data into a higher-dimensional space, making it easier to separate the different classes in the data. The linear kernel simply calculates the dot product of the input vectors.

The "-c 1" parameter set the cost of the SVM model to 1. The cost parameter controls the trade-off between maximizing the margin (the distance between the decision boundary and the closest training examples from each class) and minimizing the classification error. A higher cost will result in a larger margin but potentially more misclassifications.

The "-b 1" parameter specified that probability estimates should be calculated for the SVM model. This allows the model to output a probability that a given example belongs to a specific class, rather than just a binary prediction.

After the model is trained, the "svmpredict" function is used to predict labels for the "testlabel" and "testdata" variables using the trained model. The "-b 1" option is again specified, which will return the probability estimates for each prediction. The predicted label, likaccuracy, prob_values are returned.

The likaccuracy is the mean accuracy of the predicted labels.
The predict_label is the predicted label for the testdata.

The prob_values are the probability of each class.

4.3.6. Software Tools

Software tools are specialized computer programs or applications that are designed to help researchers process, analyze, and visualize EEG data. These tools offer researchers various features, such as signal processing techniques, feature extraction, and statistical analysis, to aid in the analysis of EEG data. Some EEG software tools also provide features for artifact removal, data cleaning, and data visualization. Popular EEG software tools include MATLAB, EEGLAB, FieldTrip, BESA, Neuroscan, MNE-Python and so on. Using these software tools is crucial for researchers who work with EEG data to efficiently process and analyze complex data, which can lead to more accurate and insightful research findings.
In this study I have used MATLAB as the software tool, I was able to preprocess and analyze EEG data, as well as visualize the results. The flexibility and power of MATLAB allowed me to apply various signal processing techniques and statistical analyses to the data, which ultimately helped me gain more insight into my research questions. Additionally, MATLAB's extensive library of functions and tools made it easier to perform complex analysis tasks.
MATLAB was an essential tool in my research, and it has helped me produce more accurate and insightful research findings.

4.3.6.1. MATLAB

Engineers and scientists utilize the software environment MATLAB to research, plan, and create systems and products. It enables users to perform a wide range of tasks, such as developing user interfaces, connecting to programmed written in other languages, analyzing data, developing algorithms, and creating models and applications, as well as to express mathematical computations in the MATLAB language, a matrix-based programming language. Mathematical operations and built-in functions in MATLAB make it simple to execute calculations, create graphs, and carry out numerical procedures. It is widely utilized in scientific and engineering subjects including physics, chemistry, mathematics, and all engineering disciplines. To expand the functionality of the MATLAB technical computing environment, Mathworks, Inc. and other developers have created a variety of toolboxes, which are collections of functions.

4.3.6.1.1. EEGLAB

MEG, EEG, and as well as other event-related physiological signal or data are processed using the EEGLAB toolbox in MATLAB. Some of its main features which make it an important tool for EEG are event-related statistics, time-frequency analysis, artefact rejection, ICA along with visualization of data are some of its important features. EEGLAB has a command history also instructional and help panels, features that enable switching to custom or batch scripting from GUI-based data exploration. It is also compatible with a wide range of operating systems. When applied to a single dataset or a collection of datasets arranged as an "EEGLAB study set," it is helpful for studying and modelling event-related brain dynamics. Additionally, EEGLAB offers a structured programming environment that enables the automated modification and display of event-related EEG data. By releasing EEGLAB "plug-in" features that can be accessible directly from the EEGLAB menu, new methodologies with the community can be shared by the method creatorsand researchers.

4.3.6.1.2. Bio signal Processing Toolbox

Analysis, preprocessing, and feature extraction from regularly and unevenly sampled signals are all possible with the help of the Signal Processing Toolbox in MATLAB. In addition to features for extracting features for example envelopes, and change points detecting the signal patterns as well as peaks, to determine the similarity between signals, measuring SNR and distortion, Tools for analysis and filter design, power spectrum estimation, smoothing, detrending, smoothing and resampling are also included in this toolbox. For modal and order analysis of vibration signals it also has resources. The toolbox's Signal Analyzer app offers simultaneous preprocessing and analysis of various signals in the frequency, time including time-frequency domains. It also allows for the study of lengthy signals and the extraction of particularly interesting segments. Digital filters may be designed and analyzed using a variety of algorithms and responses with the Filter Designer App. Sub bands (delta, theta, alpha, beta, and gamma) from raw EEG data with the following frequency ranges are also extracted, those frequency sub bands are gamma= from 35 to 50Hz, beta= from 12 to 35Hz, alpha= from 8 to 12Hz, theta= from 4 to 8Hz and delta= from 0.5 to 4Hz. Band pass IIR filter can also be created using the signal processing toolbox.

4.3.6.1.3. Statistics and ML Toolbox

To describe, analyze, and model the data Applications and functions are available via the Statistics and ML Toolbox in MATLAB. This tool enables exploratory data analysis. There are tools for utilizing Classification and Regression Learner applications or AutoML to infer conclusions from data using regression and classification techniques. To evaluate and extract features from multidimensional data Regularization, Principal component analysis (PCA), dimension reduction and feature selection are some of the methods available in this toolbox which are effective to be used. For unsupervised ML, it offers k-means, boosted decision trees (BDTs), SVM, and other clustering methods. It can also create embedded C/C++ code utilizing interpretability techniques like partial dependency graphs and LIME. Even if they don't fit in memory, big datasets can be handled by the toolkit. In this work, it is used to create an SVM classifier utilizing features derived from EEG data and estimated emotions. It is installed to enable the usage of ML techniques in.

4.4 Summary

Data was collected from 25 participants using a 128-channel device and text stimuli. As the data was in raw form so prep processing was done on the EEG data using EEGLAB which included down sampling, re-referencing, and filtering the EEG signals to eliminate noise and artifacts. Four feature extraction techniques, CNN, WT, PSD, and Raw data were used to extract features from pre-processed EEG signals. The Monte Carlo approach is applied to randomly selecting training and testing samples to ensure the reliability and validity of results of this study. T-tests were used to identify the most relevant features which were then fed to SVM classifier against each feature extraction method. MATLAB was used for the analysis of EEG data.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Overview

In this chapter, the methodologies and techniques used for experimenting and detecting emotions using MATLAB code are described in detail. The results of these experiments are also presented and analyzed. The MATLAB code implemented for emotion detection is thoroughly evaluated and tested, and the outcomes of these tests are noted. The chapter includes a detailed discussion of the results obtained from each phase of the study; The discussion also includes a comparison of the results obtained with each method. Overall, this chapter provides a comprehensive overview of the experimentation and results related to emotion detection using MATLAB code.

5.2. RESULTS

After the implementation of each feature extraction method in the MATLAB along with SVM for the classification the following results are generated against each subject,

Classification performance was evaluated in terms of accuracy sensitivity, specificity which are defined as,

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} * 100 \qquad \textit{Equation 10}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad \textit{Equation 11}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad \textit{Equation 12}$$

True Positive (TP) refers to a correct prediction of a specific class. True Negative (TN) means that the actual emotion is not part of the given class, and the prediction is also not the given class. False Positive (FP) is the number of instances where the prediction is the given class, but the actual emotion does not belong to that class. False Negative (FN) occurs when the prediction is not the given class, but the actual emotion does belong to that class.

Table 2 Performance measurements for CNN

Specificity	*Sensitivity*	*Accuracy*
0.86	0.86	0.80

Table 3 Performance Measurements for WT

Specificity	*Sensitivity*	*Accuracy*
0.79	0.71	0.75

Table 4 Performance Measurements \for PSD

Specificity	*Sensitivity*	*Accuracy*
0.76	0.68	0.72

Table 5 Performance Measurements For Raw Data

Specificity	*Sensitivity*	*Accuracy*
0.73	0.57	0.65

The results of each subject against each feature extraction method are given in the table below.

Table 6 Result Of Each Subject Against Each Methods

SUBJECT NO	**RAW DATA**	**PSD**	**WT**	**CNN**
SUBJECT 1	64%	70%	72%	87%
SUBJECT 2	66%	72%	76%	90%
SUBJECT 3	65%	72%	76%	75%
SUBJECT 4	63%	70%	75%	77%
SUBJECT 5	81%	75%	74%	76%
SUBJECT 6	65%	75%	70%	85%
SUBJECT 7	60%	74%	77%	77%
SUBJECT 8	67%	70%	80%	80%
SUBJECT 9	65%	73%	75%	78%
SUBJECT 10	60%	77%	79%	80%
SUBJECT 11	66%	71%	76%	78%
SUBJECT 12	64%	72%	75%	84%
SUBJECT 13	68%	73%	74%	81%
SUBJECT 14	62%	74%	78%	82%
SUBJECT 15	66%	75%	73.39%	79%
SUBJECT 16	65%	76%	77%	75%
SUBJECT 17	64%	77%	79%	85%

SUBJECT NO	RAW DATA	PSD	WT	CNN
SUBJECT 18	66%	78%	76%	80%
SUBJECT 19	67%	79%	75.40%	76%
SUBJECT 20	64%	80%	73%	83%
SUBJECT 21	63%	69%	75%	80%
SUBJECT 22	65%	71%	73%	82%
SUBJECT 23	62%	73%	77.41%	80%
SUBJECT 24	66%	75%	72%	81%
SUBJECT 25	64%	77%	78.40%	80%

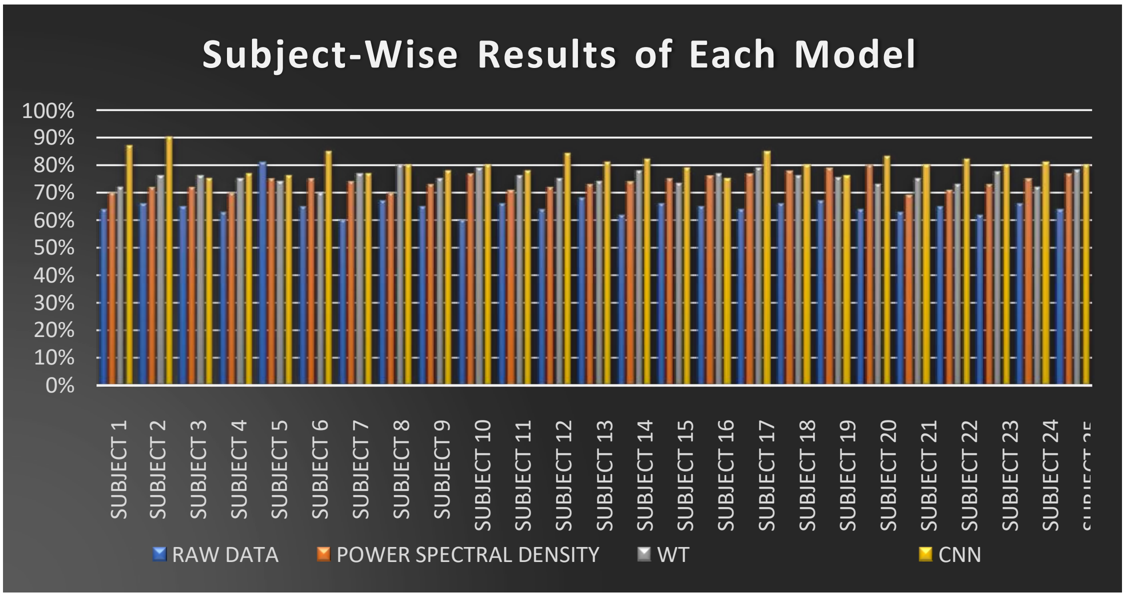

Figure 51 Graphical representation of the following results against each subject.

Chart 1: Graphical representation of the following results against each subject

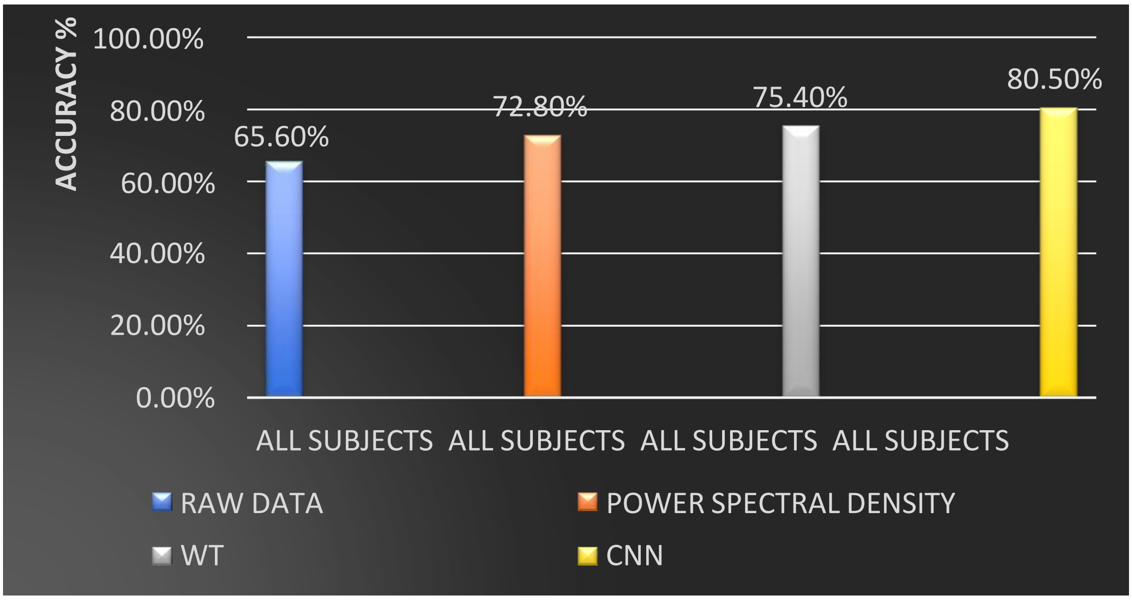

Figure 52 Comparison of each feature extraction method.

5.3. Analysis

The results of this study are highly encouraging, showing that advanced feature extraction methods such as CNN, WT, and PSD can significantly improve the performance of EEG text-based stimuli classification. The result of applying CNN on EEG text-based stimuli dataset was particularly impressive, achieving an accuracy of 80%. This is a very good result, and it suggests that the CNN model was able to effectively learn and extract relevant features from the EEG data that are indicative of the different stimuli.

The application of the WT and PSD methods on the same dataset also showed promising results, with accuracies of 75.40% and 72.80%, respectively. This indicates that both the WT and PSD methods were able to extract meaningful features from the EEG data that were useful for classification. The fact that all three methods performed well on the dataset demonstrates the robustness of the dataset and the effectiveness of these feature extraction methods.

Furthermore, even though the use of raw features resulted in the lowest accuracy of 65.60%, it is still a respectable result, and it illustrates the potential of the raw EEG data for classification tasks. It shows that with proper preprocessing and feature extraction, raw EEG data can still be used effectively for classification tasks.

The results of this study are highly promising, and they demonstrate the effectiveness of advanced feature extraction methods such as CNN, WT, and PSD in improving the performance of EEG text-based stimuli classification. It is a well-conducted study, and the resultsare robust and encouraging. It opens the door to further research in this field and it is a valuablecontribution to the field of EEG-based research.

5.4. Summary

The study demonstrated that advanced feature extraction methods, such as CNN, WT, and PSD, significantly improve the performance of EEG text-based stimuli classification. The CNN method achieved an accuracy of 80%, which suggests that it effectively learned and extracted relevant features from the EEG data. The WT and PSD methods also showed promising results, with accuracies of 75.40% and 72.80%, respectively. The study indicated that all three methods are effective in extracting meaningful features from the EEG data, highlighting the robustness of the dataset and the potential of raw EEG data for classification tasks.

CHAPTER 6
CONCLUSION AND FUTURE WORK

The results of this study are highly encouraging, showing that advanced feature extraction methods such as CNN, WT and PSD significantly improve the performance of EEG emotion classification on text-based stimuli. The result of applying CNN on EEG text-based stimuli dataset was particularly impressive, achieving an accuracy of 80%. This is a very good result, and it suggests that the CNN model was able to effectively learn and extract relevant features from the EEG data that are indicative of the different stimuli.

The application of the WT and PSD methods on the same dataset also showed promising results, with accuracies of 75.40% and 72.80%, respectively. This indicates that both the WT and PSD methods were able to extract meaningful features from the EEG data that were useful for classification. The fact that all three methods performed well on the dataset demonstrates the robustness of the dataset and the effectiveness of these feature extraction methods.

Furthermore, even though the use of raw features resulted in the lowest accuracy of 65.60%, it is still a respectable result, and it illustrates the potential of the raw EEG data for classification tasks. It shows that with proper preprocessing and feature extraction, raw EEG data can still be used effectively for classification tasks.

The results of this study are highly promising, and they demonstrate the effectiveness of advanced feature extraction methods such as CNN, WT, and PSD in improving the performance of EEG text-based stimuli classification. It is a well-conducted study, and the results are robust and encouraging. It opens the door to further research in this field and it is a valuable contribution to the field of EEG-based research.

6.1 Future Work

As data was collected using three different colors, providing a foundation for further investigation into the potential impact of color on emotions. It could be hypothesized that certain colors elicit stronger emotional responses than others. For example, anger presented in red may provoke a more intense emotional response than if presented in gray or blue. To better understand the influence of color on human emotions, the future work will involve analyzing the EEG data while considering color as well as text as the basis of our study.

REFERENCES

1. LABERGE, D. and R. KASEVICH, *Descartes' error: Emotion, reason and the human Brain Descartes' error: Emotion, reason and the human Brain, 1994.*

2. Zheng, W.-L., J.-Y. Zhu, and B.-L.J.I.T.o.A.C. Lu, *Identifying stable patterns over time for emotion recognition from EEG.* 2017. **10**(3): p. 417-429.

3. Duan, R.-N., J.-Y. Zhu, and B.-L. Lu. *Differential entropy feature for EEG-based emotion classification*. in *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*. 2013. IEEE.

4. Zheng, W.-L. and B.-L.J.I.T.o.a.m.d. Lu, *Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks.* 2015. **7**(3): p. 162-175.

5. Kim, M.-K., et al., *A review on the computational methods for emotional state estimation from the human EEG.* 2013. **2013**.

6. Koelstra, S., et al., *Deap: A database for emotion analysis; using physiological signals.* 2011. **3**(1): p. 18-31.

7. Plutchik, R., *Emotions and life: Perspectives from psychology, biology, and evolution*. 2003: American Psychological Association.

8. Izard, C.E.J.A.r.o.p., *Emotion theory and research: Highlights, unanswered questions, and emerging issues.* 2009. **60**: p. 1-25.

9. Teplan, M.J.M.s.r., *Fundamentals of EEG measurement.* 2002. **2**(2): p. 1-11.

10. Liu, Z.-T., et al., *EEG emotion recognition based on empirical mode decomposition and optimal feature selection.* 2018. **11**(4): p. 517-526.

11. Pane, E.S., A.D. Wibawa, and M.H. Pumomo. *Channel selection of EEG emotion recognition using stepwise discriminant analysis*. in *2018 International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM)*. 2018. IEEE.

12. ZHANG, G., et al., *A review of EEG features for emotion recognition.* 2019. **49**(9): p. 1097-1118.

13. Oude Bos, D.J.C.S., *EEG-based emotion recognition-The Influence of Visual and Auditory Stimuli.* 2006: p. 1-17.

14. Li, T.-H., et al. *Classification of five emotions from EEG and eye movement signals: Discrimination ability and stability over time*. in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*. 2019. IEEE.

15. Cao, K.J.T., China: Tianjin Med. Univ, *The research of the EEG frequency power feature in three basic emotions.* 2019.

16. Subha, D.P., et al., *EEG signal analysis: a survey.* 2010. **34**(2): p. 195-212.

17. Bhise, P.R., S.B. Kulkarni, and T.A. Aldhaheri. *Brain computer interface based EEG for emotion recognition system: A systematic review*. in *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*. 2020. IEEE.

18. DAŞDEMİR, Y., et al., *Emotion analysis using different stimuli with EEG signals in emotional space.* 2017. **2**(2): p. 1-10.

19. Hulliyah, K.J.T.J.o.C. and M. Education, *Analysis of Emotion Recognition Model Using EEG (EEG) Signals Based on Stimuli Text.* 2021. **12**(3): p. 1384- 1393.

20. Khasnobish, A., et al., *Analyzing text recognition from tactually evoked EEG.* Cognitive neurodynamics, 2017. **11**(6): p. 501-513.

21. Alarcao, S.M. and M.J.J.I.T.o.A.C. Fonseca, *Emotions recognition using EEG signals: A survey*. 2017. **10**(3): p. 374-393.
22. Gunes, H., et al. *Emotion representation, analysis and synthesis in continuous space: A survey*. in *2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG)*. 2011. IEEE.
23. Alotaiby, T., et al., *A review of channel selection algorithms for EEG signal processing.* 2015. **2015**(1): p. 1-21.
24. Chanel, G., et al., *Short-term emotion assessment in a recall paradigm.* 2009. **67**(8): p. 607-627.
25. Betts, J.G., et al., *OpenStax College & Rice University*. 2013.
26. Davis, T.J.P.t., *What is well-being? Definition, types, and well-being skills*. 2019.
27. Lovén, L., et al. *Wellbeing in smart environments: definition, measurement, prediction and control*. in *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*. 2018.
28. Stewart-Brown, S.J.B., *Emotional wellbeing and its relation to health: Physical disease may well result from emotional distress*. 1998, British Medical Journal Publishing Group. p. 1608-1609.
29. Hockenbury, D.H. and S.E. Hockenbury, *Discovering psychology*. 2010: Macmillan.
30. Feldman, L., et al., *The experience of emotion.* 2007. **58**(1): p. 373-403.
31. Cherry, K.J.V., July, *Emotions and Types of Emotional Responses.* 2019. **17**.
32. James, W., *What is an Emotion? Mind os-IX.* 1884.
33. Cannon, W.B.J.T.A.j.o.p., *The James-Lange theory of emotions: a critical examination and an alternative theory.* 1987. **100**(3/4): p. 567-586.
34. Silberman, E.K., H.J.B. Weingartner, and cognition, *Hemispheric lateralization of functions related to emotion.* 1986. **5**(3): p. 322-353.
35. Davidson, R.J.J.P., *Affective neuroscience and psychophysiology: Toward a synthesis.* 2003. **40**(5): p. 655-665.
36. Russell, J.A.J.J.o.p. and s. psychology, *A circumplex model of affect.* 1980. **39**(6): p. 1161.
37. Remington, N.A., et al., *Reexamining the circumplex model of affect.* 2000. **79**(2): p. 286.
38. Lopes da Silva, F., *Electrophysiological Basis of MEG Signals. Teoksessa: MEG: an Introduction to Methods (toim.) PC Hansen, ML Kringelbach & R. Salmelin*. 2010, Oxford University Press, Inc.: New York.
39. Niedermeyer, E. and F.L. da Silva, *Electroencephalography: basic principles, clinical applications, and related fields*. 2005: Lippincott Williams & Wilkins.
40. Schuller, B., et al. *Speaker independent speech emotion recognition by ensemble classification*. in *2005 IEEE international conference on multimedia and expo*. 2005. IEEE.
41. Kumar, J.S. and P.J.P.e. Bhuvaneswari, *Analysis of Electroencephalography (EEG) signals and its categorization–a study.* 2012. **38**: p. 2525-2536.
42. Alfimtsev, A., et al., *A new methodology of usability testing on the base of the analysis of user's EEG.* 2015. **3**(5): p. 105-111.
43. Salma, N., et al., *Using EEG signal to analyze IS decision making cognitive processes*, in *Information Systems And Neuroscience*. 2018, Springer. p. 211-218.
44. Nykopp, T.J.H.H.U.o.T., *Statistical modelling issues for the adaptive brain interface.* 2001.
45. Gibbs, F.A., et al., *The electro-encephalogram in epilepsy and in conditions of impaired consciousness.* 1935. **34**(6): p. 1133-1148.

46. Sohaib, A.T. and S. Qureshi, *An Empirical Study of Machine Learning Techniques for Classifying Emotional States from EEG Data*. 2012.
47. Jacobs, J., et al., *EEG oscillations and recognition memory: theta correlates of memory retrieval and decision making.* 2006. **32**(2): p. 978-987.
48. Baldauf, D. and R.J.S. Desimone, *Neural mechanisms of object-based attention.* 2014. **344**(6182): p. 424-427.
49. Correa, A.G., et al. *Artifact removal from EEG signals using adaptive filters in cascade*. in *Journal of Physics: Conference Series*. 2007. IOP Publishing.
50. Farnsworth, B.J.i.h.i.c.b.w.-i.-e., *What is EEG (Electroencephalography) and How Does it Work?* 2018. **8**.
51. Farnsworth, B.J.G.H.C., Denmark, *Eeg (electroencephalography): The complete pocket guide.* 2019.
52. Lee, Y.-Y. and S.J.P.o. Hsieh, *Classifying different emotional states by means of EEG-based functional connectivity patterns.* 2014. **9**(4): p. e95415.
53. Nomenclature, S.E.P.J.J.o.c.N., *American electroencephalographic society guidelines for.* 1991. **8**(2): p. 200-2.
54. Olguin, D.O., F. Bouchereau, and S. Martinez. *Adaptive notch filter for EEG signals based on the LMS algorithm with variable step-size parameter*. in *Proceedings of the 39th International Conference on Information Sciences and Systems*. 2005. The Johns Hopkins University Baltimore, MD.
55. Moretti, D.V., et al., *Computerized processing of EEG–EOG–EMG artifacts for multi-centric studies in EEG oscillations and event-related potentials.* 2003. **47**(3): p. 199-216.
56. Fatourechi, M., et al., *EMG and EOG artifacts in brain computer interface systems: A survey.* 2007. **118**(3): p. 480-494.
57. Kassam, K.S., et al., *Identifying emotions on the basis of neural activation.* 2013. **8**(6): p. e66032.
58. Lindquist, K.A., et al., *The brain basis of emotion: a meta-analytic review.* 2012. **35**(3): p. 121.
59. Marín-Morales, J., et al., *Affective computing in virtual reality: emotion recognition from brain and heartbeat dynamics using wearable sensors.* 2018. **8**(1): p. 1-15.
60. Fredrickson, B., *Positive emotions broaden and build. Advances in experimental social psychology47, 1-53. doi: 10.1016*. 2013, B978-0-12-407236-7.00001-2.
61. Hu, X., et al., *EEG correlates of ten positive emotions.* 2017. **11**: p. 26.
62. Ang, A.Q.-X., et al., *Emotion classification from EEG signals using time-frequency-DWT features and ANN.* 2017. **5**(3): p. 75-79.
63. Li, Y., et al., *The influence of positive emotion and negative emotion on false memory based on EEG signal analysis.* 2021. **764**: p. 136203.
64. Abadi, M.K., et al. *Decoding affect in videos employing the MEG brain signal*. in *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*. 2013. IEEE.
65. Atkinson, J. and D.J.E.S.w.A. Campos, *Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers.* 2016. **47**: p. 35-41.
66. Han, K., D. Yu, and I. Tashev. *Speech emotion recognition using deep neural network and extreme learning machine*. in *Interspeech 2014*. 2014.
67. Milton, A., S.T.J.C.S. Selvi, and Language, *Class-specific multiple classifiers scheme to recognize emotions from speech signals.* 2014. **28**(3): p. 727-742.
68. Perikos, I. and I.J.E.A.o.A.I. Hatzilygeroudis, *Recognizing emotions in text using ensemble of classifiers.* 2016. **51**: p. 191-201.

69. Shaheen, S., et al. *Emotion recognition from text based on automatically generated rules*. in *2014 IEEE International Conference on Data Mining Workshop*. 2014. IEEE.
70. Kapoor, A. and R.W. Picard. *Multimodal affect recognition in learning environments*. in *Proceedings of the 13th annual ACM international conference on Multimedia*. 2005.
71. Kessous, L., G. Castellano, and G.J.J.o.M.U.I. Caridakis, *Multimodal emotion recognition in speech-based interaction using facial expression, body gesture and acoustic analysis.* 2010. **3**(1): p. 33-48.
72. Carvalho, S., et al., *The emotional movie database (EMDB): A self-report and psychophysiological study.* 2012. **37**(4): p. 279-294.
73. Soleymani, M., et al., *A multimodal database for affect recognition and implicit tagging.* 2011. **3**(1): p. 42-55.
74. Kurdi, B., S. Lozano, and M.R.J.B.r.m. Banaji, *Introducing the open affective standardized image set (OASIS).* 2017. **49**(2): p. 457-470.
75. Sneddon, I., et al., *The belfast induced natural emotion database.* 2011. **3**(1): p. 32-41.
76. Gross, R., et al., *Multi-pie.* 2010. **28**(5): p. 807-813.
77. Koolagudi, S.G. and K.S.J.I.j.o.s.t. Rao, *Emotion recognition from speech: a review.* 2012. **15**(2): p. 99-117.
78. Kim, J.J.R.s.r. and understanding, *Bimodal emotion recognition using speech and physiological changes.* 2007. **265**: p. 280.
79. Khalfa, S., et al., *Brain regions involved in the recognition of happiness and sadness in music.* 2005. **16**(18): p. 1981-1984.
80. Abadi, M.K., et al., *DECAF: MEG-based multimodal database for decoding affective physiological responses.* 2015. **6**(3): p. 209-222.
81. Bradley, M.M. and P.J.J.U.o.F. Lang, Gainesville, FL, Tech. Rep. B-3, *The International Affective Digitized Sounds (; IADS-2): Affective ratings of sounds and instruction manual.* 2007.
82. Lang, P.J., et al., *International affective picture system (IAPS): Technical manual and affective ratings.* 1997. **1**(39-58): p. 3.
83. Basu, A. and A. Halder. *Facial expression and EEG signal based classification of emotion*. in *International Conference on Electronics, Communication and Instrumentation (ICECI)*. 2014. IEEE.
84. Chen, L.S., et al. *Multimodal human emotion/expression recognition*. in *Proceedings Third IEEE International Conference on Automatic Face and Gesture Recognition*. 1998. IEEE.
85. De Silva, L.C. and P.C. Ng. *Bimodal emotion recognition*. in *Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition (Cat. No. PR00580)*. 2000. IEEE.
86. Jenke, R., A. Peer, and M.J.I.T.o.A.c. Buss, *Feature extraction and selection for emotion recognition from EEG.* 2014. **5**(3): p. 327-339.
87. Hjorth, B.J.E. and c. neurophysiology, *EEG analysis based on time domain properties.* 1970. **29**(3): p. 306-310.
88. Saltzberg, B., N.R.J.E. Burch, and C. Neurophysiology, *Period analytic estimates of moments of the power spectrum: A simplified EEG time domain procedure.* 1971. **30**(6): p. 568-570.
89. Acharya, U.R., et al., *Deep CNN for the automated detection and diagnosis of seizure using EEG signals.* 2018. **100**: p. 270-278.
90. Zheng, W.-L., et al. *EEG-based emotion classification using deep belief networks*. in *2014 IEEE international conference on multimedia and expo (ICME)*. 2014. IEEE.

91. Luck, S.J., *Event-related potentials*, in *APA handbook of research methods in psychology, Vol 1: Foundations, planning, measures, and psychometrics.* 2012, American Psychological Association: Washington, DC, US. p. 523-546.
92. Frantzidis, C.A., et al., *On the classification of emotional biosignals evoked while viewing affective pictures: an integrated data-mining-based approach for healthcare applications.* IEEE Trans Inf Technol Biomed, 2010. **14**(2): p. 309-18.
93. Eimer, M. and A.J.N. Holmes, *An ERP study on the time course of emotional face processing.* 2002. **13**(4): p. 427-431.
94. Hinterberger, T., et al., *A brain-computer interface (BCI) for the locked-in: comparison of different EEG classifications for the thought translation device.* Clin Neurophysiol, 2003. **114**(3): p. 416-25.
95. Barr, R.E., J.J. Ackmann, and J.J.I.J.o.B.-M.C. Sonnenfeld, *Peak-detection algorithm for EEG analysis.* 1978. **9**(6): p. 465-476.
96. Khalili, Z. and M.H. Moradi. *Emotion recognition system using brain and peripheral signals: using correlation dimension to improve the results of EEG*. in *2009 International Joint Conference on Neural Networks*. 2009. IEEE.
97. Zhang, Q. and M.J.N. Lee, *A hierarchical positive and negative emotion understanding system based on integrated analysis of visual and brain signals.* 2010. **73**(16-18): p. 3264-3272.
98. Yuen, C.T., et al., *Classification of human emotions from EEG signals using statistical features and neural network.* 2009. **1**(3).
99. Kedem, B. and S. Yakowitz, *Time series analysis by higher order crossings*. 1994: IEEE press New York.
100. Petrantonakis, P.C., et al., *EEG-based emotion recognition using hybrid filtering and higher order crossings.* 2009: p. 1-6.
101. Petrantonakis, P.C. and L.J.J.I.T.o.i.T.i.B. Hadjileontiadis, *Emotion recognition from EEG using higher order crossings.* 2009. **14**(2): p. 186-197.
102. Liu, Y. and O. Sourina. *EEG databases for emotion recognition*. in *2013 international conference on cyberworlds*. 2013. IEEE.
103. Liu, J., et al. *Emotion detection from EEG recordings*. in *2016 12th international conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD)*. 2016. IEEE.
104. Pradhan, N., D.N.J.C.i.b. Dutt, and medicine, *Use of running fractal dimension for the analysis of changing patterns in EEGs.* 1993. **23**(5): p. 381-388.
105. Lutzenberger, W., et al., *The scalp distribution of the fractal dimension of the EEG and its variation with mental tasks.* 1992. **5**(1): p. 27-34.
106. Kulish, V., et al., *Analysis and visualization of human EEGs seen as fractal time series.* 2006. **6**(02): p. 175-188.
107. Aftanas, L.I., et al., *Non-linear dynamic complexity of the human EEG during evoked emotions.* 1998. **28**(1): p. 63-76.
108. Wang, Q., O. Sourina, and M.K. Nguyen. *Eeg-based" serious" games design for medical applications*. in *2010 international conference on cyberworlds*. 2010. IEEE.
109. Sourina, O., V. Kulish, and A. Sourin. *Novel tools for quantification of brain responses to music stimuli*. in *13th International Conference on Biomedical Engineering*. 2009. Springer.
110. Sourina, O., A. Sourin, and V. Kulish. *EEG data driven animation and its application*. in *International Conference on Computer Vision/Computer Graphics Collaboration Techniques and Applications*. 2009. Springer.

111. Liu, Y., O. Sourina, and M.K. Nguyen. *Real-time EEG-based human emotion recognition and visualization*. in *2010 international conference on cyberworlds*. 2010. IEEE.
112. Patil, A., C. Deshmukh, and A. Panat. *Feature extraction of EEG for emotion recognition using Hjorth features and higher order crossings*. in *2016 Conference on Advances in Signal Processing (CASP)*. 2016. IEEE.
113. Oh, S.-H., et al., *A novel EEG feature extraction method using Hjorth parameter.* 2014. **2**(2): p. 106-110.
114. Kroupi, E., A. Yazdani, and T. Ebrahimi. *EEG Correlates of Different Emotional States Elicited during Watching Music Videos*. in *Affective Computing and Intelligent Interaction*. 2011.
115. Wong, K.F.K., et al., *Modelling non-stationary variance in EEG time series by state space GARCH model.* 2006. **36**(12): p. 1327-1335.
116. Gramfort, A., et al., *Time-frequency mixed-norm estimates: Sparse M/EEG imaging with non-stationary source activations.* 2013. **70**: p. 410-422.
117. Delorme, A. and S.J.J.o.n.m. Makeig, *EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.* 2004. **134**(1): p. 9-21.
118. Klimesch, W.J.B.r.r., *EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis.* 1999. **29**(2-3): p. 169-195.
119. Wang, X.-W., D. Nie, and B.-L. Lu. *EEG-based emotion recognition using frequency domain features and SVMs*. in *International conference on neural information processing*. 2011. Springer.
120. Liu, Y. and O. Sourina. *EEG-based valence level recognition for real-time applications*. in *2012 international conference on cyberworlds*. 2012. IEEE.
121. Nie, D., et al. *EEG-based emotion recognition during watching movies*. in *2011 5th International IEEE/EMBS Conference on Neural Engineering*. 2011. IEEE.
122. Aljalal, M., et al. *Feature extraction of EEG based motor imagery using CSP based on logarithmic band power, entropy and energy*. in *2018 1st International Conference on Computer Applications & Information Security (ICCAIS)*. 2018. IEEE.
123. Nezam, T., et al., *A novel classification strategy to distinguish five levels of pain using the EEG signal features.* 2018. **12**(1): p. 131-140.
124. Unruh, L., et al., *S9. Resting EEG changes in schizophrenia.* 2018. **44**(Suppl 1): p. S327.
125. Ogata, K., et al., *P2-4-8. Alpha band power can predict MEP amplitudes: An online EEG-TMS study.* 2018. **129**(5): p. e39-e40.
126. Thomas, K.P., A.P.J.C. Vinod, Systems,, and S. Processing, *EEG-based biometric authentication using gamma band power during rest state.* 2018. **37**(1): p. 277-289.
127. Cohen, E., et al., *EEG power spectrum maturation in preterm fetal growth restricted infants.* 2018. **1678**: p. 180-186.
128. Hashemi, M., et al., *Optimal model parameter estimation from EEG power spectrum features observed during general anesthesia.* 2018. **16**(2): p. 231-251.
129. Kent, B.A., S.M. Strittmatter, and H.B. Nygaard, *Sleep and EEG Power Spectral Analysis in Three Transgenic Mouse Models of Alzheimer's Disease: APP/PS1, 3xTgAD, and Tg2576.* J Alzheimers Dis, 2018. **64**(4): p. 1325-1336.
130. Sale, P. *Use of EEG signal information to optimize training and promote plasticity*. in *Converging Clinical and Engineering Research on Neurorehabilitation III: Proceedings of the 4th International Conference on NeuroRehabilitation (ICNR2018), October 16-20, 2018, Pisa, Italy 5*. 2019. Springer.

131. Zouridakis, G., et al. *Spectral power of brain activity associated with emotion—a pilot MEG study*. in *17th International Conference on Biomagnetism Advances in Biomagnetism–Biomag2010*. 2010. Springer.
132. Kothe, C.A. and S. Makeig. *Estimation of task workload from EEG data: new and current tools and perspectives*. in *2011 annual international conference of the IEEE engineering in medicine and biology society*. 2011. IEEE.
133. Li, M. and B.-L. Lu. *Emotion classification based on gamma-band EEG*. in *2009 Annual International Conference of the IEEE Engineering in medicine and biology society*. 2009. IEEE.
134. Jaušovec, N., K. Jaušovec, and I.J.N.L. Gerlič, *Differences in event-related and induced EEG patterns in the theta and alpha frequency bands related to human emotional intelligence.* 2001. **311**(2): p. 93-96.
135. Zhang, Q. and M. Lee. *Emotion recognition in natural scene images based on brain activity and gist*. in *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*. 2008. IEEE.
136. Li, Y., et al., *Abnormal functional connectivity of EEG gamma band in patients with depression during emotional face processing.* 2015. **126**(11): p. 2078-2089.
137. Ekman, P., et al., *Universals and cultural differences in the judgments of facial expressions of emotion.* 1987. **53**(4): p. 712.
138. Gerla, V., et al., *P01-Comparison of short-time Fourier transform and continuous WT for frequency analysis of sleep EEG.* 2018. **129**(4): p. e14.
139. Rayatdoost, S. and M. Soleymani. *Cross-corpus EEG-based emotion recognition*. in *2018 IEEE 28th international workshop on machine learning for signal processing (MLSP)*. 2018. IEEE.
140. Zhao, G., et al., *Emotion analysis for personality inference from EEG signals.* 2017. **9**(3): p. 362-371.
141. Murugappan, M. and S. Murugappan. *Human emotion recognition through short time EEG (EEG) signals using Fast Fourier Transform (FFT)*. in *2013 IEEE 9th International Colloquium on Signal Processing and its Applications*. 2013. IEEE.
142. Lin, Y.-P., et al., *EEG-based emotion recognition in music listening.* 2010. **57**(7): p. 1798-1806.
143. Lan, Z., et al. *Stability of features in real-time EEG-based emotion recognition algorithm*. in *2014 International Conference on Cyberworlds*. 2014. IEEE.
144. Murugappan, M., et al. *Time-frequency analysis of EEG signals for human emotion detection*. in *4th Kuala Lumpur international conference on biomedical engineering 2008*. 2008. Springer.
145. Mohammadi, Z., et al., *Wavelet-based emotion recognition system using EEG signal.* 2017. **28**(8): p. 1985-1990.
146. Zhuang, N., et al., *Emotion recognition from EEG signals using multidimensional information in EMD domain.* 2017. **2017**.
147. Zhang, Y., X. Ji, and S.J.N.l. Zhang, *An approach to EEG-based emotion recognition using combined feature extraction method.* 2016. **633**: p. 152-157.
148. Riaz, F., et al., *EMD-based temporal and spectral features for the classification of EEG signals using supervised learning.* 2015. **24**(1): p. 28-35.
149. Huang, N.E., et al., *The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis.* 1998. **454**(1971): p. 903-995.
150. Shahnaz, C. and S.S. Hasan. *Emotion recognition based on wavelet analysis of Empirical Mode Decomposed EEG signals responsive to music videos*. in *2016 IEEE Region 10 Conference (TENCON)*. 2016. IEEE.

151. Mert, A., A.J.P.A. Akan, and Applications, *Emotion recognition from EEG signals by using multivariate empirical mode decomposition.* 2018. **21**(1): p. 81-89.
152. Hinton, G.E. and R.R.J.s. Salakhutdinov, *Reducing the dimensionality of data with neural networks.* 2006. **313**(5786): p. 504-507.
153. Qian, N.J.N.n., *On the momentum term in gradient descent learning algorithms.* 1999. **12**(1): p. 145-151.
154. Duchi, J., E. Hazan, and Y.J.J.o.m.l.r. Singer, *Adaptive subgradient methods for online learning and stochastic optimization.* 2011. **12**(7).
155. Tieleman, T. and G.J.C.N.n.f.m.l. Hinton, *Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude.* 2012. **4**(2): p. 26-31.
156. Kingma, D.P. and J.J.a.p.a. Ba, *Adam: A method for stochastic optimization.* 2014.
157. Ruder, S.J.a.p.a., *An overview of gradient descent optimization algorithms.* 2016.
158. Kiranyaz, S., T. Ince, and M.J.I.T.o.B.E. Gabbouj, *Real-time patient-specific ECG classification by 1-D CNNs.* 2015. **63**(3): p. 664-675.
159. LeCun, Y., et al., *Gradient-based learning applied to document recognition.* 1998. **86**(11): p. 2278-2324.
160. Krizhevsky, A., I. Sutskever, and G.E.J.C.o.t.A. Hinton, *Imagenet classification with deep CNNs.* 2017. **60**(6): p. 84-90.
161. Kiranyaz, S., et al. *CNNs for patient-specific ECGclassification*. in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 2015. IEEE.
162. Kiranyaz, S., T. Ince, and M.J.S.r. Gabbouj, *Personalized monitoring and advance warning system for cardiac arrhythmias.* 2017. **7**(1): p. 1-8.
163. Avci, O., et al., *Wireless and real-time structural damage detection: A novel decentralized method for wireless sensor networks.* 2018. **424**: p. 158-172.
164. Avci, O., et al., *Structural damage detection in real time: implementation of 1D CNNs for SHM applications*, in *Structural Health Monitoring & Damage Detection, Volume 7*. 2017, Springer. p. 49-54.
165. Abdeljaber, O., et al., *Real-time vibration-based structural damage detection using one-dimensional CNNs.* 2017. **388**: p. 154-170.
166. Abdeljaber, O., et al., *1-D CNNs for structural damage detection: Verification on a structural health monitoring benchmark data.* 2018. **275**: p. 1308-1317.
167. Ince, T., et al., *Real-time motor fault detection by 1-D CNNs.* 2016. **63**(11): p. 7067-7075.
168. Kiranyaz, S., et al., *Real-time fault detection and identification for MMC using 1-D CNNs.* 2018. **66**(11): p. 8760-8771.
169. Abdeljaber, O., et al., *Fault detection and severity identification of ball bearings by online condition monitoring.* 2018. **66**(10): p. 8136-8147.
170. Eren, L., T. Ince, and S.J.J.o.S.P.S. Kiranyaz, *A generic intelligent bearing fault diagnosis system using compact adaptive 1D CNN classifier.* 2019. **91**(2): p. 179-189.
171. Eren, L.J.M.P.i.E., *Bearing fault detection by one-dimensional CNNs.* 2017. **2017**.
172. Goodfellow, I., Y. Bengio, and A. Courville, *Deep learning*. 2016: MIT press.
173. Karpathy, A.J.N.n., *Cs231n CNNs for visual recognition.* 2016. **1**(1).
174. Tong, S. and N.V. Thankor, *Quantitative EEG analysis methods and clinical applications*. 2009: Artech House.