NEGATIVE EMOTIONS RECOGNITION USING fNIRS BASED CLASSIFICATION

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Dedication

"In the name of Allah, the Most Gracious, the Most Merciful"

I dedicate this thesis to Allah, the ultimate source of all knowledge, wisdom, and guidance. In every step of my academic journey, His divine light has been a beacon, illuminating the path of understanding and discovery.

"Allah is the Best of Planners"(Quran 8:30)

To Allah, I offer my heartfelt gratitude for the countless blessings He has bestowed upon me. It is by His mercy that I have had the privilege to pursue higher education, delve into the depths of knowledge, and engage in the pursuit of truth.

This work is dedicated to Allah as an expression of my unwavering faith and trust in His divine wisdom. It is a humble acknowledgment that every achievement, no matter how great or small, is a result of His grace.

I pray that Allah continues to bless me with His guidance and inspiration, allowing me to contribute positively to the world through the knowledge and insights gained during this academic journey. May His wisdom continue to be the driving force behind my endeavors.

As I embark on this path of lifelong learning, I place my trust in Allah, knowing that He is the Best of Planners, and that with faith, perseverance, and His guidance, I can overcome any challenge that lies ahead.

"To Allah we belong, and to Him we shall return." (Quran 2:156)

Acknowledgements

"In the name of Allah the most Merciful and Beneficent"

Firstly thanks and praise to Allah, the Almighty, Due to His blessings I am able to complete my thesis successfully.

I want to express my profound and sincere appreciation to my supervisor, Dr. Sumaira Kausar, for giving me a chance to work under her watch. Her auspicious commitment, support, kindness, and profitable pieces of advice helped me shape my work into its final structure.

Special thanks to my family, the ones towards whom expressing gratitude would not be enough, for the overwhelming love and care they present to me. Without their appropriate direction, it would have been incomprehensible for me to finish my study. Because of my parents for their consolation warmth, consideration, petitions, and giving me genuine happiness at whatever point I am discouraged.

Last, but not least, I want to thank all my friends and colleagues especially Dr. Zareena Kausar supported me during my worst times and gave me a quiet environment during the entire course of my research work. The pieces of advice they gave and their helpful criticism were indeed encouraging.

Abstract

The emotional wellness of a person includes one's thoughts, emotions, and ability to deal with life's challenges. A sign of emotional wellness is having the ability to talk with someone about your emotional concerns and share your feelings with others. A psychotic patient is not emotionally well, and it is very important to know to what extent the patient is unwell. To answer this question, this research investigated the negative emotions of humans. The researchers have used electro Ensphelography (EEG) method to find emotions, however, in this study, the use of an emerging technology of the present, called fNIRS (functional near infra-red spectroscopy), is selected because the accuracy of correct detection of emotions using this technology is proved by researchers. However, the detection of negative emotions has not been studied yet. In this research data from 10 healthy patients is recorded for three emotions: sad, angry, and neutral. To record emotions the fNIRS data acquisition system was used. The data is filtered, features are extracted and then data is classified for the three emotions mentioned above. One deep learning model and five machine learning models named the LSTM (Long Short Term Memory), Decision Tree, K-NN (K-Nearest Neighbours), Random Forest, SVM (Support Vector Machine), and Naive Bayes are applied to classify the data for three emotions. The percentage maximum accuracy of the emotion detection out of these models is 99% through LSTM, whereas, a minimum accuracy of 76% is achieved through Naive Bayes. The remaining models gave accuracies of 98% through the Random forest, the Decision tree, and the K-NN, and 88% through SVM. The accuracies are found improved as compared to those achieved through EEG as per existing literature. This verifies the efficacy of the methodology that acquires data through fNIRS technology and is classified using different classifiers.

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LIST OF SYMBOLS

Fnirs	–	Functional Near-Infrared Spectroscopy
EEG	–	Electroencephalogram
ML	–	Machine Learning
PFC	–	Prefrontal cortex
HBO	–	Oxy-hemoglobin
HBR	–	Deoxy-hemoglobin
BCI	–	Brain computer interface
MEG	–	Magnetoencephalography
FMRI	–	Functional magnetic resonance imaging
TD	–	Time-Domain
CW	–	Continuous-Wave
FD	–	Frequency-Domain
NIRS	–	Near-infrared spectroscopy
DPF	–	Differential path length factor
AI	–	Artificial Intelligence
GSR	–	Galvanic Skin Response
EVP	–	Electronic voice phenomenon
SAM	–	Self-Assessment Manikin
ANS	–	Automatic Nervous system
CNS	–	Central Nervous System
SVM	–	Support vector machine
NB	–	Navies Bayes
LSTM	–	Long Short-Term Memory
KNN	–	k-nearest neighbor
RNN	–	Recurrent neural network

CHAPTER 1

INTRODUCTION

Psychological disorder, defined in the American Psychiatric Association's diagnostic manual [1], is an illness that causes disturbance in behaviors, emotions, and cognition. Emotions means how the patient feels in different situations, whereas, cognition refers to how he/she thinks. Among many psychological disorder conditions anxiety and depression are the most commonly experienced [2][3]. These disorders, anyway, create distress and affect the abilities of the patient to perform functions in different life domains and therefore need to be well treated by psychiatrists. A key to such treatments is the accurate identification of the disorder type and hence the disturbing factors, especially the emotions.

A person's capacity to handle life's hardships is a measure of their mental health. The capacity to communicate with someone about your emotional difficulties and express your sentiments with others is a sign of emotional health. Emotions play a vital role in human society in our daily lives. The complex psycho-physiological processes of emotions are connected to a wide range of internal and external actions. However, emotion recognition is the reproving area in this era of high computation facilities which has been a fundamental focus of researchers. The goal of effective computing, though, is to create artificial intelligence that can recognize, comprehend, and control emotional states in humans.

Recently, scientists have developed an interest in using different models to forecast the outcome of emotional states. This is supported by several legal and technological experts. ML algorithms need pre-processed data which increases the human effort but on the other hand deep learning algorithms are also used for predicting emotional decisions. Artificial intelligence is easy to use because data pre-processing effort is reduced while using these techniques. However, according to Scientific American, there is a question that is one of the key issues about the future of humanity and it is: Is it possible to detect human emotions using wearable technology?

The research on methodologies to find the emotions of human beings using wearable technology is a hot topic of this decade. Many researchers[4], have used electroencephalography (EEG) to find emotions to an acceptable level of accuracy. However, in my study, I have proposed the use of one of the emerging technologies of the present. This is called fNIRS (functional near infra-red spectroscopy)[5], the effectiveness of which over EEG is shown by researchers[6] during this decade. The fNIRS is easier to use and more comfortable and has high portability, fewer restrictions, low running cost, and relative robustness against emotion and electrical artifacts. This advantage may be especially crucial for emotion recognition research, as unwanted signals from device noises and claustrophobic environments are avoided, allowing for a more natural emotional experience. fNIRS is particularly adept at assessing prefrontal cortex (PFC) activity, a key region involved in emotional processing, along with the frontopolar cortex and the front lateral PFC. An increasingly popular neuroscientific research method is optical neuroimaging, using functional near-infrared spectroscopy (fNIRS). Similar to fMRI, fNIRS analyzes blood oxygenation changes without invasive procedures. It relies on alterations in light absorption, typically between 750 and 1,200 nanometers, detected by sensors and emitted by sources onto the skull's surface. This non-invasive technique allows the measurement of changes in tissue hemodynamics (blood perfusion) and oxygenation in the human brain[7]. The level of brain blood oxygenation is indeed reflected in hemodynamic responses. It's commonly recognized that brain electrical signals are indicative of underlying hemodynamic processes. The founders of NIRx, Professors Randall L. Barbour and Ray Aronson, introduced the idea of tomographic imaging — multi-distance spectroscopic observations in densely dispersed media, in 1988. This technique depends on diffusely scattered light. This method has now been widely adopted and played a key role in the development of fNIRS tomography in the present day. The fNIRS sensors can measure brain activity, which gives the functional component its name. This is accomplished by assessing hemodynamic responses and total hemoglobin changes in the cerebral cortex. Additionally, fNIRS offers a non-invasive way to obtain a high-resolution brain signal in real-time. An fNIRS signal is illustrated in Figure 1.1

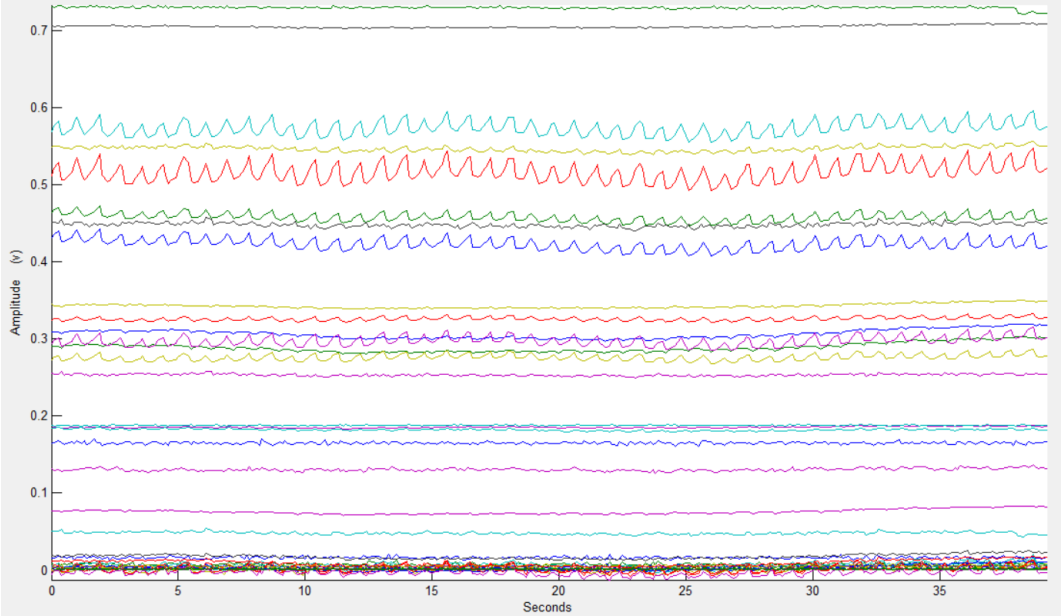

Figure 1.1: Raw fNIRS signals

EEG, often known as electroencephalography, is a non-invasive method for tracking the electrical activity of the human brain.[8]. As said, it is a non-invasive method that acquires electrophysiological intentions from the brain surface using electrodes. EEG measures voltage variations as the result of energy produced inside the neurons of the brain[9]. EEG, to put it simply, is the process of capturing the normal electric activity of the brain over time using several electrodes applied to the scalp. [8][11]. Analytical applications usually focus either on event-related responses or by means of the spectral content of EEG[10]. An EEG signal is shown in Figure 1.2[11].

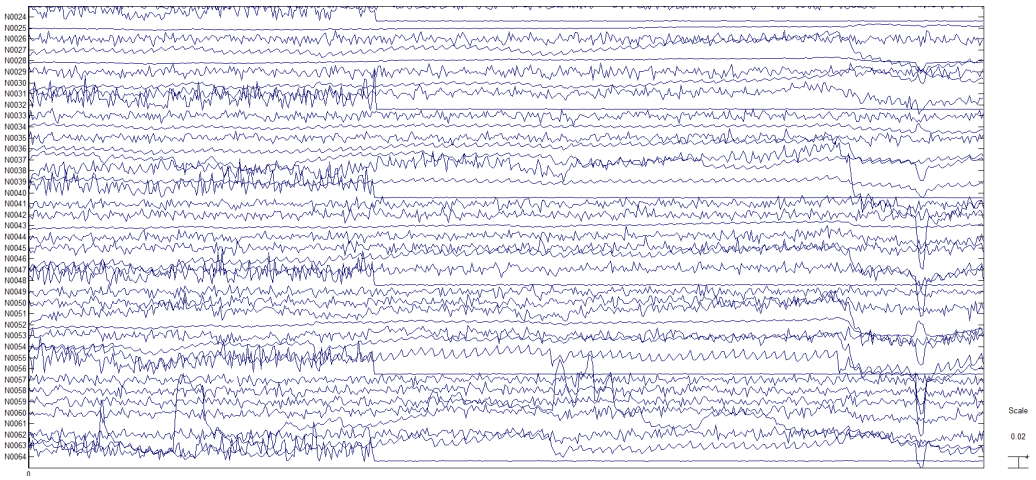

Figure 1.2: Raw EEG signals

To test the effectiveness of the suggested technique, trials for recognizing the three emotions out of many: sadness, neutrality, and angerness are being proposed for this research. The data will be filtered, features will be extracted and then data will be classified for the three emotions. It is proposed to use fNIRS's complimentary features for emotion recognition. This includes the use of signal mean, peak, and minimum values as features. Machine learning models are proposed to classify the data for three emotions. The accuracy of the classification of emotions is then determined and compared for different classifiers. The classifying techniques proposed for this study include LSTM, Decision tree, K-NN, Random forest, SVM, and Naive Bayes.

1.1 Motivation

The motivation behind this research is rooted in the belief that amidst the shadows of depression, there exists a wellspring of hope and strength waiting to be illuminated. Through our exploration, we aspire to offer a guiding light to those who walk the path of depression, reminding them that they are not alone. Welcome to this thesis journey where we're exploring feelings, especially for people who often feel really sad. The mission is like being a detective, looking for clues to help people find happiness again. I am excited because I believe that understanding these feelings can light up a path of hope for others. A goal is to show that even when life gets tough, there's a way to detect it and make it better.

Motivation of Using fNIRS

fNIRS has many advantages over EEG, hence selected for brain signal acquisition by researchers. Following are a few of these advantages that motivated to find a research gap in this field:

- fNIRS provides more precise information of brain activity in comparison to EEG which measures electrical activity on the scalp.

- fNIRS is less sensitive to artifacts like muscle movements, eye blinks, and electrical interference. This makes data interpretation more robust for studies with sensitive patients like Psychic.

- fNIRS provides extended continuous recording sessions compared to EEG. The latter is prone to signal degradation over time due to factors like electrode drift and impedance

- fNIRS provides information from deeper cortical layers, even subcortical regions, allowing for a broader range of brain activity monitoring.

Motivation of Using Negative Emotions

Negative emotions are a necessary part of human life. They serve several purposes ranging from survival intuitions to self-awareness and personal growth. Although knowledge of both positive and negative emotions is essential, negative emotions give more and more valued understanding and awareness. They, in turn, provide opportunities for growth and flexibility in human life. Negative emotions are also very pertinent to psychic patients.

Come along with me as I discover how feelings can be recognized, guiding psychiatrists to brighter days for their patients. May my findings empower individuals, families, and communities to embrace their emotions, foster resilience, and embark on a journey toward a brighter, more vibrant existence. Let's learn and grow together!

1.2 Research Gap

The literature review has revealed that negative emotions detection using fNIRS is not researched yet, although it is very important in case of studies with sensitive humans like psychic patients. This study is, therefore, designed to overcome this gap.

1.3 Research Objectives

With a goal to measure negative emotions for the identification of unwellness of psychiatric patients using fNIRS, the following objectives are designed for this research:

1. Collect and pre-process the data on the negative emotions of healthy patients.

2. Classify the emotions.

1.4 Research Scope & Limitation

The research scope is to use the fNIRS data acquisition technique for acquiring data on emotions and classifying these emotions. However, the research has the following limitations.

1. The emotions will be related to the feelings of psychiatric patients. They are usually negative or neutral emotions.

2. The number of emotions will be limited to three.

3. The data will be taken of selected emotions from healthy patients only.

1.5 Significance of the study

The main contribution of the study is an analysis of data of psychiatric patients' emotions taken using the emerging fNIRS technique. A significance of this study is the outcome that will confirm if the new technique enhances the accuracy of the classification of emotion recognition and will be helpful to psychiatry in the identification of the type of psychological disorder.

1.6 Thesis Outline

In thesis layout, Chapter 1 describes the introduction, problem statement, aims, objectives, Research Scope and limitations, and significance of this research. Chapter 2 presents the literature review of existing works on emotion classification, scientific perspectives on emotion, and BCI. Chapter 3 presents the functional near-infrared spectroscopy. It briefly describes the component of fNIRS, nirs regions of interest, and Specialized Details of NIR-Sport.

Chapter 4 details the methodologies of experiment conduction, data pre-processing, and processing. In experiment conduction, the demographic information of participants, the experiment paradigm, and the signal acquisition methods are presented. The data pre-processing includes methods used to filter data, channel selection, and calculation of change in light reduction at a given wavelength. The processing method, however, highlights which data classification techniques are selected and details the theoretical background of selected classification methods. In Chapter 5, we explore a comprehensive analysis of the performance of diverse machine learning models within the domain of emotion classification, exploiting brain wave data as the underlying data set. We evaluated each model's performance utilizing an array of critical metrics, including precision, recall, F1-score, accuracy, and loss. Here's an in-depth summary of the findings for each model. Chapter 6 concludes the thesis with a summary of the research and possible future work.

CHAPTER 2

BACKGROUND

2.1 LITERATURE REVIEW

In previous studies, a lot of research aims have been undertaken to extract valuable characteristics from EEG data with the intention of facilitating emotion recognition. Numerous prototypes aimed at perceiving and providing feedback on emotions have been created and subjected to thorough testing in previous research. For example, Ekman and Friesen [12] introduced the concept of 'root emotions' which include fear, joy, anger, surprise, sadness, and disgust.

D. Jude Hemanth et al. [13] used Kohonen neural networks for human emotion analysis. The DEAP Database's EEG waves are utilized as input for ANN to recognize human emotions. Kohonen Neural Networks classify emotions as angry, happy, sad, and relaxed. Recently, Shashank Joshi et al. [14] describe an emotion classification located on EEG signals. In this project, authors employed techniques of recurrent neural network and k-nearest neighbor. They attained maximum classification accuracy of 94.844 percent and 93.438 percent, respectively. A. Chatchinarat et al. [15] proposed using Fuzzy C-Mean (FCM) to derive fuzzy rules for use in the fuzzy inference system (FIS) for categorization. The approach used EEG data to learn and generate rules. The findings showed that the method outperformed fuzzy classification using fixed rules and Support Vector Machine (SVM), with accuracy values of 55.77 percent, 49.62 percent, and 54 percent, respectively.

Muzaffer Aslan [16] GoogLeNet-based deep learning method was employed to perceive emotions using (EEG) waves. With the use of the Continuous Wavelet Transform (CWT), which is more conscious of Time-Frequency fluctuations in EEG waves, EEG waves were transformed into EEG pictures. In this research, the researcher used the GAMEEMO dataset and (k-NN),(SVM), and the Extreme Learning Machine (ELM) classifiers for emotion classification. They gained 98.78 percent, 98.53 percent, and 98.41 percent accuracy

in classifiers. Zeynab Mohammadi et al.[17] proposed an emotion recognition system based on wavelet using an Electroencephalogram. EEG data were divided into frequency bands using discrete wavelet transformations, and subsequently, numerous characteristics were recovered. To detect emotional states from retrieved features, the KNN and SVM classifiers were utilized. Kitsuchart Pasupa et al.[18] established a method for anticipating how people will react to abstract graphics by employing eye-tracking technology and image attributes. An enhanced prediction algorithm that used the user's eye movement as implicit feedback while gazing at the image. Using both eye movement information and an image feature to detect a user's sentiment yielded more accurate predictions than using only the image feature.

Multimodal and wearable devices have also been used for human emotion recognition in the past. Wei-Long Zheng et al.[19] proposed Recognizing Human Emotions Using a Multimodal Framework that incorporates both brain waves and eye movements. They integrated EEG and eye movements to integrate users' internal cognitive processes with external subconscious behaviors in order to increase human emotion recognition accuracy. They applied a principal component analysis (PCA)-based method for preprocessing, power spectral density, and differential entropy for feature extraction and Support vector machine classifier. Chunting Wan et al. [20] proposed a Multimodal biosignal system using wearable sensors in emotion recognition and virtual reality (VR) as a stimulus source. A wearable forehead bio-signals acquisition pad and Head-Mounted Displays (HMD) are attached. This system recognized human emotions in virtual reality environments. Yongrui Huang et al. [21] proposed a multimodel system. Electroencephalogram and facial expression are the input signals. A neural network classifier detects emotional moods (happiness, neutrality, sadness, and fear) for facial expression identification. Two support vector machine (SVM) classifiers recognize emotion moods and emotion intensity levels (strong, ordinary, and weak) for EEG detection. Two decision-level fusion approaches use a sum rule or a production rule to detect both EEG and facial expressions. The researchers have used electroencephalography (EEG) to find emotions. However, Xin Hu et al. [22] presented FNIRS for recognition of different positive emotions. Using fNIRS, the researcher explored the brain hemodynamic responses to various pleasant emotions. They used fNIRS signals and three different wavelengths of Near-infrared light (785, 808, and 850 nm) that were used to detect the concentration change of deoxy-hemoglobin (HbR) and oxy-hemoglobin (HbO). Individual-level binary classifications of HbO-based hemodynamic responses to positive emotion groups revealed unique classifications. The study results show an average of 73.79

percent accuracy for encouragement vs. 11.49 percent for harmony and 73.29 percent 11.87 percent for playfulness vs. harmony.

Table 2.1: Literature Review

Paper Title	**Senors**	**Modalities**	**Emotions**	**Classifier**
Xin Hu	Fnirs	Brain's hemodynamic responses	love, gratitude,serenity, interest, awe, pride, amusement, inspiration, hope, and joy	Binary
Wei-Long Zheng	EEG	Eye Movement & brain wave	Sad, Fair, Happy,Neutral	SVM
Yongrui Huang	EEG	Brain and peripheral signals	Sad, Fair, Happy, Neutral	SVM, Neural network
Shashank Joshi et al.	No	Brain signal	good, neutral, negative	RNN and kNN
Zeynab Mohammadi	EEG	Video (movie clips)	Arousal level, Valence level	KNN,SVM, GELM,DBN, DBN-HMM
Muzaffer Aslan	No	Brain signal	Postive, Negative	SVM, k-NN, ELM
D. Jude Hemanth	EEG	Brain signal	Happy,Angry ,Sad,relax	Kohonen neural network
Kitsuchart Pasupa	Software	Images	Original, fear,anger,sad	SVM
A. Chatchinarat	EEG	Brain signal	NO	Fixed rules, SVM
Chunting Wan	HMD Bio Pad, VR	Eye blink, Skin Conductance Reaction	Good and bad mood	LDA

Electroencephalography (EEG) is less user-friendly and less resilient to

head movement than fNIRS, which can offer greater spatial resolution. ([23] [24] [7][25].To test the effectiveness of the suggested technique, trials for recognizing the three emotions out of many: sadness, neutrality, and angerness are being proposed.

2.2 A SCIENTIFIC VIEW OF EMOTION

2.2.1 Models of Emotions

Emotion models also contribute to content personalization, enabling platforms to recommend movies, music, or other content that aligns with users' prevailing emotional states. Many scholars study in order to provide a definition for emotion and define the set of emotions. That is okay, but a natural collection of distinct emotions has yet to be identified. Many researchers do not think that emotion can be detected immediately. They think that self-assessment, remarkable behavior, context, and physiological data can discern emotion. According to psychologists, the start of emotion is linked to stimuli, and sensations and emotions do not occur in isolation. Psychologists believe. There are two types of models: classified models[26] and dimensional models[27]. Darwin (1965) proposes an emotional theory, which Tomkins interprets. Tomkins claimed that there are nine primary emotions[28].

According to Paul Ekman's[29] fundamental emotion theory, there are six universal, biologically intrinsic emotions: happiness, sorrow, fear, wrath, disgust, and surprise. His studies on facial expressions and the Facial Action Coding System (FACS) revealed that these emotions are exhibited consistently throughout cultures. Ekman's work emphasizes the universality of human emotions and the importance of facial expressions in detecting and interpreting these emotions. While cultural standards can impact how emotions are expressed, the underlying emotional experiences are universal. Ekman's efforts have substantially increased our understanding of the essential significance of emotions in human behavior and communication. Then further, few emotions is classified into subsections[30][31][32][33][34][35], which concentrated on positive and negative emotions. Other researchers concentrated on specifics and divided emotions into larger groups. Emotion models are shown in table 2.2[36].

Table 2.2: Summary of Categorized Emotions Models

Reference	**Emotions**
(Ekman & Oster, 1979)	Fear, sadness, happiness, anger, disgust, and surprise
(Arnold, 1960)	Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness
(Panksepp, 1982)	Expectancy, rage, fear, panic
(Tomkins, 1962)	Surprise, interest, joy, rage, fear, disgust, shame, and anguish.
(Johnson-Laird, 1989)	Happiness, sadness, fear, anger, disgust
(Frijda, 1986)	Desire, happiness, interest, surprise, wonder, sorrow
(Gray, 1985)	Rage and terror, anxiety, joy
(Izard, 1977)	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
(James, 1884)	Fear, grief, love, rage
(McDougall, 2003)	Anger, disgust, elation, fear
(Weiner & Graham, 1984)	Sadness, happiness
(Mowrer, 1960)	Pain, pleasure
(Watson, 1925)	Fear, love, rage

In contrast, some researchers argue against the notion of emotions being organized into discrete circuits and critique the category-based paradigm due to its perceived limitations. One of these limitations is that the intricate emotional states experienced in everyday life may not be adequately represented by a limited number of distinct categories. Nevertheless, expanding the range of possible labels can complicate the process of annotation and diminish the level of agreement among researchers and annotators[37]. As a result, these researchers advocate for dimensional emotion modeling, a different method. This paradigm proposes that emotions are the result of two or three distinct physiological systems. Valence and arousal are two important variables for understanding and categorizing emotions. Valence denotes the pleasantness or unpleasantness of an emotional state, ranging from severely negative (-1)

to extremely positive (1). Arousal, on the other hand, assesses emotional intensity on a scale of 0 to 1, ranging from low (calm and unexcited) to high (intense and stimulating). These dimensions enable researchers to generate a two-dimensional emotional landscape, revealing the type and strength of diverse emotions, which is useful in psychology, neurology, and other sciences. The third to power, which represents the intensity of emotions.

Russell's "Circumplex model" is another widely used dimensional model.[27], which has two dimensions, arousal, and valence. As shown in Figure 2.1[38]

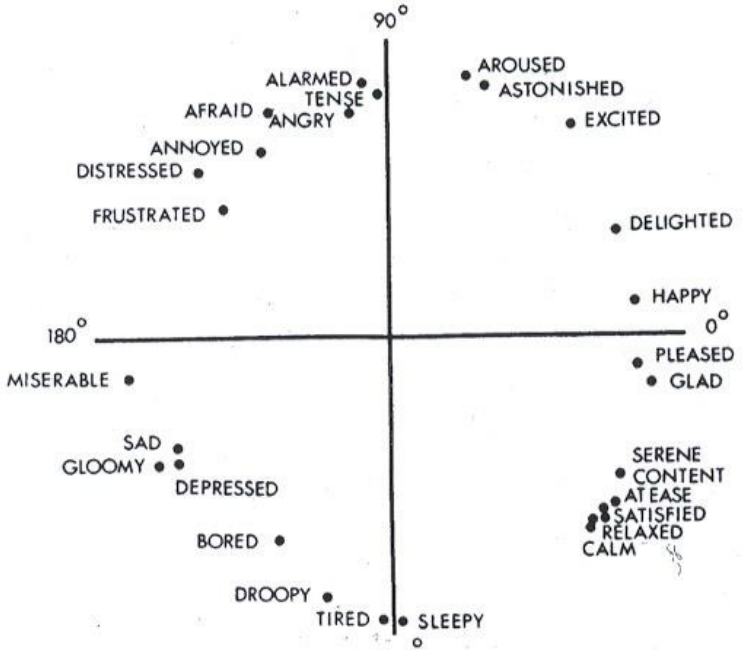

Figure 2.1: Circumplex model

Several studies have shown that emotional states experienced in ordinary human interactions can be complex and nuanced, as evidenced in disorders such as depression. As a result, utilizing a single label may fail to represent the complexities of emotional states in our daily interactions. As a result, the dimensional emotion model was chosen for this study because it provides a more comprehensive framework for understanding and portraying the complexities of emotional experiences.

2.2.2 Emotion Elicitations, Annotation, and Ground Truth

An emotion is a multifaceted mental and physiological state characterized by distinct feelings, such as joy, anger, or fear, which can be deliberately induced or naturally elicited by various stimuli. [39][40] .In psychology, be-

havioral studies, and social sciences, the phrases "induced expression" and "naturalistic expressions" are frequently used to describe various sorts of stimuli or reactions. Induced expressions refer to stimuli or responses intentionally generated by researchers to elicit specific reactions or behaviors from study participants. This approach is valuable for manipulating variables in controlled studies and observing how individuals respond to predetermined situations. For instance, in a psychology experiment, researchers might employ induced expressions by presenting participants with a series of emotionally charged images to provoke a range of emotional reactions. Naturalistic expressions, in contrast, pertain to stimuli or responses that occur spontaneously and are not intentionally manipulated by researchers. These expressions reflect how individuals naturally respond to stimuli or situations in their everyday lives. The primary objective of studying naturalistic expressions is to gain insights into how people react in their genuine environments, free from external interference. For instance, observing people's reactions in public settings, such as their responses to an impromptu street performer, offers researchers a glimpse into real-world behaviors and responses that are neither guided nor artificially induced by external stimuli. In emotion recognition research, induced expressions are commonly used[41]. Nonetheless, choosing the correct stimulus to evoke a certain feeling is a significant difficulty in emotion elicitation. In study settings, many stimuli such as events, pictures[42], music[43], or movies[44] have been used to elicit emotions. Annotating the ground truth for emotion elicitation trials or target emotions is another problem in emotion detection[45]. Emotions are essentially subjective experiences that differ from person to person, making determining the "ground truth" difficult. Individual characteristics, societal standards, personal experiences, and circumstances all have an impact on emotions. While there are several ways and methodologies for studying and assessing emotions, it is not possible to develop an ultimate or generally agreed-upon "ground truth" for emotions. Subjectivity rating collects personal opinions on a subject and is used for product evaluations, ratings, and assessments, frequently using Likert scales to provide qualitative data modified by individual viewpoints.are commonly utilized by researchers[46]. The term "self-reporting belief"[47] refers to individuals expressing their own ideas and opinions using methods such as questionnaires and surveys, which are extensively used in psychology, social sciences, and market research to collect subjective data. It has been demonstrated to be an effective instrument for analyzing emotional reactions in a wide range of scenarios, including responses to sights, sounds, and various stimulis[46]. The Self-Assessment Manikin (SAM) is one such tool that assesses people's emotional

experiences[46]. An "annotator" is another method for determining ground truth. A person or entity who adds comments or annotations to something in order to provide further context or information. They improve comprehension by annotating papers, tagging photos, and adding comments to videos. Annotators can be researchers, editors, or anybody who improves information using annotations. The annotators would be able to assess the user's emotional arousal and valence[48].

The self-assessment manikin (SAM) will be used in this study to collect basic emotions based on observed emotion, and I will then map different emotions into the quadrants of the two-dimensional valence-arousal model. Shown in figure 2.2[1]

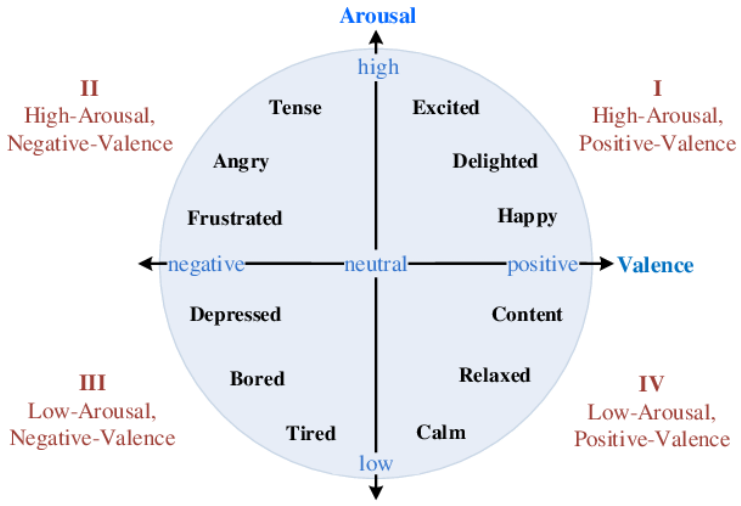

Figure 2.2: Dimensional of emotions

2.2.3 Using physiological Signals to evaluate emotional states

Measuring emotional moods via physiological signals is a multidisciplinary activity that entails monitoring numerous bodily systems and evaluating the data to get insights into an individual's emotional well-being. To catch these signals, scientists use a variety of ways. Monitoring heart rate and heart rate variability to assess arousal and emotional regulation, assessing electrodermal activity (EDA) to measure skin conductance changes associated with emotional arousal, and using electroencephalography (EEG) to detect distinct brainwave patterns linked to different emotional states are some of the techniques used[49] facial expressions can provide valuable significant information

[1]https://www.researchgate.net/figure/Core-emotions-established-in-the-circumplex-model$_{fig1_3}$24664655

about an individual's emotional state[50]. Physiological signals give a direct window into a person's emotional state, eliminating the need for self-reporting or vocal representation.[29][51]. Heart rate, blood pressure, skin conductance, and other autonomic nervous system reactions are normally involuntary and regulated by the central and autonomic nervous systems. Because these responses are not under direct conscious control, it is difficult for humans to intentionally fake or manipulate them.[52]. The responses of heart rate, blood pressure, Galvanic Skin, and skin conductance are reliable indicators for the recognition of emotions[53] [54].

This is especially relevant in specific contexts such as deception detection and lie detection. Emotion recognition methods concentrate on observing changes in the two main elements of the nervous system: the Central Nervous System (CNS) and the Autonomic Nervous System (ANS), aiming to uncover the true inner emotions of individuals. Physiological responses, including brain activity, respiration, Galvanic Skin Response (GSR), heart activity, and skin temperature, originating from both the Central Nervous System (CNS) and the Autonomic Nervous System (ANS), give important insights into a person's own emotional states. These are solid signs that you can recognize emotions. [53] [54].

Two different types of sensors can be used to record these physiological data: Wireless physiological sensors and tethered laboratory sensors. Sensors for tethered laboratories These sensors are physically connected to data collection systems by cables. They are commonly used in research settings and under controlled circumstances because they provide accurate and quick data collection. Examples include wired EEG electrodes, wired ECG sensors, and other wired monitoring apparatus. Due to the absence of physical wires, wireless physiological sensors offer more flexibility and mobility. They are frequently used in everyday tasks, athletics, healthcare, and remote monitoring. Examples include wearable fitness trackers, wireless heart rate monitors, and wireless EMG sensors. The electrical activity of the brain is measured using EEG (Electroencephalography) sensors. They are made up of scalp-mounted electrodes, amplifiers that strengthen weak brain signals, and data collection systems that capture and process EEG data. Brain-computer interfaces, neuroscience research, and clinical diagnostics all make use of EEG sensors. An electrocardiogram, or ECG, is a medical test that captures the electrical activity of the heart. To identify cardiac disorders such as arrhythmias and heart attacks, electrodes are placed on the skin. These electrodes produce a visual depiction of the heart's rhythm. It is a frequently used tool in emergency and cardiology care. PPG (Photoplethysmography) technology is frequently used

by smart wristbands to track a variety of physiological indicators, principally heart rate and occasionally blood oxygen levels. Stress prediction, for example, has demonstrated the significance of these wearable sensors.[55][55] as well as emotion recognition[56].

2.3 Brain Computer Interface

A Brain-Computer Interface (BCI) is a cutting-edge technology that creates a direct communication channel between the human brain and external devices or computer systems[57]. BCIs bridge the gap between neural activity in the brain and control of various applications or technology. These interfaces have far-reaching consequences in the fields of healthcare, assistive technology, and human-computer interaction. The effectiveness of BCI is dependent on improved signal processing algorithms that decode and interpret collected brain signals. These algorithms mine brain data for patterns, frequencies, and other properties to infer meaningful information about the user's intents or orders. This processed data is then utilized to control or provide feedback to external equipment. BCIs have a wide range of applications, including assistive technologies for people with impairments, such as facilitating communication or operating wheelchairs or robotic limbs. BCIs are also used in neurorehabilitation, gaming, and cognitive enhancement. It can be utilized as a neuro-rehabilitation method to improve such patients' motor and cognitive skills[58]. Signal noise, accuracy, and user training are among the issues that BCIs encounter. It is divided into five phases. As shown in Figure 2.3[59]

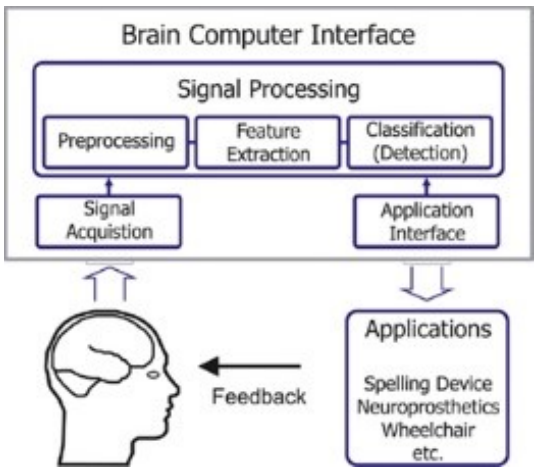

Figure 2.3: Five stages of a BCI system

2.3.1 BCI types

BCI is split into three categories:

Active BCI

Active BCIs allow users to operate external equipment or communicate directly with computers using their brain impulses, potentially benefiting those with impairments. They entail capturing brain signals (for example, EEG), processing them to extract commands, and delivering user feedback. Assistive technology, neurorehabilitation, and other applications confront problems such as signal noise and user training. The goal of the research is to make them more accessible and user-friendly.

Reactive BCI

Reactive BCIs passively monitor brain activity and activate actions or events based on observed patterns without requiring direct user input. They are used in neurofeedback therapy and research to examine brain reactions. Users do not actively control the UI.

Passive BCI

Passive BCIs detect and analyze brain activity without the need for user intervention. They are used to monitor mental states, recognize emotions, and conduct neuroscientific research, but privacy problems must be addressed. Users go about their daily lives while data is quietly gathered.

2.3.2 BCI Techniques

Invasive

An invasive Brain-Computer Interface (BCI) system is a type of neurotechnology that includes inserting electrodes or similar sensors directly into brain tissue or onto the surface of the brain. In contrast to non-invasive BCIs, which use external sensors to detect brain signals (such as EEG electrodes on the scalp), invasive BCIs provide more precision and access to more detailed neural data. They are, however, more obtrusive and risky because they require surgery. Invasive BCIs are commonly used in both research and clinical contexts, notably for persons suffering from severe neurological diseases such as paralysis or locked-in syndrome, when non-invasive BCIs may not give the necessary level of precision. These technologies allow direct contact between the

brain and outside devices. Model of signal acquisition via an invasive shown in Figure 2.4[2].

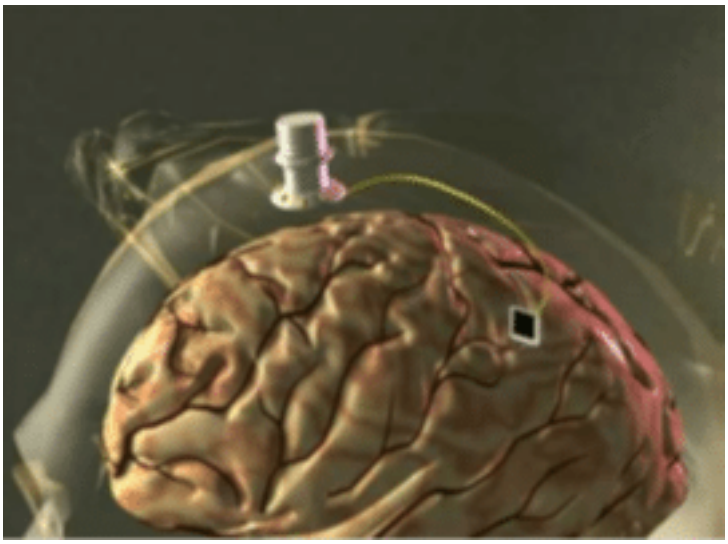

Figure 2.4: Invasive

Semi-invasive

In terms of invasiveness, a semi-invasive Brain-Computer Interface (BCI) device falls between non-invasive and completely invasive BCIs in the field of neurotechnology. It often comprises the insertion of sensors or electrodes on or just beneath the surface of the skull, with no direct penetration into brain tissue required. In comparison to non-invasive BCIs (which rely on external sensors such as EEG), this technique provides improved signal quality and precision while being less invasive and dangerous than fully invasive BCIs that require surgical implantation. Semi-invasive BCIs find a balance between invasiveness and effectiveness, making them suitable for applications such as movement control or communication for people with neurological diseases. Model of signal acquisition via a semi-invasive shown in Figure 2.5[3].

[2]https://neurotechjp.com/blog/5-startups-of-interest/
[3]http://learn.neurotechedu.com/introtobci/

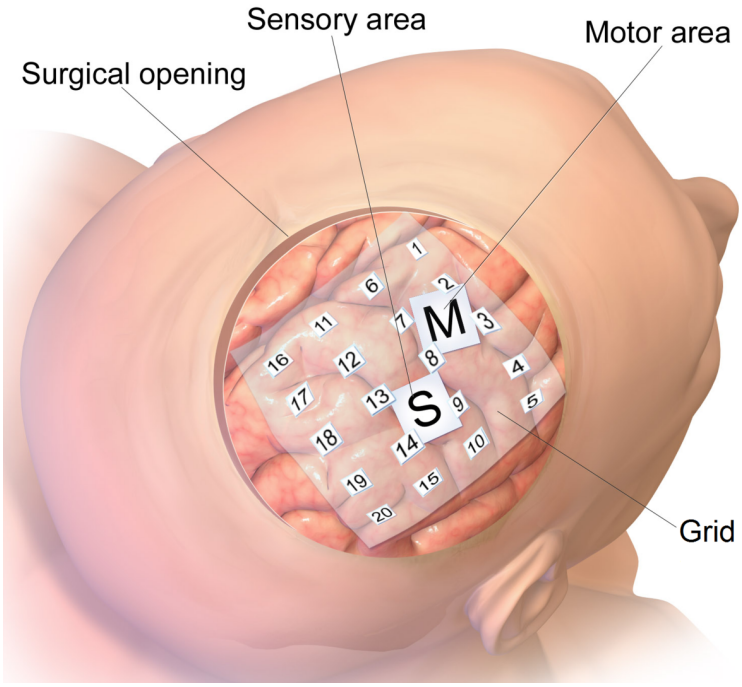

Figure 2.5: Semi-invasive

Non-invasive

Within the field of neurotechnology, a non-invasive Brain-Computer Interface (BCI) system operates without the necessity for surgical operations or the insertion of electrodes into the brain. It instead uses external sensors placed on or near the scalp to detect and interpret electrical activity or other physiological signals produced by the brain. Electroencephalography (EEG), (fMRI), and (NIRS) are examples of non-invasive BCI technology. These non-invasive systems are used for a variety of functions, including communication, control of external equipment, and study of brain function. Non-invasive BCIs are thought to be safer and more user-friendly than invasive approaches, making them appropriate for a wide range of applications such as assistive technology and cognitive neuroscience research. Model of signal acquisition via a non-invasive shown in Figure 2.6[4].

[4]https://www.slideshare.net/ajaygeorge91/bci-ppt

Figure 2.6: Model of signal acquisition via a non-invasive

2.3.3 Non-Invasive BCI systems

1. EEG
2. fMRI
3. MEG
4. fNIRS

Electroencephalography

The term "electroencephalogram" was invented by Hans Berger, who used it to record the first human brain activity. Gary Walter used electrodes to investigate how the brain's electrical impulses change dynamically in response to various cognitive tasks. Electroencephalography (EEG) is a non-invasive procedure that uses electrodes on the scalp to record the electrical activity of the brain. It divides brainwaves into frequency bands, each of which corresponds to a particular mental state.EEG electrodes detect and enhance electrical impulses produced by neurons in the brain. EEG brainwaves are classified into numerous frequency bands, which include delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz). Each of these frequency ranges corresponds to a distinct set of mental states and cognitive processes. Alpha waves, for example, are connected with relaxation, whereas beta waves are associated with alertness and active cognition. The electroencephalogram (EEG) is frequently used in clinical diagnosis (e.g., epilepsy) and research to analyze real-time brain functions. Although it has good temporal resolution, its spatial precision is restricted when compared to other neuroimaging approaches. EEG technological advances are improving its applicability in studying brain activity and neurological illnesses. When

it comes to gathering exact characteristics of the brain, EEG has a limited spatial resolution despite its excellent temporal resolution. activity.[60][61]. Figure 2.7 shows the EEG system[5].

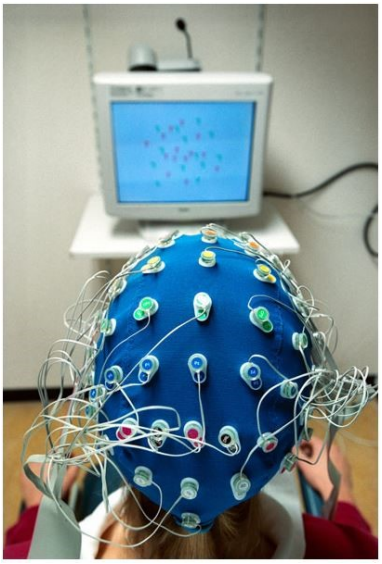

Figure 2.7: EEG headset for acquiring EEG signals from brain

Functional magnetic resonance imaging

The non-invasive neuroimaging technology functional magnetic resonance imaging (fMRI) is used to observe and investigate brain activity. It monitors variations in blood flow and oxygenation levels in various brain areas, revealing neuronal activity and functional connections. The participant lies inside a magnetic resonance imaging (MRI) machine during an fMRI session. Different brain regions demand more oxygenated blood as they grow more active. The magnetic characteristics of oxygenated and deoxygenated blood are measured by fMRI, which creates comprehensive maps of brain activity. Because it does not utilize ionizing radiation, it is suitable for repeated usage. Although fMRI has a high spatial resolution, allowing researchers to localize brain activity in specific areas, it has a low temporal precision when compared to methods such as EEG.FMRI scanners take up a lot of room and require a complex electrical environment.[62]. As shown in Figure 2.8 FMRI scanner.

[5]http://www.magaemg.com/knowledge/electroencephalography-eeg/,Finland

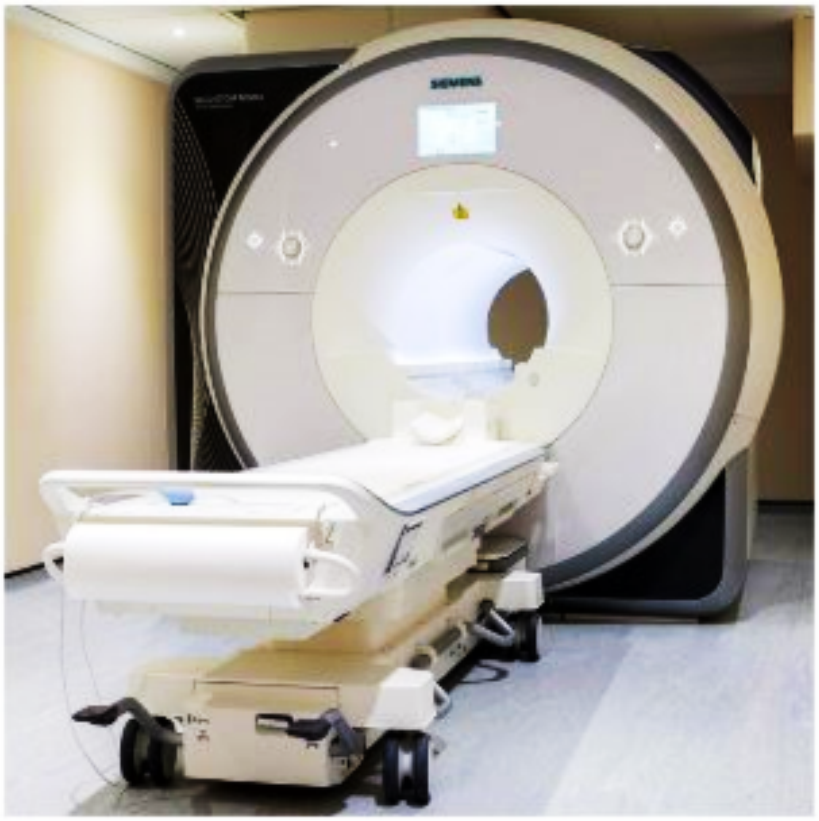

Figure 2.8: State of the art FMRI scanner

Magnetoencephalography

Magnetoencephalography (MEG) is a non-invasive neuroimaging technology that measures the magnetic fields created in the brain by neuronal activity. MEG has a high temporal and spatial resolution, making it an excellent tool for researching brain function and localizing neuronal activity.A participant wears a helmet-like apparatus containing sensitive sensors known as superconducting quantum interference devices (SQUIDs)[63] during a MEG session. These sensors detect the small magnetic fields produced by electrical currents in the brain's neurons. MEG can capture brain activity with millisecond precision, providing insights into cognitive process timing.MEG is very effective for properly locating the origins of brain activity. Researchers and doctors may generate functional brain maps by integrating MEG data with structural MRI (magnetic resonance imaging) scans, which demonstrate where certain cognitive functions, such as speech production or visual processing, are situated in the brain. As shown in Figure 2.9[58].

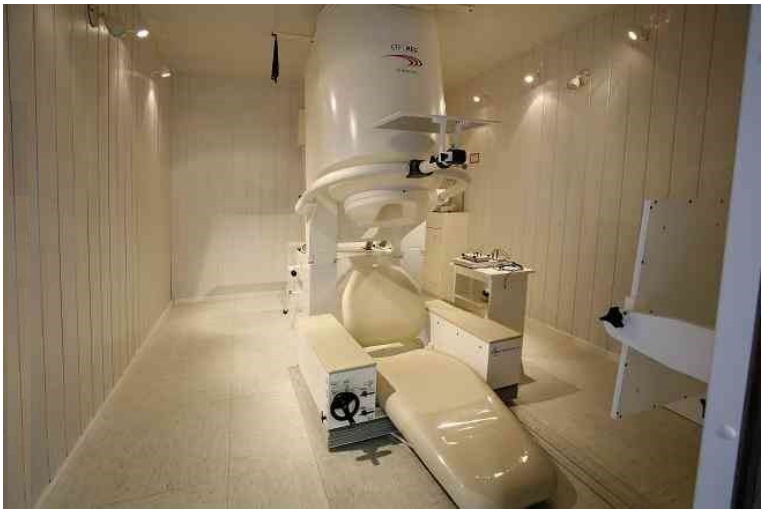

Figure 2.9: MEG scanner

Functional near-infrared spectroscopy

The change in hemodynamic response concentration during neuro-activation is measured using the non-invasive BCI technique known as functional near-infrared spectroscopy (fNIRS), since the introduction of the principle of fNIRS in 1977 by Jobsis.In fNIRS (functional Near-Infrared Spectroscopy) experiments, researchers use optodes to produce near-infrared light to collect brain impulses. The wavelength range for fNIRS functioning is typically between 650 and 1000 nm. Despite these limitations, fNIRS has received a lot of attention in recent decades, exciting researchers all over the world and ushering in a new age of progress in the field of Brain-Computer Interfaces (BCI)[64]. Because of its non-invasiveness, convenience of use, and capacity to give real-time insights into brain activity, it has proven to be a vital tool in neuroscience research, cognitive psychology, and therapeutic applications. Researchers are increasingly interested in the potential of fNIRS for applications such as brain-computer communication, mental workload evaluation, and neurological condition monitoring.

In our research we used Fnirs due to the key advantage of fNIRS is its portability, making it a preferred choice over bulky fMRI scanners for certain applications. However, it's important to note that fNIRS systems offer a moderate level of temporal and spatial resolution in comparison to techniques like fMRI and EEG. Figure 2.10 shows a fNIRS instrument[58] [6].

[6]http://www.sh-dz.net/iss-imagent-functional-brain-imaging-system.html

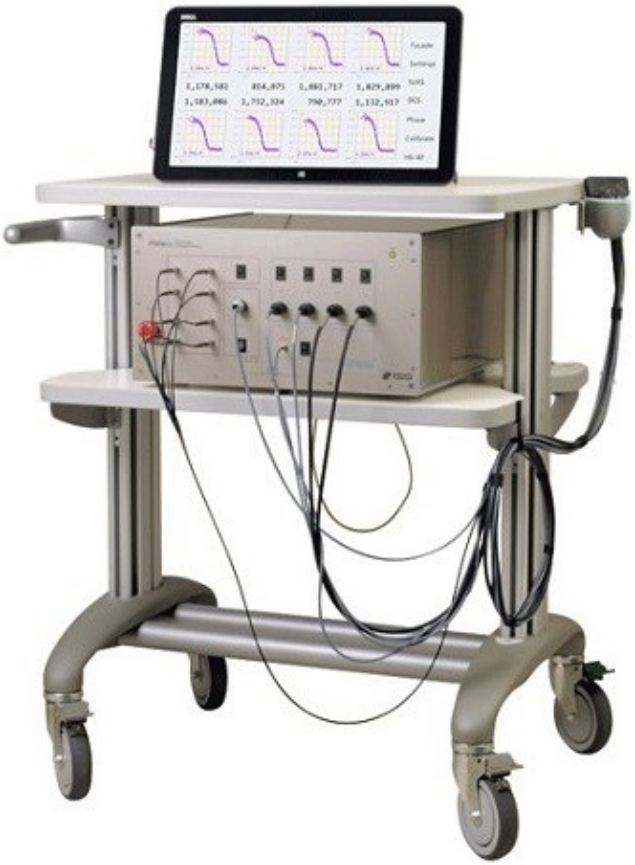

Figure 2.10: State of the art fNIRS instrument

Table 2.3: Comparison of Technologies

	Best		**Worst**
Signal Depth	FMRI (Full Brain)	EEG (full brain)	FNIRS (∼1.5cm into cotex)
Spatial Resolution	FMRI (1 voxel= -3mm)	FNIRS (1 channel=∼1cm)	EEG (poor,unless great effort and cost spend)
Sampling Rate	EEG (250-2000 Hz)	FNIRS (1-200Hz)	FMRI (<=2 Hz)
Cost	EEG ($5k-200k)	FNIRS ($10k-400k)	FMRI (a few billions $)
Portability	FNIRS (few accessories)	EEG (many accessories)	FMRI (stationary)
Motion Tolerance	FNIRS (just don't move optodes on scalp)	EEG (don't move muscles around head)	FMRI (don't move upper body)
Participant Comfort	FNIRS (snug cap,can fidget or even walk, no safety risk)	EEG (goopy cap,can't move,no safety risk)	FMRI (lying still,loud machine, safety risk)

2.4 Machine Learning

An essential component of artificial intelligence, machine learning, gives computers the ability to learn on their own and make wise decisions. It centers on the creation of statistical models and algorithms that let computers identify patterns in data and use those patterns to make predictions. The core idea behind machine learning is its ability to mine vast datasets full of input qualities and related output labels for useful data and insights. The choice and quality of datasets significantly impact the performance of machine learning models. The establishment of features triggers the start of model training. Algorithms adjust their internal structures during this phase by minimizing a predetermined objective function, typically using optimization strategies like gradient descent. Models are then validated and put to the test on a variety of datasets

to determine their effectiveness and make sure they can generalize to new data. Depending on the specific job, several assessment measures are utilized, including accuracy, precision, recall, F1-score, and others. Hyperparameter tuning, which involves changing the parameters guiding the learning process, improves model performance further. The final step in machine learning is deployment, which involves the incorporation of trained models into practical applications for automated judgment or prediction. This stage marks the end of the machine-learning process and calls for smooth integration into software platforms or operational settings. As a dynamically developing discipline, machine learning continually unearths new uses in a variety of fields, such as autonomous driving, medical diagnostics, speech and picture recognition, natural language processing, and recommendation systems. It continues to be at the cutting edge of technical advancement, improving constantly thanks to continued research and development activities. Types of machine learning are the following:

Supervised machine learning

Supervised machine learning, uses labeled training data to train computers to make predictions or judgments. It entails building a model that can generalize and make accurate predictions on new, previously unknown data by employing input attributes and associated output labels. Several fields, including image recognition, natural language processing, and recommendation systems, employ this technique extensively. As a result, it is a basic approach to leveraging existing knowledge and data to address real-world difficulties.

Unsupervised machine learning

Unsupervised machine learning, a subset of artificial intelligence, is the process by which computer systems study and extract insights from unlabeled data without regard for established output labels. This subset of machine learning is generally used to uncover hidden patterns, structures, or correlations in datasets. Unsupervised learning techniques commonly used include clustering, which groups data points into meaningful clusters, and dimensionality reduction, which lowers data complexity while maintaining crucial information. Unsupervised learning is useful for a variety of tasks, such as customer segmentation, anomaly detection, and feature extraction, especially when the underlying data structure is unknown and the primary goal is to obtain a better understanding of the data's intrinsic properties.

CHAPTER 3

FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (FNIRS)

The term "fNIRS" refers to functional near-infrared spectroscopy. Our fNIRS sensors can measure brain activity, which gives the functional component its name. This is done by monitoring changes in total, oxy-, and deoxyhemoglobin in the cerebral cortex, which are caused by neuro-activation of the internal brain. Additionally, fNIRS offers a non-invasive way to obtain a high-resolution brain signal in real-time. figure 3.1 shows Fnirs system [1].

Figure 3.1: Portable fNIRS system

The founders of NIRx, Professors Randall L. Barbour and Ray Aronson, introduced the idea of tomographic imaging multi-distance spectroscopic observations in densely dispersed media in 1988. This technique depends on

[1] https://nirx.net/

diffusely scattered light. This method has now been widely adopted and played a key role in the development of fNIRS tomography in the present day. Table 3.1 shows NIRx fNIRS Technology Service Overview [2].

Table 3.1: NIRx fNIRS Technology Service Overview

Whole-head	lab-based and portable/mobile fNIRS systems
Truly wireless	wearable fNIRS systems
Multi-modal compatibly	EEG, fMRI, TMS, eye-tracking, MEG, etc.
Neurofeedback/BCI:	export and analyze raw, unfiltered data for real-time subject feedback
High-quality data	even on subjects with thick dark hair, by using superior light source technology
Versatility	multiple extensions to meet the needs of a wide variety of labs (e.g., cap sizes to fit all ages, etc.)
Upgradability	expand your NIRx system to enhance your ongoing research capabilities
Reliability	NIRx end-users receive lifetime technical support from our global team of experienced fNIRS researchers and engineers, and exclusive access to our extensive online support center and technical webinars

(fNIRS) is a neuroimaging method that is quickly developing. Gowerlabs systems are at the leading of this development, making it possible to study human brain function in a non-invasive, simple-to-use, and portable manner. Here, we outline the underlying science that underlies our technology.

A Rush of Blood to the Head

The billions of neurons that make up our brains require a constant supply of glucose and oxygen to function, just like any other cell. The metabolic demand of neurons rises when they are active, firing action potential signals and communicating with one another by releasing neurotransmitter molecules. Local blood vessels will begin to rapidly expand in response to this increased

[2]https://nirx.net/

activity to ensure that they do not get exhausted from oxygen or glucose. As a result, locations close to activated neurons see an inflow of oxygenated blood. Although the mechanisms underlying neurovascular coupling are complicated, the blood flow response to an increase in neuronal activity is consistent and well-understood. This relationship exists between neuronal activity and the localized response of the blood vessels. As a result, localized changes in cerebral blood flow may be measured, and this is a great proxy for measuring brain activity.

Seeing Red

The red and near-infrared regions of the electromagnetic spectrum exhibit relatively low absorption rates in human tissues, allowing near-infrared light to penetrate several centimeters into the tissue. This phenomenon can be easily observed in everyday life, such as when your fingers appear to emit a reddish glow when held near a white light source. While violet, blue, green, yellow, and orange light are absorbed by the tissues in your hand, a significant portion of red light is transmitted through your fingers and is visible to the eye.

Despite the lower absorption of red and near-infrared light, it's important to note that there are still molecules within human tissues that absorb light at these wavelengths. Hemoglobin, the molecule responsible for transporting oxygen in the bloodstream, serves as the primary absorber of near-infrared light in tissue. Furthermore, the absorption spectra of oxygenated and deoxygenated hemoglobin in the red and near-infrared ranges differ significantly. This discrepancy results in oxygenated blood appearing noticeably brighter red to the naked eye compared to deoxygenated blood. The image of fingers placed over a white light source illustrates this phenomenon, where only red light is visible due to the absorption of other parts of the visible spectrum by the hand's tissues. As shown in Figure 3.2 [3].

[3]https://nirx.net/

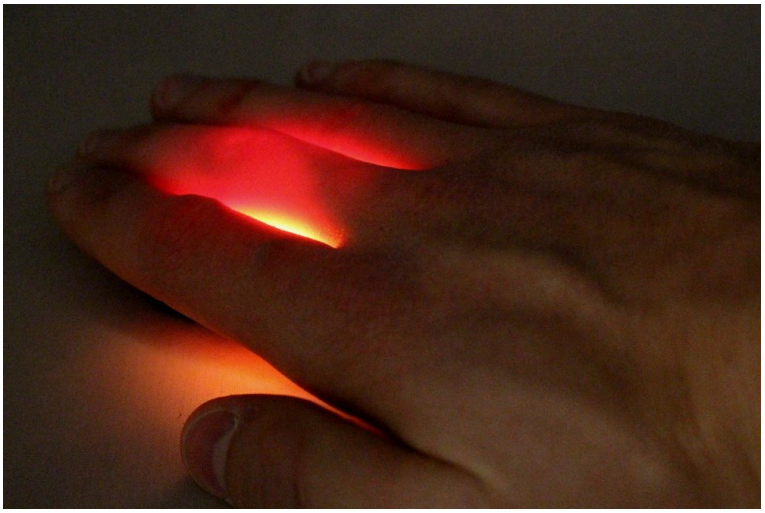

Figure 3.2: Spectrum of red light

While red and near-infrared light is generally less absorbed by human tissues compared to other colors, it's important to note that These tissues still have chemicals that absorb light at these wavelengths. Hemoglobin, the molecule responsible for oxygen transport in the bloodstream, is the primary absorber of near-infrared light in tissue. What's particularly significant is that the absorption spectra of oxygenated and deoxygenated hemoglobin in the red and near-infrared ranges differ notably. This distinction results in oxygenated blood appearing significantly brighter red to the naked eye compared to deoxygenated blood.

The Gowerlabs NTS Optical Imaging System utilizes two distinct near-infrared wavelengths of light, generally 780nm and 850nm (but 685 nm and 850nm are also often employed) to efficiently quantify changes in the concentration of both types of hemoglobin. This allows for precise monitoring of alterations in hemoglobin concentration and provides valuable insights into brain activity and blood flow dynamics. As shown in Figure 3.3 [4].

[4]https://nirx.net/

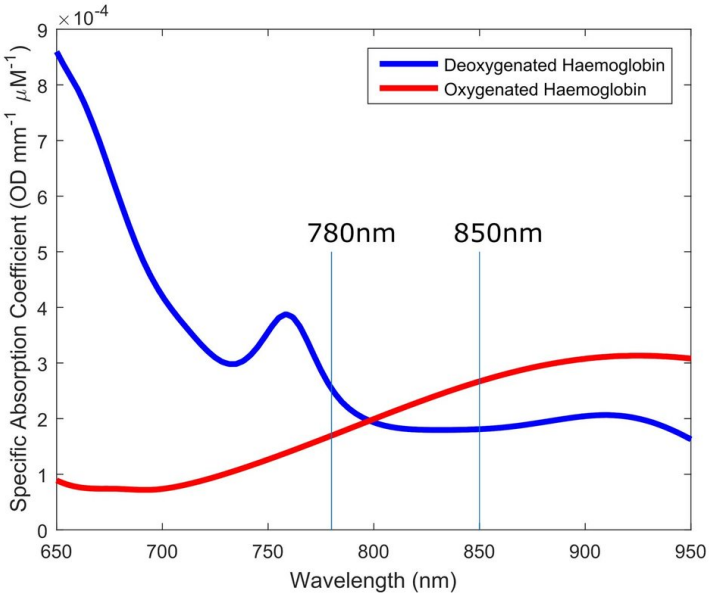

Figure 3.3: Wavelengths of HBO and HBR

A Window to the Brain

The study of the human brain benefits greatly from two essential characteristics: the near-infrared light transparency of human tissues and the distinct absorption characteristics of oxygenated and deoxygenated hemoglobin. By directing two specific wavelengths of near-infrared light into the scalp and observing the scattered light a few centimeters below the surface, we can determine the concentrations of oxygenated and deoxygenated hemoglobin in the brain. This capacity stems from the close relationship between neural activity and local blood flow. When there is an increase in neuronal activity, there is a corresponding local surge in oxygenated blood volume, leading to an increase in oxyhemoglobin and often a simultaneous decrease in deoxyhemoglobin. This phenomenon is known as the Hemodynamic Response Function (HRF). The typical fNIRS hemodynamic response function (HRF) recorded by the Gowerlabs NTS Optical Imaging System illustrates an increase in oxyhemoglobin concentration (HbO) accompanied by a minor decrease in deoxyhemoglobin concentration (HbR) as oxygenated blood flows into the active brain region. The total hemoglobin concentration (HbT) encompasses both forms of hemoglobin and plays a crucial role in these processes. As shown in Figure 3.4 [5].

[5]https://nirx.net/

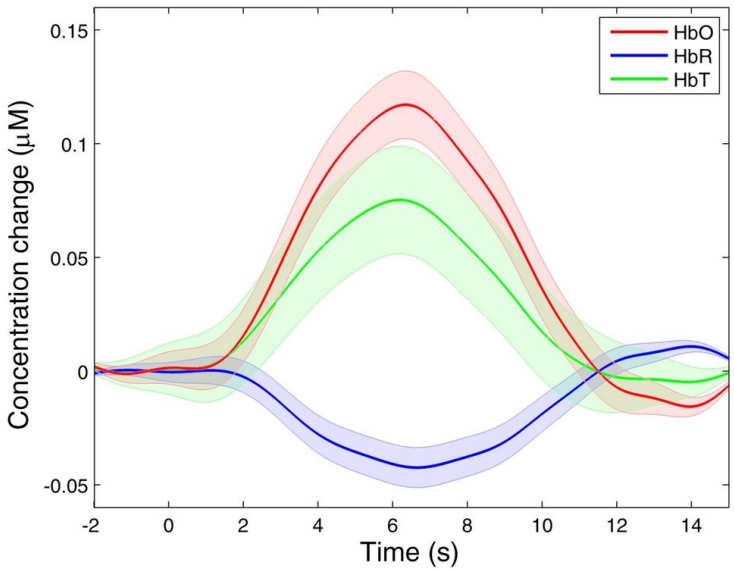

Figure 3.4: Hemodynamic response

3.1 NIRS Regions of Interest

All NIRx systems allow for adjustable probe placement, allowing data to be collected from any area of the head (the probes can also be configured to capture data from the periphery via fNIRS). Figure 3.5 shows brain region[6]. Using a NIRx fNIRS system, it is simple to measure the following areas:

[6]https://nirx.net/

Figure 3.5: Brain Regions

3.1.1 fNIRS Brain Regions of Interest

1. Pre-frontal cortex
2. Dorsa-lateral pre-frontal cortex
3. Supplementary motor area
4. Premotor cortex
5. Primary Motor cortex
6. Somatosensory cortex
7. Posterior parietal cortex
8. Primary auditory cortex
9. Broca's / Wernicke's area
10. Primary visual cortex

Pre-frontal cortex

The prefrontal cortex (PFC) is a crucial part of the brain that is engaged in many intricate processes. A non-invasive technique called functional near-infrared spectroscopy (fNIRS) monitors variations in total, oxy-deoxy,

and oxyhemoglobin in various brain regions, including the PFC. Multi-channel fNIRS devices can assess pre-frontal brain activity in investigations of cognition, decision-making, or language, for example, and can cover the entire PFC. Since fNIRS can be set up almost instantly and is very portable, patients can move around freely. As a result, it can be effectively used in psychology, sports and rehabilitation sciences, and many other domains when carrying out daily tasks. The frontal lobe and cerebral cortex are included in the PFC. It is important for many executive processes, including planning complicated cognitive actions, maintaining attention, and engaging in goal-directed behavior. Additionally linked to personality formation include conscious decision-making, regulating social behavior, and personality expression, the pre-frontal cortex. Additionally, the PFC is connected to short-term memory as well as the control of language and voice. Figure 3.6 shows pre-frontal probes. [7]

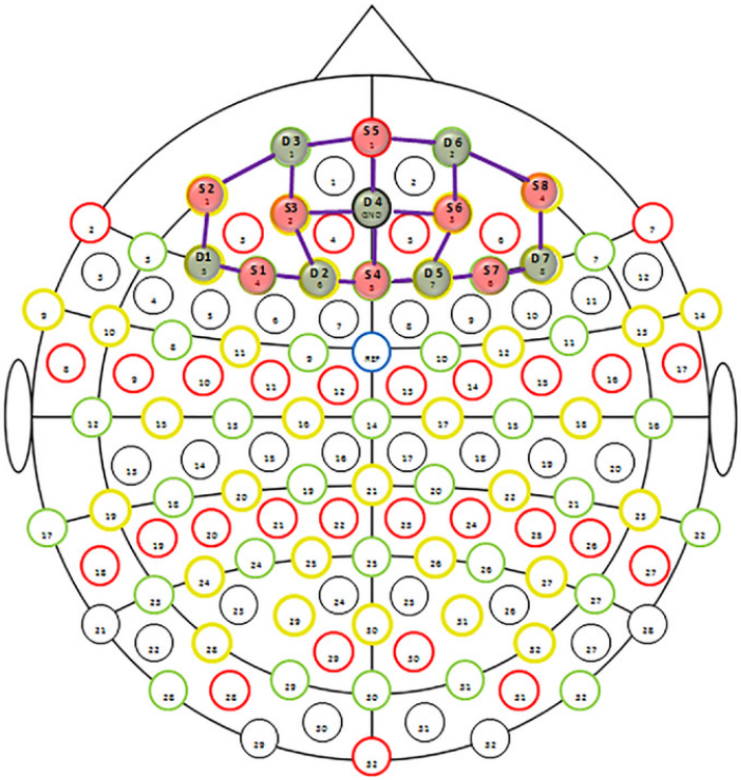

Figure 3.6: Pre-frontal probes

[7] https://nirx.net/

3.2 fNIRS System

fNIRS works on the principle that neural activity is accompanied by changes in blood oxygenation levels. When neurons are active, they require more oxygenated blood. Hemoglobin, the protein responsible for carrying oxygen, absorbs light differently when it is oxygenated (oxyhemoglobin) or deoxygenated (deoxyhemoglobin). fNIRS devices utilize near-infrared light to measure the differential absorption of these two forms of hemoglobin.

3.2.1 Components of an fNIRS System

Light Source

The light source in fNIRS devices is usually comprised of multiple light-emitting diodes (LEDs) that emit near-infrared light. The choice of wavelengths is crucial as they determine how deeply the light can penetrate brain tissue. Common wavelengths used are around 730 nm and 850 nm, as these wavelengths strike a balance between penetration and sensitivity to changes in hemoglobin concentrations.

Photodetectors

Photodetectors, typically silicon photodiodes, are responsible for detecting the intensity of the light that has traversed the brain tissue. These detectors convert the intensity of the light into an electrical signal, which is then processed for analysis.

Optode

Optodes are the optical elements that facilitate the transmission and detection of light. They come in pairs – a source optode and a detector optode – and are placed on the scalp. The distance between these optodes determines the measurement depth in the brain. Shorter distances provide information from shallower regions, while longer distances reach deeper brain structures.

Light Propagation

Near-infrared light is released and penetrates through the scalp, skull, and brain tissue. Along the way, it is absorbed, scattered, and attenuated by various tissues. The detectors measure the light intensity that has reached them, which carries information about the absorption characteristics of hemoglobin in the brain.

Channels

The number of optodes, or channels, in an fNIRS system, determines the spatial coverage of the brain. More channels provide better spatial resolution but may also increase the complexity of data analysis.

Signal Processing Unit

The collected raw data from the photodetectors undergoes signal processing to extract meaningful information. This processing includes filtering to remove noise, converting raw intensity to optical density, and using algorithms to separate the contributions of oxyhemoglobin and deoxyhemoglobin. Some systems also use algorithms to account for superficial tissue interference.

Data Analysis Software

The processed data is then analyzed to extract relevant information about brain activity. Various analysis methods are used, such as correlation-based methods, general linear modeling, and machine learning techniques. Researchers analyze changes in hemoglobin concentrations to infer neural activation patterns.

3.2.2 Types of fNIRS Systems

Continuous-Wave (CW) Systems

CW fNIRS devices emit a continuous light signal, and changes in intensity are measured. These systems provide relatively simple data but can suffer from limitations due to signal contamination from the skin and other superficial tissues.

Time-Domain (TD) Systems

TD fNIRS devices emit short pulses of light and measure the time it takes for the light to travel through the tissue and be detected. This method enables greater depth resolution and improved signal-to-noise ratio.

Frequency-Domain (FD) Systems

FD fNIRS devices use modulated light sources and measure the phase shift and amplitude attenuation of the detected light. This technique offers improved accuracy and can distinguish between shallow and deep brain structures.

3.2.3 Applications

fNIRS has a wide range of applications, including cognitive neuroscience, clinical studies, developmental psychology, and brain-computer interface research. It's used to study brain activation during tasks like language processing, problem-solving, motor activities, and social interactions.

3.2.4 Commercial fNIRS Systems

1. Hitachi ETG-4000

2. NIRx NIRSport

3. TechEn CW6

4. Shimadzu LABNIRS

5. Artinis PortaMon

3.3 NIRsport

An accessible, segmental, and reliable functional near-infrared spectroscopy (fNIRS) device is the NIRsport. Our most cutting-edge fNIRS platform, with a variety of features and capabilities, is the NIRSport2 system. We designed a system that boasts excellent signal quality, broad versatility, and modularity as our starting point, as well as the insight into future research, needs to offer the most ideal user experience and the highest success in science. The revised version, NIRsport-2, puts out a number of ready-to-implement innovations and units to satisfy the needs of numerous cognitive neuroscience applications. The fact that both of these devices are portable and are made to function in harsh environments is their main advantage. The creation of a wearable and portable system is made easier by this capability. The technical specifications of the device are listed in table 3.2 as [8]:

[8]https://nirx.net/

Table 3.2: Specialized Detail of NIRSport

Maximum Sources	16(can be configured to 8,and upto 64 in multi-device mode)
Maximum Detectors	16(can be configured to 8,and upto 64 in multi-device mode)
Source Wavelengths	Led: 760nm and 850nm
Source illumination type	Led
Sampling Rate	Up to 240Hz
Detector Sense	Silicon photodiode(sipd) or avalanche photodiode(apd)
Operation Mode	Usb,wifi,stand alone,direct-to-device recoding mode:no computer,tablet, no smartphone required
Optode Type	Single tip, or specialized dual tip c optodes(faster setup time and better contact to skin) , blunt tip(infant and child applications, better comfort)
Key Measurement Features	Time multiplexing, full frequency-encoded measurement and dynamic gain state switching
Detector Dynamic Range and Senitivity	>80 db opt measurement dynamic range
Event synchronization	Wireless (Isl: lab streaming layer), cable(8 bit ttl input)
Data Format	Raw light intensity:tab delimited(may be analysed in any environment)
Headgear	Nirscap: freely configurable, measures whole head, fit all ages ranges,multi-modal
Power Suppy Voltage and consumption	90 to 250 vac(50Hz-60Hz);175w max
Dimensions(wxhxl),Net Weight	162mm * 125mm * 60mm, 970g

3.3.1 NIRSport2 Advantages

Modularity and Scalability

The modularity of this system's setup, which includes 8 sources and 8 detectors, is critical. It has excellent scalability, allowing you to expand the system from its base configuration of 8×8 to handle up to 80 sources and 80

detectors, or you can choose the intermediate option of 16 x 16.

What's more, this system can fully synchronize up to 5 devices, increasing its versatility and adaptability for a variety of applications and research purposes. Because of its scalability and synchronization capabilities, it is an adaptable solution for a wide range of scientific and technological undertakings.Figure 3.7 shows modularity and scalability [9]

Figure 3.7: Modularity and Scalability

Signal Quality

The system is outfitted with high-powered dual LEDs that can give a maximum light of 32mW, and customers can choose next-generation APD detectors with sensitivity as low as 33 pW. What distinguishes this system is its exclusive automated technology, which provides ultra-fast signal tuning for both the source and the detector, speeding the data-collecting process. Variable tension spring holders are used to improve user experience and measurement quality by enabling optimal coupling with the scalp while ensuring comfort during data collection. The system includes a comprehensive array of short-distance detectors, allowing for configurable data-collecting configurations. Furthermore, the addition of probe-level 9-axis accelerometer(s) broadens the system's capabilities, allowing it to record motion-related data and extend its range. As shown in Figure 3.8 [10].

[9]https://nirx.net/
[10]https://nirx.net/

Figure 3.8: Short distance channels

Versatility

The NIRSport2 is a versatile research platform designed for a wide range of applications and modalities such as EEG, VR, TMS, and MRI. Its lightweight and compact shape, measuring 162 mm x 125 mm x 60 mm and weighing around 900 grams, makes it excellent for motion-related research. It has wireless connectivity as well as onboard storage for untethered data capture. The system also offers integration solutions for applications using other modalities, such as EEG, VR, and MRI. It has a high-density architecture with 48 sources and 48 detectors, providing for improved data collection capabilities when coupled to several NIRSport2 devices. As shown in Figure 3.9 [11].

[11] https://nirx.net/

Figure 3.9: Versatility of NIRSport2

3.3.2 NIRSport2 Functionality

The NIRSport2 is a cutting-edge software platform created to promote usability, flexibility, and natural workflow. The NIRSport2 is a versatile and user-friendly wireless functional near-infrared spectroscopy (fNIRS) platform designed to measure hemodynamic responses in the cerebral cortex. The NIRSport2 is built to withstand the rigors of scientific research. It can provide reliable data collection even in challenging conditions, ensuring that the research results are accurate and consistent. This platform is known for its modularity and robustness, making it suitable for various cognitive neuroscience applications.

One of the key features of the NIRSport2 is its ability to monitor changes in oxyhemoglobin, deoxyhemoglobin, and total hemoglobin, providing valuable insights into neuroactivation and brain function. Researchers and scientists can use this platform to investigate how the brain responds to various cognitive tasks, stimuli, or experimental conditions.

Moreover, the NIRSport2 offers a range of readily available upgrades and modules that can be easily integrated into the system. These upgrades allow researchers to customize the platform to meet specific research needs and explore a wide array of cognitive neuroscience applications. Whether you're studying language processing, memory, attention, or other cognitive processes, the NIRSport2's flexibility makes it a valuable tool for advancing our understanding of the human brain.

CHAPTER 4

METHODOLOGY

This chapter details the methodologies of experiment conduction, data pre-processing, and processing. In experiment conduction, the demographic information of participants, the experiment paradigm, and the signal acquisition methods are presented. The data pre-processing includes methods used to filter data, channel selection, and calculation of change in light reduction at a given wavelength. The processing method, however, highlights which data classification techniques are selected and details the theoretical background of classification chosen methods. The flowchart given in Figure 4.1 clearly indicates this whole process from data acquisition to the classification of data for three emotions i.e. Sad, Neutral, and Anger.

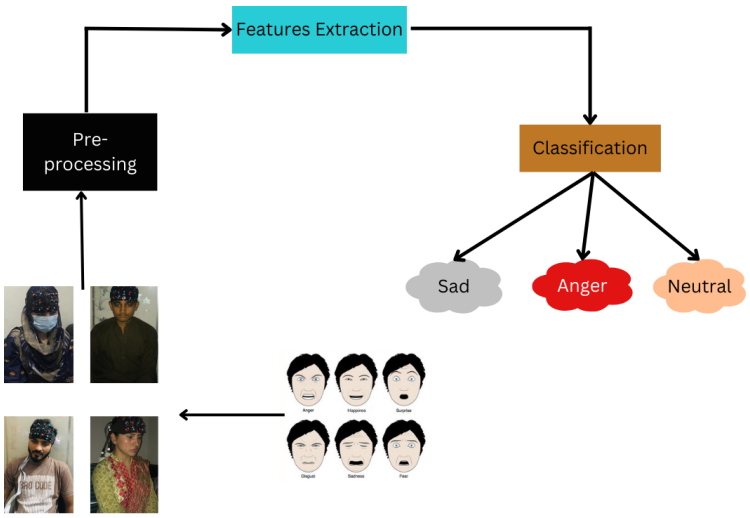

Figure 4.1: Flowchart of Methodology

4.1 Experimental Paradigm

Before the experimental trials begin, the user will be given an explanation of the operation of the NIRSport Core System, in particular, the safety measures put in place to allow termination of the equipment operation should an emergency arise. A brief demonstration of the experiment will be given. The age, gender, and demographic characteristics of the participants will also be collected. After the briefing and collection of information, the process of experimentation will start. In the experiment, the participant will be required to wear a headset in order to record the brain responses (signals) using a non-invasive fNIRS head cap (sensors) to study the possibility of classifying brain signals due to various physiological and mental exercises. In order to record offline training fNIRS data, the subject will be required to sit in a quiet and dimly lit room selected for this purpose. The subject will be trained using the NIRSport software, in which one will have to think that he/she is watching video and getting emotional Several trials of this practice will be carried out for training purposes.

The three emotions were drawn out in the experimental environment, we used targeted film clips as the stimuli. We collected highly emotional target film clips. There are ten participants (3 females, 7 males) and three emotional film clips (anger, sad, neutral). After each trial, the subject will be asked to relax for 45 seconds. There will be five number of trials for each subject. Participants were asked to watch clips that contain emotions and evoke the corresponding emotions. The article ratings were based on this how they actually felt when they saw the clips, no how they thought music videos should look. Second when participants did not evoke the right emotions or when the arousal emotions were not strong enough were rejected. After each trial, the subject will be asked to relax for 45 seconds. There will be five number of trials for each subject

After watching each film clip, participants reported their emotional states on arousal and valence. Arousal refers to the intensity or activation level of an emotional experience. It represents how stimulating or calming an emotional state is. On a numerical scale, arousal is often represented as ranging from (0 to 1). Valence refers to the pleasantness or unpleasantness of an emotional experience. It represents the emotional state's positive or negative quality. On a numerical scale, valence is often represented as ranging from (-1 to 1). Classify these three emotions based on these dimensions. Sadness is typically characterized by a negative valence (unpleasant feeling) and low arousal (a sense of calm or deactivation). A neutral emotion falls in the middle of the valence scale, indicating neither positive nor negative feelings. It also has low

arousal. Anger is characterized by a negative valence (unpleasant feeling) and high arousal (intense activation).

Neutral, sadness, and anger, emotion keywords are used in this dataset. The experimental trial was carried out in the Bio-Mechatronics research laboratory at the Air University. These research studies were conducted in accordance with the most recent Helsinki Declaration's ethical guidelines[65], and the Air University local ethics committee gave its approval. The experimental paradigm for acquiring brain signals from the fNIRS head cap is given in Figure 4.2

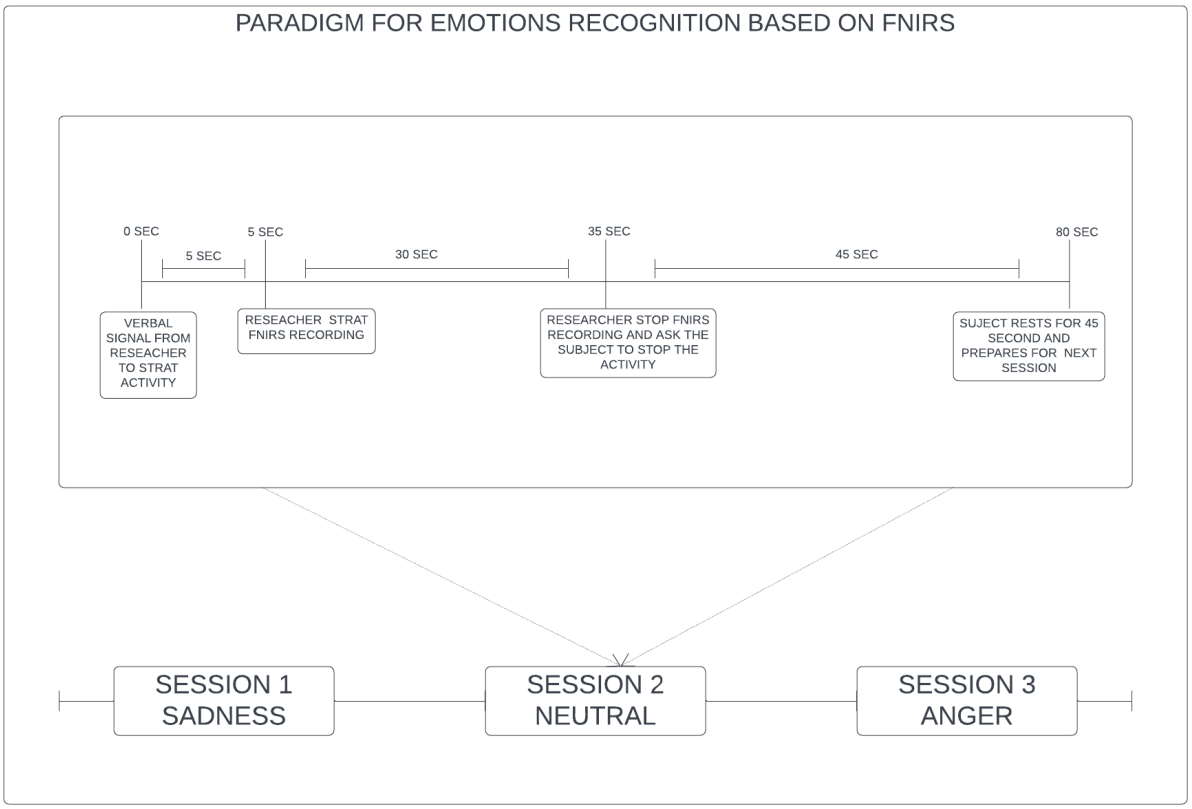

Figure 4.2: Experimental Model for Signal Acquisition

4.2 fNIRS Signal Acquisition

NIRx Technologies' created fNIRS headset responds to the 3 cm source-detector separations that are considered to be the industry standard [66][67]. The optodes are calibrated once the subject puts on the cap. Provides an

analysis of the calibration's outcome. Figure 4.4 depicts the problematic setup. Optodes can be seen by the boxes. The color bar shows whether or not the optodes are in touch with the scalp, which determines the colors. The color white represents a separation between the scalp and the optodes. The red color suggested that the connection between the scalp and the optode needed to be changed because it was crucial. Sometimes hair gets in the way and simply reconnecting the optode to the cap allows for a better connection. If the problem is not resolved by this time, a clinical gel is used to fix the hair. The firm includes the gel in the packaging with the machine and has certified that it is healthful and safe to use with optodes. The yellow color denotes an acceptable connection. Acquiring the signals is possible. In this case, the machine calibrates its own operating conditions. Where the connection is satisfactory, the machine increases the gain factor for the optodes, and it is saved in a conditions file that is later utilized for signal processing. The green hue indicates that the optodes have been correctly placed on the surface of the head and that a great connection has been made for data collecting. This can be analyzed in Figure 4.3.

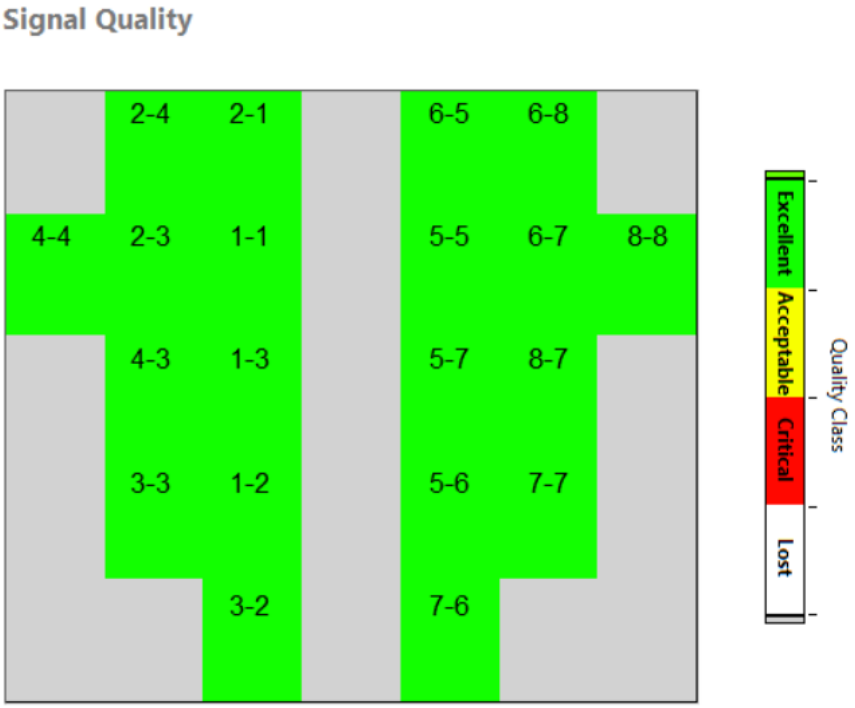

Figure 4.3: Visual representation of Perfect optode settings

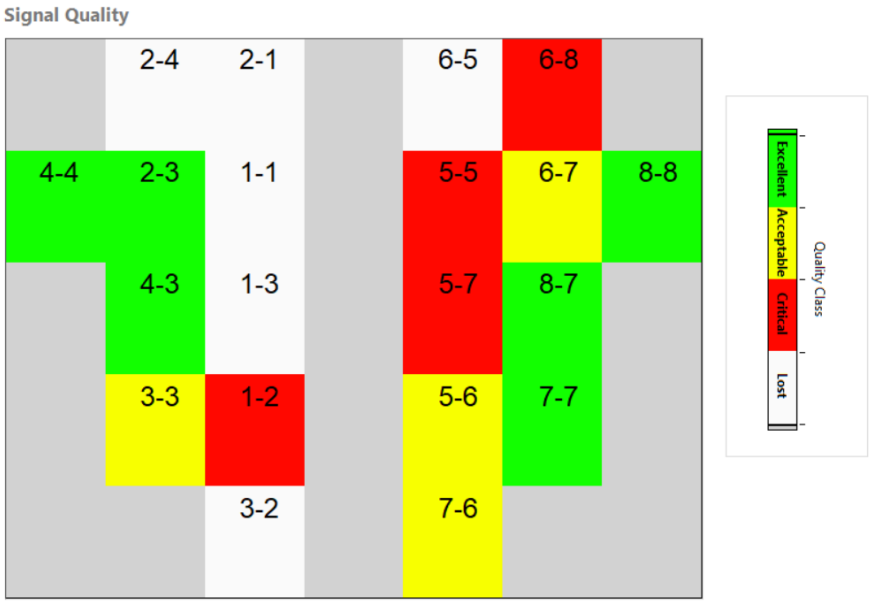

Figure 4.4: Visual representation of problematic setup settings

After the optodes are installed, the signal collection starts. The subjects had to carry out particular tasks that fNIRS concurrently indicated. The participants were sitting in regular chairs around 100 cm from the emotion signals that were visible to them, but the illumination of the screen didn't interfere with the optical sensors. [23]. The setting for the signal extraction was created. A 20-channel fNIRS system was used to record the fNIRS signals at a sampling rate of 7.6 Hz. Oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) concentration changes were monitored using near-infrared light with two distinct wavelengths (760 and 850 nm). Fifteen probes (8 sources and 7 detectors) were positioned to cover the frontal cortex (probe spacing 30 mm) for a total of 20 channels.

4.3 fNIRS Signal Processing

The raw light intensity values are obtained from changes in blood oxygenation in the brain. These values are acquired using dual-tip optodes at two different wavelengths, 760nm and 850nm. These 760nm wavelength and 850nm wavelength are sensitive to changes in HBR and HBO hemoglobin concentrations in the blood. The acquired data is processed in the nirsLAB environment, which is specialized software for working with fNIRS data. Data segments with unwanted information, such as the initial 0-5 seconds, periods after 35 seconds, and any other unexpected spikes or discontinuities, are re-

moved. This is likely done to eliminate noise or artifacts from the data. Any sudden jumps or abrupt changes in the data, known as discontinuities, are further removed to ensure a smoother dataset. Smooth the data with a bandpass filter before analyzing the hemodynamic states. To elicit the most emotional responses, signals corresponding to the last 30 seconds of each film clip were collected. (following the procedure[68]) These hemodynamic states are now being used.

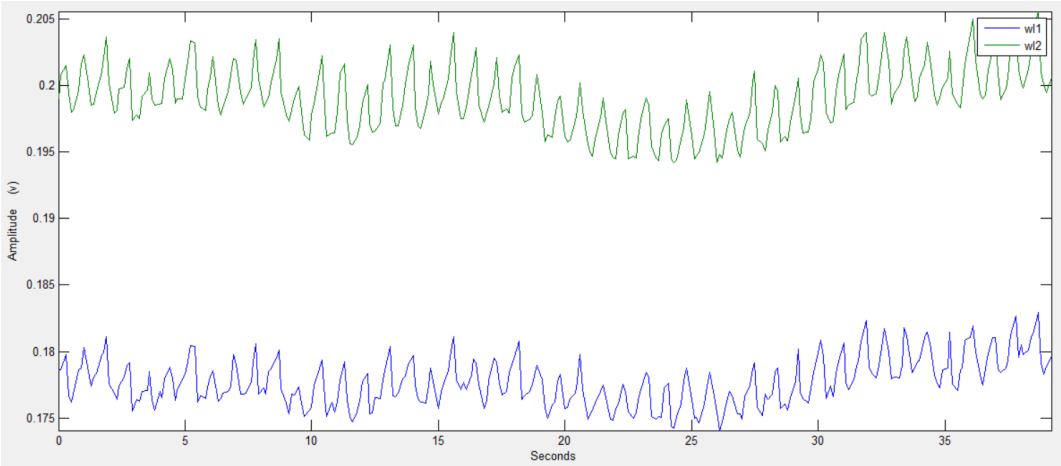

Figure 4.5: wavelength as wl 1 from 760nm and wl 2 from 850nm

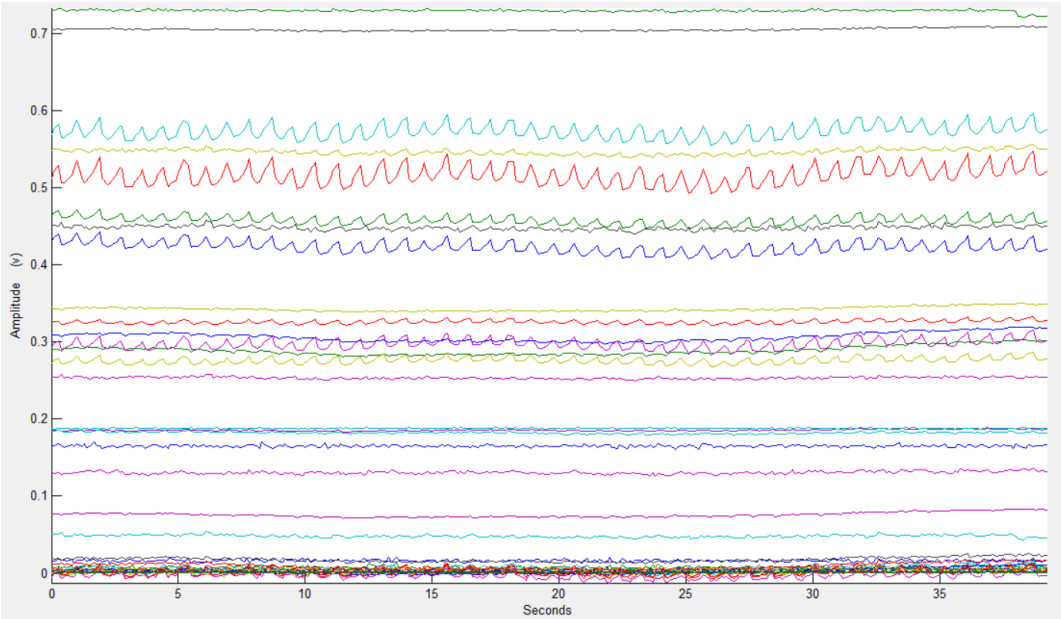

Figure 4.6: The raw signals of all channels

Figure 4.5 shows the raw fNIRS signals obtained from both wavelengths

(760nm,850nm). Figure 4.9 likely illustrates a comparison between the filtered and raw data at both wavelengths, demonstrating the effect of the band-pass filtering process in terms of noise reduction and signal enhancement. NirsLAB uses the firls and filtfilt MATLAB commands for filtering. Firls computes the parameters of a linear-phase filter, and Filtfilt applies these filter parameters to the data. Finite Impulse Response (FIR) filters are utilized for this purpose. The roll-off parameter defines the width of the transition frequency band, indicating how quickly the filter transitions between attenuating (cutting) frequencies and allowing (passing) frequencies within the specified range. A higher roll-off value results in a steeper and narrower transition band, while a lower value produces a gentler and wider transition. The width of the transition band is calculated as 4.1 and 4.2 for each of the upper and lower limits of frequency.

$$Upperlimit = 1 + (Roll - off)/2 \tag{4.1}$$

$$Lowerlimit = 1 - (Roll - off)/2 \tag{4.2}$$

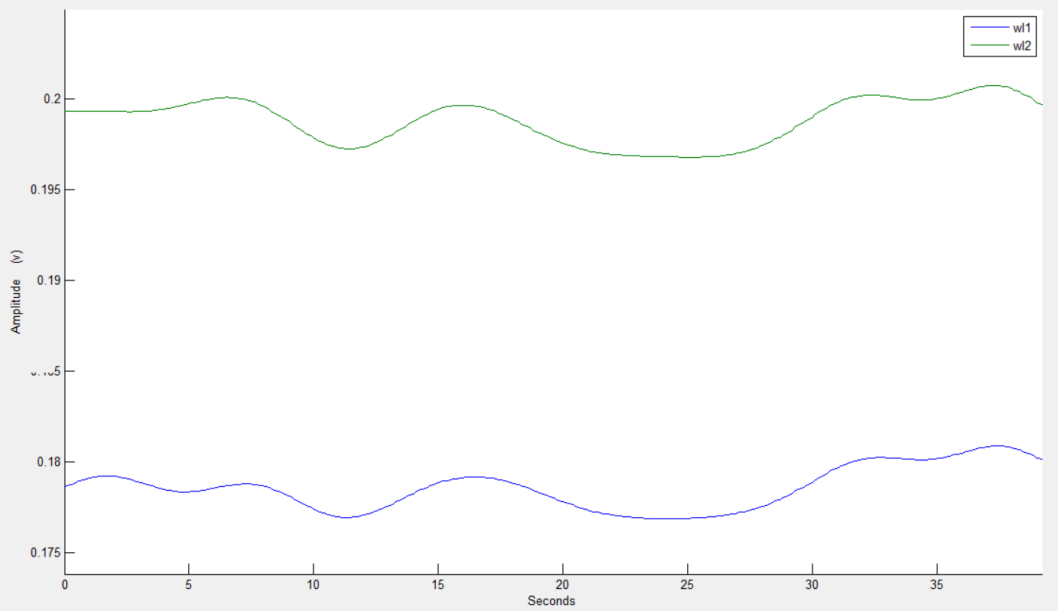

Figure 4.7: The signals at both wavelengths have been filtered using a band-pass filter with a frequency range of 0.01Hz to 0.2Hz, and the default roll-off value of 15 has been applied

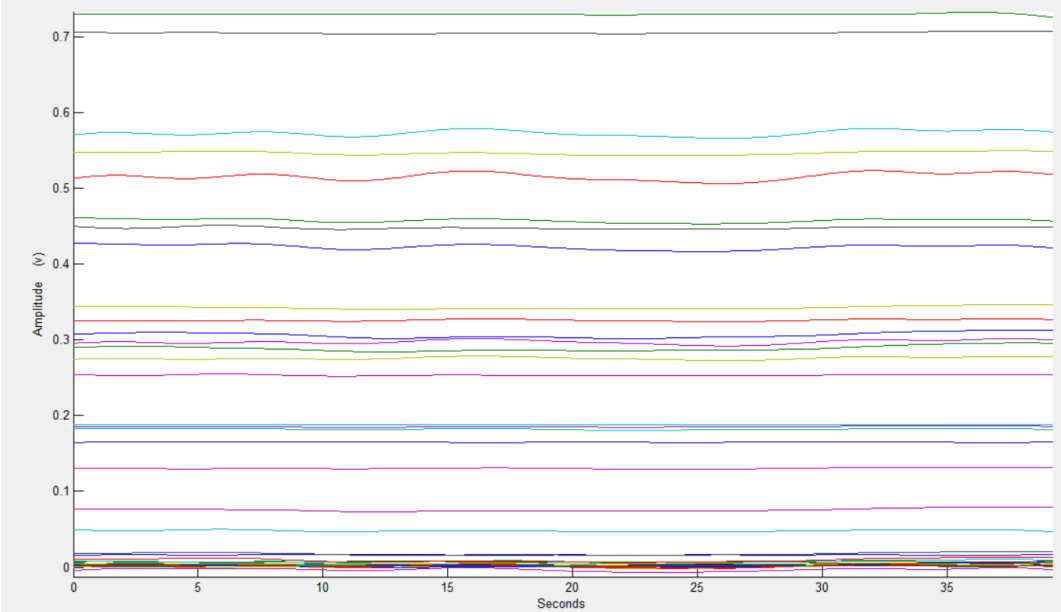

Figure 4.8: The Filter signals of all channels

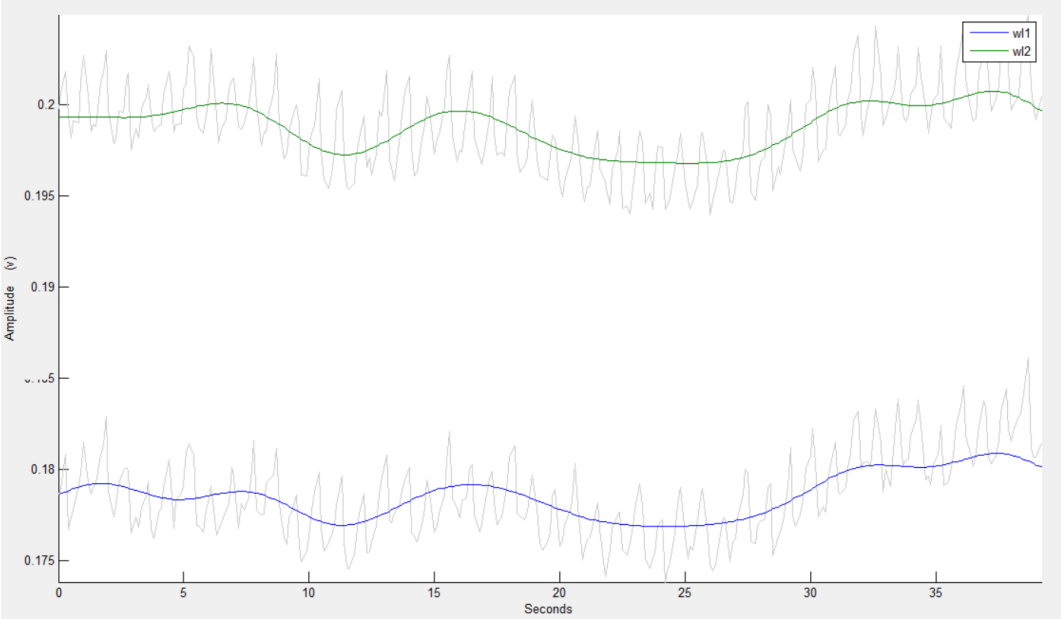

Figure 4.9: Campare Between Original and Filtered Signal

The data that are now free from unwanted noise and artifacts are used to determine changes in blood flow by applying something called the modified Beer-Lambert Law[69][70][71]. This law helps us understand how light is absorbed and scattered in the brain, which gives insights into changes in blood oxygen levels.

These changes in blood flow are shown in real-time using the NIRStar® system, and they're also calculated later on in nirsLAB. The modified Beer-Lambert Law involves certain parameters like absorption coefficients and the distance between the measurement points.

In NirsLAB, we can adjust these parameters as needed, but in NIRStar®, they're fixed and calculated on the spot. Specifically, the values used for real-time calculations are as follows: for 760nm, the absorption coefficients are 3.843707 for deoxygenated blood and 1.4865865 for oxygenated blood; for 850nm, the values are 1.798643 for deoxygenated blood and 2.526391 for oxygenated blood. The distance between measurement points is typically set to 3.0cm. The unit for absorption coefficient is (1/cm)/(mmol/L), which represents the amount of light absorbed per unit distance and concentration. It is defined as Mathematically(4.3)

$$\triangle A(\lambda) = \epsilon(\lambda).\triangle c.d.DPF(\lambda) + g(\lambda) \tag{4.3}$$

The variables can be defined as: A: Light reduction, or

$$\triangle A(\lambda) : changesinlightreductionatagivenwavelength(\lambda) \tag{4.4}$$

$$\epsilon(\lambda) : lossofthechromophoreatacertainwavelength(\lambda) \tag{4.5}$$

$$\triangle c : Changesobservedinthechromophoreabsorption \tag{4.6}$$

$$DPF(\lambda) : differentialpathlengthfactorforacertainwavelength(\lambda) \tag{4.7}$$

$$g(\lambda) : scatteringofthelightwaveatacertainwavelength(\lambda) \tag{4.8}$$

The separation between the light's source and detector (referred to as "d") is considered significant, while the factor "g" is disregarded in situations where only light attenuation is being studied, as is the case in continuous-wave NIRS) [72][73][74][75]

A dimensionless correction factor called the differential path length factor (DPF) accounts for the lengthened journey length brought on by light scattering in biological tissue. When multiplied by the separation between the source and detector, the DPF provides the actual path length that light travels within the tissue cell. [76][23][77][78]

In NIRx technologies, a fixed DPF value (7.25 for 760nm and 6.38 for 850nm) compensates for tissue scattering. Figure 4.10 in nirsLAB displays hemodynamic states, with the color bar representing oxygenation concentration, and optodes are denoted by red and yellow dots labeled according to the international system.[79]

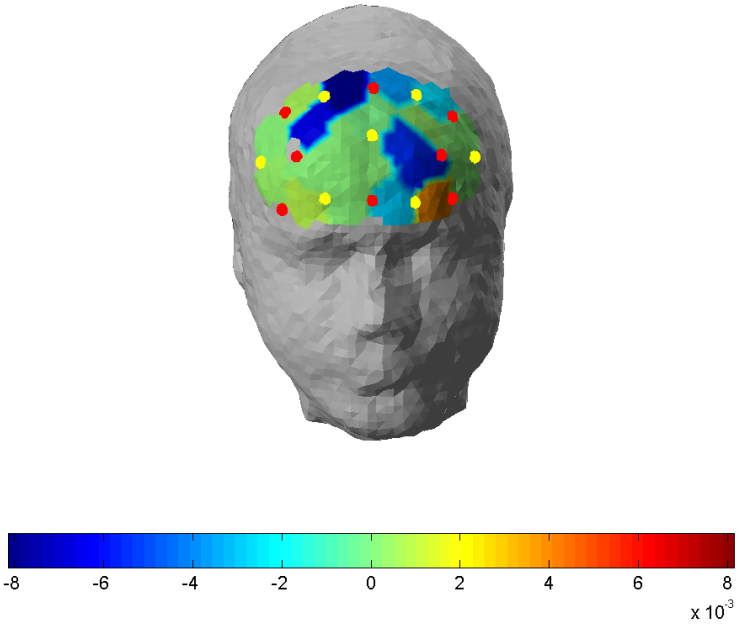

Figure 4.10: The illustration represents rest. "Cool Region"

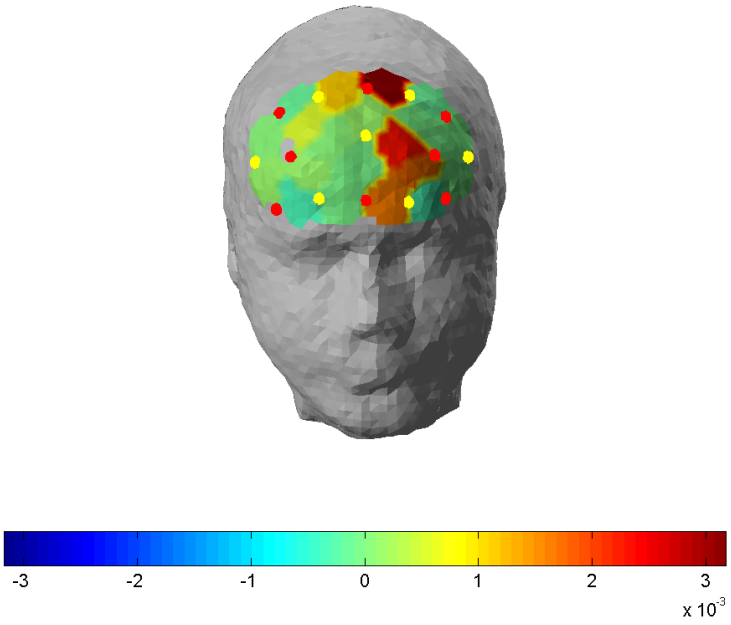

Figure 4.11: shows hemodynamic changes hence the "hot" values emotion.

4.4 Channel Selection

In our study, channel selection played a critical role in our analysis. Figure 4.12 displays changes in oxygenated hemoglobin (HbO) across all 20 channels during brain activity monitoring. However, not all optodes accurately captured the true concentration changes. This underscores the necessity of carefully choosing channels that are sensitive to the brain activity of interest. To enhance the quality of our data, we employed signal averaging. Notably, during emotional states, certain channels exhibited significant activity, while others did not. In particular, channels 14, 15, and 17 showed minimal activity and were subsequently excluded from our classification process. Channel selection, therefore, played a pivotal role in identifying the most informative channels for classification in our study.

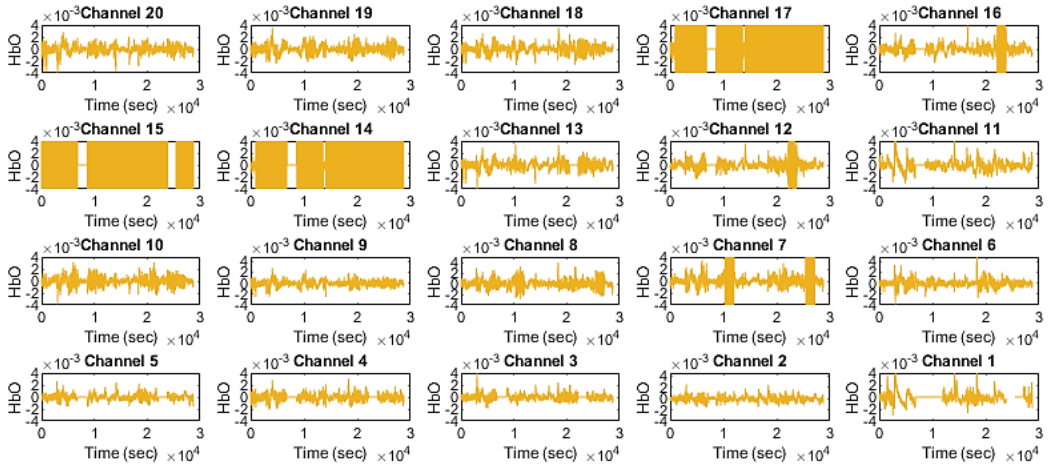

Figure 4.12: Optode-wise hemodynamic states visualization

4.5 Classification Process

After selecting data from various channels, features are extracted from the chosen data samples. These features are then used as input features for the classifier. The three emotions were divided into categories using classifiers. To comprehensively evaluate the performance of data, the classifiers were implemented, namely, Long Short-Term Memory (brain waves LSTM),k-nearest neighbors(KNN), decision trees, random forest, support vector machine(SVM), and Navies Bayes (NB). The training size is 0.8 and the test size is 0.2 of the model to obtain the accuracy.

4.5.1 Long Short-Term Memory (LSTM)

It's really good at understanding and working with data that comes in sequences, like time-series data or sentences in a paragraph With their ability to effectively capture temporal dependencies and patterns over extended sequences, LSTMs have become a cornerstone in fields such as natural language processing, speech recognition, and time series

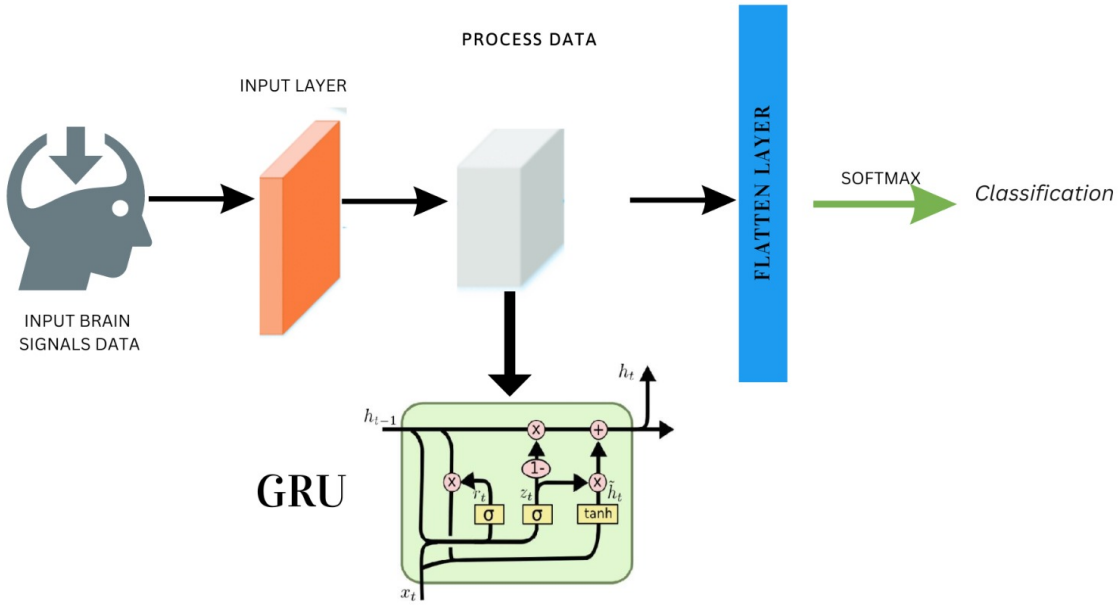

Figure 4.13: LSTM Architecture

Architecture and Mechanism

At the heart of LSTM networks lies a sophisticated architecture designed to overcome the limitations of traditional recurrent neural networks (RNNs). The primary innovation of LSTMs is the integration of specialized memory cells and gating mechanisms. These mechanisms include the input gate, forget gate, and output gate, collectively orchestrating the flow of information within the network. The memory cell serves as a reservoir of information that selectively retains and updates crucial context over time, enabling LSTMs to capture and remember long-term dependencies in sequential data.

Gating Mechanisms

The gating mechanisms embedded in LSTMs are the key to their remarkable ability to model sequences effectively. The input gate determines which portions of the current input should be incorporated into the memory cell, thus influencing the new information that enters the memory. The forget gate, on the other hand, decides what information should be discarded from the memory cell, enabling the network to selectively retain relevant context while discarding noise. The output gate, the final component, regulates the flow of information from the memory cell to produce the network's prediction, which is based on the memory's stored context.

Forget Gate

At the start of an LSTM neural network cell's operation, the key decision is to determine whether to retain or forget the information from the preceding time step. This choice is carried out through a component termed the forget gate. The forget gate's equation

$$ft = (Xt * Uf + Ht - 1 * Wf) \tag{4.9}$$

Let's try to understand the equation, here Xt: The current timestamp is used as input. Uf: weight linked to the input Ht-1: The previously hidden state of the timestamp Wf: It's the weight matrix connected to the hidden state. A sigmoid function is then applied to it. This will result in (ft) being a number between 0 and 1. This (ft) is then multiplied by the previous timestamp's cell state, as seen below.

$$Ct - 1 * Ft = 0...ifFt = 0(forgeteverything) \tag{4.10}$$

$$Ct - 1 * Ft = Ct - 1...ifFt = 1(forgetnothing) \tag{4.11}$$

Input Gate

The input gate is used to rate the significance of fresh data brought in by the input. The equation for the input gate

$$it = (Xi * Uf + Ht - 1 * Wi) \tag{4.12}$$

Here,

Xt: The current timestamp is used as input Ui: weight linked to the input Ht-1: The previously hidden state of the timestamp Wi: It's the weight matrix connected to the hidden state. Once more, we've utilized the sigmoid

function on it. This means that the value of I at time step t will fall within the range of 0 and 1.

New Information

$$Nt = tanh(Xt * Uf + Ht - 1 * Wf) \tag{4.13}$$

The updated information that is meant to be incorporated into the cell state is determined by a function involving the previous hidden state at time step t1 and the input x at the current time step t. Tanh is the activation function in this case. The value of the new information will fall within the range of -1 to 1 as a result of the application of the hyperbolic tangent (tanh) function. If (Nt) has a negative value, the information is subtracted from the cell state; When the new information possesses a positive value, it is integrated into the cell state during the ongoing time step. Nonetheless, the new information Nt will not be directly added to the cell state. the updated equation:

$$Ct = Ft * Ct - 1 + it * Nt \tag{4.14}$$

Output Gate

The output gate's equation is similar to the two gates.

$$Ot = (Xt * Uo + Ht - 1 * Wo) \tag{4.15}$$

Just like before, the sigmoid function ensures that its value falls between 0 and 1. Using the output Ot and the "tanh" function applied to the updated cell state Ct, we can figure out the current hidden state.

$$Ht = Ot * tanh(Ct) \tag{4.16}$$

In other words, the concealed state is affected by both Ct and Ot. You can use the SoftMax function on the concealed form to find the final output at the current time step.

$$Output = Softmax(Ht) \tag{4.17}$$

The prediction is the output.

Learning Long-Term Dependencies

One of the most compelling aspects of LSTMs is their proficiency in learning and representing long-range dependencies within sequences. This is achieved through the strategic interaction of the memory cell and the gating mechanisms. By selectively incorporating, retaining, and discarding information, LSTMs can capture relationships between elements that are separated by significant temporal gaps. This stands in stark contrast to traditional RNNs, which often struggle with the vanishing gradient problem, preventing them from effectively modeling distant dependencies.

Applications Across Domains

LSTMs have propelled advancements in various domains reliant on sequential data analysis. In natural language processing, LSTMs excel at modeling complex linguistic structures and nuances. This proficiency enables them to perform tasks such as language modeling, sentiment analysis, and machine translation, where context over extended sequences is critical. In speech recognition, LSTMs are invaluable due to their capacity to handle variable-length input sequences and capture intricate phonetic patterns. Additionally, their prowess in time series forecasting has led to improved predictions in fields like finance, weather prediction, and industrial processes.

Challenges and Considerations

While LSTMs offer remarkable capabilities, they are not without challenges. Extremely long sequences can still pose difficulties, and even LSTMs may encounter difficulties in capturing dependencies that span very large time gaps. Additionally, training LSTMs on extended sequences can be computationally intensive, necessitating optimizations to balance accuracy and efficiency. Furthermore, the intricate nature of LSTMs can make it challenging to interpret their internal workings, raising concerns about model explainability in specific applications.

Advancements and Variants

Over time, researchers have extended the LSTM framework and introduced variants to address specific challenges. Gated Recurrent Units (GRUs) offer a simplified gating mechanism, achieving a balance between memory retention and computational efficiency. Attention mechanisms have also been integrated with LSTMs to enable the network to focus on specific parts of the

input sequence, enhancing performance in tasks that require selective attention.

At its core, the network begins with an input layer meticulously crafted to align with the number of features found in the input data, ensuring seamless integration of information. To prepare the data for processing within LSTM layers, a crucial step involves using dimension. This expansion is a common requirement when working with LSTM layers, especially in the context of sequence data. The heart of the network lies in its LSTM layer, equipped with an impressive battalion of 256 units. This LSTM layer is specially configured to return sequences of data. The primary objective here is to harness the power of LSTM's memory cells to capture intricate sequential patterns embedded within the input data. In transitioning from the LSTM layer to the final output, a flattened layer is employed, serving the essential purpose of converting the LSTM layer's output into a streamlined, one-dimensional array. This transformation paves the way for seamless processing in subsequent layers. At the network's culmination, the output layer takes center stage, featuring 3 distinct units equipped with a softmax activation function. This configuration is well-suited for tasks involving multiple classes, as softmax serves as a reliable tool for multi-class classification.

Moving into the operational phase, the model undergoes a rigorous compilation process, whereby it is armed with categorical cross-entropy loss as its guiding metric for optimization. The Adam optimizer, a stalwart in the field of gradient descent, is enlisted to orchestrate the fine-tuning of weights. In the quest for precision, the model's performance is scrutinized using accuracy as the chosen evaluation metric. With the stage set, the model embarks on its training journey, leveraging the training dataset over a span of 10 epochs.80% of the data was trained while 20% of it was assigned to test and validate A critical aspect of this phase involves the validation split, which reserves 10% of the data to monitor the model's progress and forestall overfitting. Through this iterative process, the model's weights are dynamically adjusted, converging towards minimizing the categorical cross-entropy loss. Finally, as the culmination of its training odyssey, the model is put to the test. It faces the crucible of the test data, subjecting itself to rigorous evaluation. The outcome of this evaluation manifests in two key dimensions: the measurement of loss and the assessment of accuracy. Together, these metrics offer valuable insights into the model's performance, encapsulating its prowess in classifying brain signals within the given classification task.

A comprehensive machine learning workflow is demonstrated, illustrating the key steps involved in training and evaluating multiple classifiers using

sci-kit-learn.In support Vector Machine (SVM) Classifier, The data is split into training and testing sets using the train-test-split function. An SVM classifier with a radial basis function (RBF) kernel is initialized for one-vs-one classification. The SVM classifier is trained on the training data using fit. Predictions are made on the test data, and the results are stored in y-pred. In Decision Tree Classifier, The data is split into training and testing sets again. A Decision Tree classifier is created. The classifier is trained on the training data. Predictions are made on the test data and stored in y-pred. In the k-Nearest Neighbors (k-NN) Classifier, Once more, the data is split into training and testing sets. A k-NN classifier with 3 neighbors is created. The classifier is trained on the training data. Predictions are made on the test data and stored in y-pred. In the Random Forest Classifier, The data is split into training and testing sets, but this time the test size is 30%. A Random Forest classifier with 50 estimators is created. The classifier is trained on the training data. Predictions are made on the test data and stored in y-pred. In Naive Bayes Classifier (Gaussian Naive Bayes), Finally, the data is split into training and testing sets one more time. A Gaussian Naive Bayes classifier is created. The classifier is trained on the training data. Predictions are made on the test data and stored in y-pred.

CHAPTER 5

RESULTS & ANALYSIS

5.1 Performance Evaluation

To thoroughly evaluate the performance of the categorization model, we have used a range of indicators. These measurements include mean Average Precision (mAP), recall, and precision across various classification accuracy levels. In the section that follows, each measure is explained in further detail.

5.1.1 Precision

We used the precision metric to assess how accurate our forecasts were. Precision measures the proportion of correctly predicted positive instances to all positively anticipated instances. This indicator, for instance, responds to questions like what percentage of instances of each illness class are accurately diagnosed, and vice versa. Precision is more broadly defined as the similarity of several measurements. It represents a unique measure that is unaffected by accuracy results. The correlation between true positives (TP) and the total of true positives and false positives (FP) is what determines it. Technically speaking, TP and FP values are used to calculate precision.

$$Precision = TP/TP + FP \tag{5.1}$$

5.1.2 Recall

To measure the probability of the correct disease classification and the true positive rate. The recall is the ratio of properly predicted positive data to all data in an actual class. We used the recall metric to measure the exact multi-class classification.

$$Recall = TP/TP + FN \tag{5.2}$$

5.1.3 F1 Score

The F1 score is a widely used metric for evaluating performance of a classification model, especially in situations where the dataset is imbalanced. It considers both precision and recall simultaneously to provide a balanced measure of a model's accuracy. In multiclass classification, the F1 score can be calculated for each class, and then a suitable aggregation method (e.g., micro, macro, weighted) is applied to obtain an overall F1 score for the entire classification task. The formula for calculating the F1 score for a single class in multiclass classification is given by:

$$F1 = 2(precision * recall/precision + recall) \tag{5.3}$$

5.2 Comprehensive Analysis

In this section, we explore a comprehensive analysis of the performance of diverse machine learning models within the domain of emotion classification, exploiting brain wave data as the underlying data set. The data set has three distinctive emotional states: "Neutral," "Sad," and "Anger." We evaluated each model's performance utilizing an array of critical metrics, including precision, recall, F1-score, accuracy, and loss. Here's an in-depth summary of the findings for each model.

In the realm of emotion classification, our investigation into several models has yielded intriguing insights. The LSTM (Long Short-Term Memory) model stands as a formidable contender, boasting an astonishing accuracy of 99%. Notably, it excels in precision, recall, and F1-score for all three emotional classes. For neutrality, it achieves perfection, with precision, recall, and F1-score all reaching 1.00. Furthermore, it exhibits a remarkable ability to discern sadness, achieving a precision of 0.98, a recall of 0.99, and an F1-score of 0.99. Similarly, for anger, it maintains high precision (0.99) and recall (0.98), resulting in an F1-score of 0.99. This robust performance underscores the LSTM model's proficiency in accurately identifying a wide range of emotional states. The model surfaces as an exceptional performer, exhibiting a formidable training accuracy of 99% Moreover, during the validation phase, the LSTM model displays an impressive accuracy of 98%Its ability to generalize effectively to unseen data is underscored by the strong validation accuracy, emphasizing its robustness in capturing emotional patterns within brain wave data.

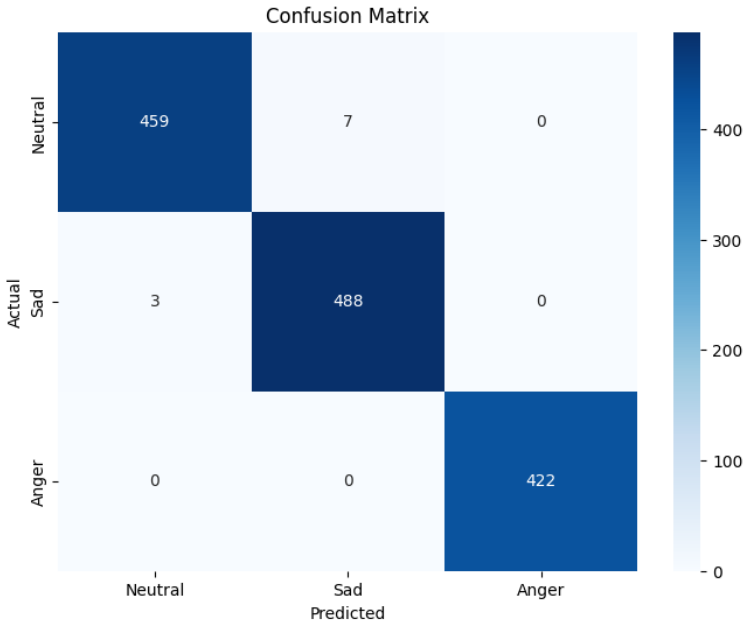

Figure 5.1: Confusion matrix of LSTM

Figure 5.2: Model Loss and Accuracy of LSTM

On the other hand, the Support Vector Machine (SVM) model achieved a respectable accuracy of 88%. While it showed strong precision and recall for "neutral" emotions, it faced challenges in accurately identifying "Anger" as shown in Table 5.1

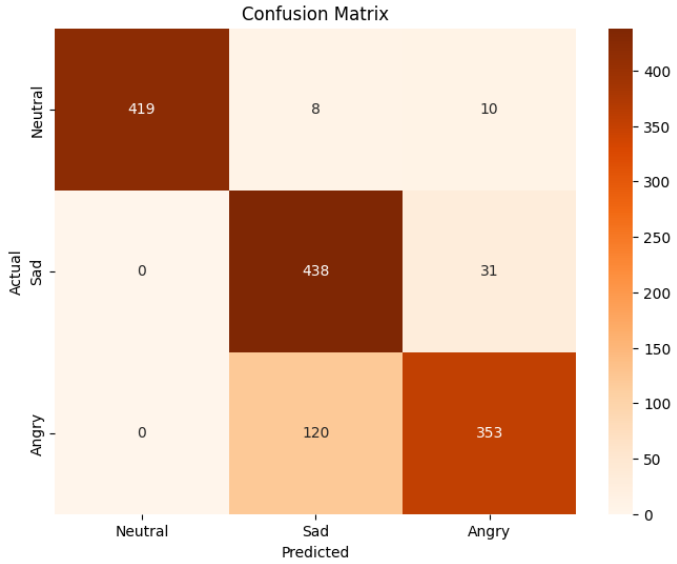

Figure 5.3: Confusion matrix of SVM

The Decision Tree and Random Forest models also deliver commendable outcomes, boasting an accuracy of 98%. They share a common trait of consistently high precision, recall, and F1-scores across the neutral, sad, and anger classes, demonstrating their reliability in emotion classification. As shown in Table 5.1

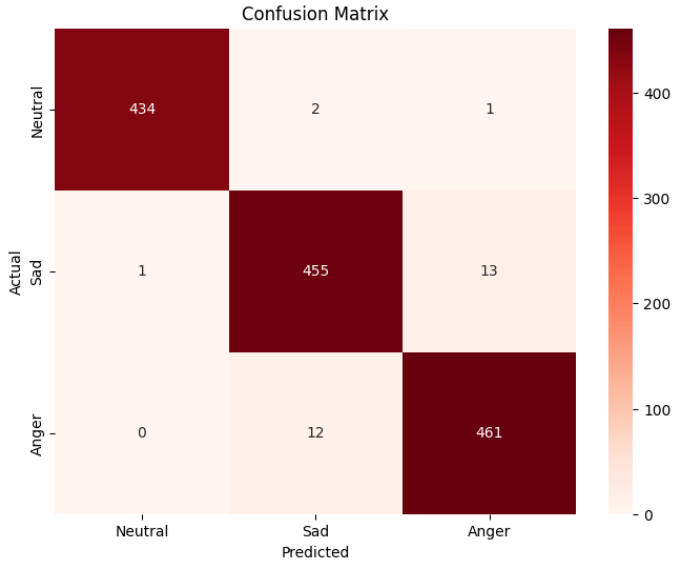

Figure 5.4: Confusion matrix of Decision Tree

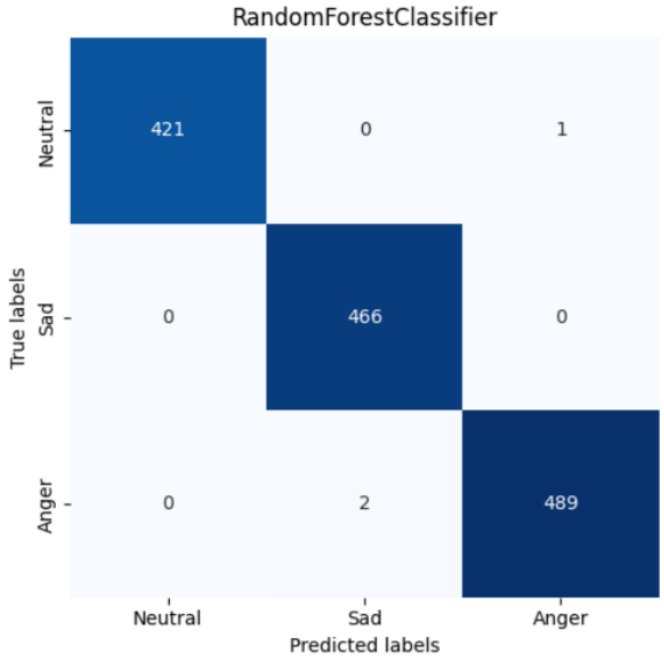

Figure 5.5: Confusion matrix of Random Forest

Similarly, the K-Nearest Neighbors (KNN) model also achieved an accuracy of 98% and demonstrated consistently high performance across all classes. As shown in Table 5.1

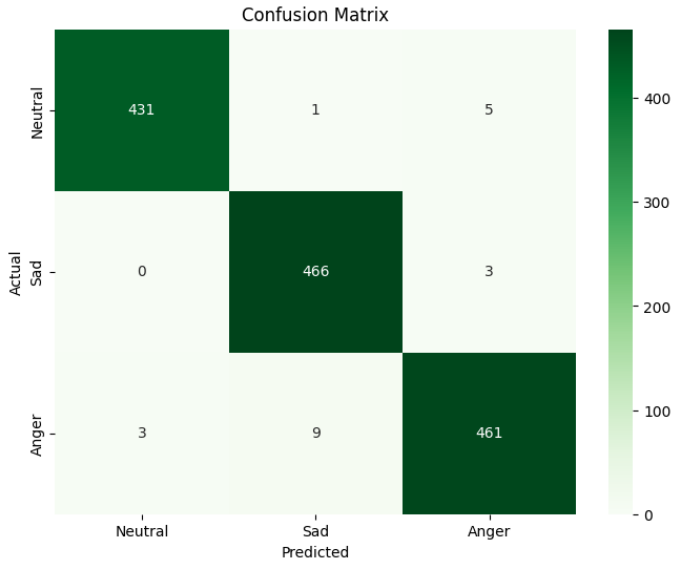

Figure 5.6: Confusion matrix of K-NN

Conversely, the Naive Bayes (NB) model presented the lowest accuracy at 76% and displayed difficulties in both precision and recall, particularly for

the "Anger" class. It exhibited lower precision, recall, and F1-scores compared to other models. As shown in Table 5.1

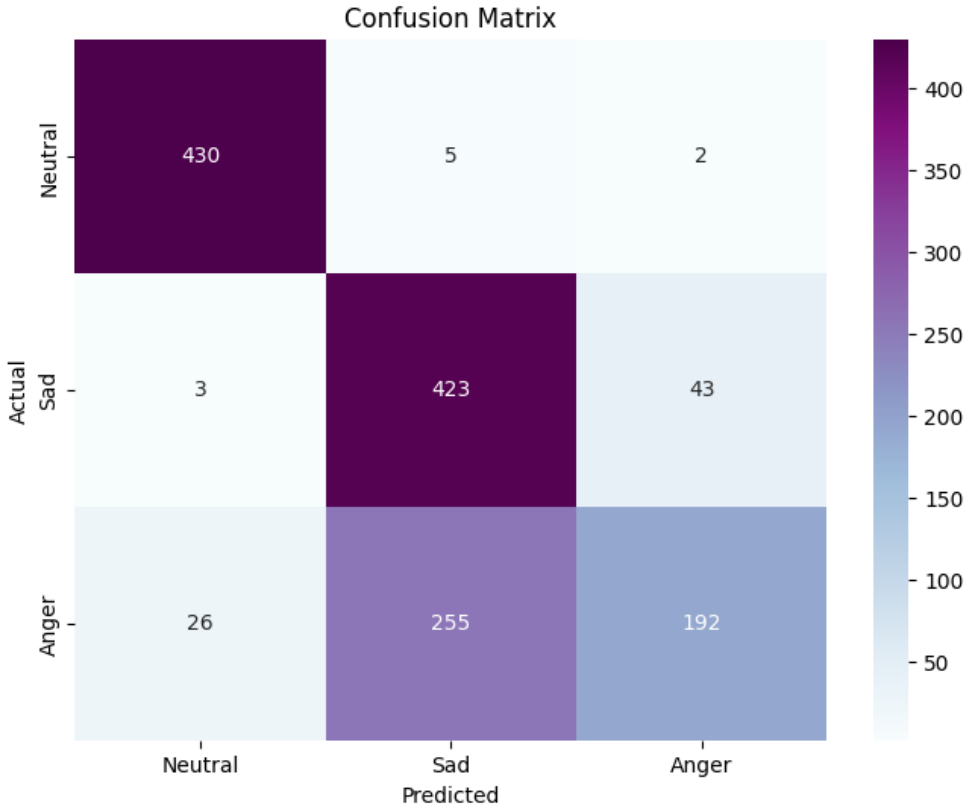

Figure 5.7: Confusion matrix of Navies Bayes

Neutral Emotion: In identifying neutral emotions, all six models achieved commendable results, reflecting their capacity to recognize this emotional state accurately. The LSTM model excelled with a precision, recall, and F1-score of 1.00, signifying perfect classification. The Decision Tree and Random Forest models followed closely, achieving high precision, recall, and F1-scores. Similarly, K-Nearest Neighbors (KNN) demonstrated remarkable precision and recall for neutral emotions. Naive Bayes showcased its proficiency with a precision of 0.94, and SVM displayed perfect precision. These findings indicate that all models, to varying degrees, excel in identifying neutral emotions.

Sad Emotion: In the realm of sadness, the LSTM model emerged as a standout performer, achieving a precision of 0.98, recall of 0.99, and an F1-score of 0.99, demonstrating its excellence in capturing this emotional state. The Decision Tree, Random Forest, and KNN models also delivered reliable results, with strong precision, recall, and F1-scores. Conversely, Naive Bayes showed limitations in recognizing sadness, with a precision and recall of 0.62

and 0.90, respectively, resulting in a lower F1-score of 0.73. SVM, while achieving a recall of 0.93, displayed a lower precision, leading to an F1-score of 0.85, indicating room for improvement.

Anger Emotion: For anger, the LSTM model again demonstrated its prowess, achieving a precision of 0.99 and a recall of 0.98, resulting in an F1-score of 0.99. Both the Decision Tree and Random Forest models displayed consistent high precision, recall, and F1-scores for anger. KNN also performed well, with strong precision and recall. In contrast, Naive Bayes showed limitations in capturing anger, with a precision and recall of 0.81 and 0.41, respectively, resulting in an F1-score of 0.54. SVM exhibited a similar pattern, with a lower recall and F1-score for anger.

Table 5.1: Evaluation of Classifier for Emotions

Emotions	Neutral			Sad			Anger		
Classifier	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
LSTM	1.00	1.00	1.00	0.98	0.99	0.99	0.99	0.98	0.99
RF	0.99	0.99	0.99	0.97	0.97	0.97	0.97	0.97	0.97
DT	0.99	0.99	0.99	0.97	0.98	0.97	0.97	0.98	0.97
KNN	0.99	0.99	0.99	0.98	0.99	0.99	0.98	0.97	0.98
SVM	1.00	0.96	0.98	0.77	0.93	0.85	0.90	0.75	0.81
NB	0.94	0.98	0.96	0.62	0.90	0.73	0.81	0.41	0.54

A comparative analysis underscores the LSTM model's exceptional performance, while Random Forest, Decision Tree, and KNN models also demonstrated strong capabilities in emotion classification. SVM and NB, though achieving moderate accuracy, showed variability in precision and recall across emotion classes. These findings provide valuable insights for model selection, aligning the choice with specific application requirements and trade-offs. Future work may benefit from statistical significance tests to discern the significance of performance differences among these models.

Table 5.2: Model Accuracies

Models	**Accuracy**
LSTM	99%
Decision Tree	98%
K-NN	98%
Random Forest	98%
SVM	88%
Naive Bayes	76%

These results not only advance our understanding of machine learning algorithms for emotion classification but also carry implications for real-world applications. The subsequent section delves deeper into these findings, discussing their relevance to the research objectives and practical utility in diverse domains.

CHAPTER 6

CONCLUSION & FUTURE WORK

This study represents a significant advancement in the field of emotion classification and harnessing the potential of fNIRS (functional near-infrared spectroscopy) brain wave data. The research investigation has yielded valuable insights and noteworthy findings that hold implications for both practical applications and neuroscientific understanding.

6.1 Conclusions

(i)

The practical implications of this work are profound. The integration of fNIRS technology, known for its non-invasive and real-time monitoring capabilities, offers a new dimension to emotion recognition. This has far-reaching implications, from the healthcare sector where it can aid in the diagnosis and treatment of emotional disorders, to human-computer interaction scenarios where it can enhance user experiences based on emotional states. The real-time and portable nature of fNIRS technology opens doors to applications that were previously challenging to implement.

(ii)

One of the central findings of this study lies in the performance of various machine learning models. Notably, the LSTM models demonstrated perfect accuracy rates. The Random Forest, KNN, decision tree achieved an exceptional score, and the LSTM, with its strong training and validation accuracy, showcased the power of machine learning when coupled with fNIRS data. These models have the potential to serve as formidable tools in decoding the complex landscape of human emotions.

(iii)

Beyond practical applications, this study contributes to neuroscientific understanding. The interpretability of machine learning models provides a glimpse into the neural signatures associated with various emotional states.

This intersection of machine learning and neuroscience holds promise for unraveling the intricate neural processes underpinning human emotions. It paves the way for a deeper understanding of how the brain processes emotions, which has implications not only for affective computing but also for psychology and neuroscience research. However, it is paramount to underscore the ethical considerations inherent in the use of brain wave data. Ensuring privacy, obtaining informed consent, and implementing robust data security measures must remain integral to the development and deployment of fNIRS technology. Upholding these ethical standards is imperative to sustain public trust and safeguard participant rights.
(iv)

In summary, this thesis not only advances the capacity to recognize and understand human emotions but also exemplifies the potential of interdisciplinary collaboration. By uniting machine learning, neuroscience, and ethical principles, we are well-positioned to continue unraveling the intricate tapestry of human emotions, guided by the powerful lens of fNIRS technology.

6.2 Future Work

Looking ahead, future research may explore real-time emotion recognition in clinical contexts, where fNIRS technology can bridge the gap between neurological insights and therapeutic interventions. Additionally, the fusion of fNIRS data with other physiological and behavioral data sources presents exciting prospects for a more comprehensive understanding of emotional states.

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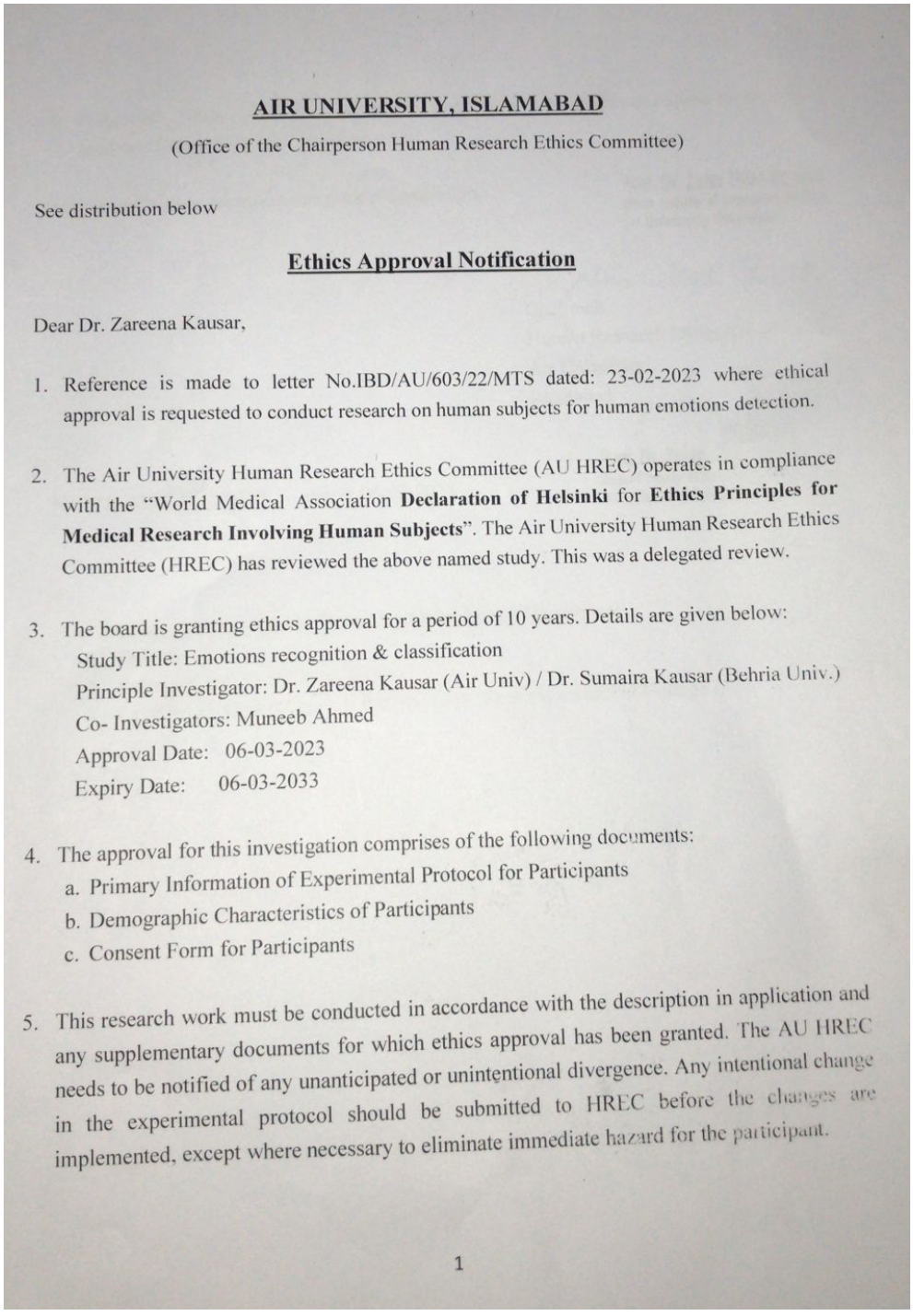
APPENDIX A



AIR UNIVERSITY, ISLAMABAD

(Office of the Chairperson Human Research Ethics Committee)

See distribution below

Ethics Approval Notification

Dear Dr. Zareena Kausar,

1. Reference is made to letter No.IBD/AU/603/22/MTS dated: 23-02-2023 where ethical approval is requested to conduct research on human subjects for human emotions detection.

2. The Air University Human Research Ethics Committee (AU HREC) operates in compliance with the "World Medical Association **Declaration of Helsinki** for **Ethics Principles for Medical Research Involving Human Subjects**". The Air University Human Research Ethics Committee (HREC) has reviewed the above named study. This was a delegated review.

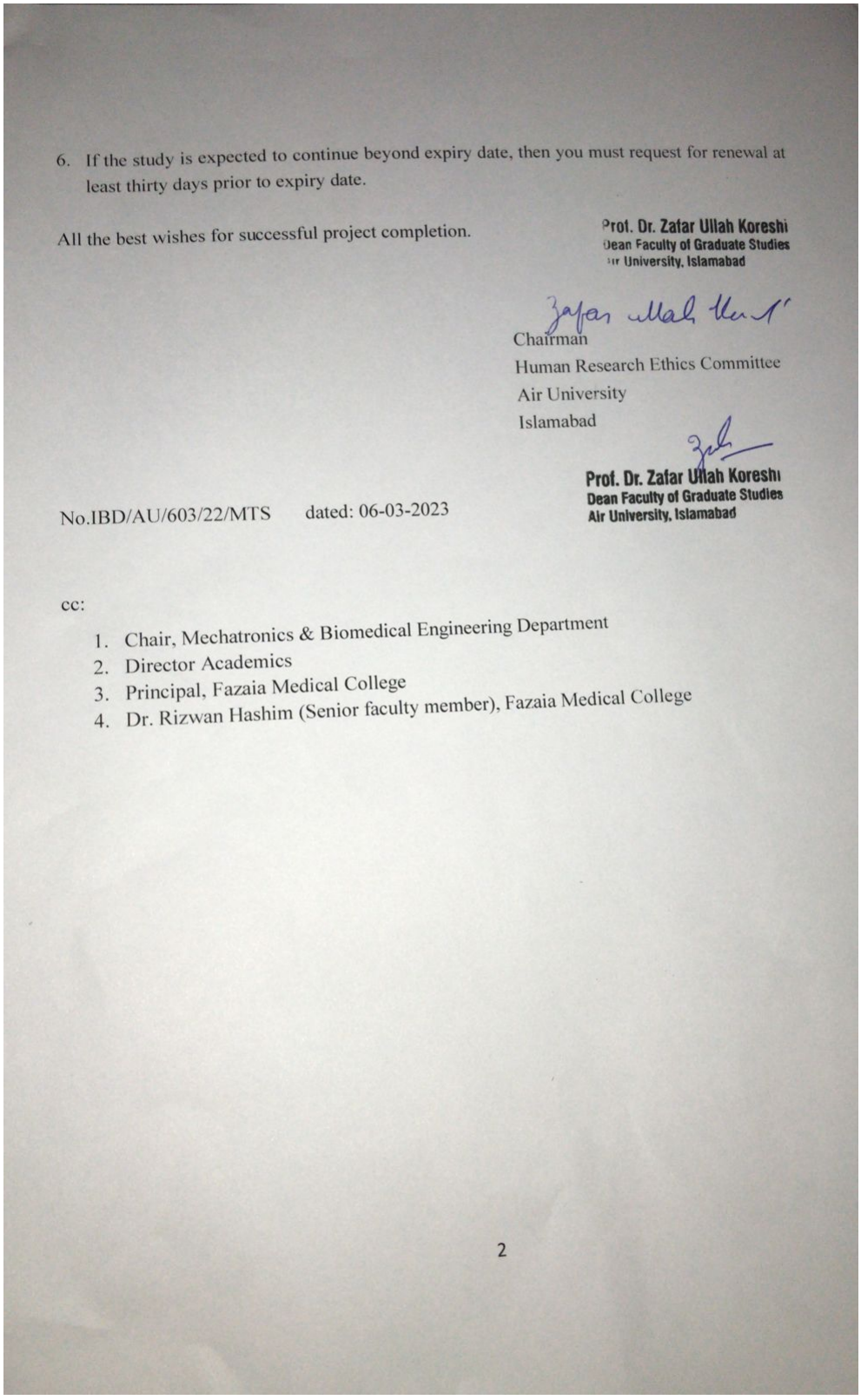
3. The board is granting ethics approval for a period of 10 years. Details are given below:
   Study Title: Emotions recognition & classification
   Principle Investigator: Dr. Zareena Kausar (Air Univ) / Dr. Sumaira Kausar (Behria Univ.)
   Co- Investigators: Muneeb Ahmed
   Approval Date: 06-03-2023
   Expiry Date: 06-03-2033

4. The approval for this investigation comprises of the following documents:
   a. Primary Information of Experimental Protocol for Participants
   b. Demographic Characteristics of Participants
   c. Consent Form for Participants

5. This research work must be conducted in accordance with the description in application and any supplementary documents for which ethics approval has been granted. The AU HREC needs to be notified of any unanticipated or unintentional divergence. Any intentional change in the experimental protocol should be submitted to HREC before the changes are implemented, except where necessary to eliminate immediate hazard for the participant.

1

Figure 6.1: Ethics Approval Form



6. If the study is expected to continue beyond expiry date, then you must request for renewal at least thirty days prior to expiry date.

All the best wishes for successful project completion.

Prof. Dr. Zafar Ullah Koreshi
Dean Faculty of Graduate Studies
Air University, Islamabad

Chairman
Human Research Ethics Committee
Air University
Islamabad

Prof. Dr. Zafar Ullah Koreshi
Dean Faculty of Graduate Studies
Air University, Islamabad

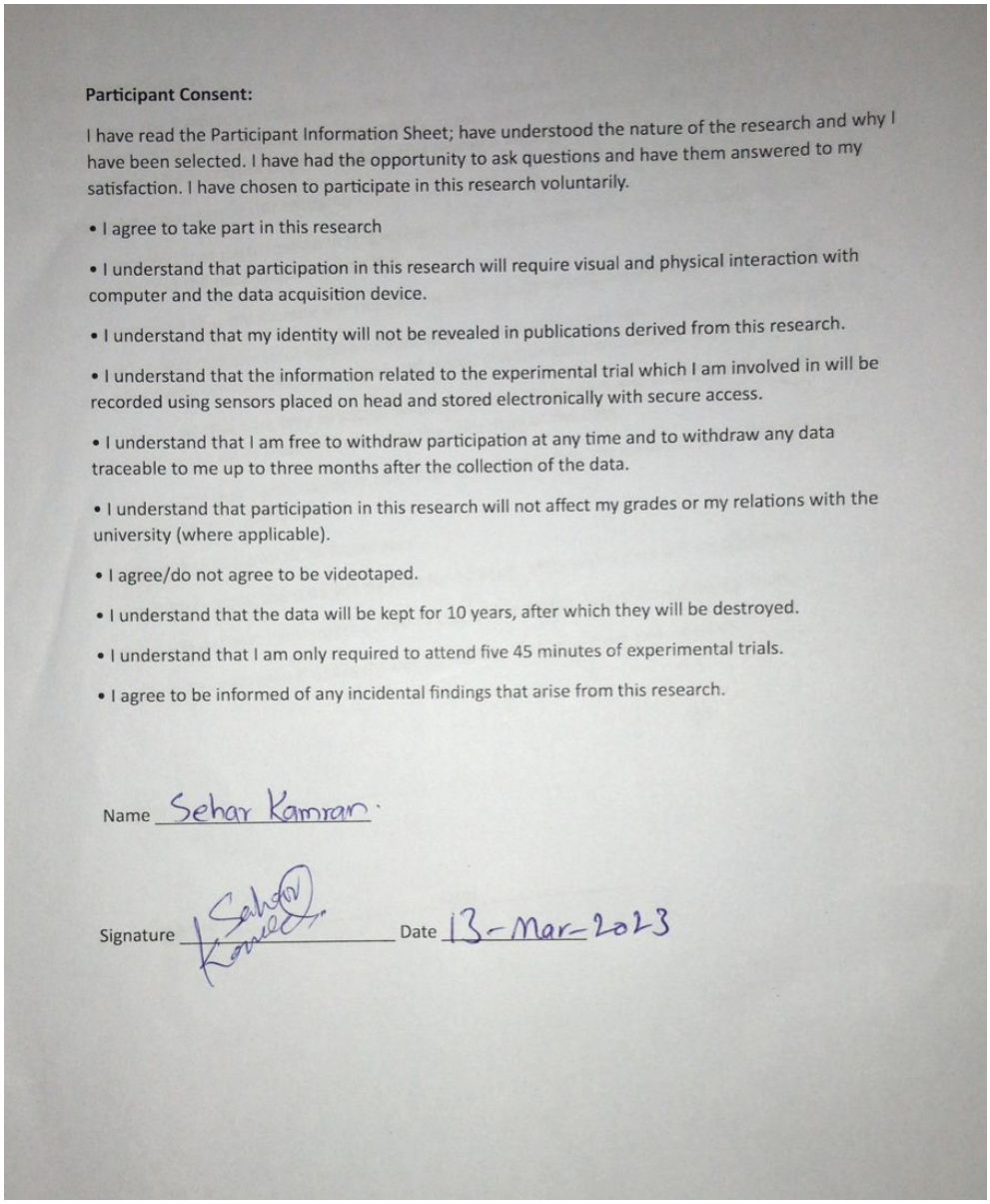
No.IBD/AU/603/22/MTS dated: 06-03-2023

cc:

1. Chair, Mechatronics & Biomedical Engineering Department
2. Director Academics
3. Principal, Fazaia Medical College
4. Dr. Rizwan Hashim (Senior faculty member), Fazaia Medical College

2

Figure 6.2: Ethics Approval Form



Participant Consent:

I have read the Participant Information Sheet; have understood the nature of the research and why I have been selected. I have had the opportunity to ask questions and have them answered to my satisfaction. I have chosen to participate in this research voluntarily.

- I agree to take part in this research
- I understand that participation in this research will require visual and physical interaction with computer and the data acquisition device.
- I understand that my identity will not be revealed in publications derived from this research.
- I understand that the information related to the experimental trial which I am involved in will be recorded using sensors placed on head and stored electronically with secure access.
- I understand that I am free to withdraw participation at any time and to withdraw any data traceable to me up to three months after the collection of the data.
- I understand that participation in this research will not affect my grades or my relations with the university (where applicable).
- I agree/do not agree to be videotaped.
- I understand that the data will be kept for 10 years, after which they will be destroyed.
- I understand that I am only required to attend five 45 minutes of experimental trials.
- I agree to be informed of any incidental findings that arise from this research.

Name Sehar Kamran.

Signature Sehar Kamran Date 13-Mar-2023

Figure 6.3: Participant Consent Form

NEGATIVE EMOTIONS RECOGNITION USING fNIRS BASED CLASSIFICATION

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