Emotion Recognition by Exploiting Temporal Resolution of EEG signals using Transformation and Learning Methods

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Individuals are free to articulate thousands of emotions. Emotion can be associated with feelings articulated by or observable by voice intonation, a facial expression of body language, an initial response from one's mood relationship with others and most strikingly, a predicament within thus they are. Recognizing sentiments is a daunting task due in part to the non-linear features of the EEG signal. This paper addresses advanced pre-processed DEAP dataset EEG signals for emotional recognition. The valence and arousal components of the raw EEG signal are first retained in the PSD approach Fast Fourier transform (FFT). Power Spectral Density (PWD) consisting four features are being selected for all 32 participants. Features derived from the PSD are considerably less accurate precise. Through implementing 10-fold cross validation on the DWT (discrete wavelet transformation) to get the time-based features, Gradient boosting Classifier gave the best result among six different classifiers. Our proposed method provides 93.12% accuracy by using a benchmark dataset. The results of experiments on DEAP datasets indicate that our system.

Keywords: Electroencephalogram (EEG), Fast Fourier transform (FFT), Power Spectral Density (PWD), Discrete Wavelet Transformation (DWT)

Dedicated to our loved ones for all their support and inspiration.

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Nomenclature

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

BCI Brain Computer Interface

CNN Convolutional Neural Network

DCT Discrete Cosine Transformation

$DEAP$ Dataset for Emotion Analysis using Physiological signals

DNN Deep Neural Network

DWT Discrete Wavelet Transformation

EEG Electroencephalography

EMD Empirical Mode Decomposition

FFT Fast Fourier Transform

FN False Negative

FP False Positive

GSR Galvanic Skin Response

HA High Arousal

HRV Heart Rate Variability

HV High Valence

LA Low Arousal

LV Low Valence

PSD Power Spectral Density

SVM Support Vector Machine

TN True Negative

TP True Positive

Chapter 1

Introduction

With the advent of technologies the world has changed drastically. Life was burdensome until the introduction of modern day technologies and the ordinary tasks absorbed so much of our attention.Fro human being, technologies offer enormous opportunities. And In this modern era of technology the application of emotion recognition has grown exponentially over the years. It has its grasp over the areas of Medical Science, Computer Engineering, IT development sector, etc. Emotion recognition is an area of focus and is the mechanism of emotionally showing the human behavior. With the aid of comprehensive details such as facial expressions, gestures and verbal speech these emotions are observed. Facial expressions and feelings are unyielding structures with many variants. Consequently, they cannot be limited to just seven predefined unique instances. Current technologies, for example, will reveal a pleased and shocked smile. However, with a transitional term between two simple emotions (like a mixture of happy and shocked, or sad and disgusted) description would not be as precise. Sometimes we don't know the exact amount of potential emotional states that can be included from an expression. And if we can describe a collection of emotions, subsequent problems emerge from the blurry existence of emotional states, and their inconsistency over time. For instance, by monitoring name, age , gender and current emotional condition, it can recognize individuals in a crowd, observe residents for suspicious behavior. It will be used to deter offenders and possible threats from doing so preventively. According to previous work of various researchers, many research work on emotion identification by using EEG can be found. Emotion detection tends to follow other advances such as natural language processing, and these indicators of advancement are made more likely by combining rapidly powerful processors, technological development in sophisticated algorithms, and other similar developments. Emotion recognition based on language, expression, body posture and stance is possible, but the consistency and validity of the emotion is difficult to guarantee through these approaches. Physiological signs appear to represent actual feelings of people even more reliably than facial gestures, postures or speech, according to research. Physiological signals such as Electrooculography (EOG), Electrocardiogram (ECG), and Electromyography (EMG) are secondary physiological responses, but much stronger than facial gestures, postures, or voices. Among these physiological signals, Electroencephalogram (EEG) provides more precise outcomes [56]. Since emotion regulation is closely connected to the brain's cerebral cortex. We selected EEG signals because of its clear objectivity and higher accuracy to apply our methods to identify and interpret emotions.

1.1 Thesis Overview

Emotional responses are the body's reactions to a condition provided specifically by any outside factors such as other people, associations, objects or institutions. Emotions can be classified in two unique ways; Dimensional approach and emotional input approach [39] , [33] . Two terms that characterize emotional stimuli in dimensional representation are Valence and Arousal. Arousal is from our reptilian subconscious [63] , [27] . It promotes a fight-or - flight reflex that has enabled our survival. On the other hand, valence refers to the enjoyment or discomfort of an emotional stimulation [23] . The dimensional framework according to which emotions can be interpreted using particular parameters originating from psychophysiology is an alternative way to emotion analysis [21], [56]. In Valence-Arousal interpretation is used for affective video characterization [56]. Visual signs, such as fluid movement, and basic audio properties, such as signal energy, are used to model the dimensions of emotion to this end. In the same representation, using regression techniques to predict musical emotions is used [33]. Physiological signals derive from the primary and autonomic nervous systems. Five physiological steps are usually taken for HCI [8].

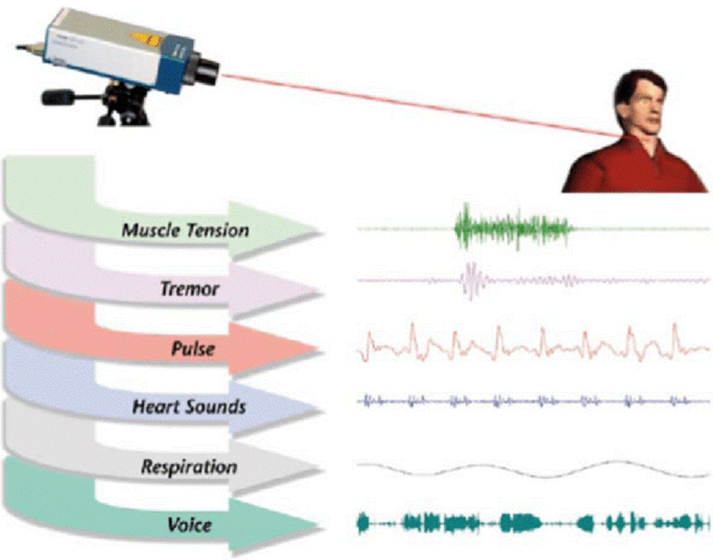

Figure 1.1: Classification of recorded signals

In Fig 1.1, we can see that the classification of signals that are being recorded. In representing people's feelings, signals that are physchological produces more accurate result and better findings. [62] , [31] . Among these, EEG signals provide the best specificity for emotional identification. Emotion generation allows impulses in the brain, more generally known as brainwaves, to be produced. Complex interconnections and billions of neurons occur in the human brain. By using the EEG system, brain function is recorded. Using electrodes located on the human skull, readings are taken. This makes the EEG signals in nature non-linear, static and unpredictable, making it hard to interpret emotions.

In Fig 1.2 we can see all the commercially available EEG electrods and cap samples around.

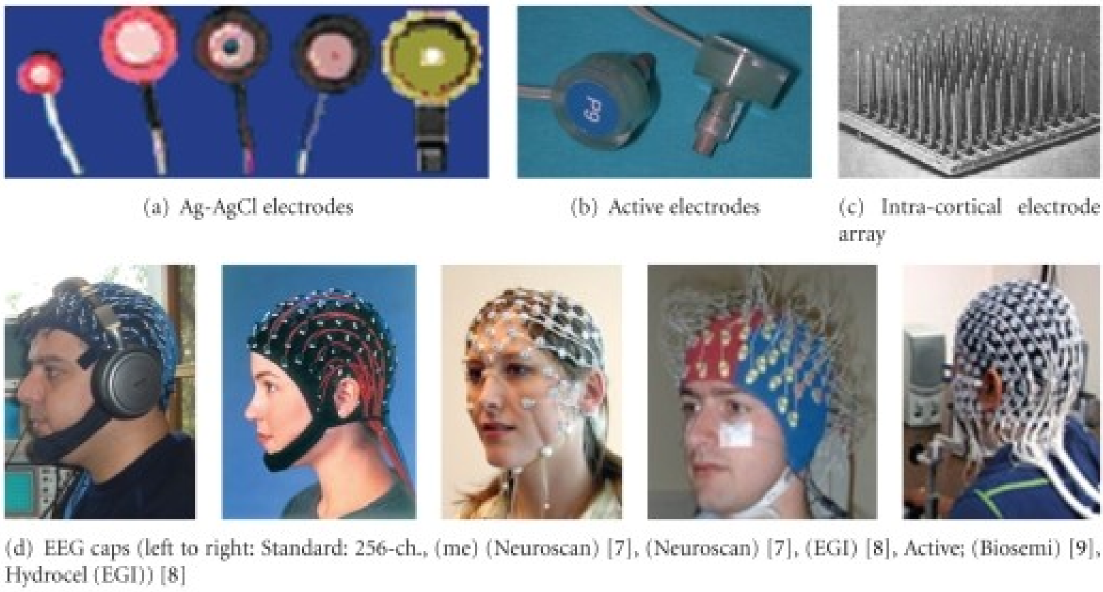

Figure 1.2: Sample of electrodes and cap in order for the analysis of invasive applications

In this paper We chose to use PSD and FFT in this paper to derive characteristics from EEG signals [7] to get features. DEAP dataset is used for the evaluation of the proposed method [22] , [46]. As proposed by James Russell, CNN is used for classification of emotion into quadrants of valence and arousal to extract the features.

1.2 Thesis Contribution

In this research paper, we tried to detect Emotion by harnessing synchronization EEG Signal Resolution using Transformation and Learning Methods. We established out the dataset and carried out first the PSD extraction and then DWT extraction. Several features were extracted from EEG data and applied different classifier. Then we proposed Deep Function Model Outcome of gradient boosting classifier after applying DWT. As we found DWT as the best extraction and gradient boosting classifier as the better classifier to build our model for getting the best output.

1.3 Thesis Orientation

The following sections of this paper has been ordered in the way described be-low. Chapter 2 is Literature Review which is a description of the related works and various methods and techniques similar to our proposed methodology. Chapter 3 con-sists of the background study of our thesis which includes the anatomy of the brain structure, Brain waves, EEG Analysis with Various Algorithms, and various machine learning algorithms. It also contains a brief description of our dataset. Chapter 4 describes our proposed plan for predicting our Emotion recognition. Chapter 5 comprises of the results we obtained and the relevant discussions concerning these results. The entire paper is concluded and summarized in Chapter 6.

Chapter 2

Literature Review

In 2018, Li, M., Xu, H., Liu, X., Lu, S. [52] worked on the influence of accurate emotion recognition, indifferent bands of frequency and different channels. By using valence and arousal emotional channels were classified and got four features using DWT. They calculated Entropy as well as energy.

Apart from that, in 2019, Ullah, H., Uzair, M., Mahmood, A., Ullah, M., Khan, S. D., Cheikh, F. A. [60] used EEG signals to reduce cost and get a more accurate result. Electrodes electrodes placed on the scalp. Various bands of frequency level were used and. For multiple channel EEG signal focused emotion identification, SDEL algorithm is preferred and widely applied. It was inspired by various methods, biologically inspired method (empirical mode decomposition to create division of EEG signals and turned them into IMF, Wavelet inspired method (45 emotion states extracted using SVM), Deep learning-based method () and feature and channel selection methods (filtering, embedded and hybrid methods; searching algorithm). Kernel learning was approached by embedding sparsity and it was solved by NSPCA formula.

On top of that, in 2019, George, F. P., Shaikat, I. M. Ferdawoos, P. S. [51] took a multi modal DEAP data set which was their source of brain signals and proposed a model that focuses on the statistical features of very accurate domain of time and frequency. As the experimental data group in their data set were initially converted into the domain of frequency from the initial domain of time using FFT, hence the application of various bands were possible to use as these bands too are most significant for emotion recognition. Later, they used SVM classifier to train the model and k-fold cross validation to remove biases. The authors also used two sets of emotions which were valence and arousal to reach their accuracy level of 92.36%.

Furthermore, in 2018, Zhang, Y., Zhang, S., Ji, X. [55] showed their work on feature extraction from EEG with the help of decomposition model of empirical as well as auto regressive model. After that they built the structure of EEG focused human emotion identification model in order to prepare the classification of states. In that research work, the authors applied models known as valence and arousal in order to provide the presentation of states of human emotion. In their research method, two of all available channels were selected in order to apply EMD as well as AR for the extraction of feature. As a result, they got more than 77% accuracy where they used classes of two level while preparing valance space with the help of well known data set called as DEAP data set.

On a different note, in 2018, Alazrai, R., Homoud, R., Alwanni, H., Daoud, M. [50] created three calculation model of analysis in order to fetch the accurate measurement of how a model is performing in terms of counting the effect of various signal groups. This gives a overview of different sectors of human brain and also deducts the dimentionality of features that are based on time-frequency after extraction. This is gained after removing the human brain signals of different class. The research work also shows the average segmentation accuracy which is gained from separating various human emotion segments different label which can be found in pg. 5 ranging from 73% to 86%. The proposed model gets better results than already existed standard studies on human emotion identification. The extraction of features allowed to develop a group of profile-focused supporting vectored format that are considered as machine based classifiers in order to classify the human brain signals known as EEG of every participating individual into various human emotion segments. These are explained with the help of human emotion tagging schemes.

Additional to that, in 2018, Y. Yang, Q. J. Wu, W.-L. Zheng, B.-L. Lu [48] proposed to discriminate three human emotions with sub network nodes are functioned as unseen layers which are not dependent on anything for feature representation. Features from sub-nodes modified into mapping space for more reliable cognition. Experimental results from two different EEG data sets with both single and multiple modality.

Chapter 3

Background Analysis

In this chapter, we conduct an extensive review of the background data related to our study. Our research is focused in the study of the biological and electrochemical relation of the brain. Section 3.1 aims at the anatomical aspects, functions, and composition of the brain as an unit. We learn more about the lobes and its functions. Section 3.2 presents us with a clear understanding of the brainwaves and their forms, such as Alpha, Beta, Gamma etc.

3.1 Basic structure of the Human Brain

In human body comparison to being one of the most significant organs. human brain is also the major composite parts. The brain, which as the center of command for the whole body; it sums us as who we are. It receives information from our senses, and it controls our movement and thoughts. The brain as well as the spinal cord together are the creator of center point nervousness system, all bodily functions alongside the peripheral nervous system are regulated through them. In Fig 3.1, we can the different parts of Human brain.

3.1.1 Brain Stem

It located below our brain, interacting with spinal cord of Brain. It acts like a relay by linking the spinal cord to the brain and cerebellum Center. It consists of three parts; medulla oblongata, pons mid-brain. It is done out of a blend of gray matter and white. It works as a switch for regulating brain wake and sleeping cycles, and also controlling body muscle tone. In addition, it supervises functions such as blood pressure, oxygen levels, puking, wheezing, coughing, reflex swelling, homeostasis.

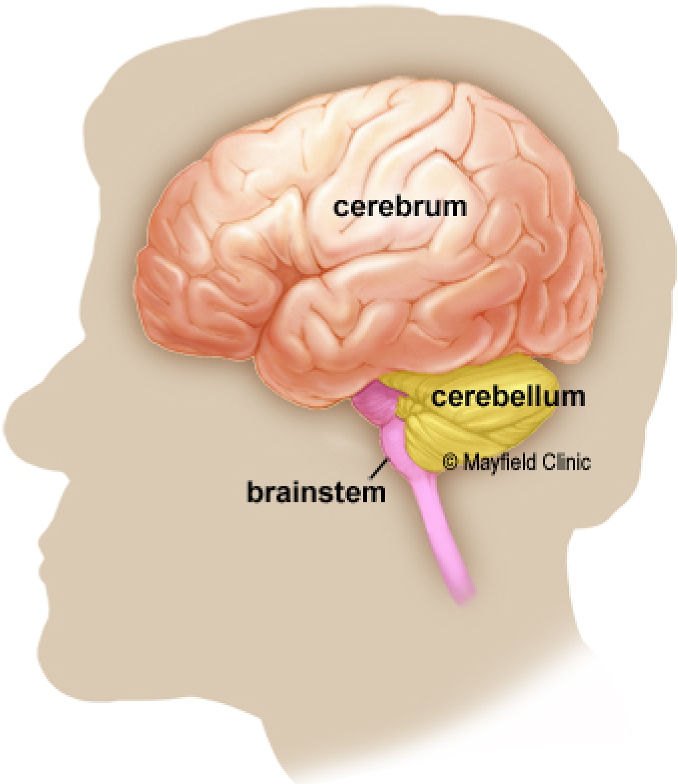

Figure 3.1: The brain has three main parts;The cerebrum,cerebellum and brain stem

3.1.2 Cerebellum

It is located underneath the cerebrum and posterior to the stem of the brain. It's hyperbolic and hemispherical in shape. It continues to carry out the task of controlling engine functions such as Balancing, posture, and neuromuscular control. The Cerebellum does the Synchronization and finesse of motor actions, for example writing, attempting to speak and walking.

3.1.3 Cerebrum

This is basically the bulk of the brain. It holds both the right-left hemispheres. The two hemispheres are connected by fibers called the corpus callosum. The left hemisphere controls the body's right half and vice versa. The cerebral cortex is an outer gray matter layer that covers the core of white matter. These fibers send data back from one to the next. Nevertheless, some functions are assigned to each side of the brain, independently. The left side controls composing, measurements, cognitive processes, monologue, for example, while the right-side controls spatial capacity, imagination, creativity, musical aptitude, etc. Close to 92 percent of the population of the world can be found with the dominance of the left hemisphere in language and hand use, which illustrates why few people use the left as writing hand. .

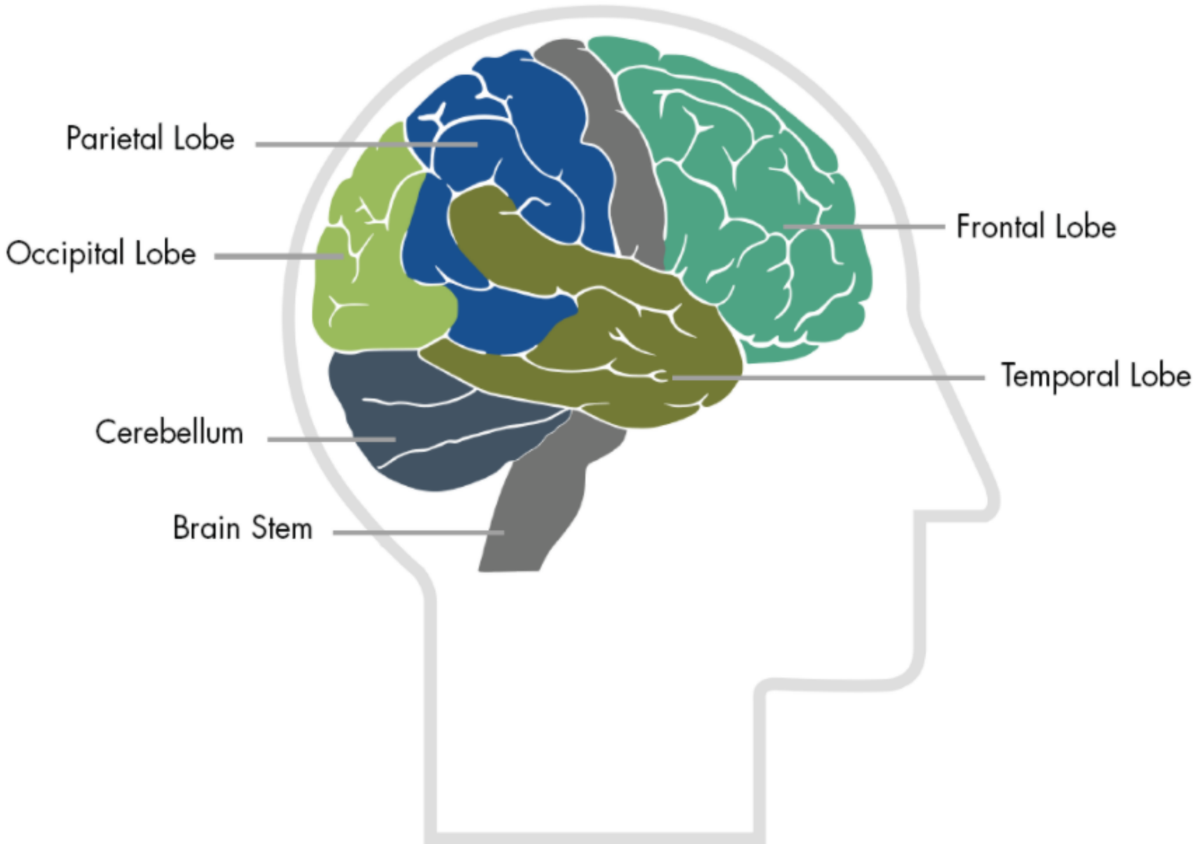

Figure 3.2: Visualization of Lobs

The cerebral cortex is generally classified in four segments, generally all of them are known as lobes. All four lobes are interconnected with various purpose ranging from compromise to hearing perception. In Fig 3.2, The different Lobes and their position in the human brain are shown.

3.1.4 Frontal Lobe

Frontal lobe, which is situated at the start of the brain and is related to cognitive abilities, thinking, cognition of large and verbal speech. At the rear of the front lobe is Motor Cortex, which is very similar to the central sulcus. The motor cortex absorbs input from various brain lobes and uses this data to direct the body. Frontal lobe, if affected, can bring about changes in sexual behavior , social participation, focus, increased risk-taking.

3.1.5 Parietal Lobe

The parietal projection, which is within the mid-brain locale and is capable for the administration of tangible physical counseling, such as squeezing, rubbing, and detecting distress. Here, a portion of the brain, known as the somatosensory cortex, was found, which is basic to the incitement of the human body 's faculties.

3.1.6 Temporal Lobe

The worldly projection, which lies at the foot of the brain. This projection is additionally where the essential auditory cortex is show, that's vital to interpret sounds and the voice we are ready to listen to. Also, the hippocampus, being within the transient projection, making this portion of the brain is additionally intensely interrelated with memory arrangement. In the event that there's a harm in worldly projection it can cause memory, discourse recognition and dialect aptitudes issues.

3.1.7 Occipital Lobe

At the back of the brain, occipital projection is found and is related to the clarifying of the data and visual signal. The essential visual cortex moreover found within the occipital flap. That gets and surveys information from the retinas of the eyes. The harm in this flap can be exceptionally perilous. It can cause visual issues, such as trouble in recognizing objects, color daze, and incapable in recognize letters.

3.2 Brainwaves

There are billions of neurons in the brain, and thousands of others are interatomic to each neuron. Communication is taking place between them due to the tiny electrical currents that drive the neurons sideways. Since then, there have been enormous brain circuit structures. When all these neurons are capable of creating electrical beats together and in this direction. This will swell through the swarm, because it has the capacity to picture a wave in a sports field, finally coming out in a "brainwave." The brain has various specialised districts that coordinate totally different attribute, considering ways in which, and disturbance. sure motions frequently mirror explicit ready to communicate ranges and network within among the brain. beneath In Fig 3.3, numerous variety of Brainwaves and their extend and states square measure appeared.

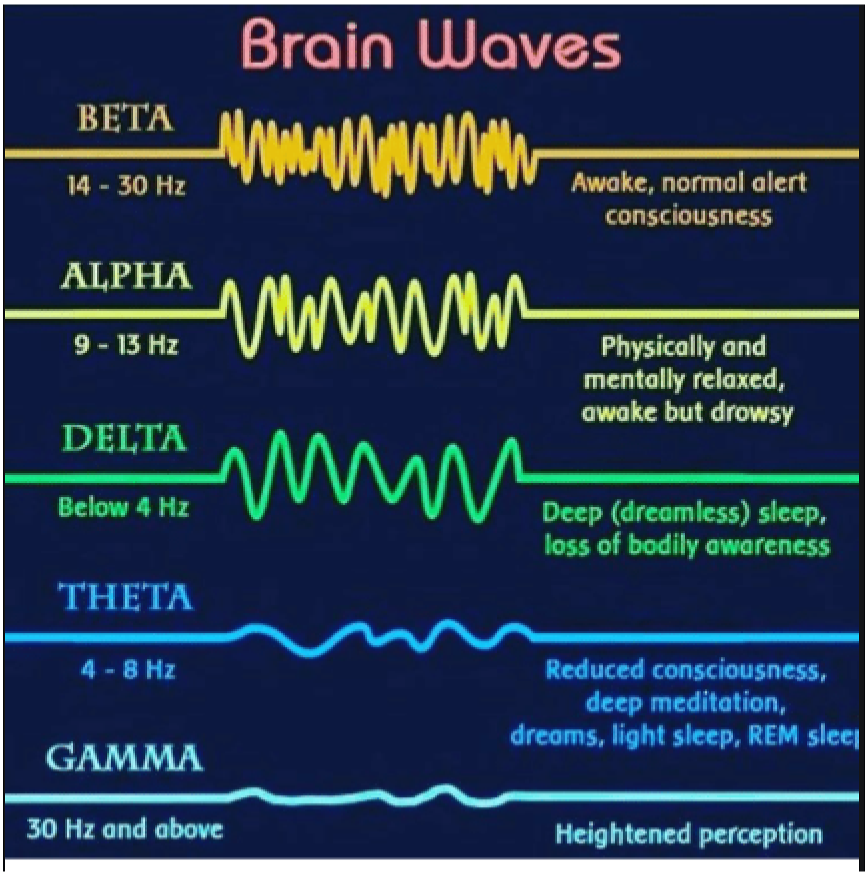

Figure 3.3: Types of Brain waves

3.2.1 Alpha

Alpha brainwaves are the easiest to calculate and discovered initially among all wavelength. When we close our eyes, they become detectable, and our mind can relax. In Fig 3.4, the range and states of Alpha waves are shown.

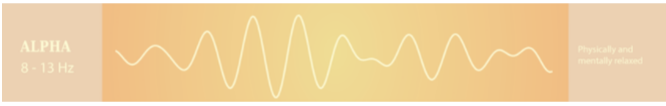

Figure 3.4: Alpha brainwave

3.2.2 Beta

Beta brainwaves can easily be identified when we are actively thinking. Brainwaves can be identified in this range of frequencies when humans are actively engaging or even doing activities that require attention. Its states are being alert or being active in imagination or thinking. In Fig 3.5, the range and states of Beta waves are shown.

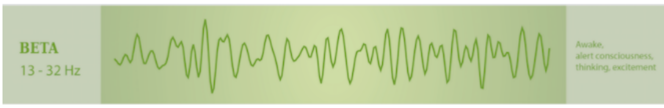

Figure 3.5: Beta Brainwave

3.2.3 Delta

Although being the slowest brainwaves, Delta also strongest when we are living restorative sleep which is in a state that too dreamless. Here, healing and rejuvenation are stimulated, which is why getting sufficient sleep each night is so vitally important. In Fig 3.6, the range and states of Delta waves are shown.

Figure 3.6: Delta Brainwave

3.2.4 Theta

Theta brainwaves are highly strongly detectable when we are dreaming in our sleep (like the movie Inception), but Deep meditation and Daydreaming can also help in finding Theta brainwaves. Automatic task that the mind can disengage like brushing teeth or showering. Exploratory study has proved theta waves have a positive association with memory, creativity and psychological well-being. Its states are being creative, Insightful, Dreaming. In Fig 3.7, the range and states of Theta waves are shown.

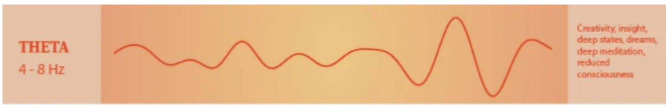

Figure 3.7: Theta brainwave

3.3 EEG Analysis with Various Algorithms

German psychiatrist Hans Berger [16] made the historic breakthrough of EEG [17] in 1929. Hans Berger proposed the process of brainwave tracking by placing electrodes on human skull. While his approach was initially met with opposition by introducing the use of convolutional neural networks [54], it was later accepted. Since then, more and more researchers have been engaging in this area to study computer-human behavior through evaluation of emotional reactions [25],[38]. The EEG system is considered non-invasive because it in no way stimulates or impacts the brain. EEG involves the placement of electrodes on the human skull, which picks up brain signals originating from electro-chemical stimulation inside the brain neurons [31] . The EEG machine absorbs electro-chemical signals and transfers them on to an amplifier to make them visible on a paper or a screen [53] .Easy process and non-invasiveness, EEG has surfaced as the best form of brainwave detection [35]. The electrodes are placed on an EEG cap. Two pair of electrodes (Fig 3.5) makes up a channel and an EEG cap has around 16, 32, 64 or 128 channels [43], [32]. The electrodes have cables connected to transfer the data obtained from the EEG cap. Various methods such as Bio-Semi [51], B-Alert [51], and Bio-Radio 150 [40] can be used to transfer information from EEG cap [35] electrodes. The EEG machine tracks numerous sounds during brainwaves due to blinking of the eyes, muscle contraction and even instrument noise. Independent Feature Analysis (ICA) should be used as stated in [11] and [12] in order to eliminate discrepancies. Noise is reduced by using band pass filters. Noise can be minimized further by maintaining good conducting at the scalp contact points [14]. The most important step for the implementation of machine learning algorithms is feature extraction [49] . This is achieved to limit huge dataset and to build various combinations of variables to achieve high precision. There are, however, many complications. There are several people with different distinctive response that show the same type of emotion for a particular context. There are different classifiers available to extract feature from the data generated by an EEG machine.

3.3.1 Gradient Boosting Classifier

Gradient Boosting is a recursive functional gradient algorithm, i.e. an algorithm that mitigates a loss function by sequentially selecting a feature pointing towards the negative gradient [15] .It employments two novel strategies: Gradient-based One Side Inspecting and Select Highlight Bundling (EFB) [61] Gradient Boosting Classifier has three main modules: Loss function, Weak learner and Additive model [2].It supports various analytical functions including regression, ranking, and classification [57]. It consists of statistical properties of your outcomes, calculated for each degree. This is the mean of each class for a single input variable (x), and the variance of the value [47] .

3.3.2 Extra Trees Classifier

It is a type of learning technique for an ensemble that aggregates the outcomes of several de-correlated decision trees accumulated in the "forest" to generate the outcome of classification [1] , [9] .Each Decision Tree is built from the initial training sample in the Extra Trees Forest. Then every check node incorporates a random set of k options from that every call tree should verify the simplest feature to section the info. This random sample of options results in the creation of many de-correlated call trees [40] .

3.3.3 Light Gradient Boosting Machine

The Light Gradient Boosting Machine is a decision-based gradient boosting device that increases model performance and limits the use of memory [28] . It uses 2 novel techniques: Gradient-based One facet Sampling and Exclusive Feature Bundling (EFB)[30] .

3.3.4 Extreme Gradient Boosting

Each test node then has a random range of k characteristics from which the best attribute to segment the data must be decided by each decision tree. This random sampling of features contributes to the creation of many decision trees that are de-correlated.[44]. It has features like: Speed, Input type, Sparsity, Customization, and Performance.

3.3.5 K Neighbors Classifier

It identifies patterns in a non-parametric classification or regression system applied. The performance can be calculated according to whether k-NN is used for classification or regression. The features would be classified according to its number of neighbors. Similarly, for regression, the output will be shown as the average value of objects of k nearest neighbor.

3.3.6 Linear Discriminant Analysis

These are the same properties calculated over the Gaussian multivariate for many variables, as are the means and the co-variance matrix, respectively [47] . For many variables, these ar constant properties measured over the mathematician variable, severally the means that and therefore the matrix of co variances [3] .

Chapter 4

Proposed Model

In this research, the proposed methodology we first selected DEAP dataset as the primary source of EEG signals and preprocessing EEG signals using PSD and but later, we used DWT instead of PSD to preprocess EEG signals, since we got better results using DWT to preprocess EEG signal instead of PSD. After that, several features were extracted from the preprocessed data. After the features were extracted, multiple classifiers were used for classification and the results of emotional recognition were created. In Fig 4.1 we can see the block diagram of our proposed model.

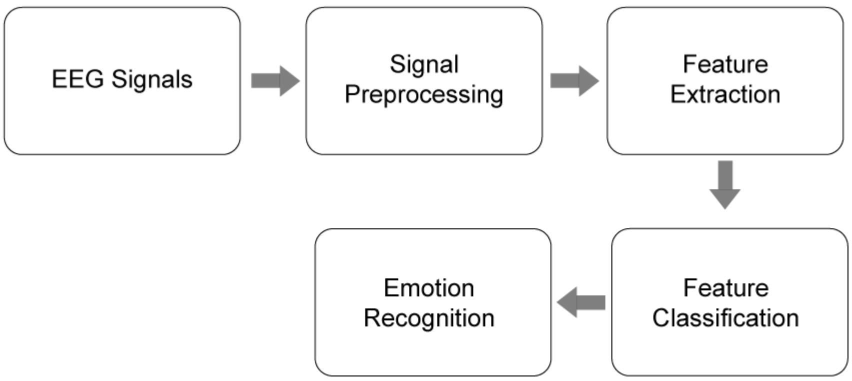

Figure 4.1: Block diagram of the proposed method

4.1 Data description

In our paper, as our source of brain signals, we used a DEAP dataset [16]. It is explained briefly in Table 4.1. The graphical record signals and peripheral physiological signals of thirty two participants were recorded after they were observation music videos. The dataset contains thirty two channel graphical record signals and eight peripheral physiological signals[15] . The emotional music videos embody forty one-minute long little clips and subjects were asked to try to to self-assessment by assignment price. it's ensured that this information can't be tampered with as files area unit created to be browse solely moreover the gathering of information was done five times for every take a look at to make sure trustworthy data [17]. Every one of the two compress organizers contain 32 members each with the information put away in a 3D grid portrayal (40 $\times$ 40 $\times$ 8064) speaking to video/preliminary $\times$ channel $\times$ information, with the numeric class esteem marks saved money on a similar document as a 2D framework.In the wake of reformatting the information during information readiness the refreshed dataset contained 204,800 $\times$ 8065. A sum of 11.2 GB worth of tested EEG information with an extra 15 GB crude face recording information is accessible for reference. s from 1 to all day distinctive status, to be specific, valence, excitement, strength, preferring, and commonality. There are 32 .bdf documents, each with 48 recorded channels at 512Hz. (32 EEG channels, 12 fringe channels, 3 unused channels and 1 status channel). The .bdf documents can be perused by an assortment of programming toolboxs, including EEGLAB for MATLAB and the BIOSIG tool stash [45]. The information was recorded in two separate areas. Members 1-22 were recorded in Twente and members 23-32 in Geneva. Because of an alternate amendment of the equipment, there are some minor contrasts in the arrangement.

Table 4.1: Summary of DEAP Database

DEAP Database content summary	
Number of Participants	32
Number of Videos	40
Selection method	Subset of online annotated videos with clearest responses
Rating Scales	Arousal Valence Dominance Liking Familiarity
Rating Values	Continuous Scale of 1-9
Recorded Signals	Peripheral physiological signals Face video

The excitement and valence were focused. Along these lines, a more modest passionate feature score (ei) is nearer to the nonpartisan state [45]. For each video, the one-minute long segment with the highest emotional highlight score was chosen to be extracted for the experiment.

$$e_i = \sqrt{a_i^2 + v_i^2} \tag{4.1}$$

4.2 Signal Preprocessing

For the purpose of our research work, we have chosen a down sampled (to 128Hz), preprocessed and segmented version of the data in pickled python/numpy formats [54]. This rendition of the information is appropriate to those wishing to rapidly test a characterization or relapse method without the problem of handling all the information first. Each compress document contains 32 .dat (python) records, one for every member. Each participant file contains two arrays, the layout of which is explained in Table 4.2. Some same code to load a python datafile is below:

```
import cPickle
x = cPickle.load(open('s01.dat', 'rb'))
```

Table 4.2: Format of data arrays

Array Name	Array Shape	Array Contents
Data	40 x 40 x 8064	Data 40 x 40 x 8064 video/trail x channel x data
Labels	40 x 4	video/trail x label (valence, arousal,dominance, liking)

For the investigation of the EEG correlation, the Power Spectral Density (PSD) approach was taken [25] which is based on the Fast Fourier transform (FFT), was adopted to obtain the characteristics of brain signals in the frequency domain. The computational cycle was followed for various recurrence groups and utilized as a pointer of the degree of mind movement inside every one of these groups. The DEAP information has just been down-examined to 128 Hz and low-pass sifted to eliminate frequencies over the ideal reach. The force ghostly thickness can be viewed as both of the accompanying [38]

The averages of the square of the magnitude of the Fourier transform:

$$S_x(f) = \lim_{T\to\infty} E\left\{\frac{1}{2\pi}\left|\int_{-T}^{T} x(t)e^{-2j\pi f\mathcal{T}}dt\right|^2\right\} \tag{4.2}$$

The Fourier transform of the autocorrelation function:

$$S_x(f) = \mathcal{F}\left\{R_x(\mathcal{T})\right\} = \int_{-T}^{T} R_x(\mathcal{T})e^{-2j\pi f\mathcal{T}}dt$$
$$\text{Where } R_x(\mathcal{T}) = E\{x(t) * x(t+\mathcal{T})\} \tag{4.3}$$

After utilizing PSD, we have incorporated the utilization of DWT. The DWT is an elective strategy to control ghastly thickness for estimating the noticeable quality of various frequencies in the EEG. The Discrete Wavelet Transform involves a cascade of processing steps [44]. At each stage there is a high-pass and a low-pass filtering process. From the high-pass channel detail coefficients are recouped for the higher recurrence range while the low-pass channel brings about what are called estimation coefficients, which are passed onto the following stage. It is a joint time recurrence goal investigation and hence is a decent strategy to extricate the subtleties just as approximations of any sign [47].

EEG signals are non-fixed in nature and in this manner are examined by growing, contracting and moving one model capacity likewise alluded to as the mother wavelet which is to be explicitly chosen for the given sign [40] .

$$\boldsymbol{\psi}_{a,b}(t) = \frac{1}{\sqrt{a}}\boldsymbol{\psi} \quad \left(\frac{t-b}{a}\right) \tag{4.4}$$

Where, a=scaling factor and b=shifting factor

The mother wavelet should satisfy the admissibility of condition given by

$$C_\psi = \int_{-T}^{T} \frac{|\psi,(\omega)^2|}{\omega} d\omega < \infty \tag{4.5}$$

For playing out the time-recurrence investigation, the sign is over and over went through a couple of high pass channel [g(n)] and low pass channel [h(n)], that isolates the frequencies from the middle, as lower recurrence band and upper recurrence band. The DWT breaks down the sign into two coefficients specifically the nitty gritty coefficients and the guess coefficients [51]. The guess coefficient is again partitioned into new estimation and definite coefficients. Completing this cycle iteratively gives a lot of guess coefficients and detail coefficients at various levels [44].

4.3 Feature Extraction

According to the DEAP data collection experiment, participants provided related information after watching the videos. According to that information, every video shown in the experiment can be divided into four quadrants (HAHV, LAHV, LALV, HALV) which is shown in Fig 4.2.

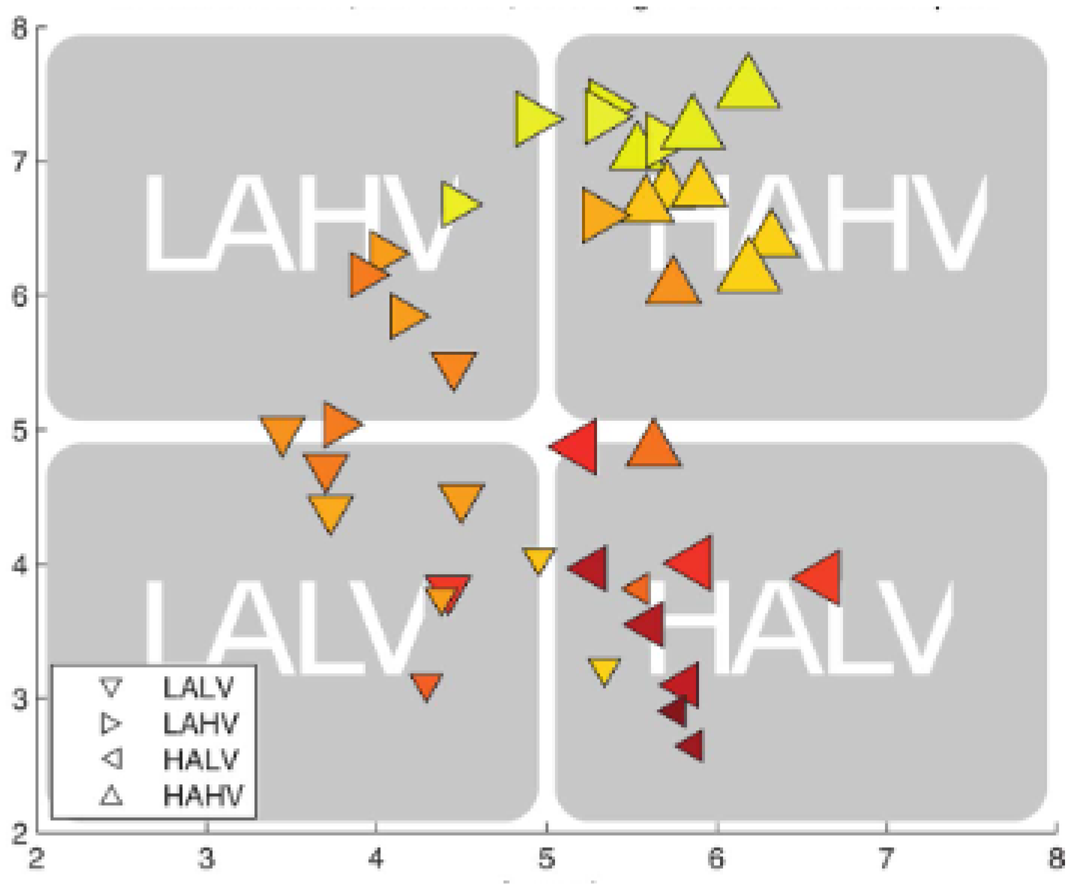

Figure 4.2: Stimulus locations, dominance and liking in Arousal-Valence Space

The mean areas of the upgrades on the excitement valence plane(AV plane) for the four conditions (LALV, HALV, LAHV, and HAHV) appeared in Fig 4.4. Preferring is encoded by shading: Dark red is low loving and splendid yellow is highliking. Strength is encoded by image size: Small images represent low predominance and huge for high strength Based on something over the top, too less or ideal degree of excitement or valence people had various reactions for various music recordings. This is appeared in Fig 4.2 setting them in the relating quadrant. Recordings chose for use in the investigation are featured in green in Fig 4.3. For every quadrant, the most extraordinary video is itemized with the tune title and a screen capture from the video [32] .

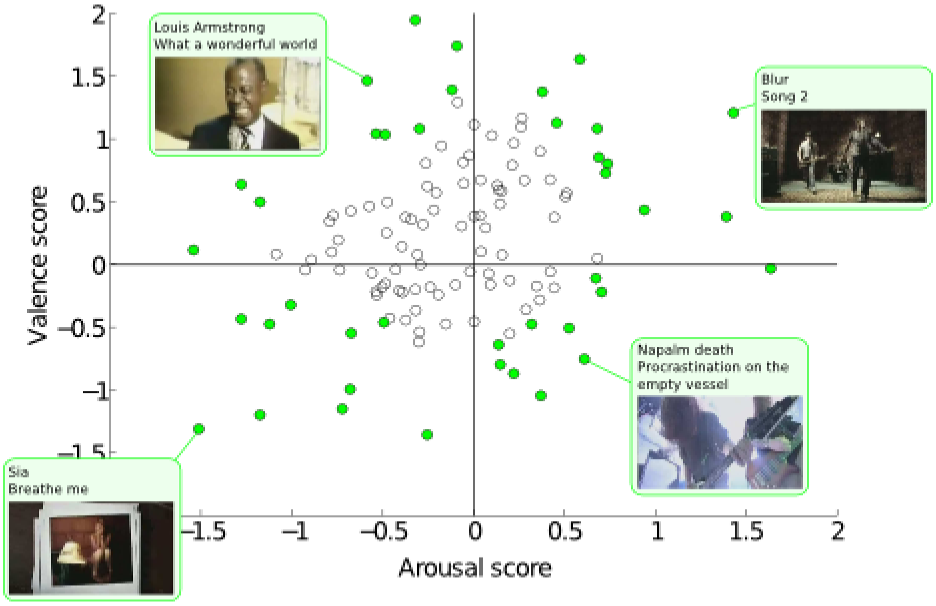

Figure 4.3: List of 40 music video and Their Corresponding Quadrant

To change time space highlights to recurrence area includes, certain strategies are applied, for example, wavelet change (WT), quick Fourier change (FFT), Hilbert Huang change (HHT) and head part examination (PCA) [34] . Based on some effective results of the previous paper, In this paper we used a two-dimensional model to represent the output. The output for valence, arousal respectively: 0≥low and 1≥high [26] .

When we started extracting features first the EEG signals were observed into four brain waves. EEG signals will display all the waves at the same time shown in Table 4.3, however the state of an individual depends on which of these waves has ascending value [28] .

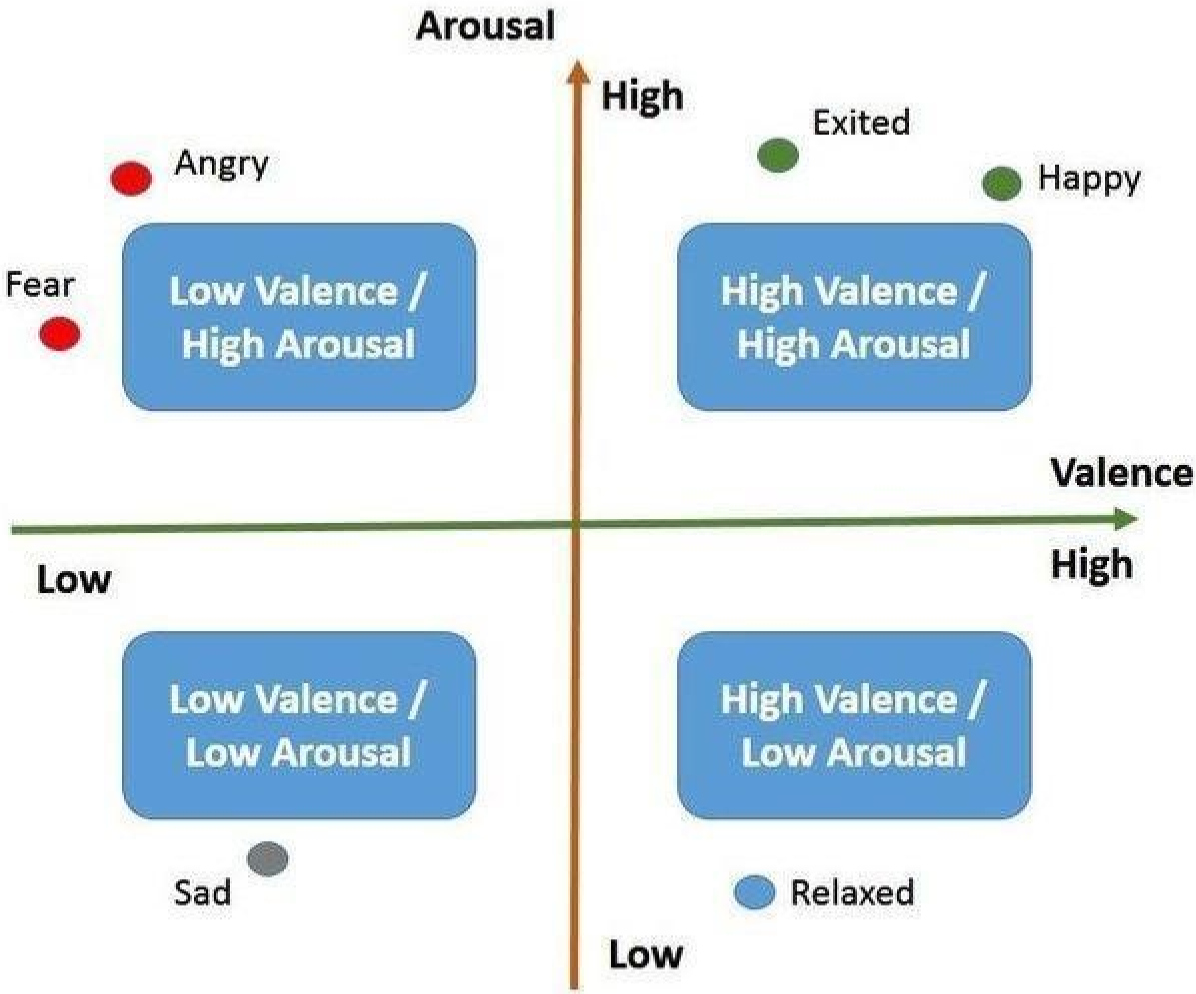

Figure 4.4: Arousal-valence based emotional states

A few sign attributes of EEG have been utilized to be the highlights. The broadly utilized element is PSD, the intensity of the EEG signal in centered recurrence groups [18] . The EEG signal with window 1 second was decayed to 5 recurrence groups that are Delta (0–4Hz), Theta (4–8Hz), Alpha (8–16Hz) and Beta (16–32Hz) by Wavelet Transform as appeared in Table 3. At that point the PSD from each band was registered to be the component. Since EEG Signals from each trail have 120 seconds, there are 120 examples for every path. Because of 5 preliminaries, there are 600 examples for every member. With 10 members, the complete examples are 600. All examples were named dependent on the viable responses[5] . Then the PSD from each band was computed to be the feature **Bailey**. The highlights were standardized for every member by scaling somewhere in the range of 0 and 1 as

Table 4.3: Type of features extracted by using Power Spectral Density

Frequency Band	Frequency Range (Hz)	Frequency Bandwidth (Hz)	Category
Delta	0-4	4	Slowest
Theta	4-8	4	Slow
Alpha	8-16	8	Moderate
Beta	16-32	16	Fast

appeared in (6) to decrease bury member inconstancy [39]

$$\text{normalize } (X_i) = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{4.6}$$

After extracting features using PSD, various classifiers were implemented and analysis was performed based on the DEAP dataset. After that, several time based features were extracted by using DWT **Bailey**. According to the Table 4.4, these features are wavelet energy, wavelet entropy, standard deviation and covariance.

Table 4.4: List of Discrete Wavelet Transform Features extracted for this research

Type of features extract by using Discrete wavelet transform
Wavelet Energy
Wavelet Entropy
Standard Deviation
Covariance

4.4 Emotion Classification

In order to classify the features, in our research paper we have implemented different classifiers like Gradient Boosting Classifier, Extra Trees Classifier, Light Gradient Boosting Machine, Extreme Gradient Boosting, K-neighbors Classifier, Linear Discriminant Analysis etc [8]. According to Table 4.4. The purpose of implementing multiple classifiers was to consider several important factors regarding emotion detection and conclude accuracy of different classifiers [36], [13] .

Among them Gradient Boosting Classifier performed well comparatively shown in

Table 4.5: Outcome of implementing different classifier using PSD features

Sl	Model	Accuracy	AUC	Prec	TT(Sec)
0	Gradient Boosting Classifier	0.6112	0.5298	0.6379	206.9001
1	Extra Trees Classifier	0.6101	0.5632	0.6318	1.5985
2	Light Gradient Boosting Machine	0.6034	0.5364	0.6265	113.6705
3	Extreme Gradient Boosting	0.5933	0.5368	0.6266	53.6799
4	K Neighbors Classifier	0.5788	0.5384	0.6464	1.2753
5	Linear Discriminant Analysis	0.552	0.5242	0.6295	7.6437

Table 4.5. We have projected better accuracy while training the classifier with cross validation[6]. In this approach, we reserve 50% of the dataset for validation and the remaining 80% for model training [24].

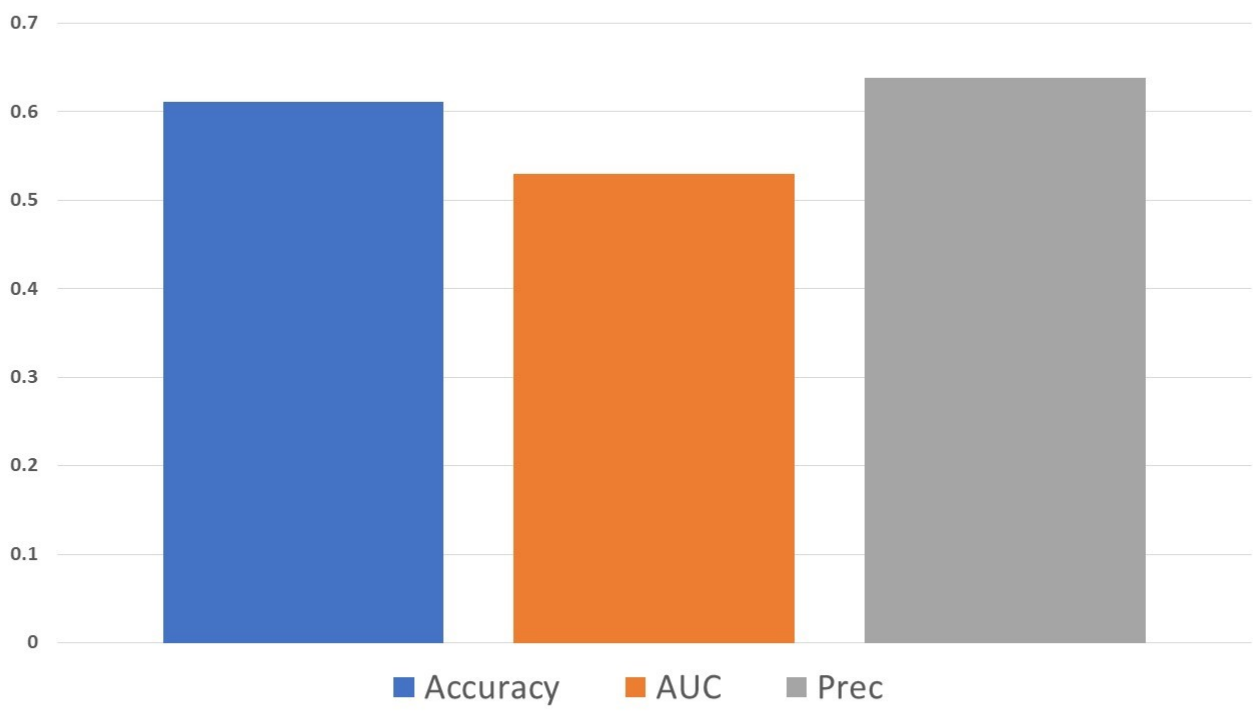

Figure 4.5: Outcome of gradient boosting classifier after applying PSD

As PSD features are mainly just a measure of human presence of mind, we performed DWT with the same classifiers to get the time-based features [59] . Note that, here each wave has been divided into segments of 6, hence there are a total 10 segments [20].

Table 4.6: Outcome of implementing different classifier using Discrete Wavelet Transform Features

Sl	Model	Accuracy	AUC	Prec	TT(Sec)
0	Gradient Boosting Classifier	0.8812	0.7298	0.7339	213.9001
1	Extra Trees Classifier	0.8101	0.7632	0.6427	1.5385
2	Light Gradient Boosting Machine	0.7034	0.5364	0.6225	112.6705
3	Extreme Gradient Boosting	0.6933	0.6382	0.6216	51.6799
4	K Neighbors Classifier	0.6788	0.6383	0.6434	1.3753
5	Linear Discriminant Analysis	0.652	0.6244	0.6225	5.6437

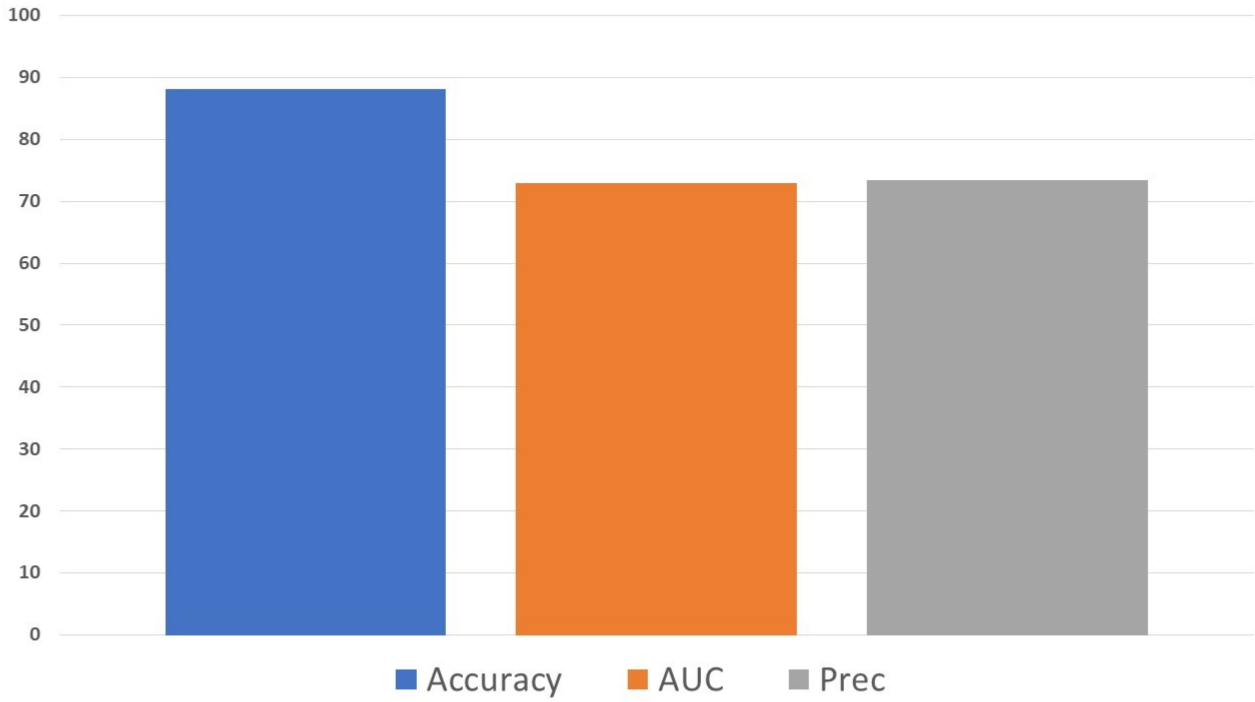

Figure 4.6: Outcome of gradient boosting classifier after applying DWT

Later on we used DWT to extract (shown in Table 4.6), different features from the EEG signal. In the event that the wavelet coefficient attributes are profoundly like the mother wavelet work qualities, we can expect to have high performance in feature extraction [19] , [18]. So as to do that, the single model capacity called the mother wavelet is utilized to decay the information signal dependent on scaling and moving boundaries [21] , [10]. Another advantage is that it helps wavelet transforms so that the windows vary and in order to isolate signal discontinuities, it helps by providing very short basic functions that work effectively and more precisely [21] , [23]. Here we saw significant change of better results especially in the Accuracy, AUC and

Prec. part. To be very specific here we can see in Gradient boosting classifier the accuracy of PSD feature is 61%, but later on it went up to 88% (shown in Fig 4.6) when we implemented DWT. Significant changes have been noticed in the AUC and Prec. part as well. In PSD features the AUC of Gradient boosting classifier was 52%, later on when we implemented DWT, the result was far better(72%). Same goes for Prec as well(from 63% to 73%). In both the charts being shown here we see DWT is giving us far better accuracy.

Chapter 5

Results and Analysis

Afterward by using grid search algorithm we performed hyper tuning of the parameter of Gradient Boosting Classifier. As we know grid search finds the optimal hyper parameters of a model which results in the most 'accurate' predictions.10 fold cross validation was implemented on our trained model. Here we took 10 samples of the trained model and randomly partitioned into the same number of subsamples. Repeating 10 times, this process randomly divides all given data into k equal subsets [4]. This assures us with the least possibility of biasness The hyper tuned parameters after 10-fold cross validation are in Table 5.1 and Table 5.2:

Table 5.1: Details of parameters used (1)

ccp aplha	criterio	Learning rate	Max depth	Min samples leaf
0	Friedman_mse	0.16	30	1

Table 5.2: Details of parameters used (2)

Min sample-split	N-estimators	Sub-sample	total	Validation fraction
2	100	0.9	0.0001	0.1 height

We get the hyper tuned gradient boosting classifier outputs in Fig 5.1 and later on we trained them up with 10-fold cross validation which is giving us promising results.

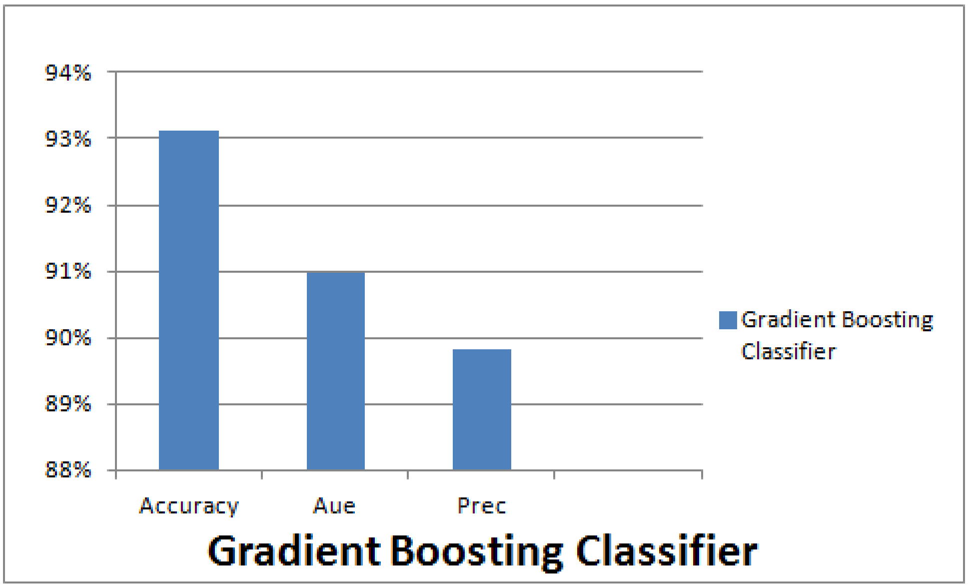

Figure 5.1: Hyper tuned Gradient Boosting Outputs

If we analyze our final findings we get a much better result than what we got from the PSD features. We observed that if we had taken 80% data which we trained and 20% data that we tested on, there would be a larger number of biasness. Which is why we implemented various classifiers and finally Gradient Boosting Classifier showed the best result among 6 of them. Later, to avoid overfitting of any variance we tuned our model which increased accuracy. Lastly, 10 fold cross validation was performed not only because it is the best tool against overfitting but also to decrease biases. Finally we got an accuracy of 93.12%. The accuracy of AUC(90.98%) and Prec.(89.39%) were very promising as well.

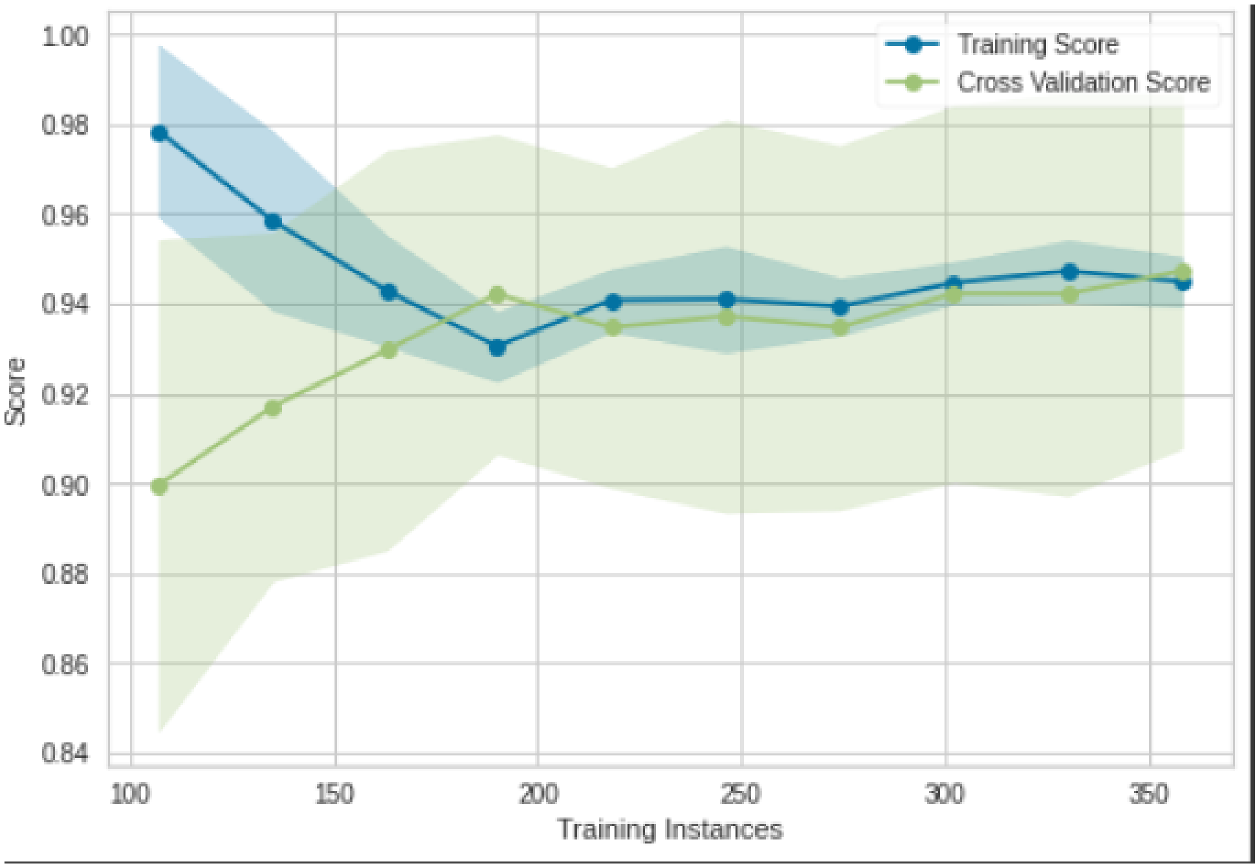

Figure 5.2: Learning Curve

In the learning curve, Fig 5.2 we see that our training score line is much higher than cross validation score in most of the points which proves our used machine learning model is much more efficient.

Error rate

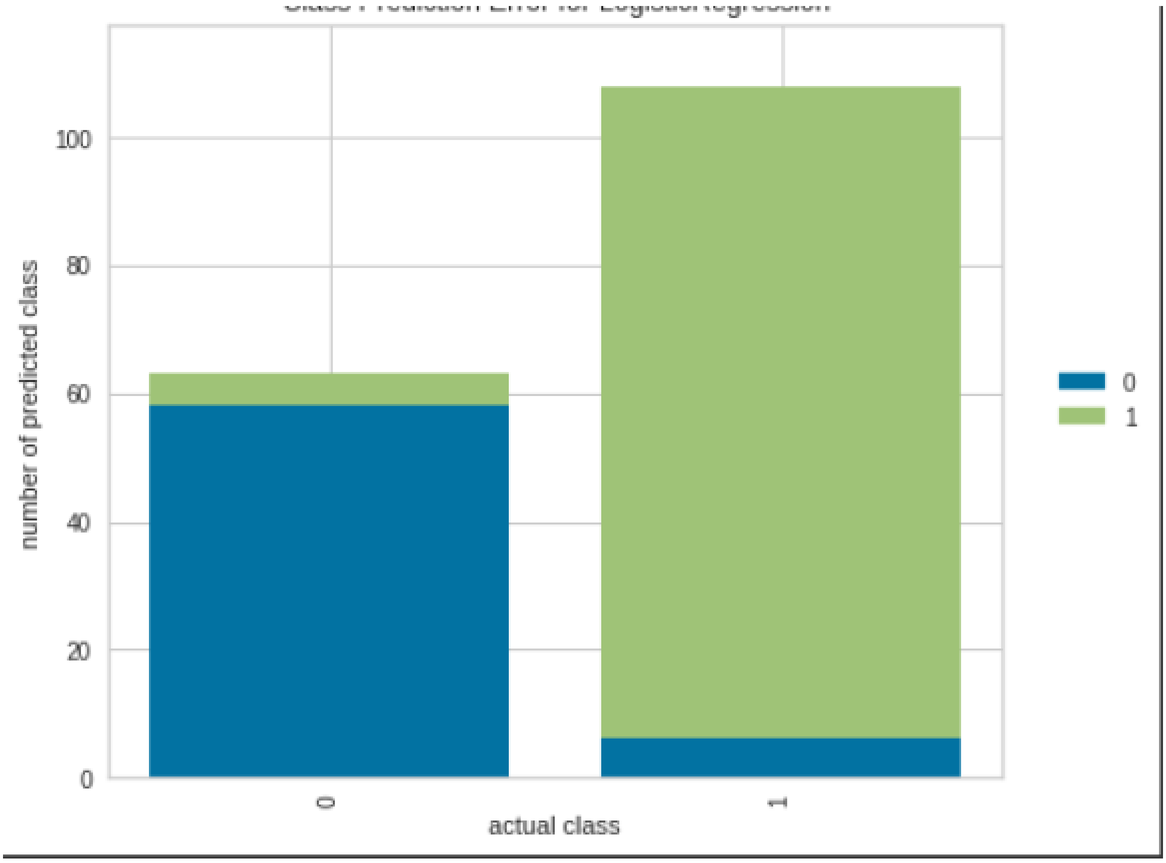

Figure 5.3: Error Rate

Fig 5.3 basically focuses on the percentage of the accurate prediction. We subtracted the accepted value from the experimental value to get the percentage error rate which is pretty low here. Our accuracy rate is based on 0 (zero) and 1. We trained the model in a way so that it can predict zero and one properly. As the number of predicted classes is close to perfect, it proves that our trained model has a higher accuracy rate and low error rate.

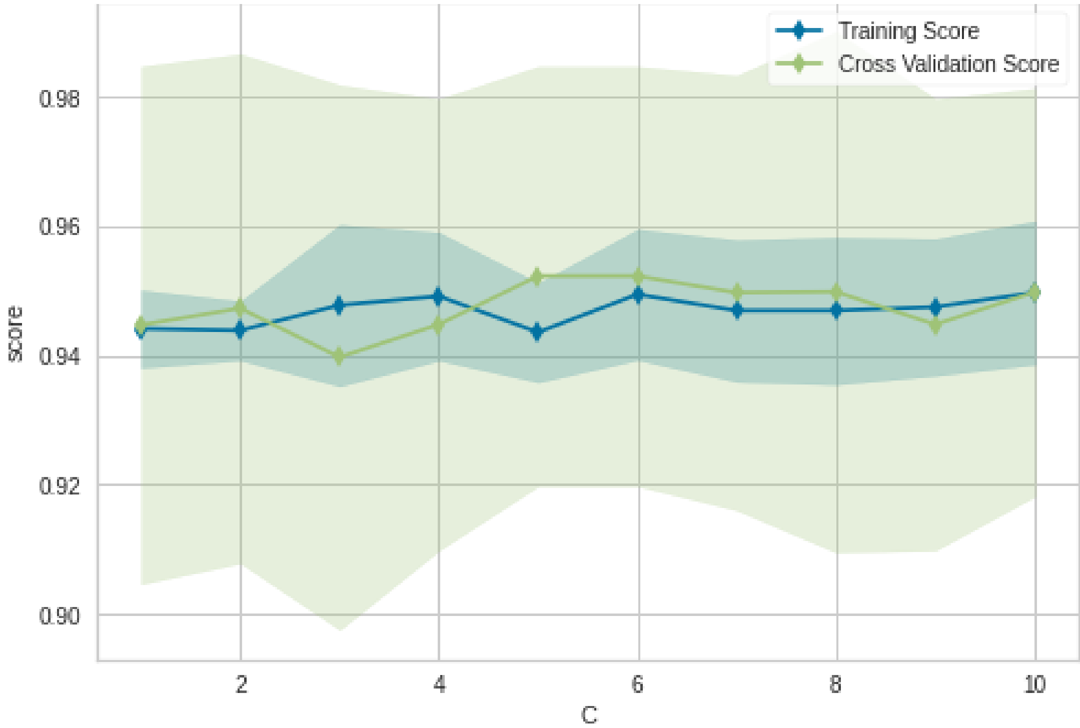

Figure 5.4: Validation Curve

In Fig 5.4 which is our validation curve, we can see that even after performing cross validation we are receiving the readings which are close to the training score. Note that, in the first place we performed cross validation to avoid overfitting of any variance and to increased accuracy. This validation curve shows that our cross validation score is overlapping our training score.

Figure 5.5: Decision Boundary

In Fig 5.5 which is our decision boundary, we divided an area into two to demonstrate the usable and unusable decisions that can be used in classification. We wanted to show the classification categorically hence we chose the logistic regression pattern. Apart from that, as we had binary output, logistic regression should show the best form of decision boundary. Here we clearly see that, green is the zone or area for one and blue is the area for zero. Very few of the values overlapped each other. Meaning the method we picked is giving acceptable results.

DEAP dataset being a public dataset we tried to compare our final findings with the existing results and also analyzed the existing methods which have been used for extracting features. It can be observed that some methods work on only one emotion and some work on only two states of emotion. However for our work we only used two states of emotions (valence and arousal) and considered only the statistical features.

Furthermore, we can see that while we implemented PSD features, our accuracy in all the classifiers was limited to more or less 60%. After implementing DWT and later on by hyper tuning the gradient boosting classifier we get an accuracy of 93.12% which we think is a great accomplishment. We also used 10 fold cross validation to make sure that our result doesn't get biased. Thus It can be said that our finding result is way more efficient than the existing approaches and it is clearly shown in Table 5.3.

Table 5.3: Accuracy of Existing Approaches based on DEAP Dataset

Reference	Emotions	Features	Accuracy(%)
[29]	Stress and calm	Statistical, PSD and HOC	71.40
[37]	Valence, arousal and dominance	Statistical AND hfd	71.40
[41]	Excitation, happiness, sadness and hatred	WT(db5), SE, CC and AR	78.60
[42]	Anger, surprise and other	HHS, HOC and STFT	78.60
[58]	Valence and arousal	Statistical	92.36
Our model	Valence and arousal	Statistical, PSD and DWT	93.12

Chapter 6

Conclusion

In recent years, there are obviously both pros and cons of technology use. Using a machine or a mobile phone has become a part of normal life for many individuals. With this rate of technology rising with great acceleration, emotion recognition has also kept its pace with technology. There are various approaches to the recognition of emotions, such as facial features, hand signals and sounds. There is a general downside to emotion recognition in these forms of methods. Even, they can be falsified at will. This makes these techniques inaccurate and not necessarily effective. This is the reason why specialists have been using electroencephalogram (EEG), which is a method for emotion recognition that is very distinctive. The DEAP dataset was used in our research to capture the preprocessed EEG signals in order to differentiate the various forms of emotions, including valence and arousal. The first phase of our research allowed the sample dataset to be compressed by converting the data to the frequency domain from the time domain format by applying FFT to extract all the bands that are important to the emotion of recognition. After extracting the features, we finally get an accuracy of 93.12%. We would like to incorporate our emotion recognition approach in the future, to enable autistic individuals or mentally disabled individuals to communicate their feelings, we would also like to help marketers market their goods more by recognizing the emotion of clients, as they rely on feelings when making purchasing decisions.

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