Development of Intelligent Model Using Machine Learning Tools For Brain Signal Analysis

A Thesis Submitted

In

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Of

Bachelor of Technology

Submitted by:

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Declaration of Authorship

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"It does not take much strength to do things, but it requires a great deal of strength to decide what to do."

-Elbert Hubbard

Abstract

The Capability of Human Brain to comprehend and process complex emotions makes it more advanced than the brains of any other species on planet Earth. The power to process emotions is the source of some highly respected values in the society like motivation, confidence and courage. Thus the study of emotions has a very wide range of applications in neuroscience, psychology, cognitive science, computer science and artificial intelligence. In neuroscience crucial emotion data can help in better understanding and predictive modelling of the human brain. In Psychology, the stimuli analysis can provide greater insights into understand cause and effect scenarios. Whereas in the field of Artificial Intelligence, the study of emotion data can help provide better learning models that can be applied in other areas of research and business.

In this project we have focused our attention on Binary Emotion classification using the EEG (Electroencephalogram) data received. The data was collected in preprocessed and down sampled (128Hz) form. The data contained an experiment performed on 32 subjects who were shown 40 one-minute long videos and their EEG response collected. Thus, the data containing the subject ratings for Valence and Arousal was taken and two videos were chosen, one for Low Valence and Low Arousal(LALV) and another for High Valence and High Arousal (HAHV). The EEG data for those videos were taken from different subjects. The features for the data were extracted through autoregressive coefficients and the features were trained in SVM classifier. Significant results were obtained in the process. The results provided have given us the hope that the methodology can be used to deal with much larger datasets.

Acknowledgements

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We also thank our friends who has supported and guided us to roll the project out of the hanger.

Forwarding Certificate

This is to certify that project entitled “Development of intelligent model using Machine Learning Tools For Brain Wave Analysis” is submitted by following 8th semester students and is a bonafide work done by them in partial fulfillment of the requirement for the degree of Bachelor of Technology in Electrical Engineering of National Institute of Technology Silchar, Assam, under the guidance of Prof. Nidul Sinha,, Department of Electrical Engineering, NIT Silchar.

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Certificate of Approval

This is to certify that project entitled "Development of Intelligent Model Using Machine Learning Tools for Brain Wave Analysis" is submitted by following 8th semester students and is a bonafide work done by them in partial fulfillment of the requirement for the degree of Bachelor of Technology in Electrical Engineering of National Institute of Technology Silchar, Assam, under the guidance of Prof. Nidul Sinha, Department of Electrical Engineering, NIT Silchar.

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CHAPTER 1

INTRODUCTION

The Brain being the largest and most complex organs of the Human Body. It is made up of 100 billion nerve cells that communicate in trillions of synapses. The human brain along with the nervous system is result of years of evolution from assisting the body in mere survival to develop complex cognitive abilities. Thus among all the variety of brains that evolution has ever produced, the Human Brain is the most developed.

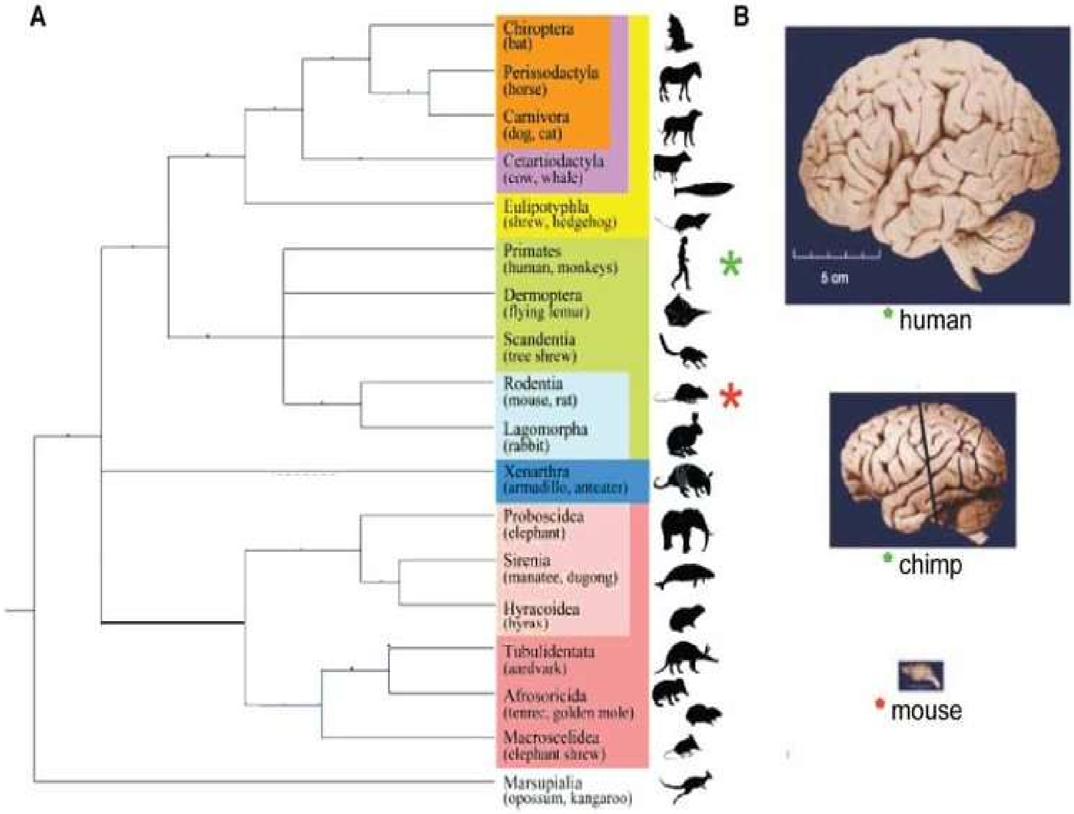

Figure a: Evolution and brain size in mammals. A , Mammalian phylogeny showing the evolutionary relationships of the mammalian orders. Primates (green asterisk) and Rodentia (red asterisk), the primary orders discussed in this thesis, are highlighted. Image modified from Nishihara et al. 2006. B, Lateral views of adult human, chimp and mouse brains showing their relative size. Green and red asterisks reflect the position of these species on the phylogeny presented in A. Scale bar, 5 cm. Images modified from Hill & Walsh 2005.[1]

As mentioned above, the Human brain contains 100 billion neurons more than 100,000 km of interconnections, and has an estimated storage capacity of 1.25×10^{12} bytes ([2], [3]). These impressive numbers have led to the idea that our cognitive capabilities are virtually without limit. The brain performs in such a way that different areas of the brain are capable of different functions and work together to perform daily tasks. All human thoughts, emotions and behaviours is due to the communication between neurons inside the brains through electrical pulses which are interpreted from the EEG Data or The Brain Waves data.

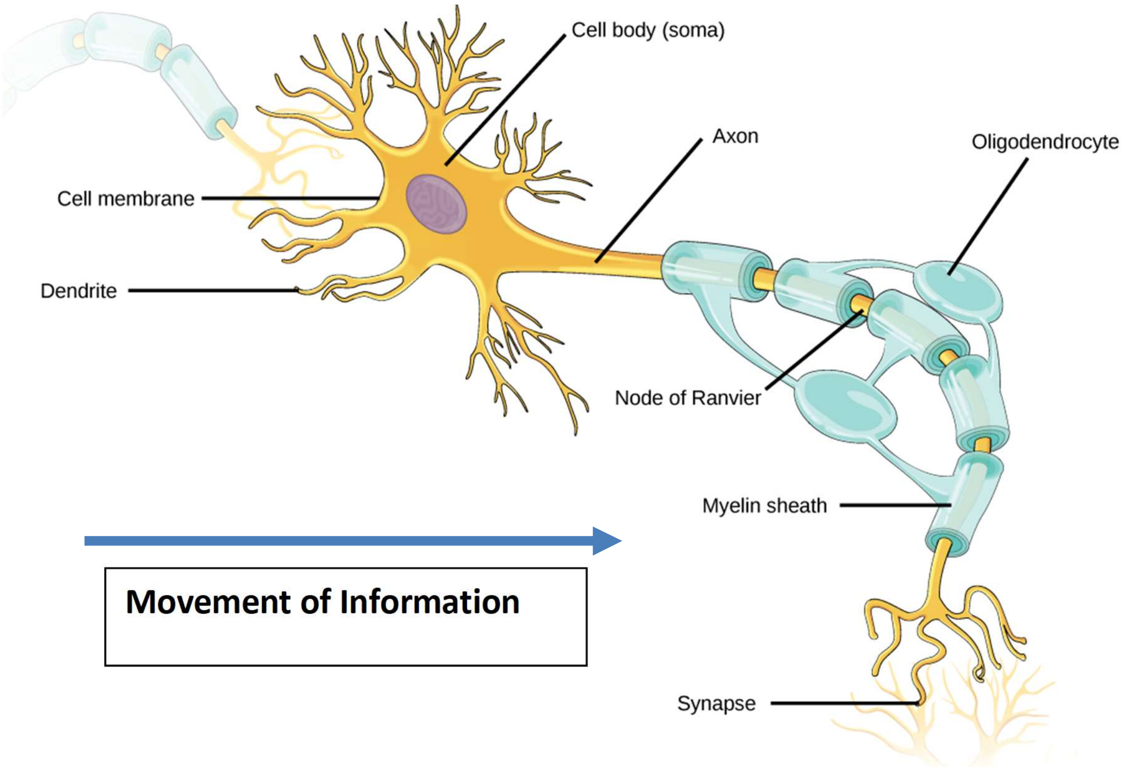

Figure b: Neuron in the central nervous system: This neuron diagram also shows the oligodendrocyte, myelin sheath, and nodes of Ranvier (*Source: https://courses.lumenlearning.com/boundless-psychology/chapter/neurons/*)

This project involves the development of intelligent model for analyzing human emotions using the method of deep learning. The data is collected from the database created by *S. Koelstra and Team in 2012[7]* which is a multimodal (EEG, Physiological and Video signals) dataset for analyzing the human emotions. Emotional analysis from the EEG has recently caught the attention of speakers due its potential to revolutionize the fields of entertainment, medicine and psychiatry. The scientists and the researchers are constantly looking to optimize Machine Learning algorithms and the perquisites of it which include Data Mining, feature selection and extraction for emotion classification through EEG data. In this project also, emphasis has been laid on the optimization through the EEG data.

1.1 Motivation

Analyzing the human mind has always been a challenge to the humans themselves due to wide variations of its scope which depends upon the person which possesses that particular brain. But, human brain has one great capability which is almost common in all the human beings (The rate may differ) i.e. the ability to learn, rationalize and process complex feeling and emotions. Extensive research is being done to understand the origin and effect of emotions inside the human brain and to understand the circuitry which leads to such complex and intelligent behaviors.

If we are able to train our machines to process tasks which are as complex as the human emotions and reflex actions, we may be able to execute complex challenging computational tasks in fraction of seconds or even less. Our various states of consciousness are directly connected to the ever-changing electrical, chemical, and architectural environment of the brain. Daily habits of behaviour and thought processes have the ability to alter the architecture of brain structure and connectivity, as well as the neurochemical and electrical neural oscillations of your mind.

The “neurochemicals of happiness”—endorphins, endocannabinoids, dopamine, serotonin and oxytocin—can make us feel good when we do things like exercise and spend time with loved ones by changing the chemical environment of the brain. The *electrical* environment of the brain and brain waves fine-tune our consciousness. New findings that stimulating alpha waves can boost creativity and reduce depression. Also, analysis of brain waves can provide us with a breakthrough in analyzing the science behind addiction. The study of the brains of the criminals can help us to understand and control the criminal activities throughout the world. The study of children brains and the effect of different environments on their brain activity may lead us to provide better upbringing to the coming generation. Also by being able to extract important parameters, we will be able to provide clinicians with something very unique.

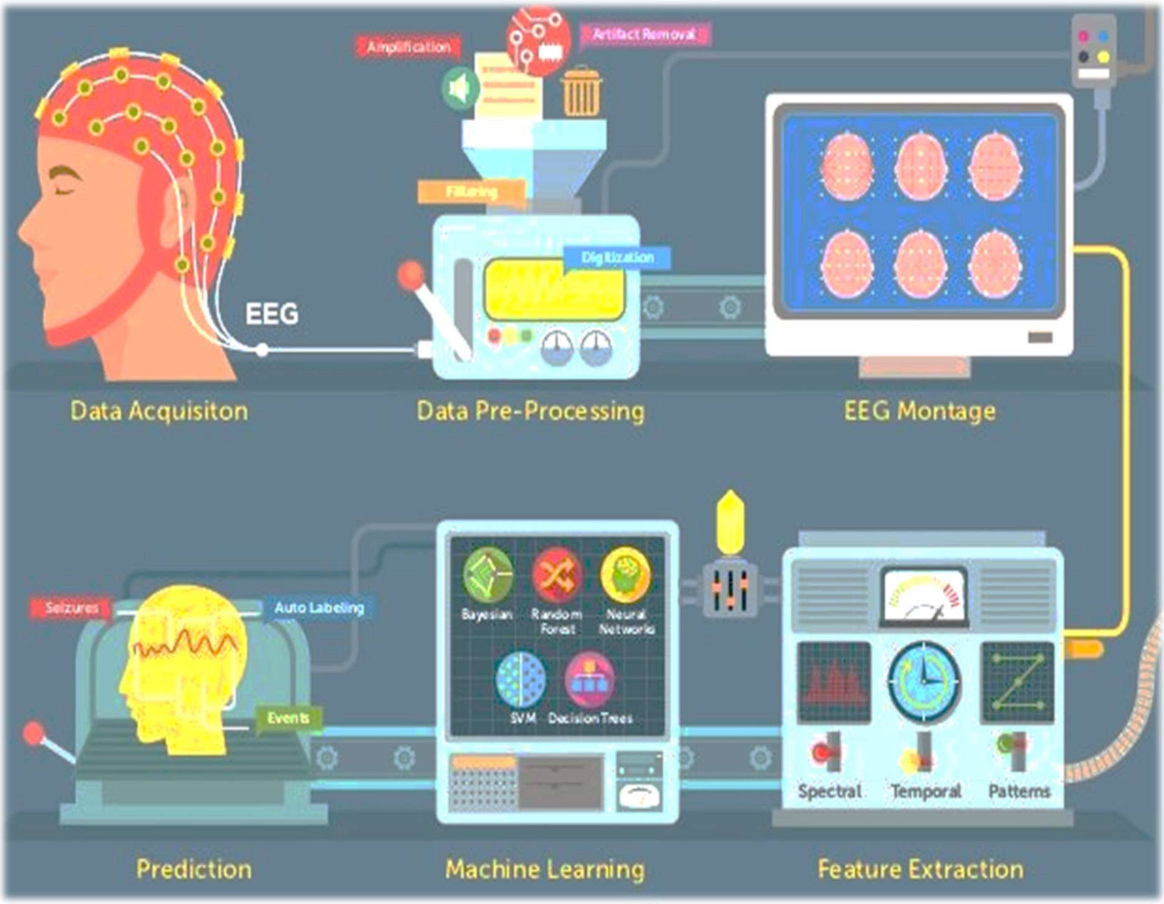

Figure c: Flowchart for Analysis through EEG data
Source:http://epscicon.vidyaacademy.ac.in/wpcontent/uploads/2017/12/eeg.jpg

As far as the EEG data is concerned many researchers have used it for emotion classification in the past. EEG is the comprehensive reflection to actions of the hundreds of millions of neurons in cortex, and characteristics of EEG differ widely in different mental states, emotional changes and physiological status. The main advantage of using EEG signals is that it reflects real emotion and can easily be processed by computer systems [4]. The application system of EEG usually contains signal acquisition and pre-processing, extracting signal features associated with the event and system modelling. Thus the EEG data received from the DEAP data set [7] will be the basis of our further work.

1.2 Prime objectives

Sample EEG data has been collected from 32 people. Electroencephalography , or EEG, is the physiological method of choice to record the electrical activity generated by the brain via electrodes placed on the scalp surface. The data required for that purpose is collected from a publically available DEAP dataset(*Koelstra et al., 2012*). The data received is processed and down sampled and as a result we can readily use it for emotion analysis without the requirement of any EEG device and related machinery.

The report primarily focuses on analyzing the data and the signals recorded through 32 channels. The people were subjected to different emotional situations which were:

i) Excited/Happy/Pleased
ii) Relaxed/Peaceful/Calm
iii) Sad/Bored/Sleepy
iv) Annoying/Angry/Nervous

The emotion sates are expressed mathematically on Valence Arousal plane. The predictions regarding the emotions is done keeping Valence and Arousal as the parameters and the accuracy is calculated.

The Deep Learning Algorithms are applied to develop an intelligent model for emotion detection. The emotion classification will be binary which would differentiate LALV and HAHV emotions. Using deep learning which is a subset of machine learning, we study the signals transmitted within the neural network. The data will be tested and analyzed through different deep learning techniques and combined with statistical/mathematical implications to arrive at suitable models for analyzing the brain wave data. Also, the channel activity will also be monitored based on the signal data.

1.3 Organization of thesis

This thesis report is separated into distinct chapters. A brief description of each chapter is as follows:

1. Chapter 1: This chapter provides a general introduction, outline of the thesis topic, methodology that employed to ensure that the stated goals and objectives were achieved. The chapter also includes a description of our motivation to choose the subject topic.

2. Chapter 2: This chapter contains the literature review describing the methods, emotion states and accuracy

3. Chapter 3: This chapter gives a description of how the data was collected through various modes.

4. Chapter 4: This chapter Explains in detail the methodology used for emotion classification including the Data Pipelining tools used.

5. Chapter 5: This chapter discusses the results and the conclusions derived and the further scope of improvements and suggestions.

CHAPTER 2

LITERATURE REVIEW

Extensive Research has been done in the field of Brain Wave Signal analysis which include acquiring and processing EEG data, Analysis of emotions and reflex actions. Our work is focused primarily on emotion detection through Deep Learning Algorithms. As a result, we have focused our attention extensively on the Deep Learning techniques and data pipelining.

- The data collection was done from the DEAP DataSet provided by *Sander Koelstra et al., 2012*[10]. The team has made preprocessed and down sampled physiological Dataset publically available for Deep Learning analysis.
- In order to understand the Data, a paper on similar lines published by *Mohammad Soleymani et al., 2012* [17] where they created a Multimodal Database for Affect recognition and Implicit tagging thus providing a deeper insight into how the data collected refers to the original scenario.

The data once collected needs to go through a lot of pre-processing techniques before they are finally used for Deep Learning Emotion Classification. Significant research has been done in the field and various methods of Data Normalization, Dimensionality reduction and Feature selection has been found to be effective in aiding the classification process.

- In *Mehmet Sirac¸O ¨zerdem . Hasan Polat et al., 2017* [18], Effective methods like Discrete Wavelet Transform is used for feature selection of EEG signals.
- In *Guolu Cao et al., 2019* [19], Z-Score Normalisation is used and Principle Component Analysis is used for Dimensionality Reduction.
- In *Sreeshakthy. M et al., 2015* [20], Particle Swarm Optimisation is used for feature selection and Dimensionality reduction.
- *Vaishnavi L. Kaundanya et al.,2015* [21], First DWT coefficients were calculated and the features Mean, Variance, RMS, Standard deviation, Skewness, Entropy and power were used
- *Yi-Hung Liu, 2013* [22] et al., Discrete Fourier Transform coupled with PCA is used for feature selection and dimensionality reduction.

- *Raja Majid Mehmood and Hyo Jong Lee et al.* [23] Hjorth Parameters for Feature Selection and Dimensionality reduction.

For Emotion classification, impressive research has been done by many researchers and phenomenal accuracies were derived from those algorithms which go as high as 94.4%. The Deep Learning Algorithms that are being used have a great deal of dependency on techniques of Data Pipelining. Selecting the correct feature extraction technique coupled with the right Deep Learning classification algorithms are observed to be very crucial in deciding the classification accuracy.

Also, it was also seen that no feature extraction technique is perfectly suitable for all the classification algorithms (Although methods like DWT have a fair compatibility with most of the classification algorithms). Therefore, researchers have been applying many permutations and combinations when it comes to the emotion classification. As mentioned above, the statistical manipulation of extracted features is also seen to provide better results. The Deep learning analysis tools that were used range from simple regression analysis to more Deep and Complex Neural Network algorithms. Sometimes a combination of various Deep Learning algorithms are used like the SVM and k-NN [23].

The various classification algorithms that were applied are:

- k-Nearest Neighbor Algorithms – *Heraz and C. Frasson et al., 2007* [6]
- The GA Fisher classifier – *Sheng Zhanga, Jie Gaob et al.,*[24]
- Support Vector Machine(SVM) – *Y.-P. Lin et al., 2010* [7]
- Convolutional Neural Networks (CNN) – *Guolu Cao Yuliang Ma et al.* [19]
- kNN in combination with LDA – *Murugappan et al.* [26]
- SVM along with LDA – *Bahrdwaj et al., 2015* [29]
- MLPNN along with Knn – *Mehmet et al., 2017* [18]
- Kernel Eigen-Emotion Pattern(KEEP) and Adaptive Support Vector Machine (ASVM) – *Yi-Hung Liu et al., 2013* [22]
- kNN in Combination with SVM – *Raja Majid Mehmood et al.* [23]
- Adaptive neuro-fuzzy inference system (ANFIS) - *Lee G et al.* [30]

The accuracies obtained in different methodologies are summarized in the Table below:

Sl. No.	Reference	Method Description	Emotion states	Accuracy
1	[5]	Power of alpha and beta, then PCA, 5 participants, classification with FDA	Valence and arousal	Valence: 92.3%, arousal: 92.3%
2	[6]	Amplitudes of four frequency bands, 17 participants, evaluated KNN, Bagging	Valence (12), arousal (12) and dominance (12)	Valence: 74%, arousal: 74%, and dominance: 75%
3	[7]	Power spectral density and asymmetry features of five frequency bands, 26 participants, evaluated SVM	Joy, anger, sadness, and pleasure	82.29%
4	[8]	Spectral power features, 11 participants, KNN	Positive, negative and neutral	85%
5	[9]	Asymmetry index of alpha and beta power, 16 participants, SVM	Four quadrants of the valence-arousal space	94.4% (participant dependent), 62.58% (participant independent)
6	[10]	Spectral power features of five frequency bands, 32 participants, Gaussian naive Bayes classifier	Valence (2), arousal (2) and liking (2)	Valence: 57.6%, arousal: 62% and liking: 55.4%
7	[19]	Z-Score Normalisation Followed by PCA and finally classification using CNN	Valence (Two Categories), Arousal (Two Categories)	Valence: 84.3±4.0% Arousal: 81.2±3.0%
8	[20]	DWT method for feature extraction, k-NN for classification	Positive and Negative Emotions	83.2%
9	[30]	Adaptive neuro-fuzzy inference system (ANFIS).	Positive and Negetive Emotions	78.45%
10	[26]	Wavelet features of alpha, beta and gamma, 20 participants, classification with KNN and LDA	disgust, happy, surprise, fear and neutral	83.26%

Table (1)

CHAPTER 3

DATA COLLECTION

3.1 Brain Waves

Brain waves were discovered by **German neurologist Hans Berger** in the mid-1920s. They are the synchronized electrical pulses from masses of neurons communicating with each other. Brain activity is characterized by a combination of brain waves which are of four types as shown in the figure (1). In Brain Wave signal analysis we emphasize on Analysis part of BCI system.

Brain waves are produced by synchronized electrical pulses from masses of neurons communicating with each other. The electrical activity, which is obtained through the EEG test exhibits significant complex behavior with strong non-linear and dynamic properties. A typical EEG signal, measured from the scalp, will have an amplitude of about 10 µV to 100 µV and a frequency in the range of 1 Hz to about 100 Hz.

The pattern of brain waves changes depending on one's level of consciousness and cognitive processing. For example, when one feels fatigued or dreamy, slower brainwaves are likely dominant at that time.

Brain activity is generally characterized by a combination of brain waves. Depending on what one is doing at the time, a particular brain wave will be dominant over the others. This balance is important: When one's brainwaves are not balanced properly, that individual may experience both emotional and neuro-physical health concerns.

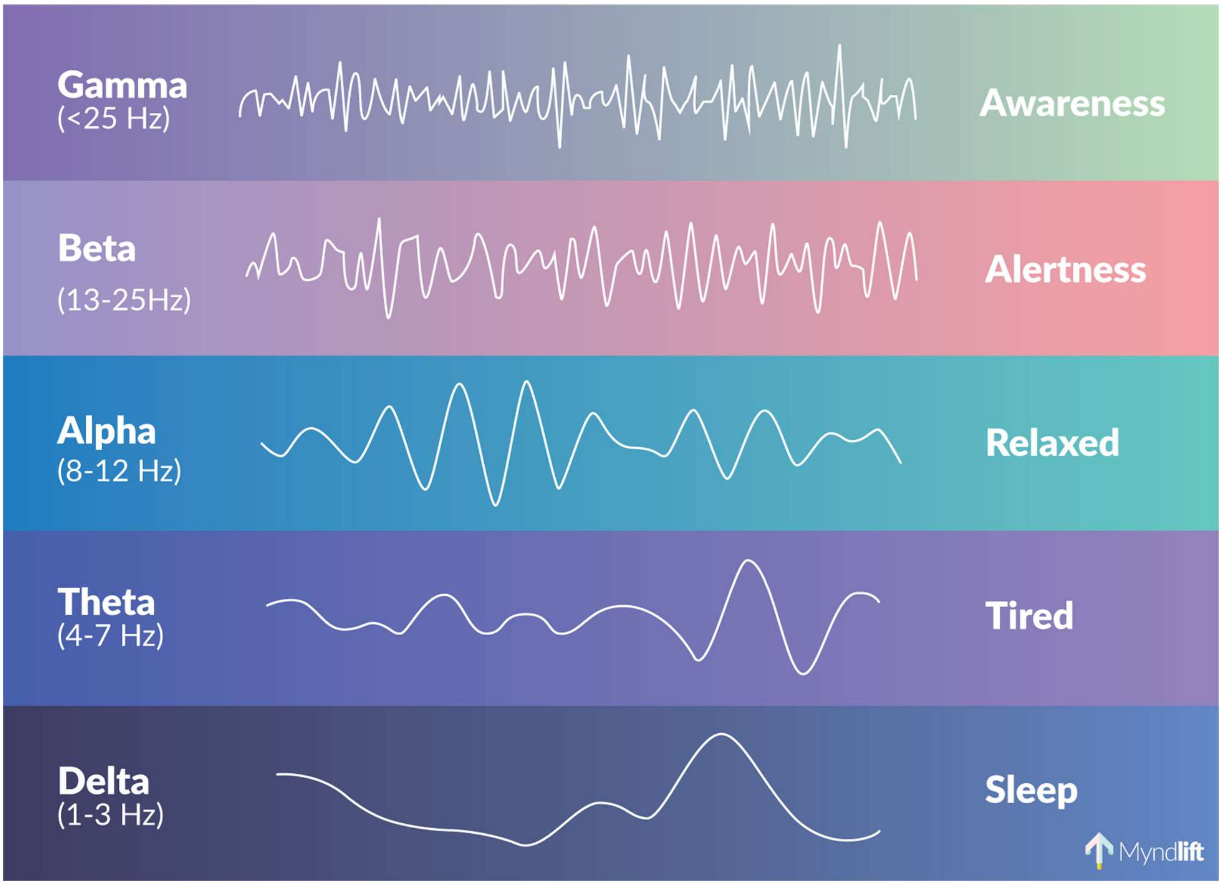

Figure (d)

3.1 Brain Computer Interface:

Brain computer interface also known as BCI is a unidirectional computer-based-system that obtains brain signals, analyzes them, and translates them into commands that are passed on to an output device to facilitate user's intention. The primary goal of a BCI is to restore useful function for people who have developed neuromuscular disorders, such as amyotrophic lateral sclerosis, cerebral palsy, stroke, or spinal cord injury.

The two kinds of BCI are as follows:

a) **Non-Invasive BCI**- A non-invasive brain-computer interface is one that can work without intrusive procedures into the brain. A non-Intrusive Brain-Computer Interface mostly works on the principles of EEG (Electroencephalography**),** Near-infrared spectroscopy (NIRS)

b) **Invasive BCI**- An invasive brain-computer interface involves the surgical implantation of a device into the user. For example ECOG (Electrocorticography).

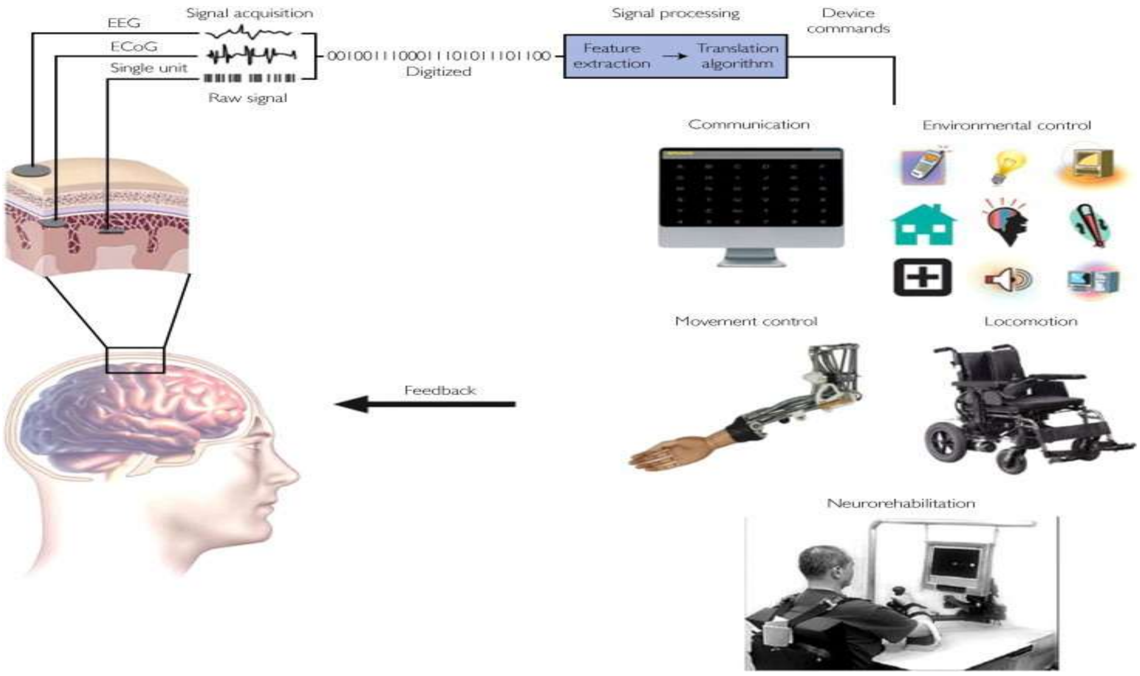

Figure (e)

A number of options are available based on the type of experiment and availability of recording apparatus as stated above.Out of the above methods, EEG is preferred for data collection in brain signal analysis because of:

1) High temporal resolution

2) Non-Invasive nature of data acquisition

3) Fast and Dynamic

3.2 EEG (Electroencephalogram)

The EEG data is collected using three EEG electrodes which are placed on the scalp of the person. The 10-20 system of data collection is employed. The numbers ‘10’ and ‘20’ refer to the fact that the distances between the adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. The EEG data has gained a lot popularity as compared to other emotional analysis tools and is an important tool as far as the Brain Computer Interface (BCI) is concerned. The EEG measures the spatial distribution of voltage fields and variation over time which is calculated by taking the sum of excitatory and inhibitory postsynaptic potentials from apical dendrites of pyramidal cells in outer layer of cerebral cortex and modified by input from subcortical structures, e.g. thalamus, ascending reticular activating system.

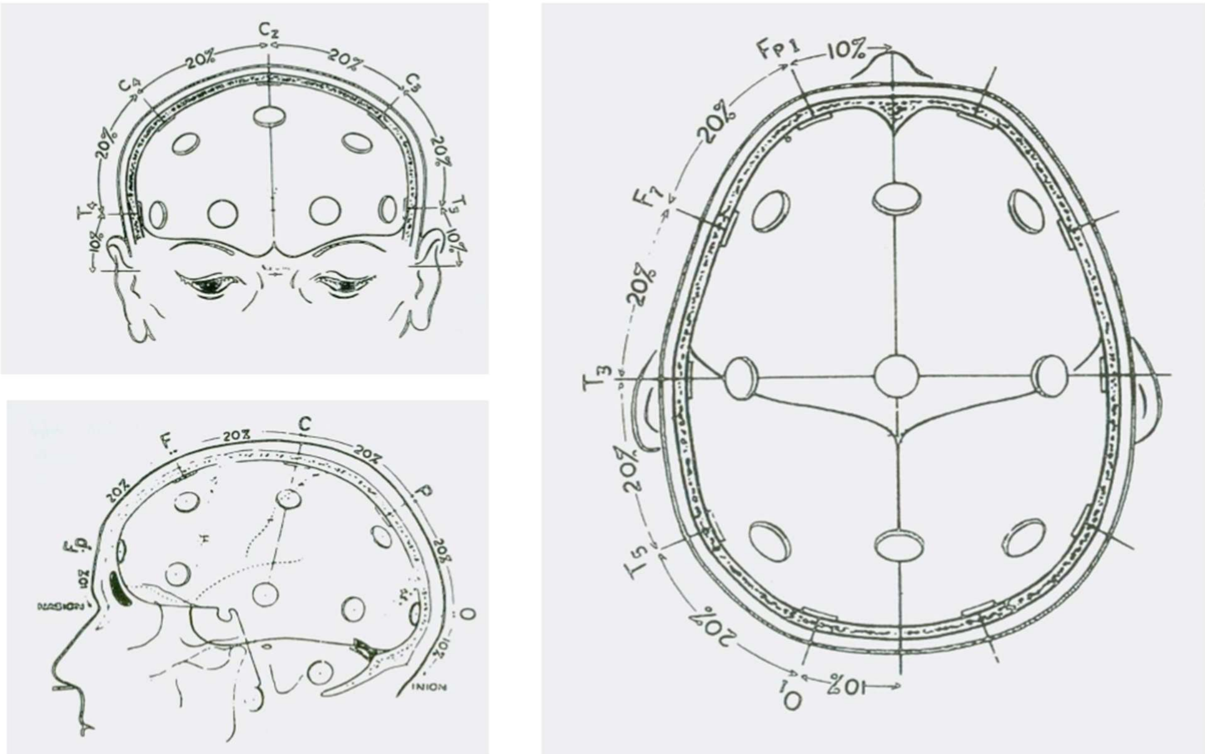

Figure f: Placement of Electrodes in 10-20 EEG system

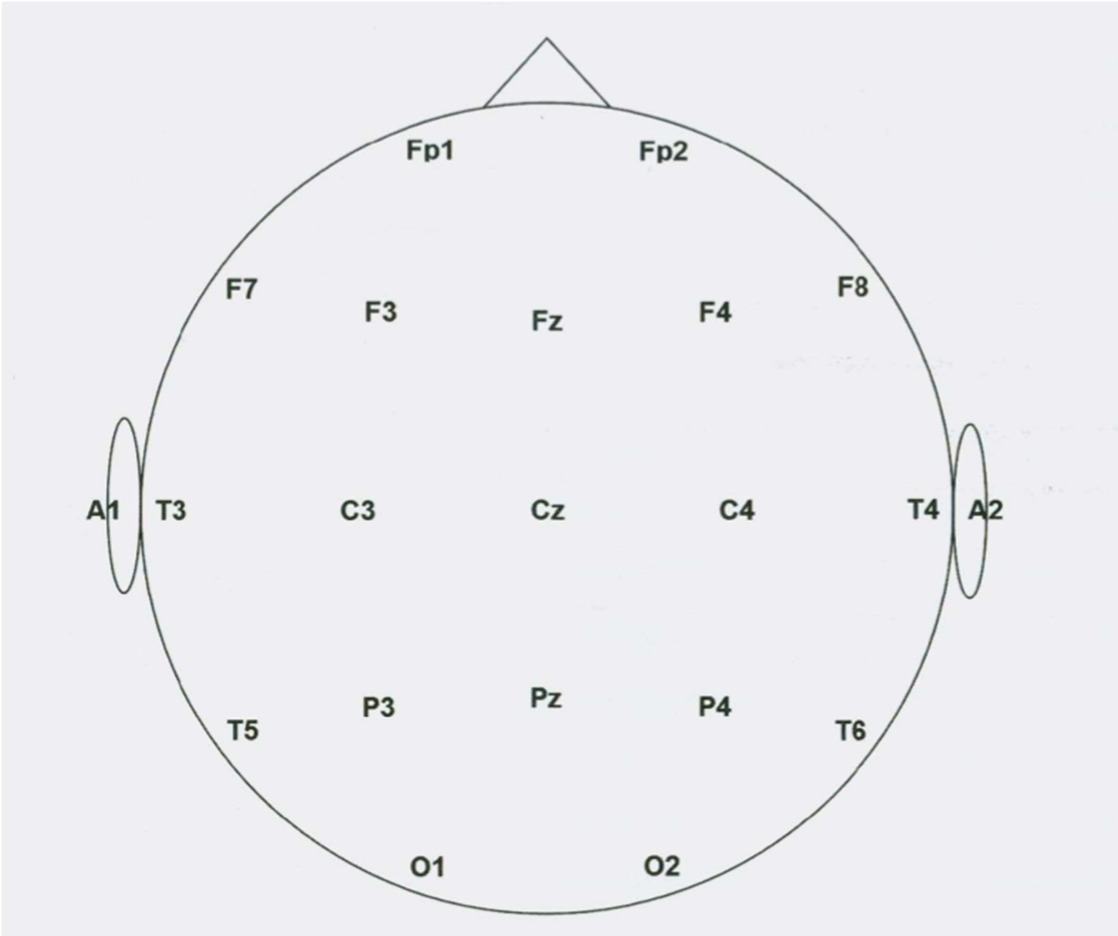

Figure g: Schematic diagram for placement of electrodes

The EEG data is collected from the Deap Data set provided by Koelstra and Team for Deep Learning analysis of EEG data.

3.3 Emotion Data Collection and Analysis

The Human decision making process, daily activities and behaviour is mainly driven by their emotions. Experts have been studying Human emotions from time immemorial as an important part of studying the Human mind. Recent research coupled with development of medical science has introduced multiple modalities towards the analysis of human emotions.

The methods of data collection for emotion analysis can be mainly classified into two broad categories *Non-Physiological Data* and *Physiological data*. The non-physiological data includes words, facial expressions, body language etc. The

Physiological data includes those obtained from EEG and those from the CNS and PNS.

The Electrochemical signals sent across the neurons are primarily responsible for all the brain activity that can be observed. The signals sent across the neurons generate a field which is sensed by EEG and signals are generated. The signals have their own frequency range and each frequency range has its own significance.

	DELTA	**THETA**	**ALPHA**	**BETA**	**GAMMA**
PATTERN	Consistent	Consistent	Consistent	Irregular	Irregular
FREQUENCY(Hz)	1-4	4-7	7-13	13-39	>40
BRAIN STATE	Deep dreamless Sleep	Drowsiness, daydreaming	Resting, relexed yet alert	Alertness, active concentration	Higher mental activity, consciousness

Table(2): Mind states depend on the frequency range of the brain waves. Similar pattern is seen in case of emotions

Representing emotions in forms of mathematical data is in itself a big challenge which bothers the researchers and has been triggering wide-spread research. The emotions can be analysed in discrete and continuous spaces. The discrete space can classify only discrete emotions such as happiness and sadness and is suitable for unimodal systems [15]. Although discrete system has its own benefits, representing emotions on the continuous dimensional spaces provides great deal of mathematical opportunity towards emotion detection and classification. The emotions can be rated on a continuous arousal, valence 2D space or Arousal, Valence and Dominance 3D space. In the arousal valence 2D space, the arousal ranges from calm to excited and Valence ranges from unpleasant to pleasant. [16]

In this project we are focusing on the classification of emotions based on the Arousal-valence scale. Data is prepared catering to High Arousal High Valence

Spaces and Low Arousal Low Valence Spaces and they are classified through Deep Learning Algorithms.

3.4 The DEAP Dataset

A research was done by Sander Koelstra and team to make a database readily available for EEG signal analysis for the researchers. The experiment was done in two parts. *The First Part*, contains the research done in selecting the target stimuli which could induce similar emotions irrespective of the subjects. The music videos were collected from Last.fm website where the users give emotional feedback about various music videos. A list of emotional keywords was taken from [14] and expanded to include inflections and synonyms, yielding 304 keywords. Next, for each keyword, corresponding tags were found in the Last.fm database. For each found affective tag, the ten songs most often labeled with this tag were selected. This resulted in a total of 1084 songs. After that a significant bit of filtering was done considering other factors such as demographic effects on emotions and ruling out the music videos whose emotional tags were contradictory to the actual emotion in the video. Thus, a list of 120 videos was made uploaded online for users to listen and give online ratings. On the basis of the online ratings given by the users, 40 videos were finally shortlisted for experiment.

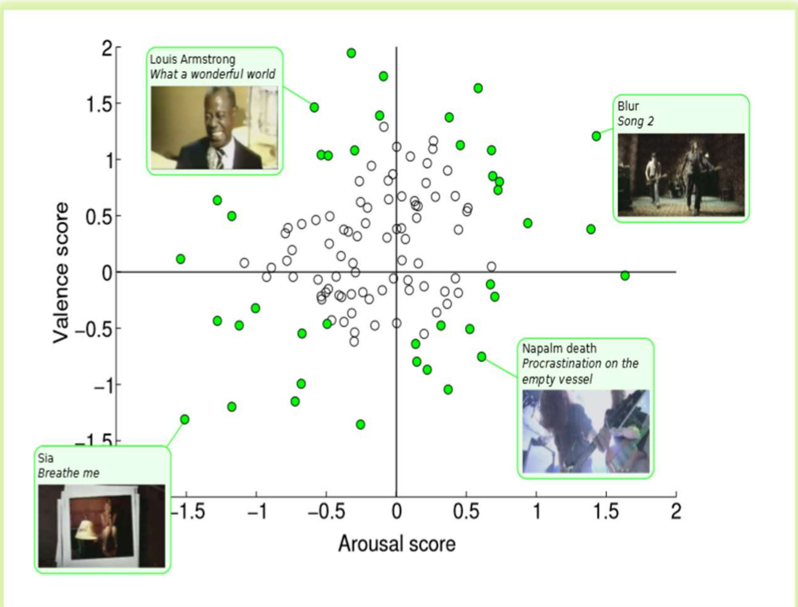

Figure h: μx/σx value for the ratings of each video in the online assessment. Videos selected for use in the experiment are highlighted in green. For each quadrant, the most extreme video is detailed with the song title and a screenshot from the video.

Note: The Graph is taken from Koelstra et al., 2012 [10]

The data was originally collected at 512 Hz on 48 recorded channels (32 EEG channels, 12 peripheral channels, 3 unused channels and 1 status channel). The data was then processed and down sampled to 128 Hz and segmented to store in a MATLAB compatible format. Thus the data is intrinsically well suited for running Deep Learning Algorithms and testing their accuracy.

There are 32 subjects who were shown 40 videos and the data collected. The data is thus stored in the same format with the labels of the ratings provided by the subject for each video at the time of experiment. So, there are 32 subject files and each file contains two arrays:

Array Name	Array Shape	Array Contents
Data	40 x 40 x 8064	Video/Trail x Channel x Data
Labels	40 x 4	Video/Trail x label (valence, arousal, dominance, liking)

Table (3): Data Description of each participant file

The Dataset is collected from the DEAP dataset total of 8064 samples were collected for each channel for each person in different types of videos for a period of 60 seconds (1 minute). So, for each person, the data is collected in a matrix of 40*40*8064. The further analysis is done based on the data collected.

CHAPTER 4

WORKING METHODOLOGY

4.1 Deep Learning

Deep learning is a function of artificial intelligence that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence (AI) that has networks capable of learning unsupervised from data that is unstructured or unlabeled and utilizes a hierarchical level of artificial neural networks to carry out the process of machine learning.
Most deep learning methods use neural network architectures, which is why deep learning models are often referred to as deep neural networks.

The term "deep" usually refers to the number of hidden layers in the neural network. Traditional neural networks only contain 2-3 hidden layers, while deep networks can have as many as 150.

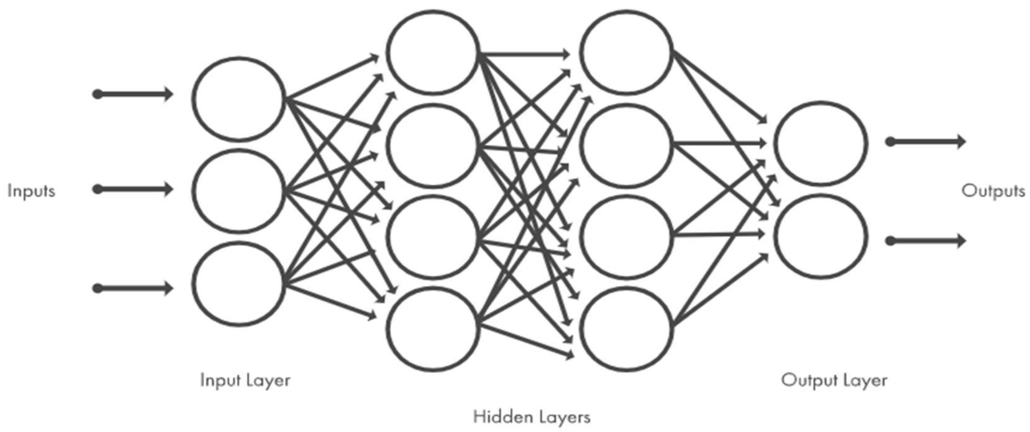

Figure i: Neural networks, which are organized in layers consisting of a set of interconnected nodes. Networks can have tens or hundreds of hidden layers

Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction. A key advantage of deep learning networks is that they often continue to improve as the size of your data increases.

The three most common ways people use deep learning to perform object classification are:

- **Training from Scratch-** To train a deep network from scratch, one needs to gather a very large labeled data set and design a network architecture that will learn the features and model. This is good for new applications, or applications that will have a large number of output categories. This is a less common approach because with the large amount of data and rate of learning, these networks typically take days or weeks to train.

- **Transfer Learning-** Most deep learning applications use this approach. This a process that involves fine-tuning a pretrained model. One starts with an existing network, such as AlexNet or GoogLeNet, and feed in new data containing previously unknown classes. After making some tweaks to the network, one can now perform a new task, such as categorizing only dogs or cats instead of 1000 different objects. This also has the advantage of needing much less data (processing thousands of images, rather than millions), so computation time drops to minutes or hours.

  Transfer learning requires an interface to the internals of the pre-existing network, so it can be surgically modified and enhanced for the new task.

- **Feature Extraction –**

  A slightly less common, more specialized approach to deep learning is to use the network as a **feature extractor**. Since all the layers are tasked with learning certain features from images, one can pull these features out of the network at any time during the training process. These features can then be used as input to a machine learning model such as support vector machines (SVM).

4.2 Data preparation

Our Aim is to classify the positive and negative emotions, our goal was to select the videos which has been rated High Arousal High Valence and Low Arousal Low Valence most number of times.

The Excel file containing the participant ratings “participant_ratings.xls” was opened in MATLAB and average of the Arousal and Valence ratings for each video was calculated. The average value of Valence and Arousal for each video was again averaged by the formulae.

Step 1: Calculate the average value of valence for i^{th} video.

- $Avg.\ Value\ of\ Valence(i) = \frac{Sum\ of\ Values\ of\ valence\ of\ i^{th}\ video}{32}$

- $Avg.\ Value\ of\ Arousal(i) = \frac{Sum\ of\ Values\ of\ Arousal\ of\ i^{th}\ video}{32}$

Step 2: Calculate the Net average value for i^{th} video.

- $Net\ Average(i) = \frac{Avg.\ Value\ of\ Valence(i) + Avg.\ Value\ of\ Arousal(i)}{2}$

Looking at the Net Average value of each video, it was found that Video with Experiment_ID = 3 has was rated High Arousal High Valence Maximum number of times. Whereas, Video with Experiment_ID = 23 has was rated Low Arousal Low Valence Maximum number of times.

After that, the valence and arousal values for video with Experiment_ID 3 and 23 were averaged for each subject. It was found that subject 2 and 26 were among the subjects who gave the highest ratings for Video 3 whereas subject 4 and 29 were among the subjects who gave the lowest ratings for video 23. As a result, the most responsive data set was prepared using these insights.

```
data = xlsread('F:/Project Data/metadata_xls/participant_ratings.xls');
data(:,1:2) = [];
data(:,5:7) = [];
data(:, 2) = [];valarousal = zeros(40,2);
arousaldata = zeros(40,1);
for(i=1:length(data))
    loopvar = data(i,1);
%      if(loopvar == 0)
%      loopvar = 40
%      end
valarousal(loopvar,1) = valarousal(loopvar,1) + data(i,2);
valarousal(loopvar,2) = valarousal(loopvar,2) + data(i,3);
end
valarousal = valarousal./32;
avgarray = (valarousal(:,1)+valarousal(:,2))/2;
maxvid = find(avgarray==max(avgarray(:,1)));
minvid = find(avgarray==min(avgarray(:,1)));
minmaxsub = zeros(32,2);
ctmax = 0;
ctmin = 0;
for(i=1:length(data))
    if(data(i,1)== maxvid)
        ctmax = ctmax+1;
        minmaxsub(ctmax,1) = (data(i,2)+data(i,3))/2;
    end
    if(data(i,1)== minvid)
        ctmin = ctmin+1;
        minmaxsub(ctmin,2) = (data(i,2)+data(i,3))/2;
    end
end
```

Figure j: Code Snippet for Data Preparation

The Final Matrix contained 128 rows and 8064 columns. The first 64 rows were for HAHV (Row 1-32: 32 channel response for Video with Experiment_ID 3 for subject 2, Row 33-64: 32 channel response for Video 3 for subject 26). The next 64 rows were for LALV (Row 65-96: 32 channel response for Video with Experiment_ID 23 for subject 4, Row 97-128: 32 channel response for Video 23 for subject 29).

4.2 Feature Extraction

Autoregressive Coefficient was used for feature extraction of data.

The coefficients a_i of an autoregressive (AR) model of a signal $x(n)$ enter the model definition in the following way:

$$x(n) = \sum_{i=1}^{N} a_i x(n-i) + e(n)$$

where $e(n)$ is zero-mean white noise and *N* is the model order. i.e. the signal is modelled as the output of a linear time-invariant filter with transfer function.

$$H(z) = \frac{1}{1 - \sum_{i=1}^{N} a_i z^{-1}}$$

and with input signal *e*(*n*). There is no simple interpretation of specific values of the coefficients a_i. You have to look at the whole polynomial 1 - $\sum_{i=1}^{N} a_i z^{-1}$, e.g. by computing the power spectrum of the AR model of *x*(*n*) :

$$S_x(z) = {\sigma_e}^2 \left| \frac{1}{1 - \sum_{i=1}^{N} a_i z^{-1}} \right|^2, \qquad z = e^{i\theta}$$

Where ${\sigma_e}^2$ is the variance of $e(n)$. So the AR coefficients are the parameters of a specific signal model, and they do not have a simple interpretation comparable to mean or variance of a random process. However, in general they represent a much more detailed description of the signal than mean and variance alone. Thus, with the help of Autoregressive coefficients, the data was of 8064 columns was converted to 63 columns. Thus, Feature extraction and Dimensionality reduction was made possible.

4.3 Classification Algorithm

A Support Vector Machine (SVM) classifier was used for emotion detection.

Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well.

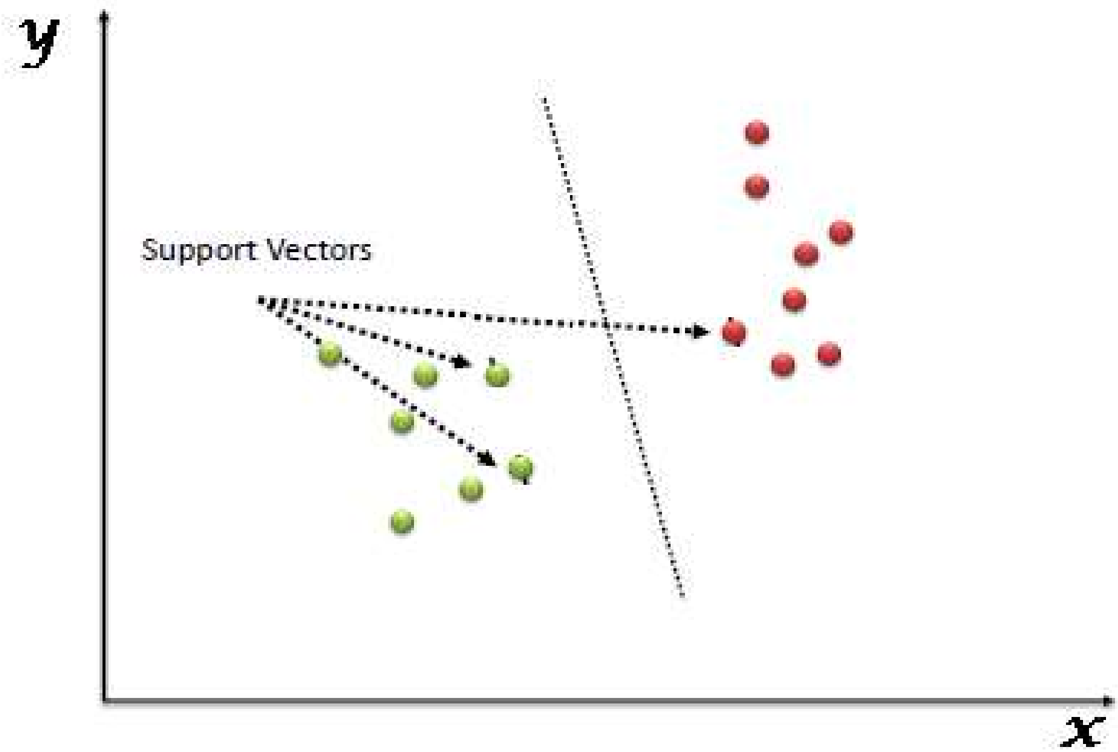

Figure k: Graphical Representation of SVM classification: the hyper plane separates the two classes

Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features. If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a two-dimensional plane. It becomes difficult to imagine when the number of features exceeds 3. Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyperplane. These are the points that help us build our SVM.

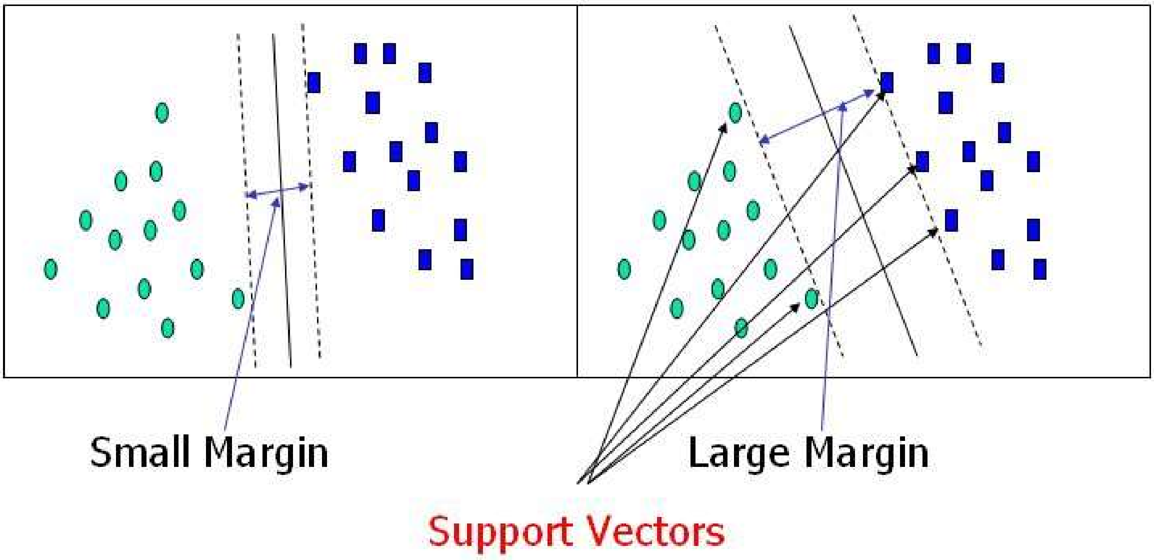

Figure I

The extracted features (The Autoregressive coefficients) were used as the inputs for the classifier. A cross validation of 70-30 hold out proportion was used which 70% of the data was used for training the classifier and the remaining 30% was used for testing purpose.

The classification accuracy can be calculated by below mentioned formula:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ Number\ of\ predictions}$$

And now, since we are classifying two types of emotions here (LALV and HAHV), it can be called binary classification. The formula for the same is:

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

$$TP = True\ Positives, TN = True\ Negatives, FP = False\ Positives\ and\ FN = False\ Negatives$$

Given below is the schematic summary of the working methodology

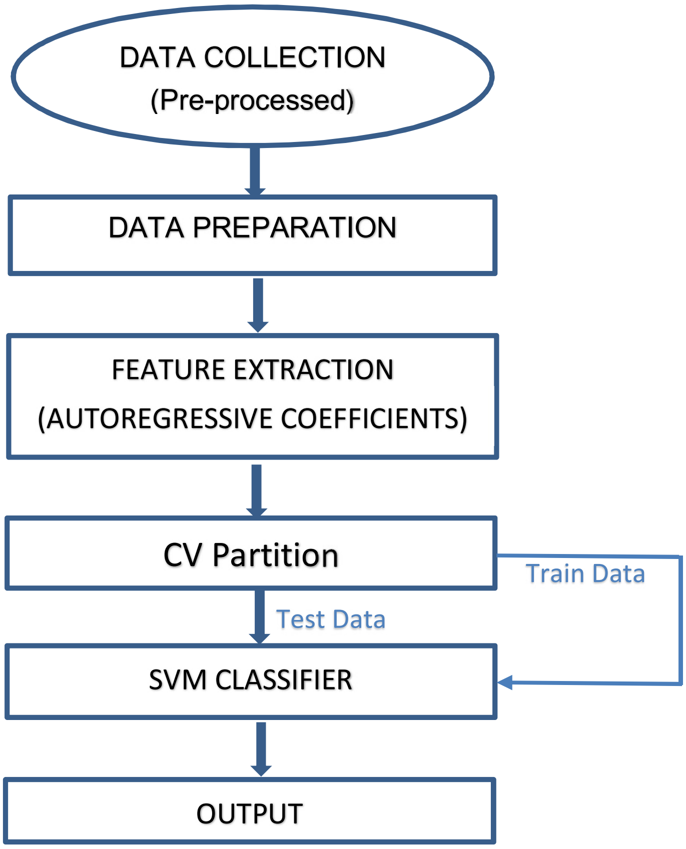

Figure m: Working Methodology

CHAPTER 5

RESULTS AND DISCUSSION

The proposed method is implemented in MATLAB 2018a. It was found that Autoregressive Coefficient feature extraction method went hand in hand with the Support Vector Machine classifier. In the project we tried to classify two types of emotions using SVM. Thus the classification was binary. So, the autoregressive coefficients along with SVM is well suited for binary classification of emotions. We found out that the classification **accuracy was as high as 97%**. As we were quite selective about the data, it would be interesting to know how the methodology fairs with bigger and more variant data.

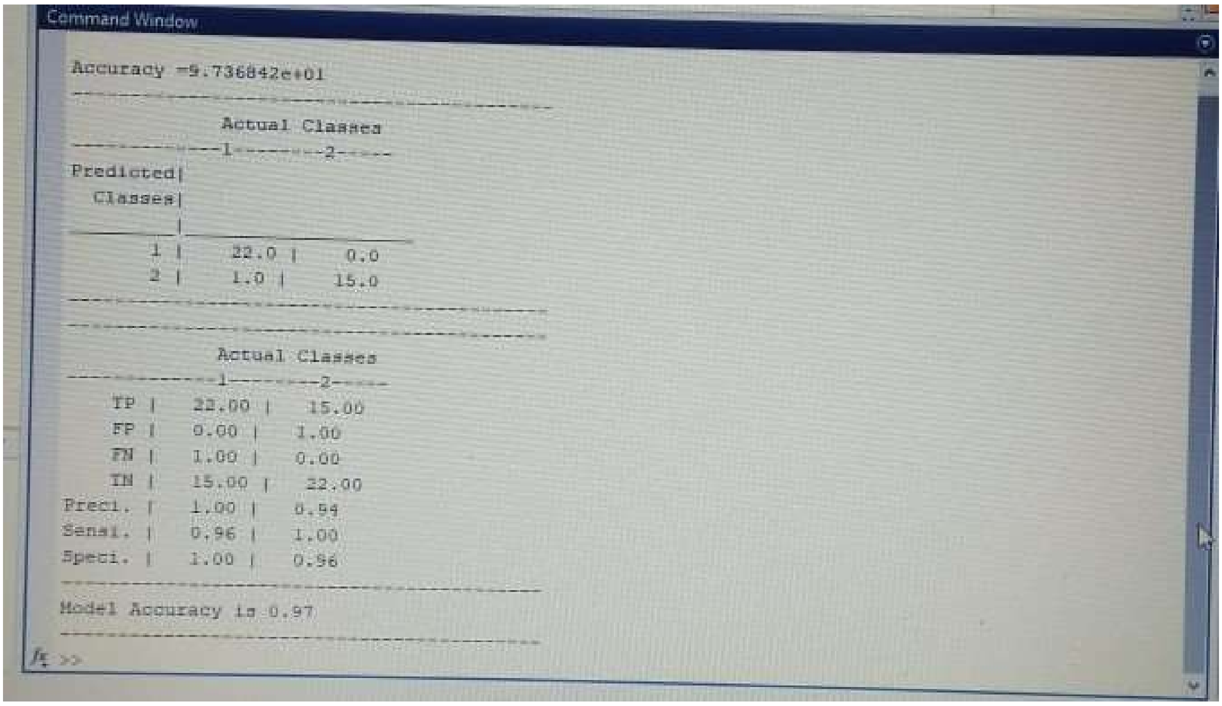

Figure n: Classification Accuracy

The Channel selection through the above method The data has been collected and is being processed through the above mentioned technique. Various statistical models have also been tried but have failed. As a result, the above mentioned technique need to be followed to arrive at the objective.

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