Electroencephalogram based Emotion Recognition with Graph Convolutional Network Model

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Declaration

It is hereby declared that

1. The submitted paper is our own original research completed while pursuing a degree at BRAC University.
2. Except as properly referenced by complete and correct referencing, the study does not include content previously published or written by a third party.
3. The paper does not contain any content that has been approved or applied for any particular academic or other institution's degree or certificate.
4. We have acknowledged all main sources of help.

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Ethics Statement

Our research is honest and of the greatest caliber. Participants in our study article deserve to maintain their integrity and anonymity. Because we conducted our investigation objectively and our analysis is unbiased and independent. Hopefully, this research analysis will add some new aspects to humanity in the future to contribute to their progress.

Abstract

Recently, researchers have focused on understanding human sentiment using mechanical devices or reactions to any machinery activity. Computerization is becoming more prevalent in today's environment. People are unaware of the proper way of expressing their emotions to others. People are unsure how to respond in some situations. Emotional intelligence is a collection of abilities that includes emotional awareness and self-control. In 1995, Daniel Goleman's book Emotional Intelligence popularized the term. Emotional intelligence has five components: self-awareness, motivation, self-regulation, and social abilities. Emotion indicates a broad phrase that alludes to a human being's cognitive or intelligible and psychological comeback to the perceived circumstances of another person. Emotional response or sensitivity towards others boosts one's chances of assisting others and displaying sentiment. Some people have been traumatized, handicapped, or have a disability that makes it difficult for them to express themselves. Our goal is to evaluate human sentiment and the factors working behind emotions using EEG signals to identify a person's feelings. We propose a deep learning-based approach with a hybrid model for detecting emotions such as happiness, sadness, etc. The electroencephalogram, abbreviation of EEG, is a medical evaluation that computes the electrical activity of the cerebrum using electrodes or wires placed on the scalp. Using EEG-based emotion recognition, the computer can see inside the user's head to study their mental state. To achieve this goal, our mission is to discover the cognitive stimulation that plays a crucial role in generating happiness and sadness in the human brain via brain signals using Deep learning(DL) approach and hybrid Graph Convolutional Network(GCN) model.

Keywords: Emotional Intelligence , machinery activity , EEG, emotion , brain signal, Deep learning , hybrid model, GCN.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

AI Artificial Intelligence

BCI Brain Computer Interaction

CLI Cognitive Load Index

CLT Cognitive Load Theory

CNN Convolutional Neural Network

DCT Discrete Cosine Transformation

DL Deep Learning

DWT Discrete Wavelet Transform

EEG Electroencephalography

EI Emotional Intelligence

FFT Fast Fourier Transform

FM Fibromyalgia

GCN Graph Convolutional Network

HCI Human Computer Interface

LSTM Long Short-Term Memory

MLP Multilayer Perceptron

SVM Support Vector Machine

Chapter 1

Introduction

Emotional intelligence, the abbreviation of EI, is narrated as the capability to detect in addition to controlling a person's own psychology as well as acknowledging and managing feelings of other people. EI is a set of capabilities that presume emotional awareness, or the capability to acknowledge and relate someone's psychology; the potential to embrace those emotions and act towards them as activities like reasoning and problem resolving; and the potential to manage emotions, which incorporates both the capacity to control someone's psychology and the capability to support others in doing so. Dr Daniel Goleman who is an analyst and behavioral science writer, mentioned about emotional intelligence in his book called Emotional Intelligence.Which was published in 1995. According to Dr Goleman, emotional intelligence is a person's ability to control his feelings to communicate appropriately and efficiently. According to Daniel Goleman, there are five essential components to emotional intelligence, a psychologist from the United States was influential in popularizing it. The integrants are empathy, self-consciousness, impulse, self-regulation, people skills [**1**].

From the components of EI, emotion is a vast idea to grasp.According to renowned psychologists Daniel Goleman and Paul Ekman: cognitive, emotion, and compassion these three terms are deeply connected. When we witness a person agonizing , we might be competent to promptly put ourselves in their place and empathize to feel what they are feeling. Empathy and sympathy are also two forms of emotion.It comes in a variety of forms. Affective, somatic, and cognitive empathy has been narrowed down to three categories. Sympathy and empathy are strongly related words, with comparable histories and situations in which both might be applied, but they are not interchangeable.

The term "cognitive" refers to tasks performed consciously in mind. Cognitive abilities include learning accurate information, often knowledge that can be easily tested. Anything or any event that induces a specific functional reaction in an organ or is a stimulus. Participation in various activities and discussions that occurs usually in a community to improve cognitive and social performance, in general, is referred to as mental stimulation.

To measure emotion, we are planning to use EEG. It is used to calculate any brain activity. Electroencephalogram is a medical procedure that uses electrodes which are most likely metal discs that are attached to the skin of the skull, to measure brainwave activity. Electrical impulses allow our brain cells to communicate. They are constantly active, even while we are resting. This report is presented as wavy lines on a machine that delivers an EEG recorded report. Our brain's billions of sensory neurons send tiny electrical messages in the form of brain waves. The wires detect our brain signals, which the EEG machine amplifies and records in a wave pattern on lined paper or a computer screen. Electrodes that are tiny metal discs with thin wires, are set down to one's scalp at the time of the procedure. The electrodes measure small electrical charges created from human neuron activity. The recorded waveform reflects the electrical activity of the cortex. EEG activity is measured in microvolts and is relatively low (mV). EEGs are mainly used in detecting brain disorders in our medical industries. EEGs are safe and painless and do not cause any discomfort in most cases [**2**].

1.1 Problem Statement

A cognitive mental process reaction such as rage or terror is subjectively experienced as a powerful sensation and is frequently followed by physiological and emotional changes in the body [**3**]. To relate emotion, EEG, and cognition, all these terms, our research stands to detect tenderness in the human brain by using cognitive stimuli with the help of an electroencephalogram. The computer can see inside the user's head to observe their mental state using EEG-based emotion recognition. Emotion recognition based on neuropsychological technologies can improve the human-technology relationship. Artificial agents that can identify human affective states may assist persons with social behavior problems by virtual diagnosing them and counseling them on how to handle their circumstances. An emotion is a sensation such as enthusiasm, love, fear, rage, or hatred that can be triggered by your surroundings or the individuals you are with [**4**]. It's necessary for good socio-cognitive performance. Previous studies have employed electroencephalography (EEG) to examine brain energization in various parts of the brain to understand empathy's neurophysiological underpinnings better. Many studies have found that prefrontal cortical or cerebral cortical asymmetry, or the variance in energization between the bisections of the brain, significantly impacts empathetic behaviors. All these findings indicate that more robust right prefrontal triggering is associated with psychology-related responses to other people's agonizing thoughts. This is in learning from valence theory, where it is claimed that the left bisection of the brain is better at rectifying positive emotions, and the right hemisphere or right bisection is better at rectifying negative emotions [**5**].

1.2 Background Research

For our thesis, we conducted some background research. According to recent research approaches, researchers try to identify emotion via facial expressions due to any surrounding reaction. Emotion detection technology based on EEG signal analysis has emerged as a key concept in Artificial Intelligence(AI). We look at current exceptional efforts in EEG-based emotion recognition. At both the psychological and physiological levels, recognition is presented. It aids researchers in determining prospective future study fields [**6**].

Researchers at the University of California, Berkeley, concentrated their efforts on 18 physically fit persons. This was the first time electroencephalography (EEG) has been used to build a functional connection network for pain emotion. By observing changes in their connectivity, alterations in network architecture can also explain the activation state of different brain areas [**7**].In another paper, we found that Electroencephalography (EEG) provides superiority over other approaches because it is easier to contribute urgent medical services in high-traffic hospitals. There are a few studies on virtual reality-based emotion classification because virtual reality incorporates mesmerizing senses, including sight, hearing, and perception of "being there," there are a handful of studies on virtual reality-based emotion categorization [**8**]. As part of our background research, we learned from a paper that at the time of listening to music, Emotion arousal and emotion valence are two different brain tasks that may be monitored with EEG. Emotion arousal corresponded with high-frequency brain waves like beta and gamma to determine happiness and sadness. The writer of the paper investigated the connection in the middle of EEG brainwaves and music-generated psychological responses [**9**]. Brain areas entangled in processing one's pain might also be activated when empathizing with another person's pain. Patients with fibromyalgia had higher activations in reactions to suffering and non-suffering pictorial representation, recommending that even somatic impulses with bodily meanings might act on the emotional state [**10**].

1.3 Research Objectives

Our mission is to uncover the cognitive stimulus that plays an essential role in activating emotion in the human brain via brain signals.

1. To reach our goals we are have used two different dataset.
2. DREAMER is a multimodal database including electroencephalogram (EEG) and electrocardiogram (ECG) information generated during affect inferencing using audio-visual stimulation. Following each simulation, signals from 23 individuals were recorded, as well as their self-assessment of their emotional state in valence, arousal, and dominance. All indications were collected using portable, wearable, wireless, low-cost, off-the-shelf equipment. And GAMEEMO For 20 minutes, subjects played four computer games: dull, peaceful, terrifying, and humorous. The SAM form was used by participants to rate each computer game on a scale of arousal and valence.
3. The purpose of this dataset was to provide alternative data for emotion recognition and to evaluate the performance of wearable EEG devices compared to traditional ones. We plan to extract alpha, beta, and theta signals from our dataset EEG signal.
4. From these signals, we will extract features. Those EEG signals represent valence, arousal, and dominance.

5. We will use this valence, arousal, and domination to determine if a person is happy or sad using Deep learning based approach and hybrid Graph Convolutional Network model(GCN).

Chapter 2

Literature Review

In this chapter, we will look at some of the related work that's been done in this field of empathy assessment.

An emotion is a feeling such as joy, love, fear, fury, or hatred that can be generated by your circumstances or the people around you.The recognition of emotional emotions from photos of faces is demonstrated. This paper aimed to discuss the most commonly used strategies for understanding and identifying facial emotion responses published in recent years. For this purpose, 51 articles from the literature were reviewed, encompassing 94 distinct methods obtained from well-established scientific databases, and whose works were categorized according to their main construction idea. The works under consideration may be classified into two categories: conventional and approach designed explicitly with neural networks in mind. When compared to the neural network counterpart, the collected statistical analysis revealed that the traditional methods had somewhat higher identification accuracy but lower adaptability. Furthermore, the current study verified the most often used resources for gesture and emotion recognition, demonstrating the advantages and disadvantages of each and confirming a genuine need for trustworthy information in both fake and natural experimental circumstances.

Computational Facial Emotion Recognition is a fascinating and challenging topic to research. In the context of human-computer interaction, designing and implementing computational algorithms capable of understanding facial emotions from human faces opens up a new field of possibilities. The sooner we can create such recognizers, the better we will be able to comprehend natural areas such as psychology, neurology, human cognition, and learning. Many efforts have been made in the literature to address the emotion recognition problem using face photos. Over the last five years, there has been widespread acceptance of NNB methods, which the introduction of CNN-based methodologies has bolstered. A thorough literature review was conducted to choose 51 publications that met the inclusion and exclusion criteria, giving 94 diverse strategies **[11]**. What are the most widely used approaches and tactics for overcoming the problem of emotion recognition from face images or videos? What role do CNNs play as a global pattern in the challenge of facial expression recognition?

Emotion detection technology based on EEG signal analysis is now an essential idea in Artificial Intelligence. It has enormous promise in emotional health care, human-computer interaction, multimedia content recommendation, and other areas. Although various works have been dedicated to studying EEG-based emotion identification, the substance of these evaluations needs to be updated. Furthermore, such publications are either fragmented in importance or focus on individual procedures used in this domain while ignoring the holistic view of the entire technological route. As a result, we evaluate this paper from the standpoint of scholars attempting to take the first step on this issue. We examine current exemplary efforts in the field of EEG-based emotion identification. Conduct research and create a tutorial to help researchers get started—the scientific underpinning for EEG-based emotion detection. Recognition is introduced at the psychological and physiological levels.

Furthermore, we divide the examined works into numerous categories. Technical ways demonstrate the theoretical foundation and research purpose, allowing readers to grasp better why These strategies are being researched and implemented. Finally, this study discusses current issues as well as future research. It helps scholars decide on potential following research areas.

Researchers with a broad background are increasingly interested in emotion identification. Affective Computing is the process of enabling computer systems to precisely interpret, detect, and grasp emotional information provided by humans in the context of fundamental human-computer interactions. The essence of emotion detection research is the application of statistical machine learning algorithms to recognize distinct emotional states of people in real-time or online. Emotion recognition has long been a study topic in information retrieval. The identified emotion states can be utilized for emotion-related IR needs or to enhance user profiles to increase the subject relevance of recommended multimedia material.

Furthermore, the identified emotion can guide various emotion disorder therapies and music-assisted treatment. In this review, we focus on EEG-based emotion identification tasks and strive to include additional information about current approaches. Other activities are mental effort, motor imagery, event-related potential, epileptic detection, and sleep stage scoring. We give a tutorial to help scholars get started right away. We also discuss potential future directions in this discipline, such as the large-scale pre-trained EEG model used in emotion identification [**6**].

So, Around the globe there has been many different kinds of brain research investigating how the brain processes emotion. Music is one of the ways to evoke emotions.While listening to music there are many different kinds of changes in the brain and it can be measured with EEG.EEG has several advantages in carrying out this experiment which requires stimulations. For the experiment [**9**]the author had to know the handedness of the participant as the brain is cross wired. It is essential to know the handedness because it determines the dominant hemisphere. To invoke positive emotion they used many genres of music and to elicit negative they mixed noise with it. Self responses of the subjects were also noted.Four kinds of musical sections are used with EEG based classifiers. Features were gained by asymmetric power signals. During the experimentation the author evaluated the connection between EEG signals and emotion responses generated by four emotional music sections. For the machine learning algorithm the author used SVM supervised learning.Author suggested the approach to record EEG signal before hearing the music , during hearing the music and after hearing the music. This will help to understand the difference in different states. The left and right hemisphere both are examined in the same way which gives great results.

There has been much research about human emotion recognition throughout the recent years. As empathy is an emotion, emotion recognition can be related to empathy recognition. Humans have emotions which are fundamental for everyone and it plays an important role in human lifespan. Emotion is basically used in logical making determination, various perceptions, interaction between humans, and to a certain case, human intelligence and EQ themselves. With the academic community's rising interest in establishing some significant emotional connections between peoples and various machines, there is a demand in reliability and deployable systems for detecting a person's emotional states. Recently in using (EEG), developments of emotion recognition have gained strong interest from the research community as the latest developments in consumer wearable EEG solutions can provide a less costly, portable, and simple solution to identify the emotions. From the years 2009 to 2016, the last review was conducted on this paper. This paper will update on the current progress of emotion recognition using EEG signals from these years. The focus of this paper review [**8**]mainly focuses on emotion and its element as well as its stimuli type and ecclesiastical approach to study its size and EEG related hardware, and also machine learning classifiers. Moreover, this classification approach also helped in this case.. From this state art review, they can suggest some research opportunities which are basically future based. Proposing a new technique to deliver stimuli in the form of virtual reality is one example. Finally, an extra section that can be devoted specifically to review only VR studies. Also, within this research, domain is needed as the incentive for this proposed new approach using VR. It's known as a stimuli ecclesiastical device. This paper is useful for the research community working on emotion and its recognition. Furthermore, using EEG signals are needed in this case for those who are dabbling in this field.

Another research suggests [**12**],EEG, PET scans, and fMRI are among the techniques that may be used to examine affective processes in the human brain. merging EEG with other non-invasive biometric information detecting technologies to improve emotion identification is a viable approach. The combination between external events and the individual's psychological state causes changes in the electrical characteristics of the skin. A group of forty-four participants were required to watch a succession of emotive stimuli while their EEG activity, biometric signals, and eye location were all recorded simultaneously. The EDA data were analyzed to see which persons self-regulate their physiological activity while observing affective stimuli.

Thirty-one photos were retrieved from the International Affective Picture System (IAPS). Images were shown at 5-second intervals, and neutral images were shown following the images that produced the higher valence ratings. Empatica Wristband was also part of the technology employed in the experiment. The Tobii T60 Eye Tracker generates reflection patterns on the corneas of the user's eyes. Image sensors record these reflection patterns, along with other visual information about the person. The collected data was used to identify the various emotions that users felt while watching a specified set of stimuli.

In addition this research paper [13] says,Emotions have an impact on how people make decisions and interact with their environment. New paradigms of human-computer interaction are needed to identify and recognize them. In this paper, we describe a system architecture in which videogames can stimulate participants to extract characteristics that can correlate with information from emotion and personality traits. AMIGOS is a dataset used to investigate the link between affect, personality, and mood. While watching videos, participants took part in two experimental setups.

First, we looked at the classification system. Second, we analyzed classification performance using only EEG data and participants' sex, age, and personality traits. We investigated three possible categorization situations in the first studio instance. To acquire categorical data, we employ a threshold of 5.0 for arousal and valence responses. We eliminated the observations with missing personality and EEG data from the 640 AMIGOS short-video observations (16 videos 40 people).Using simple machine learning models, the classifiers were chosen to test and compare the emotion recognition accuracy. The goal was to see if the accuracy of any of the scenarios utilizing different feature sets improved when compared to the accuracy reported in AMIGOS work using the PANDAS framework in Python. Adopting a feature selection procedure in emotion recognition tasks improves classifier performance. Filter and wrapper techniques are the two types of feature selection methods. Filter approaches have the advantages of being computationally simple and fast, and independent of the classification algorithm. Using feature importance selection, we looked into how the characteristics contributed in percentage to forecast the various label possibilities.

Various research shows that the part in the brain which is activated by pain also activates during empathetic situations . So, there is countless research done on this behavior of the brain. This research paper [14] shows observation of an empathy network, in which regions of the brain are activated when people are given stimulation of pain in various ways. It is observed that the empathy network takes stimuli and infers the activity into the self and gives response. It shows that anterior insula(AI) and anterior midcingulate cortex(aMCC) are very much important for empathy for pain stimulation. It is also observed that empathy can be modulated by a person's characteristics.

Lemm and colleagues' experiment shows that generation of empathy based on inference and perception show similar activation of the brain areas (vmPFC, STS, TPJ, PCC). Empathy can be modulated through a person's trait of empathy. In such cases people tend to feel more empathetic toward an ingroup persons where AI of the brain is activated and feel less empathetic for other group where the activation of NAcc in the brain is activated, this shows that empathy can be opposed between in group and out-group of people and enable antagonistic behavior.

Another research in this field shows how humans are empathetic towards humanoid robots. Robots have been utilized as emotional escorts. As a result, research [7] on the effects of robot-induced emotions in human-robot interactions. Mostly, these effects may vary from those experienced by people who are becoming increasingly essential. The author surveyed 18 healthy people in most cases, however two datasets may be eliminated . It can be eliminated from any more analysis for significant artifacts in the EEG recording. Stimulation: 1st half of the hand was touched with a knife while the other half was touched with a toothbrush (in a painless condition and painful case). Three sessions made up the experiment. EOG artifacts were corrected using the Journal Pre proof ICA technique, and studies with seemingly incorrect answers were removed. They also employed EEG recordings and acquisitions. Participants completed two questionnaires one week prior to the ERP recording. Empathy Index and Interpersonal Reactivity Index Interactions between distant brain regions are at the heart of cognitive activity. According to a neuroimaging research on empathy, painful imagery activated the ACC and the right middle frontal lobe. Changes in network topology can also be used to explain how different brain regions are activated. ERP is an easy and renowned technique for demonstrating the secular dynamic of pain and empathy according to EEG-based studies. Under painful and painless conditions, acquires events which have potentials produced by people and robotic hands. The signals from a person's hand stimulus and the signal from the robot hand stimulus were larger. Emotional Reactions Subjects scored higher for human pain situations than painless ones, and higher for human pain conditions than robot pain conditions, according to the results of the questionnaire. indicate. However, no significant relationship between emotional response and network indicators was discovered, which could be a limitation of their research. Because most papers use a qualitative approach to empathy, there are few quantitative investigations on the mechanism of empathy in the literature. This is the first study to employ EEG to create a pain empathy functional connectivity network. Finally, this research highlights the differences between people and robots. This can be considered as proof of a functional link between humans' ability to empathize with humans and robots.

According to this paper's **[10]** authors, areas associated with processing a person's pain have been found to be active during compassionate perception of some other person's suffering, according to neuroanatomy. Patients with fibromyalgia (FM) had higher action potentials in photos of suffering and non-suffering, implying that even somatic stimuli with somatic meanings can affect the emotional state. The goal of the study was to see if the LEPs and EEGs of healthy individuals and FM patients changed when they saw their own or another's stimulated hand.

The experiment built a "twin-type" model that might aid mutual compassionate engagement in the inclusion or exclusion of painful stimulations. The Empathy for Pain Scale (EPS) scored patients higher than controls, but the difference was insignificant. As a result, a history of severe pain could alter compassionate behavior towards controls, modulating the experience according to on-task peculiarity.

Chapter 3

Background Analysis

3.1 EEG Signal

The characteristics of cerebral activity captured by electroencephalography (EEG) are typically capable of approximating active prospects that the brain elicits with varying latencies and densities at each instantaneous [**15**]. The functional modality of electroencephalography (EEG) makes it possible to collect brain waves or signals that are related to different states from the surface of the scalp. Moreover, vast numbers of neurons make up the human brain, and these neurons play a crucial part in regulating how the body responds to internal and external sensorimotor events [**16**]. This cortical electrical activity is what it reflects. For a thorough study, the EEG signal must be measured correctly. Additionally, choosing the right site is crucial.

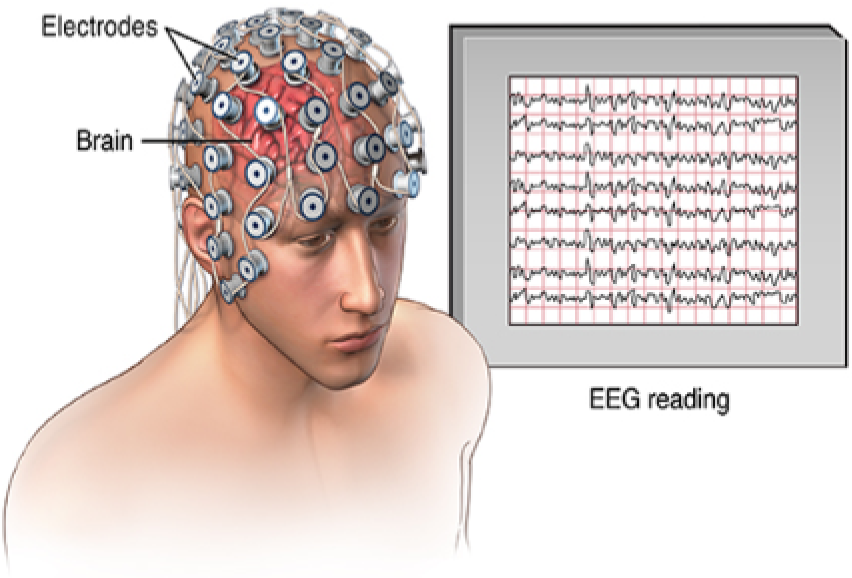

Figure 3.1: EEG Signal processing
[**17**]

Since the wave is so tiny, a microvolt is required to measure it. Frequency is the most important factor to consider when evaluating EEG signals. In fact, Greek numerals are employed to designate EEG waves in order to reflect their frequency range. The waveforms delta's rage is from 0.5 to 4Hz, theta's range is from 4 to 7Hz, alpha's range is from 8 to 12Hz, sigma's range is from 12 to 16Hz, and beta are among the most frequently researched waveforms which is from the range of 13 to 30Hz [**18**]. We require an EEG device with the ability to detect and record frequency bands in order to measure brain electrical activity. It is helpful today for many types of research, including clinical and scientific studies. Finally, we attempted to manage an EEG machine, but for various reasons we were unable to do so. As a result, we worked with a few pre-existing datasets that had previously been obtained using EEG machines.

3.2 Cognitive Load Index (CLI)

Cognitive load, as it is commonly understood, measures "how hard a cognitive system needs to work to execute a given job." (Just et al., 2003) The quantity of working memory (WM) or visual attention capabilities required to complete a task is a measure of cognitive load [**19**]. Although the Cognitive load theory had a solid foundation by the latter part of 2000, research for the Cognitive Load Index, had been ongoing. When measurements of overall cognitive load fall short of reflecting such changes in cognitive processing, EEG is recognized as a physiological marker which can function as an active, ongoing indicator of mental strain, identifying minor shifts in monetary burden. Objective metrics, task difficulty, and learning outcomes are all in some way markers of cognitive load. An established index for CLI is the entity related Desynchronisation/ Synchronization (ERD/ERS) [**20**]. On the other hand, human may exhibit brain waves resembling the neural stimulation system in monkeys [**21**]. The equation is shown by :

$$\gamma = \frac{\rho_b - \rho_t}{\rho b} * 100 \tag{3.1}$$

Here, γ is a measurer of the cognitive load index , 'b' is a baseline phase and 't' is a test cycle and these belong to band power. For each window of the EEG signal analysis, the TAR index was employed as another index to measure the cognitive load. According to some light-based tests which are basically physiological tests, a person's visual, cognitive, functional, or behavioral performance can be directly inferred from neural activity [**22**].

3.3 Brain Waves (Cortical Potential)

Brain is one of the important human organs. The brain is a sophisticated organ that manages every bodily function as well as mind, memory, empathy, sensation, motor function, vision, respiration, warmth, and hunger. With the aid of nerves, the brain's primary role is to quickly send messages to every part of the body. Axons and dendrites combine to form the neuron, which is the primary component of a nerve fiber. Each neuron is related to every other neuron. Neurotransmitters hold these neurons in place. A few nerves are directly connected to the brain in this location. Some had the opportunity to access the psyche via a controlling line that goes down the back of the spine, for illustration. The Central Nervous System is created once this vertebral line links the brain [**23**].

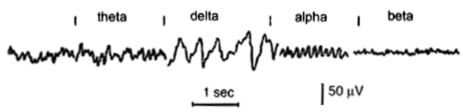

Figure 3.2: Brain waves
[**24**]

Brainwaves are created by electric impulses that are synced and come from millions of neurons interacting with one another. Different frequencies are present in our brainwaves. Both the quick and the slow among them. Alpha, beta, gamma, delta and theta are the traditional names for these EEG categories or bands [**25**]. Steven Feldon claims that the visual system makes up one third of how our brain functions. However, the brain changes over time and picks up data from a variety of internal functions. Researchers from the UCLA Neurology Department assert that when a person's vision is impaired, their minds shift radically in a way that shows how the brain can rebuild itself in the absence of tactile input [**23**]. Nevertheless, the purpose of brain computer interfaces is to track brain activity in order to design future human-machine interactions. A BCI may monitor activity in the brain using a variety of techniques that can broadly be categorized as non-intrusive and intrusive.[**26**] We only use non-intrusive approaches, specifically electrical psyche signals as determined by electroencephalograms (EEG), due to the risks generated by continuously carefully embedded devices in the brain and our concerns [**27**].

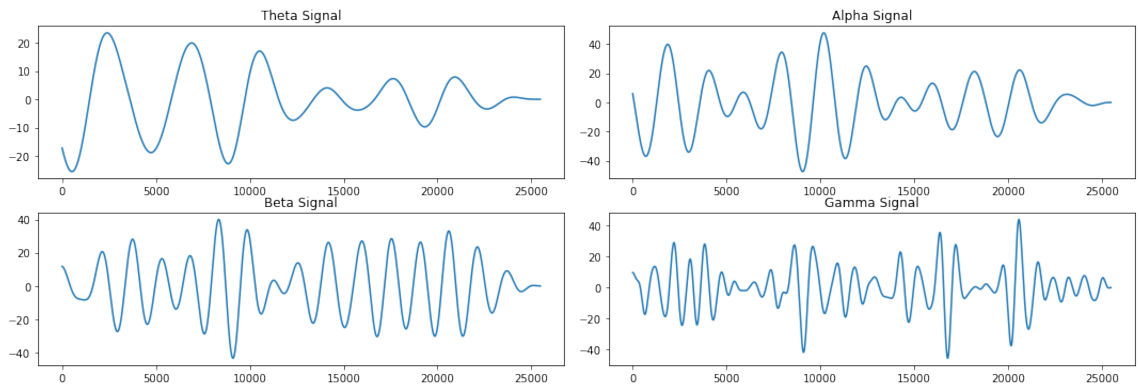

Figure 3.3: Different Types of Brain waves (from our model)

3.3.1 Alpha waves

The effects of alpha waves include a sense of peace, a boost in inventiveness, and an improvement in a person's capacity to learn new things. The most obvious methods

for extending your capacity to remain in an alpha state include mindfulness and meditation, however other approaches can be seen too [**28**]. Alpha is also the range of periodicity between theta and beta. In the unlikely event that we are driven, a phenomenon known as "alpha blockage" may arise, characterized by intense beta oscillation and minimal alpha [**29**].
When the alpha wave is too low, there are certain issues; as a result, individuals experience anxiety, sleeplessness, and chronic stress. Nonetheless, a high alpha wave range stimulates imagining. Alpha waves are typically present in adult humans. For instance, after accomplishing a project, people participate in a test that analyzes alpha waves. Alpha waves are a byproduct of a tranquil workout or contemplation [**30**]. In a typical alertness state when the person is soundly asleep, alpha waves are visible on the electroencephalogram (EEG). For another instance we can say, when someone reads a book, his/her brain interprets the words by reading and gives them interpretation based on the information it receives from their eyes. Brain waves are produced by all of these messages electrically sparking against one another in a specific way [**23**].
In a normal brain, beta waves are active . This repetition is obvious in rational reasoning that is clever. Beta waves, which have a greater frequency and minimal amplitude, are frequently seen in awake people. They tend to have a stimulating effect and are engaged in cognitive and rational reasoning. Focus is made possible when there are enough beta waves in our brains [**31**]. When a person is focused, alert, and actively pondering, beta EEG is visible. We place a focus on rational reflection actions. When our brains are overly beta, we may feel too much stress and anxiety. Then beta action will normally increase after consuming caffeine or another energizer [**29**]. On the other side, ADHD has been associated with fewer beta waves. Two signs of weak cognition include depression and bad decision making [**32**]. However, beta waves mostly appear when a person is awakened, and stressed, intense emotions and anxiety can all cause a rise in beta power.

3.3.2 Gamma waves

Higher brain processes like intellect and memory are linked to gamma waves. Gamma waves have been proven to enhance working memory in a recent study. The following advantages of gamma waves - A person's mental acuity and capacity for problem-solving can both be enhanced [**33**]. Gamma waves have a tiny intensity and must form more quickly than other waves. Gamma waves can be divided into two categories- low-gamma waves which have a low frequency rate from 30 to 60 Hz and the frequency range of high gamma waves are from 60 to 200 Hz [**34**]. Gamma waves are considered the fastest waves for the human brain. Besides, for memory, training, and data preprocessing, gamma waves are crucial. The entire brain is susceptible to gamma waves' effects. Additionally, they have a profound impact on cognitive abilities that require complexity [**35**].

3.3.3 Theta waves

Internal attention, mindfulness, prayer, and intuitive consciousness all produce powerful theta waves. It refers to the inner self and reflects the transitional condition between waking and sleeping. Adults who are awake find it odd, however youngsters under the age of 13 find it quite acceptable. Additionally this is typical while sleeping [**36**]. Theta wave has a very low frequency. Mostly produced in a profound and dense manner. Sleep or daydreaming are associated with theta waves. Such types of brainwave patterns can show spontaneous or instinctive behavior [**37**]. Additionally, generating enthusiasm and intuition is the ideal result. Increased theta waves result in excitability and impair the thinking capacity effectively. This indication or signal may also lead to depression and is in charge of weakening initiatives. They have an unusual connection to task complexity. Greater undertaking barriers can be caused by a rise in theta wave intensity [**23**].Theta waves are near the low portion of the electromagnetic spectrum. They move more quickly than delta waves but they are slow in terms of alpha waves. Theta waves are detected by an EEG between 4 and 8 Hz [**38**].

3.3.4 Delta waves

The slowest brain waves yet observed in humans are called delta waves. Infants and toddlers seem to exhibit them most frequently, and they are linked to the utmost level of calm and regenerative, therapeutic sleeping [**27**].In addition, they've been connected to unconscious real talents like controlling metabolism and heartbeat. We feel entirely energized after a solid sleep during night because enough delta waves are created [**29**].While thinking while one is in a state of deep sleep or excessive exhaustion, such as a coma delta waves occur. If the affected person struggles to retain conscious awareness or has cognitive difficulties, unexpected delta behavior in cases of cerebrum injury may happen [**37**].Elevated brain waves known as delta waves are related to profound sleep stages. Other than deep sleep, the delta waves are linked to other aspects of brain activity. For instance, for waking patients, frontal delta waves (mostly high) are linked to brain remodeling [**39**].

3.4 Wavelet transform

An influential approach identified as Wavelet transform was envisioned to resolve the issues connected with FT, FFT, and STFT. As it works on a number of co premise rather than a solitary level and identifies inconstant sensor issues to be an outgrowth to Fourier Transform in that Wavelet Transform could be considered. For delivering details about the rate and schedule components of indicators we are using wavelet analysis which is type of rate and schedule interpretation. Wavelet analysis is a form of horizontal convolution of indicators that also symbolizes tangible info regarding methods and tangible attributes of forms of media and artifacts.Through correlation to other regenerate mechanisms like FT and STFT, Wavelet Transform had already proven to be extra productive for signal representation. Featuring a differential frame rate that is inclusive at minimal wavelengths and constricted at longer wavelengths, resulting in an efficient period of wavelength precision across all resonant frequencies is The primary benefit of the wavelet transform. Overall, wavelets are designed to have precise attributes which end up making each other effective for waveform filtering. By turning, moving, doubling, and combining them, wavelets are integrated by a method called convolution [**40**].

3.4.1 DWT

In our algorithm DWt plays an important role.DWT was an important part of our algorithm. Confining all these wavelength and period sectors a quicker oscillating mechanism is used called a wavelet. To demonstrate as well as inexact indicators or features utilizing a constellation of tasks is the general concept behind Wavelet transform. T The municipal properties of indicators across the latency and recurrence sectors can be described by wavelets . The monitoring spectrum in the time sphere is relatively small when using a lesser level, though in fourier transform this is similar to using specific intensity for large aspect ratio analysis, that is, utilizing spectral wavelets for direct perception.This same consistent wavelet transform of x(t) is characterized as follows:

$$\Psi_{p,q}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-q}{p}\right) \tag{3.2}$$

DWTs are required for distinct wavelets because EEG stimuli are distinct. In contrast to the prolonged WT, the DWT restricts the p and q of the wavelet premise feature ψ(p,q) to sub coordinates, resulting in the linearization of magnitude and deflection [**41**]. The function is $\psi_{m,n}(t) = 2^{-\frac{i}{2}}\psi\left(2^{-m}t - n\right)$, where $m \in Z, n \in Z$, the DWT is,

$$WT_x(m,n) = \int x(t)\psi^*_{m,n}(t)dt \tag{3.3}$$

3.5 Fourier Transform

The Fourier Transform is a computational representation that facilitates in the evolution of indicators respectively in three zones, those are from spectral purview to wavelet transform or many more. FT has numerous implementations in mechatronics and general relativity, including sensor manufacturing process and Transponders. We will go over the Fourier transform strategy, characteristics, graphs, Discrete wavelet vector change, and Spatial sinusoid turn with comprehensive interpretations in our research [**42**].

3.5.1 Fast Fourier transform (FFT)

Fast Fourier transform is considered one of the most successful approaches to sensor features . To compute a FT sequence the FFT algorithm was used by us. For operating in the fourier transform, wavelet transform, or spatial domain, and equally software the FFT sprouts are analyzed . Where N is the vector's variable , it works by converting an N-time entity sensor into an N-time entity sensor in a mono juncture. The second phase involves forecasting the N intensity variety for each of the N time entity sensors. Finally, to expedite the CNN training phase, the N continuum was polymerized into a narrow band spectrum. The equations of FFT are:

$$H(p) = \sum_{t=0}^{N-1} r(t) W_N^{pn} \tag{3.4}$$

$$r(t) = \frac{1}{N} \sum_{p=0}^{N-1} H(p) W_N^{-pn} \tag{3.5}$$

H(p) is identified as the fourier coefficients of r(t) [**43**].

3.6 Discrete Cosine Transformation

DCT is the mechanism which generates a predefined series of content coordinates of every cosine feature at highly variable harmonics. To transform the correlations of a sporadically and coaxially enlarged Fourier Analysis sequence, DCT is commonly used . In both the latency and intensity areas, the bode plot of the sensor is zero. The precise frequency band is symmetrical, but the illusory frequency band is rare. We can convert standard spectrums to the mel recurrence using given bellow equation:

$$X_p = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n + \frac{1}{2}\right) P\right] \tag{3.6}$$

Here, lists of real numbers are represented as N , and Xp is considered as a collection of N data values [**43**].

3.7 Statistical features

Statistics is the use of mathematical concepts to function implemented or systematic files. Placing emphasis on the numerical outcomes of this relevant data, we work with relevant data utilizing quantitative functionalities. People can acquire and acquire increasing amounts of comprehensive description on how facts and figures, in specific, assemble our information, and how other machine learning approaches can be appropriately utilized to attain quite exact and contextual remedies [**43**].

3.8 Poincare

A starting to emerge modeling approach , the Poincare, where it carries a set of interims and graphs every frequency against the next increment. The structure of this narrative arc has been demonstrated in interventional setups to distinguish among wholesome and unsanitary areas of study. In a response variable, it is utilized for illustrating and characterizing the relationship among two sequential variables. Because protracted causative link and cognition are illustrated in the complexities of differences in respiratory time signatures, the goal of this research was to broaden the Poincare graph by procedure, rather than among two sequential points, to include the affiliation among consecutive variables in a sequential manner [**43**].

3.9 Power spectral density(PSD)

Welch approach is an improved classification process for governing the mean spectrogram. A moment sequence is confined to the Welch mechanism. The goal of Spectral Density is to reduce the fluctuation inside the outcome PSD explained about which intensity spectrum disparities are significant and may be very effective for future research [**43**]. The respective formula typically characterized by the The Welch mechanism of the PSD are :

$$P(f)=\frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)\omega(n)e^{-j2\pi f}\right|^2 \tag{3.7}$$

$$P_{\text{welch}}(f)=\frac{1}{L}\sum_{i=0}^{L-1} P(f) \tag{3.8}$$

3.10 Hjorth

Bo Hjorth introduced Hjorth parameters in 1970 as markers of statistical characteristics used in time flow/domain in signal processing. Activity, Accessibility, and Sophistication are the parameters. They are frequently employed in the feature extraction process for EEG signal analysis [**43**].

The signal strength and variance of a time function are both expressed by the activity parameter. This may represent the frequency domain power spectrum surface. This is expressed by the equation that goes like this:

$$\text{Activity } = \operatorname{var}(y(t)) \tag{3.9}$$

The mobility parameter indicates the power spectrum's mean frequency or standard deviation as a percentage. This is determined by the following :

$$\text{Mobility } = \sqrt{\frac{\operatorname{var}\left(\frac{dy(t)}{dt}\right)}{\operatorname{var}(y(t))}} \tag{3.10}$$

The frequency change is denoted by the Complexity parameter. This parameter measures the signal's proximity to a sine wave; if the signal is more similar, the value corresponds to 1, and vice versa. This is expressed by the equation that goes like this:

$$\text{Complexity } = \frac{\text{Mobility }\left(\frac{dy(t)}{dt}\right)}{\text{Mobility }(y(t))} \tag{3.11}$$

3.11 Model approaches

After collecting data, building a subset of the top performing features, several feature selection approaches will be used. Following that, a number of Linear Model Feature Rankings could be used. To construct feature importance rankings, this strategy may employ some distinct Scikit-Learn linear models. Recursive feature elimination will be employed in the second step. This method generates rankings by ordering features from most to least important, then discarding the worst performers. Thirdly, Random Forest Feature Ranking will be utilized to determine and rank the feature significance using the Random Forest attribute which can be called feature importances. To integrate the approaches, all will be integrated into a single matrix and factor plots will be created.

Basically, these are the proposed plans for our research. And we will implement these according to our plan as soon as we arrange an EEG machine and collect data from real life experiments. For now, we are using the existing Dataset and in order to progress this research for the current situation, there are a few things that have been implemented or tried to use. For example, MLP, SVM, Random Forest, Neural Network, LSTM, Convolutional Neural Network, KNN, GCN and so on.

3.11.1 Multi-layer Perceptron (MLP)

The multi layer perceptron (MLP) is a feed forward neural network augmentation and there are three types of layers and these are represented in Figure 3.4. These layers are - input layer, output layer, and hidden layer [**44**]. The perceptron, which was introduced in 1958, is credited with being the first practical artificial neural network [**45**]. The MLP network method is depicted in Fig 3.4.

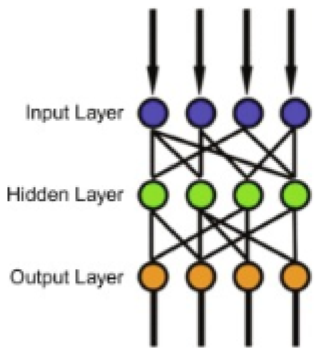

Figure 3.4: Multi-layer Perceptron
[**44**]

The input and output layers are the major emphasis, however it is the hidden layer that reliably calculates probability scores. The output of the MLP network is expressed by Eq 12.

$$y_k^o = f_k^o\left(b_k^o + \sum_{i=1}^{s} w_{ik}^o y_i^h\right) = f_k^o\left(b_k^o + \sum_{i=1}^{s} w_{ik}^o f_i^h\left(b_i^h + \sum_{j=1}^{N} w_{ji}^h x_j\right)\right) \tag{3.12}$$

$Where$, k = 1, ... , L

Multi-Layer perceptrons are comprehensive estimator neural network models that can estimate any uninterrupted function. We can see that these models are called SEE models. For example, Perception neurons are used to create MLPs. Let's go over the general structure of a perceptron before going over the overall structure of MLPs. As shown in Fig 3.5, a perceptron accepts n characteristics as input (x = x1, x2,..., xn), and these characteristics have a corresponding weight. Features for numerical input are required. Before using a perceptron, input qualities that are not numeric must be transformed to numeric input attributes [**44**].

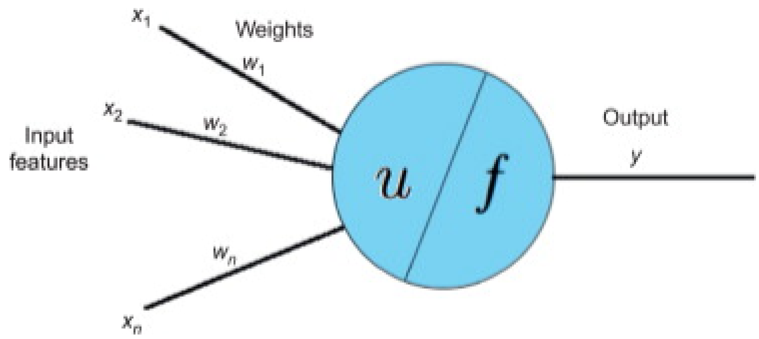

Figure 3.5: Perceptron with n input characteristics
[**45**]

Input features' weighted sum can be seen in Eq 13, where u is an input function.

$$u(x) = \sum_{i=1}^{n} w_i x_i \tag{3.13}$$

Here, the activation function can be seen in Eq 14.

$$y = f(u(\mathbf{x})) = \begin{cases} 1, & \text{if } u(\mathbf{x}) > \theta \\ 0, & \text{otherwise} \end{cases} \tag{3.14}$$

Lastly, since we tried many models, in this sequence we worked with Emotion-specific EEG signals that were elicited using several samples of emotional videos as stimulus. Furthermore, the alpha power which basically is hemisphere asymmetry, leads to brain activity that were recovered as a vector which is called feature vector for training an MLP to learn various emotion categories, such as - joy, rage, sadness, and pleasure [**46**]. In addition, in a similar way, our research will be based on such actions where we use MLP to learn our emotion category , specifically empathy.

3.11.2 SVM (Support Vector Machine)

SVM is a supervised machine training method that is usually used including both regression and classification difficulties. Though there can be seen arguing with regression difficulties, categorization is the best fit. The goal of the SVM method is to discover a hyperplane which may be focused in an N-dimensional space that categorizes data points clearly [**47**].

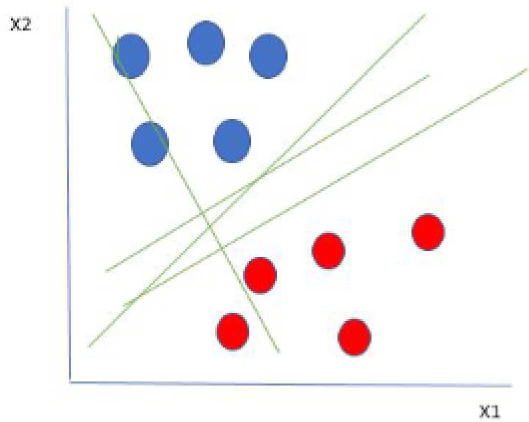

Figure 3.6: Separable data (linear) - Usage of SVM

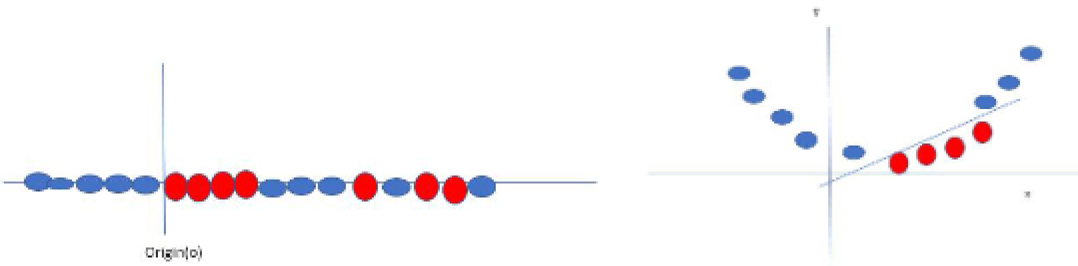

Figure 3.7: Usage of SVM
[**47**]

It's evident from Fig 3.6 that there are several lines (our classification model is a line even though we're only considering input data characteristics, x1 and x2) that separate our datasets or classify them into red and blue spheres. So, how then do we pick the best line, or even more broadly, the optimal hyperplane, to separate our data points.

From Fig 3.7 , it can be seen that SVM overcomes this by utilizing a kernel to create a new variable. This designates a line point xi and yi works as a function of which is a distance from the origin (o). The random item or variable y is formed as a function of which is also distance from the origin under this scenario.

3.11.3 Random Forest

Random forest is indeed a Supervised Machine Learning Algorithm that is commonly utilized in regression and classification scenarios. It generates decision trees on continuous or discrete and uses their democratic majority for categorization and means for regression.

Among the most essential characteristics of the Random Forest Algorithm is its ability to manage data sets with both dependent and independent variables, as in regression and classification. It produces superior outcomes for categorization tasks.

Before we can grasp how the random forest works, we should first comprehend the ensemble approach. Ensemble basically refers to the combination of numerous models. As a result, rather than a single model, a group of models is utilized to create predictions. Two types of ensemble methods are bagging and boosting.

Bagging refers to generating various training subsets using a sample training dataset through replenishment, and the end result is determined by majority votes. Boosting refers to transforming weak classifiers into strong classifiers by constructing sequential models with the highest precision. For instance, ADABOOST and XG-BOOST.Bagging and boosting is shown in figure 3.8 below.

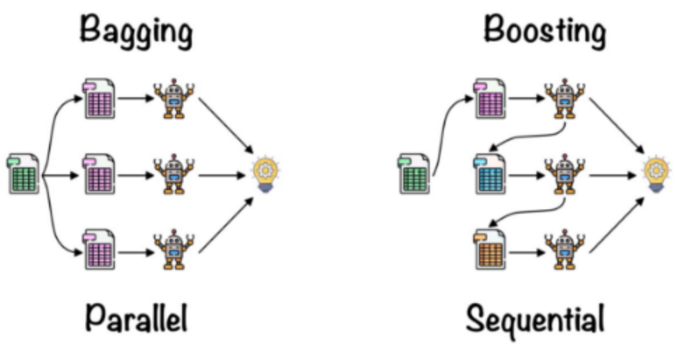

Figure 3.8: Workflow of Bagging and Boosting
[**48**]

On one of our approaches, we have used Random Forest Classifier taken using scikit-learn library, where total data was pre-processed with min-max scaling and then randomly split and trained for classification [**48**].

3.11.4 Neural Network(NN)

A neural network is a set of methods that attempts to identify dynamic linkages in a batch of data using a method that replicates how the human brain works. In this context, neural networks are sets of neurons that might be endogenous or synthetic.

Because neural networks can respond to changing input, they can produce the desired outcome without rewriting the creative environment. The artificial intelligence-based notion of neural networks is rapidly picking up steam in the creation of trading algorithms [**49**]. The representation of a simple neural network is shown below in figure 3.9. In our research, we have randomly taken some datasets and preprocessed

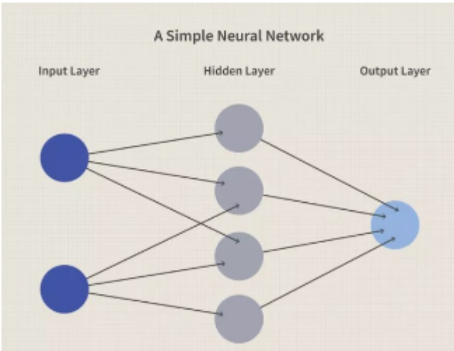

Figure 3.9: A simple Neural Network
[**49**]

and scaled all that data. It has 2 hidden layers and 1 output layer. First hidden layer has 64 neurons and activation of tanh and the second hidden layer has 180 neurons and activation of tanh. In the output layer 2 outputs will be predicted and have sigmoid activation function. Also, Adam optimizer to optimize our model and for calculating loss we used sparse categorical cross entropy as loss function.

3.11.5 Convolution Neural Network (CNN)

Features taken out from the native EEG dataset are transmitted to the CNN first. It involves many convolution-merging coating sets and one output coating. Features are sequenced into portrayal formation with many one dimensional riddles in convolutional coats before providing it to the CNN.Following the merging layer, the data is further compressed to smaller pixels. The back-propagation algorithm is applied to grasp the network weights and strainers in the convolution coats [**50**]. The basic structure of the proposed EEG classification system is shown below in the figure 3.10.

In Fig 10, it shows an EEG classification sequence which is related to CNN. We have performed a number of feature extractions like, Fast Fourier Transform (FFT)

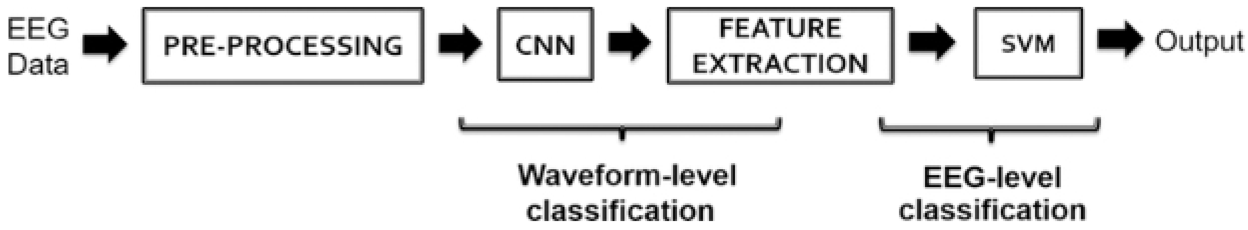

Figure 3.10: The basic structure of the proposed EEG classification system [51]

and wavelet transform to pre-process data.Then every transform data is mean normalized and convert those mean data to absolute values. After That, compared those data and took closely two values of mean normalized data to get the output (675,62,3).Moreover, we used 1D convolution and max pooling and sent them to a neural network, which has three hidden layers and one output layer. Also tanh activation used in all layers. Also, adam optimizer to optimize our loss values and for calculating loss we used sparse categorical cross entropy as loss function.

3.11.6 LSTM

Long-Term Memory Networks (LSTMs) are a category of RNN. In aspects of time series forecasting, the Long-Term Memory network has been shown to be more impactful than force feed neural networks and recurrent neural networks due to its aptitude to preferentially recall crucial data or value systems for a longer amount of time. LSTM network is generally used for time series or pattern content processing, categorization, or projection [52].As it is trained using back-propagation through time (BPTT) and also induces the disappearing slope issue for that lengthy patterns could be tough to understand with conventional RNN [53].To address it, the RNN cell is modified with a recurrent network, such as an LSTMs organelle. To just use LSTM for EEG frequency refining. Each test is subjected to a wobbling intersecting frame to generate a function framework as in pattern of encoding statistics and used as the sequence input to the LSTM network to formulate an unique approach in our research. For generating a function framework as in the pattern of encoding statistics, which is used as the sequence input to the LSTM network, each test is subjected to a wobbling intersecting frame. The LSTM architecture, overall, consists of a memory cell, an input gate, a forget gate, and an output gate.Which data is preserved in ram and which is not are governed by these gates. These gates govern which data is preserved in ram and which is not. The ram contributed to the LSTMs neuron allows it to recognise preceding strides. The layer of the network is crucial to LSTMs. Using three input LSTM can eliminate or add data to the lstm unit.

For both lengthy or brief intervals of time the LSTM keyframe cognitive neuron records or recognizes attributes.The input gate, while the other hand, governs how much additional knowledge or significance circulation through into nucleus of an LSTM interface, the forget gate handles how much metadata or relevance remains in the cytosol of the LSTM layer, and the output gate regulate how much data

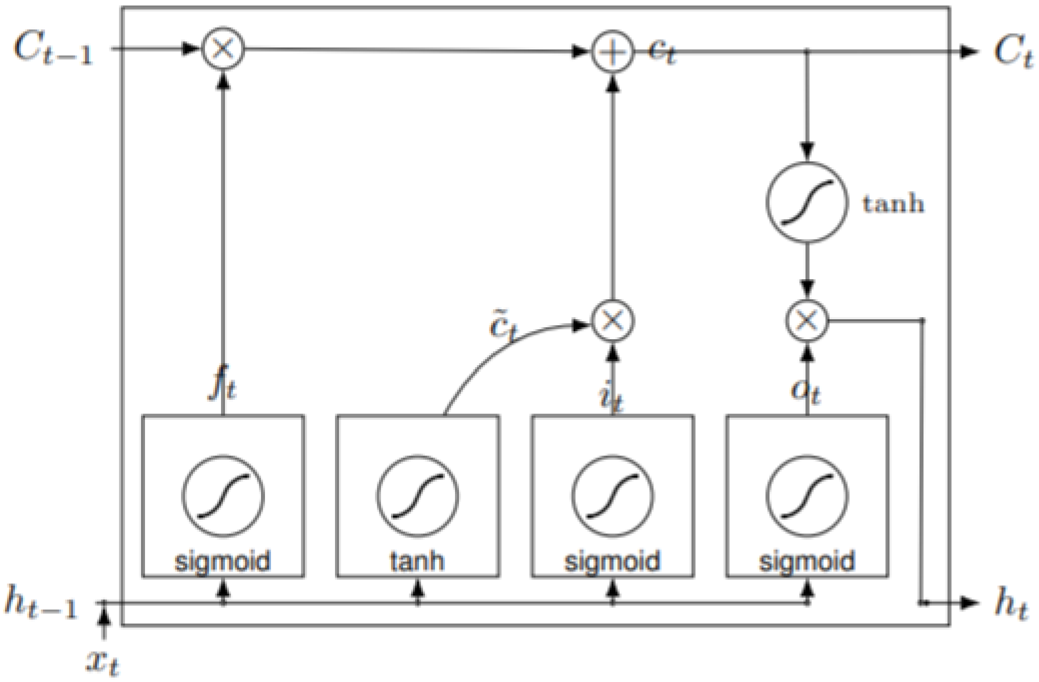

Figure 3.11: LSTM cell architecture [**53**]

or significance preserved in the oocyte of the LSTM layer is utilized to calculate excitation. Imaging system employs a RNN with two LSTM stacks.

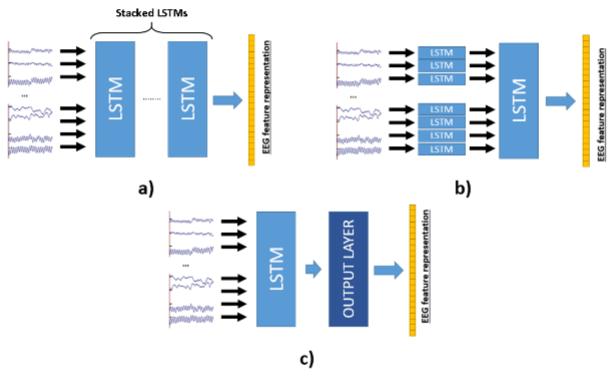

Figure 3.12: LSTM-based architecture for EEG signal Classification based-on Channel LSTM [**54**]

3.11.7 K-Nearest Neighbor

K-Nearest Neighbor is used as a non invariable method and extremely quick learning process as it does not require any preconceptions about the source info.and uses the current dataset as training. The Supervised Learning approach is used by K-Nearest

Neighbor which is also known as a primary Machine Learning method. The K-NN mechanism presupposes resemblance in between new statistics and current instances and assigns the lawsuit to the category with the highest similarity to the selected groups.Classifying by recognition the adjacent neighbor data based on resemblance or range in between data sources. As it is capable of getting higher recognition accuracy,rapid and easy recognition accuracy this method is used by many scholars [**55**].

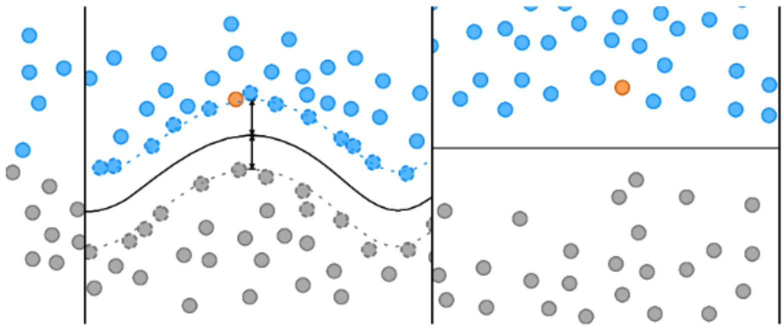

Figure 3.13: Examples of classification of a test vector using k-nearest neighbor [**56**]

Chapter 4

Methodology

Overview:

Figure 4.1: Top level overview of the Proposed System

Top level overview of the Proposed System:

Figure [1] shows our methodology of our proposed model. Here in the first step the diagram shows the Dataset collection step, we have collected our Dataset form the [citation of Dreamer dataset] website and which has EEG data for numerous subjects. After data collection, the next step is the signal processing step, where the raw signal from the dataset is passed between a band pass filter to extract signals between a specific range and then theta, alpha, beta signals are filtered. These signals are then used in feature extraction methods like signal statistics, Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Hjorth, Poincare, Power Spectral Density (PSD). Following is LSTM layer, followed by 2 1d convolution layer to further preprocess the feature extracted data of the signal. This is the final feature values which splitted into 80% training data and 20% testing data. All the data is passed to the GCN layers and training is performed in the training dataset and finally we have tested our Model with the test data. These steps performed a classification with a 100% accuracy in our proposed model for dreamer dataset and 92.76% accuracy of GAMEMO datset, and detailed explanations of each layer are given in the following pages.

4.1 Data Description

4.1.1 Dreamer Dataset

DREAMER is a multimodal database that contains electroencephalogram as in EEG and electrocardiogram as in ECG signals generated during affect inferencing with audio-visual stimulation. Signals from 23 subjects were monitored, as well as the subjects' self-assessment of their emotional state in valence, arousal, and dominance following each stimulation. All of the signals were gathered utilizing portable, wearable, wireless, low-cost, off-the-shelf technology, which has the potential to facilitate the adoption of emotional computing technologies in daily applications. In addition, the Emotiv EPOC wireless EEG headset and the Shimmer2 ECG sensor were implemented for EEG and ECG, respectively.

The proposed database's characterization findings for valence, arousal, and dominance are identical to those obtained for existing databases that employ non-portable, costly medical standard instruments.

The suggested database was made accessible for academics to conduct a more comprehensive study of these capturing devices' potential for physiological response identification applications [**57**] .

4.1.2 GAMEEMO Dataset (Database for Emotion Recognition System)

This dataset contains EEG signals from computer games. They were obtained from 28 individuals using the 14-channel Emotiv Epoc+ wearable and portable EEG machine. Subjects played four unique computer games, boring, calm, frightening, and hilarious, for five minutes each, totaling 20 minutes. These 20 minutes of EEG data were collected for each participant. Participants assessed each computer game using the SAM form on a scale of arousal and valence. In the data repository, they supplied both raw and preprocessed EEG data. The rating score and SAM form for each subject were also provided. The goal of this dataset was to give alternative data for the emotion identification procedure and compare the performance of wearable EEG devices to traditional ones. There were 29 distinct folders in the main folder of GAMEEMO, where 28 folders were for subjects, and one folder was for gameplay. S01, S02,... were the participants who participated in the experiment. Each game's gameplay is displayed in the Gameplay folder. SAM ratings were also available [**58**].

4.2 Signal Preprocessing

The Dreamer Dataset contains EEG signals. EEG signals Here audio and video stimuli were provided to capture the EEG signals. EEG signals tend to have a lot of noise due to movements and artifacts. In that case, Analyzing the data with noise is quite difficult. In different frequency ranges, the signal provides different information about the stimuli and subject. For emotion recognition, the frequency range is considered from 4-30 Hz. So, we focused on the 4-30hz range to get the best information regarding the emotion the stimuli induces. We use the Bandpass filtering technique to filter the EEG signal into the 4-30hz frequency range From this technique we achieve the required data from the EEG signal with minimum noise. A sample raw signal of the AF3 channel is shown in Fig 4.2.

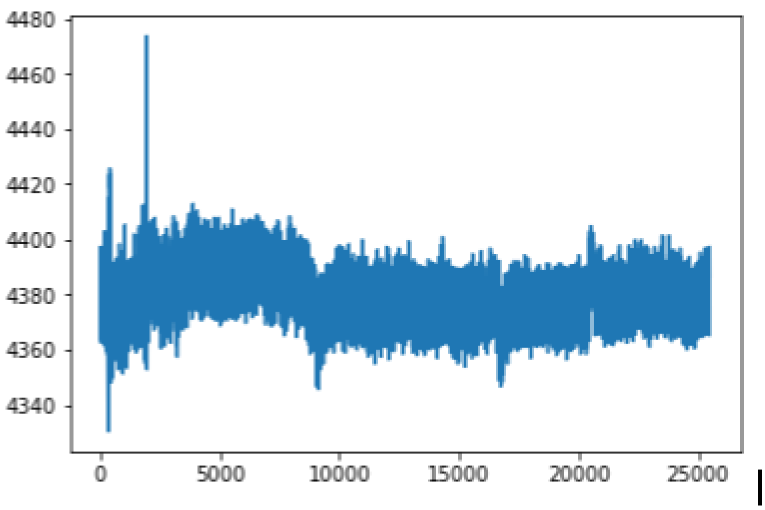

Figure 4.2: Sample EEG signal in time Domain

The Bandpass filtering technique uses two attributes: low pass and high pass. This removes the frequencies under the low pass and above the high pass. It keeps the frequencies from the range of low to high pass. In our proposed method of the feature fusion-based approach, we filtered the signal data of each channel in the 4-30hz range. This allows us to remove most noise. The signals were divided into 3 more sub-frequency bands which are alpha, beta, and theta. These 3 bands, especially the beta band are the most widely used frequency bands for EEG data and emotion recognition. The ranges we used for these bands in our proposed method are theta from 4-8 Hz, alpha 8-13 Hz, and Beta 13-20 Hz. Sample EEG signal of these 3 bands is shown in Fig 4.3.

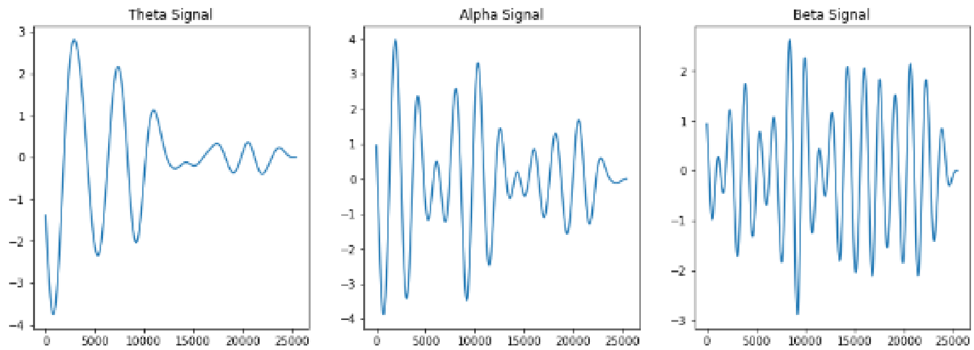

Figure 4.3: sample EEG signal of 3 bands in frequency domain of AF3 channel

4.3 Feature Extraction

After doing the preprocessing we move towards extracting features from the frequency bands. First, To get the coefficients we use the Fast Fourier transform(FFT). Sample FFT transformation of alpha,beta and theta band shown in Fig 4.4 . Then we compute the mean and maximum of the coefficients. So, we get a total of 6 coefficients for 14 channels.

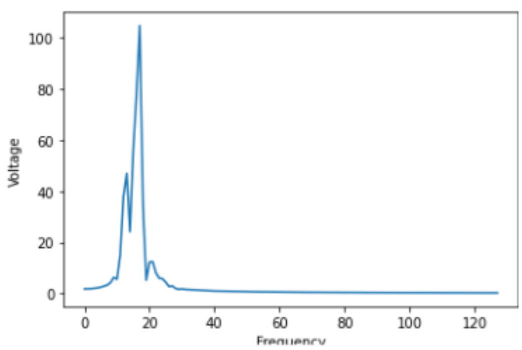

Figure 4.4: Sample signal in frequency domain using FFT

Secondly, we use the Discrete cosine transformation(DCT). In the same way as FFT, we get the mean and maximum of the coefficient. Here also we get 6 features for each channel.

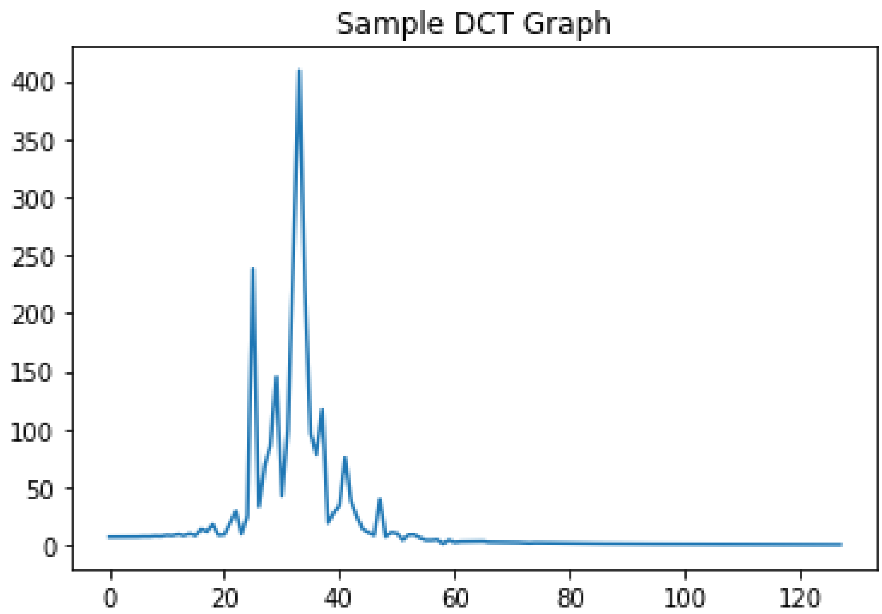

Figure 4.5: Sample signal in frequency domain using DCT

In our analysis, we computed the Hjorth parameter. For 3 bands we computed Hjorth activity, Hjorth mobility, and Hjorth complexity as features. We get 9 features for each channel in this process.
5 statistical features (mean, median, skewness, max, variance) for each band were calculated. So, we get 15 features for each channel.

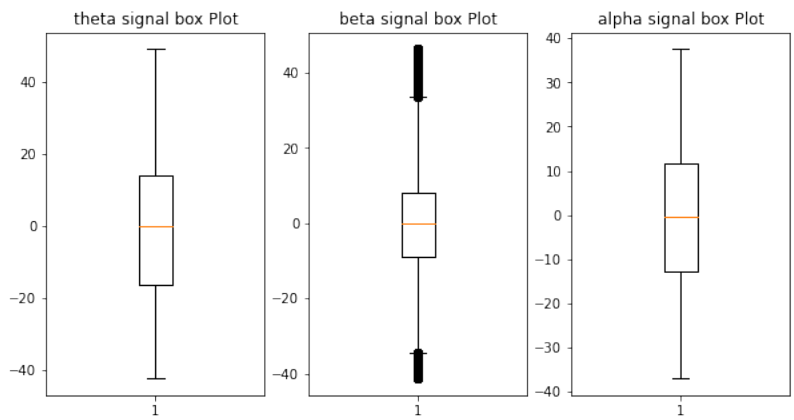

Figure 4.6: Signal box plot

We also calculated two parameters of Poincare. The First one is SD1 which means the standard deviation of the distances of data points from axis 1 and SD2 is from axis 2.

$$\mathrm{SD1} = \frac{\sqrt{2}}{2}\mathrm{SD}\left(P_n - P_{n+1}\right) \tag{4.1}$$

$$\mathrm{SD2} = \sqrt{2SD\left(P_n\right)^2 - \frac{1}{2}SD\left(P_n - P_{n+1}\right)^2} \tag{4.2}$$

Including these two features we get a total of 6 features from the 3 bands for each channel.
The power spectral density(PSD) was retrieved and the mean was extracted from the 3 band by using the welch method. Here, we get 3 features for each channel.

4.4 Feature Ratio and Scaling

In our proposed method, we used 4s of the pre-tail signal. This was taken as a baseline signal. Similar to the stimuli feature extraction we extract features from the baseline signals at a 128 Hz sampling rate. Then we divided the stimuli features by the baseline features to get our final features. This helps us to get the noticeable values required in our approach because this reduces the noise in the stimuli features caused by the pre-tail signals. We do not need to do this for Gameemo Database as it does not provide baseline signals. This was done in this paper [**57**]. Now we are done with extracting the features. We have to scale the features to remove the large differences among them. We have collected 23*18(subjects*stimuli) = 414 data points. From the Gameemo dataset we have collected 28*4(subjects*stimuli) = 112 data points. For each data point or row, we have 630 features. We use the Min-Max scaling method to scale the data. This scaler transforms each value individually between 0 to 1.The formula of min-max scaling is:

$$X_{new} = \frac{X_i - \mathrm{Min}(X)}{\mathrm{Max}(X) - \mathrm{Min}(X)} \tag{4.3}$$

4.5 Data distribution of self-assessment ratings

4.5.1 Emotion model

Discrete and dimensional models are the two types of model used to classify various emotions. The Discrete emotion model encompasses positive and negative, two types of emotion. And Dimensional model can be described with the Arousal-Valence model.A sample representation of the Arousal-Valence coordinate model is shown in Fig 4.5 . In this coordinate system emotions are divided into 4 different regions. The 1st region is for the emotions that have high arousal and positive valence. For example, Happy, Joy etc The 2nd region encompasses high arousal Negative Valence emotions. The 3rd region contains emotion with Low arousal and negative valence which are sad emotions. The 4th region holds emotional states with Low arousal and high valence. So, Basically the upper region represents high arousal, Lower region represents low arousal. The Right side of the model shows emotions with positive Valence and left side represents negative valence [**59**].

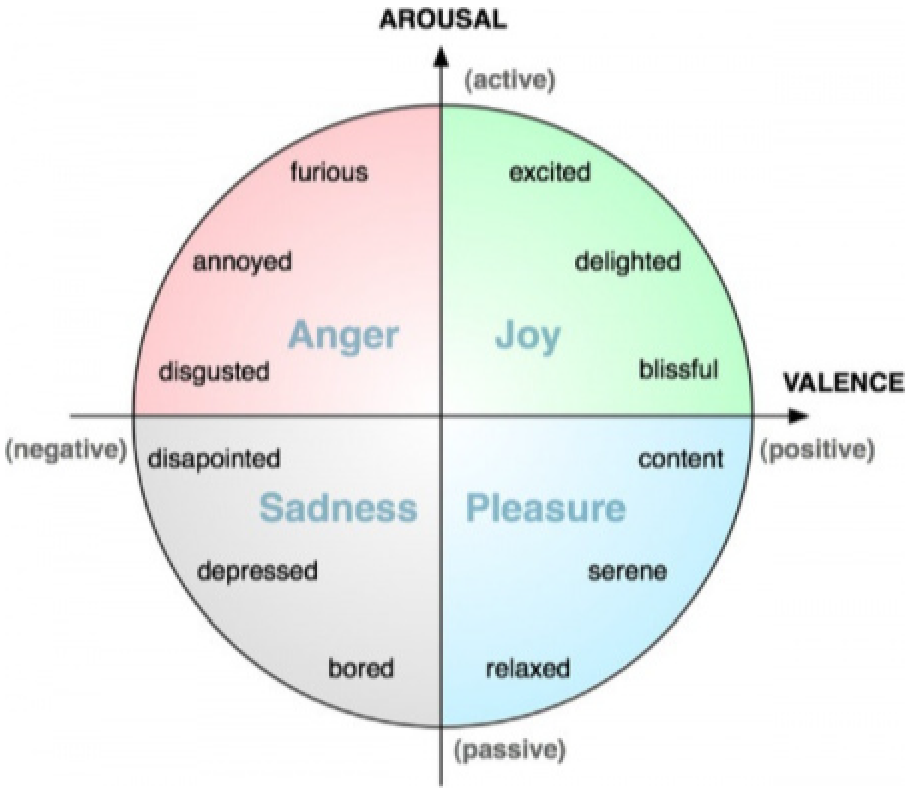

Figure 4.7: Dimensional Emotion model

Arousal: In the dreamer database,Stimuli number 5 and 16 is the stimulus for excitement. The Self Assessment Rating(arousal) for stimuli 5 and 16 is used for considering the high arousal level. Observing the average and standard deviation of these two stimuli we get 3.70 ± 0.70 and 3.35 ± 1.07. Then Stimuli numbers 1 and 11 are for calmness. The self-assessment ratings of calmness are used for the low arousal level. Observing the average and standard deviation of them we get 2.26 ± 0.75 and 1.96 ± 0.82

From these numbers, we can deduce that a rating < 2 can be considered as low, and a rating > 2 can be considered high-level arousal [**43**]. In the Gameemo dataset, The SAM ratings show the range for valance and arousal is (1-9). So, we considered, rating =>5 is high arousal otherwise low arousal.

Valence: Stimuli number 7 and 13 is the stimulus for happiness. The Self Assessment Rating(valence) for stimuli 7 and 13 is used for considering the positive valence. Observing the average and standard deviation of these two stimuli we get 4.52 ± 0.59 and 4.39 ± 0.66. Then Stimulus number 4,15 and 6,10 is for fear and disgust. The self-assessment ratings of fear and disgust are used for the negative valence. Observing the average and standard deviation of them we get 2.04 ± 1.02, 2.48 ± 0.85, 2.70 ± 1.55, and 2.17 ± 1.15 . From these numbers we can deduct that, a rating < 4 can be considered negative, and a rating > 4 can be considered a positive valence.[**43**] Similarly, for the gameemo dataset we considered rating $=> 5$ is High valence otherwise low valance.

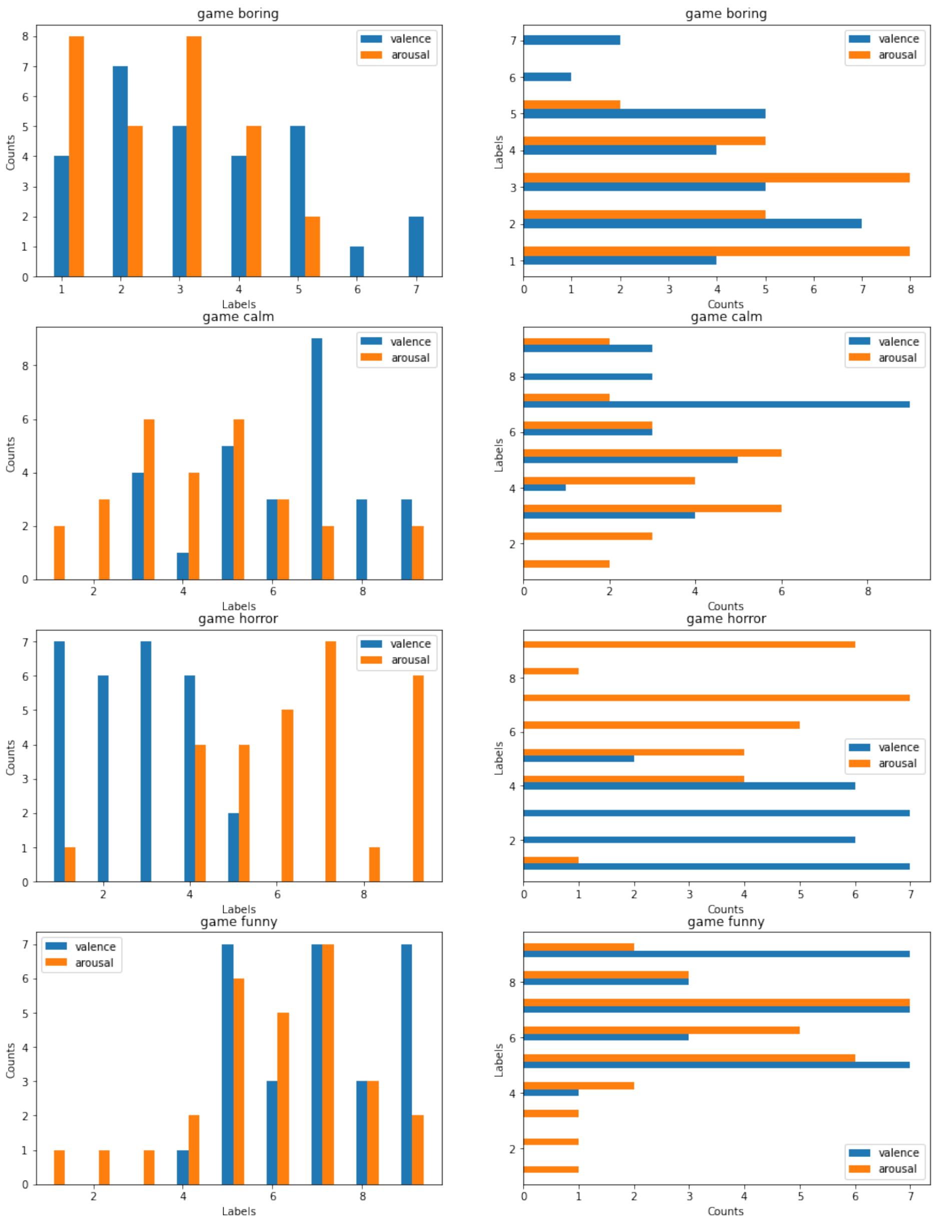

Figure 4.8: Arousal-Valance Distribution in Gameemo dataset

4.5.2 Data distribution

Emotion: Now in our proposed method we are classifying happy(positive) and sad(negative) emotions. Happy is labeled 1 and sad is labeled 0. We consider the data in the happy class if it has high arousal($rating > 2$) and positive valence ($rating > 4$). On the other hand, the sad class is determined with low arousal ($rating < 2$) and low valence ($rating < 4$). The data distribution according to these is shown in figure[18], here 349 is in the sad category and 65 is in the happy category. In similar way, for the gameemo dataset We consider the data in the happy class if it has high arousal($rating => 5$) and positive valence ($rating => 5$). On the other hand, the sad class is determined with low arousal ($rating < 5$) and low valence ($rating < 5$).

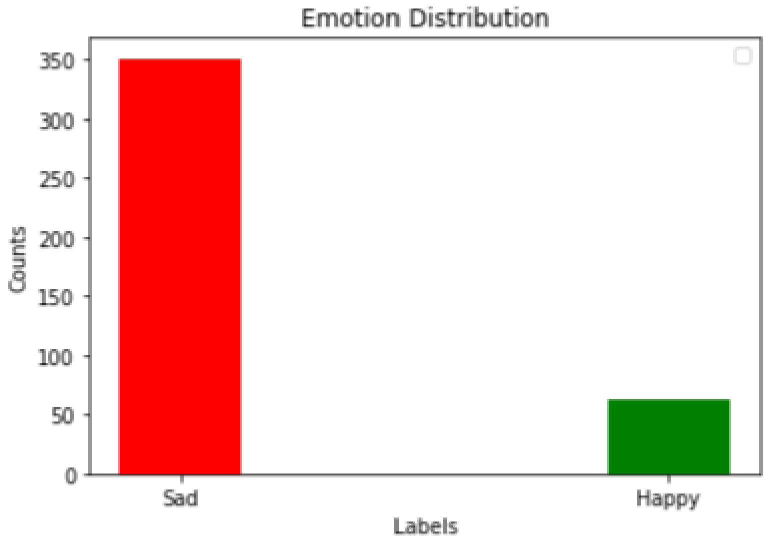

Figure 4.9: Overall data distribution of happy and sad category on DREAMER dataset

4.6 Proposed Model

We are proposing a hybrid model containing LSTM, CNN and 2 Graph Convolutional Network (GCN) layers for our emotion classification.

$$ForgetGate : -f_t = \sigma\left(x_t * U_f + H_{t-1} * W_f\right) \tag{4.4}$$
$$InputGate : -\mathrm{i_t} = \sigma\left(\mathrm{x_t} * \mathrm{U_i} + \mathrm{H_{t-1}} * \ \mathrm{W_i}\right) \tag{4.5}$$
$$OutputGate : -o_t = \sigma\left(x_t{}^* U_0 + H_{t-1}{}^* W_0\right) \tag{4.6}$$

1. First the data is fit through a LSTM layer of 10 units inside the layer. LSTM is an advanced approach of RNN, where the problem of vanishing gradients are solved and a long term memory is added in the LSTM layer, making LSTM more suitable for keeping memory of past data. An LSTM cell uses both, a long term memory and a short term memory and the cell is divide into 3 gate categories, forget Gate which decides whether to keep or forget past data, input gate which takes new information and updates the cells values and the it's weight matrix, output gate makes an output based on the past 2 gates to generate an output based on the activation function. Sigmoid function was used as both activation for each hidden cell and recurrent output as we are using a binary classification model. As we are using data based

on EEG, The output values are passed to other cells and generate output of the 10 hidden cells. As we are using EEG data, we need a model which can produce outputs depending on the time series and past relevant output thus using LSTM for producing output for further preprocessing and transforming data into a new dimension and pass on to the next layer was considered a good option [**60**].

2.

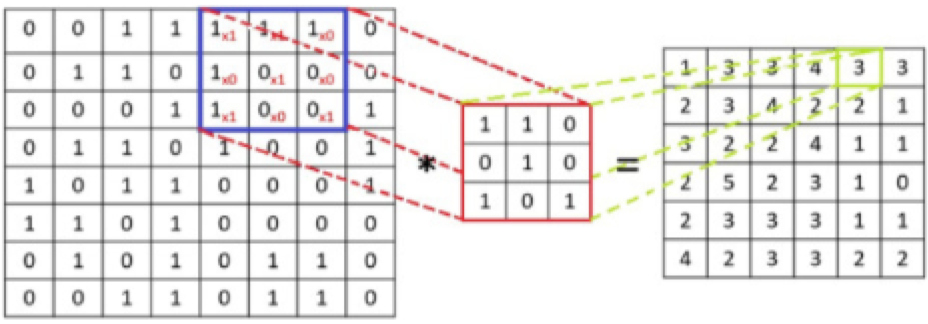

Figure 4.10: CNN with its layers

In the next two steps, one dimensional convolution layers are used. Convolution layers are used mostly for image classification where the image layers are passed through filters which parameters should be learned. Image uses 2D convolution, where the input images are mapped into the filter using kernels of fixed size and sliding of the filter around the image layer and taking the product with the filter to make a spatial position which acts as an activation map. Every filter is stacked and each component of the activation map works as an output neuron which is connected to a local region of the image. The neurons share the same parameter and as it is connected to the local neurons each value of the product takes the maximum output of its neighboring region and shares the weights, this makes less layer parameters and more efficient learning and generalization [**61**]. However in this paper, we are using 1D convolution which works on the same principle but instead of the input being 2D it is 1D and so is the kernel. First convolution layer maps the feature vectors from the LSTM layer with 68 filters, with a kernel size 3 and passes the filtered values to the next convolution layer and repeats the process. This process makes the feature vectors more efficient to learn and reduce excess parameters and as the layers act as a neuron activation this helps in improving the chances of classification results [**62**].

3. Final Layer is the Graph Convolutional Network (GCN) Layer. The processed feature vectors from the convolution layer and LSTM layer are then fitted to the GCN model. In this research, a two layered GCN was used for node classification. Graph Convolution Network is a graph based approach for node classification which is increasingly being used in the machine learning community for its ability to classify connected nodes or similar nodes, and for many cases it performs various deep

learning models for multi-class classification. The GCN model requires three things, an adjacency matrix for the graph to be classified (edges), feature vectors (nodes), edge weight vector (degree matrix). When node vectors are fitted to the model, each node computes a message using a deep neural network with 2 hidden layers of 32 units in the nodes to create a message vector. Then the message vector is passed to its neighbors. The neighbors then aggregates the neighboring node vectors with weighted average functions and stacks the aggregated message and then again computes the new node vectors inside the hidden layers of the node. This generates new weights and new vectors which can be classified.

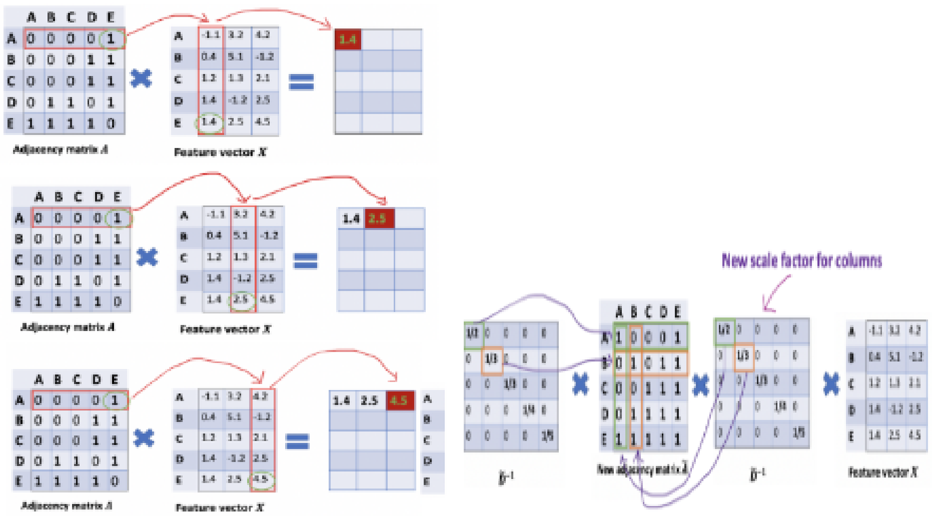

Figure 4.11: GCN layers

$$f\left(H^{(l)}, A\right) = \sigma\left(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \tag{4.7}$$

In the following :

- A is adjacency matrix
- D is the degree matrix
- X is feature matrix
- W is the weight vector of the hidden layers

$$\begin{gathered}\tilde{A} = A + \lambda I_N \\ \tilde{D}^{-1} \tilde{A} \tilde{D}^{-1} X \\ \tilde{D}^{-1} \tilde{A} \tilde{D}^{-1} X\end{gathered} \tag{4.8}$$

The intuition is that in each node, first matrix multiplication of the node features with adjacency matrix provided as shows in the above diagram, however the adjacency matrix does not include the self node, so eq 4.7 in the right is used with lambda = 1 to tackle that problem. However we cannot just make multiplication of the A and X matrix which can cause vanishing or exploding gradients, rather we use the edge weight matrix and the eq 4.7 to make a weighted average multiplication to create the messages shown in Fig 4.11. This message is then passed in the neural network in the nodes where it is multiplied with a weight vector and then finally an activation function, in this research "gelu" function, is used to classify the node. eq. 4.7 shows the generalization of 1 GCN layer. The final node features are then passed in the next GCN layer and the whole GCN process is repeated. So in the training phase, we have used 300 epochs, in each epoch in the GCN layer the weight matrix is updated and sigmoid function is used for classification neuron firing.

4.
At this stage our model is ready as was tested with unseen data and our model has successfully predicted each and every class perfectly with a 100% accuracy, precision and f1 score as shown in table 4.1.

	precision	**recall**	**f1-score**	**support**
0	1.00	1.00	1.00	72
1	1.00	1.00	1.00	11
accuracy			1.00	83
macro avg	1.00	1.00	1.00	83
weight avg	1.00	1.00	1.00	83

Table 4.1: Accuracy and Precision score for proposed mode on DREAMER Dataset

Chapter 5

Result and Analysis

5.1 Result

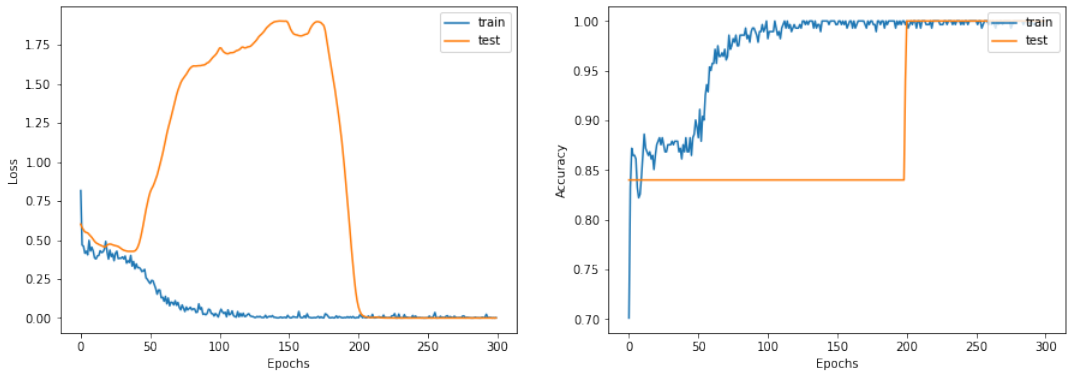

Figure 5.1: Accuracy graph and matrix of our proposed model

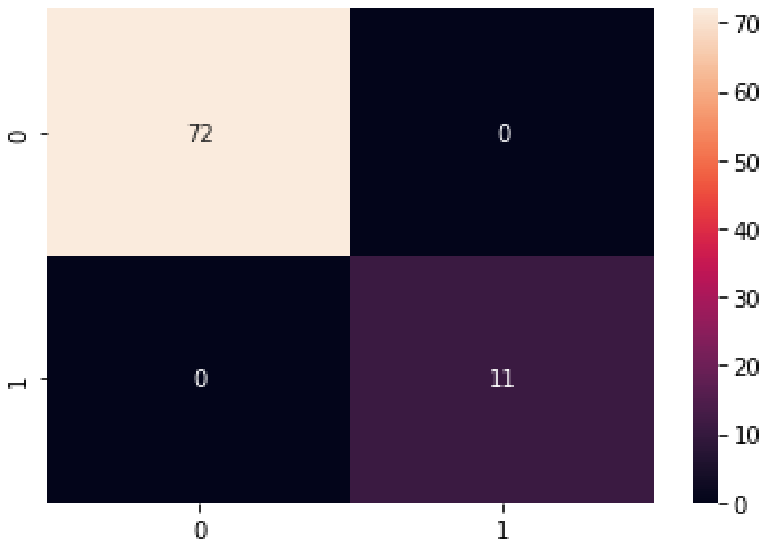

Figure 5.2: Accuracy graph and matrix of our proposed model

In the approach to classify happy and sad feelings using EEG signals we have tried various models which were mentioned earlier, however our proposed hybrid model using LSTM, CNN and GCN, have successfully predicted two classes with 100% accuracy as shown in the graph. The accuracy graph in Fig 5.1 shows the gradual increase in training accuracy and the loss graph showing the loss is decreasing, which shows that the model is performing better after each epoch. However the validation accuracy shows a sudden increase in accuracy, which confirms the model in the last epochs adjusted the weights in the GCN model accurately. The confusion matrix on Fig 5.2, done on testing unseen data shows that there are no false positives or false negatives and all the true positives and true negatives have been identified clearly based on the testing dataset. Thus it can be said that our proposed model is able to identify each signal data to its designated labels. We have also tested the model on few random rows of our extracted features on Gameemo dataset and achieved a accuracy of 92.76%. The table below shows the comparison between various models we have used for our classification in two dataset.

Due to the ambiguous training and validations score as show in Figure 5.2 have also applied stratified five fold cross validation on our model for three iterations and obtained maximum accuracy of 100%, average accuracy 94.58 % and minimum accuracy of 87.75% from the three iterations. This shows that our model still out performs many other deep learning models for classification

Models	**Accuracy of DREAMER**	**Accuracy of GAMEEMO**
LSTM	92.54%	70%
CNN+LSTM	93.28%	76.69%
MLP	97.5%	56.52%
LSTM + CNN + GRU	90.48%	73.9%
SVM	92.8%	75%
KNN	87.81%	83%
Random Forest	88.10%	91%
GCN	95.20%	75.22%
LSTM + CNN + GCN	100% and 94.58% (K-fold)	92.76%

Table 5.1: Accuracy graph for all models

5.2 Analysis

It can be observed that machine learning models tend to give lower accuracy than deep learning models. In the table K Nearest Neighbors and Random Forest gives the lowest accuracy among the models, however the support vector machine performs better in comparison to the machine learning models. On the other hand, deep learning models show a variety of classification accuracies very close to each other. Further , observation is that deep learning models like LSTM and CNN work better with fusion or combined for example, compared to the LSTM model fusion of LSTM

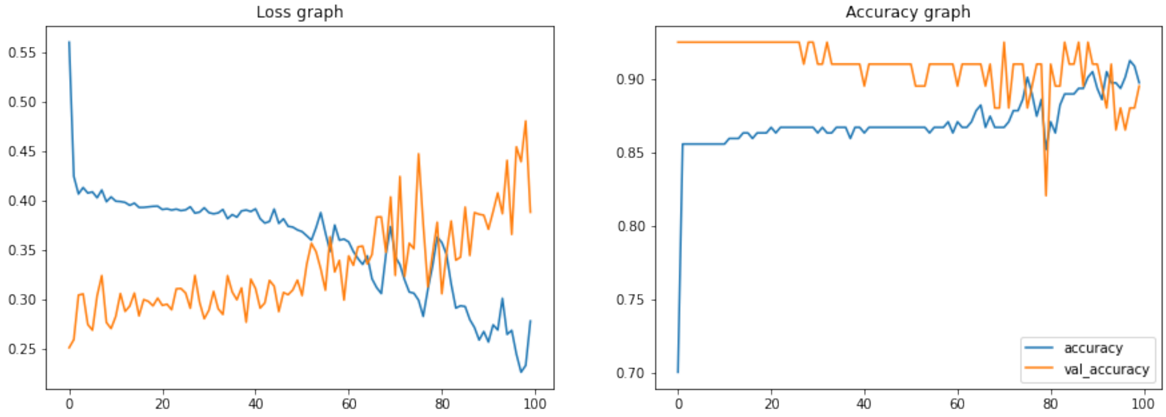

Figure 5.3: LSTM Loss and Accuracy graph

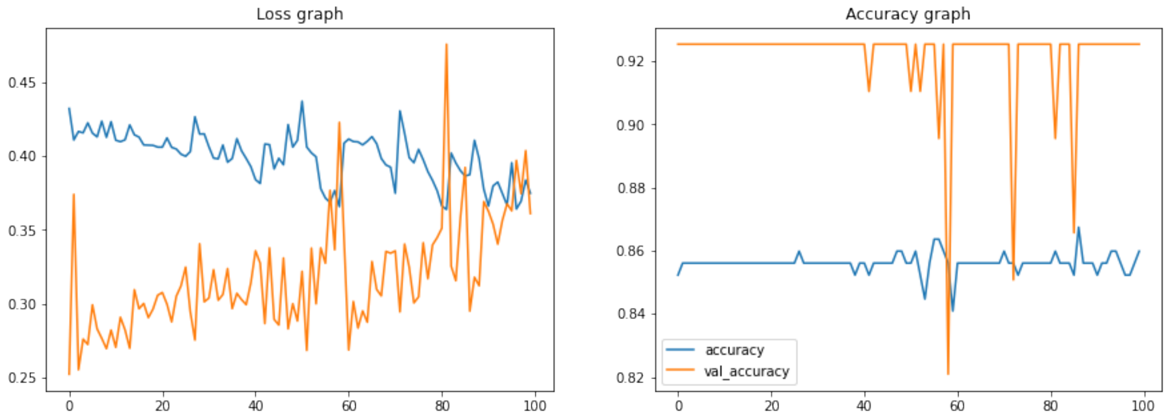

Figure 5.4: CNN + LSTM Loss and Accuracy graph

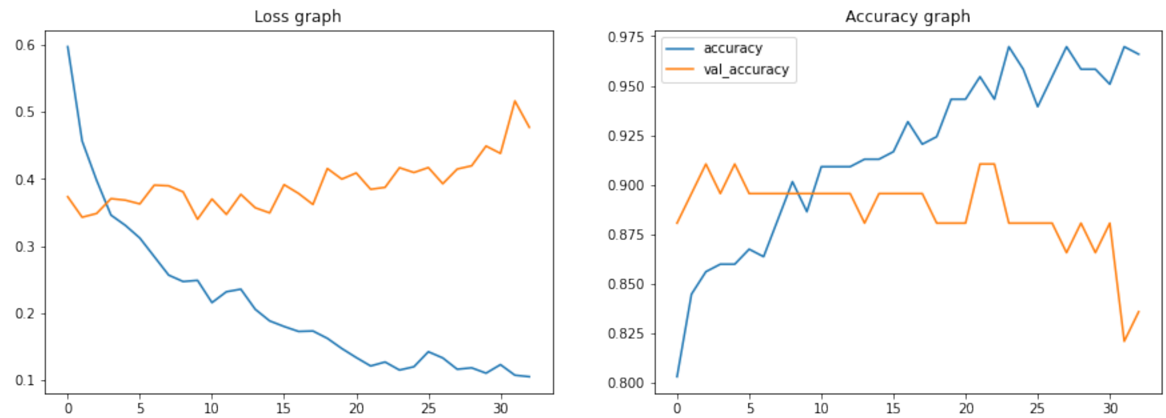

Figure 5.5: MLP Loss and Accuracy graph

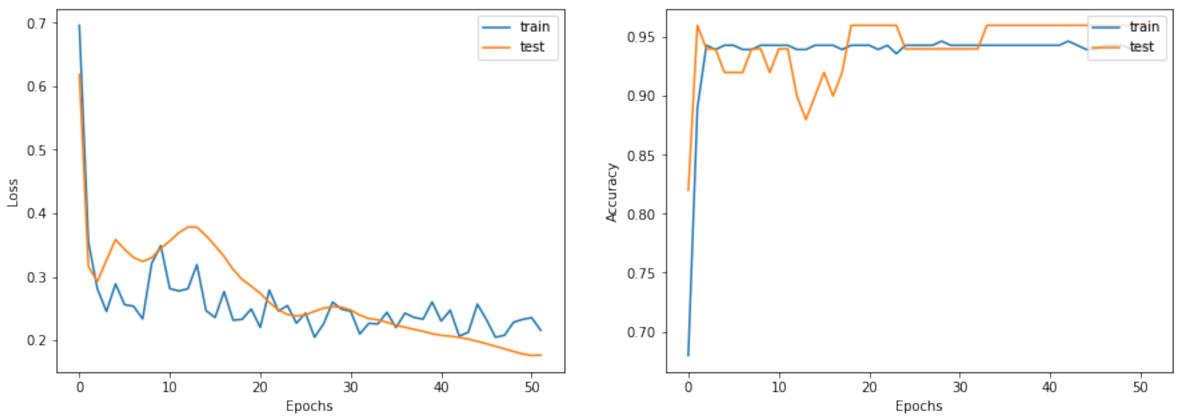

Figure 5.6: GCN Loss and Accuracy graph

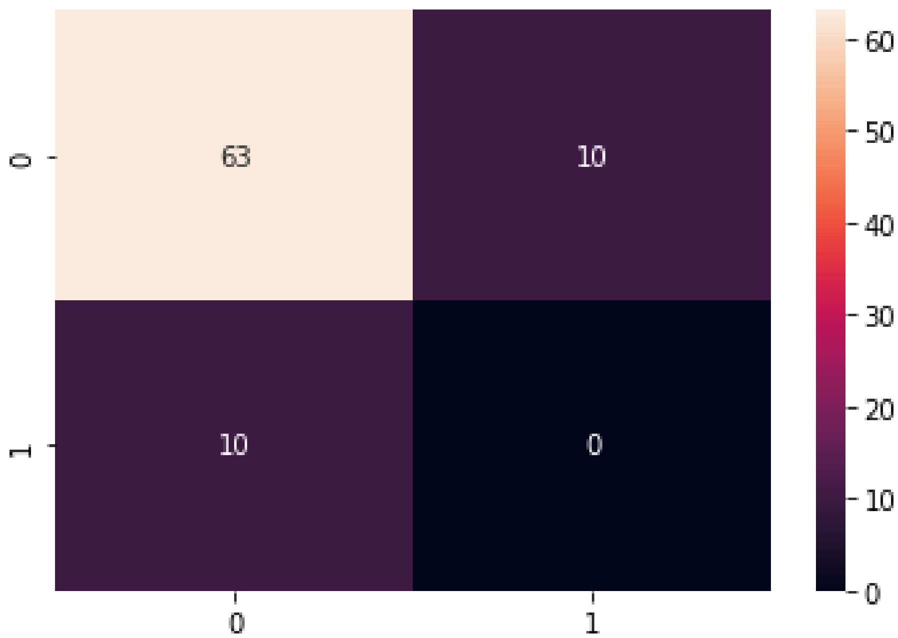

Figure 5.7: LSTM Confusion Matrix

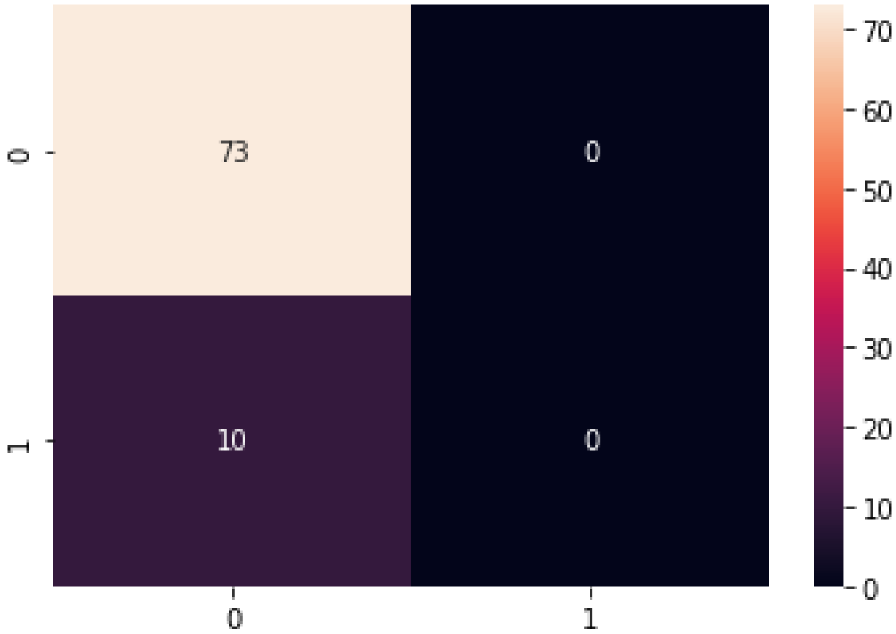

Figure 5.8: CNN + LSTM Confusion Matrix

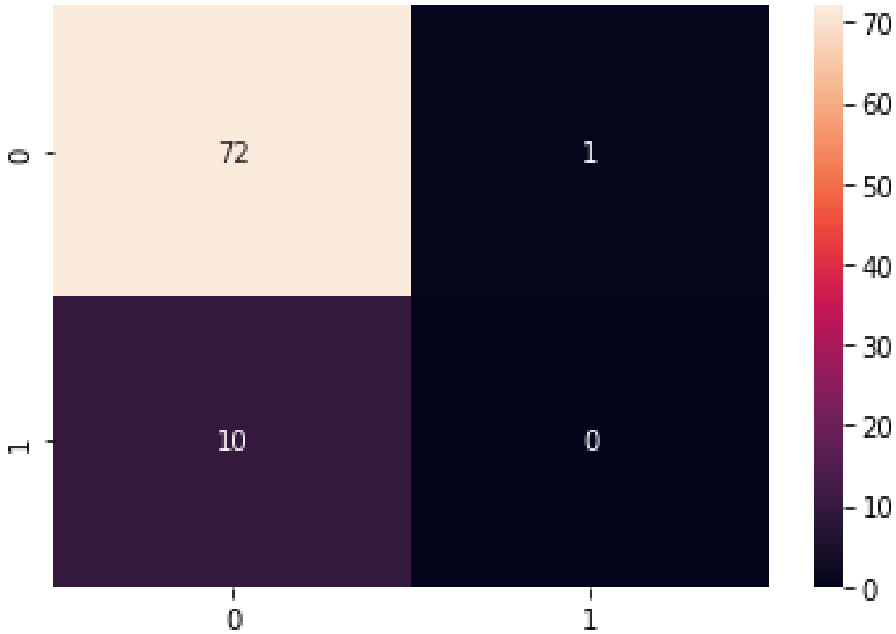

Figure 5.9: MLP Confusion Matrix

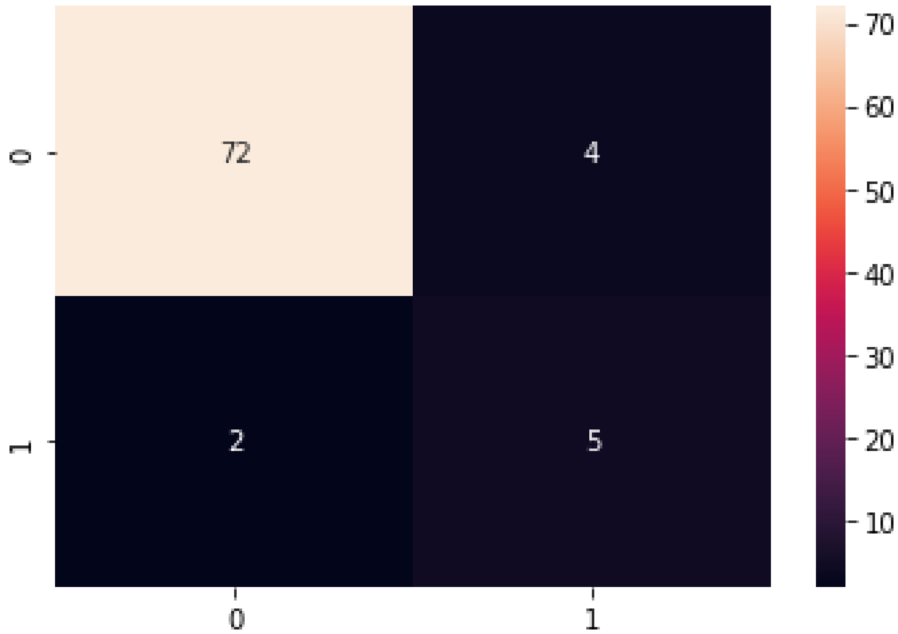

Figure 5.10: GCN Confusion Matrix

and CNN give better accuracy. This works for GCN also, only the GCN model gives validation accuracy of 96.8%, whereas, our proposed model gives better accuracy of 100%, because the data passes through LSTM layer which keeps data information based on each LSTM cell and passes it through a learned classifier and activation functions, and gives output and then output which is passed through two CNN layer for better familiarity and shared maximum value with shared weight distribution between the neighbors give an output which is more efficient data to be trained in the GCN layers.

Chapter 6

Conclusion

6.1 Future Works

At first, the objective of this research was to find a way to measure Emotional Intelligence(EQ). The concept of EQ is quite new. It is a very important attribute to solve real world problems.AI or artificial intelligence is very popular nowadays. Though not all problems can be solved by AI. Emotional intelligence is required in many instances. Emotional intelligence refers to a collection of abilities that includes emotional awareness, empathy, and self-control. In 1995, Daniel Goleman's book Emotional Intelligence popularized the term. Emotional intelligence has five components: self-awareness, motivation, self-regulation, and social abilities.Initially in the research empathy was chosen. . Our goal is to evaluate the difference between compassion and empathy using an EEG signal in order to identify a person's feelings. For this approach a EEG signal based data was required. The database for this purpose can be created with our own experimental setup. In the same way as the Dreamer dataset we can use audio and video stimuli to induce empathy and compassion in our subjects then collect the EEG signals. Our proposed model is now classifying the Happy and sad emotions. In the future we can use this model to classify empathy and compassion as well. For implementing our model in the real world we need to work with more real world raw EEG signals or data. Also , now we are doing binary classification . In the future we want to use multi class classification and accurately measure emotional intelligence.

6.2 Conclusion

To sum up, we want to wrap up our research with our findings from the accuracy we got. Recently, academics have been working on identifying types of emotion and the brain-computer interaction sector. The modern world is becoming increasingly mechanized. People are unaware of the importance of communicating their feelings to others. People don't even know how to behave in a specific situation, let alone exhibit their emotions to others. Some people have been traumatized, crippled, or have a disability that makes it difficult for them to express themselves. The goal of this study is to use an EEG signal to detect a person's level of emotion to identify their feelings. We extracted features from the brain signals as alpha, beta, theta, and delta waves. After necessary pre-processing with Wavelet transform, Fourier transforms, Hjorth. Then fitting our datasets to MLP, SVM, Random forest, NN, CNN, LSTM, KNN, and finally the GCN hybrid model with CNN and LSTM which is the main contribution of our research. From the accuracy results we have found that LSTM has 92.54%, MLP has 97.5%, CNN+LSTM has 93.28%, CNN+LSTM+GRU has 90.48%, Random forest has 88.10%, K-nearest-neighbor has 87.81% and finally from SVM arousal has 92.8% and valence has 87.805% accuracy respectively. Our research outperforms many other research in emotion recognition and a revolutionary approach to sentiment evaluation.The system exceeds most of the best systems in the literature that employ comparable but fewer of our modalities, particularly in arousal recognition.In LSTM + CNN + GCN got the accuracy of 100% for DREAMER dataset and 92.76% for GAMEEMO dataset. For the face modality, data from the facial depth or the facial image has been employed individually in the system. Because the minimal acquired data might have a detrimental impact on recognition, a data augmentation phase was used to add sounds to the obtained data to produce additional data. Whether combined with different modalities, systems that use many channels of EEG inputs outperform our suggested method by a wide margin.This multimodal emotion identification approach might be utilized in education to help teachers, parents, and schools understand their children's emotions. As a result, students' potential emotional abnormalities can be discovered. As a result, possible emotional challenges in students may be addressed in real-time, and instructors' burdens can be decreased.This study will also utilize a predictive technique to explore the neurophysiological roots of human emotion for individual circumstances. According to our findings, future brain-computer interfaces may be able to forecast a user's personality types and emotional responses to maximize the benefits of technology and its engagement. Finally, our goal is to find the cognitive stimulation that plays a crucial role in producing sentiment in the human brain through brain signals to achieve this goal.

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