Emotion Recognition using Brian Signals based on Time-Frequency Analysis and Supervised Learning Algorithm

by

Prommy Sultana Ferdawoos Hossain (ID: 16241002)
Istiaque Mannafee Shaikat (ID: 14101072)
Fabian Parsia George (ID: 14301059)

Supervisor
Dr. Jia Uddin

Co-Supervisor
Dr. Mohammad Zavid Parvez

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Dedicated to all our loved ones for their love and inspiration

BRAC University

STATEMENT OF THESIS AUTHORSHIP

We hereby declare that this is our own work to the best of our knowledge and belief and we understand that it does not contain any material that has been published or written by another researcher, nor does it contain any material which, to a substantial extent, has been accepted for any award of any other degree or diploma at BRAC University or any other educational institution, except where due acknowledgements made in the thesis.

Signatures of the Authors:

____
Prommy Sultana Ferdawoos Hossain
ID: 16241002

____
Fabian Parsia George
ID: 14301059

____
Istiaque Mannafee Shaikat
ID: 14101072

BRAC University

STATEMENT OF THESIS APPROVAL

The thesis of Prommy Sultana Ferdawoos Hossain, Fabian Parsia George, and Istiaque Mannafee Shaikat has been approved by the following supervisory committee members.

Signatures of the Supervisory Committee Members:

Dr. Jia Uddin, Supervisor Assistant Professor Department of Computer Science and Engineering BRAC University	Date Approved

Dr. Mohammad Zavid Parvez, Co-Supervisor Assistant Professor Department of Computer Science and Engineering BRAC University	Date Approved

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BCI	Brain Computer Interface
DEAP	Dataset for Emotion Analysis using Physiological signals
EEG	Electroencephalography
FDA	Food and Drug Administration
FFT	Fast Fourier Transform
IAPS	International Affective Picture System
ICA	Independent Component Analysis
KNN	k-Nearest Neighbor
SVM	Support Vector Machine
2D	2 Dimensional
3D	3 Dimensional

ABSTRACT

Over the years many groundbreaking research involving Brain Computer Interface (BCI), has been conducted in order to study emotions of human beings, to build better-quality human-machine interaction systems. On the other hand, it is also quite possible to log the activities of brain in real-time and then use it to distinguish patterns related to emotional status. BCI creates a mutual understanding between the users and its environment for measuring emotions through brain activities. Electroencephalogram (EEG) is a well-accepted method to measure the brain activities. Once the system records the EEG signals, we analyze and process these activities to distinguish different emotions. Previous researchers used standard and pre-defined methods of signal processing area with fewer channels and participations to record their EEG signals. In this thesis, a novel method was proposed that extracted features from EEG signals based on time-frequencies analysis and supervised learning algorithm was used to classify different emotional states. Our proposed method provides 92.36% accuracy by using a benchmark dataset, where 32 participants were used to carry out this experiment.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Our main motive solely relied on enhancing the field of education. We analyzed several research papers related to this field and came up with the idea of determining the student attention level. It is very important for a student to remain attentive in class while the faculty is dictating a lecture. Although, being physically present in class, students drift away from the lecture repeatedly. As a result, the students fail to accomplish desired grades. While on the other hand, faculties lose their enthusiasm to deliver his/her best in class. Absence of student attention in class is not abnormal for various reasons: poor conveyance strategies by the faculty, lack of motivation of the students, and so on. Furthermore, these issues turn out to be more intense as it is troublesome for the instructor to recognize the state of attention of the students remotely, with respect to distance learning. Consequently, remote measurement of attention would be an exceptionally helpful apparatus, providing feedback to the instructor progressively.

After reading various research papers, we found out that emotions of an individual are required to be recognized prior to determining the attention level of the students. Thus, we decided to work on emotion recognition using EEG signals and could successfully detect emotions with a decent accuracy using our own proposed method. In the future, we would like to measure the student attention level using our proposed approach and utilize this concept in various educational institutions of our country.

1.2 Thesis overview

The main aim of Brain Computer Interface (BCI) is to provide individuals that have serious motor disabilities, the ability to control their devices more effectively for instance, computer, speech synthesizer and neural prostheses [29]. A BCI system is known to detect particular patterns in a human brain that relays to the person as they initiate a control action. The work of the BCI is to translate these patterns into a relevant command. Later on, different EEG signal processing algorithms are run on the commands in order to distinguish the patterns. This report will discuss, the efficient way, in detecting various patterns of human emotions through the use of SVM classifier. The report mainly **focuses** on following positions; the preprocessing discussed the signal enhancement, feature extraction, feature selection, feature classification.

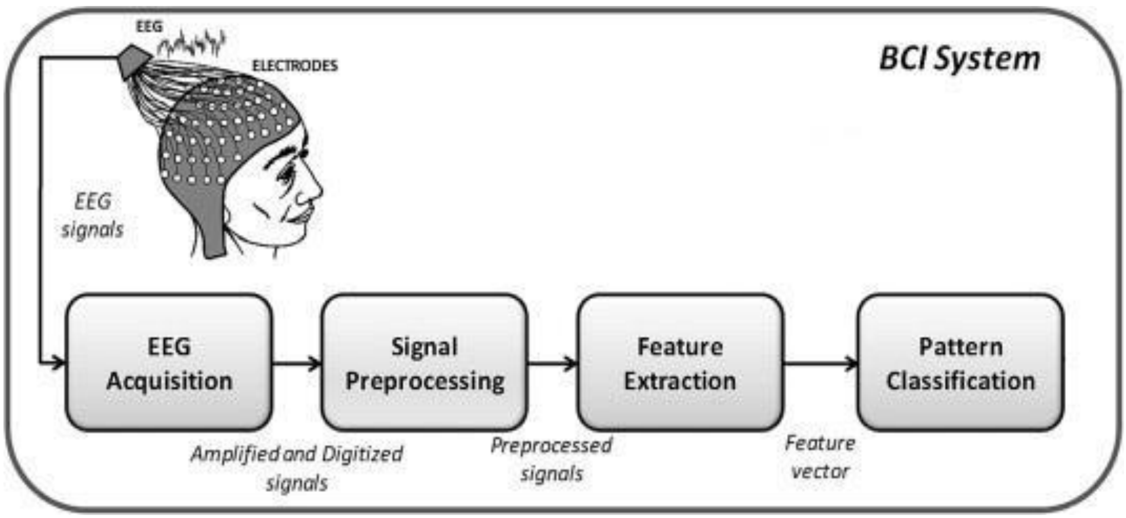

Figure 1.1. The Block Diagram of BCI system [43]

To read a brain activity we use the help of an Electroencephalograph (EEG) machine by placing several electrodes around the human skull. The signals generally convey physiological information activities related to the brain, in an indirect manner. There are several applications of these signals. For instance; they are incorporated into the new technological devices that has technology embedded into it permits Brain-Computer Interfaces. It has a major impact in the health sector, for its intrinsic signal clarification system. BCI is made out of a collection and refining of signals and identifying patterns and control system as shown in Figure 1.1.

Charles Darwin was not only famous for his creative manuscript about the theory of evolution but also known to be an early experimental psychologist. He was the first to conduct studies in recognize emotion in human faces stated by Peter Snyder, a neuroscientist at Brown University. Darwin published a book "The Expression of the Emotions in Man and Animals" in 1872, which discussed the idea that emotion had an evolutionary history that could be detected past cultures and species – though it was an unpopular view at the time. Darwin as talked about the remarkable similarities in behaviors between animals and human beings in expressing emotions [1].

Emotions are a vital approach for social interaction as it evokes us to effectively interact with another human being. James Russell states that any discrete emotion can be recognized from their level of arousal and valence using his Circumplex Model of Emotion as illustrated in Figure 1.2 [42].

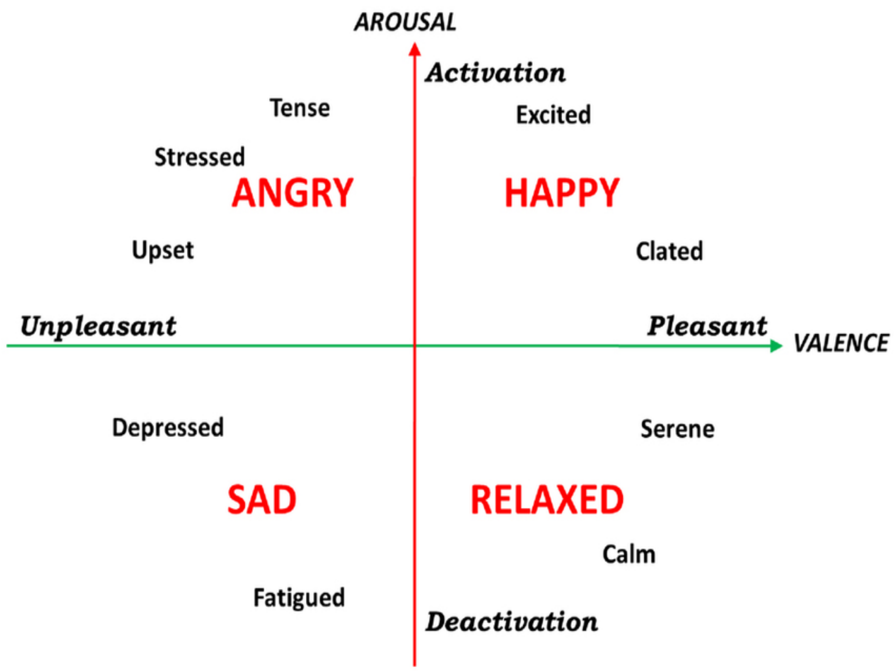

Figure 1.2. The Circumflex Model of Emotion by James Russell [42]

Emotions were first predicted by [4] using EEG signals. Emotions cause signals to be generated in the brain in a form of waves and these signals are recorded through the use of a technique known as Electroencephalography (EEG). Several methods are used to record these signals such as; facial expression, speech signals and self-rating [6-10]. However, computers often fail to acknowledge all the detailed emotional inputs for processing, such as the hand gesture, or the tone of the voice, thus leading to vague and biased outcome [6]. Although some approaches use self-rated emotions by the participants that can affect the end result as the presence of anomalous trials can be significant [10]. After the extensive use of EEG signals on the field of research it has been observed that human emotions can be displayed more accurate with EEG signals than with facial gestures, speech signals, or self-reporting information [5, 11].

Although several investigations and experiments have only included a handful number of participants and the methods used on those experiments are adequately simplified due to which it cannot be used broadly for multiple subjects [12, 13, 14]. Different methodologies were used in different studies for the feature extraction process of the sample entropy [17].

Support Vector Machine (SVM) [17], Neural Network [23], and k-nearest neighbor (KNN) [24]. Referring to the previously specified issues, we proposed a methodology for extracting high-level features and classifying these with a novel classifying algorithm to obtain an optimum result. Our approach for recognizing emotions is as follows. For our research, we used Dataset for Emotion Analysis using Electroencephalogram (DEAP) [25] and extracted features via FFT. The extracted features were then fed into SVM classifier to classify emotions.

Alluding to the already indicated issues [5, 6, 10-14], a novel approach, for determining emotion in view of time-frequency analysis, is proposed and assessed with EEG signals from DEAP dataset [20]. In the proposed model, at first, the EEG signals from just the prefrontal cortex are recovered for additional work emotional activities occur essentially in the frontal and temporal lobe of the brain [85, 86]. Moreover, this likewise diminished the total number of channels that are to be utilized as a part of the feature extraction strategy, as the redundant channels are as of now eliminated beforehand. This prompts less computational cost and therefore expanded the productivity of the calculations used as a part of our method [77]. Existing strategies, working with frequency groups, divided all the five sorts of frequency groups, in particular delta (0.5-4 Hz), theta (4-7 Hz), alpha (7-13 Hz), beta (13-30 Hz), and gamma (30-60 Hz) [65, 66]. As indicated by the cutting edge technique, the emotional and cognitive activities of the brain can be very much connoted using the alpha, beta, and theta frequency bands [62] and we extracted these bands by applying FFT in this paper. At that point, the removed bands were distributed among the four emotional quadrants, which are high excitement high valence (HAHV), low arousal - high valence (LAHV), low arousal - low valence (LALV), and high arousal - low valence (HALV). The information in every particular quadrant was then averaged for all participants. The purpose behind averaging the samples as per the quadrant is because of the irregularity in emotions felt by the participants. Not every participant feel a similar emotion for a specific video which demonstrates that few samples in the EEG signals are odd and in this way can incredibly influence the final product. The concept of averaging is to lessen the data deviation and to measurably achieve near the actual value. This likewise enhanced the precision of the classification process. To the best of our insight, this approach of determining the average of every quadrant has not been utilized by any other existing strategies. At last, the statistical features, extracted in the frequency domain, were then fed into the SVM classifier with a specific end goal for emotion classification.

This research work will be submitted in IEEE SMC TC on Visual Analytics and Communication (see details in appendix.)

1.3 Thesis Orientation

The subsequent sections of the paper have been organized as follows. Chapter 2 features the related work and existing approaches based on our proposed method. Chapter 3 provides a thorough analysis of the background information related to our work. Chapter 4 introduces the dataset used in this paper, as well as the proposed approach for recognizing emotion. Chapter 5 provides the experimental results, along with the related discussions. Finally, Chapter 6 concludes and summarizes the report.

CHAPTER 2

LITERATURE REVIEW

Due to the rise in demands of computer with applications that as the capability of detecting emotion state of the user, the studying emotions in the field of informatics has increased [40]. Participant's emotion was examined while they answered a few questionnaires with specific questions on the Likert scale. The questions were divided into specific categories such as; the description of the situation, emotional reaction to a circumstance and the rate they could control their emotion. Based on the answers given by the participants, emotions could be distinguished [41]. However, this was not a very efficient technique as it involved participants to answer all the questions and manual evaluations of the answer. This was one of the reason for inventing new methods for classifying emotions for instance through physiological thoughts.

Affective computing intents to enhance the interactions between machines and humans by understanding their emotions, thus making their communication productive, simpler and constructive. Researchers have performed several studies on detecting human emotion using different approach each time. To illustrate, Lee et. al. in [3] conducted a research on speech signals. The purpose of the study was to recognize positive and negative emotions by collecting relevant information from the language spoken in a call center. They gather data based on the verbal communication, expressions and voice intonation of the callers. However, the authors suspects there are ambiguity and false simulations in the data they collected observing facial expression and spoken language in the emotion reorganization system.

It is commonly known that emotions are essentially parallel to the way an individual communicates with each other as well as with machines [2]. Human beings are capable of understanding an emotional state of other being and behave accordingly in order to improve the condition of the situation. They are able to do this because emotions are recognized not only through words, but via voice intonation, facial expressions and most importantly body language, which a machine fails to achieve. Additionally, in the field of affective computing different approaches have been applied to recognizing emotion based on signals received. Although, most of our emotional states come internally, many of the researchers focus on classifying emotion based on external expression, such as gesture [15], facial expression [16] and speech projection [17]. If we looked on a case when someone is angry or smiling and does not speak a word during a low emotional state in contrast to their social gathering [18]in which case the person's external expression can be brought into light.

Many researches concentrate on distinguishing the activity that generates alpha and beta brainwaves [27]. Although, studies show that there is a strong relationship between the cognitive activities done by the brain and the decrease in the activity in the alpha band [14]. Several methods are applied to recognize different emotion patterns in the brain. Choppin [49] applied neural networks to categorize one out of six emotions with 64% accuracy. Takahashi [50] achieved an accuracy of 41.7%, after using several bio-signals such as; heartbeat, skin condition and EEG with three dry electrodes for recognizing five different emotion (joy, fear, anger, relaxation, sadness). Oude [51] used EEG signals from BraInquiry EEG PET device to recognize emotions. In this method Oude uses limited number of electrodes and a linear classifier based on FDA algorithm.

Researchers on this field desire to prove if a particular pattern in a brain activity exists or is common for all human being. Extensive studies have been conducted experimenting the neural correlation of emotions. The outcome was dissatisfactory which yielded to the conclusion that there is no processing module that could recognize a specific type of emotion. Rather, they are distributed pattern in the brain activity indicating different neural signatures of each type of emotion [19]. Table 2.1 shows the efficiency and feasibility of the results obtained from models, which was designed to recognize the types of emotion from a brain activity by researchers. The emotions of the participant are provoked by different types of stimulus such as; video, music or images (International Affective Picture System, IAPS). The table also mentions the different approaches used by the researchers to conduct their experiment. According to the paper [10], Balconti et al. discovered that brain waves are influenced based on the rise and fall of valence and arousal level. By observing the Valence-Arousal model in Figure 2.1, we can compare dimensions of arousal, positive and negative emotion, with valence, strong and weak emotion, based on different forms of stimuli. Regard to this figure, one can distinguish how strong (arousal) and positive (valence) their emotion was.

Table 2.1 Studies on Recognizing Emotion through Different Method and Spur

Study	Stimulant	No. of channels	Method used	Emotional status	Percentage Accuracy
[8]	IAPS	2	17 participants, Amplitude of the frequency bands, KNN classifier	Neutral, happy, sad	75.20%
[11]	IAPS	8	11 subject, Spectral power features, KNN	Neutral	85%
[12]	Video	62	20 subjects, features of gamma, alpha and beta wavelength, KNN and LDA	Surprised, fear, happy, neutral	83.26%
[20]	Video	32	32 subjects, band features, Gaussian and Bayes classifier	Liking and arousal	56.45%
[21]	Music	14	9 subjects, Time-frequency (TF) analysis, KNN and SVM	Like and dislike	86.52%
[22]	Music	24	26 subjects, density of the frequency bands, SVM	Happy, disgust, sad and fear	83.26%

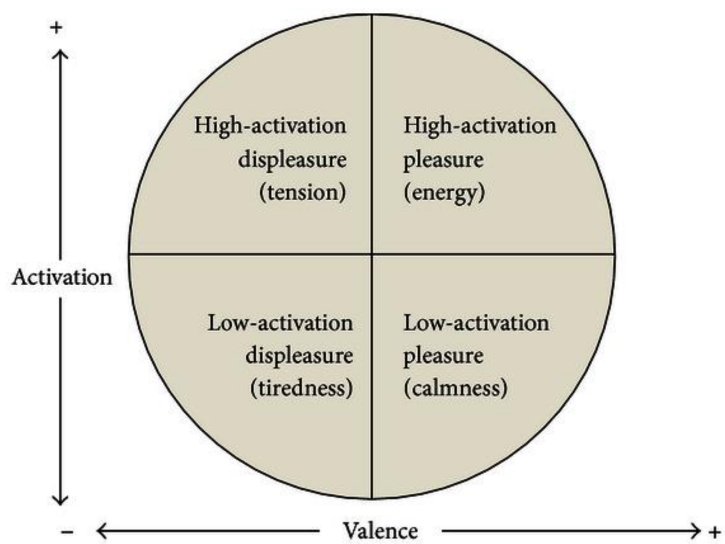

Figure 2.1. Valence-Arousal Model [42]

In the following chapter, basic structure of human brain as well as which part of the brain signals are used for our research on emotion recognition will be discussed in details.

CHAPTER 3

BACKGROUND ANALYSIS

3.1 Basic structure of the Human Brain

The Brain is a forty-eight-ounce organ that is located in the head close to the sensory organs [26]. A human brain acts as a control center for all functions of the human body [35]. The brain makes the body aware of the internal and external surrounding by generating a constant stream of sensory signals. Likely, [67] it demonstrates the significance of conscious and unconscious mind. Memory, emotions, imaginations, intelligence, breathing, internal temperature and secretions of gland are a few things carried out by the brain. There are five senses in a human body through which the brain receives information of the outside world. [36] These are hearing, sight, smell, taste, touch. The brain is also capable of controlling our understanding to a particular situation, speech, functioning of our limbs and many organs within our body. It also dictates our response to a stressful situation by administering our heartbeat.

A brain is compiled of 3 major components; Brain Stem, Cerebrum, Cerebellum.

3.1.1 Brain Stem

It connects the spinal cord with the brain, it is known as the most inferior section of the brain. The brain stem coordinates as a relay center connecting the spinal cord to the cerebrum and cerebellum. [37] Brain stem consists of three regions; medulla oblongata, pons, midbrain. The brainstem is made out a mixture of grey and white matter known as reticular formation. Which controls the body’s muscle tone and acts as a switch that controls the brain wake and sleep cycles. Additionally, the brainstem manages functions related to homeostasis, blood pressure, oxygen levels, vomiting, sneezing, coughing and swelling reflexes.

3.1.2 Cerebellum

It is located inferior to cerebrum and posterior to Brain stem. It is wrinkled and hemispherical in shape. [38] It performs the task to control motor functions such as balancing, posture, coordinating muscle activities. The Cerebellum conducts the synchronization and finesse of motor actions such as writing, speech and walking.

3.1.3 Cerebrum

[36] It is the largest part of the brain containing both the left and right hemispheres. The hemispheres are linked with a series of fibers called corpus callosum that transmits information from one side to other. Each hemisphere controls the opposite side of the body. [37] For instance, if one suffers from a brain tumor on the right hemisphere than they would encounter weak or paralyzes through the left side of the body, vice versa. However, there are some tasks performed separately by each hemisphere. Such as; the right hemisphere controls creativity, musical skills, spatial ability, while the left side administers speech, writing, calculations, comprehension.

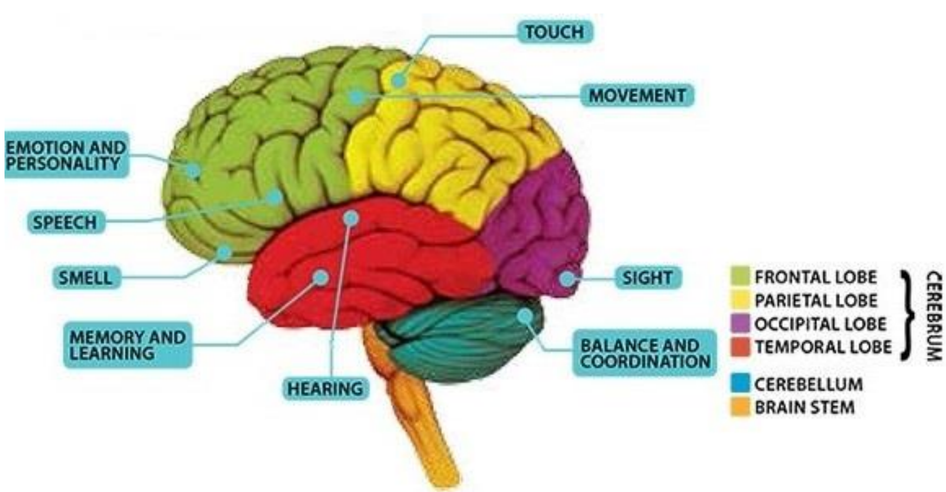

Figure 3.1. Functions of a Human Brain and the major components of a brain [44]

Each hemisphere could further be classified into four distinct sections known as lobes. These are frontal, parietal, occipital and temporal lobe (Figure 3.1). Each lobe is responsible in performing specific a particular type of function. Such as [36-38]

3.1.4 Frontal Lobe

- Personality, emotion, behavior
- Judgment, planning, problem solving skill
- Writing and speaking
- Motor skills
- Self-awareness, intelligence, concentration

3.1.5 Parietal Lobe

- Spatial (dimension) and visual concept
- Translating messages from the signal received through vision, hearing, sensory and memory
- Sense of pain, temperature, touch
- Interpreting language and words

3.1.6 Occipital Lobe

- Deduce vision (movement, light, color)

3.1.7 Temporal Lobe

- Memory
- Sequencing and organizing
- Understanding different language
- Hearing

It's crucial to understand that no one lobe functions alone. There is a complicated relationship between the lobes and the hemispheres. Messages are passed around the lobes, from one side of the hemispheres to other and to structures deep within the brain through a specific pathway. These routes are made up of brain cells, nerve cells (neurons) and glia cells (Figure 3.2).

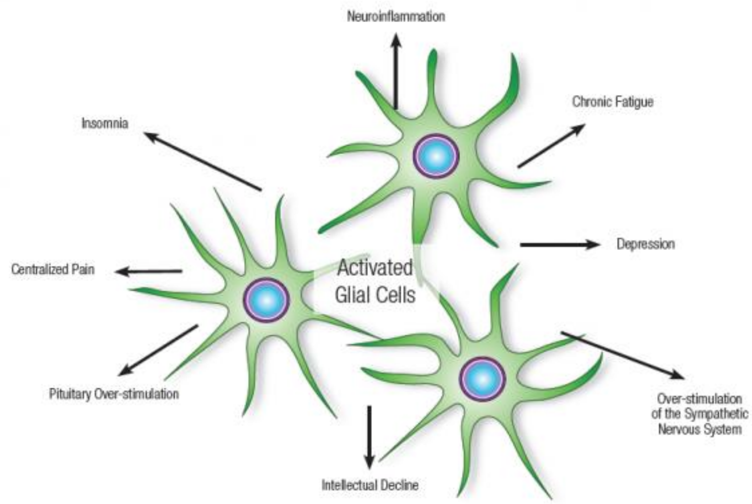

Figure 3.2. One type of Glia cells [46]

Glia cells provide nourishment, support and protection towards nerve cells. There are about 20-50 times more glia cell than nerve cells in a human brain.

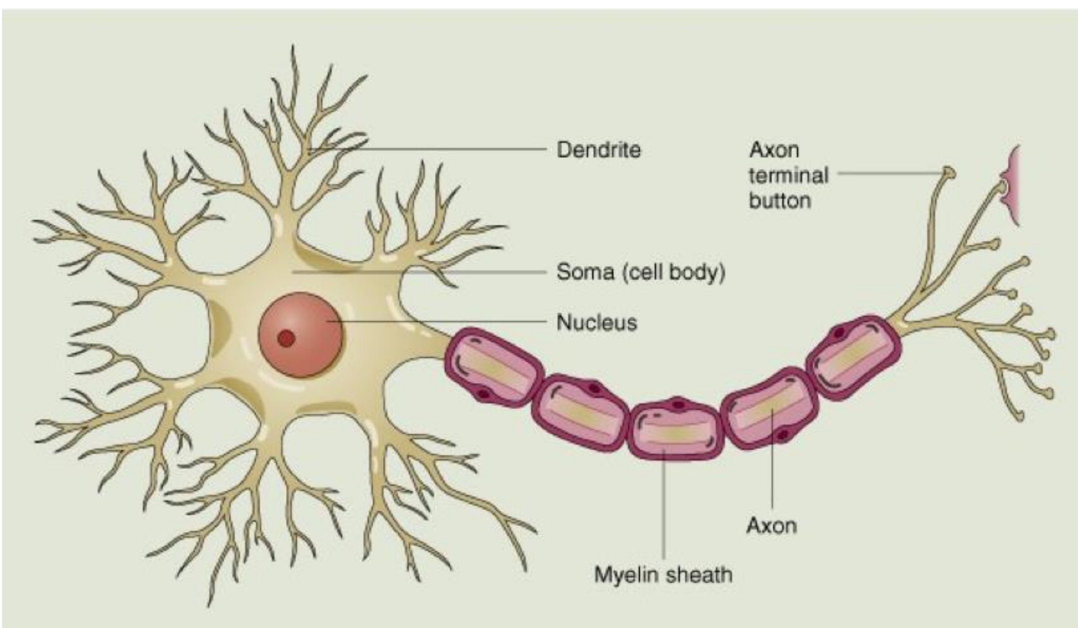

Figure 3.3. The Structure of Nerve cell [47]

[37, 38] Nerve cells could be large or small in sizes. However, they have certain common features in common such as; dendrite, soma and axon (Figure 3.3). The dendrite acts like probes, carrying messages from one neuron to another. [38] The cell body than receives their messages and filters out the relevant information and passes on to the end of the neuron, axon, which later on, transfers that message, neurotransmitter, in a sac into the open space, between the axon and another neurons dendrite, called the synapse. These neurotransmitters are passed on among several nerve cells until it reaches its allocated muscle or cell in the body. Hence, the neurons transmit information in a form of chemical or electrical signals in order to control our behavior, emotions and thoughts.

In our research the EEG signals are only retrieved from the prefrontal cortex for further work since emotional activities occur mainly in the frontal and temporal lobe of the brain [20,60].Additionally, this also reduced the total number of channels that are to be used in the feature extraction method, as the irrelevant channels are already discarded beforehand. This lead to less computational cost and thus increased the efficiency of the algorithms used in our technique [77]

3.2 Brainwaves

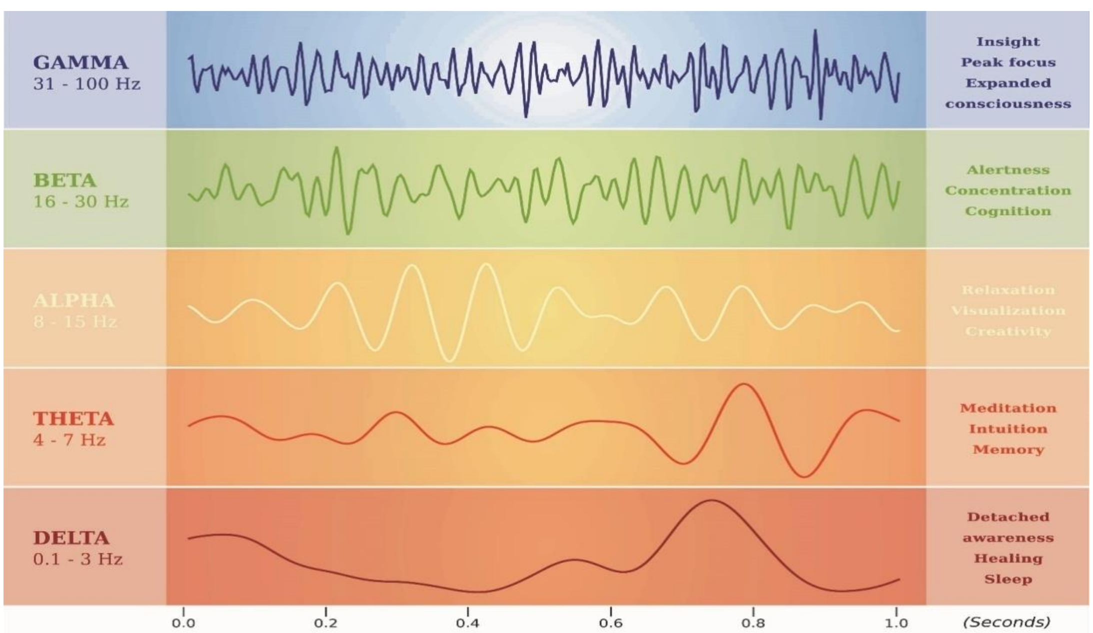

Figure 3.4. Human brainwaves [48]

[30, 36] The synchronized electrical pulses create “Brainwaves”. Brainwaves are measured in the form of Hertz (cycles per second). It would be convenient for us to consider brainwaves as a form of musical notes. [34] Where the low frequency waves are like drum beats piercing deeply and the frequency that are of higher pitched are more like a high frequency flute. As a result, like an opera both low and high frequencies blend together in harmonics.

These brain waves constantly keep on changing based on our actions and feelings. Brainwave frequencies can be divided into bands that are fast, moderate and slow waves format. When higher frequencies are dominant human being undergoes hyper-alert and weirdness. Whereas a person feels dreamy, slow, tired when low frequencies are commanding. Hence, brainwaves display specific behavior according to the location it gets generated. Brainwave bands could be classified into five particular types (Figure 3.4):

3.2.1 Alpha

It is known as the ‘power of now’. It consists of a frequency between 7.50 to 13.0 Hz. It is higher in amplitude. It is mostly seen in the posterior region of the right and left hemisphere. [35-38] These waves are prominent during quite flowing thoughts, especially when eyes are closed and a person is relaxing and quickly disappears when the eyelids open. Thus, Alpha wave supports mental synchronization, alertness and learning.

[39] When there are consisted amount of alpha frequency waves in the brain, a human being feels too relaxed, and is unable to focus and constant daydreaming. However, when the amount of alpha frequency is less one suffers from high amount of stress, anxiety, OCD and insomnia. During its most normal state a person feels relaxed.

3.2.2 Beta

It is known as “fast activity”. Its frequency ranges between 14 to 38 Hz [38]. It can be observed to be sequentially distributed on both side of the brain specifically in the frontal region. It will be on a reduced level or absent in areas with cortical damage. Beta waves govern the normal conscious state when one is involved in performing any sort mental tasks. They appear often when the person is anxious, alert, judgment, problem solving or simply when they have their eyes open.

[54] A high concentration of beta wave causes adrenaline level to rise, leading to a stressful mind state, high arousal and the inability to relax. Although, when little it can one witness depression, daydreaming and poor cognition but in a normal amount a person is able to solve problem, access memory, and focus.

3.2.3 Delta

[38] It has a frequency range between 0.5 to 3 Hertz. It tends to have the slowest wave speed with the highest amplitude, like a drum beat. Delta wave is dominant in babies of one year old but it is more prominent in adults. It is seen during a dreamless sleep, in most rooted meditation, when showing empathy and in healing.

Extensive amount of delta wave can cause serious brain damage, inability to think and face difficulty in learning. Although when too little of it can lead to poor sleep, inability to rejuvenate body and revitalize the brain. However, in a normal amount the human body will have functioning immune system, natural immune system and deep sleep.

3.2.4 Gamma

It's one of the fastest brainwaves. It processes data from different part of the brain simultaneously. [36] The gamma waves pass information around in a quiet manner. The mind needs to be in a peaceful state to acquire these waves. It was once thought to be as brain noise, though later on researchers proved it to present during a state love and "high virtue". Researcher are quite uncertain about how it is actually generated though for certain it is generated when one is in state of spiritual emergence.

Anxiety, high arousal and stress can also be caused due to high amount of gamma waves in the brain. On the other hand, too little of it cause depression and learning disability. However, an optimal amount of can contribute data processing, perception, cognition, learning and binding senses.

3.2.5 Theta

[37, 38] The frequency of theta has a range between 3 to 8 hertz. It is known for its slowest speed. It is witnessed when one slowly withdraws from the external world and focuses on the feeling generated within. It considered normal when witnessed in the brain activity of a child up to an age of thirteen. Though it is considered as an abnormal wave when found in an awaken adult. It can be found during deep meditation and when drift into sleep. During the phase of theta waves human beings are either in a state of dream or beyond the normal state of awareness. It is also generated when we have a nightmare, fear from any object, when thinking of a troubled past as well as this wave aids in learning, memory and intuition.

Extensive level of theta wave can control depression, impulsivity and in attentiveness and a minimal amount will cause anxiety, poor emotional awareness, and stress. But, a right content will emotional connections, creativity and relaxation.

As it was discussed earlier, emotional activities cause the brain to generate signals in the form of waves. These signals, which can be subdivided into 5 frequency bands, hold a correlation with the emotional activities [78]. These 5 different types of frequency bands are comprised of delta, theta, alpha, beta, and gamma [79]. As stated by [79], the alpha, beta, and theta can well represent the emotional and cognitive process of the brain than the other 2 bands. This is why, we have extracted these 3 bands using Butterworth band pass filter after applying FFT on the EEG signals.

3.3 EEG Analysis with Various Algorithms

[31] Electroencephalography is a device that was first introduced to the world by Hans Berger [4][5]. Berger was a neuropsychiatrist from the University of Jena in Germany. He putted the idea forth about the change in brain activity based upon different utility, for example; sleep, anesthesia, epilepsy. Although, Berger's idea was initially disregarded as an inaccurate conclusion but later on became a field of study after conducting several experiments on the matter that is. [6] Over the decades the researcher's community became keener in establishing a connection between human and

computers interaction by observing the emotional response [32, 33]. At the beginning the results were obtained though subjective self-reports autonomic and neuro-physiological measurements and many more measure. However, due to its portability, low cost and maintenance, and easy-to-use solution for defining emotion, EEG machines have become the best tool for the approach [7].

An EEG machine is an equipment that generates electrical activity of a brain. It is a tool used by neurobiology researchers and in hospitals to diagnose a medical condition, for instance; brain tumor, seizure, head injuries. The device consists of electrodes, amplifier, display screen and a computer controller. [6] As the iron and zinc chemical substances shift within the neurons in order to cause an electrical impulse, the electrodes read this fluctuation of voltage and passes it to the amplifier which enhances the signals to a level that that can be displayed on the screen which could either be printed out by a galvanometer or stored on the hard drive.

The electrodes are in placed on an EEG cap. Each pair of electrodes (Figure 3.5) makes up a channel and there are about 14, 32, 64 or 128 channels in an EEG cap [14]. There are cables attached to the electrodes in order to transfer the data collected from the EEG cap. There are several data-collection hardware such as Bio-Radio 150 [8], Bio-Semi [9] and B-Alert [10] and among this Bio-Radio 150 is most often used due to its wireless transmitter feature in serialized data packets. Later on, the data would need to be pre-processed as then it would contain various types of noises such as, blinking and movement of the eye, instrument noise [29], skin opposition noise and other muscle movement noise. Different techniques would then be used to screen out the noise.

First, by ensuring the proper conductive between the electrode and scalp skin impedance can be reduced [8]. Second, to reduce the instrument noise or noise over the wireless communication can be decreased by passing the raw data through the band-pass filter [11]. Lastly, when the data received is corrupted, also known as artifacts, by other Bio-signals. Independent Component Analysis (ICA) can be used to remove these artifacts as described in [12] and [13].

Computation of valence and arousal levels are calculated by applying machine learning algorithm on the EEG signals. Subjects with low valence and arousal level are removed from the experiment, in order to make the results more reliable. Machine learning algorithm is known by a common heading called feature extraction. Researchers run this algorithm in order to reduce the large set of data obtained from the EEG machine. The term mostly describes the methods of building different combination of variables to represent the data with a sufficient accuracy.

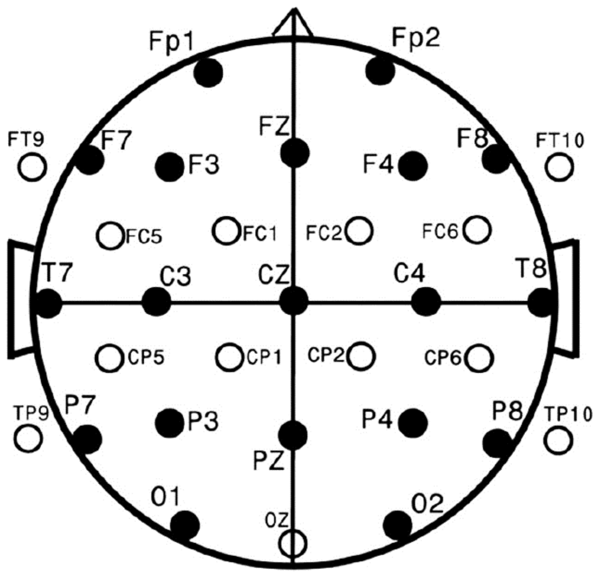

Figure 3.5. Placement of electrodes on the head and different channels [45]

However, there are several problems that arise due to stereotype people [24]. There are many individuals that express the same type of emotion for a particular circumstance with different characteristic response pattern. There are several different types of classifier available to extract feature from the data created by an EEG machine. To name a few:*k*-NN, ANN, SVM, Regression Tree, Bayes Network.

3.3.1 K-Nearest Neighbor

It recognizes patterns in a non-parametric method applied for classification or regression [73]. Depending on whether k-NN is used for classification or regression the output can be determined [72].

- If the k-NN is used to for classification than class membership will be created. In which an object will be classed based on its number of neighbors. If the k=1, then the object will be simply assigned to the class of the single nearest neighbor.
- In k-NN regression, the output will be displayed as a form of average value of the objects k nearest neighbor.

3.3.2 Artificial Neural Networks

They are a computing learning system. The system improves its performance by learning progressively by considering examples. [73] If we considered a system that was assigned a task to identify cats from various pictures without providing any prior knowledge of how a cat looks like. The ANN system would first try to list the attributes that best describe a cat and look through the sample data inputted and then the system will try to correctly identify the object.

3.3.3 Bayesian Network

This system is based on a probabilistic graphical model that represents several variables on their conditional dependencies thought the direct acyclic graph (DAG). [71] For instance, by using the Bayesian network algorithm we can distinguish a relationship between diseases and symptoms after we have inputted all the necessary data needed for the analysis into the system.

3.3.4 Decision Tree Learning

This is also known as regression tree. [70] This approach is one of a predictive modeling often used in statistics, data mining, and machine learning. The system generates a tree model; in which the leaves would represent labels of the class, the branches would be the classes that would lead then to the leaves and the target variable will of a set of values continuously.

3.3.5 Support Vector Machine

It is known as an associated learning algorithm that analyzes data by classification or regression. [28] It builds a hyperplane or a set of hyperplanes in a high or infinite dimensional space which can be used to analyze the data. [71] The hyperplane separates the variables that are at the closest distance to the training set of any class. Since the higher the marginal line the lower will be the generalization error of the algorithm. SVM map's the original problem that appears at a finite dimensional space into a high dimensional space in order to linearly separate the set of discriminate, which would not have been possible in the original space.

However, to keep the computational weight reasonable, [72] SVM algorithm ensures that the computation between the dot products and the variables are kept similar to the original spacing. SVM achieve this by defining these two elements in the term of kernel function *k(x, y)* according to the particular problem at hand. The hyperplanes in the higher dimensional space will be defined as a set of points those dot products with a vector in that space is constant. The vectors that will be used to define the hyperplane can be chosen with linear combinations with parameter $\propto_i$of images of feature vector $x_{i,}$that would occur in the database. By choosing this hyperplane the points of x what will be used in the feature space will be mapped into the hyperplane and the relation can be written as such;

$$\sum_{i} \propto_i k(x_{i,}x) = constant \tag{1}$$

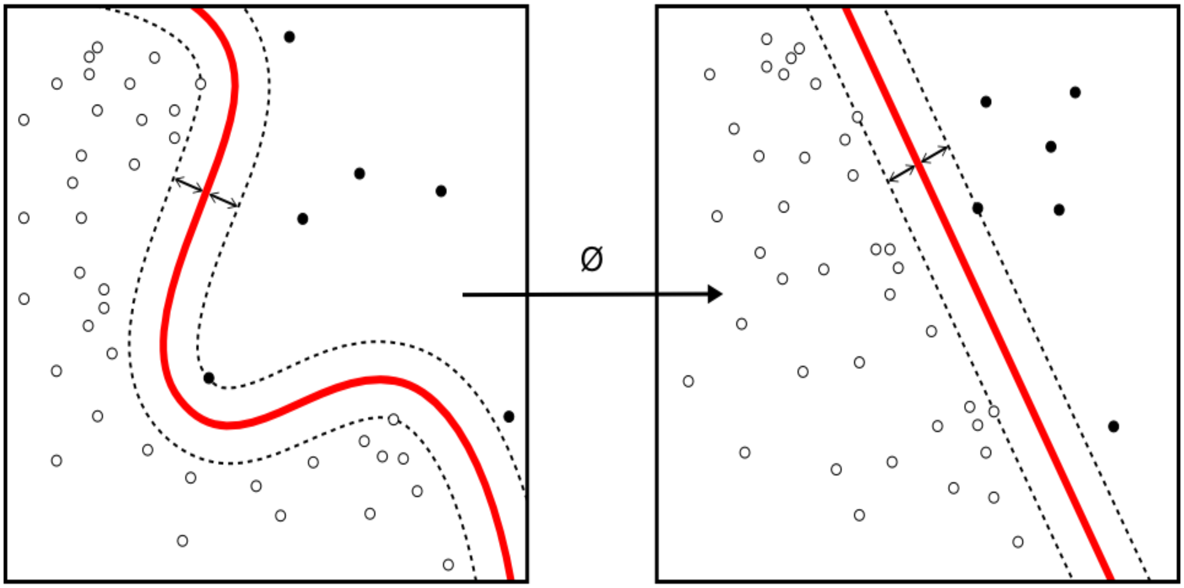

Figure 3.6. Input space and feature extraction using SVM [52]

The *k(x, y)* value grows smaller as y moves further away from x and each element in sum equation measure the degree of closeness of the test point x to the corresponding data base point $x_{i,}$. In this way we can measure the closeness of each test point to the data points in the original data sample or any of the other sets of discriminate (Figure 3.6).

According to paper [25], where the researchers applied different type of classifiers on an EEG generated data to recognize emotions and the accuracy level of each technique. They use the IAPS method as a stimulant. The results were as such; Artificial Neural Network – 48.78%, *k*-Nearest Neighbor - 52.44%, Regression Tree – 52.44%, Bayesian Network – 52.44% and Support Vector Machine – 56.10% and random guess generated 33.33% accurate result. As a result, we decided to use SVM as our classifier for recognizing emotion after reading several journals and research papers [26-33].

Support Vector Machine (SVM) is measured as one of the most efficient classifiers for classifying emotions [80, 81, 82, 66]. The basic perception of the SVM is to determine a decision hyperplane in order to classify data samples into two classes. The optimum hyperplane for differentiating two groups is determined by maximizing the distances between nearest data point of both the classes and the hyperplane [83]. The classification procedure includes predicting a confusion matrix model by partitioning the sample data into a training set and a test set, for training and validation respectively, using a technique called k-fold cross validation This technique randomly divides the data into k equal subset of the data and is repeated 10 times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set [76].

In the following chapter, proposed method, how the data is being collected and processed as well as the emotion classifier which is being used will be discussed in details.

CHAPTER 4

PROPOSED MODEL

For our research we obtain [56, 57] the EEG signals from a Database for Emotional Analysis using Physiological signals (DEAP). Through this database we obtain pre-processed EEG data that consisted user's affective ratings. This database is a publicly available to anyone interested in working with EEG dataset. For this research, EEG signals were first accumulated and then preprocessed. [58] Followed by the extraction of bands of specific frequencies and subsequently, suitable features were extracted and fed into the classifier. Lastly, SVM classifier was used to classify theses selected features as shown in Figure 4.1.

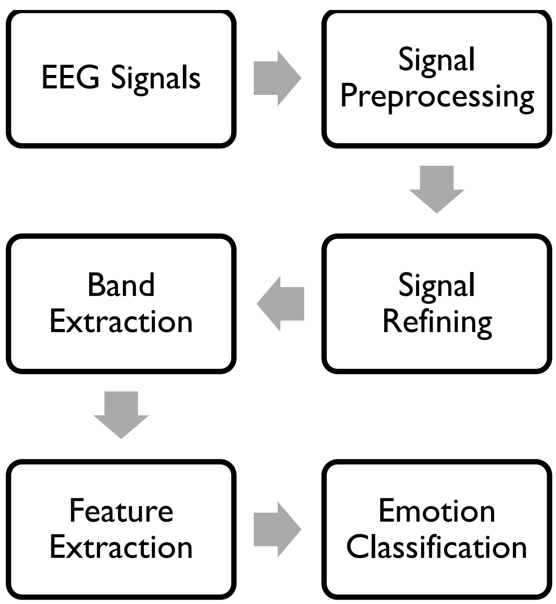

Figure 4.1. Workflow of the Proposed Model

4.1 Experimental Setup

[53] For the experiment about 32 AgCl electrodes were used on 16 male and 16 female participants, to record their EEG signals at a sample frequency of 512 Hz. These participants were between the age of 19 to 37. The participants were allowed to take a break such as snacks, after attending 20 music video trials. Each trial lasted for about sixty-three seconds and at the end of each trail a manual rating was done by the subjects on a scale of 1-9, in order to determine the four different emotions for instance; Arousal, Dominance, Liking and Valence, Table 4.1.

The participants watch music videos that consisted emotional contents. Each video was about one-minute long. The EEG signals were obtained with Biosemi Active Two system to record the EEG signals, at a frequency sample of 512Hz, where thirty-two electrodes were placed over scalp. As these electrodes picks on the electrical activity created by the nerve cells of the brain.

Table 4.1 Physiological Experiment [53]

Number of participants	32
Number of videos	40
Rating scale	Arousal Valence Dominance Liking
Recorded signals	32-channel 512 Hz EEG Peripheral physiological signals

The experiment, for recoding the EEG data for the DEAP dataset, started with giving the participants two-minute baseline to relax before videos are played for the subjects. There are 40 videos each representing 40 trails which were carried out in the following steps [53];

a) The participants are shown a two-second screen that consist the number of the trial along with the progress of the participant.

b) A five-second baseline would be provided for the relaxation.

c) Then the one-minute video is displayed

d) Each participant is then asserted for arousal, valence, liking and dominance.

4.2 Data Description

[53, 69, 70] In this research, the DEAP Dataset [62, 63, 64] was used source of brain signals. This dataset is used to analyze the human affective states. The experiment was carried out in a controlled light environment. Two computers were used that was synchronized periodically with the help of markers – one for recording the signals and another for presenting the stimuli. The dataset consists of two parts. The first part consists of rating by 14 to 16 volunteers on 120 one-minute extracts of music videos based on arousal, valence and dominance. On the other hand, the second part contains data of subject's ratings, physiological recordings and facial expression videos on the 32 participants as they watched a subset of 40 music video that was played in a 17-inch screen but 800x600 resolution was maintained to minimize the eye movements.

For our research, we decided to work with the pre-processed data file that consisted of the EEG signals of each participant. There are two arrays for each participant, as showcased in Table 4.2.The data array in Table 4.2 stores the EEG signals of all the 32 participants and all the videos are inclusive while the label array contains the video ID in accordance to the emotion; arousal, dominance and liking.

Table 4.2 Contents of Each Participant Files [53]

NAME	**SIZE**	**DESCRIPTION**
Data	40x40x8064	Video/trial x channel x data
Label	40x4	Video/trial x label (valence, arousal, dominance, liking)

4.3 Signal Preprocessing

The data was pre-processed by referencing it down to 128Hz. [55, 56] The signals were passed through the band-pass filter which was set to 4 Hz on the minimum and 45Hz as maximum and the Electrooculography artifacts, EOG, an independent component analysis, were used to remove any form of eye movements. Each video was recorded for 63 seconds but, to create a common reference, the data was averaged. Additionally, the data was segmented into 60 seconds by removing 3 seconds pre-trial baseline and ordering the file name as Experiment_id.

4.4 Signal Refining

In order to extract bands, the data would need to be rearranged to make it appropriate for the extraction process. As mentioned in section 4.3, the data obtained from DEAP dataset was used for this research it contained 32 files each representing a participant. There are arrays in each file; one was a 3D array labeled “data” with array shape of 40x40x8064. This array consisted of Video/trial x Channel x data. While the other one was a 2D array named “Label” with a size of 40x4 and it contained video/trial, label (valence, arousal, dominance, and liking). Throughout the course of our research we used the 3D data array. In order to record the EEG signals, 40 channels were used, out of which 32 were EFG channels and 8 were peripheral channels. Based on the previous studies conducted, we can state that emotions are mostly focused in the frontal and temporal areas of the brain.

However, in order to reduce the computational costs of our proposed model, we choose to work with few particular channels that related to the frontal lobe of the brain [62, 65]. [73] These channels are Fp1, F3, F7, FC5, Fp2, Fz, F4, F8, FC6 and FC2. Feature extraction and classification were the most challenging task as we needed to manipulate the data as per our requirements. Hence, the preprocessed data was allocated into 40 files each representing music video used in the DEAP dataset. Each video file contained an array of size 8064x352, in which the rows would represent the length of the data and the columns would represent the total number of channels of the 32 participants as described in Table 4.3.

Table 4.3 Array representation of the Video File

Array Name	**Array Size (Row x Column)**	**Array Contents (Row x Column)**
Video_no	8064 x 352	Data x subjectNo_channelNo

4.5 Band Extraction

The EEG signals used in this research were recorded on a time domain. Several researches proved that to obtain a prominent accuracy, features need to be extracted in the frequency domain [63] and this can be achieved by applying Fast Fourier Transform (FFT) to the time domain signal. FFT is an algorithm that is often used to convert signal from the time domain to the frequency domain.

FFT is defined for a vector with uniformly sampled points by:

$$y_{k+1} = \sum_{j=0}^{n-1} w^{jk} x_{j+1}\,, where\ \ w = e^{\frac{-2\pi i}{n}} \qquad (2)$$

As we mentioned in the previous chapters, emotional activities generate electrical signals in a form of wave in the brain. These brain waves can be subdivided into 5 frequency bands that hold a correlation with the emotional activities [60]. As mentioned in chapter 3, the 5 different types of brainwaves are alpha, theta, beta, delta and gamma. [61] Among these entire bands, three of band, alpha and beta, can specifically represent the emotional and cognitive process of the brain than other 2 bands. Hence, we have extracted these 3 bands using Butterworth band pass filter after applying FFT on the EEG signals.

4.6 Feature Extraction

In the experiment [65] provided information regarding emotions that they felt by watching each video. It is assumed that each video can be placed in any of the 4 quadrants, which are HAHV, LAHV, LALV and HALV as illustrated in Figure 4.2. As each individual will respond differently for a specific video, the result generated for the EEG signals will be an irregular sample.

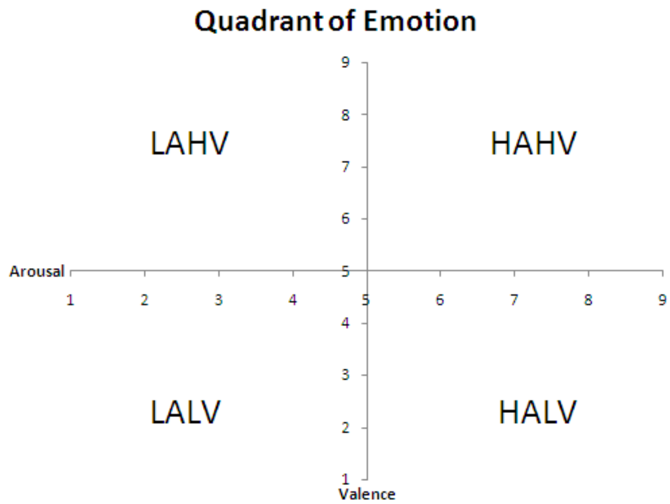

Figure 4.2. The quadrant of the emotion

[59] In order to reduce inconsistency in each quadrant in the sample, erroneous samples are required to be discarded. In our research, to minimize the data deviation, the extracted band values of the videos were averaged according to their corresponding quadrant as illustrated in Table 4.4.

Table 4.4 List of 40 videos (Experiment_Id) and Their Corresponding Quadrant

HAHV	LAHV	LALV	HALV
1	8	16	10
2	9	22	21
3	12	23	31
4	13	24	32
5	14	25	33
6	15	26	34
7	17	27	35
11	18	28	36
-	19	29	37
-	20	30	38
-	-	-	39
-	-	-	40

After sorting the video in accordance to their quadrant and averaging the bands of all the videos from each quadrant, we created four video files and it all contained the average values of the extracted bands. Once the band values were scaled, the features of the input signals were then extracted. For our paper, we have extracted both the statistical features I and statistical features II as illustrated in Table 4.5.

Table 4.5 Types of features extracted for classification

Statistical Features I	Statistical Features II
Minimum	Skewness
Maximum	Kurtosis
Menu	Wave entropy
Variance	Power bandwidth
Standard Deviation	-

4.7 Emotion Classification

There are several numerous machine learning algorithms used in several existed studies out of which Support Vector machine (SVM) is measured as one of the most efficient classifiers for recognizing emotions. [55, 67, 68, 65, 66] The basic perception of the SVM is to determine a decision hyperplane in order to classify data samples into two cases. The optimum hyperplane for differentiating two groups is determined by maximizing the distances between nearest data point of both the classes and the hyperplane [62]. The classification procedure includes predicting a confusion matrix model by partitioning the sample data into a training set and a test set, for training and validation respectively, using a technique called k-fold cross validation. This technique randomly divides the data into k equal subset of the data and is repeated 10 times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set. Figure 4.3 shows a visual representation of the k-fold cross validation.

Figure 4.3. Visual Representation of k-fold Cross Validation [84]

In our paper, different combinations of features were used for training and testing the SVM classifier in order to generate the confusion matrix model. This model was then used to find the accuracy depending on the k-fold cross validation. Here, we integrated SVM with 10-fold cross fold validation with the parameters, C and gamma, which were selected by the grid-search method. In order to implement SVM, LIBSVM [75] library is used, which is a widely used library for support vector machines [60].

In the following chapter, features box plot is provided and classification results are being illustrated with different feature combinations accordingly.

CHAPTER 5

RESULT AND DISCUSSION

Classifying the statistical features for obtaining a decent outcome was not an easy process. Various aspects were required to be considered prior to reaching to a conclusion as the initial trials did not generate a satisfying output. In this paper, 10-fold cross validation was incorporated with the SVM classifier using the regularization and kernel parameter, which were selected via a grid-search approach. In order to determine the accuracy of k-fold cross validation for the classification technique, (3) was used.

The equation for accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (3)$$

where TP: the number of true positive, TN: the number of true negative, FP: the number of false positive, and FN: the number of false negative.

At the very beginning, prior to averaging the extracted band values according to their corresponding quadrants, all the statistical features from Table 4.5 were then used to train and test the SVM classifier with a specific end goal to construct the confusion matrix model. This model was then used to discover the accuracy relying upon the 10-fold cross validation. However, the very first trial did not provide a logical output since the accuracy was only found to be 2.03%. This occurred because the features, before averaging the data, do not contain distinguishable characteristics (see box-whisker plot in Figure 5.1).

A box-and-whisker plot was used to graphically represent each feature through their quartiles, as shown in Figure 5.1.

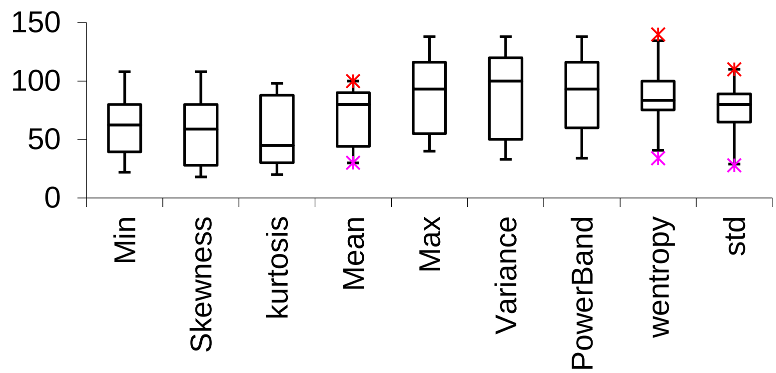

Figure 5.1. Boxplot of the Statistical Features before Averaging the Video Data

Furthermore, we segregated all the features into various and unique combinations. After testing with several feature combinations by feeding them into the SVM, the following combinations provided a reasonable result:

1. Feature combination A: mean, standard deviation, variance.
2. Feature combination B: skewness, kurtosis, wave entropy.
3. Feature combination C: minimum, maximum, variance.
4. Feature combination D: wave entropy, power bandwidth. The percentage of accuracy before averaging the data of the 4 combinations of feature is summarized in Table 5.1.

It can be observed from Table 5.1 that the feature combinations do not offer satisfactory outcome prior to averaging the data because not all the participants feel the same emotion for a specific category of video. Hence, The SVM classifier could not create an accurate model due to the irregularity in the data for each quadrant.

Table 5.1 Accuracy from different quadrants before averaging the video data

Feature Combination / Quadrant Accuracy (%)	**HAHV_LALV**	**HALV_LAHV**
A	5.34±1.20	2.21±1.20
B	9.36±2.30	19.11±8.30
C	1.23±0.20	5.69±2.50
D	5.61±0.50	4.13±2.30

Even though the accuracy for classification improved by a certain amount after partitioning the features into various combinations, it was still not a satisfactory result. We then averaged the band values, in accordance to their quadrant to reduce the data deviation and thus improve the accuracy of the classification process. Once the data were averaged, these were scaled and the statistical features were extracted as discussed in chapter 4. The feature combinations were once more fed into the classifier.

It was observed that the accuracy for classification improved by a significant amount as illustrated in Table 5.2. It can be noticed that the combination B provided better result with an accuracy of 92.36% for the quadrant HAHV_LALV and 89.11% for the quadrant HALV_LAHV, whereas the combination C provided least result with an accuracy of 11.23% for the quadrant HAHV_LALV and 15.69% for the quadrant HALV_LAHV.

Table 5.2 Accuracy from different quadrants after averaging the video data

Feature Combination / Quadrant Accuracy (%)	**HAHV_LALV**	**HALV_LAHV**
A	25.34±5.20	21.21±3.20
B	92.36±6.30	89.11±8.30
C	11.23±5.20	15.69±3.50
D	54.61±10.50	42.13±9.30

The reason for feature combination B providing the optimum result is that the features skewness, kurtosis, and wave entropy can be distinguished from each other. The samples do not overlap and are significantly deviated from each other. This can be easily represented with a boxplot graph for the individual features as shown in Figure 5.2.

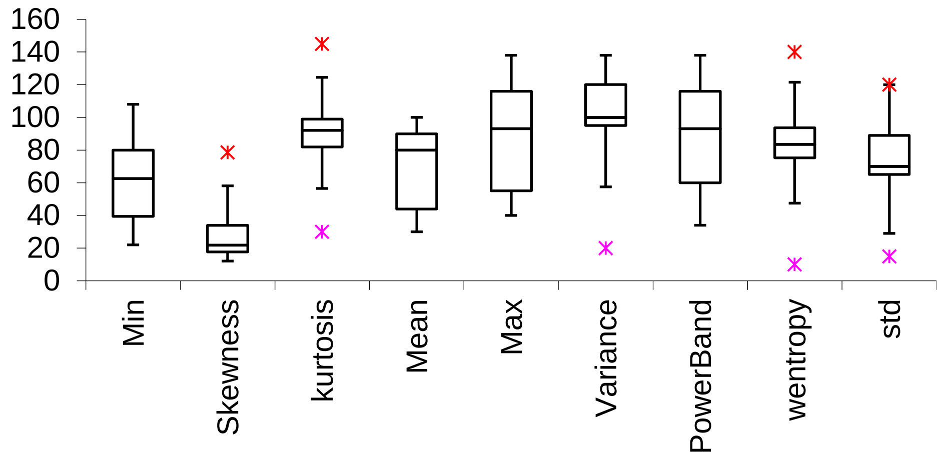

Figure 5.2. Boxplot of the Statistical Features after Averaging the Video Data

As DEAP is a public dataset, we took a step forward to compare and analyze the existing work that have already used the DEAP dataset for recognizing emotions with our proposed approach. Table 5.3 illustrates some of the existing methods for emotion recognition using the DEAP dataset. It also provides information regarding the emotions identified, the features extracted and the accuracy for emotion classification by each method. It can be observed that most of the existing methods extracted more than one type of features and few identified more than two emotions. However, for our work, only the statistical features were considered for the feature extraction process and only two states of emotion were identified, namely valence and arousal. Furthermore, it can be also seen from the table that the accuracy of the existing methodologies is limited within 80%, whereas our proposed approach provided an accuracy of approximately 92.36%. Thus, it can be said that our approach is more efficient in terms of classifying emotions than many of the existing approaches.

Table 5.3 Accuracy of Existing Approaches based on DEAP Datatset

Reference	**Emotions**	**Features**	**Accuracy (%)**
85	Valence and arousal	DWT, WE, and Statistical	71.4
86	Male/female valence and male/female arousal	Statistical, Linear, and Non-statistical	78.6
87	Stress and calm	Statistical, PSD, and HOC	71.4
88	Valence, arousal, and dominance	Statistical and HFD	71.4
89	Valence and arousal (two and three classes)	FFT	71.4
90	Valence and arousal (two and three classes)	AR with Burg method	78.6
91	Valence and arousal	SE	71.4
92	Excitation, happiness, sadness, and hatred	WT (db5), SE, CC, and AR	78.6
93	Anger, surprise, and other	HHS, HOC, and STFT	78.6
94	Valence and arousal	MRMRM and Statistical	71.4
95	Valence and arousal	HOS	71.4
96	Valence and arousal	DWT	71.4
Proposed Approach	Valence and arousal	Statistical	92.36

CHAPTER 6

CONCLUSION

In the recent years, emotion recognition has become a high developing subject in field of research. The applications of emotion recognition have left an outstanding imprint in different fields including education and research. Conventional methodologies used facial expressions or voice pitch to recognize feelings, notwithstanding, facial gestures and spoken dialect can prompt one-sided and questionable outcomes. This is the reason specialists have begun to utilize electroencephalogram (EEG) which is a very much characterized technique for emotion recognition. Some methodologies used standard and pre-defined strategies of the signal processing area and some worked with either less channels or less subjects to record EEG signals for their work. In our research, DEAP dataset was used to collect the preprocessed EEG signals in order to distinguish the different type of emotions, namely valence and arousal. The first step of our research required the sample dataset to be compressed by transferring the data from the time domain format to frequency domain by applying FFT to extract the alpha, beta and theta frequency bands that are significant for recognition emotion. Subsequently, the bands that were extracted were averaged in correspondence to their quadrant and the averaged band values are used to extract statistical features and to the best of our knowledge, this approach of averaging the data has never been attempted or used before. After that, the extracted features were scaled and various feature combinations were imputed into the SVM classifier for emotion recognition. Based on our approach we predict the 92.36% accuracy. It can be observed that the features such as skewness, kurtosis, and wave entropy have provided better classification accuracy than any other statistical features. In the future, we would like to measure the student attention level in realtime using our proposed approach and utilize this concept in various educational institutions of our country.

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