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Emotion Recognition from EEG Signals using Machine Learning

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ABSTRACT

The beauty of affective computing is to make machine more emphatic to the user. Machines with the capability of emotion recognition can actually look inside the user's head and act according to observed mental state.

In this thesis project, we investigate different features set to build an emotion recognition system from electroencephalographic signals. We used pictures from International Affective Picture System to motivate three emotional states: positive valence (pleasant), neutral, negative valence (unpleasant) and also to induce three sets of binary states: positive valence, not positive valence; negative valence, not negative valence; and neutral, not neutral. This experiment was designed with a head cap with six electrodes at the front of the scalp which was used to record data from subjects.

To solve the recognition task we developed a system based on Support Vector Machines (SVM) and extracted the features, some of them we got from literature study and some of them proposed by ourselves in order to rate the recognition of emotional states. With this system we were able to achieve an average recognition rate up to 54% for three emotional states and an average recognition rate up to 74% for the binary states, solely based on EEG signals.

ACKNOWLEDGEMENT

First and foremost, we would like to thank to God for the strength that keeps us standing and for the hope that keeps us believing that this challenge would be possible and more interesting. We also wanted to thank our families who inspired encouraged and fully supported us in every trial that came our way.

We are deeply grateful to both Dr. Benny Lövström and Dr. Johan Hagelbäck. Dr. Benny as our supervisor throughout our thesis working period, he deserves special recognition for his openness, friendly approach and specially for giving different suggestions and discussions. Thank you very much! We would like to thank again Dr. Johan Hagelbäck for his constant support and giving us our thesis topic. He inspired us greatly to work in this project and his willingness to motivate us contributes tremendously to our thesis.

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LIST OF ABBREVIATION

ANS	Autonomous Nervous System
ARFF	Attribute-Relation File Format
BDF	BioSemi Data Format
CSV	Comma Separated Value
ECG	Electro Cardiograph
EDF	European Data format
EEG	Electroencephalography
EMG	Electromyography
EOG	Electro-Oculogram
ER	Emotion Recognition
HCI	Human-Computer interaction
HHI	Human-Human Interaction
HRI	Human-Robot Interaction
IAPS	International Affective Picture System
KNN	K-Nearest Neighbor
RMS	Root Mean Square
SVM	Support Vector Machine
WEKA	Waikato Environment for Knowledge Analysis

1 INTRODUCTION:

Human being interacts with different machines throughout their life. Similarly, emotions are vital and inevitable in every human's life. Most interactions between machines and humans are discrete and overt events where machine knows about human only when explicit command are sent, like by pressing button. Hence, interaction between machines and humans is less autonomous and less intelligent. Scientists have come up with the evidence that emotional skills are a basic component of intelligence. Reeves and Nass [1] have shown that replacing one of the humans in Human-Human Interaction (HHI) with a machine follows the same fundamental rules of HHI. Hence, it has become essential to come up with the system where it can detect the human emotion it is working with, i.e. to induce the machine with the emotional intelligence so that the system can emulate the property of implicit communication which exist in human interaction. Affective computing is the study and development of system that can recognize and act accordingly to the human affects or emotions. Picard who is a pioneer working in the field of Affective computing states that "Emotion plays the vital role in rational decision making, understanding, learning and other various cognitive function". Therefore, development of aforementioned system would open the gate for more meaningful, robust, natural, and reliable interaction between machines and humans.

Different kinds of methods have been devised to recognize the underlying emotion of a person. Notably, emotion recognition (ER) from facial expression [2], voice intonation [3], gesture, and signal from Autonomous Nervous System (ANS) like heart rate and Galvanic Skin Response (GSR) had been being carrying out [4][5]. ER from Electroencephalography (EEG) signals is relatively new in the field of affective computing. ER from EEG signals overcome some of the drawback that arises while using the technique of ER from facial expression, GSR, heart rate, like facial expression can be easily faked, for example a person might be really feeling pain inside but he might show the expression of happy. Signal from ANS are more susceptible to noise, for example, GSR signals might not only originate from emotional influence but may also from physical influence. On the contrary, signal from central nervous system like EEG is captured form the origin of emotional experience. Moreover, EEG signals which have fine resolution are easy to record with affordable cost.

Different techniques and step are needed to classify the emotion from EEG Signals. These steps includes the recording of Signals, pre-processing of recorded raw signals to remove the artifacts from it, extracting the most suitable feature from processed signals, formatting the dataset and evaluating it with the use of machine learning tool.

1.1 THE BRAIN

1.1.1 The brain

The brain is the most complex and one of the largest organs of human body. It is made up of more than 100 billion nerves. The brain is responsible for all kind body's action and reaction. It continuously receives sensory information and analyzes them and responds accordingly controlling all kind of bodily action and function like feeling, hunger, thirst, body movement, sleep and all other activities which leads to survival of human being.

1.1.2 Structure of human brain

From function point of view, the brain is divided into three parts. The first part is large brain which is also known as **cerebrum**. This part is responsible for controlling the function such as language and reasoning. The second part is **brain stem** which controls visual and auditory function and third part is the little brain or **cerebellum** which takes control of coordination and movement.
Brain is also divided into several lobes [6]:

- The frontal lobes are responsible for problem solving, reasoning, judgment, parts of speech
- The parietal lobes manages movement, handwriting
- The temporal lobes is responsible for hearing
- The occipital lobes handle visual functioning

1.2 ELECTROENCEPHALOGRAPHY (EEG)

The brain activity produces the different kinds of signals like electrical and magnetic signals [3]. This activity can be recorded using different kind of approaches, which are normally classified as invasive and noninvasive. In invasive methods surgical intervention are made to implant certain device in the brain whereas in noninvasive methods no such intervention is made. Among the different noninvasive methods, Electroencephalography is one of the most commonly used methods to record the brain signals [3]. EEG is regarded as direct and simple noninvasive method to record the brain electrical activity, represented as voltage fluctuation resulting from current flow within the neurons of the brain [8]. EEG waves which can be represented as the signal over time are recorded by the electrodes places on scalp over the brain.

1.2.1 Types of Signals

EEG is a measure of voltage as the function of the time. EEG characteristic are highly dependent on the degree of activity of cerebral cortex [3][9]. In general, the EEG signal represent the combination of waveform and are generally classified according to their

1) Frequency
2) Magnitude
3) Wave morphology
4) Spatial distribution
5) Reactivity

The most common classification uses EEG waveform frequency band [10] under which EEG signals can be decomposed within 5 different frequency bands.
Hence, the five different frequency bands along with the mental state associated with them are briefly described as below.

1.2.2 Delta waves (δ)

Delta waves are found in between the frequency range of 0-4 Hz which are detected during the deep sleep or coma. Such waves have higher amplitude and are measured in <100 micro volts. Figure 1.1 shows a Delta wave where x-axis is time in seconds.

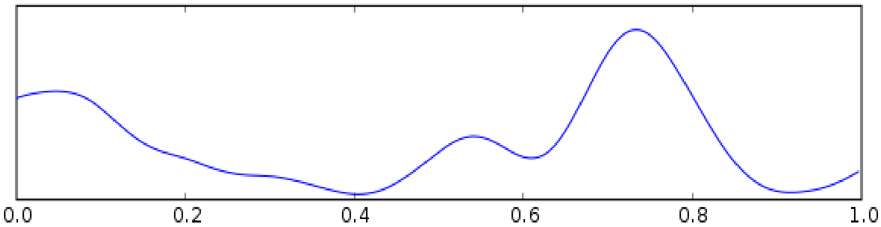

Figure 1.1 - Delta Wave [9]

1.2.3 Theta waves (θ)

Theta waves are under the frequency range of 4-8 Hz. Theta rhythms are observed during creative thinking, in state of focusing. Such waves are also observed during short term memory task. In the figure 1.2 a Theta wave is shown where x-axis is time in seconds.

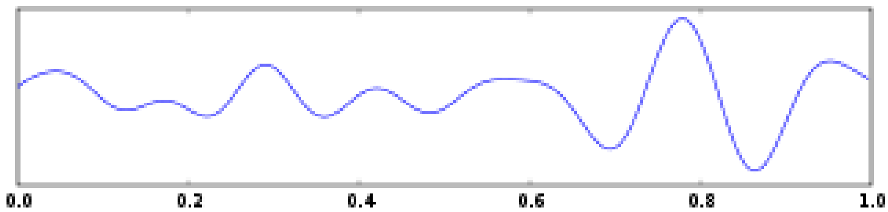

Figure 1.2 - Theta Wave [9]

1.2.4 Alpha waves (α)

Alpha waves are found in between the frequency range of 8-13 Hz. These waves are originated from the occipital lobe of brain during the state of relaxation and calm. It has also found that the activity of Alpha rhythm reflects the vision functioning of human being [9]. The figure 1.3 depicts an Alpha wave where x-axis is time in seconds.

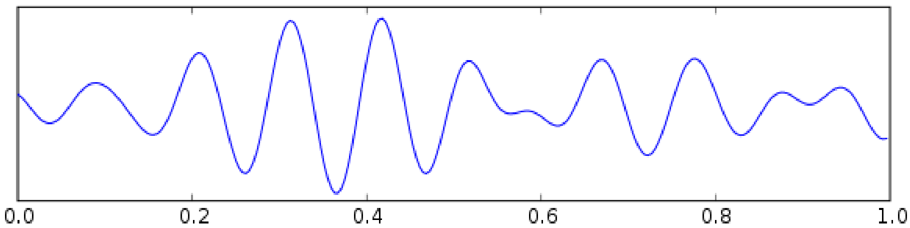

Figure 1.3 - Alpha Wave [9]

1.2.5 Beta waves (β)

Beta waves are present between the frequency ranges of 13-30 Hz. These waves are associated with anxious thinking and active concentration which are originated from the central area of brain. Beta wave is like figure 1.4 where x-axis is time in seconds.

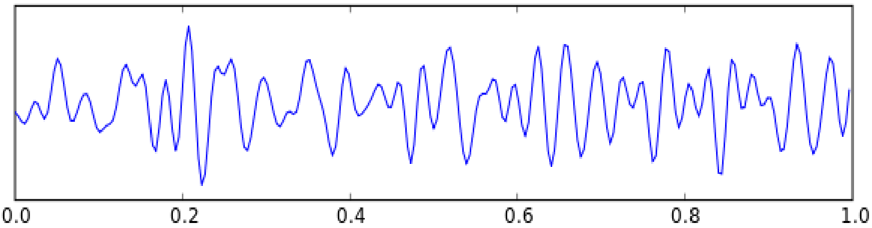

Figure 1.4 – Beta Wave [9]

1.2.6 Gamma waves (γ)

Gamma waves are found between the frequency ranges of 30-100Hz.
Mental state associated with these waves is multi-tasking and conscious waking state. The figure 1.5 shows a Gamma wave where x-axis is time in seconds.

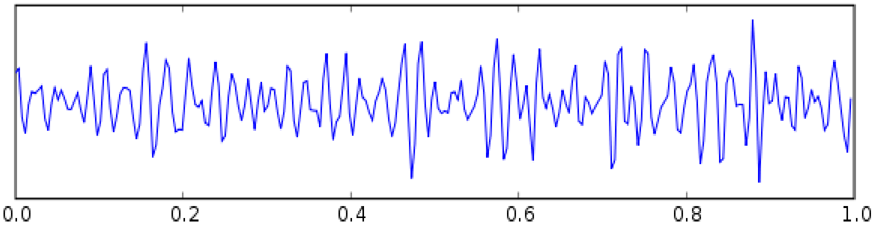

Figure 1.5 – Gamma wave [9]

1.3 ARTIFACTS

Artifacts or noise are the undesirable signals which contaminate the brain waves during measurement of the EEG signals. Such artifacts are broadly divided into two categories.

a) Physiological Artifacts: These are the artifacts that are originated from the Human body due to various bodily activities like eye movement and blinking, heart rate, movement of head, jaw and tongue, and respiration. The artifacts that are caused by the eye movement and blinking are called the EOG (electro-oculogram) which are below the frequency range of 4Hz. ECG (electro-cardiogarphy) is another artifact caused by heart rate are present and EMG (electro-myography) which is caused by movement of head and muscle are mostly present above the frequency of 30Hz. Among all these Physiological artifact, EMG and EOG artifacts are mostly taken into account for the HCI study [11][12][13][14].

b) Non-physiological artifacts: Such artifacts are originated from outside the human body. The main sources of non-physiological artifacts are 50/ 60 Hz power line interference, variation in electrode impedance, dirt and wire quality.

1.4 CLASSIFICATION OF EMOTION

Several measures have been devised for classifying the human emotion. Such classification is generally divided into two perspectives namely Dimensional and Discrete perspectives. Discrete perspectives analyses emotion in a way that every specific emotion (e.g. fear, sad, happy, etc.) maps to its own unique parameter of environment, physiology and behavior [15]. In Dimensional perspective, human emotions are organized in few fundamental dimensions. The most commonly assumed dimension is arousal and valence proposed by Russell [16] in his bipolar model of emotion classification. In this dimension, valence represent from negative to positive whereas arousal represent from not excited to aroused or dull to intense. The dimensional model is the most commonly used model for the classification of emotion because all discrete emotions can be represented in dimensional model by proposing that each discrete emotion represent the combination of several dimensions. For example anger can be represented by negative valance and high arousal [16][17][18]. The figure 1.6 shows the Arousal/Valence dimension in a diagram.

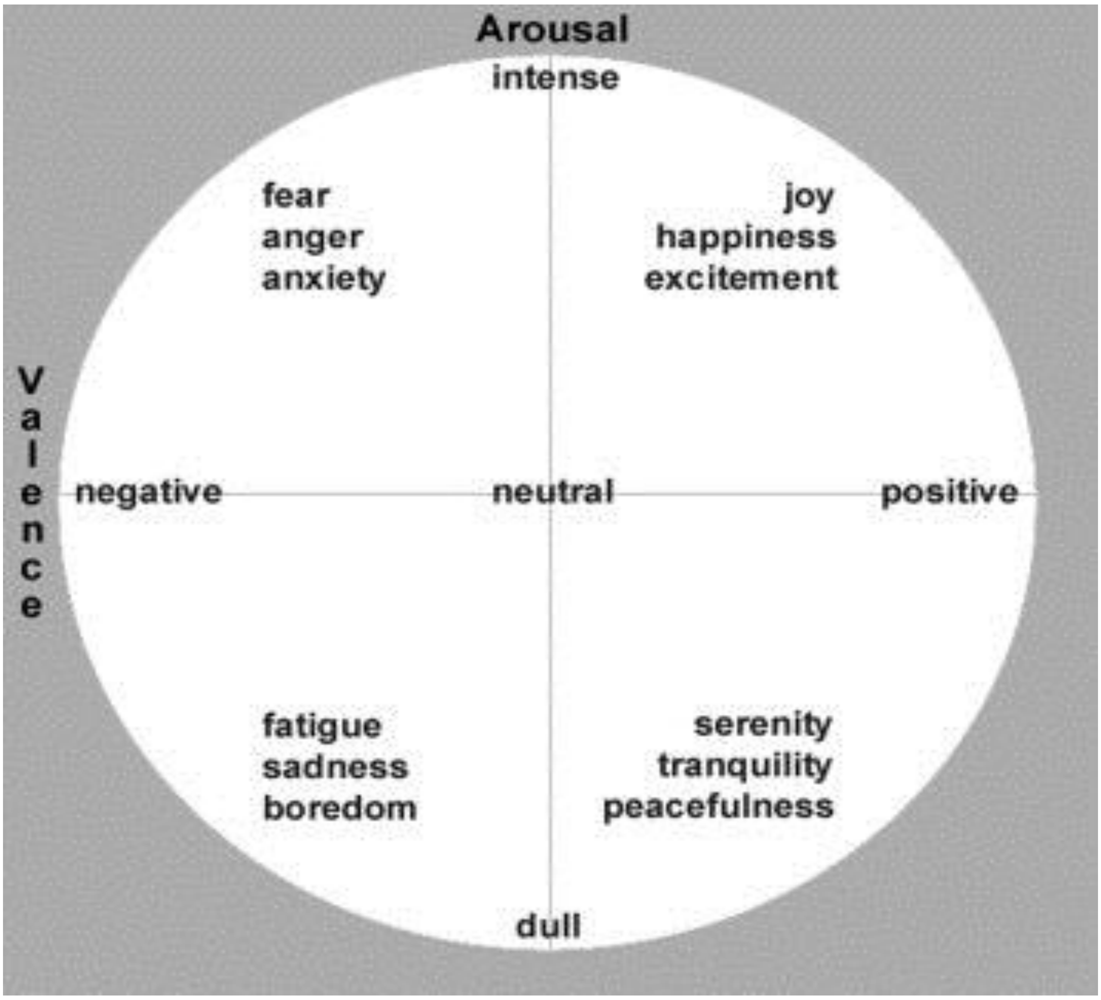

Figure 1.6 – Arousal/Valence model [16]

1.4.1 Machine Learning Technique to Classify EEG Data

Machine Learning is the branch of artificial Intelligence which deal with the development and study of the system where known data samples are used to learn the machine in order to learn the unknown data samples. There are different Machine learning techniques to classify the EEG data with their own pros and cons. Currently, Support vector Machine, Artificial Neural Network and K-nearest neighbor (KNN) are commonly used to classify the EEG data [9].

2 BACKGROUND AND PROBLEM DEFINITION

Research in the field of ER is ever growing as the applications that incorporate the Brain Computer interaction is also growing. Making robots acts socially, where socially means being able to read other's emotion and act accordingly [15], would increase the effectiveness of HRI. Previously, attempts have been made to recognize the emotion with different technique like from face and voice with varying degree of accuracy. It had been possible to recognize the emotion from face with the accuracy of 70-80 percent under controlled environment [19].

Emotions are not always displayed, sometimes they are unrevealed by the human. In psychology, explicit differentiation has been made among the physiological arousal and behavioral expression (affect) [19].
Facial expression and voice represent the second aspects of emotion: expression, which can be easily adapted and its interpretation is not objective. For this reason, attention had been given to Physiological aspects like heart rate, Galvanic skin response, EEG, Pupil dilation [19][20]. Among them, however, several studies on Emotion recognition have been carried out from EEG [9][15][19][21].

2.1 PROBLEM FOCUSED WITHIN EEG EMOTION RECOGNITION TECHNIQUES

There has been much research done in ER from EEG with different result. This different result has been due to diversity in different aspects of methods used in the research. The diversities are mainly in aspects of emotion selection, experiment environment, techniques of data preprocessing and feature selection. Due to all this factors, it is not easy to compare and chose the method which can be said as the best classifier. Hence, there is always room for the development of better classifier suitable for specific application.

2.2 AIMS AND OBJECTIVES

Hence, taking the above aspects in the mind and providing the knowledge we have in this field, we have been motivated in this thesis to address the following issue

- How accurately the EEG signals can be classified
- What are the best features to extract from the EEG signals which can be mapped to specific emotional state

3 TOOLS USED

In order to process the recorded signals, we need to use some softwares as a platform. In this chapter we present a brief introduction to the softwares we used throughout this project.

3.1 EDF BROWSER

EDF Browser is a free open-source, multiplatform viewer and toolbox for time series storage files like EEG data. European Data Format (EDF) is a standard file format designed for exchange and storage of medical time series. It offers a graphic visualization of the signal, as well as an integrated list of trigger marks present in the file. It also provides filtering functionalities, power on the frequency bands computation, as well as the possibility of down-sampling the signal. This program converts all the signals in an EDF to a plain ASCII text-file. Internally it includes a header and one or more data records. The data records contain consecutive fixed-duration epochs of the poly-graphic recording. The header contains some general information (patient identification, start time…) and technical specs of each signal (calibration, sampling rate), coded as ASCII characters. A screenshot from EDF browser is shown in figure 3.1.

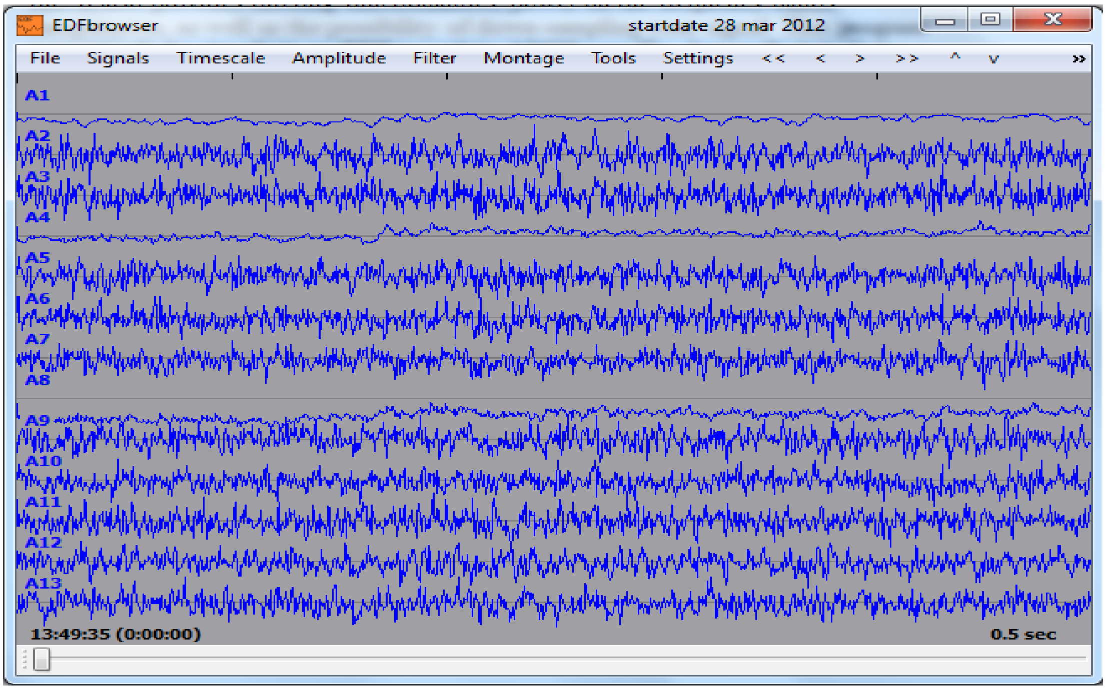

Figure 3.1 – EDFbrowser [29]

3.2 MATLAB

MATLAB is a powerful tool, especially with the signal processing toolbox. It integrates computation, visualization, and programming environment. Furthermore, MATLAB is a modern programming language environment: it has sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming. MATLAB has functionality to analyze data, develop algorithms, and create models and applications. The language tools and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages. These factors make MATLAB an excellent tool for teaching and research. It provides vast range of different functionalities for analyzing and processing EEG data filtering, time/frequency transforms, feature extraction etc. The figure 3.2 is the screenshot from MATLAB.

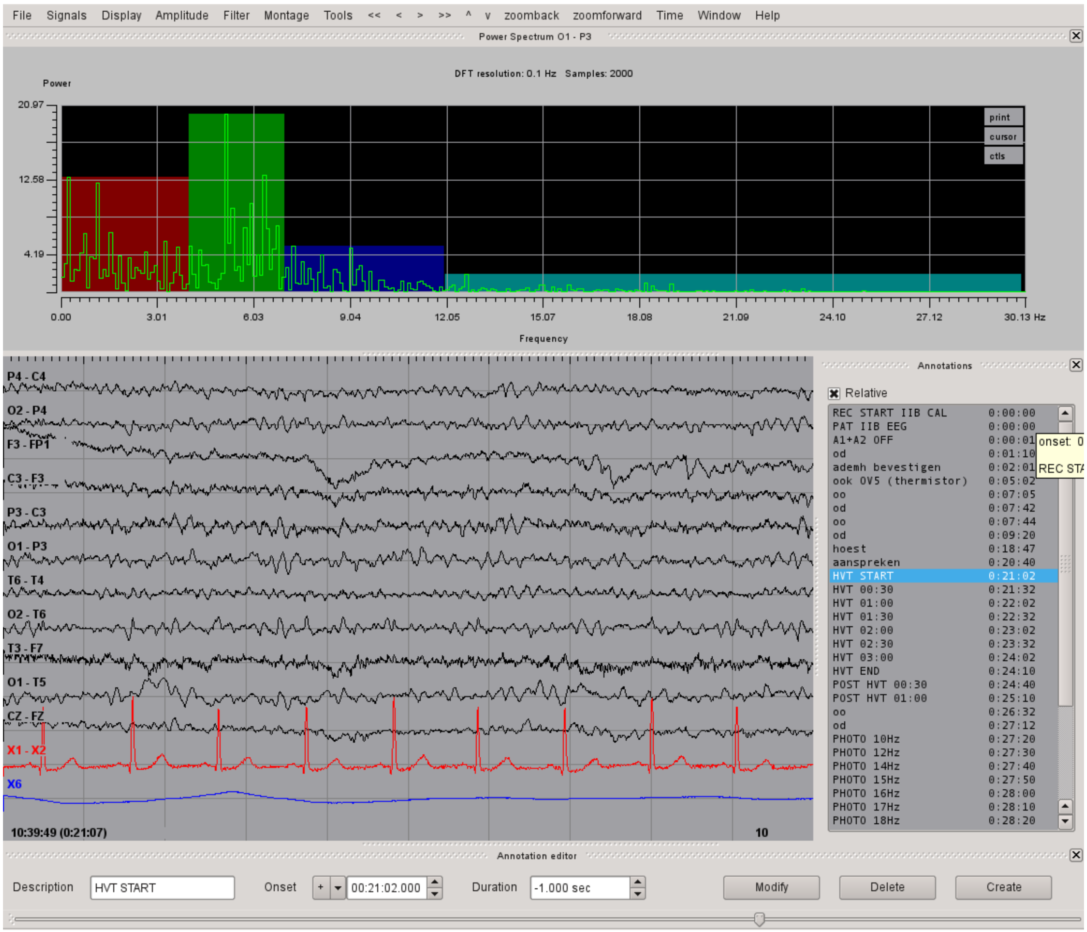

Figure 3.2 – Manipulating EEG Signals and their Annotations [9]

3.3 WAIKATO ENVIRONMENT FOR KNOWLEDGE ANALYSIS

Waikato Environment for Knowledge Analysis (WEKA) is an open-source collection of machine learning algorithms for data mining tasks. The software is a widely accepted standard in the field and is commonly used in a variety of applications, ranging from biomedical to financial data analysis. WEKA is written in the Java programming language and is normally run under a Java Virtual Machine. Each machine learning algorithm implementation requires the data to be present in its own format, and has its own way of specifying parameters and output. We use Explorer window for our project as shown in figure 3.3.

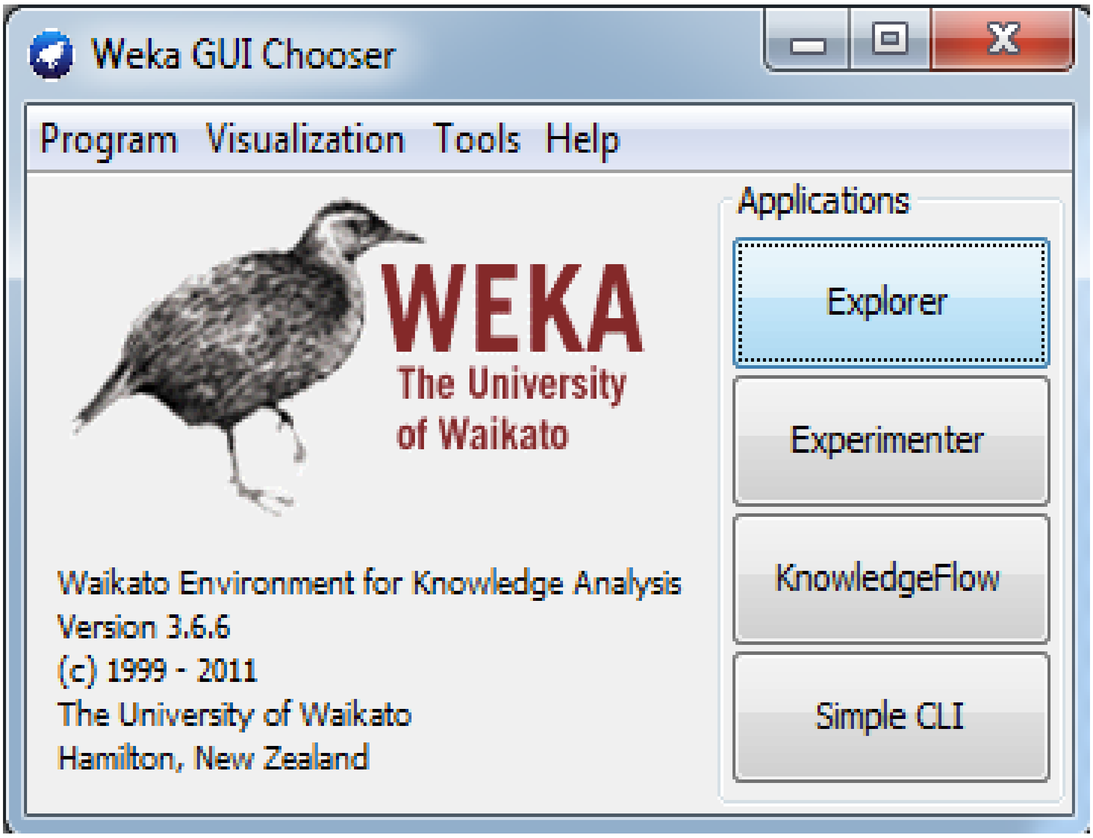

Figure 3.3 - Waikato GUI Chooser [29]

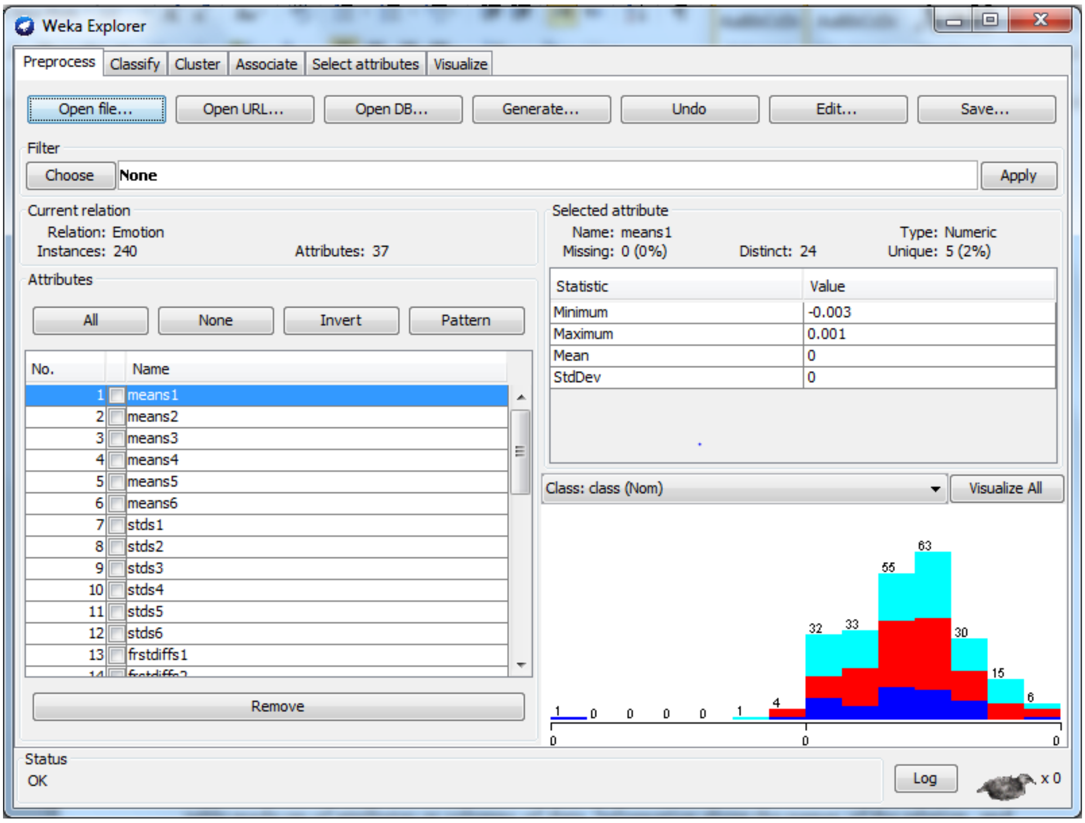

Figure 3.4 – WEKA Explorer [29]

The WEKA system uses a common file format to store its data sets and thus presents the user with a consistent view of the data regardless of what machine learning scheme may be used. This file format, the Attribute-Relation File Format (ARFF), defines a data set in terms of a relation or table made up of attributes or columns of data. Information about the names of the relation, and the data types of the attributes are stored in the ARFF header, with the examples or instances of data being represented as rows of data in the body of the ARFF file. Attributes are currently allowed to take on three different data types: integers, real or floating point numbers and enumerations. The following code is a kind of data set recognizable by WEKA machine learning tool.

```
@RELATION Emotion
@ATTRIBUTE stds1 NUMERIC
@ATTRIBUTE frstdiffs1 NUMERIC
@ATTRIBUTE secdiffs1 NUMERIC
@ATTRIBUTE mins1 NUMERIC
@ATTRIBUTE maxs1 NUMERIC
@ATTRIBUTE class {pv,n,nv}
@DATA
```

Here the data gathered by using different methods are written down and are separated by comma. The number of each line of data is called an instance that is exactly the same as the number of the attributes.

4 DATA ANALYSIS

In order to classify different emotions, we need to record EEG signals from different subjects and then process them to extract different features. The data sets are made from the features and then we classify the dataset. In this chapter, we explain about analyzing data in details step by step.

4.1 EEG DATA COLLECTION

We were given the EEG signals that have been already recorded before. Even though, we didn't carry out the experiment by ourselves, we would like to give a short over view about the procedure of whole experiment. BioSemi active two systems and software called Actiview were used to capture the EEG signals. The signals were captured based on the international 10-20 system of electrode placement. The 10-20 system or International 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment [24].

All the signals that were generated were saved in BioSemi data format (BDF) [25]. Each subject had been asked to sit over the chair calmly in front of the lab computer and had worn suitable BioSemi head cap and adjust it well to fit over the head. Electrode holders and pin-type active-electrodes had been chosen according to the experiment design. Electrode holders had been filled by electrode gel using syringe and pin-type active-electrodes had been inserted into the electrode holders. High sampling rate of 2048Hz has been chosen in order to reduce the risk of losing valuable data.

The main objective of this experiment was to induce different emotional states on the subject based on the different kind of picture shown to them. In order to achieve it, International Affective picture system (IAPS) [23], which is a general picture database and especially designed for the experiment to be conduct within research, was used. For the automatic projection of each IAPS picture, a special interface was made. The total of 30 pictures was shown to each subject. These 30 pictures are constituted of 6 different picture of each emotion cluster of neutral, positive arousing/calm, negative arousing/calm. Each picture was shown for 5 second with a black screen gap of 5-12 second. The purpose of showing black screen is to reset the emotional state of the subjects and offering them the time to relax and having no emotional content within them. Also a cross shape projection had been displayed for the duration of 3 seconds in order to attract the sight of the subjects. This process had been repeated for each picture. The average length of the signal recorded was around 13 minutes for each subject. Figure 4.1 shows BioSemi layout mapping of the electrodes placement. In this experiment, the electrodes Fp1, F3, C3, C4, F4, and Fp2 were used which represent the channels of A1, A4, A8, A23, A27, and A30 on EDFbrowser respectively. The first letter of each electrode represents the specific lobe of the brain from where the signal is recorded. The specific letter that is mapped to specific brain lobe is listed below:

- F-Frontal lobe
- C-Central lobe

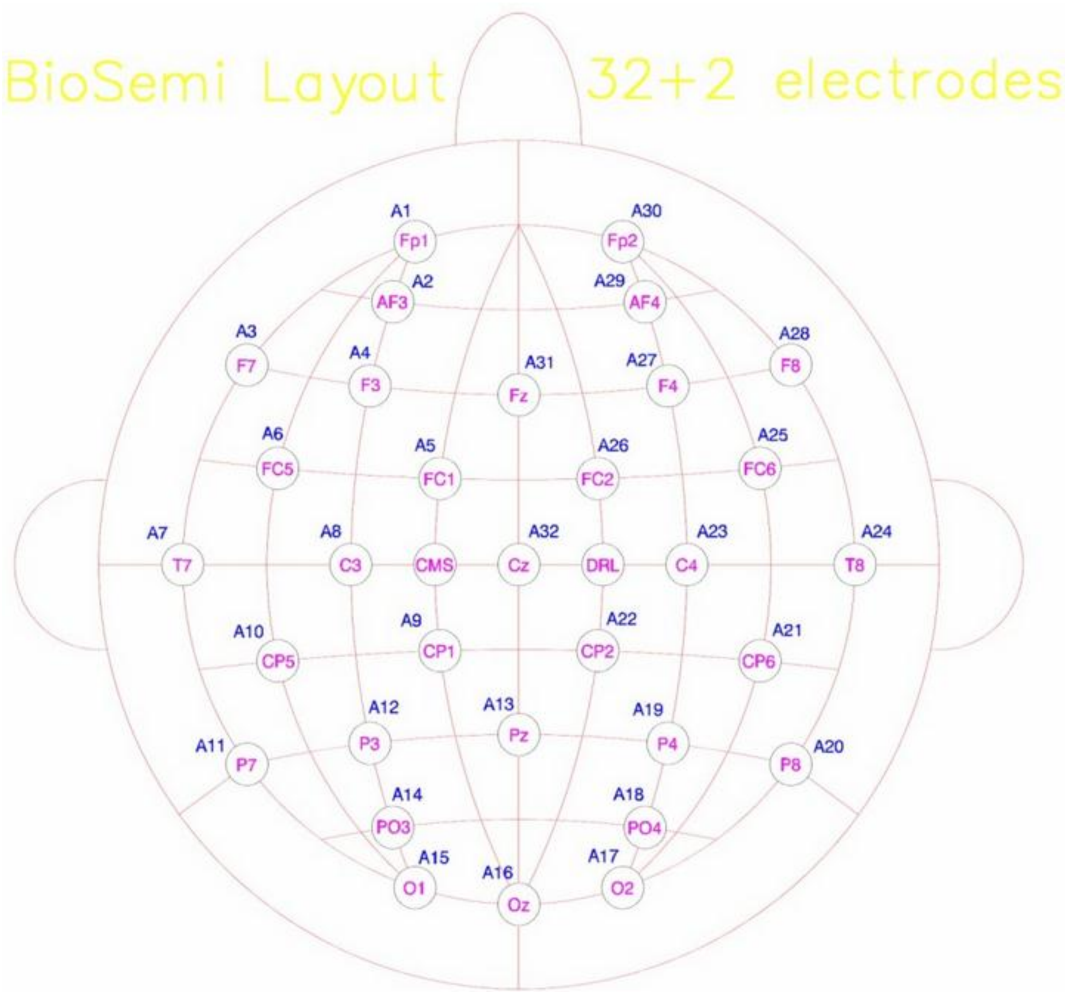

Figure 4.1 – BioSemi layout of electrodes placement [30]

4.2 EEG DATA PROCESSING

The recorded signals as described in above section need to be further processed to get rid of noise (chapter 1.3) embedded in it. The signals thus obtained are again used to extract only signals that were generated on each subject when the IAPS picture was shown from total length of signal. Finally, we extract a number of features from those signals. So, all these processes are described under different heading in following steps.

- **EEG band pass filtering**

As far as the noise embedded in the recordings is concerned, such as superimposed artifacts from various sources, they can be effectively reduced by appropriate band pass filtering. More particularly, the influence of eye blinking is most dominant below 4 Hz; heart-functioning causes artifacts around 1.2 Hz, whereas muscle artifacts affect the EEG spectrum above 30 Hz. Non-physiological artifacts caused by power lines are around 50-60 Hz.

Another reason to choose the band pass filtering is due to particular interest in the area of EEG frequency range. As we have already described in section 1.2.1, EEG signals can be isolated in 5 different frequency bands where each specific frequency band is more prominent in certain states of mind. Based on this fact, the two frequencies we choose that are most important in this paper are Alpha (8-12 Hz) and Beta (12-30 Hz).

So to cater the need of both removing the artifacts while retaining the signals within the particular band of interest, i.e. frequencies within the Alpha (8-13 Hz) and Beta (13-30 Hz) bands, we apply the 10th order “Butterworth band pass filter”. Consequently, by extracting the Alpha and Beta frequency bands only from the acquired EEG recordings, we make sure to remove most of the physiological and non-physiological artifacts. We chose 10th order because high order filters provide greater roll off rates between pass band and stop band, and can be necessary to achieve the required levels of stop band attenuation or sharpness of cutoff [26]. The lists of below are some advantages of Butterworth filter which leads us to choose it [27].

- Maximally flat magnitude response in the pass-band.
- Good all-around performance.
- Pulse response better than Chebyshev.
- Rate of attenuation better than Bessel.

In EDFbrowser by choosing the filter from the top menu we are able to apply the filter we would like to have on our signal as being depicted in the figure 4.2.

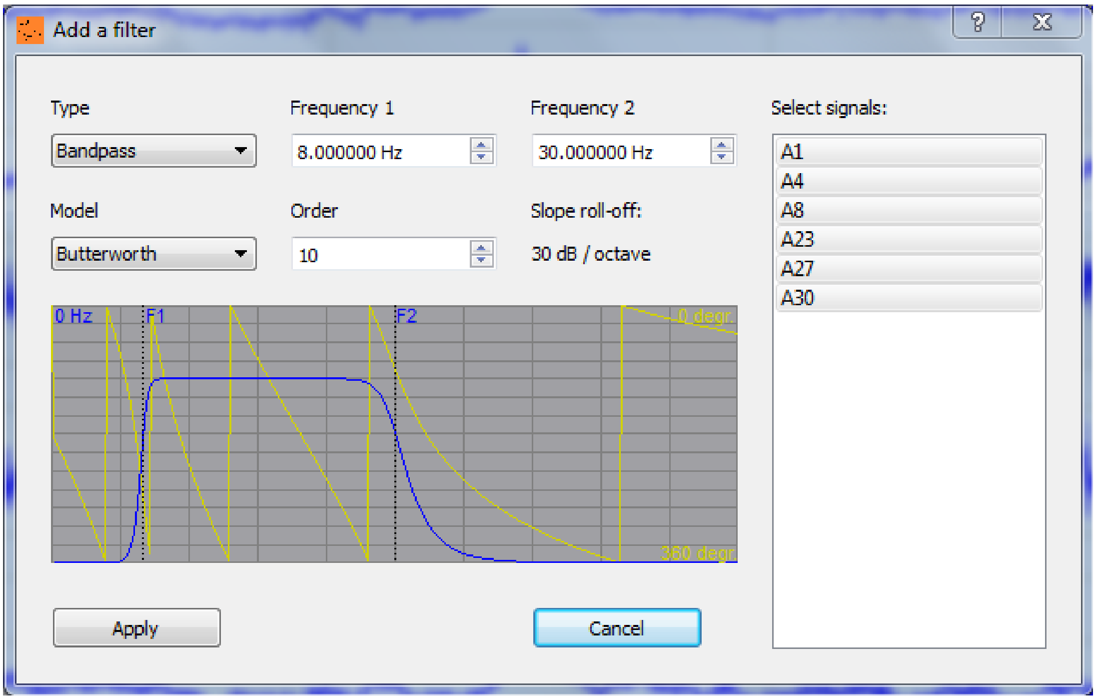

Figure 4.2 – Applying a filter [29]

The result of this filtering will be new signals with frequencies between 8 Hz and 30 Hz like the figure 4.3.

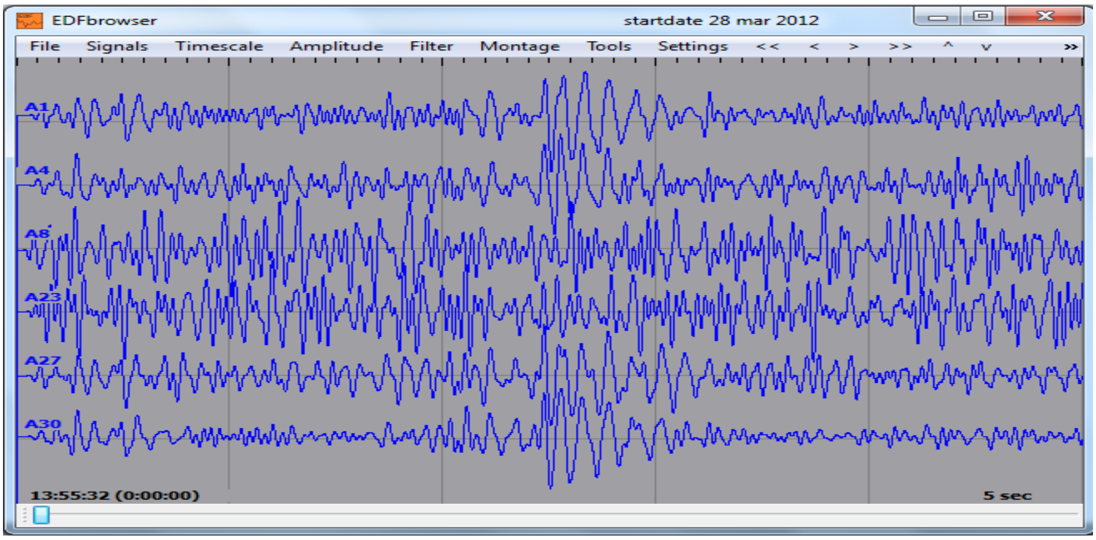

Figure 4.3 – Sample filtered signal [29]

- **EEG data segmentation**

The filtered signals we get from above step is further needed to be processed in order to get the signals that are generated when stimuli is shown to subject from whole length of signal. That is, we are here motivated in retaining 30 segments of signals each of length 5 seconds for each subject for which IAPS picture are shown. While segmenting the signals, we take the signals only from 6 sensors.

So the procedure is like that the file which has been saved as BioSemi data format (BDF) is opened by EDF browser then according to the electrodes mapping on the BioSemi layout, Six channels A1, A4, A8, A23, A27, and A30 (see the figure of the section 4.1) are selected as shown in figure 4.4.

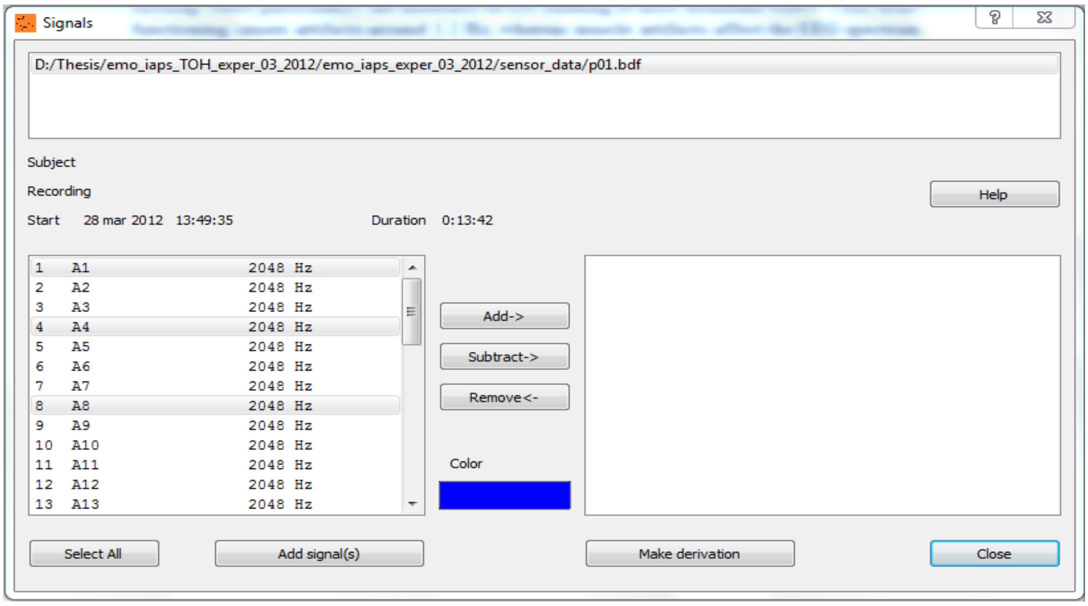

Figure 4.4 – EDF browser, Signal dialog [29]

Then selected channels are added for further processing. By fitting the pane the recorded signals can be seen on the screen. The following figure shows the raw signal of the experiment of one of the subjects which whole of the experiment is 13 minutes and 42 seconds and each page shows 10 seconds of the signal.

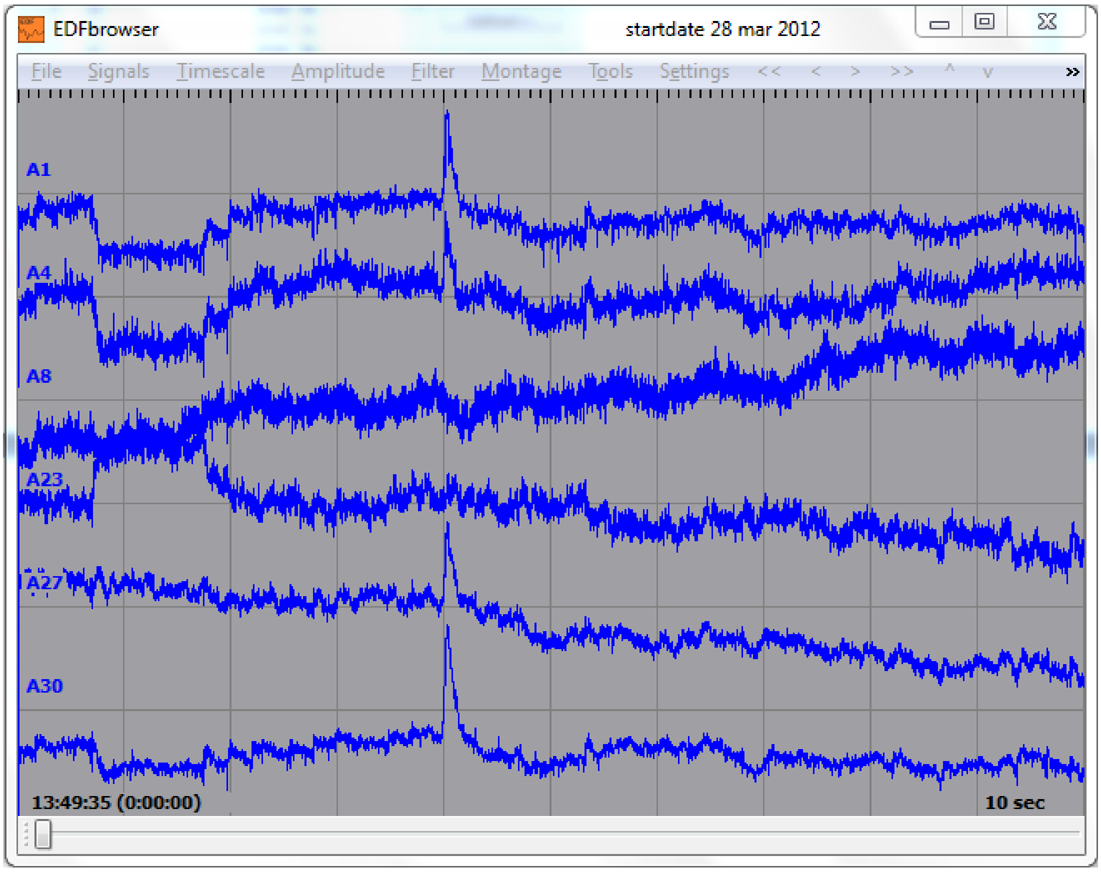

Figure 4.5 – Sample of selected signals [29]

Each subject's recording time slot is available and have been logged on a text file, so we know the timing of each second of the experiment. For example for this particular experiment the base line is started at 13:54:22 and has been finished at 13:55:21 for the duration of 59 seconds (when we talk about a baseline, in essence, we are talking about the duration of signal for which subject are not shown any picture before actually starting the experiment). Then cross shape projection is started at 13:55:29 to attract the sight of the subject and at 13:55:32 the first IAPS picture is displayed for the subject for the duration of 5 seconds that means the picture is ended at 13:55:37 and after that the cross is started again and this process is repeated until 30 pictures are completed that are displayed for the subject.

The data of 5 seconds of picture is what we are looking for and is essential for further processing and extracting the features for making data set. So now, we must take out the 5 seconds of the signal according the time of displaying the pictures. By using the tools in the top menu and choosing reduce signals, duration or sample rate we are able to have the exact data while the picture was showing to the subject. The channels which had been used in the experiment are selected and then by calculating exact seconds of begins and end time of displaying picture we have the 5 seconds of the signal. For example, this subject's first picture had been displayed from the second 358 to 362. The figure 4.6 shows how to obtain the signal for the first picture.

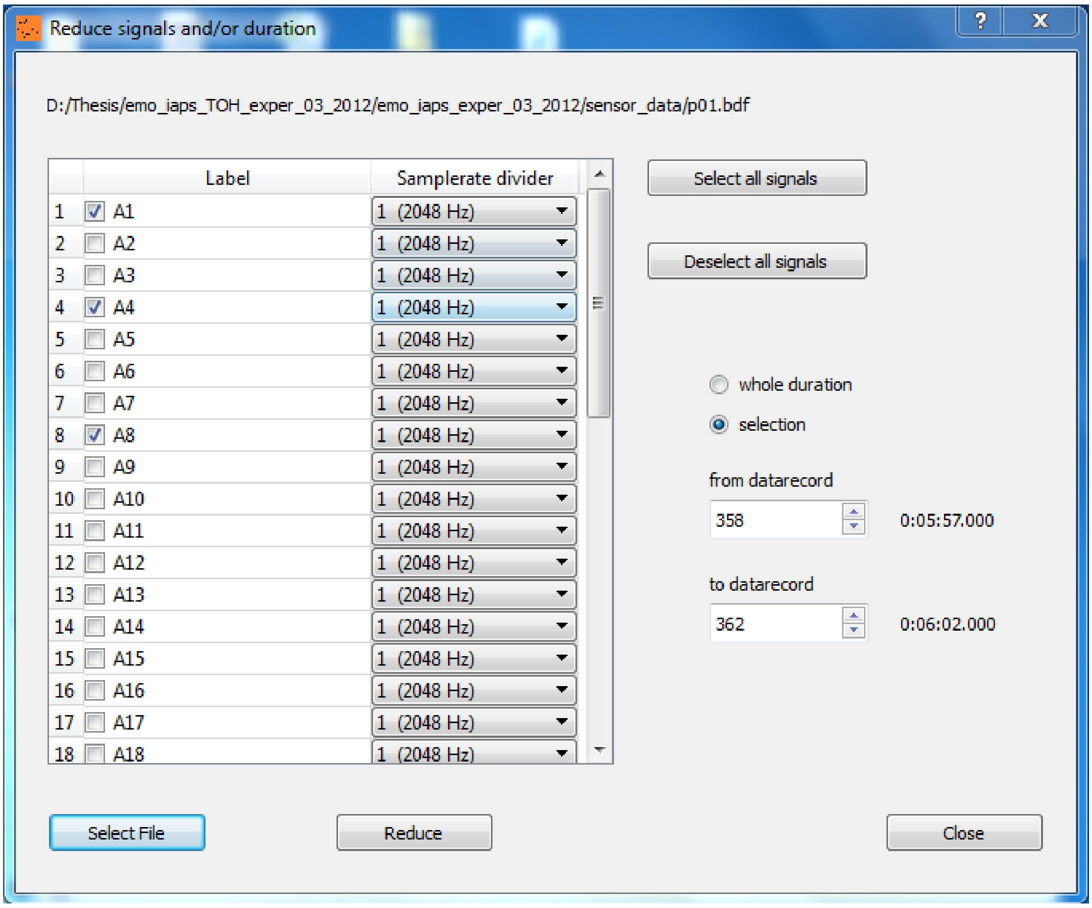

Figure 4.6 – Reduce signals or duration [29]

By pushing the ‘Reduce’ button, the 5 seconds of the signal is saved and then it can be reopened for further processing. Figure 4.7 depicts this signal as well. It shows that start time of the signal is at 13:55:32 and the whole duration is 5 seconds.

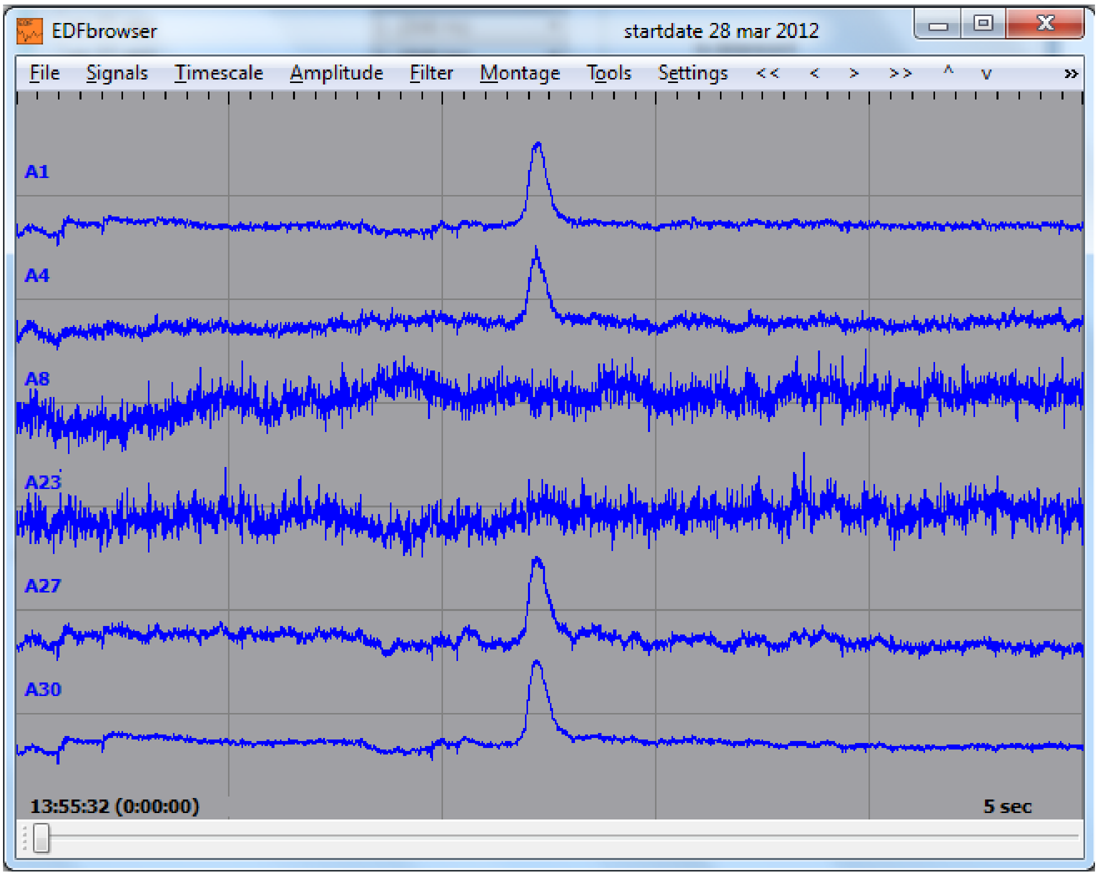

Figure 4.7 – Reduced signal [29]

- **EEG feature Extraction**

Now, we have the signals in which the noise and artifacts have been removed from it and we should make decision which features to be extract from this signal in order to make some data sets which will be used as input of machine learning tool to learn the machine what kind of emotion is depicted by these signals.
At the first stage, the six features which are listed as below were decided to be extracted from each 5 seconds segment of the filtered signals.

- The maximum value
- The minimum value.
- The difference of the mean value of the baseline from the mean value of the raw signal (filtered signal).
- Standard deviation.
- The mean of the absolute values of the first difference of the signal.
- The mean of the absolute values of the second difference of the signal.

In order to extract the above features we need to convert or export the filtered signal which has been saved as a BDF file to ASCII. EDF browser lets us to do this by using the tool from the top menu. By clicking on the export EDF/BDF to ASCII from the tool menu, the signal will be converted to a text file which contains numerical data that can be used in MATLAB.
After exporting the signal to ASCII, it is the time to copy the data into an excel file and save it as a Comma Separated Value (CSV) file, that makes a readable file for MATLAB. The header of the CSV file conducts us that we have time in the first column and 6 channels (6 electrodes or sensors) for the signal which is for each 5 seconds of pictures. This process is repeated for 30 pictures for each subject. The header of the CSV file is shown in the figure below.

Time	1	2	3	4	5	6

The data for each 5 seconds picture takes 10240 samples. The data for 30 pictures (each picture has duration of 5 seconds) are prepared and the features mentioned above must be extracted now.

The first feature to extract is the difference of the mean value of the baseline from the mean value of the raw signal. In order to do this we should calculate the mean value of the baseline. The procedure of gathering data of the baseline is same as gathering data of the pictures. Later on after that the mean of the raw signal was calculated, the mean of the baseline removed from it which had been calculated before. The code 4.1 in MATLAB was used for calculating the mean of the baseline and the pictures as well.

```
m=csvread('1st_pic.csv', 1, 0);
N=10240;
mean=0;

 for i=1:N
 mean=mean+m(i,2);
end

mean=mean/N;
```

Code 4.1 – The difference of the mean value of the baseline from the mean value of the raw signal

We should note that the name which is used in the command “csvread” is differed for different subjects. This procedure is repeated for all 6 channels (electrodes or sensors) and for all 30 pictures. After calculating the mean values of the baseline and mean values of each picture, difference of these values (Removing average of baseline from average of our signals) were saved in an Excel file in order to be used later for formatting our data.

The second feature to extract is Standard Deviation. The code below was used to calculate standard deviation of the signals on each sensor. For doing this, the mean value calculated in first feature is used to calculate the Variance of the signal (Different pictures on each sensor have different mean values) and then by taking the square root of the variance, we will have the standard deviation. The code 4.2 shows how Standard Deviation was calculated.

```
m=csvread('1st_pic.csv', 1, 0);
var=0;
mean=-0.4687;
N=10240;
 for i=1:N
 var=var+(m(i,6)-mean)^2;
 end
 var=var/(N-1);
 sd=sqrt(var);
```

Code 4.2 – Standard Deviation

The third feature is mean of the absolute values of the first difference of the signal, to calculate this feature we should first have the difference between each sample, so if we have in this case 10240 samples and consider it as N, we will have N-1 sample after the calculation. Then we take the absolute values of the first difference and then divide it by N-1 sample to find the mean value, the code 4.3 shows how this feature was calculated.

```
data=csvread('1st_pic.csv',1,0);
N=10240;
sum=0;

for i=1:(N-1)
    y(i)=data(i+1,7)-data(i,7);
end

for i=1:(N-1)
    y(i)=abs(y(i));
end

for i=1:(N-1)
    sum=sum+y(i);
end

fdif=sum/(N-1);
```

Code 4.3 - Mean of the absolute values of the first difference of the signal

The fourth feature is mean of the absolute values of the second difference of the signal. The procedure of finding this feature is same as the absolute values of the first difference but instead of having the difference between each sample, we have the difference between each two samples so there will be N-2 samples available and at the end to find the mean value, the sum of the absolute values is divided by N-2. In the code 4.4, calculating of this feature is presented.

```
data=csvread('1st_pic.csv',1,0);
N=10240;
sum=0;

for i=1:(N-2)
   y(i)=data(i+2,7)-data(i,7);
end

for i=1:(N-2)
   y(i)=abs(y(i));
end

for i=1:(N-2)
   sum=sum+y(i);
end

secdif=sum/(N-2);
```

Code 4.4 - Mean of the absolute values of the second difference

The fifth feature is Minimum of the signal, fortunately in MATLAB there is a function called ‘min’ that finds the minimum of a vector or data. So by using this function the minimum of the signal gathered by each electrode can be detected. For the sixth feature that is Maximum of the signal there is also a function called ‘max’ which finds the maximum of a vector that here is our data saved as a CSV file.

After calculating all six features on each channel (electrodes or sensors), the result was saved on an Excel file which will be used to make data set.

We again calculated the four other features which we proposed.
Those four features which were decided to extract from the signals are listed below.

- Mean of absolute values which is calculated after removing mean of the baseline from the signals.
- Root Mean Square (RMS).
- The mean of the absolute values of the first difference of the **envelope** signal.
- The mean of the absolute values of the second difference of the **envelope** signal.

To extract the mean of absolute values, that is calculated after removing mean of the baseline from the signals, the mean of the baseline calculated before was used to remove it from the signal and then the absolute of the samples were taken and the they were summed up and then divided by whole the samples to find the mean value. Here the code 4.5 was used for this feature.

```
data=csvread('1st_pic.csv',1,0);
y=data(:,2)-(-0.4674);
y=abs(y);
sum=0;
for i=1:10240
sum=sum+y(i);
end

mean=sum/10240;
```

Code 4.5 – Mean of absolute values

The next feature is Root Mean Square, The square root of the average of the squares of a variable quantity. In terms of voltage, the root mean square voltage is called the effective voltage, as opposed to the peak voltage which corresponds to the maximum amplitude of the voltage variations. RMS power (in watts) is similarly called the effective power. The code 4.6 shows how the RMS is calculated.

```
data=csvread('1st_pic.csv', 1, 0);
N=10240;
sum=0;

for i=1:N
   sum=sum+data(i,2)^2;
end

mean=sum/N;
rms=sqrt(mean);
```

Code 4.6 – Root Mean Square (RMS)

Before instructing how to extract two other features, we should explain about an envelope signal. When we talk of the envelopes of signals we are concerned with the appearance of signals in the time domain. Qualitatively, the envelope of a signal y(t) is that boundary within which the signal is contained, when viewed in the time domain. It is an imaginary line.

This boundary has an upper and lower part. We will see these are mirror images of each other. In practice, when speaking of the envelope, it is customary to consider only one of them as ‘the envelope’ (typically the upper boundary).
Although the envelope is imaginary in the sense described above, it is possible to generate, from y(t), a signal e(t), having the same shape as this imaginary line [29].
In conclusion, envelope is the apparent signal seen by tracking successive peak values and pretending they are connected. The advantage of using envelope to find

the mean of the absolute values of the first difference and second difference of the signal is that the diversity between the samples is greater than the raw signal and it makes sense to use it, each sensor's signal has different amplitude so when use the envelope of the signal the diversity of the first and second difference of the signal is great and it can be used instead in the data set.

The mean of the absolute values of the first difference of the envelope signal, is extracted after finding the envelope of the signal on each sensor. To find the envelope there is a function called 'hilbert' in MATLAB for which the absolute value of the output will be the envelope of the first signal. In this case the number of samples is same as the absolute values of the first difference of the signal as N-1. Then absolute values of the first difference of the envelope were calculated like the code 4.7.

```
data=csvread('1st_pic.csv',1,0);

envelope=hilbert(data);
absEnv=abs(envelope);
N=10240;
sum=0;
for i=1:(N-1)
  y(i)=absEnv(i+1,2)-absEnv(i,2);
end
for i=1:(N-1)
    y(i)=abs(y(i));
end

for i=1:(N-1)
sum=sum+y(i);
end

fdif=sum/(N-1);
```

Code 4.7 - The mean of the absolute values of the first difference of the envelope signal

The same procedure was used while finding the mean of the absolute values of the second difference of the envelope signal and also like the absolute value of the second difference the number of sample is N-2. The code 4.8 was used to calculate it.

```
data=csvread('1st_pic.csv',1,0);

envelope=hilbert(data);
absEnv=abs(envelope);
N=10240;
sum=0;
for i=1:(N-2)
  y(i)=absEnv(i+2,2)-absEnv(i,2);
end
for i=1:(N-2)
    y(i)=abs(y(i));
end

for i=1:(N-2)
sum=sum+y(i);
end

secdif=sum/(N-2);
```

Code 4.8 - The mean of the absolute values of the second difference of the envelope signal

The processing of the EEG signal were completed by repeating all the explanations above on the data of 8 subjects and 10 features were extracted for all 30 pictures for each subject and saved into an Excel file.

4.3 EEG DATA FORMATTING

The numerical values we got from the calculation in MATLAB are formatted in Attribute Related File- Format (ARFF) [22] which is the acceptable file format for the input in WEKA. The attributes were declared for features of each signal. For example, Signal (Fp1) has its all features declared as attributes. The value we input in file makes the Instances of ARFF with the class values declared at the end of each instance.

As in this paper, one of our objectives is to investigate the classification result with different combination of the features; we first look into how we made the combination of different features from all 10 features we calculated:

- **Features set I**: This set of features includes 6 different features namely mean value, Standard deviation, Minimum value, Maximum value, Mean of the absolute value of first and second difference of the signals.
- **Features set II**: This feature set is made up from combination of 4 other different features proposed by ourselves which are namely mean of absolute value, RMS, Mean of the absolute value of first and second Difference of Envelope signals.

- **Features set III**: This set of feature is combination of 3 most uncorrelated features among all 10 features. The goal of this step is to avoid the repeated use of features which carry similar property from the signal. To find these 3 most uncorrelated features, we made the correlation matrix of all 10 features from the signals of 30 pictures displayed to three different subjects. After analyzing the outcome of the correlation matrix, we could see mean value, mean of absolute value of second difference of signal and mean of absolute value of first difference of Envelope of signal as the most uncorrelated features among all 10 features.
- **Features set IV**: This feature set is the combination of 4 most correlated features to class value. As the class values had been considered as nominal (positive valence, neutral, and negative valence), in order to find the correlation, we needed to change these nominal class values into the numbers. We considered positive valence as 1, negative valence as -1, and neutral as 0. By using MATLAB to find the correlation between the features we made a 30x10 matrix that each column and row indicates the features, we consider this matrix as X, the result of finding correlation between these features is a 10x10 matrix. We also made a 30x1 matrix that 30 rows indicate each class value of each picture as the 1 column that it is for each sensor; we consider this matrix as Y. We found the correlation between the matrices X and Y and the result would be a 10x1 matrix. By looking at the 10x1 matrix we chose the highest value of it and then we looked at the result of matrix between the features (10x10 matrixes) and we removed three features that had the highest values. It means 3 features which are mostly correlated to each other were removed and one feature was selected. Then the second highest value of the 10x1 matrix was chosen and by looking at the 10x10 matrix, three other highest values which had not been chosen before were selected to remove. This procedure is repeated for all the sensors of a subject and between selected features those which had been repeated more were chosen to make data set with them. The features which were selected by this method are the difference of the mean value of the baseline from the mean value of the raw signal, the minimum of the signals, mean of the value which is calculated by removing mean of the baseline from the signals, and the mean of the absolute values of the first difference of the envelope signal.

Hence, we made four different features set from all 10 features calculated which can be summarized in the table below:

Features set	Feature combinations
I	Mean value, Standard deviation, Minimum and Maximum value, Mean of the absolute value of first and

	second difference.
II	Mean of absolute value, Root mean Square, Mean of the absolute value of first and second Difference of Envelope signals
III	mean value, mean of absolute value of second difference of signal and mean of absolute value of first difference of Envelope of signal
IV	Mean value, Minimum value, mean of absolute value, the mean of the absolute values of the first difference of the envelope signal.

Table 4.1 -Feature set and Feature combination used

With above described features combination, we used following model to design the ARFF file as described below:

Model A: Data formatting based on picture

In this Model, each instance or the row of the data set is the combination of features from all signals acquired from different sensors.

- **Dataset consisting feature set I (A1)**

The formation of data for single picture shown to subject looks like as shown below
S1F1S1F2S1F3S1F4S1F5S1F6…..S6F1S6F2S6F3S6F4S6F5S6F6 class value
Where S1 represent the Signal 1 and F1, F2, F3, F4, F5 and F6 represent the features extracted for this signal and so on. We repeat the same process for all the pictures shown to each subject.

- **Dataset consisting of feature set II (A2)**

The formation of data is exactly is the same as A1 apart that we use only four features.

S1F1S1F2S1F3S1F4…..S6F1S6F2S6F3S6F4 class value
Where S1 represent the Signal 1 and F1, F2, F3 and F4 represent the features extracted for this signal and so on. We repeat the same process for all the pictures shown to each subject.

- **Dataset consisting of feature set III (A3)**

The formation of data is exactly the same as A1 apart that we use only four features.
S1F1S1F2S1F3…..S6F1S6F2S6F3 class value
Where S1 represent the Signal 1 and F1, F2, and F3 represent the features extracted for this signal and so on. We repeat the same process for all the pictures shown to each subject.

- **Dataset consisting of features set IV (A4)**

The formation of data is exactly is the same as A1 apart that we use only four features.

S1F1S1F2S1F3S1F4…..S6F1S6F2S6F3S6F4 class value

Where S1 represent the Signal 1 and F1, F2, F3 and F4 represent the features extracted for this signal and so on. We repeat the same process for all the pictures shown to each subject.

Hence, using model A, we made the total of 4 different dataset based on the combination of the features used which can be made more clear by following table.

Dataset	Features set used
A1	I
A2	II
A3	III
A4	IV

Table 4.2 - Formatting dataset using different combination of features

4.4 EEG DATA CLASSIFICATION

Each data set which has ARFF format is classified by WEKA machine learning tool. During the classification all the default parameters in WEKA is used along with 10-cross fold validation which is standard value for the cross fold validation.

5 RESULTS AND DISCUSSION

In this section the classification results and a discussion regarding these is carried out. When each dataset are made ready, they are passed to classification software WEKA where all the default parameters in WEKA are implemented. 10 fold cross validation which is the standard value for the cross validation is used. The technique used for the classification is Support Vector Machine. The reason we chose the SVM for classification of dataset is due to the fact that various studies have shown SVM is better choice when it comes to classification of emotion from EEG signals [9][31][32][33].

First, dataset A1 was used for the classification where five 2D emotional states, i.e. neutral, positive and negative valence, positive and negative arousal are used to classify, yielding us the accuracy result of 15.23%.

Then we classify the entire datasets, but this time we classify the emotion on only valence axis, i.e. Positive valence, neutral or Negative valence. The classification result are like 36.25% from datasets A1, 36.875 for datasets A2, 36% for datasets A3 while datasets A4 could classify up to 54%. These all result can be summarized in the graph below.

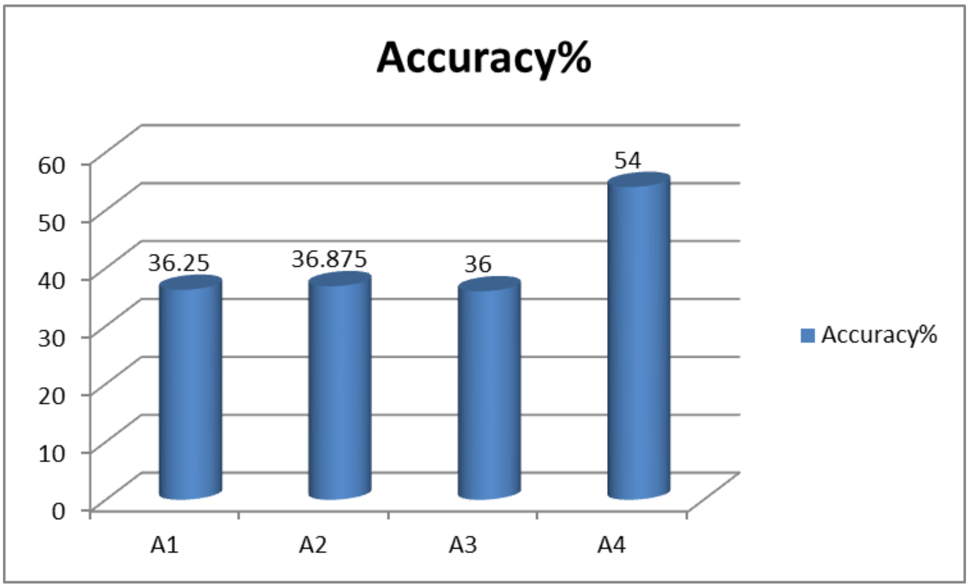

Figure 5.1 – Accuracy of result for different data set for three emotional states

The third classification we carried out is on binary class value. Classification with binary class values includes classification of emotions which are either positive valence or not positive valence, neutral or not neutral and negative valence or not negative valence. We classified all these 3 set of two binary class values for all four data set. While classifying the emotion that are either positive valence or not positive valance, accuracy result is 58.75%, 62%, 60% and 66% for dataset A1,A2,A3 and A4 respectively, while for the emotion that needed to be classified either as neutral or not neutral, we got the accuracy of 80.83%, 83%, 81%, and 85% for dataset A1,A2,A3 and A4 respectively and negative or not negative valence were classified with the accuracy of 58.33% for dataset A1, 59% for dataset A2, 61% for dataset A3 and 71% for A4. The graphical representation of result is shown below.

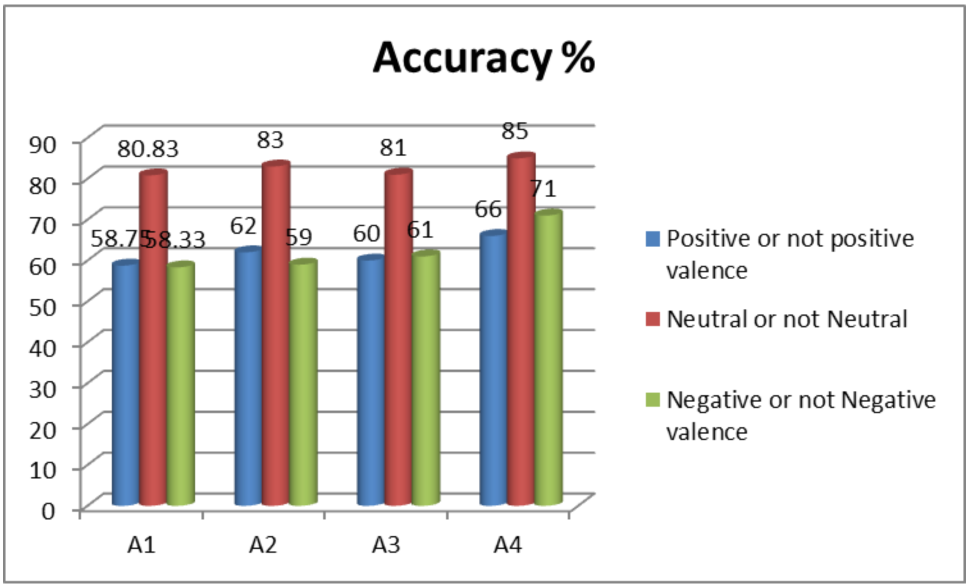

Figure 5.2 – Classification result for binary emotional states

Hence, according to the graph presented above, we can see varying degree of accuracy provided by different dataset. Same difference can also be seen, in this case significantly, based on the number of emotion taken into account for the classification.

First reason in having the different accuracy result is due to different data set that means due to different combination of features used for the classification of emotion. It is because features extraction is vital in affective computing because the signals are in bulk space making them difficult to analyze in that way. So there arises the question which features should be taken in account and which features to exclude. Another reason which makes it difficult for the feature extraction is the phenomenon of person stereotype. It is that, under the same context, different individual expresses same emotion with different characteristic response. In our case, based on the observation from the accuracy result we got, accuracy result was slightly increased when we used the features that were correlated with the targeted affective state. When doing so, we could exclude the less important features.

There is also clear diversity in the accuracy result based on the number of emotions taken into consideration. When we take 2 dimensional emotion states, our accuracy is quite low, but the result gradually bumps up when we decrease the number of emotion to classify. We can say this is the clear indication that our data is much more complex and still contains the much noise to classify the multiple numbers of emotions at the same time. This might be also due to case that the numbers of instances are lower in compare to the number of features used for the classification as a rule of thumb total number of instance in dataset should be greater than 10 times the number of attributes or features used.

There have been various research done in the field of emotion recognition using EEG signals yielding different result. However, the comparison of result among these studies has always been difficult. Still, considering some of the common aspects within the procedure of research, we can present the comparative study of result of this paper with the papers in [15] and [9]. Authors of [15] have classified 3 emotional states from EEG signals recorded from 5 subjects using the system based on SVM with the accuracy of 47.11%. Authors used 90 IAPS picture to induce the emotion on 3 emotional categories, pleasant, neutral and unpleasant. Similarly, the authors of [9] got the average accuracy of 56% during the classification of emotion from 15 different subjects from EEG signals. The experimentation used in paper [19] and in this paper is exactly the same where 6 different IAPS pictures were shown to subject for each emotion to induce emotion in 5 different categories of arousal-valence model of emotion representation. Here, authors have come up with the strange result of having different classification accuracy for different set of subjects even though data from all the subjects have been collected and processed exactly in the same way. Authors claim the reason behind this difference in accuracy is due to diversity in the data.

Apart from above mention study, authors of [5] could classify six distinct emotions (happiness, surprise, anger, fear, disgust, and sadness) from 16 different subjects with the accuracy of 85%.

Hence, the different study shows different result. The reason behind the variation in result in different study can be summarized below:

- Different EEG data collection methods.
- Different EEG data screening methods.
- Selection of different EEG data features.
- Different EEG data formatting methods.
- Different EEG data classification methods and their parameters.

6 CONCLUSIONS AND FUTURE WORK

In this study, we have evaluated the feasibility EEG signals for the classification of emotional states.

For this, we were given the data previously collected in controlled environment. These data were pre-processed to remove the artifacts and 10 features were extracted from the processed data. Four different combinations were made among 10 different features to make four different dataset. Each dataset was formatted in acceptable format for the classification software WEKA. The classification was carried out with the use of support vector machine as the selected technique yielding us the accuracy result of 54% when 3 emotional states were used to classification and average classification result of 74% when the binary emotional states were used for the classification.

Even though we got the promising result from our study, there is still room for the improvement to get even better result. Such improvement can be achieved by adding more subjects which will result in increase in dataset size. Other technique like Peak detection, Thresholding can be used for EEG data processing. EEG signals can also be isolated into separate frequency band of Alpha and Beta to check if that gives some interesting result.

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