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Emotion Recognition with Asymmetry Features of EEG Signals

By

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Abstract

Currently the study of affective computing (AC) includes a focus on researching emotion regulation and recognition. Recent studies in this field have utilized deep learning architectures to enhance emotion recognition from EEG signals. An alternative approach to deep learning is to use feature engineering to extract relevant features to train supervised machine learning models. Current theories in the neuroscience field can guide this feature engineering process. Neuroscientists have suggested various models to clarify how emotions are processed. One of these models suggests that positive emotions are processed in the left hemisphere, while negative emotions are processed in the right hemisphere. This emotional processing model has inspired previous studies to propose asymmetrical features to predict emotions. However, none of these studies have statistically evaluated whether the inclusion of asymmetrical features could yield benefits such as increased accuracy or reduced training time. To address that direction, this research presents both statistical evaluations for emotion regulation and a comparable model for emotion recognition. The outcomes show that brain hemispheres and frequency bands participate differently in processing emotions and observed the presence of the two asymmetry emotion processing models but in different frequency ranges. Also, the results from this study imply that by using asymmetry EEG, emotion recognition approaches can use fewer features without significantly compromising performance.

Acknowledgement

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I would like to take a moment to express my deepest appreciation towards my parents, Rokeya Akhter and Md. Rafiqul Islam for their endless-unconditional support and unparalleled guidance. Their encouragement has been invaluable, not only during my thesis work but throughout my life. Finally, I want to appreciate the motivation provided by my little nephew Farshaad, whose smile gave me the strength to stay focused on my research.

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Chapter 1 Introduction

1.1 Emotional Psychology

Emotion is a mental reaction that reflects the psychological states that include subjective, physiological, and behavioral reactions. It is a state of feeling, but it does not point to the feelings or moods. Though emotions and feelings are interdependent and connected with each other, feelings are mainly influenced by our emotions. Emotion is not a unitary system, but it connects with our thinking process. It assumes in theory that our emotional system is placed in our central nervous system, and it reacts more quickly than we can imagine. Emotions could vary based on age, gender, culture, working environment, etc. Emotion not only influenced our feelings but also plays a major role in thinking, actions, social activities and relations, decision making, official relations, mental health, and overall of our reactions.

While stating the types of emotions, we can find that there are more than 25 types of emotions that we deal with in our daily life (a recent survey finds 27 types [DMKC20, VeLa15]). However, there are eight primary emotions that categorize the broad range of emotions we experience, namely, fear, sadness, anger, joy, interest, surprise, disgust, and shame. These primary emotions have subcategories that can exceed 27. Robert Plutchik's theory [PlKe13, Plut82] also identifies fear, sadness, anger, joy, surprise, disgust, anticipation, and trust as the main emotions, as graphically represented in Figure 1.1. There are also many other theories present such as 'Book two of Aristotle's theory' which mentions nine emotions, 'Charles Darwin theory' which mentions 34 emotions, and so on.

Emotions are a complex and fascinating aspect of human experience. Among the wide range of emotions, there are instances where certain emotions overlap or even interchange. For instance, both sad and happy events can evoke a sense of surprise. Moreover, emotions can combine and lead to create a new emotional state. For example, the blend of joy and trust can lead to the formation of love. However, pinpointing a specific emotion can be challenging due to the rapid changes in our emotional state. Furthermore, emotions have a significant impact on our physiological and psychological well-being, and they can be influenced by various factors in our lives. Therefore, the study of emotions has become a popular topic in diverse research disciplines.

Despite existing several emotions, we missed one of our emotions which is neutral. Though a person does not react or feel any emotion toward a certain subject or incident, still it regards as one of the emotions. Again, a neutral emotion can represent one's preference in a way or indicate a lack of preference altogether. Because it is always not necessary to feel something toward an event; indifference can arise in certain cases. For instance, if we present a square or any geometric figure to an audience and they do not experience any emotional response, it demonstrates an indifferent reaction (except for some individuals who may display curiosity about the reason for showing that figure). Furthermore, neutral emotion is an effective emotional state when we want to neutralize our other emotions.

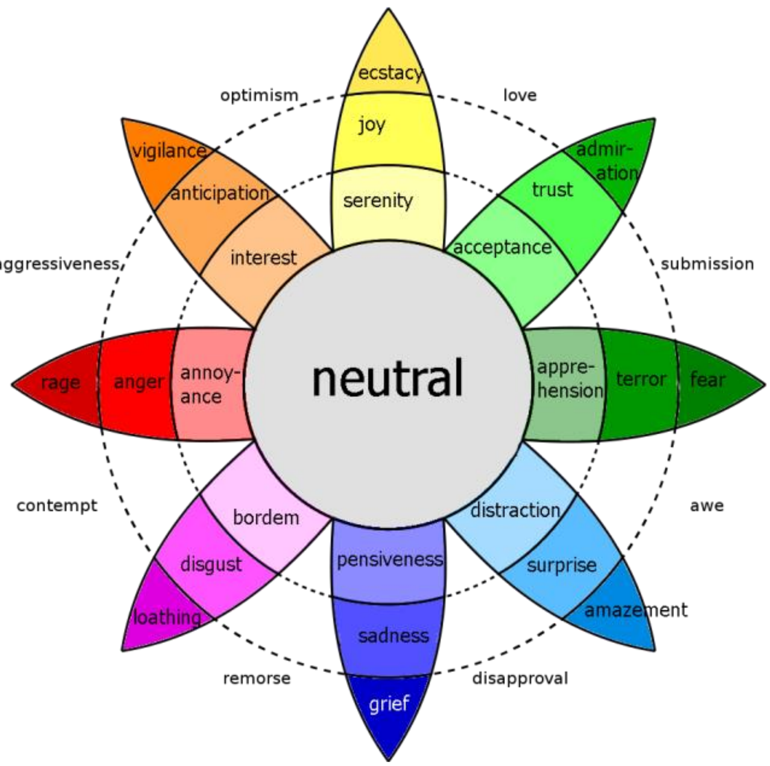

Figure 1.1

Robert Plutchik's theory - wheel of emotions [Gala23]

Our emotion is a complex reaction of our consciousness, and it is reflected by our behaviour. Several factors come into play when it comes to the activation, functionality, and regulation of emotions. Moreover, emotions can exert influence over one another, with the ability to suppress or override certain emotional states. All of these processes occur within our central nervous system, which serves as the orchestrator of our emotional experiences. Though one emotion presence at a time in our nervous system, but the occurrence of an emotion depends on the focus or attention to the subject [Breh99]. Neurons in our nervous system actively respond to environmental stimuli and are interconnected. As they receive input and information from the external world, they project this information to one another, giving rise to the generation of our emotions. The complexity of our brain is challenging to describe, and this complex system serves as the origin of our emotional experiences.

1.2 Overview of EEG

Electroencephalogram (EEG) is a technique used to record an electrogram of the electrical activity on the scalp. It is providing a trace of the electrical potentials of a tissue of any human organ (such as the brain) made by means of electrodes placed directly on the location of the specific tissue [ReLe10]. Our brain is the center unit of our mental processes and behavioral responses. It produces electricity with the help of our nerve cells (neurons). This provides enough energy to carry our mental processes and daily activity. Neurons serve as the structural and functional units of the nervous system, with two important components: the axon and the dendrite. Neurons are linked by this axon and dendrite. These components enable the transmission of electrical impulses and signals among groups of neurons, establishing the neural connections to facilitate the communication.

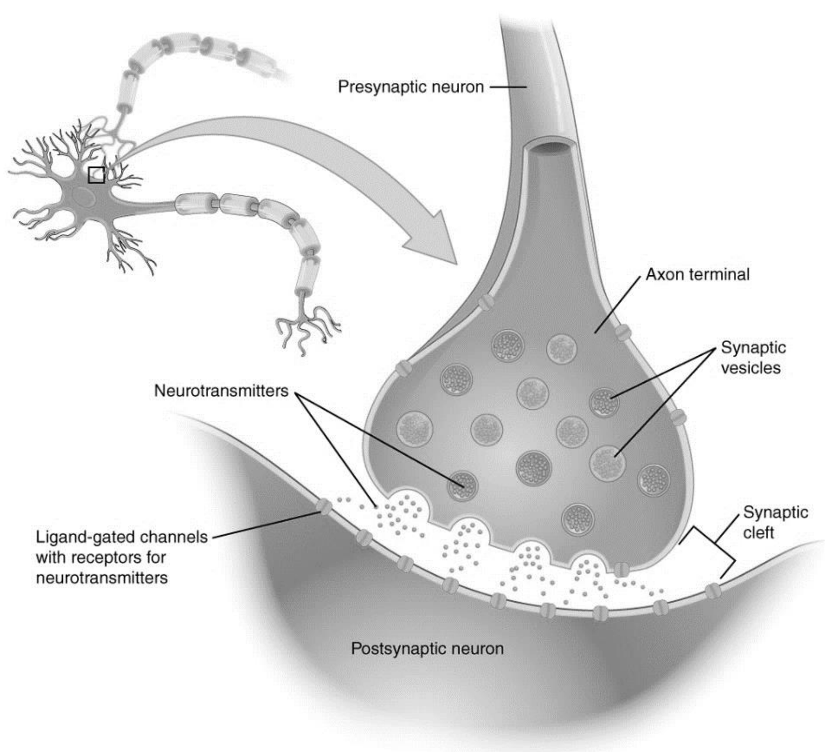

Figure 1.2
Neuron communication
[BDJJ16]

EEG is defined as the electrical activity, which is normally recorded at the scalp of the human brain, generated by the transmission of neurons within the brain. This activity is generated by the transmission of signals among neurons within the brain. EEG captures the summed synchronized synaptic activities occurring within a population of cortical neurons. In the central nervous system (CNS), cortical neurons play a crucial role as electrically excitable cells. They transmit and process information through electrochemical signaling, facilitated by synapses. These synapses enable communication and the exchange of signals between neurons, contributing to the intricate network of information processing in the CNS. There are two main types of electrical activities associated with cortical neurons, that is, action potentials and postsynaptic potentials [FaPe18]. A synapse refers to the site of connection between the terminal portion of one neuron and the membrane of another neuron. Synapses can be broadly classified into two categories: chemical synapses and electrical synapses (refer to Figure 1.2). In mammals, chemical synapses are the predominant type, forming connections between neurons and non-neural cells, including muscle cells and sensory cells. On the other hand, electrical synapses are less common in mammals but can be found in certain regions of the nervous system, such as the retina of the eye and the human brain [CuDD22].

At a chemical synapse, there is a process of chemical transmission that occurs, involving the release of a specialized substance called a neurotransmitter or neuromodulator [Sakm07]. This chemical messenger carries information from the presynaptic neuron (the sending neuron), and its axon terminals are responsible for transmitting the action potential to the postsynaptic neuron (the receiving neuron). The postsynaptic neuron's dendrites receive this information through receptors located on their membrane (refer to Figure 1.3). As a result, the membrane of the postsynaptic neuron undergoes a temporary change in its electrical polarization, known as the postsynaptic potential. This change in polarization allows for the transmission and processing of signals within the nerve cell.

Cognitive-perceptual, linguistic, emotional, and motor processes are known for their remarkable speed, occurring within tens to hundreds of milliseconds. The EEG's high temporal resolution makes it highly suitable for capturing these rapid, dynamic, and temporally sequenced cognitive events. In particular, postsynaptic potentials play a significant role in EEG recordings. These postsynaptic potentials, characterized by their longer duration (typically ranging from 50 to 200 ms) and greater potential field, are widely recognized as the primary contributors to EEG signals [HuZh19].

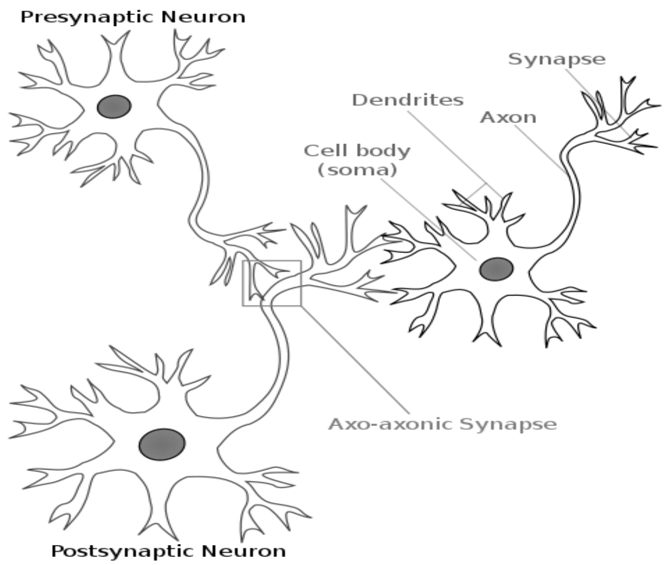

Figure 1.3
Synapse's role in neurons communication [Dave19]

The pyramidal neurons, responsible for transforming synaptic inputs into patterned outputs of action potentials [SaHa15], constitute the main component of the cerebral cortex and are located close to the scalp. Neurons, in general, exhibit a high degree of polarization and typically possess a single axon and dendrites . In the case of pyramidal neurons, their highly polarized structure is oriented predominantly perpendicular to the cortical surface. Due to their orientation and prominence in the cerebral cortex, cortical pyramidal neurons are considered to be the primary generators of the scalp EEG signal [SaHa15].

An EEG signal can find the changes in brain activity, and it could play a vital role to detect brain disorders and might also be helpful to diagnose and treatment. Conditions such as head injury, sleep disorders, epilepsy, stroke, and seizure disorders can be evaluated through EEG signals analysis. Additionally, EEG can aid in confirming brain death and monitoring anesthesia levels by continuously assessing brain activity. To ensure high-quality EEG signals, the EEG measurement system should consist of several essential elements. These include electrodes with conductive media, amplifiers with filters, an analog-to-digital converter, and a recording device [HuZh19]. Along with these proper electrode placement and consideration of the number of electrodes are important factors to ensure accurate signal acquisition. Furthermore, it is important to address artifacts or non-EEG signals since the EEG system records electrical activity from both the brain and external sources of noise. Therefore, caution must be exercised, and noise should be taken into account when collecting EEG signals.

1.3 Motivation

Emotions are dynamic and subject to change based on events and circumstances. Only one emotion can be active in the brain at a time, and the transition between emotions is individualized and influenced by various factors. While there are variations in how individuals process emotions, most people exhibit consistent patterns of emotion processing in specific brain regions, with exceptions found in certain conditions like schizophrenia and autism.

Along side, neuroscientists have proposed various theories concerning the activation of brain regions during emotional processing. One theory suggests that positive emotions like joy, happiness, and excitement activate the left hemisphere, while negative emotions such as fear, anger, and sadness activate the right hemisphere. However, another theory presents a different perspective, suggesting that the right hemisphere is responsible for processing all emotions, while the left hemisphere contributes to logical analysis and decision-making. While there are differences in theories, they have found support in various research studies. This complexity makes it challenging to favor a single theory over others, especially due to the absence of clear evidence confirming the correctness of a specific model. Nonetheless, these theories offer valuable insights into understanding how specific brain regions are activated during emotion recognition and regulation.

The recognition and regulation of emotions have received widespread attention in the current era of human-machine interaction. Prior research has motivated the development of emotional processing models and machine learning techniques for detecting emotions. Several machine learning models and tools have been developed for emotion recognition as well as for the identification of emotion regulation processes. Researchers have applied different datasets and different data types to build these models. Also, they have chosen the best techniques based on their specific data. Some of the research accept human (as a subject) direct participation to provide more accurate data, considering that emotions vary from person to person. Furthermore, research in this field extends beyond human reactions or expressions and includes extensive studies where researchers incorporate neural activity analysis. With the aid of deep learning techniques, emotions can be classified from the brain activities' images and brain signals, broadening the scope of emotion research.

EEG signals offer a valuable means to perceive participants' emotions by capturing the underlying neural activities involved in our emotional system. EEG signals contain valuable information about the evolving dynamics of these neural activities over time. Moreover, employing EEG signals offers the advantage of bypassing the need for direct monitoring of participants' facial expressions, thereby preventing any disruptions or potential misinterpretations of their contributions.

1.4 Problem Statement

Emotions and reactions exhibit variations in human interactions, brain functioning, and disorders. While each emotion holds its own unique significance, there are some fundamental emotions that encompass and encapsulate various aspects of other emotions. These include happiness, sadness, fear, and neutrality. These four emotions represent positive, negative, stress-related, and non-reactive states, respectively, encompassing a wide range of our emotional experiences.

This research aims to address two key objectives. The first goal is to classify the four basic emotions, namely happiness, sadness, fear, and neutrality. The second goal is to measure hemisphere activation patterns during the classification of these emotions. The research will not focus on real-time processing but will utilize data collected from real-time experiences as a basis for analysis [ZLLL18].

Each emotion exhibits distinct patterns of activation, making it essential to explore the activation of different channels for each emotion. Even within the same hemisphere, the activation of channels can vary significantly. This implies that a particular brain region may be highly active in predicting one emotion but not as actively engaged in other emotions. Consequently, certain features may appear irrelevant in the predictive model for specific emotions. This research aims to investigate the presence of irrelevant features in the dataset, shedding light on the involvement of channels and frequency bands in processing specific emotions. By identifying the ratio of frequency bands across EEG channels, we can recognize the relevant features necessary for constructing an interpretable predictive model. Such analysis will offer valuable insights into which neuronal information holds more significance in recognizing different emotional states, thereby aiding in the design of effective emotion recognition approaches.

1.5 Objectives

Emotion recognition is a process that is used to identify and understand our emotional states by analyzing our expressions and reactions. Emotion is known as a mental state. According to American Psychological Association (APA), emotion is defined as a complex reaction pattern [Vand07]. Also, APA explained that emotion is involving experiential, behavioural, and physiological elements, and how an individual attempts to deal with his/her personal significant matter or event.

The primary objective of this research is to explore the processing of emotions on distinct hemispheres of the brain to accurately predict emotional states. To achieve the primary goal this research will be conducted three experiments, each with distinct and specific objectives as given below,

1. **Specific Objective 1: Statistical Analysis**
   Compare the energy activation of both brain hemispheres during emotion processing.
2. **Specific Objective 2: Predictive Model Analysis with Asymmetry Features**
   Evaluate and compare the performance and computational expenses of various machine learning models when utilizing asymmetric features.
3. **Specific Objective 3: Relevant Asymmetry Features for Emotion Prediction**
   Identify the relevant frequency bands and channels that are involved in the processing of emotions.

These three objectives will be designed based on the concept of brain asymmetry. We will assess the extent of brain asymmetry in processing different emotions and examine the predictive capacity of brain asymmetry information in recognizing various types of emotions. By analyzing the involvement of brain asymmetry in emotional processing, we aim to gain insights into how hemispheric differences (brain asymmetry information) contribute to the recognition and understanding of different emotional states.

1.6 Thesis Organization

The rest of the thesis is organized as follows,

- Chapter 2 explores the various aspects of emotion recognition and regulation, focusing on different techniques to recognize emotions. It presents previous studies that are related to EEG signals and their applications.

- Chapter 3 presents a detailed theoretical view of collecting and processing of the EEG signals, machine learning algorithms, and methods that use for statistical evaluation and model evaluation.

- Chapter 4 describes the implementation of the process from the data collection to the model selection process. Also, it provides the processes of statistical evaluation of the EEG channels and frequency bands.

- Chapter 5 analyzes the outcomes of the applied models and how the asymmetry features of EEG signals are related to the processing of emotions.

- Chapter 6 provides a brief summary of the research findings. It discusses the important discoveries and suggests potential areas for further research, leading to a thorough conclusion for this thesis.

1.7 List of Publication

The research conducted in this thesis has been published in the following journals and conferences:

- Journal:

Mouri, F. I., Valderrama, C. E., Camorlinga, S. G. (2023), "Identifying Relevant Asymmetry Features of EEG for Emotion Processing," in Frontiers in Psychology.

- Conference Paper:

Valderrama, C. E., Mouri, F. I., Camorlinga, S. G., "Evaluating the Benefits of Asymmetry Features for Emotion Recognition," in IEEE Canadian Conference On Electrical and Computer Engineering, 2023, Regina, Saskatchewan.

Chapter 2 Background Study

Identifying our emotional states through the analysis of our expressions and reactions is the fundamental concept behind emotion recognition. Changes in facial expression, vocal expression, and bodily expression actively contribute to the identification of emotions. In the field of psychology, changes in behavior are observed to discern one's emotional state. In the field of Human-Computer Interaction (HCI), these changes are transformed into features and utilized to construct models using Machine Learning (ML). Artificial Intelligence (AI) studies these changes and incorporates all the necessary information to develop improved models. The design of these models is continuously adjusted based on the category of information, as AI endeavors to create suitable models for specific types of information.

Emotion regulation is one of the fast-growing areas in psychology encompassing the states that are influenced by our emotions. Emotion regulation can be affected by previous emotions from experiences and can be triggered by other emotions. Thus, it can be stated that emotional regulation can be controlled or spontaneous. In our daily lives, different emotions trigger various responses, and emotion regulation impacts our reactions. For instance, contemplating a problem may heighten anxiety, while considering the consequences of an incident may alleviate anger. Engaging in meditation or focusing can aid in achieving calmness, and conversely, experiencing happiness may lead to engaging in conversations with friends. Emotion and its regulation are intricately interconnected, and both possess the ability to exert equal influence.

2.1 Psychological Emotion Recognition

In psychology, emotion recognition involves identifying emotional states through the observation of nonverbal cues. Additionally, verbal and contextual information contribute to conveying our emotions. Nonverbal cues, such as visual and auditory signals, are influenced by emotions and impact our behavior and expression [Bänz14]. These nonverbal cues encompass facial expressions, vocal cues, posture, and gestures. Through these cues, we naturally recognize and interpret people's emotions. This comprehensive understanding of emotions serves as a crucial component in our daily lives.

2.1.1 Visual Processes

The visual impression is of our emotions visible on our faces. In the cases of understanding the emotion of our opposite side standing ones, the first thing that comes to our notice is their facial expression. Various facial features like the eyes, lips, eyebrows, and open mouth shape contribute to identifying the emotion being expressed. Body movements also play a role in emotion recognition. Facial expressions are particularly helpful in recognizing emotions in individuals with psychological disorders [EdJP02, JoTa03]. Furthermore, different age groups exhibit distinct visual expressions [SuRH07]. Additionally, the factors influencing emotions and the intensity of the same emotion can vary. Again, elderly individuals often exhibit facial movements, especially in the eyes, that are different from those of children [JoTa03, TaFa93]. Though emotions such as happiness, sadness, fear, anger, or disgust leave clues on the face, there are challenges in accurately identifying the exact emotion. Some emotions exchange quite similar expressions such as happiness and enjoyment, anger and disgust, fear, and surprise, and so on. Additionally, individuals may suppress their emotions and not display them visibly to others, making it difficult to identify their emotional state.

2.1.2 Auditory Processes

Facial expressions and vocal expressions can work together to provide more effective result to identify any emotion, but it is also visible to us that these two abilities can work individually and independently [BäGS09]. Though vocal pitch can influence our tone to some extent, the combined use of facial and vocal expressions enhances the complete expression of emotions. For instance, high pitch may convey our anger (a negative emotion) whereas low pitch may convey sadness (another negative emotion). On the other hand, a high pitch with an enthusiastic tone may express enjoyment (or any positive emotion) whereas a low pitch with a disrespectful tone may express disgust (or any negative emotion) [GaLi10]. Recognizing emotions through vocal expressions can aid in identifying early stages of psychological disorders or tendencies towards psychopathy. Moreover, this process facilitates the recognition of emotions in individuals with existing psychological and behavioral disorders such as autism and schizophrenia.

2.1.3 Behavioural Processes

Bodily expressions convey effective information regarding our emotions. Behavioral processes of our bodily expression combine physiological and psychological behavior [Alam18]. For example, usually smiling or laughing due to happiness, crying because of sadness, trembling due to fear or anxiety, taking deep breaths while frustrated, and so on. Our body posture and gesture (especially hand gestures) provide a lot of information regarding our emotions and help to express them. Sometimes bodily expressions show more about the emotions with the intensity level and along with this, they speak about the underlying thoughts that influence our emotions without our awareness. Therefore, in certain psychological disorders, body gestures contribute to the recognition of emotions alongside facial expressions [GuPi07, JoTa03].

2.2 Automated Emotion Recognition

Emotion recognition is an active research area in affective computer science. Expressing and understanding our emotions is a complex system that originates in our brain and involves interactions with other parts of our body. Emotions have an impact on our voice and behavior, and they can also be influenced by external factors such as the voices, behaviors, and words of others, and as well as various scenarios, pictures. Even Specific visual cues, texts, and tones can evoke our specific emotional state. It is a bidirectional process where emotions can be identified and influenced by these factors. Apart from visual cues, technology provides ways to recognize emotions. Techniques such as EMG (Electromyography), fMRI (Functional Magnetic Resonance Imaging), and EEG (Electroencephalography) capture changes in our voice, brain activity, and facial expressions. These techniques contribute to the development of automated emotion recognition systems, enabling machines to detect and interpret our emotional states.

2.2.1 Emotion Recognition by Voice

The sound produced by a person when they speak is their voice. Voice can vary in qualities such as smoothness, normality, harshness, coldness, roughness, and calmness, among others. These differences arise due to various elements of vocal qualities, including tone, pitch, volume, rate, intensity, pace, and more. The voice holds the power to alter the meaning of speech and convey the emotions and feelings of the speaker. It is intricately linked to our emotions, as they can influence the way our voice sounds. For instance, when someone feels nervous or fearful, physiological changes occur, such as an increased heart rate and changes in blood pressure. Even though these symptoms may not be visible to others, they affect the person's voice, often causing it to tremble. Thus, if a person's voice exhibits signs of trembling, we can recognize the emotion of fear. These vocal features are manifested through voice expression, which is generated by speech parameters such as rate, average pitch, pitch range, intensity, articulation, and more [MuAr93]. From those features' perspective, emotions like fear, anger, or joy tend to be associated with loud, fast, and high-pitched speech, while sadness, tiredness, or calmness are linked to slow and low-pitched speech. These vocal features play an active role in the recognition of emotions. By analyzing these vocal features and parameters, researchers can gain insights into the emotional states of individuals [DePW96, LeNP01].

2.2.2 Emotion Recognition by Image

Emotions can be triggered by images and images can also represent or express our emotions. In either case, we can recognize our emotions. Smiling or colorful images can make us happy and these images themselves convey specific emotion. However, to recognize a person's emotion, we can analyze the image of their facial expression and body posture. Figure 2.1 illustrates a facial expression captured in an image. By examining the features of the face, we can interpret the emotion being expressed [EkCo11]. For instance, if the corners of the mouth are raised into a smile, it shows happiness or joy. On the other hand, an intense gaze accompanied by furrowed eyebrows indicates anger. Through the analysis of facial expressions and body postures in images, we can gain insights into the emotions being conveyed by individuals.

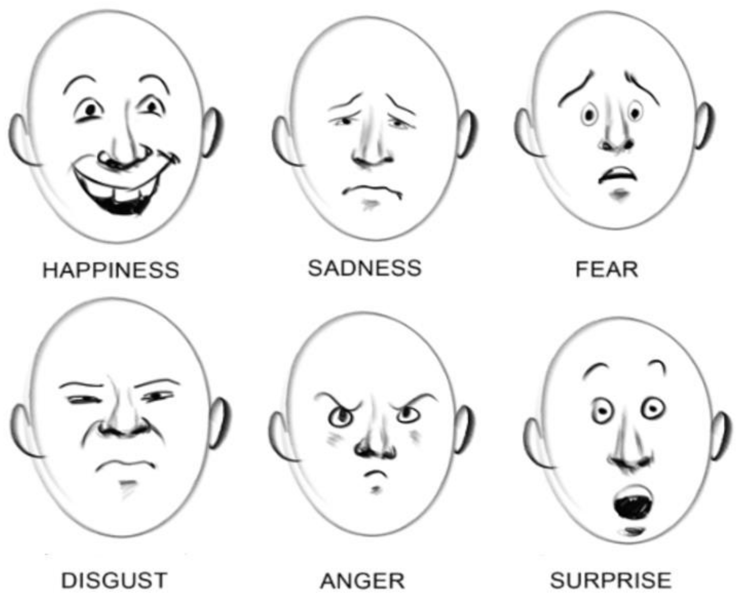

Figure 2.1
Facial expression of basic six emotions [Copp00, EkCo11]

In the case of generating the features, the program focuses on the facial regions such as the lips, mouth, eyebrows, eyes, and facial muscles. The Facial Action Coding System (FACS) helps to point out the changes due to the facial movements based on Action Units (AUs). These AUs enable the observation of facial expressions, allowing us to recognize emotion using AI models [Lili19].

2.2.3 Emotion Recognition by Text

Words convey our emotional states and by analyzing the texts we can recognize emotions are hidden there. Certain words like 'love', 'beautiful', 'merry', 'cupcake', and 'excellent' indicate positive emotions such as happiness, joy, and calm. Conversely, words like 'miserable', 'sorry', 'hate', 'depressing', 'hardship', and 'hectic' suggest negative emotions like sadness, fear, and anger. Additionally, there are words like 'mood', 'curiosity', 'glance', 'usual', 'icon', etc., which do not represent specific positive or negative emotions but rather neutral emotions.

Studying the text is a research area of Natural Language Processing (NLP) and emotion recognition and detection are getting a spotlight in this research area. In this research domain, emotion recognition involves sentiment analysis of text, predicting sentiments as emotions. For example, it includes detecting the mood of music by analyzing the lyrics [Rasc16] and developing toolkits to recognize emotion [CaLN17].

2.2.4 Emotion Recognition by EMG

Electromyography (EMG) is a neuroelectrophysiological test that observes the integrity of facial nerves. Facial electromyography (fEMG) is a specific technique that measures muscles movements in the face. Facial EMG signals are recorded by attaching small electrodes on the skin over those muscles that are actively contributed to detect the muscles movement due to facial expression (refer to Figure 2.2).

To obtain more accurate signals from EMG requires careful consideration of the intensity of facial expressions. Since EMG involves physiological data, caution must be exercised during signal collection, as placing electrodes on the face may increase awareness and potentially lead to exaggerated expressions or overstated reactions [NCBW15]. By analyzing these signals, we can extract effective features that aid in the development and enhancement of machine learning models [JMWY14] for predicting the emotion for any particular facial movement.

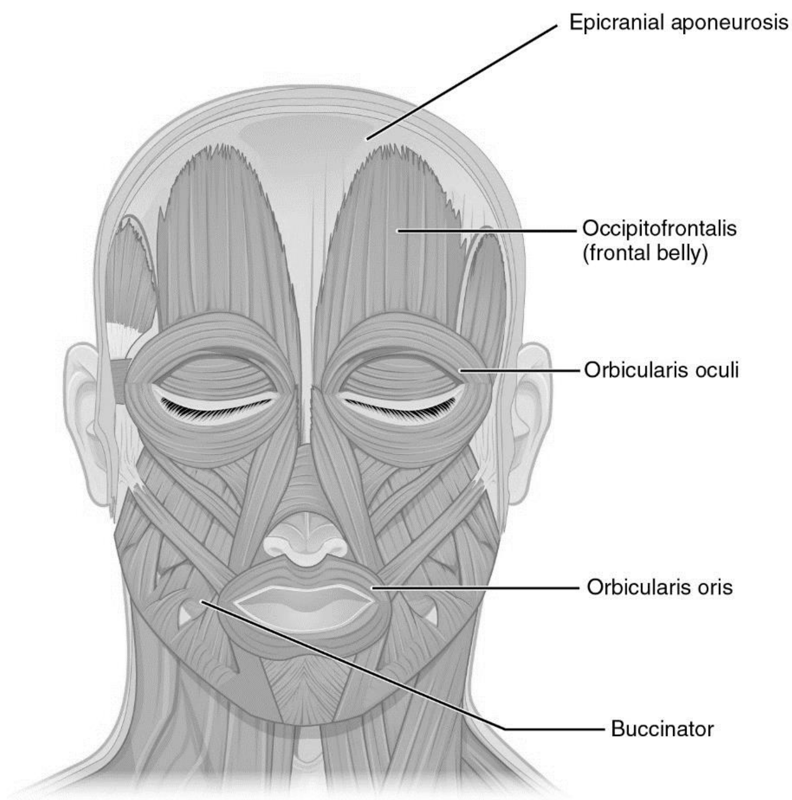

Figure 2.2
Location of common facial muscles in Facial EMG [BDJJ13]

2.2.5 Emotion Recognition by fMRI

Functional magnetic resonance imaging (fMRI) is a technique used to observe brain activity during the perception of emotions. When experiencing emotions or observing facial expressions of emotions, specific regions of the brain become activated. Even when individuals are unable to outwardly display their emotions through expressions, words, or gestures, different areas of their brains are stimulated and exhibit active responses (refer to Figure 2.3). Therefore, fMRI is an effective method for studying patients who may have limited physical activity due to injury or other factors that reduce activity levels. Additionally, it can be used to detect brain activity during sleep or to observe emotions that are activated during dreams.

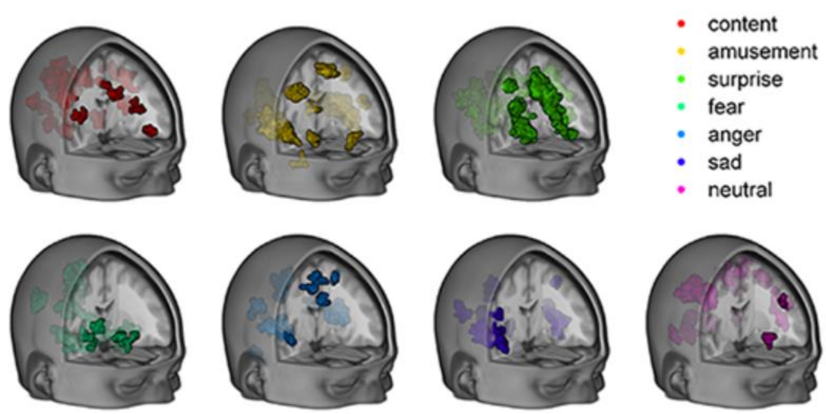

Figure 2.3
Brain activity for different emotion [KKHL16]

The features extracted from fMRI data are generated using techniques such as anatomical automatic labeling (AAL) [CCLW18]. These features involve measuring the neural response signals known as BOLD (blood oxygen level-dependent) from fMRI [CCLW18, JSDS05] and then these features are utilized to build the model for emotion recognition.

2.2.6 Emotion Recognition by EEG

An electroencephalogram (EEG) is a test that records brain activity in a form of signals through small metal discs that are known as electrodes. Those electrodes are either attached directly to the scalp or placed using a headband or a head cap to ensure proper placement (see Figure 2.4). EEG is a safe procedure in most cases, although there may be a slight risk for individuals with seizure disorders, although such cases are rare. In such situations, the assistance of a medical team can be beneficial. EEG signals allow for real-time monitoring of brain activity.

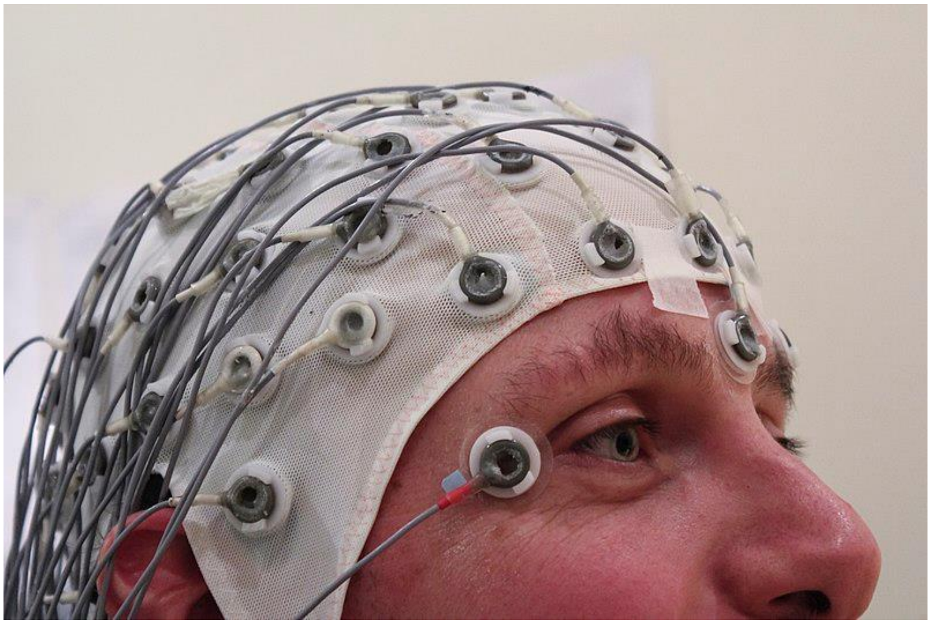

Figure 2.4
EEG electrodes' placement and EEG test device (cap) [Hope12]

EEG help to monitor the brain activity or the brain status for brain injury, brain tumors, and dementia, while in a coma and it can also diagnose confusion, fainting, sleep disorders, or memory loss.

EEG signals' primary contributor is the postsynaptic neurons, and each neuron collects the activities of multiple neural sources, resulting the spatial smearing of signals and determining the spatial resolution of EEG. Even if we use many electrodes in an EEG system, the spatial resolution will remain small since the voltage fluctuation of any two adjacent points on the scalp is very similar [FeCT01, Free80]. Therefore, poor spatial resolution may affect observing the real-time brain activity while operating. Furthermore, EEG signals provide poor signal-to-noise ratios and thus cannot be used to identify the location of drugs and neurotransmitters within the brain.

EEG signals patterns show favorable results to recognize emotions. EEG signals are capable of capturing the muscle movements such as eye blinking, eyebrows movements, head movements, clenching teeth, and more. which are associated with different emotional states and expressions. However, during the capture of these movements, EEG signals may be susceptible to noise or electrical interference. To mitigate the impact of these factors and enhance the quality of the signals, advanced algorithms and filters can be employed. [CDPD20].

In EEG data acquisition, it is important to exercise caution during data collection and ensure proper preparation of the skin. Additionally, it is crucial to simultaneously collect data from the active electrodes. Various machines for electrode placement are available, and the standard protocol established in 1958 by the International Federation in Electroencephalography and Clinical Neurophysiology [Jasp58], known as the International 10-20 System [Knot93], is widely utilized. This system consists of 75 electrodes, each with a naming convention comprising one or two alphabets representing the brain region and a number indicating the distance from the midline (refer to Figure 2.5 for illustration). A higher number indicates a greater distance.

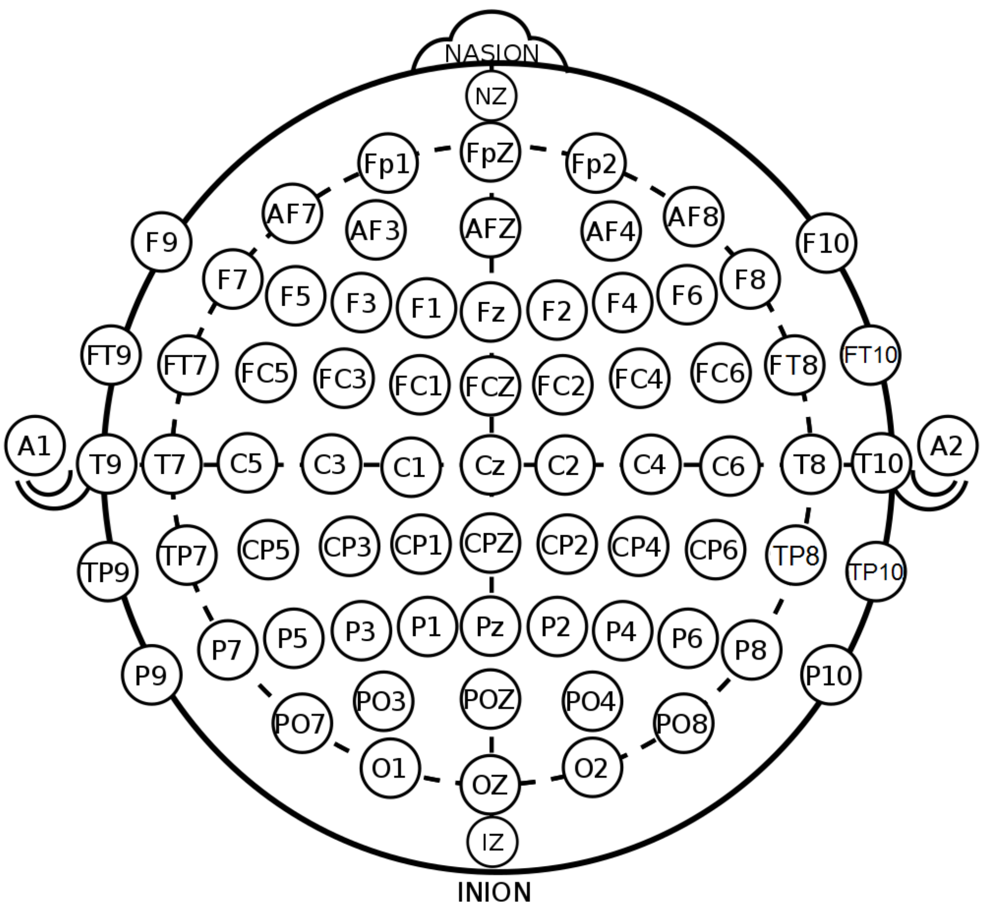

Figure 2.5 International 10-20 System for electrode placement [Oxle17]

Here, the brain regions are labeled as follows: FP for frontal pole, F for frontal, C for central, P for parietal, O for occipital, and T for temporal. The electrodes are numbered, with odd numbers assigned to the left side and even numbers assigned to the right side. The letter 'z' indicates the midline. Additionally, EEG signals consist of different frequency bands that are directly associated with different brain states. For example, the gamma frequency band indicates a state of concentration, while the theta frequency band is associated with sleepiness, and so on. These frequency bands provide insights into the current brain state and can be useful for understanding cognitive processes and emotional states.

EEG data are currently getting significant attention for monitoring the emotions recognition and emotion regulation. It proves to be valuable in monitoring mental stress levels and levels of attentiveness during work or focused activities. The majority of research efforts are concentrated on developing models for predicting emotions and analyzing EEG data. However, it should be noted that EEG data itself is unbiased and noisy, requiring careful attention to adjust and improve the models and techniques for both classifying emotions and collecting data. Preprocessing work and various approaches for feature extraction have also been proposed to enhance the analysis of EEG data.

2.3 Research Experiment on EEG

EEG signals are broadly used, not only in computer science research and development of various tools, but also in psychological research, clinical research, as well as observations. Researchers are continuously searching for techniques to improve the experience of using EEG signals by developing better tools that can effectively process the signals, analyze them more accurately, and perform more effectively. This section highlights some of the research work where EEG signals have been employed for prediction, observation, and the creation of tools.

2.3.1 Real-time Emotion Recognition with EEG

Real-time emotion recognition can help to provide complete and engaging experiences to the users. Liu et al. worked with the fractal dimension (FD) to recognize emotions [LiSN10]. To calculate FD, they applied two algorithms Box-counting [BlBS90] and Higuchi [Higu88]. After evaluating the algorithms, they found that the Higuchi provide more accurate results. Therefore, they analyzed the EEG data with the Higuchi algorithm. They used International Affective Digitized Sounds (IADS) database for sound clips and collected EEG data using Emotiv [Emot00] and PET 2-channel bipolar [Neur00] devices, along with questionnaires. They analyzed the arousal and valence levels and designed their algorithms for emotion recognition in real time. Here arousal refers to the level of activation or energy in an emotion, indicating how intense or exciting it feels. Valence, on the other hand, describes whether an emotion is positive or negative, indicating whether it feels pleasant or unpleasant. However, in their algorithm, FD values could differ among the subjects, but the pattern of emotion for one subject is consistent. Later that pattern would be matched with the real-time emotion state. They did emotion mapping to Haptek Activex for visualization and converting the emotion levels into the discrete values. Lan et al. focused on monitoring the valence level in real-time [LLSW15]. In their study, they used EEG data from DEAP [KMSL11] for emotion analysis. They used four levels for valence and interpreted them as very unpleasant, unpleasant, pleasant, and very pleasant. Then also added a rating value to determine the levels. They applied the SVM classifier to train the model and did this training after combining the channels in group of two or more channels [LLSW15].

Liu et al. have created a database with 16 film clips that are selected from Chinese film [LYZS17]. The duration of each clip is 1 to 3 minutes where presents independent content that indicate specific emotions. This dataset contains sadness, anger, fear, and disgust as negative states of emotion; joy, romance, warmth, well-being, love, mutual affection, amusement, and contentment as positive states of emotion; and neutral states of emotion. They used 14 channels for collecting EEG signals. The authors employed the short-time Fourier transform (STFT) with a 2-second window and 50% overlap to extract features. Subsequently, a feature selection algorithm was applied to choose 105 features. The model was implemented in MATLAB, utilizing SVM for emotion classification. The authors successfully classified eight emotions: joy, amusement, and tenderness from the positive emotions; anger, sadness, fear, and disgust from the negative emotions; as well as neutral emotion. Additionally, they developed a prototype system as a human-machine interface. The experiment assessments were conducted in four sections. The first section compared non-neutral vs. neutral emotions, the second section compared positive vs. negative emotions, the third section evaluated valence and arousal, and the fourth section classified the default eight emotion classes. In the third assessment, each class was tested individually against similar emotions. For example, in case of valence, involved distinguishing joy vs. amusement vs. tenderness, while in case of arousal, it focused on differentiating anger vs. sadness vs. fear vs. disgust. The accuracy of each section was evaluated individually to analyze the model's ability to recognize discrete emotions [LYZS17].

2.3.2 EEG based Emotion Recognition in Music Listening

Music influences our emotions, and the emotion of music can sometimes align with our present emotions or even induce changes in our emotions. While listening to music, our emotions undergo transformations that can be recognized through EEG signals. Lin et al. conducted a study on EEG signals collected during music listening [LWJW10]. The EEG data were obtained from 26 healthy participants, including 16 males and 10 females. They utilized a 32-channel EEG device with electrodes arranged according to the international 10-20 standards. The researchers aimed to classify four emotions (joy, anger, sadness, and pleasure) by employing two classifiers: multilayer perceptron (MLP) and SVM. Both classifiers achieved an average accuracy of over 74%. Their study had two objectives: identifying emotion-specific features of EEG and evaluating the effectiveness of different classifiers. They extracted features using power spectrum density and calculated asymmetry indexes. Additionally, they normalized the feature vectors to a range from 0 to 1 before classification and compared the performance of each feature type with the classifiers [LWJW10]. Their study revealed that the most significant changes in accuracy were attributable to a specific feature, namely spectral power asymmetry.

Since music can influence our mood and have an impact on our well-being, it is often utilized as a therapeutic approach. Sourina et al. proposed the integration of EEG with music therapy [SoLN12]. By analyzing EEG signals, a machine can identify the emotions of patients in real-time, allowing for the selection of music that aligns with their emotional state during treatment. The authors utilized PET 2-channel bipolar [Neur00] and Emotiv [Emot00] to collect EEG data, conducting two experiments to gather the necessary data. In both experiments, they focused on the Arousal-Valence model and after the stimuli, they used questionaries for assessment. Then, they proposed an algorithm that will help to predetermine the music for the therapy session and can be able to adjust the music to the patient’s current emotional state. To implement the algorithm, they labeled the emotions into six types such as sad, frustrated, fear, satisfied, pleasant and happy. Additionally, they set the therapies as pain, anxiety, depression, stress, stroke, etc. So that therapies can be added later into the system. However, it should be noted that their proposed algorithm was not tested on actual patients, and its implementation remains subject-dependent. [SoLN12].

2.3.3 Tools Based on EEG Signals

Hou et al. developed the CogniMeter, a tool designed for monitoring users' emotional state, mental workload, and stress levels in real-time [HLSM15]. With the help of this tool, we can observe mental states visually in real-time as for any other study. In this study, they used 14 channels which are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Various features were employed for different purposes, including power spectrum features for recognizing mental states, fractal dimension features for emotion recognition, and statistical features for analyzing brain states. The statistical features vector consisted of six statistical features: mean, standard deviation, mean of absolute values of first differences, mean of absolute values of second differences, mean of absolute values of the first differences of normalized signals, and mean of absolute values of the second differences of normalized signals. While extracting the feature they were using 4 seconds sliding window (512 samples) with 3 seconds overlapping (384 samples).

To recognize emotions, the model was trained using an SVM classifier, while the level of mental workload was determined by calculating the theta band power from channel P8. Here they included rating methods for arousal, valence, dominance, and mental workload along with stress level. The study also incorporated rating methods for arousal, valence, dominance, mental workload, and stress level. By examining the correlation between these factors, the combination of valence and mental workload was used to assess the stress level. In this study, they classified emotions as positive and negative. They categorized the mental workload as low, medium, and high. Stress levels were classified into six levels such as relaxed, low, lower-medium, medium, higher-medium, and high These two types classifications were displayed in a dynamic meter within their implemented tool [HLSM15].

Delorme et al. have developed an open-source toolbox named EEGLAB [DeMa04]. This toolbox provides various functionalities for visualizing EEG data, including scalp mapping and event-related potential (ERP) image plotting. It also offers features for data preprocessing, such as artifact removal, rejection, filtering, and epoch selection. The toolbox incorporates independent component analysis (ICA) as well. EEGLAB can collect data, event information, and the channels' locations in different types of formats such as binary, ASCII, EGI, Neuroscan, etc. However, it uses one single form to store the data, acquisition parameters, events, channel locations, and epoch information as a data set. It also allows the user to remove the data channels. This toolbox is developed in MATLAB. This toolbox is designed into three layers. The top layer's functions provide a user-friendly interface so that users do not need to interact with the MATLAB syntax. This layer has menu options that will help users to operate the EEGLAB functionalities. But in the middle layer users can modify or add their customized scripts with the help of EEGLAB data structures and signal functionalities. This EEGLAB toolbox is available [Sccn23] (http://www.sccn.ucsd.edu/eeglab/) under the GNU public license for non-commercial use. They also analyzed the limitations of this toolbox and highlighted the disadvantage of using MATLAB to process EEG data [DeMa04].

2.3.4 SSVEP with BCI System

Steady-State-Visual Evoked Potentials (SSVEPs) is being used with brain-computer interface (BCI) system when visual attention is mostly required. Monitoring the EEG signals with VR (virtual reality) has opened a new path for research. However, the virtual environment can sometimes influence our reactions, and the design of stimuli can impact the virtual experience. Achieving a more realistic experience can lead to more accurate results.

Auda et al. conducted a study on the effects of different butterfly shapes in a virtual reality environment [AGKS22]. Here they recorded EEG signals with OpenBCI Ganglion. They worked with virtual reality for the integrated SSVEP stimuli in VR. This motivation for this study arose from the need to compare the classification accuracy of abstract stimuli (e.g., menu items and blending objects) that match the appearance of the VR environment [ArSa18, RJAK21]. In this work, they worked in two sections, one for summarizing the use of SSVEP's usual frequencies and the other for evaluating their different approaches of them. But in both cases, they focused to state the effects on the classification accuracy. Also, they followed their research questions to state the studies' outcomes. This study was conducted with the data collected from 12 participants. In the first study, they selected nine frequencies from a set of 72 unique frequencies, and later chose the three frequencies that provide the best classification accuracy. In the second study, they added changes in the looks of the butterfly's appearance to create a more realistic experience [AGKS22].

Carvalho et al. conducted research using a 16-channel cap (with electrodes arranged at O1, O2, Oz, POz, Pz, PO4, PO3, PO8, PO7, P2, P1, Cz, C1, C2, CPz, FCz) and involving seven subjects to perform the experiments [CCUS15]. Their work focused on feature extraction, feature selection, and classification but before starting the feature extraction they pre-processed the EEG signal by filtering with an analog Butterworth bandpass filter (5-50 Hz), a notch filter (58-62 Hz), and Common Average Reference (CAR). After analyzing the 36 techniques, they found the best methodology is a linear classifier that uses the Welch method for feature extraction and incremental Wrappers to carry out feature selection. One more notifiable matter is the occipital channels (Oz, O1, O2) are most frequent but the selected channels are not always on the occipital zone. Also, the channel selection process depended on the individual subject [CCUS15].

2.3.5 EEG Database for Emotion Recognition

Zheng et al. conducted a study using 62 electrodes but considering the difficulties of wearing such a cap in real-life scenarios, they used six temporal electrodes to build their framework [ZLLL18]. In this work, they designed the framework 'EmotionMeter' with six electrodes that are responsible for emotion and recognized four emotions with EEG signals' characteristics and eye movements. Their study involved three EEG recording setups: 1) T7 and T8; 2) *T7, T8, FT7*, and FT8; and 3) *T7, T8, FT7, FT8, TP7*, and TP8. They also provided the SEED-IV dataset for research purposes. Here they extracted features from EEG signal with power spectral density (PSD), differential entropy (DE), and short-term Fourier transform (STFT) with a window size of 4 seconds. For eye moments they used different parameters such as pupil diameter, dispersion, fixation, blinking duration, saccade, and event statistics. The classification process employed Support Vector Machines (SVM) with a linear kernel. Furthermore, to enhance recognition, they applied a deep learning algorithm called restricted Boltzmann machine (RBMs). The models achieved an accuracy of over 80% for the identical experimental setup and achieved an accuracy of more than 60% for the distinct experimental setups, across all three setups.

Liu et al. studied two EEG databases for emotion recognition [LiSo13]. Visual stimuli are collected from the IAPS (International Affective Picture System) database that contains photos from different areas, and all photos are labeled with valence, arousal, and dominance rating. Audio stimuli are collected from the IADS (International Affective Digitized Sound system) database which contains the same levels as the IAPS used and the rating of all emotions in the range from 1 to 9 for the sound clips. In this study, they utilized the Emotiv [Emot00] device which contains 14 electrodes and is standardized by the American Electroencephalographic Society [Knot93]. Also, they included questionaries after the simulations as a form of self-assessment of participants' emotions. They used Self-Assessment Manikin (SAM) [BrLa94] which is a non-verbal and picture-based assessment, was used to evaluate emotional state. After that, the researchers established correlations between the EEG signals and the rating scales, demonstrating the reliability of their dataset in comparison to other literature. Additionally, they used the DEAP database [KMSL11] as their benchmark database for comparison. They employed SVM algorithm for classifying the emotion and the results showed that the performance of their proposed SVM algorithm is similar in terms of accuracy [LiSo13].

2.4 Brain Asymmetry for Emotions

Brain activation varies when recognizing and regulating emotion. There have many models are proposed by the neuroscientists to explain the brain activity by introducing brain asymmetry. Among all, two major models are experimented mostly by many computational experiment and psychological research to analysis the brain asymmetry. The first model is 'The right-hemisphere model' which shows the preferred nature of right-hemisphere to process any emotion over the left hemisphere [BCOW98, DEYH05]. This model is also known as 'the right-hemisphere dominance of emotion' and it indicates that right-hemisphere is specialized for the perception, expression, and experience of emotion. The second model is 'the valence model' or 'the valence lateralization'. This model implies that the right-hemisphere is focusing more for processing negative emotions whereas left-hemisphere is dealing more with positive emotions [AhSc85, Davi95].

The second model has been supported by additional studies using noninvasive functional neuroimaging techniques, namely fMRI [OKRH01] and EEG [JoFo92]. For instance, Schmidt et al. [ScTr01] analyzed EEG signals collected while stimulating subjects by listening to music, finding that positive emotions were more active in the left frontal channels, whereas negative emotions were more active in the right frontal area. Despite the evidence supporting the asymmetry models, inconsistencies have also been found in processing of the emotions which are not only different in the hemispheres but also across the neural frequency bands (delta, theta, alpha, beta, and gamma) [PCLL11].

Indeed, researchers have focused on the alpha band (8 - 12 Hz) to analyze hemispheric asymmetries for different emotions using a methodology known as frontal alpha asymmetry (FAA) [BTHJ13]. Specifically, FAA compares the electrical activity in the alpha band of the right and left hemispheres in the frontal and prefrontal areas, detecting more cortical activity in one hemisphere when its electrical activity is lower than in the other hemisphere [AlCN04, GSMY97]. The foundation of FAA relies on the fact that EEG power is inversely related to activity, indicating that lower power means more cortical activity [LiWi74]. For example, [ZZGZ18] used the FAA methodology to analyze EEG signals collected from subjects watching videos evoking tenderness and anger, reporting that the left hemisphere had more cortical activity when the subject's perceived tenderness, whereas the right hemisphere had more cortical activity when watching angry videos. Unlike the alpha band, power in beta and gamma does not show asymmetrical behavior during emotion processing, as observed in previous studies [DESS90]. Instead, these frequency bands show similar behavior when processing emotions. For example, research by Aftanas et al. [ARSM06] found that happiness resulted in a reduction of the power beta and gamma bands across the entire cortex, whereas anger led to an increase in beta and gamma power in the frontal regions of both hemispheres.

Inspired by the brain asymmetry for processing emotion, previous researchers have attempted to improve the accuracy of machine learning models to predict emotional states [AhLo14, HGAZ12, LZTS22, SBTC22]. Pane et al. [PaWP19] used a random forest to classify four emotions (happy, sad, relaxed, and angry) from five EEG pairs (F7-F8, T7-T8, C3-C4, O1-O2, and Cp5-Cp6) under four different scenarios. The first scenario used the brain activity of both hemispheres to train the random forest. In contrast, the second scenario used only the information from the right hemisphere to train the random forest, whereas the third scenario used only the information from the left hemisphere. The fourth scenario used information from the right hemisphere to predict negative emotions (sad and angry) and information from the left hemisphere to predict positive emotions (happy and relaxed). The authors reported that the fourth scenario using the T7-T8, C3-C4, and O1-O2 electrode pairs obtained the best performance for predicting emotions, thus suggesting that the inclusion of emotional lateralization is beneficial for emotion recognition approaches.

Similarly, Zheng et al. [ZhLu15] used asymmetry features calculated by taking the difference and ratio of EEG electrodes from the left and right hemispheres to train a support vector machine and a combination of deep belief networks (DBNs) to recognize positive, neutral, and negative emotions. The authors found that the performance of asymmetry features varied across the frequency bands, achieving the best performance for the beta and gamma bands. However, after comparing the performance of their asymmetry features with that of a model using the electrical activity of all EEG electrodes, they decided to discard the asymmetry features due to their lower performance. Li et al. [LWZZ21] further explored the discrepancy of emotional expression between the left and right hemispheres by using a complex deep-learning model, achieving an accuracy of 58.13% and 74.43% for detecting four emotional states across 15 subjects. Other studies have also focused on recognizing emotion from EEG signals using deep-learning neural networks [LDLC20, TLSC20].

2.5 Summary

Recognizing and comprehending human emotions is a crucial component in deciphering how to engage with them in an efficient manner. We are recognizing emotion from physiological information and psychological views. Our behaviour changes according to our emotions. Therefore, automated emotion recognition techniques are used by researchers to extract information that assists others in recognizing emotions with ease, even when the individual is not displaying or concealing their reaction. Also, the concept of emotion recognition can be applied to create tools and frameworks to study the factors and information that are related to our emotions. To collect those data, we observe a person's behaviour towards a certain incident, audio or video clip, or image. Also, sometimes we use a device to transform our reaction as signals that initializes from the brain, facial movements due to our emotions. Those systems help to collect and analyze our reaction from those signals and recognize our emotion. Among the various ways of recognizing emotion, the use of EEG signals has become a popular approach. EEG signals reflects the brain activity. EEG can be recorded using BCI systems, allowing to monitor the real-time experience with real-time emotional changes.

Various datasets, tools, and frameworks are being utilized to enhance the evaluation and application of EEG signals with greater effectiveness and efficiency. The analysis of brain activities can be efficiently conducted by utilizing EEG signals, as they are generated directly from the brain. It has been observed by researchers that their findings on certain occasions have corroborated the emotion-processing theories that have been established in neuroscience.

Chapter 3 Theoretical Framework

This thesis work is focused on using the electroencephalogram (EEG) signals from the human brain to build machine learning model (ML) models for emotion recognition and later influence to analyze emotional regulation by identifying brain activity. Hence, from collecting the signals to building the models require steady steps to look for the effectiveness of the process. In this process, we need to collect EEG signals as data from the human brain activities, process the collected data to generate effective features, and then build the models which will be more aligned with the dataset. This thesis will also work on the strength level of the recognized emotion based on the collected EEG signals. Therefore, this chapter provides a brief outline of the required theories and techniques in the form of a theoretical perspective.

3.1 EEG Signal Processing

Electroencephalogram (EEG) signals are generated from brain activities. To obtain preferred EEG signals, we need to set up the data collection environment with the device. Since the EEG device helps to collect the data, it is required to pay attention to the measurements of the setup such as electrodes' type and their position, filters, converter, recording device with pre-planned trails, and dataset (e.g., image, audio, video, etc.). Also, we need to be attentive toward the participant while collecting the data from their reaction and brain activities.

3.1.1 Electrodes

EEG device contains channels with electrodes and based on the role of collecting EEG signals, electrodes are grouped into three types. Among them, two types of electrodes, the active electrode (A) and the reference electrode (R) are performed together to assemble the electrical activity with their potential irregularity [TeOt02]. And the third one is ground electrodes which help to reduce the noise that is created by the system. Thus, makes the EEG system mostly to have many active electrodes but one reference electrode and one ground electrode. In collecting the data, we always prefer to record the minimal changes in the brain activity based on the potentials' changes. Therefore, Ag-AgCl electrodes take the preference to be used in the EEG system [Luck14, PBBD00, TeOt02]. There are two methods for electrode placement, such as wet electrodes and dry electrodes.. In wet electrodes, it's important to consider the impediments that arise from using gel or saline as the conductive medium between the electrodes and the scalp. On the other hand, dry electrodes are more convenient to use, because these are made by applying microelectromechanical system techniques, and fabric-based or foam-based materials.

Electrodes number is an essential consideration while choosing our EEG device. Because different experiments [Luck14, TeOt02] show the different number of electrodes preferable with reasoning their research preference. Not only the number of electrodes but also their placement plays a vital role in choosing the EEG device. However, this thesis work has used the International 10-20 System [Knot93] which is shown in Figure 2.5. In this system, electrodes are placed at 10% and 20% points along lines of latitude and longitude and so the system is named the 10-20 System. Though the system located 75 electrodes, this study used the data from the 62 electrodes (channels).

3.1.2 Amplifier and A/D Converter with Filter

In EEG signals recording device recorded the response of electrodes with their electric voltage. These electric voltages change, or the peak of their effectiveness is noted by the amplifiers. Amplifiers amplify the signals to find well-matched microvolt signals. These microvolt signals then work to convert the signals to digital form. Since these amplifiers are developed for physiological signals, they need to satisfy some basic requirements [XiHu19]:

- The physiological process to be monitored should not be influenced in any way by the amplifier.
- The measured signal should not be distorted.
- The amplifier should provide the best possible separation of signal and interferences.
- The amplifier has to offer protection to the patient from any hazard of electrical shock.
- The amplifier itself has to be protected against damage that might result from high input voltages as they occur during the application of defibrillators or electrosurgical instrumentation.

Amplifiers assist to do both amplifying the selective signals and rejecting the superimposed noise. Because the input signals to the amplifier consist of five components, 1) the desired biopotential, 2) undesired biopotentials, 3) a power line interference signal of 60 Hz (50 Hz in some countries) and its harmonics, 4) interference signals generated by the tissue/electrode interface, and 5) noise. [TeOt02, XiHu19]. These biopotential amplifiers are performed to reject the non-required signals or electrical noise.

After processing the data by the amplifier, analog signals of each channel are converted to the digital signal form by the A/D converter. Mostly the A/D converter is present in the EEG recording device. But it is necessary to observe the settings of the A/D converter because the resolutions affect the result. Also, with the resolution settings, we may need to consider the filter uses whether the data acquisition requires the digital filters or the analogy filters. Because a suitable filter may affect the property of the signal less but instead helps to remove the affectable or unnecessary properties from the signals.

3.1.3 Experiment Setup and Data Pre-processing

In data processing, we need to consider the sampling rate for converting analog signals into the form of digital signals. The sampling rate denotes the number of samples per second or unit from a continuous signal. It is better to choose a sampling rate based on the size of the obtained data and the time of further data processing. Mostly in EEG data acquisition, the preferred sample rate is between 250 Hz and 1000 Hz because the recorded data that is faster than the 1000 Hz is not that necessary to consider.

The artifacts in the EEG signals are referred to as the non-EEG signals. In EEG recording these are divided into two sections, subject-related artifacts, and technique-related artifacts [TeOt02]. Subject-related artifacts denote the undesired physiological signals, and these are generated by physical movements, eye movements, blinking, sweating, and so on. Technique-related artifacts denote the electrical signal, and these are generated by the surrounding environments such as power line interface (50/60 Hz), impedance fluctuation, cable movement, broken wire, excessive gel or dried electrode, and low battery.

Before starting the recording, it is better to set the plan for the experiment and the trials. Also, it is best to keep the recording environment the same for all the participants but sometimes some experiments require some independent and variable changes. Since the participants are playing the leading role, it is always better to explain the experiment's environment, setup, and needs of it. These all will help them to be more involved in the experiment. Without motivation, the performance and their activeness will be distorted, and it will eventually affect the true data. Also, we need to set a reasonable duration for each trial. Because the long-time trial causes losing attention and the short-time trial does not imprint enough effects on the reaction. Also, it is a viable choice to add short rest in between trials so that the previous trial impression will not affect the next trial.

3.1.4 EEG Frequency Bands

While recording the spontaneous EEG activity (electrical activity) it shows the different waveforms for the different brain states. These waveforms define certain frequency ranges which help to perform various clinical diagnoses such as epilepsy, brain death, coma, and so on. Spontaneous EEG activity is mostly divided into five frequency bands as shown in Table 3.1.

Table 3.1
Different EEG frequency bands [NaAn23]

Name	Notation (Letter)	Frequency range	Detected region	Behavioural state
Gamma	γ	> 30 Hz	Every part of the brain	Active and focus
Beta	β	13 - 30 Hz	Frontal and central head	Active and normal
Alpha	α	8 - 13 Hz	Occipital head	Awake and closed eyes
Theta	θ	4 - 8 Hz	Frontocentral head	Drowsiness and sleep
Delta	δ	< 4 Hz	Frontocentral head	In deep sleep

The waves are collected from different regions of the brain. For instance, normally the alpha waves are measured from the occipital region in an awake person when the eyes are closed, and the beta waves are measured over the parietal and frontal lobes.

- **Delta (δ):** The waveforms are found in infants and adults while they are in deep sleep. It usually detects most prominent frontally in adults (e.g., FIRDA – Frontal Intermittent Rhythmic Delta) and posterior in children (e.g., OIRDA – Occipital Intermittent Rhythmic Delta) [NaAn23, ŞŞAA19]. Also, Temporal intermittent Rhythmic Delta (TIRDA) can be seen if an individual has temporal lobe epilepsy [NaAn23]. It also shows fewer body movements, not being attentive, and dreamless sleep. So that when we start to focus, delta activity starts to decrease [GMMN22].

- **Theta (θ):** It is classified as a slow activity. It is found in the early stages of sleep. It is mostly found in the frontocentral head region but due to drowsiness it slowly replaces the alpha rhythm. It appears when individuals can feel creative (more like imagery, fantasy) or be distracted. So that it shows a noticeable presence during the time of mediation [GMMN22].

- **Alpha (α):** Since it is found when individuals are awake but closed eyes, it indicates mental relaxation, and thinking. Also, it can help to detect the coma state [NaAn23]. it disappears when we open our eyes [ŞŞAA19]. Alpha activity shows relaxation but not drowsiness which is more like meditation or self-healing. Also, it has two sub-bands (low and high alpha) to determine the differentiation of the mental state [GMMN22].

- **Beta (β):** It is classified as a fast activity. It is more visible in the frontal head region. It appears when we are active or doing normal activity, especially when our eyes are open, thinking, or listening. It shows relaxation along with being focused. It also has sub-bands which are low-beta, mid-beta, and high-beta [GMMN22].

- **Gamma (γ):** This is the only frequency that can be found in every part of the brain. This waveform shows a high level of processing, for instance thinking, and concentrating. It helps to identify good memory which can process actively and efficiently and can prove if people face any learning disabilities [GMMN22].

There are another two bands named infra-slow band (less than 0.5 Hz) and ultra-fast band (greater than 200 Hz) [NaAn23]. But usually, these two are excluded from the experiment to focus more on the important characteristics of the other bands that influenced to make the meaningful features of brain activity. Since the brain activity shows the complex states and frequency bands helps to categorize them with their own characteristics. Therefore, several studies show the active exploration in this section to decrypting the EEG signals for the data preprocessing.

3.2 Event-Related Potentials

EEG device records the electrical activity of our brain which is produced by the simulations of some specific sensory nerves. Evoked potentials (EPs) test measures those brain responses in form of electrical activity to the response of certain sensory nerve pathways [BaCA19, WaKB05]. EPs test is mostly used in clinical diagnosis, especially to detect abnormality in our brain nerve pathways. However, it verifies that when time-locked to the psychological events, some of the brain responses, mostly with late latencies are more displayed in a time relationship to the events rather than only showing sensory processes [HaBG93, RuCo95]. Hence, Event-Related potentials (ERPs) are introduced for measuring event-related voltage changes in the ongoing brain activity that is time-locked to the sensory, motor, and cognitive effects [Pasc04]. And this credential makes it popular among psychologists, physiologists, and physicians for multiple applications.

Several aspects and statements are presented by the researchers for ERPs generating process and obtaining them. To identify the ERPs, mostly use the SNR (Signal-Noise Ratio) measures because it is often visible that the magnitude of the ERPs is smaller than the magnitude of the background EEG activity [RuCo95]. Also, determining the location of the ERPs source is more likely done by the assumptions with the explanation of scalp topography but there has an as high chance of biased results [HuZh19].

3.2.1 Common EP and ERP Components

3.2.1.1 Auditory Evoked Potentials

Auditory stimulates in the cochlea which is a part of auditory system and located in the inner ear. The responses appear within a few milliseconds of a sudden sound onset and show small voltages. The auditory process so that information from the cochlea through the brainstem and into the thalamus. Usually, averaging thousands of trials is required to obtain a clear brainstem auditory evoked potential (BAEPs). The waves are present with Roman numerals (wave I-VI) as shown in Figure 3.1. It assumes that wave I represents the activation of acoustic nerve, wave II represents cochlear nuclear nuclei, wave III represents superior olives, wave IV denotes lateral lemniscus tracts and nuclei, and wave V expresses inferior colliculi [HuZh19]. The last wave VI appears in the medial geniculate body which is the thalamic processing center of the auditory pathway, and it is considered as not useful enough in clinical needs [GuEh82].

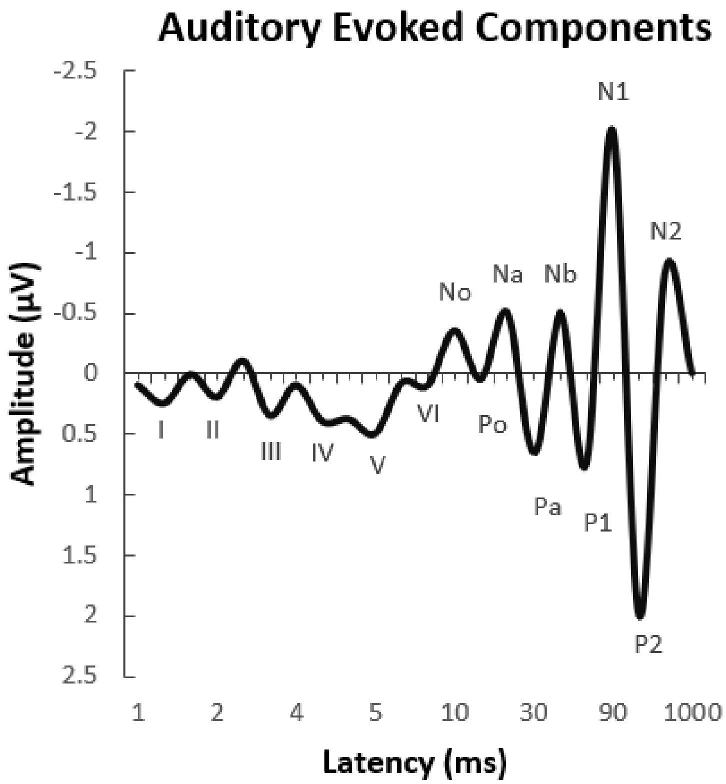

Figure 3.1
Typical sequence of auditory evoked components

The waveform has shown in Figure 3.1 is elicited by an auditory stimulus. It is shown over a period to demonstrate the auditory brainstem responses (wave I-VI), the meet latency responses and the long latency responses. The BAEPs are followed by the mid-latency which defines the responses between 10 and 50 ms; and the long-latency responses begin from the P1 as shown in Figure 3.1.

3.2.1.1 Visual Evoked Potentials

With the visual cortex, our brain receives visual information from the retinas. It also processes that information and relays it to other regions of the brain. While receiving the visual information, the visual cortex generated the electrical signals, and those work to measure the visual evoked potentials (VEPs) [HuMT23]. The visual cortex is divided into five areas named as V1, V2, V3, V4, and V5. V1 is the primary area that is highly sensitive and mostly involved in visual stimulation. V2 is the secondary visual cortex and V3 – V5 are the visual association areas. In Figure 3.2, we can see that V1 and V2 are surrounded by other areas. Each cortex is having their own responsibilities. Area V1 is mostly activated for finding any motions or motion patterns in a straightforward way and area V2 provides finer angles to see the motion of an object in 3D form after integrating the information from the V1. Both area V3 and area V4 provide attention to the orientation of the shapes, but area V4 is more selective to process the colors. On the contrary, V5 is sensitive toward motion and directions and is not influenced by the colors [BaBM12a, BoBr05]. Also, V5 is known as MT (middle temporal).

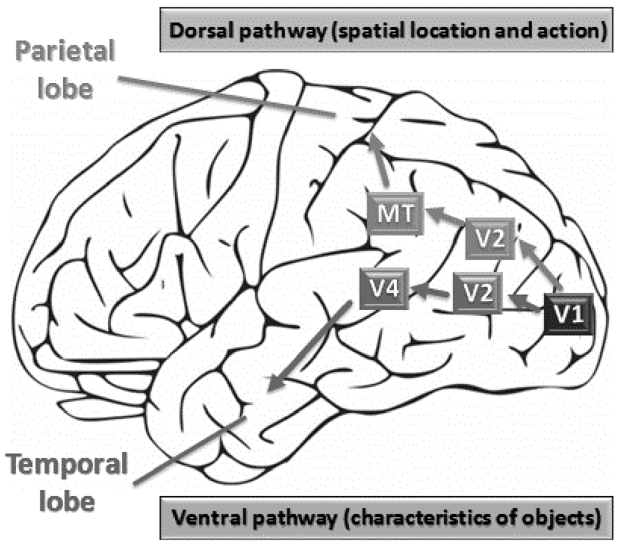

Figure 3.2
Parallel organization of the visual system [BaBM12b, HuMT23]

Figure 3.3 shows the waveforms that are formed from the visual stimulus. VEPs specified the peaks as positive and negative in a numerical sequence and peak-to-peak amplitudes are calculated from the one positive deflection to the next negative deflection, for instance, P1-N1 [HuZh19].

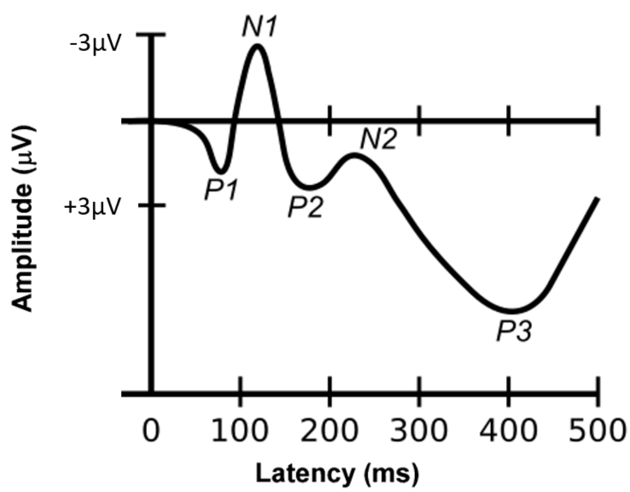

Figure 3.3
Typical visual evoked components, including P1, N1, P2, N2, P3 [Robi05]

3.2.2 Requirements and Confounding factors

When designing an event-related potential (ERP) experiment, it is a good practice to maintain some specific requirements to ensure decent quality and meaningful experiment results. Trial number, stimulus probability, time-locking, time interval, and body movements are the main requirements that need to consider while performing the ERP method. A moderate trial number is the first consideration we need to make, otherwise, researchers may face risk and lose the focus of the research. Time-locking refers to the relationship between the event and its ERP effect and its associated cognitive processes, or else we will miss the actual meaning of the participants' cognitive process or, breach the relation between the objective (presentation) and subjective (assessment). In the case of processing each trial, we need to add enough intervals so that one stimulation (ERP waveform) will not affect the performance of the other stimulation. Also, we need to control the body movements since these will add non-cerebral information to the signals [HuZh19].

Though confounding factors are not included in the experiment these can influence the result of the experiments. Habituation and fatigue can be confounding factors that occur within-subjects. When subjects participate in the same stimuli many times, they may face the habitation factor. Again, if the stimuli run for a long-time subjects may feel fatigued. These types of factors can affect the experiments. On the other side, age, sex, education level, specific cognitive ability, etc. can also influence the result. While designing the experiment researchers need to either control the factors or take these all into consideration when analyzing the experimental result [HuZh19].

3.2.3 Artifacts and Filtering

In the raw EEG signals, there is a high chance of presenting unrelated and unwanted information which are known as artifacts. Artifacts could be physiological and non-physiological and some of them can be found in Table 3.2. Physiological artifacts for the EEG signals are the other biometric data, such as eye blinking, muscle or any other body parts movements, heartbeats, and so on. Again, among these artifacts' ocular-related potential does not affect much, the brain signals from the EEG, on the contrary sometimes it adds some influential information to the EEG signals. But high-frequency activity such as muscle tension affects the immensely. On the other side, non-physiological artifacts refer to the information collected from the outside world, such as electrical interference, malfunction of the device, power interference, and so on. These all can happen due to the poor placement of the electrode, noisy environment, unstable wire connection or damaged wire, and so on. The best feasible way to avoid these kinds of artifacts is to carefully adjust the environment of the experiment [HuZh19].

Table 3.2

Physiological and non-physiological artifacts [HuZh19]

Physiological artifacts	Non-physiological artifacts
Ocular-related artifacts due to eyes movements and blinking	Power line interference artifacts (50 Hz in Europe, 60 Hz in the United States)
Electromyography artifacts due to frontalis and temporalis muscle activities	Electrode artifacts due to the poor place placement of electrode on the scalp
Electrocardiographic artifacts due to heartbeats	Malfunction of any part within EEG recording system e.g., amplifiers
Scalp perspiration and movements	Digital artifacts such as loos wiring or loosening of circuit board connections

Even after taking thorough cautious, there are several unseen/ unrecognizable artifacts that could be added to the EEG signals. In such cases, filtering is the best way for preprocessing the signal data before using it for the analyzing. A popular filtering technique is applying some frequency range and discarding the other frequencies' information that is out of the defined range. Sometimes it may cause losing some information but helps to avoid the unrelated huge data. There are usually used four types of filters for the frequency. A Low-pass filter discards the high-frequency data after deciding a certain value or threshold value and a High-pass filter acts oppositely. A Band-pass filter helps to keep the frequencies between a lower and upper bound. And Band-stop filter only keeps the frequencies that are below the lower bound and higher than the higher bound. Also, it is better to use the filtering on the continuous signals, or else research may face filtering artifacts at the epoch boundaries [HuZh19].

3.3 Fourier Transform

EEG signals are not fixed and show dynamic characteristics. Since EEG signals have non-stationary characteristics, the signals vary with the time. Some EEG Spectrum is hard to observe within a period of time, such as alpha band because the difference between the spectrum is not enough to notice. In such a case, Time-frequency distribution (TFD) helps to understand that spectral content of a signal that is changing with the time and the distribution pattern at each time point [Boas15]. Time-frequency analysis (TFA) is required to analysis the EEG signals' activity. Time frequency analysis techniques can be divided into two types, one is time-frequency power distribution and another one is time-frequency signal decomposition. The time-frequency power distribution works on the amount of signal power assigned to a given time frequency and time frequency signals decomposition works to decompose a signal.

3.3.1 Continuous Time Fourier Transform

Fourier transform gives an opportunity to find the insights of a signal or a function. It breaks the waveform and represents those time-series signals as a summation of a series of sines and cosines. By analyzing the Fourier transform of a signal allows to find the different domain of it, for instance, identifying the signal type, quantifying the signals based of time-cycles and so on. Also, Fourier transform provides assistance to evaluate the amplitudes, phases and frequencies of signal data.

If x(t) is a continuous signal, its Fourier transform will be called as continuous-time Fourier transform (CTFT).

$$F(f) = \int_{-\infty}^{+\infty} x(t) e^{-i2\pi f t} \; dt \qquad 3.1$$

Here, f is the frequency and time period T $\rightarrow\infty$.

Applying Euler's formula, equation 3.1 can be written as,

$$F(f) = \int_{-\infty}^{+\infty} x(t)[\cos(2\pi f t) - i sin(2\pi f t)] \; dt \qquad 3.2$$

3.3.2 Discrete Time Fourier Transform

In real-world, obtained EEG signals from the device is not continuous. There EEG signals are converted from the analog to digital. Therefore, we need to apply the discrete-time Fourier transform (DTFT) in place of CTFT. The sampling theorem is used for converting the continuous function into a sequence of discrete values [GoWo06, HuZh19]. According to the Nyquist-Shannon sampling theorem [PoKS19] maximum frequency can be found by sampling a signal at a rate 1/ΔT is,

$$f_{max} = \frac{1}{2\Delta T} \qquad 3.3$$

But there have some cases where it is difficult to demonstrate later, in those cases it is better to use,

$$f_{max} < \frac{1}{2\,\Delta T}$$

$$\text{Or, } \frac{1}{\Delta T} > 2f_{max} \qquad 3.4$$

If the discrete time signal is x[n], where n = 1, 2, … …, N then, DTFT of x[n] will be calculated as follows,

$$F(f) = \sum_{n=1}^{N} x[n]e^{-i2\pi fn} \qquad 3.5$$

Further to set the time and frequency domain discretized and use finite sample points, if sampling rate is F_s, the frequency domain is discretized as $f = kF_S/N$, where k = 0, 1, 2, … …, N-1

In this case, discrete Fourier transform needs to be calculated as,

$$F(k) = \sum_{n=0}^{N-1} x[n]e^{-i2\pi kn/N} \qquad 3.6$$

3.3.3 Power Spectral Density

Power spectral density (PSD) is sometimes called as spectral density or power spectrum. It is usually used to analysis any random vibration signals. PSD represents the distribution of the power of any signal over its different frequency. If the time-domain signal is V then the unit of PSD is V^2/Hz or V/√Hz or dB (i.e., $10\log_{10}(V^2/Hz)$) [HuZh19]. Power spectral density can be calculated with the fast Fourier transform (FFT). It multiplies each frequency bin that is the intervals between samples in the frequency. Calculating the two-sided power spectrum with FFT as follows,

$$PSD(f) = \frac{FFT(A)xFFT'(A)}{N} \qquad 3.7$$

Where A denotes the amplitude of the signal and FFT'(A) denotes the complex conjugate of FFT(A) [CeHa00]. To calculate the complex conjugate we need to negate the imaginary part of the FFT(A). Again, by normalizing the results we are avoiding the dependency on the frequency bin.

3.3.4 Differential Entropy

Differential entropy is a measure for the entropy of continuous random variable. It is used to measure the complexity of continuous random variables with its probability density function, it calculates as follows formula,

$$h(X) = -\int_X f(x)\log\big(f(x)\big)dx \qquad 3.8$$

Where X is a random variable and f(x) is the probability density function of X. For the time series X obeys Gaussian distribution *N* (μ, σ^2), its differential entropy can be defined as,

$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx$$

$$= \frac{1}{2}\log(2\pi e\sigma^2) \qquad 3.9$$

where, σ^2 can represent the PSD value. In a fixed frequency band *i*, the differential entropy is defined as,

$$h_i(X) = \frac{1}{2}\log\big(2\pi e\sigma_i^2\big) \qquad 3.10$$

Though EEG signals are not following any certain distribution, but it was assumed that the EEG signals followed a Gaussian distribution.

3.3.5 Discrete Wavelet Transform

The name of the discrete wavelet transform (DWT) implies that it discretizes a given signal which will seem like a wave-like oscillation. DWT decomposes a signal into some number of sets [Hoss20]. Each set acts as a time series of coefficients. Initially, need to decide the wavelet range, later it uses to search how much that wavelet is present in that given signal for a specific location (time step of the time series). The wavelet range runs over the whole signal and at each signal location, it finds a coefficient by multiplying the wavelet and the signal value of that location. These coefficients help to know the transformation of the signal.

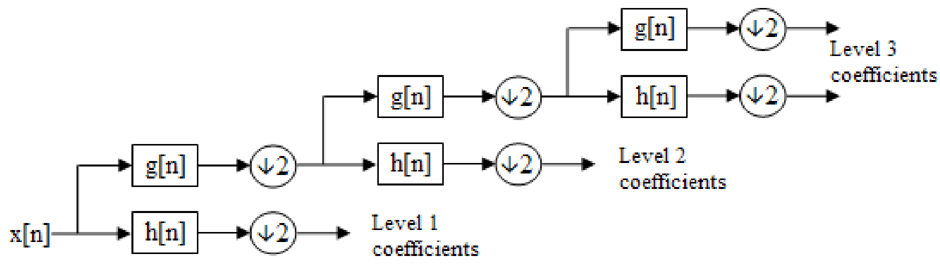

Figure 3.4

3-level DWT with filter bank [John05a]

The wavelet transform utilizes filter banks that resemble a binary tree structure to create a time-frequency representation for continuous-time signals (see Figure 3.4) . This process involves generating new frequency bands through the use of a low-pass filter and a high-pass filter and followed by subsampling the filter range. To enhance frequency resolution, this decomposition is iteratively repeated by decomposing the output filter range of the previous low-pass filter. This iterative decomposition is explained in Table 3.3 and visually represented in Figure 3.5.

Table 3.3

A signal consisting of 32 samples and a frequency range of 0 to f_n is generated by applying three levels of decomposition and four output scales,

Level	Frequency Range	Samples
1	f_n - f_n /2	16
2	f_n /2 - f_n /4	8
3	f_n /4 - f_n /8	4
3	f_n /8 - 0	4

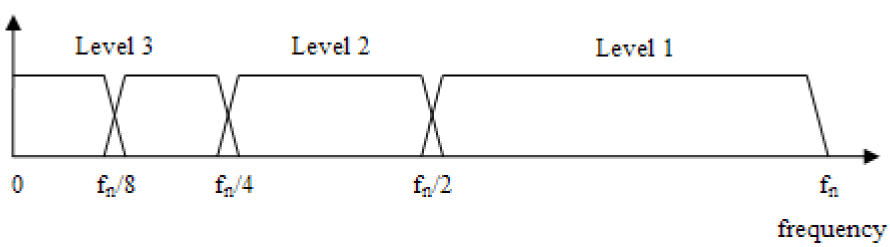

Figure 3.5

Frequency domain representation of the DWT for Table 3.3 [John05b, WTTH16]

3.4 Machine Learning Techniques

3.4.1 Mutual Information for feature relevance

While analyzing the dependence and independence characteristic of random variables, mutual information (MI) plays a significant role. It helps to deduce the data redundancy in case of having similar random variables. MI carries the information of two random variables. This information helps to observe the likelihood of two random variables which is a non-negative value. If the MI value is zero it shows that the two random variables are independent. Lower values indicate lower dependency and higher values indicate higher dependency. In machine learning analysis, MI information of the features shows the features' independent characteristics and assist to reduce the size of the feature vector.

3.4.2 Logistic Regression:

Now-a-days, logistic regression is used as a classification model, especially for biological science and social science application. Mostly, this regression model is used for categorical dependent variables, such as binary logistic regression (yes, no), multinomial logistic regression (positive, neutral, negative) and ordinal logistic regression (ratings, 1 to 4). Moreover, logistic regression provides the flexibility to build the classifying model, even when our independent variable set the relationship with our nominal, interval, ratio type, or binary-type independent variable.

Let dataset $D = \{(y_i, x_i): i = 1, 2, \ldots, n\}$, where Y_i is the i_{th} prediction that is measured in a continuous scale; $x_i = \{x_{i1}, x_{i2}, \ldots, x_{ik}\} \in \mathbb{R}^k$ is the associated feature vector, and n is the total number of samples. As in logarithm expression [BoAb19], for classifying Y_i,

$$\ln\left[\frac{P(Y_i)}{1-P(Y_i)}\right] = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 3.11$$

$$P(Y_i) = \frac{e^{\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik}}}{1+e^{\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik}}} \qquad 3.12$$

Where, the best model is decided by getting the best values of the regression coefficient $\beta_i = \beta_0, \beta_1, \beta_2, \ldots, \beta_n$ which are estimated by using maximum likelihood estimation. Also, because optimal values minimized the error and classified more accurately.

3.5 Performance Measures

3.5.1 Performance Metrics

The classification model is chosen by the best performance result. Model performance is determined by the classifier's predictive ability. In machine learning, the model's prediction ability is usually evaluated by measuring **F1-score**, **Precision**, **Recall**, **Accuracy**, and so on.

$$F1 - Score = (2xPrecisionxRecall)/(Precision + Recall) \quad 3.13$$

where,

$$Precision \ = \ Positive\ Predictive\ Value \ = \frac{TP}{TP + FP} \quad 3.14$$

$$Recall \ = \ Sensitivity \ = \frac{TP}{TP + FN} \quad 3.15$$

So, the accuracy value of a model is evaluated as follows,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad 3.16$$

Here, TP = number of true positives, FP = number of false positives, TN = number of true negatives, and FN = number of false negatives.

Accuracy may lead to choosing a poor model, especially when classifier is biased. But F1-score provides more reliable result in this case. F1-score is calculated based on the **Precision (Positive Predictive Value)** and **Recall (true positive rate or Sensitivity)** which provide high value when the false classified results are less than true classified results.

Also, besides predicting the positive value, models can also perform well to predict the negative value (opposite of interest). In that case, evaluating the model's performance for predicting the true negative value with **Specificity (true negative rate)** and **Negative Predictive Value** as follows,

$$Negative\ Predictive\ Value \ = \frac{TN}{TN + FN} \quad 3.17$$

$$Specificity \ = \frac{TN}{TN + FP} \quad 3.18$$

A model can be evaluated with its class-wise performance. **Geometric mean** helps to evaluate this performance by maximizing the accuracy of each class and balancing their accuracy. In the binary classification model, G-mean can be calculated with the Sensitivity (true positive rate) and Specificity (true negative rate) as follows,

$$G_{mean} = \sqrt{Sensitivity \times Specificity} \quad 3.19$$

But if the model is for multiclass prediction, it will be the higher root of the product for each class. Again, Sensitivity and Specificity are also used to measure **ROC-AUC (Area Under the Receiver Operating Characteristic Curve)**. ROC-AUC shows the borderline of the prediction ability of a model. The ROC-AUC score shows the model's ability in the form of probability. A higher value of the ROC-AUC score indicates a higher performance ability of the model. Besides, the **area under the Precision-Recall curve** is also applied to validate the model's performance. Unlike ROC-AUC, it uses the value of Precision and Recall, and it is mostly used when class distribution is imbalanced.

3.5.2 Cross Validation

Cross-validation is a machine learning model evaluation technique. In every iteration, resample the data in different portions for training and testing the model. The main purpose of applying the cross-validation technique is to find the best predictive model for future applications. Among the different cross-validation techniques, Leave-One-Group-Out (LOGO) offers the facility to apply the subject-independent approach. In every iteration, it leaves a complete group out of the training set and so the information of that certain group is not being leaked to the training model. In this approach, the testing result of the model provides a more practical performance experience.

3.6 Hypothesis Test

3.6.1 Null and Alternative Hypotheses

Null hypothesis (H_0) and alternative hypothesis (H_a) are two claims that are set with a contradicting situation and provide evidence for a statistical test or for a research question. The null hypothesis provides the information that there have no effects or no differences in the proposed work. In another way, it provides the evidence to assume that the proposed hypothesis is true until some other evidence is provided to reject it. Conversely, the alternative hypothesis infers that there has an effect on the hypothesis testing. If the null hypothesis states that $H_0 : \theta = 0$, i.e., the distribution of the difference is symmetric about zero corresponding to no difference in location between the two samples. The two-sided alternative is $H_1 : \theta \neq 0$ [ReNe11]. One-sided alternatives are also possible. In this research work, we use this hypothesis testing to weigh the effects of our statistical analysis in building the model. The effect of our analysis will be evaluated with the p-value. If the evaluation shows that $p \leq \alpha$ then we can reject the null hypothesis.

3.6.2 Wilcoxon Signed Rank Test

The Wilcoxon signed rank test is mostly known as a non-parametric method for the one specific problem location. Though it is difficult to express but it provides an important alternative to the parametric t-test and normal assumption in any population. Among the two types of Wilcoxon tests, we preferred to use Wilcoxon signed rank test when information gives a sign of having the differences between paired observation, because of its better performance and it generally used to compare two related samples. Also, this test is effective to do the t-test when the data does not have a normal distribution. The left and right channels of the hemisphere are provided independent samples where their pair difference shows the influence.

3.6.3 Bonferroni Correction for multiple hypothesis tests

To identify a result's significance within a statistical test, we applied p-value which is a scale to represent the probability of occurrence of an event. In the case of measuring the hypothesis test, the p-value helps to decide the rejection point for the null hypothesis and the supporting point for the alternative hypothesis. Any smaller value provides support for the alternative hypothesis and rejects the null hypothesis. The usual cut-off p-value to reject the null hypothesis is 0.05 [JaAn19]. If a p-value is less than 0.05, it is considered that the statement for the null hypothesis is rejected and shows support for the alternative hypothesis. Contrarily, if a p-value is greater than 0.05 then the null hypothesis is not going to be rejected.

In hypothesis testing, we consider the Type I error rate that infers the false-positive result and aids to reject the true null hypothesis. In this case, set the value of the Type I error rate as 5% which denotes the p-value 0.05. The Bonferroni correction method is applied to adjust the Type I error, especially when the statistical test is performed on multiple pair (dependent or independent value) comparisons in a single dataset. Bonferroni correction reduces the chances of getting false-positive results [Napi12]. To perform the Bonferroni correction, divide the p-value by the number of comparisons being made. If N is the total number of comparisons, then the Bonferroni corrected significance level of $\alpha = 0.05/N$.

3.7 Summary

EEG signals are one of the well-known techniques among the various way of analyzing emotion regulation. EEG signals are collected with the help of an EEG device which contains some electrodes that are placed on the head surface to collect the signals or channels' activity. This device also helps to convert the signal into digital signals. Not only do EEG signals carry the brain activity information, but also EEG frequency bands help to signify each activity's detail. In addition, the evoked potentials help to identify the reasons behind those brain activities. Though EEG signals' collecting device is used with caution, still it is better to take careful notes of the requirements, factors, and artifacts of the specific research, otherwise, researchers may face difficulties or lose the actual focus.

After collecting the EEG signals, researchers need to decide which type of features will be more accurate and appropriate for their research. Since EEG signals are in form of time series, the Fourier transform helps to know the insight of the signals that help to generate the features in the next such as Power spectral density, Differential entropy. To use those features, we can use different machine learning models. Choosing an ML model also depends on the research focus. The same goes for testing criteria of any model performance but mostly uses the F1-score and accuracy rate to evaluate any model's quality. On the other hand, for observing any new perception, it is better to apply the hypothesis test. As this research, is set to focus on both building predicting models and testing new perception validation, it chooses the logistic regression technique. Also, for better objective decisions for the hypothesis test, it uses Bonferroni correction.

Chapter 4 Implementation

This thesis uses the EEG signals as primary data for building model and analysing activated brain region. Previous chapter delineates the necessary theories behind this research work and this current chapter expresses how those theories are employed to develop this thesis perception. This research starts the analyzation from checking the dataset quality along with the necessary technique of the features extraction and then gradually adds next steps in different sections.

4.1 Dataset

In general, for any research work that is involved in building model, looks for appropriate and effective dataset. Because this does not only add the accurate result in the experiment but also adds the validity of that research. In this work, we used the SEED-IV database [ZLLL18]. This dataset was collected from 15 healthy, right-handed subjects aged between 20 and 24 (8 female). The subjects participated in three different sessions, which were conducted on different days. During each session, the subjects watched 24 video clips of approximately two minutes each, which aimed to evoke four emotions: happiness, fear, sadness, and neutral. In every session, the number of video clips for each emotion was six. While watching the video clips, the subject's EEG signals were recorded with a sampling rate of 200 Hz using 62 EEG channels. In total, 72 EEG signals (one per video clip) were recorded for each subject.

4.1.1 Preprocessing

To remove noise and artifacts caused by eye blinking and other physiological and non-physiological processes, here applied a bandpass filter with a range of 1-50 Hz to the EEG signals. which kept only the frequency range of the brainwaves. Next, this research work extracted features from the filtered signals using a non-overlapping window of 4 seconds. To prevent spectral leakage, multiplied the 4-second window by a Hanning window before extracting features.

4.1.2 Feature extraction:

We applied three different techniques to extract features from, the EEG frequency bands delta (1-4 Hz), theta (4-8 Hz), alpha (8-14Hz), beta (14-31 Hz), and gamma (31-50 Hz). Specifically, we used the power spectrum density (PSD), differential entropy (DE), and the discrete Wavelet transform (DWT).

4.1.2.1 Power Spectral Density:

To calculate the power in the different frequency bands, we first calculated the discrete Fourier transformation (DFT) to the filtered 4-second window. Next, we calculated the power spectrum density (PSD) for each frequency band as follows:

$$\sigma^2_{ch,\ b} = \frac{1}{N_b} \sum_{k=0}^{N_b} (X[k])^2 \qquad 4.1$$

where X is the DFT of the 4-second EEG window, and N_b is the number of frequency components in the b_{th} band.

4.1.2.2 Differential Entropy:

To calculate the DE of each 4- second EEG window, it was assumed that the EEG signals followed a Gaussian distribution, so the DE was calculated as follows:

$$DE_{ch,\ b} = \frac{1}{2}\log\left(2\pi e \times \sigma^2_{ch,\ b}\right) \qquad 4.2$$

where ch was the ch_{th} channel (e.g., FP_1, O_2, T_1), b was the b_{th} band (delta, theta, alpha, beta, or gamma), and $\sigma^2_{ch,\ b}$ was the variance for the ch_{th} channel and b_{th} band (see Eq. 4.1).

4.1.2.3 Discrete Wavelet Transform:

To decompose the signal into six levels using the Daubechies 2 (db2) function as the wavelet mother, as shown in Table 4.1. The detail coefficients from the second to the sixth level corresponded to the gamma, beta, alpha, theta, and delta bands.

Table 4.1

Frequency decomposition level for the Discrete Wavelet Transform (DWT)

Level	Frequency Range (Hz)	Coefficients	Sub-band
1	100 - 50	d1	
2	50 - 25	d2	Gamma
3	25 - 12.5	d3	Beta
4	12.5 - 6.25	d4	Alpha
5	6.25 - 3.125	d5	Theta
6	3.125 - 1.5625	d6	Delta
6	1.5625 - 0	a6	

Here used these detail coefficients of the gamma, beta, alpha, theta and delta band to calculate the percentage of energy content at each frequency band as follows:

$$E_{ch,b} = \frac{\sum_{i=1}^{N_c} d_{ch,b}(i)^2}{E_{Total}} \qquad 4.3$$

where d is the i_{th} detail coefficient of the ch_{th} channel (e.g., FP1, O2, T1) and the b_{th} band (delta, theta, alpha, beta, or gamma), N_c denotes the number coefficient at the band b, and E_{Total} is the sum of the squared coefficients over all levels.

4.2 Asymmetry Feature Analysis

4.2.1 Feature Engineering

This thesis's objective is to discover the asymmetry characteristics of the brain hemispheres in processing emotion. Hence, channels from both hemispheres were studied, and checked their supremacy tendency to participate in processing emotion. So, while researching, it discards all the EEG channels that are not located in the left or right hemispheres but in the middle. The channels from the center line were identified as the channels that do not have any paired channel. In the case of identifying the paired EEG channels focused on the EEG channels' location and if they are maintaining the equidistant from the center line. Hence discarding 8 EEG channels on the center line (FPz, Fz, FCz, Cz, CPz, Pz, POz, and Oz) and keeping 54 EEG channels that are located on the right and left hemispheres. Besides, the EEG channel AFz is not present in the dataset. In Table 4.2, we can see the 27 EEG pairs which were formed with 54 channels EEG channels by mapping equidistantly from the center line.

Using the EEG paired channels as a reference, we defined asymmetry features based on frontal alpha asymmetry (FAA) [BTHJ13]. FAA compares the electrical activity in the alpha band of the left and right prefrontal EEG electrodes using the logarithmic ratio. The log-ratio between two channels guarantees that a positive value is obtained when the value of the left channel (the numerator in the ratio) is greater than the value of the right channel (the denominator in the ratio), a value of 0 when both channels have the same value, and a negative value when the value of the right channel is greater than the value of the left channel.

Table 4.2

Paired 54 EEG channels from the left and right hemispheres. 27 channels from the left hemisphere were paired with the 27 channels from the right hemisphere. EEG channels were paired so that the distance to the midline was equal.

Pair	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Left	AF3	C1	C3	C5	CB1	CP1	CP3	CP5	F1
Right	AF4	C2	C4	C6	CB2	CP2	CP4	CP6	F2
Pair	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Left	F3	F5	F7	FC1	FC3	FC5	FP1	FT7	O1
Right	F4	F6	F8	FC2	FC4	FC6	FP3	FT8	O2
Pair	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
Left	P1	P3	P5	P7	PO3	PO5	PO7	T7	PT7
Right	P2	P4	P6	P8	PO4	PO6	PO8	T8	PT8

Therefore, calculated the asymmetry feature for PSD as follows:

$$PSD_{asymmetry_{ch_x, ch_y, b}} = \ln\left(\frac{\sigma_{ch_x, b}}{\sigma_{ch_y, b}}\right) \quad 4.4$$

where $\sigma_{ch_x, b}$ and $\sigma_{ch_y, b}$are the PSD (Eq. 4.1) of the left EEG channel x and the right EEG channel y for the frequency band b, respectively.

Similarly, for the DWT, calculated the asymmetry feature as:

$$DWT_{asymmetry_{ch_x, ch_y, b}} = \ln\left(\frac{E_{ch_x, b}}{E_{ch_y, b}}\right) \quad 4.5$$

where $E_{ch_x,b}$ and $E_{ch_y,b}$are the relative energy (Eq. 4.3) of the left EEG channel x and the right EEG channel *y* for the frequency band *b,* respectively.

Given that DE values are not always positive like PSD and DWT, and that the paired right and left EEG channels (See Table 4.2) can have DE values with opposite signs at the same time, here we did not use the logarithmic ratio to calculate the asymmetry feature for DE. Instead, we calculated the asymmetry for DE features using the difference between the pairs. Similar to the log-ratio, the difference resulted in a positive value when the DE of the left channel was greater than the DE of the right channel, 0 if both were equal, and a negative value otherwise. Thus, the DE asymmetry features were calculated as follows:

For each EEG-paired channels, an asymmetry feature is calculated as follows,

$$DE_{asymmetry}{}_{ch_x,ch_y,b} = DE_{ch_x,b} - DE_{ch_y,b} \qquad 4.6$$

Where $DE_{ch_x,b}$ and $DE_{ch_y,b}$ are the DE (Eq. 4.2) of the left EEG channel *x* and the right EEG channel *y* for the frequency band *b,* respectively.

4.3 Specific objective 1: Statistical Analysis

This research used hypothesis tests to determine if there were significant differences in the EEG channels' symmetry characteristics. Suppose one channel's feature value of a specific band on the left hemisphere is xL and its twin pair on the right hemisphere, the channel's feature value of that specific band is xR. If the difference of xL − xR is returned to zero value, then they behave as symmetry channels. This indicates that those paired channels are activated equally for processing a certain emotion. Consequently, it also implies that the larger value shows the influence and activate tendency. Later, for evaluating the statistical significance of the asymmetry analysis testing, the p-value need to be measured to evaluate whether the value of the test is reasonable for the null hypothesis.

In order to compare differences between the right and left hemispheres when processing emotions, this research was required to compare, across all 15 subjects, the PSD, DE, and DWT for each band between the EEG channel pairs (see Table 4.2). The comparison was performed by using the Wilcoxon signed-rank test. Equation 4.7 shows the null and alternatives hypothesis with the DE features for the Wilcoxon signed-rank test.

$$wilcoxon\left(DE_{ch_x,b}, DE_{ch_y,b}\right) = \begin{cases} \eta DE_{ch_x,b} = \eta DE_{ch_y,b}, & null\ hypothesis \\ \eta DE_{ch_x,b} \neq \eta DE_{ch_y,b}, & alternate\ hypotheis \end{cases} \tag{4.7}$$

Where $\eta DE_{ch_x,b}$ and $\eta DE_{ch_y,b}$ are the medians of the DE of the left EEG channel *x* and the right EEG channel *y* for the frequency band *b,* respectively.

Again, for the PSD and DWT features, we applied the logarithmic properties to Equation 4.5 and 4.6 to express the ratio as a difference as follows:

$$\Delta ch_x, ch_y, b = \ln\left(\sigma_{ch_x,b}\right) - \ln\left(\sigma_{ch_y,b}\right)$$

And, $$\Delta ch_x, ch_y, b = \ln\left(E_{ch_x,b}\right) - \ln\left(E_{ch_y,b}\right) \tag{4.8}$$

We then used the Wilcoxon signed-rank test to compare whether the distribution of the logarithmic difference between the EEG channel pairs (Table 4.2) was symmetric about zero. The null and alternative hypothesis were defined as follows:

$$wilcoxon\left(\Delta ch_x, ch_y, b\right) = \begin{cases} \eta\Delta ch_x, ch_y, b = 0, & null\ hypothesis \\ \eta\Delta ch_x, ch_y, b \neq 0, & alternate\ hypotheis \end{cases} \tag{4.9}$$

Where $\eta\Delta ch_x, ch_y, b$ was the median of the logarithmic power (for PSD) or energy (for DWT) difference in the frequency band *b* between the left EEG electrode *x* and the right EEG electrode *y*.

In total, here performed 540 hypothesis tests for the 27 pairs, four emotions, and five frequency bands. So that the significance value for the hypothesis tests is corrected by using Bonferroni (α = 0.05/540 = 0.00009) to reduce the probability of type-I error (false positives).

4.4 Specific Objective 2: Predictive Model Analysis with Asymmetry Features

4.4.1 Logistic Regression

As mentioned in Equation 3.11, in the Logistic Regression model, every feature comes along with a coefficient value β, which carries the significance of one feature. Here for a specific emotion prediction, if a coefficient is shown its value of zero, then it implies that the corresponding feature is not relevant to that emotion prediction. But if a coefficient value is shown its value greater than zero, then it implies that the corresponding feature of this coefficient is positively related to the predicted emotion and proportionally involved in classifying that emotion. On the other side of this, if the coefficient is less than zero then the corresponding feature of this coefficient is negatively related to that emotion and the relation with the classifier of that emotion is inversely proportional. By applying the logistic regression, this research evaluated each feature coefficient value and their involvement in predicting emotions.

4.4.2 Predicting Models Capacity

To evaluate the effectiveness of the asymmetry features in identifying emotions, we trained three machine models, namely logistic regression, random forest, and gradient boosting tree models, with two separate groups of features, and then we compared their performance. The first group of features corresponded to the individual features (Equations 4.1, 4.2, 4.3), having a total feature vector dimension of 270 (54 EEG channel pairs x 5 bands). On the other hand, the second group of features corresponded to the asymmetry features (Equations 4.4, 4.6, 4.5) having a total feature vector dimension of 135 (27 EEG channel pairs x 5 bands). To facilitate comparison, we referred to the models trained with the first group of features as the 'Baseline models' and the models trained with the second group as the 'Asymmetry models'.

4.4.2.1 Comparing Model Performance:

Because we used three distinct feature extraction techniques (PSD, DE, DWT), three classifiers (logistic regression, random forest, and gradient boosting tree), and four emotions (neutral, sad, fear, happy), our study had a total of 36 comparison scenarios. Additionally, we included the comparison for the overall classification, increasing the number of comparisons scenarios by nine and resulting in a total of 45 comparison scenarios for our study.

To compare the performance of the machine learning models for each comparison scenario, we utilized Dietterich's 5x2- Fold Cross-Validated Paired t-Test method [Diet98]. As explained in [Rasc18], this method is suitable for comparing predictive models because it ensures that neither the training nor test set samples overlap, thus satisfying the independent condition necessary for the paired t-test hypothesis test.

The Dietterich's 5x2-Fold method involves performing 2-fold cross-validation five times. At each iteration, the dataset is divided into two equal subsets: subset A and subset B. Two predictive models, C1 and C2, are trained using subset A, and their performance is evaluated using subset B. Then, subset A and subset B are switched, and new predictive models, C3 and C4, are trained using subset B, and their performance is evaluated using subset A. The difference in performance is calculated as:

$$ACC_A = ACC_{C1,\,B} - ACC_{C2,\,B}$$

$$\text{And, } ACC_B = ACC_{C3,\,A} - ACC_{C4,\,A} \qquad 4.10$$

Next, the average and variance of the differences are estimated as follows:

$$ACC_{avg} = (ACC_A + ACC_B)/2$$

$$s^2 = (ACC_A - ACC_{avg})^2 + (ACC_B - ACC_{avg})^2 \qquad 4.11$$

After five iterations, the variance of the differences is computed for all iterations, and the t-test statistic is calculated as:

$$t = \frac{\mathrm{ACC}_{\mathrm{A},1}}{\sqrt{\frac{1}{5}\sum_{i=1}^{5} s_i^2}} \qquad 4.12$$

where $ACC_{A,\,1}$ is the performance obtained from the first iteration. The t-statistic follows as t-distribution with 5 degrees of freedom, under the null hypothesis that the performance of models C1 and C2 is equal.

For our case, we applied the Dietterich's 5x2-Fold method using a subject-independent approach to ensure that no EEG signals from a subject were present in both the training and test sets during the same iteration. As the dataset consisted of EEG recordings from 15 subjects, in each of the five iterations, we randomly selected data from eight subjects to form subset A and data from the remaining seven subjects to form subset B. The classifiers C1 and C3 corresponded to the baseline models, while classifiers C2 and C4 corresponded to the asymmetry models. The performance metric used was the recall, which was calculated as the number of samples correctly predicted over the total number of samples.

4.4.2.2 Multiple Comparison:

Given that for each of feature extraction methods, 15 hypothesis tests were conducted (5 for each classifier), the significance level for Dietterich's 5x2-Fold Paired t-Test was adjusted using the Bonferroni correction method. Bonferroni is a conservative method that controls the type-I error rate (false positives) by dividing the original significance level by the number of comparisons. Therefore, our study set the significance level at 0.0033 (0.05/15).

4.4.2.3 Comparing Computational Time:

In addition to comparing the performance of the baseline and asymmetry models, we also assessed the time required to train these models. To this end, we recorded the time needed to fit the baseline models (C1 and C3) and the asymmetry models (C2 and C4) at each iteration of the Dietterich's 5x2-Fold method. As a result, we obtained a total of 10 fitting times for each type of model. We then used a Wilcoxon signed-rank test with a significance level of 0.05/20 = 0.0025 ($\alpha = 0.05$) to compare the fitting times of the baseline and asymmetry models.

4.4.2.4 Comparison Settings:

To ensure a fair comparison between the baseline and asymmetry models, all 45 comparison scenarios were executed using the same computational resources. Specifically, we utilized a Google Colab account with 2 cores of Intel(R) Xeon(R) CPU @ 2.30GHz, 12.7 GB of RAM, and 107.7 GB of hard drive space.

4.5 Specific Objective 3 – Relevant Asymmetry Features for Emotion Prediction

Since each emotion appears differently, its activation process for the hemispheres channels seems different too. Even activation levels for some channels in the same hemisphere may be distinctly involved. Therefore, one feature may actively be involved in predicting one emotion but not be activated enough for other emotions. In that case, that feature appears in the model for predicting that certain emotion as an irrelevant feature. This research explored this view to discover if there are any irrelevant feature(s) in the dataset. Also, looking for the fact which hemisphere's channels are present for the activation of one type of emotion along with their different frequency bands.

4.5.1 Relevant Ratio Pairs

To further investigate which asymmetry ratios between the EEG electrode pairs were most relevant for predicting each type of emotion, we used a one-vs-all approach to train a logistic regression model for each emotion. This approach involved training a separate logistic regression model for each emotion, with the corresponding emotion class labeled as 1' and the other emotions labeled as 0'. The reason for using a one-vs-all approach instead of a multinomial logistic regression was that the individual binary logistic regressions allowed us to obtain a vector of coefficients that associated which ratios between the left and right EEG channels and which frequency bands were most relevant for predicting each specific emotion of interests. In contrast, a multinomial logistic regression would select an emotion as a reference and provide three coefficient vectors comparing the odds of a sample being of each emotion relative to the reference emotions.

4.5.1.1 Subject-independent Model:

We utilized the "leave-one group-out" (LOGO) cross-validation technique to train each binary logistic regression. This technique allowed us to use a subject-independent approach to train the models, so there were no EEG signals of a subject in both the training and test sets at the same iteration. Because the data comprised 15 subjects, the LOGO performed 15 iterations. At each iteration, the EEG samples of one of the subjects were used as the test set, and the samples of the remaining 14 subjects were allocated in the training set. The training set was used to train the logistic models, and the test set was used to evaluate the prediction capability of the four emotions. For instance, for each logistic regression model, the LOGO cross-validation produced 60 accuracy rates, where 15 for each type of emotion. We compared the performances of the model using a Wilcoxon signed-rank test with a significance value of 0.05 ($\alpha = 0.05$).

At each iteration of the LOGO cross-validation, we trained the logistic regression models using the training set and evaluated the performance of our models using eight different metrics on the test set. These metrics included sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), F1-score, geometric mean (G-mean), the area under the receiver operating characteristics (AUC-ROC) curve, and the area under the precision-recall curve (AUC-PR). Sensitivity measures the proportion of true positives (samples correctly classified as belonging to the target emotion) out of all the actual target emotion samples. Specificity measures the proportion of true negatives (samples correctly classified as not belonging to the target emotion) out of all the actual non-target emotion samples. PPV measures the proportion of true positives out of all the samples classified as belonging to the target emotion, while NPV measures the proportion of true negatives out of all the samples classified as not belonging to the target emotion. The F1-score is the harmonic mean of precision and recall, while the G-mean is the square root of the product of sensitivity and specificity. The AUC-ROC measures the overall ability of the model to distinguish between target and non-target emotion samples, while the AUC-PR measures the trade-off between precision and recall for different classification thresholds.

4.5.1.2 Feature Pre-processing:

In total, we had 135 asymmetry features for each feature extraction technique (Equation 4.4-4.6), which were derived from the 27 EEG pairs multiplied by five frequency bands. Since developing subject-independent emotion recognition approaches is challenging due to the poor generalizability of features across subjects, we implemented two pre-processing feature steps to train the logistic regression model.

First, we applied the mutual information (MI) technique on the training set to select the 20% most relevant features. The MI technique selected the most relevant features by comparing the dependency between5 each feature and the emotion of interest. Features with higher MI values indicated a stronger dependency between the feature and the emotion.

Second, to further remove irrelevant asymmetry features and to avoid overfitting, we used regularization, a technique that has shown to be effective for subject-independent emotion recognition approaches [LSZZ18]. Thus, we applied elastic net regularization [ZoHa05] to train each logistic regression at each iteration of the LOGO cross-validation. The best hyperparameters for the l1-ratio (φ) and the regularization strength (C) were optimized using nested-cross validation on the training set. The grid search used nested-cross validation was defined by $\phi \in \{0, 0.1, 0.2, ..., 0.8, 0.9, 1\}$ and $C \in \{10^{-3}, 10^{-2}, ..., 10^{2}\}$.

At each of the 15 iterations of the LOGO cross-validation, the logistic regression generated a coefficient for each of the 135 asymmetry features. We stored these 135 logistic regression coefficients at each iteration. Once the LOGO cross-validation was complete, we averaged the logistic regression coefficients across the iterations, thus obtaining a set of coefficients for each type of emotion. These sets of coefficients indicated which features (i.e., asymmetry log-ratios between EEG pairs and frequency bands) were most relevant for predicting each type of emotion.

4.5.2 Relevant EEG Channels for Predicting Emotions

To identify relevant EEG channels in processing emotions, we conducted two analyses with the logistic regression coefficients. First, we identified the most relevant features for the binary prediction of the four logistic regressions by identifying the five highest and the five lowest average coefficients.

For our third analysis, we use the logistic regression classification equation, which is defined as,

$$\hat{y} = \frac{1}{1 + e^{-\left(\sum_{i=1}^{135} \omega_i f_i\right)}} \qquad 4.13$$

where $\hat{y}$ is the probability that the sample belongs to the emotion of interest, ω_i is the logistic regression coefficients associated with the i_{th} feature, which corresponds to the log-ratio of the relative the relative energy (for DWT) between the left and right EEG channels (Equation.4.5). A feature f_i was positive when the relative energy of the left channel was greater than that of the right EEG channel; zero when both channels had the same relative energies; and negative when the energy of the right channel was greater than that of the left channel. Given that the summation in the exponent of Equation 4.13 is composed of the individual product of the features and logistic coefficients, we can express it as follows:

$$\sum_{i=1}^{135} \omega_i f_i = \omega_1 f_1 + \omega_2 f_2 + \cdots + \omega_{135} f_{135} \qquad 4.14$$

In this equation, the ω_i represents the logistic regression coefficients, and the f_i represents the features of sample. It is important to note that when the summation is positive, the sample is predicted to be of the emotions of interest. Conversely, when the summation is negative, the sample is predicted not to be of the emotion of interest. Therefore, any positive product between the coefficient and the feature contributes to predicting the sample as the emotion of interest. In contrast, any negative product between the coefficient and the feature contributes to predicting the sample as not being from the emotion. Therefore, we used that fact to establish relationships between the emotions, the features, and the logistic coefficients, ω, and the features, f.

Table 4.3 shows the four different cases we used to establish the relationship between the emotions, the features f, and the logistic regression coefficients, ω. When the median feature value was positive (left energy greater than right energy), we assumed a direct relation between the left EEG channel and the emotion when the average coefficient was positive ($\omega_i f_i > 0$), and an inverse relationship when the average coefficient was negative ($\omega_i f_i < 0$). On the other hand, when the median feature value was negative (right energy greater than left energy), we assumed a direct relation between the right EEG channel and the emotion when the average coefficient was negative ($\omega_i f_i > 0$), and an inverse relationship when the average coefficient was positive ($\omega_i f_i < 0$).

Table 4.3

Relationships between the emotions, the features, and the logistic regression coefficients. The first column shows the sign of the median feature value (+ for left energy greater than right energy and - for right energy greater than), the second column shows the sign of the corresponding logistic regression coefficient (+ or −), the third column shows the product of the coefficient and the feature ($\omega_i f_i$), and the fourth column provides an interpretation of the relationship between the feature, coefficient, and emotion.

f_i	ω_i	$\omega_i f_i$	Interpretation
+	+	+	Relative energy of the left channel is **directly** related to the emotion
+	-	-	Relative energy of the left channel is **inversely** related to the emotion
-	+	-	Relative energy of the right channel is **inversely** related to the emotion
-	-	+	Relative energy of the right channel is **directly** related to the emotion

4.6 Summary

In this research, we analyze the EEG signals to find out the brain hemispheres' activation tendency for emotions processing. For this analyze, specified three research objectives (Section 4.3, 4.4, and 4.5) and experimented brain hemispheres' involvement with brain asymmetry features. Since EEG signals are recorded as digital signals, it works to extract the features by aiding the Fourier transformation with differential entropy. And to study the brain asymmetry, here we paired the channels from the left and right hemispheres based on the equal distance from the center line. Paired channels' involvement in emotion processing was analyzed with the null hypothesis. Raito value of the paired channels decides the involvement tendency. The ratio value is also used as an asymmetry feature to build the predictive model. This stage of the research evaluated the predicting capability of the asymmetry features compared to the usual features. Also, the predicting model was trained as a subject-independent model. Furthermore, this thesis worked on each emotion exclusively to identify the independent relevant ratio pairs.

Chapter 5 Result and Analysis

The preceding chapters explained the implementation of the experiments with the distinct stages that are involved in this thesis work. During the implementation process, some new aspects came to light that shed some interesting perspectives on emotion processing. Not only did the results of these experiments show similarities with previous research work, but they also supported the brain asymmetry model proposed by neuroscientists. Additionally, the asymmetry features we implemented displayed a unique quality that can be leveraged to build a model for emotion recognition. Overall, these findings are quite significant and shed light on the complexity and nuance involved in this field of study. This chapter will highlight the results of the conducted experiments and provide a comprehensive analysis to explain how they contribute to the processing of emotions.

5.1 Specific Objective 1: Statistical Analysis

Figure 5.1 shows the logarithmic difference (Equation. 4.5) between the medians of the energy of the 27 paired EEG channels for each of the five frequency bands. The difference between the paired EEG channels is indicated by color. Green colors indicate that the DE median value was higher for the left channel than for the right channel, whereas red colors indicate the opposite. The intersection between the EEG channels pair and the frequency band contains an asterisk ($*$) when the difference between the paired channels was statistically significant (Bonferroni corrected p-value 0.00009 (0.05/540); Wilcoxon rank sum test).

For the beta and gamma bands, the left channels had more relative energy than the right channels for each brain region except the frontal area (F1/F2, F3/F4, F5/F6, and F7/F8). This pattern was the opposite for the theta and delta bands, in which the right channels resulted in more relative energy for EEG channels outside the frontal area. In the case of the alpha frequency band, there was a difference among the emotions. Specifically, for sad and fear, the log differences of the relative energy between the left and right channels resulted in more positive values (green colors), while for happy and neutral emotions, those log differences were mostly negative (red colors).

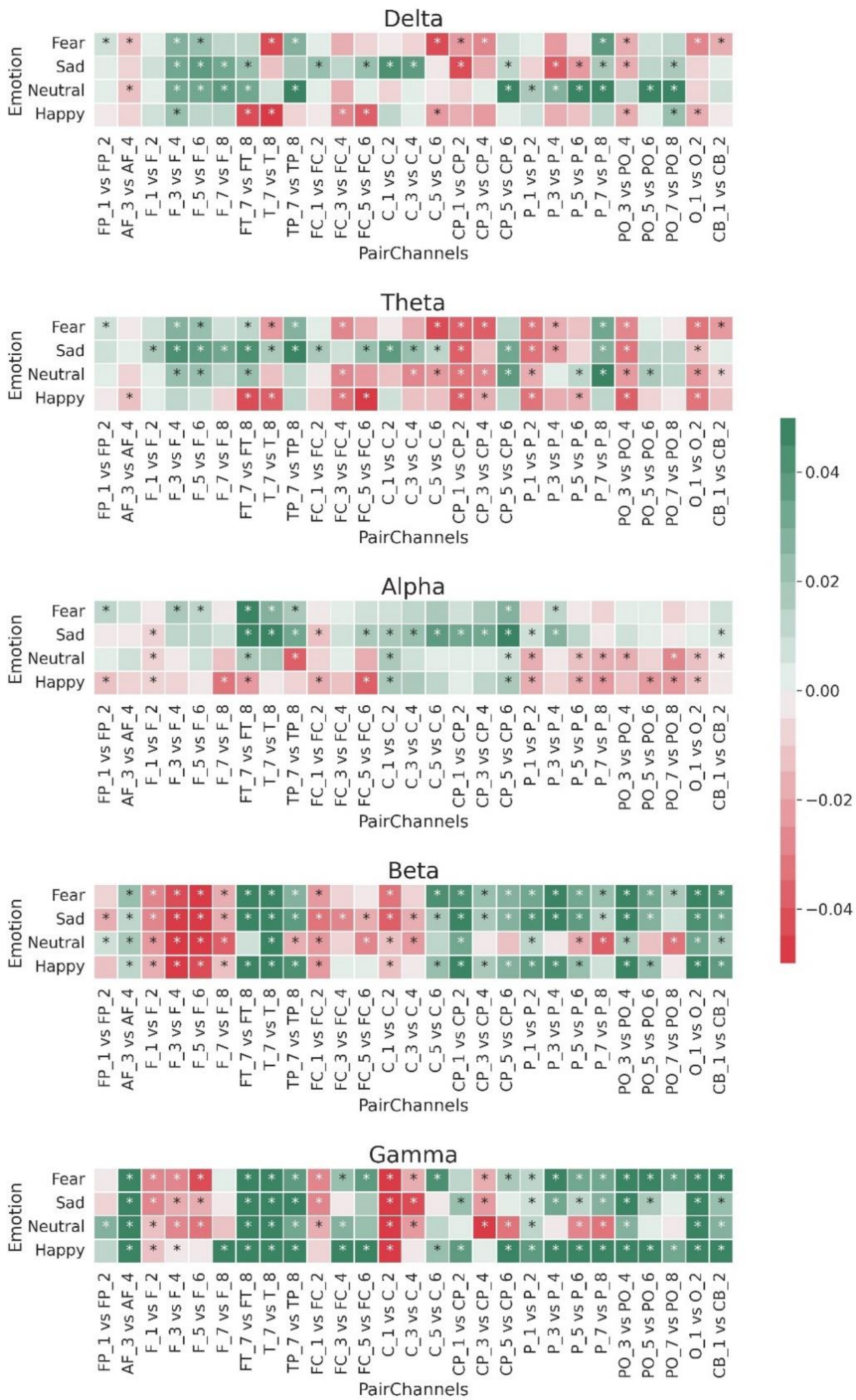

Figure 5.1
Median of logarithmic wavelet energy difference (Eq. 3) between the paired EEG electrodes for the five band frequencies: delta, theta, alpha, beta, and gamma. And * means that the difference was statistically significant (Bonferroni corrected p-value 0.00009 (0.05/540); Wilcoxon rank sum test).

5.2 Specific Objective 2: Predicting Models Analysis with Asymmetry Features

Tables 5.1, 5.2, and 5.3 show the recall for predicting the emotional states using the baseline and asymmetry features extracted with the PSD, DE, and DWT, respectively. In general, the classifiers trained with the baseline features obtained higher performance than the models trained with the asymmetry features. In detail, the overall recall for the baseline models for the different feature extraction techniques was between 31% and 33%, whereas the performance for the asymmetry models were around 28%. However, the models trained with the asymmetry features obtained a lower standard deviation throughout the five folds, thus suggesting less variance for classification across independent subjects.

The performance difference was significant only for the overall classification when using differential entropy-based features to train the random forest model. With regard to individual emotions, the baseline models performed better for all emotions except for predicting sadness whereas the asymmetry models surpassed the baseline models in seven out of nine cases. However, there were no significant differences in performance for individual emotions.

Regarding the different feature extraction techniques (PSD, DE, and DWT), features extracted with DE showed more differences between the baseline and asymmetry models, yielding the lowest p-values for the Dietterich's 5x2-Fold comparison. When comparing the overall performance of the classifiers, the gradient boosting tree model showed more differences when the models were trained using features extracted with the DWT and PSD. For DE-based features, only the random forest resulted in one significant difference. Notably, training asymmetry models required statistically significantly less time than training models using the baseline features. These significances were held for all nine cases, regardless of extraction technique and the classifier.

Table 5.1, Table 5.2, and Table 5.3 show the mean and standard deviation recall of the logistic regression (LR), random forest (RF), and gradient boosting tree (GB) for predicting neutral, sad, fear, happy, and overall emotions using the baseline and asymmetry features extracted using power spectrum density (PSD), differential entropy (DE), and discrete wavelet transform (DWT). The best result for each class is bolded. A $*$ indicates a statistically significant difference between the two features type using the Dietterich's 5x2-fold cross-validated paired t-test (two-sample t-test; Bonferroni corrected p-value 0.0033 (0.05/15)). The final column displays the time in seconds to train the baseline and asymmetry models, as well as the corresponding p-value for their comparison (two-sample Wilcoxon test). A † denotes that the Wilcoxon test p-value was significant.

Table 5.1

Mean and standard deviation recall with feature power spectral density.

Classifier	Model	Neutral	Sad	Fear	Happy	All	Time
LR	Baseline	34.5 (11.4)	**32.9 (8.7)**	**33.7 (12.8)**	**32.9 (8.4)**	**33.5 (1.7)**	22.60 (3.60)
	Asymmetry	**35.3 (5.2)**	30.7 (9.5)	19.5 (5.9)	25.5 (6.8)	27.8 (0.8)	7.36 (1.37)
	p-value	1.57	1.08	0.15	0.26	0.02	0.002†
RF	Baseline	**37.8 (11.4)**	27.3 (8.7)	**28.6 (12.8)**	**34.9 (8.4)**	**32.2 (1.7)**	713.3 (90.6)
	Asymmetry	32.2 (5.2)	**28.8 (9.5)**	22.7 (5.9)	30.2 (6.8)	28.5 (0.8)	534.9 (75.2)
	p-value	1.09	0.99	0.65	0.35	0.06	0.002†
GB	Baseline	**39.5 (11.4)**	25.5 (8.7)	**29.4 (12.8)**	**32.0 (8.4)**	**31.6 (1.7)**	114.7 (8.6)
	Asymmetry	30.7 (5.2)	**26.2 (9.5)**	29.1 (5.9)	22.6 (6.8)	27.1 (0.8)	58.1 (4.8)
	p-value	0.89	0.46	0.87	0.39	0.01	0.002†

Table 5.2

Mean and standard deviation recall with feature differential entropy.

Classifier	Model	Neutral	Sad	Fear	Happy	All	Time
LR	Baseline	**38.1 (11.5)**	24.0 (7.2)	**39.4 (13.9)**	**34.0 (6.3)**	**33.9 (1.1)**	24.8 (11.8)
	Asymmetry	33.8 (6.5)	**28.7 (13.2)**	26.2 (9.7)	19.6 (6.7)	27.1 (1.0)	10.3 (5.4)
	p-value	1.30	1.16	0.51	0.03	0.01	0.002†
RF	Baseline	**31.8 (11.5)**	12.3 (7.2)	**41.8 (13.9)**	**48.7 (6.3)**	**33.7 (1.1)**	540.3 (79.2)
	Asymmetry	23.5 (6.5)	**26.4 (13.2)**	23.4 (9.7)	35.4 (6.7)	27.2 (1.0)	434.7 (105.2)
	p-value	1.09	1.50	0.51	0.20	0.003*	0.002†
GB	Baseline	**35.1 (11.5)**	17.6 (7.2)	**37.1 (13.9)**	**41.4 (6.3)**	**32.8 (1.1)**	93.4 (15.2)
	Asymmetry	29.8 (6.5)	**27.2 (13.2)**	27.7 (9.7)	23.5 (6.7)	27.1 (1.0)	47.8 (7.8)
	p-value	1.08	1.95	0.46	0.15	0.01	0.002†

Table 5.3

Mean and standard deviation recall with feature discrete wavelet transform.

Classifier	Model	Neutral	Sad	Fear	Happy	All	Time
LR	Baseline	34.9 (9.8)	32.2 (8.1)	**33.5 (13.2)**	**33.4 (7.2)**	**33.5 (1.2)**	22.4 (9.3)
	Asymmetry	**34.9 (6.0)**	**31.9 (8.6)**	24.1 (7.9)	21.0 (4.7)	28.0 (1.3)	10.3 (7.6)
	p-value	1.63	1.40	0.18	0.16	0.05	0.002†
RF	Baseline	**36.4 (9.8)**	27.6 (8.1)	**28.8 (13.2)**	**37.5 (7.2)**	**32.6 (1.2)**	761.2 (237.7)
	Asymmetry	34.4 (6.0)	**29.5 (8.6)**	18.5 (7.9)	31.5 (4.7)	28.5 (1.3)	584.5 (208.4)
	p-value	1.01	1.72	0.36	0.09	0.09	0.002†
GB	Baseline	**38.5 (9.8)**	**28.5 (8.1)**	**25.4 (13.2)**	**33.4 (7.2)**	**31.5 (1.2)**	120.2 (36.6)
	Asymmetry	35.0 (6.0)	26.3 (8.6)	23.4 (7.9)	27.5 (4.7)	28.1 (1.3)	66.5 (34.6)

	p-value	0.86	1.49	0.45	0.35	0.01	0.002†

5.3 Specific Objective 3: Relevant Asymmetry Features for Emotion Prediction

Table 5.4, Table 5.5, Table 5.6 and

Table 5.7 present the performance metrics for the binary logistic regression models across the 15 subjects. The sensitivity (the accuracy for correctly detecting samples from the emotion of interest) and the specificity (the accuracy for correctly detecting samples not from the emotion of interest) exhibited variability across the subjects, with a mean sensitivity between 49% and 52%, and a mean specificity between 51% and 60%. The G-mean, a metric that combines these two metrics while considering data imbalance, obtained a mean value of 58%, 56%, 55%, and 55% for the neutral, sad, fear, and happy models, respectively. The ROC-AUC score showed a similar classification capacity for the models, with a mean value of 55% for neutral, 55% for sad, 52% for fear, and 58% for happy. The NPV, which indicates the precision in detecting samples that were not from the emotion of interest, exhibited the best performance across the four models, with an average value between 76% and 82%. This result suggests that the models were accurate in detecting samples that were not from the emotion of interest. The mean performance of the eight metrics for the training and testing sets were similar, indicating low overfitting during the training process.

Table 5.4

Sensitivity (Sen.), specificity (Spe.), Positive Predictive Value (PPV), Negative Predictive Value (NPV), F1-score, Geometric Mean (G-Mean), the area under the curve of the Receiver Operating Characteristics (AUC-ROC) and the area under the precision-recall curve (AUC-PR) for predicting **Neutral** across the 15 subjects.

Subject	**Sen (%)**		**Spe (%)**		**PPV (%)**		**NPV (%)**		**F1-score (%)**		**G-Mean (%)**		**AUC-ROC (%)**		**AUC-PR (%)**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	49.1%	35.3%	62.2%	64.3%	32.5%	26.8%	76.7%	72.8%	39.1%	30.4%	55.2%	47.6%	58.0%	50.3%	34.7%	25.9%
2	51.0%	54.0%	60.6%	47.1%	32.4%	27.5%	76.9%	73.4%	39.6%	36.4%	55.6%	50.4%	58.3%	50.1%	34.8%	26.9%
3	51.2%	71.2%	59.2%	37.8%	31.8%	29.8%	76.6%	78.0%	39.2%	42.1%	55.0%	51.9%	57.9%	58.4%	34.0%	36.2%

4	51.2%	59.0%	60.5%	47.7%	32.5%	29.5%	77.0%	75.8%	39.8%	39.4%	55.7%	53.1%	58.1%	56.1%	34.0%	33.2%
5	52.7%	33.5%	60.9%	72.7%	33.3%	31.3%	77.6%	74.7%	40.8%	32.4%	56.6%	49.4%	59.3%	54.9%	34.9%	32.3%
6	53.1%	36.0%	60.1%	76.5%	33.1%	36.2%	77.6%	76.3%	40.8%	36.1%	56.5%	52.5%	59.4%	61.1%	34.7%	40.0%
7	50.7%	67.0%	60.7%	48.9%	32.4%	32.7%	76.9%	80.0%	39.5%	44.0%	55.5%	57.2%	57.9%	62.1%	34.3%	37.5%
8	53.6%	45.7%	59.8%	59.2%	33.1%	29.4%	77.7%	74.6%	40.9%	35.8%	56.6%	52.0%	59.7%	54.5%	35.0%	30.1%
9	59.9%	66.8%	50.8%	46.3%	31.2%	31.6%	77.4%	79.0%	41.0%	42.9%	55.2%	55.6%	58.2%	60.9%	34.3%	39.0%
10	54.0%	41.6%	60.4%	51.9%	33.6%	24.3%	78.0%	70.5%	41.4%	30.7%	57.1%	46.5%	60.0%	44.4%	35.9%	25.0%
11	59.5%	71.2%	53.6%	35.1%	32.2%	29.0%	78.1%	76.7%	41.8%	41.2%	56.5%	50.0%	59.5%	54.0%	34.7%	28.7%
12	49.1%	72.1%	60.3%	43.6%	31.5%	32.2%	76.1%	80.8%	38.3%	44.5%	54.4%	56.1%	56.7%	62.7%	32.9%	39.8%
13	60.5%	41.6%	51.9%	62.2%	31.8%	29.0%	78.0%	74.2%	41.7%	34.2%	56.0%	50.9%	58.8%	53.2%	34.8%	29.1%
14	59.5%	38.9%	52.6%	66.1%	31.8%	29.9%	77.8%	74.5%	41.4%	33.8%	55.9%	50.7%	59.0%	52.9%	35.3%	29.5%
15	54.7%	37.2%	59.6%	62.0%	33.4%	26.6%	78.0%	72.7%	41.5%	31.0%	57.1%	48.0%	59.9%	51.8%	34.7%	28.1%
Mean	54.0%	51.4%	58.2%	54.8%	32.4%	29.7%	77.3%	75.6%	40.5%	37.0%	55.9%	51.5%	58.7%	55.1%	34.6%	32.1%

Table 5.5

Sensitivity (Sen.), Specificity (Spe.), Positive Predictive Value (PPV), Negative Predictive Value (NPV), F1-score, Geometric Mean (G-Mean), the area under the curve of the Receiver Operating Characteristics (AUC-ROC) and the area under the precision-recall curve (AUC-PR) for predicting **Sad** across the 15 subjects.

Subject	**Sen (%)**		**Spe (%)**		**PPV (%)**		**NPV (%)**		**F1-score (%)**		**G-Mean (%)**		**AUC-ROC (%)**		**AUC-PR (%)**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	53.4%	72.9%	56.8%	57.6%	31.6%	39.2%	76.5%	85.0%	39.7%	51.0%	55.1%	64.8%	57.3%	70.3%	33.4%	44.9%
2	54.1%	41.1%	57.9%	67.1%	32.5%	31.9%	77.1%	75.2%	40.6%	35.9%	55.9%	52.5%	58.2%	56.6%	34.3%	31.1%
3	54.8%	61.1%	57.3%	41.4%	32.5%	28.1%	77.2%	73.9%	40.8%	38.5%	56.1%	50.3%	58.8%	51.2%	34.8%	27.3%
4	54.1%	52.6%	57.9%	48.4%	32.5%	27.6%	77.1%	73.1%	40.6%	36.2%	56.0%	50.4%	58.7%	51.1%	34.5%	29.0%
5	54.9%	35.9%	58.2%	70.6%	33.0%	31.4%	77.5%	74.6%	41.2%	33.5%	56.6%	50.3%	59.3%	52.8%	34.8%	32.0%
6	54.5%	30.5%	58.9%	70.4%	33.2%	27.8%	77.5%	73.0%	41.3%	29.1%	56.7%	46.3%	59.4%	51.8%	35.0%	27.7%
7	52.9%	48.8%	58.0%	59.7%	32.1%	31.2%	76.7%	75.7%	39.9%	38.1%	55.4%	54.0%	57.8%	57.1%	34.4%	32.1%
8	53.8%	56.5%	58.3%	49.0%	32.6%	29.3%	77.1%	75.0%	40.6%	38.6%	56.0%	52.6%	58.7%	53.6%	34.4%	28.4%

9	54.1%	36.2%	57.9%	70.7%	32.5%	31.7%	77.1%	74.7%	40.6%	33.8%	55.9%	50.6%	58.6%	55.0%	34.0%	30.5%
10	53.6%	66.0%	57.6%	38.6%	32.2%	28.7%	76.8%	75.2%	40.2%	40.0%	55.6%	50.5%	58.1%	55.0%	34.2%	31.4%
11	54.4%	32.5%	58.6%	67.7%	33.0%	27.4%	77.4%	72.8%	41.1%	29.7%	56.5%	46.9%	59.2%	49.6%	34.6%	27.3%
12	54.5%	47.6%	57.2%	50.9%	32.3%	26.6%	77.0%	72.1%	40.5%	34.2%	55.8%	49.2%	58.4%	49.3%	34.0%	29.6%
13	54.1%	39.8%	57.8%	73.8%	32.4%	36.3%	77.1%	76.6%	40.6%	38.0%	55.9%	54.2%	58.1%	60.6%	33.5%	39.0%
14	54.0%	49.5%	55.3%	66.4%	31.2%	35.5%	76.2%	77.8%	39.5%	41.4%	54.7%	57.3%	56.7%	59.7%	32.1%	35.4%
15	54.1%	57.8%	59.0%	37.4%	33.1%	25.7%	77.4%	70.3%	41.1%	35.6%	56.5%	46.5%	59.4%	48.0%	34.8%	26.2%
Mean	54.1%	48.6%	57.8%	58.0%	32.4%	30.6%	77.0%	75.0%	40.6%	36.9%	55.9%	51.8%	58.5%	54.8%	34.2%	31.5%

Table 5.6

Sensitivity (Sen.), Specificity (Spe.), Positive Predictive Value (PPV), Negative Predictive Value (NPV), F1-score, Geometric Mean (G-Mean), the area under the curve of the Receiver Operating Characteristics (AUC-ROC) and the area under the precision-recall curve (AUC-PR) for predicting **Fear** across the 15 subjects.

Subject	**Sen (%)**		**Spe (%)**		**PPV (%)**		**NPV (%)**		**F1-score (%)**		**G-Mean (%)**		**AUC-ROC (%)**		**AUC-PR (%)**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	55.4%	34.0%	54.2%	71.9%	28.2%	28.2%	78.9%	77.0%	37.4%	30.8%	54.8%	49.4%	57.1%	56.1%	29.0%	27.2%
2	55.9%	49.6%	54.6%	48.1%	28.6%	23.7%	79.2%	74.6%	37.8%	32.1%	55.2%	48.9%	57.4%	48.6%	29.4%	23.1%
3	55.9%	40.7%	54.1%	47.9%	28.4%	20.2%	79.1%	71.3%	37.7%	27.0%	55.0%	44.1%	57.2%	42.3%	30.0%	20.5%
4	56.2%	41.5%	54.9%	66.1%	28.8%	28.5%	79.4%	77.6%	38.1%	33.8%	55.5%	52.3%	57.5%	55.1%	29.1%	26.9%
5	56.7%	67.8%	55.3%	31.0%	29.2%	24.2%	79.7%	74.7%	38.6%	35.7%	56.0%	45.8%	58.3%	49.0%	29.8%	23.7%
6	56.2%	52.8%	54.4%	51.4%	28.6%	26.1%	79.3%	77.0%	38.0%	35.0%	55.3%	52.1%	57.7%	52.3%	29.3%	28.1%
7	56.5%	36.9%	54.2%	67.8%	28.6%	27.2%	79.3%	76.8%	38.0%	31.3%	55.3%	50.0%	57.7%	54.3%	29.5%	26.0%
8	56.1%	50.2%	55.2%	50.7%	29.0%	24.9%	79.4%	75.8%	38.2%	33.3%	55.7%	50.5%	57.9%	51.3%	29.8%	26.1%
9	55.7%	66.5%	54.7%	44.0%	28.6%	27.9%	79.1%	80.1%	37.8%	39.3%	55.2%	54.1%	57.3%	56.7%	29.3%	27.6%
10	54.7%	35.1%	54.8%	62.9%	28.2%	23.6%	78.8%	74.9%	37.2%	28.2%	54.7%	47.0%	56.7%	48.7%	28.8%	24.4%
11	56.3%	55.9%	54.0%	52.1%	28.5%	27.5%	79.2%	78.4%	37.8%	36.9%	55.2%	54.0%	57.5%	54.4%	29.7%	25.5%
12	56.8%	73.2%	53.7%	42.7%	28.5%	29.4%	79.2%	83.0%	38.0%	41.9%	55.2%	55.9%	57.1%	61.1%	29.5%	34.8%
13	54.9%	66.8%	55.2%	34.2%	28.5%	24.8%	79.0%	76.0%	37.5%	36.2%	55.1%	47.8%	57.5%	48.4%	29.3%	22.8%

14	56.2%	88.5%	53.6%	18.7%	28.3%	26.2%	79.0%	83.3%	37.6%	40.4%	54.9%	40.7%	56.8%	50.7%	28.5%	23.0%
15	55.5%	23.7%	54.5%	82.3%	28.4%	30.4%	79.0%	76.8%	37.6%	26.6%	55.0%	44.2%	56.5%	56.9%	28.4%	28.3%
Mean	55.9%	52.2%	54.5%	51.5%	28.6%	26.2%	79.2%	77.2%	37.8%	33.9%	55.2%	49.1%	57.3%	52.4%	29.3%	25.9%

Table 5.7

Sensitivity (Sen.), Specificity (Spe.), Positive Predictive Value (PPV), Negative Predictive Value (NPV), F1-score, Geometric Mean (G-Mean), the area under the curve of the Receiver Operating Characteristics (AUC-ROC) and the area under the Precision-Recall curve (AUC-PR) for predicting **Happy** across the 15 subjects.

Subject	**Sen (%)**		**Spe (%)**		**PPV (%)**		**NPV (%)**		**F1-score (%)**		**G-Mean (%)**		**AUC-ROC (%)**		**AUC-PR (%)**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	56.5%	72.2%	58.0%	47.1%	26.5%	26.8%	83.3%	86.4%	36.1%	39.1%	57.2%	58.3%	59.9%	64.2%	27.9%	32.7%
2	56.5%	80.2%	56.7%	43.7%	25.9%	27.6%	83.0%	89.2%	35.5%	41.1%	56.6%	59.2%	59.2%	69.7%	28.6%	41.5%
3	57.0%	13.6%	59.1%	85.4%	27.2%	19.9%	83.7%	78.7%	36.8%	16.2%	58.0%	34.1%	61.3%	55.6%	29.5%	22.1%
4	56.3%	44.2%	57.6%	73.4%	26.2%	30.8%	83.1%	83.1%	35.8%	36.3%	56.9%	57.0%	59.9%	62.4%	28.8%	29.4%
5	56.9%	56.5%	58.0%	43.5%	26.6%	21.1%	83.4%	78.9%	36.2%	30.8%	57.4%	49.6%	60.5%	50.9%	29.7%	22.4%
6	56.5%	70.1%	56.8%	56.6%	25.9%	30.2%	83.0%	87.6%	35.5%	42.2%	56.6%	63.0%	59.5%	69.1%	28.5%	35.6%
7	56.6%	54.8%	57.4%	47.7%	26.2%	21.9%	83.2%	79.8%	35.8%	31.3%	57.0%	51.1%	59.9%	53.5%	29.1%	25.9%
8	56.9%	51.8%	56.7%	63.1%	26.0%	27.3%	83.1%	83.0%	35.7%	35.8%	56.8%	57.2%	59.8%	58.2%	28.7%	40.6%
9	57.1%	60.3%	57.6%	48.3%	26.5%	23.8%	83.4%	82.0%	36.2%	34.1%	57.4%	54.0%	60.5%	57.1%	28.8%	27.5%
10	56.7%	39.3%	57.9%	63.8%	26.5%	22.5%	83.3%	79.7%	36.1%	28.7%	57.3%	50.1%	60.2%	52.3%	29.6%	21.8%
11	57.5%	13.8%	56.6%	72.3%	26.2%	11.8%	83.2%	75.8%	36.0%	12.7%	57.0%	31.6%	59.4%	40.4%	27.4%	16.8%
12	56.7%	69.2%	59.0%	52.7%	27.0%	28.2%	83.6%	86.5%	36.6%	40.0%	57.8%	60.4%	60.7%	66.5%	29.5%	34.9%
13	57.0%	34.0%	60.2%	69.2%	27.7%	22.8%	84.0%	79.7%	37.3%	27.3%	58.6%	48.5%	62.2%	51.8%	30.7%	27.3%
14	56.5%	62.4%	56.9%	52.8%	26.0%	26.1%	83.0%	84.0%	35.6%	36.8%	56.7%	57.4%	59.1%	59.5%	27.3%	23.6%
15	58.1%	35.7%	58.7%	77.3%	27.3%	29.6%	83.9%	81.8%	37.2%	32.4%	58.4%	52.5%	61.8%	58.3%	30.8%	28.1%
Mean	56.9%	50.5%	57.8%	59.8%	26.5%	24.7%	83.3%	82.4%	36.2%	32.3%	57.3%	52.3%	60.3%	58.0%	29.0%	28.7%

Figure 5.2 shows the average coefficients of the logistic regression models for each emotion across the 15 folds of the LOGO cross-validation. The number of positive coefficients (red cells) was slightly higher than the number of negative coefficients (blue cells). Most of the average coefficients resulted in a value of 0 (312 out of 540), indicating their low relevance for predicting emotions. The median log-ratios of all the pairs across the frequency bands showed predominantly positive values (more ‘l’ than ‘r’), suggesting that left channels generally had higher relative energy compared to the right channels.

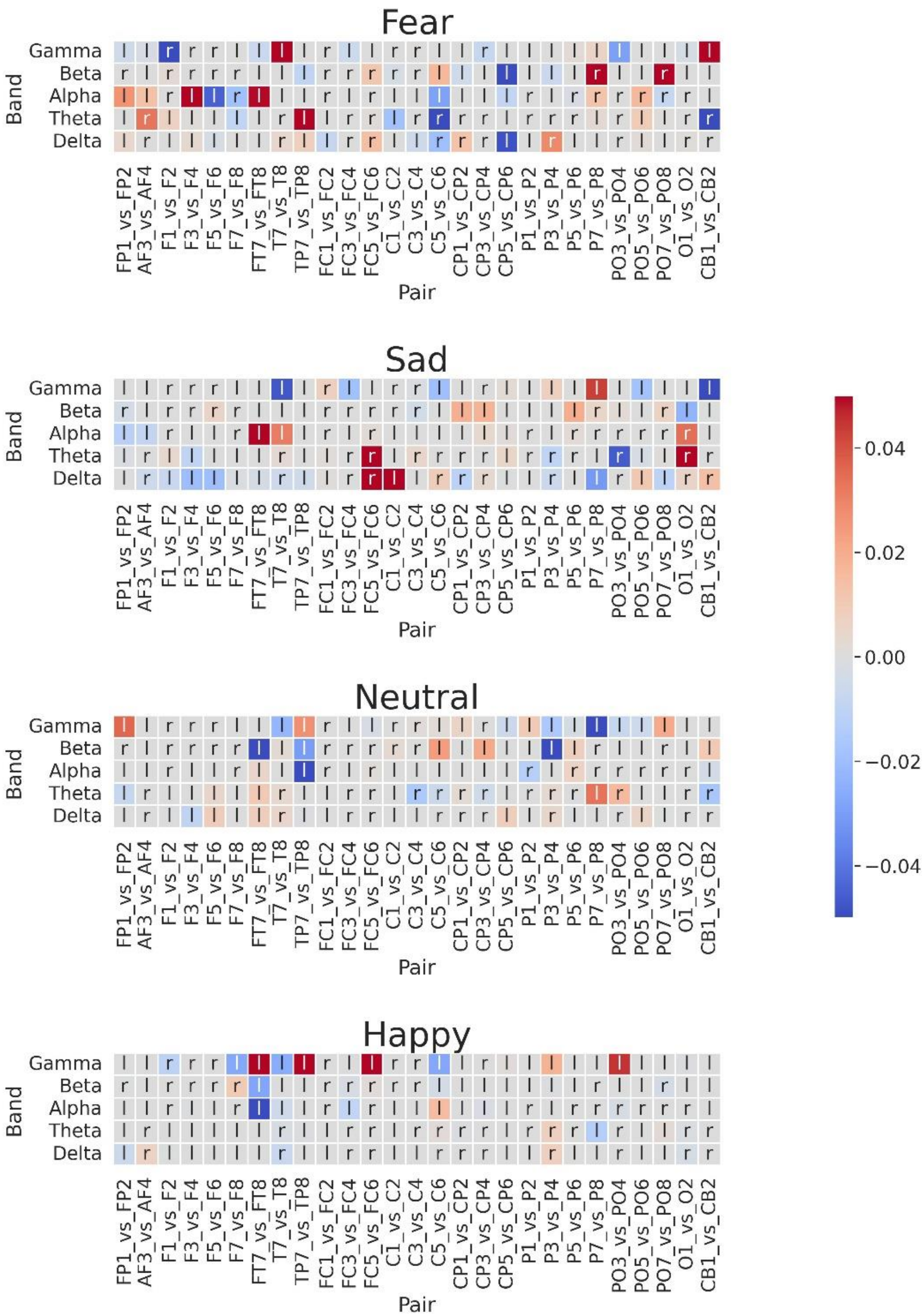

Figure 5.2 Average coefficients for the logistic regression models trained with the asymmetry log-ratio features for each individual class: fear, sad, neutral, and happy. The letter included in each cell indicates left ('l') when the median value of the asymmetry log-ratio feature (Eq. 2) across the subjects was greater than 0, and right ('r') when such a value was lower than 0.

The coefficient values varied depending on the frequency band, with gamma and alpha showing the most contrasting coefficient values for happiness, sadness, and fear. For the gamma band, the average logistic regression coefficients of the EEG pairs FC5/FC6, TP7/TP8, and FT7/FT8 were higher than 0 for predicting happiness but not for predicting sadness and fear. However, sadness and fear also exhibited an opposite pattern for the EEG pairs T7/T8 and CB1/CB2. Notably, in the alpha bands, the coefficients for predicting happiness, sadness, and fear were opposite, particularly in the frontal area for FT7/FT8.

For the neutral emotion, the pair FP1/FP2 obtained the coefficient with the highest value in the gamma band. In the gamma band, the P7/P8 pair resulted in a positive coefficient for predicting sad and fear emotions, but in a negative coefficient for predicting neutral emotion. Additionally, the OP3/OP4 coefficient in the same band was positive for predicting happiness but negative for predicting neutral emotions.

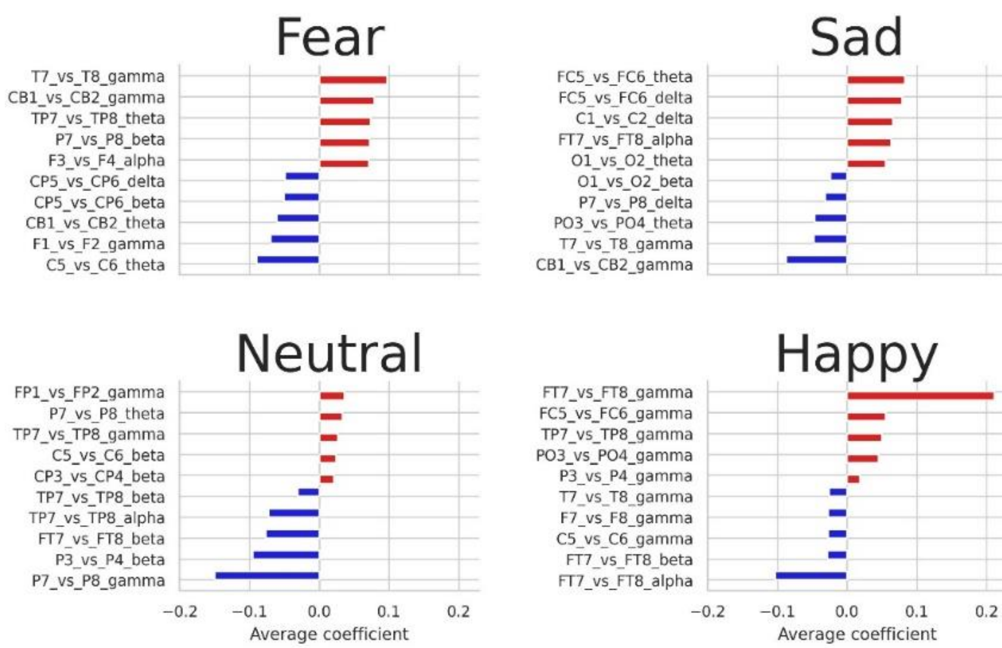

Figure 5.3 Highest and lowest five average coefficients for predicting fear, sadness, neutral, and happiness.

5.3.1 Relevant EEG Channels for Predicting Emotions

Figure 5.3 shows the highest and lowest average coefficients for predicting fear, sadness, neutral, and happiness. The most relevant frequency band for the classification of the different emotions was the gamma band, where energy log-ratios were found to be the most relevant features. Additionally, asymmetry features extracted from the beta frequency band were also relevant, especially for predicting samples that do not belong to the emotion of interest (specificity of the binary logistic regression models).

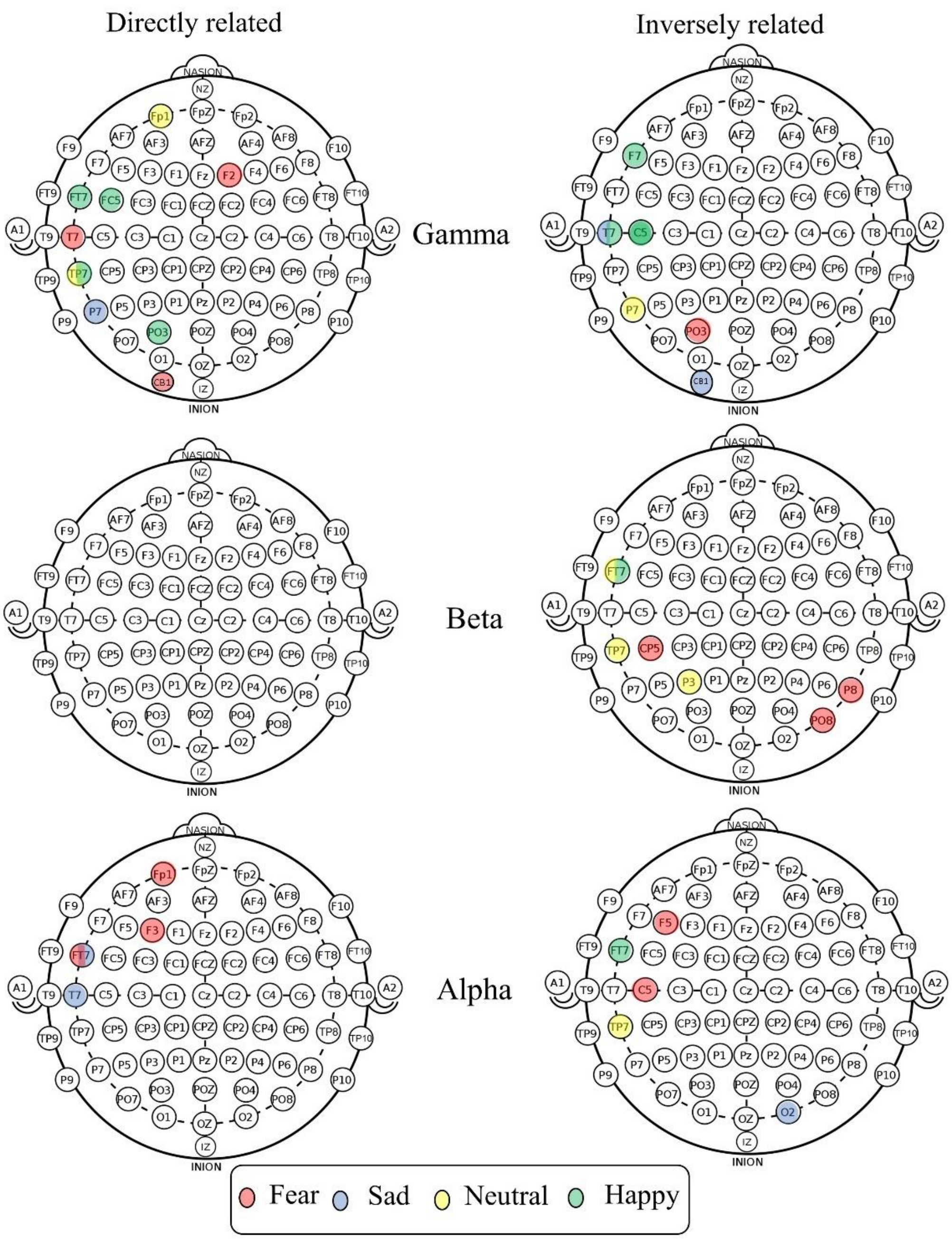

Figure 5.4 Direct and inverse relations in the higher frequency bands (gamma, beta, and alpha) for EEG channels and fear (red), sadness (blue), neutral (yellow), and happiness (green).

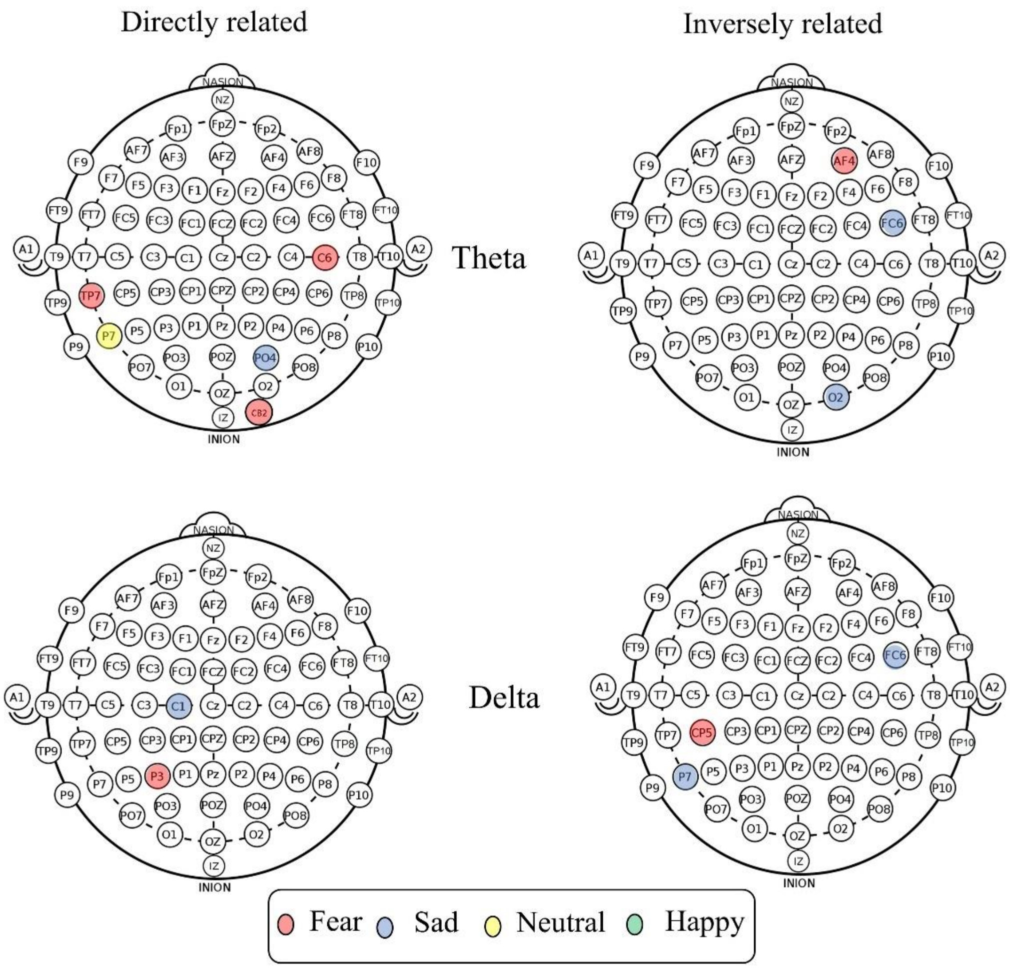

Figure 5.5 Direct and inverse relations in the lower frequency bands (theta, and delta) for EEG channels and fear (red), sadness (blue), neutral (yellow), and happiness (green).

Figure 5.4 and Figure 5.5 show the direct and inverse relationships, respectively, for the higher and lower frequency bands between all EEG channels and emotions using the highest positive coefficients and lowest negative coefficients Gamma and alpha were the frequency bands showing more associations between the emotions and relative energy of EEG channels. Most of these relationships were located in the lateral frontal, temporal, and parietal areas. Specifically, in the gamma band, greater relative energy values of T7 over T8 were9 directly related to fear and inversely related to happiness and sadness. In contrast, greater relative energy values of left EEG channel PO3 over the right EEG channel PO4 were directly related to happiness and inversely related to fear. Notably, in the alpha band, higher values of the positive energy log-ratio between FT7 and FT8 were directly related to sadness and fear, while inversely related to happiness. The beta band showed only inverse relations between the EEG channels and the emotions of interest. The lower frequency, theta and delta mostly indicated direct and inverse relationships for the negative emotions (sad and fear).

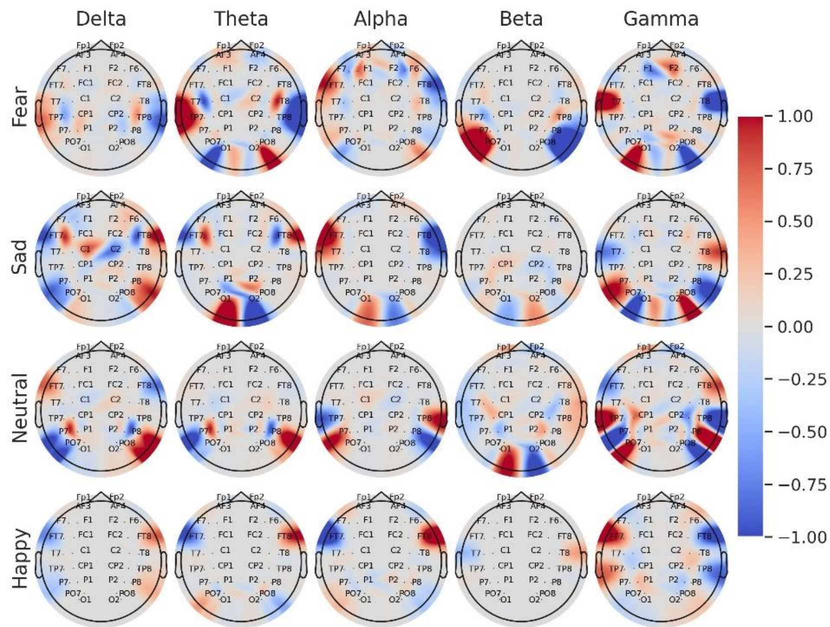

Figure 5.6
Brain topography of EEG channels and frequency bands relevant to individual emotion processing.

In Figure 5.6, Brain topography of the normalized average coefficients for logistic regression models trained with asymmetry log-ratio features for predicting each individual class, fear, sadness, neutrality, and happiness. The color tones represent the associations between the energy of the EEG channel and the emotion. Red tones indicate a direct association between the energy of the EEG channel and the emotion, whereas blue tones indicate an inverse association. Notably, most of the associations between the emotions and the energy of EEG channels were located in the lateral frontal, temporal, and parietal areas. Specifically, in the gamma band, greater relative energy values of T7 were directly related to fear and inversely related to happiness and sadness. In contrast, greater relative energy values of the left EEG channel FT7, TP7, and PO3 were directly related to happiness and inversely related to fear. Notably, in the alpha band, higher values of energy in the channel FT7 were directly related to sadness and fear, while inversely related to happiness. The lower frequency bands, theta, and delta mostly indicated direct and inverse relationships for the negative emotions (sad and fear).

5.4 Summary

It is important to understand the workings of our emotions and how they are processed, and this chapter shed light on that. Since this study delved into the various experiments here analyze their outcomes to gain insights into how emotions are processed along with the significance of all findings from those experiments.

With the help of the red and green colours, this study is able to explore various views of the brain asymmetricity for different EEG frequency bands. Also, this study showed the involvement of the frontal brain region and supported both the brain asymmetry model 'valence lateralization' and FAA theory. Besides, his research has indicated that asymmetry features can be quite valuable for creating a comparable model for emotion recognition. One of the main advantages of using asymmetry features is that they have a smaller feature vector size, which makes them more efficient for computational purposes. Furthermore, through the use of asymmetry features, we can discover that the gamma and alpha bands play a significant role in processing emotions. By analyzing the asymmetry features involvement, we can also find each EEG frequency band's direct and inverse involvement in processing positive, negative, and neutral emotions.

Chapter 6 Conclusion

Our work indicates that brain hemispheres and frequency bands participated differently in processing happiness, sadness, fear, and neutrality. Unlike the 'right-dominance' and the 'valence lateralization' models, we found that the involvement of the hemisphere is more related to the frequency bands. For the higher frequency bands (gamma and beta), the left hemisphere EEG channels exhibited higher relative energy than their right counterparts. Conversely, for the lower frequency bands (theta and delta), the relative energy of the right hemisphere EEG channels was higher than that of the left EEG channels. Also. asymmetry features can provide comparable performance for predicting emotion from EEG signals instead of using individual features from a single channel.

6.1 Discussion

This research study involves utilizing the relative energy extracted with the DWT to describe the brain asymmetry relations involved in processing happiness, sadness, fear, and neutrality. The findings from the logistic regression analysis indicate that all the frequency bands were involved in the emotion predictions, with the gamma band being the most relevant one. Furthermore, the feature selection algorithm and the elastic-net regularization technique discarded most of the asymmetry energy log-ratio features, suggesting that asymmetry from all the EEG electrodes is not necessary to make accurate predictions. Instead, the average logistic regression coefficients suggest that the most relevant EEG channels for predicting emotional states are located in the lateral frontal, temporal, and parietal regions, including FP1/FP2, FT7/FT8, T7/T8, TP7/TP8, P7/P8, and PO3/PO4. These findings provide valuable insights into the brain regions involved in emotional processing and may have important implications for developing more accurate and efficient models for emotion recognition using EEG signals.

The results of the emotion prediction model presented in this study suggest that incorporating asymmetry features can achieve statistically comparable performance for predicting neutral, sadness, fear, and happiness from EEG signals compared to using information from individual EEG nodes. Specifically, comparable accuracy performance can be achieved by training a supervised machine learning models with features extracted using PSD or DWT. Notably, the asymmetry-feature approach can achieve this comparable performance using a feature vector of half size (135 vs. 270), requiring around 30% less computational time. Moreover, the lower variance of the asymmetry-feature approach suggests that it is a more stable approach for predicting emotions across independent subjects.

The comparable performance obtained between the baseline and asymmetry models indicates that considering brain lateralization is feasible for designing emotion recognition approaches. Thus, using features that reflect the brain hemisphere asymmetry allows the inclusion of domain knowledge to facilitate emotion classification. This highlights the continued relevance of feature engineering, which has been underappreciated in recent years with the emergence of deep learning.

Regarding the comparison between negative and positive emotions, the findings of this study suggest that happiness is more opposite to fear than sadness. In detail, our logistic regression analysis showed a contradictory behavior between the coefficients for the EEG pairs in the gamma band for predicting happiness and fear. Specifically, the results suggest that higher positive values of the log-ratios PO3/PO4 in the gamma band increase the likelihood of a subject experiencing happiness and decrease the likelihood of experiencing fears. In contrast, higher values of the log-ratio T7/T8 in the gamma band increase the probability of a subject experiencing fear and decrease the probability of experiencing happiness. Similarly, for the alpha band, higher positive values of FT7/FT8 is directly related to identifying fear and inversely related to identifying happiness. Given that happiness and fear are emotions with high arousal, whereas sadness is an emotion with low arousal, it seems that the asymmetry lateralization is more pronounced for emotions that have opposite valence but higher arousal levels.

The distinct behavior shown in the alpha band between the positive (happy) and negative (sad and fear) emotions are consistent with the FAA analysis [BTHJ13]. Higher electrical activation on the frontal right hemisphere channels (FP2, F4, F6) for processing happiness indicates a large cortical resource allocation on the left hemisphere. Therefore, the left hemisphere is more involved in processing positive emotions. Similarly, higher activation on the left frontal channels (FP1, F3, F5) for sadness and fear indicates more involvement of the right hemisphere to process negative emotions. This similarity is explained by the fact that the FAA is the logarithmic difference between the power of the two hemispheres, while our asymmetry feature is the logarithmic difference between the energy of the two hemispheres. Therefore, given that power is the amount of energy divided by time, there is a natural correlation between FAA and our asymmetry feature for the alpha band.

In regard to previous work, the findings from this study also support the importance of the gamma and beta bands in processing emotions (see Figure 5.3), as previously reported by Zheng and Lu [ZhLu15]. Also, the results are consistent with them, which showed a lower performance of asymmetry features compared to a model using the differential entropy (DE) of individual EEG channels (28% vs. 33%). However, unlike them, we demonstrated that these differences are not statistically significant, and that comparable performance can be achieved using fewer features and less computational time. The findings also provide statistical evidence supporting the effectiveness of incorporating asymmetric differential information into EEG-based emotion recognition approaches, as shown in previous works [LWZZ21, PaWP19].

Additionally, logistic regression analysis of this study identified the ratios T7/T8, FT7/FT8, and FC5/FC6 as relevant EEG pairs to discriminate between positive and negative emotions, which is consistent with Pane et al. [PaWP19], who found that brain activity extracted from the pairs T7-T8, C3-C4, and O1-O2 was important for classifying different emotional states. Finally, the results are in line with Zheng et al. [ZLLL18], who also reported that neural information from the EEG nodes located in the frontal region, such as Fp1-Fp2, FT7-FT8, and FC5-FC6, is one of the most relevant for predicting different emotional states.

The interpretability of the logistic regression model allowed us to identify the relevant asymmetry relationship between EEG pairs and frequency bands for processing happiness, sadness, fear, and neutrality. This interpretability is an advantage over previous studies that used deep learning models [LWZZ21, ZhLu15], which obtained higher predictive performance, but from which it is difficult to identify patterns associated with emotion processing. Moreover, the subject-independent approach used in our work allows for identifying shared patterns for the 15 subjects included in the dataset, thus helping to identify general patterns of emotion processing that may be present across subjects.

6.2 Limitation and Future Plan

It is important to note that this research work was based on a single dataset [ZLLL18]. However, this approach can be extended to different datasets with more emotional states and subjects. When extending the work to other datasets, it's essential to incorporate modifications to the emotion classes. Moreover, adjustments to the naming of asymmetry features will be necessary if the number of channels varies from the SEED-IV dataset. We also note that the accuracy rates were lower than those obtained by the deep learning models [LWZZ21].

Another limitation of this work is that the model performances were not comparable to [LWZZ21], in which their deep learning model achieved an accuracy of around 69% for the same dataset used in this study. However, the focus of this study was more on validating whether asymmetry of the brain hemispheres can benefit emotion recognition approaches rather than building a predictive model for classification purposes. Nevertheless, the performance was similar to approaches using non-deep learning models such as Bayesian models, least-squares, and SVM [ChTC16, KaHS09, SNKB07, SuVa99], whose range was between 31% and 37%, as reported in [SuRH07]. Future work should investigate how asymmetry features can be incorporated into deep learning architectures to improve the performance of emotion recognition systems. Renowned deep learning architectures such as GANs, LSTMs, RNNs, CNNs, Autoencoders, and Deep Reinforcement Learning can effectively handle the intricacies of complex datasets. When incorporating asymmetry features into deep learning models, the complexity of the data from the asymmetry features should be carefully considered. Determining the optimal number of hidden layers is crucial to prevent issues like overfitting. The selection of an appropriate architecture type should align with the research objectives. Additionally, apart from supervised and unsupervised learning, deep learning encompasses reinforcement learning, which not only explores the model but also suggests the best possible action for a given scenario.

Nevertheless, the performance is within the expected range for non-deep learning models, such as Bayesian models, least-squares, and SVM, aiming for subject-independent predictions, as reported in Li et al. [LWZZ21]. The lower metric performances might be a consequence of using a logistic regression model, a predictive model with high interpretability but lower performance rates than deep learning models [ADSB20]. Future studies could attempt to solve this issue by using predictive models that have a balance between accuracy and interpretability, such as fuzzy modeling. This might be useful in improving the performance of emotion recognition as well as preserving interpretability.

6.3 Summary

This study aims to investigate the relationship between asymmetry EEG pairs and frequency bands for processing happiness, sadness, fear, and neutrality. Also, here compares two approaches for predicting emotions from EEG signals, finding that an approach using asymmetry features based on brain lateralization can perform comparably to an approach using information from individual EEG nodes.

The results indicated that the gamma and alpha bands in the frontal and temporal regions were more relevant in differentiating and predicting positive and negative emotions. Regarding neuroscience models, our findings support both models, but at different frequency bands. Specifically, for lower frequency bands (delta and theta), the right hemisphere was more involved in processing emotions, while for the alpha band, this study found the valence lateralization of emotion processing more relevant. Besides the comparable performance obtained between the baseline and asymmetry models indicate that asymmetry logarithmic ratios are reliable features for predicting emotions. By using asymmetry EEG pair ratios, it is possible to achieve comparable accuracy performances using a feature vector of half size (135 vs. 270), reducing the number of features and computational cost required to build emotion recognition approaches. Overall, this research results provide insights into the brain regions and frequency bands that need to be considered when developing predictive models for emotion recognition.

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