Classifying Emotional Features Based on Humour Stimulus in Three Different States Using EEG and Machine Learning

A thesis submitted towards partial fulfilment of the requirements for the award of degree of

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In

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Submitted By

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PREFACE

In today's busy life style scenario, people have become work–bound. Their main focus is just on completing their deliverables. In this process they do not pay any attention to their basic mental health which means they do not pay any heed to their need for happiness. Various surveys have stated that most people around the globe are suffering from mild to extreme cases of depression. People are not actually happy nowadays - they just pretend to be happy. Thus there is a need to arouse the emotion of happiness in them. Humour is generally considered to be the most easily available medium through which happiness can be induced in an individual. The functionality of humour is to lighten up the stressful and depressing mood and provide a feeling of relief and relaxation. The media through which emotion of humour can be induced in an individual are listening to stand-up comedy, movies or video clips containing comedy, reading novels related to comedy or even some comedy audio clippings. But all of these require sufficient amount to time and there is a lack of time in nowadays people's busy schedule. So to induce humour, there is a need of something which will induce humour without taking much time. This problem has a very easy remedy. Jokes, comic strips and punch–lines have been long been known to induce the emotion of humour. These do not take much time, or deep involvement from the readers yet can cause humour and lighten up people's mood. But what exactly happens inside our brain when we read jokes? Can the effects of reading jokes be quantified and established using biomedical signal processing tools and techniques and machine learning algorithms? These questions lead to the basic foundation of this thesis work.

This work focuses on quantifying brain dynamics before, after and while the subject is reading jokes. This is achieved using various non-linear features and machine learning algorithms. Feature extraction and classification of the three states of emotion are challenging tasks for non–stationary and fluctuating parameter present in EEG signals.

Chapter 1 starts with a brief idea of bio–electric signals, their origin and characteristics. Then it covers the anatomy of human brain, electroencephalography, its origin, characteristics, methods of acquisition, electrode placement and montages which are the basic knowledge required to work with EEG signals. The motivation behind this thesis is also discussed followed by a brief outline of the work.

Chapter 2 provides a brief theory of various tools and techniques used in this work like the wavelet transform, wavelet de-noising, time and frequency analysis tools and the non–linear tools like fractal analysis and the concepts of machine learning.

Chapter 3 presents the literature review of Electroencephalography signal and emotions related to different physiological signals. In this chapter the various signal processing and analysis techniques used in various research works related to EEG signals and machine learning are also discussed briefly.

Chapter 4 presents the methodology and results - that is the design of experiment, recording of EEG signals, choice of electrode placements, choice of montage, pre-processing of EEG signals, de-noising of the EEG signals and the observed results. EEG is a complex signal and EEG analysis methodologies require recording brain activity over various locations on the scalp. But prior work has shown that the effects of humor are detected in the frontal areas of the brain with high amount of accuracy. So, in this work the frontal electrodes are used. This chapter covers important concepts like non-linear signal analysis method like Fractal analysis. The measurement of fractal dimension is achieved via Higuchi's Fractal Dimension algorithm which is discussed in details along with key concept like K_{max} optimization. The chapter also covers classification of emotions by machine learning algorithms by focusing on two main algorithms like Support Vector Machine and Logistic Regression. Key concepts of machine learning algorithm like confusion matrix, cross validation are also discussed.

Chapter 5 deals with the discussion related to the observed results from the processing, analysis and the classification part of the experiment. Lastly in Chapter 6 the interpretations of the results are drawn giving a final conclusion to this experiment.

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1. Introduction

1.1 Bio–signals

Bio–signals are the biological or physiological signals which are produced due to some physiological processes occurring in the human body. These signals are recorded as voltage fluctuations in the time domain. These voltage fluctuations have characteristic frequencies and hence can be analysed in time domain, frequency domain and time-frequency domain. Biological signals like cardiac signals, brain signals vary with period of time and also the frequency associated with them are not static in nature. Each bio–signal contains important information such as during the physiological process chemical, electrical and mechanical activities occur which can be evaluated and estimated. But mainly the electrical activity of the physiological signals is referred to in bio–signal analysis. The electricity in biological signals or in short bio–electricity is generated by the potential difference developed in the cells of human beings. Thus by studying the bio–signals the physiological mechanism associated with it can be understood which can be fruitful for diagnosis of underlying pathology [1].

Previously medical treatment was based on data as narrated by the patients. The data given by patient is completely dependent on them, that is, these data are subjective, may be partial or even biased. Based on only this information, proper treatment of the disease cannot be done. For proper diagnosis various medical examinations are required. To perform the medical examinations, gathering of the bio–signals from the diseased portion of individual patient is necessary as these will provide the complete information about the underlying pathology.

As the application of bio-electric signals is mainly in the field of medical examinations, there comes the role bio-medical instruments or rather bio–medical engineering. Each bio–medical instrument is such designed that it can be used for acquisition of a particular bio–signal from the underlying physiological system present in the human body. The bio–electric signals as is evident from the name, picks up signals from the human body in the form electric waves. But the physiological signals generated in the human body are in the form of ions. The conversion of ions to electrical signals is required to be done otherwise the bio-medical equipments will not be able to capture the signals. This conversion is done by the help of transducer. The electrodes present in the bio–medical equipments act as the transducer. These are relatively simple in nature. As these transducers are used for capturing biological signals so these are known as bio–transducers [2]. The electrodes designed for capturing the physiological signals are of two types – micro electrodes and surface electrodes. The micro electrodes are used when the signals from a single cell is required. When the signals of many cells are required then the surface electrodes are used. In this case, the excited cells generate an electric field which is picked by the surface electrodes. Example of use of surface electrode is electromyography and electroencephalograph. The bio–signals are captured by following non– invasive techniques.

After picking up of the bio–signals, these signals are amplified for proper viewing of the signal. The captured bio–signals are in analog form. For various use of bio–signals in both clinical and research fields, these signals are required to be converted into the digital form for carrying out processing of these signals in the computer. Also the bio–signals are non-stationary in nature as it varies over time and contain artifacts or noise generated from the external environment. The removal of these artifacts is necessary for proper diagnosis in clinical field or for proper generation of features and classification in case of research field. After the processing of the bio–electric signals is done, the feature extraction part comes into play. Various statistical and non–linear features are extracted from these signals using different softwares available. The features extracted are used for the analysis of the signal like classification, disease detection, and recognition of various patterns.

The block diagram of the work carried out after picking the bio–signals is described in Figure 1.1.

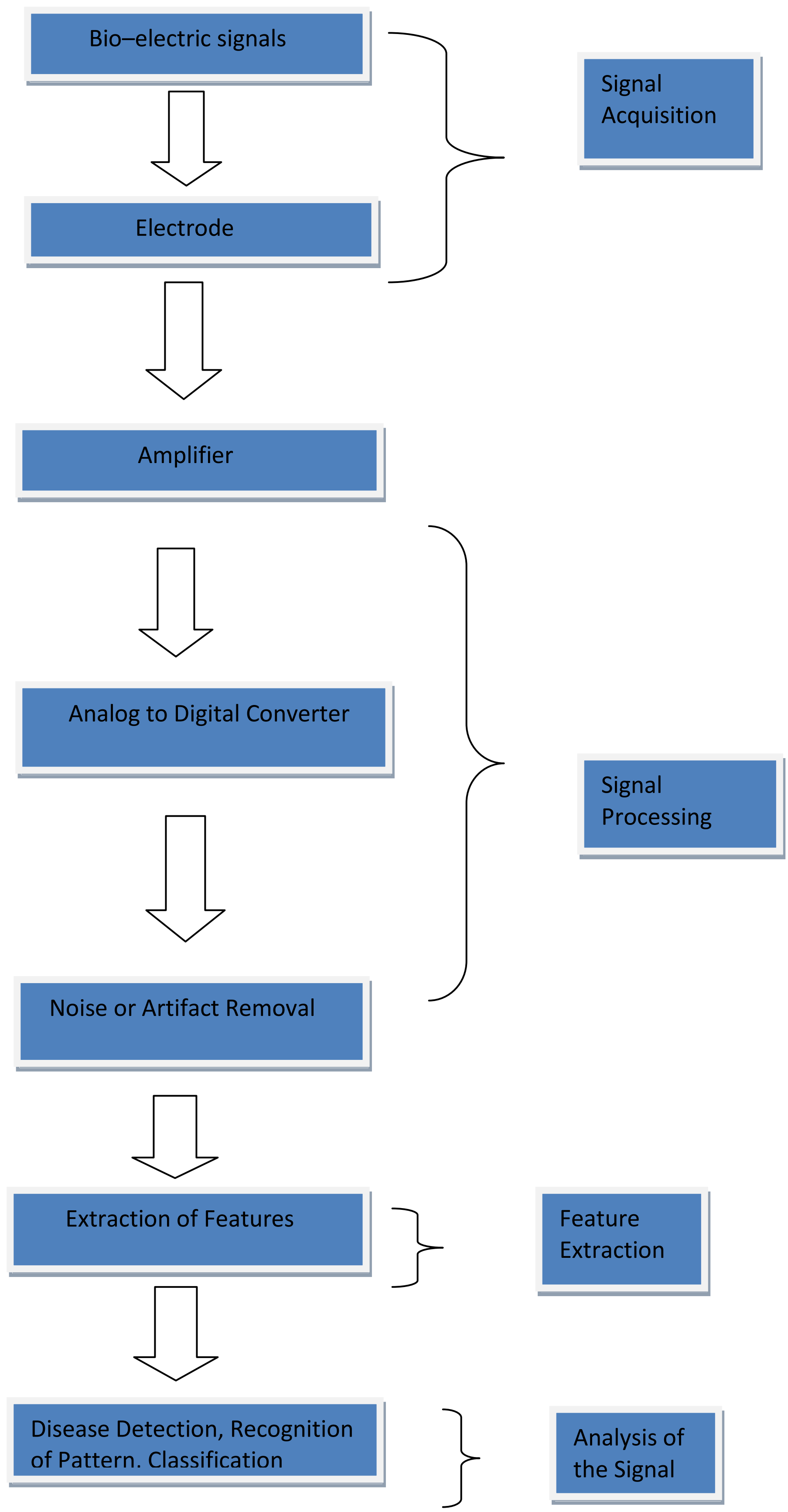


Fig. 1.1 Block Diagram of Bio–signal Processing, Feature Extraction and Analysis

The most common types of bio–signals are listed in the table 1.1.

Table 1.1: Some Bio–signals

Type of signal	Region of production in human body	Type of electrode used for acquisition	Frequency range
Electroencephalogram	Brain	Surface Electrode	0.5 – 100 Hz
Electromyogram	Muscles	Needle and Surface Electrodes	500 Hz – 10 kHz
Electrocorticogram	Cerebral Cortex [3]	Needle Electrode	100 Hz – 5 kHz
Electroretinogram		Micro Electrode	0.2 – 200Hz
Electrocardiogram	Heart	Surface Electrode	0.05 – 100 Hz
Electroneurogram	Nerve Bundles	Needle Electrode	100 Hz – 1 kHz
Electrooculogram	Front and Behind of Eye	Surface Electrode	0.1 – 20 Hz

1.2 Anatomy of human brain

The brain is the most vital part present in the human body as it is responsible for decoding the information from the outside world in such a way that it is understood by us. This information is perceived to us by our sense organs. Memory, intelligence, emotion, creativity, [4] functioning of different body parts are controlled by the brain. Being the most crucial and delicate organ, brain is protected by the skeletal structure known as the skull.

The brain is divided into three parts:-

- Cerebrum
- Cerebellum
- Brainstem

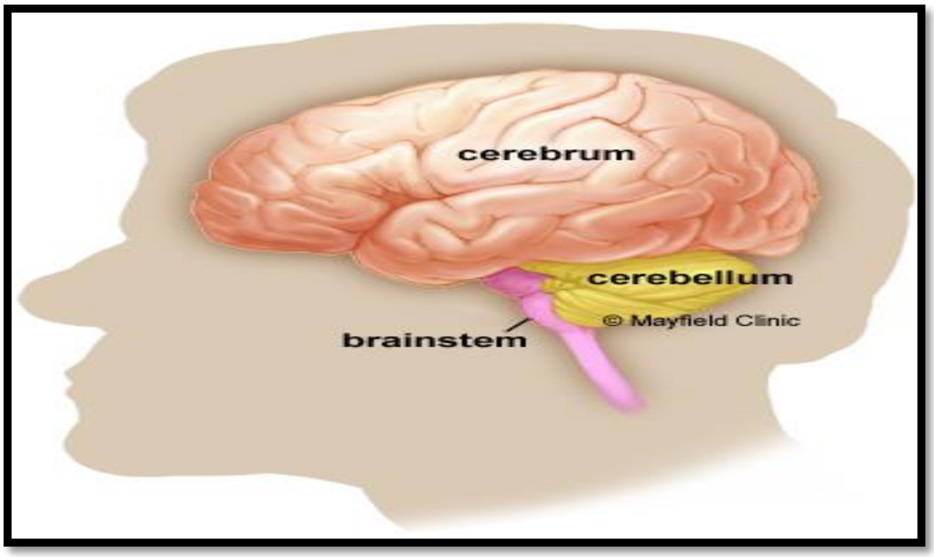


Fig.1.2: Parts of Human Brain [5]

- **Cerebrum –** Largest part of the brain consisting of two halves – right and left halves. These two divisions are joined by corpus callosum. This sends messages from one half to the other half. The most interesting thing is that each half controls just the contraposition of the body. And for this reason the left side gets paralyzed when stroke occurs in the right hemisphere. The left half is considered as the dominant part as it mainly controls the speech and language. The right half on the other hand controls mainly the processing of spatial and visual information perceived by it. The main utility of the left half is controlling reasoning, speech, writing, and arithmetic. The right half controls the creativity and artistic skills Used for identifying senses like hearing, touch, speech and vision, controlling emotions, movement of body parts, rationalising and learning.

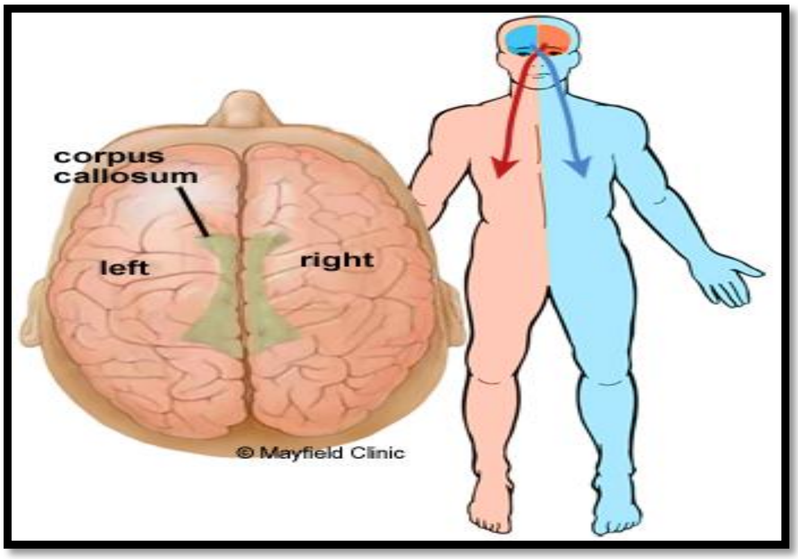


Fig. 1.3 Different parts of Cerebrum [6]

- **Cerebellum** - Located under the cerebrum. Used for balancing, maintaining body posture and movements of muscles.

- **Brainstem** – Joins spinal cord with cerebellum and cerebrum. Used for performing the natural functions of the body like beating of heart, inhalation and exhalation, digestion, sleep, etc.

Brain Lobes

There are crevices present in the cerebral halves. These crevices are responsible for partitioning the human brain into distinct lobes. In each of the two halves, there are four different lobes namely frontal, parietal, occipital and temporal. Each of these lobes is further sub divided for performing specified functions. These lobes don not function alone instead they function in a co-ordinated manner.

The functions of the different lobes are discussed below:-

- **Frontal Lobe**

- Speech
- Movement of body parts
- Intelligence
- Concentration
- Judgement
- Solving a problem
- Planning
- Controlling of emotions
- Controlling of behaviour

- **Parietal Lobe**

- Performing of various senses like vision, touch, pain, temperature, spatial
- Interpretation of words and languages

- **Temporal Lobe**

- Understanding of language
- Sequencing
- Organising
- Memory
- Hearing

- **Occipital Lobe**

- Vision – distinguishes colour, light and movement

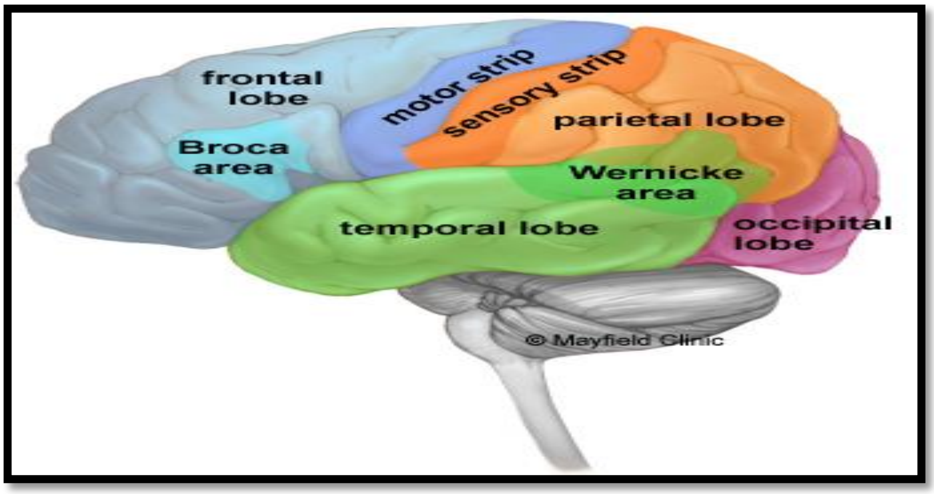


Fig. 1.4 Different Brain Lobes [7]

1.3 Electroencephalography

Electroencephalography abbreviated as EEG is a form of bio–electric signal. This bio signal is created in the nerve cell of the human body. The source of generation of EEG signal is the potential present in the plasma membrane. The potential creates an action potential. The action of billions of such nerve cells generates the EEG signal. The EEG signal is picked up from the scalp with the use of non–invasive methods like using of scalp electrodes.

1.3.1 Generation of brain waves

The human brain consists of numerous neurons which are responsible for generating the brain's electric charge. There are transport proteins present in the plasma membrane which pumps the various ions across it to maintain the electrical charge of the neuron [8]. For propagation of action potentials and maintenance of resting potentials, the neurons continuously exchange ions. As ions containing similar charges repel each other, so the ions of numerous neurons when generated, they push their neighbouring ions which in turn push their neighbours thus forming a wave. Such waves are known as brain waves and the process of production is known as volume conduction.

1.3.2 Characteristics

- Frequency ranges from 0.1 Hz to 100 Hz although 0.5 Hz to 50 Hz is considered as the main part. The behavioural states are associated with the different frequency bands.

- The amplitude of the EEG waves ranges from 2 micro volt to 200 micro volt.

- The electrodes used for recording of the EEG signal can be wet silver / silver chloride electrodes, active dry gold electrodes, passive dry solid gel electrode, hybrid-multi-spike electrodes.

- It is a non–stationary in nature as the features of the brain varies over period of time.

- It is non–linear in nature.

- Sampling rate ranges from 250 Hz – 2000 Hz.

- It is recorded without positioning of the electrodes on the actual surface of the brain. So it is recorded by non–invasive techniques.

- It is quite tolerant to body movements of the subjects. Still the movements recorded can be eradicated.

- Unlike many other bio–medical equipments, EEG does not have exposure to magnetic fields of high intensity which produces some faulty data and also is not recommended for patients having metallic implants or pacemakers.

- For analysis of the EEG signal, various methods like time-domain, frequency–domain, time–frequency domain analysis, non–linear extraction of feature, statistical feature evaluation and deep learning and machine learning are used.

- When an audio or visual stimulus acts on the subject under consideration, evoked response is recorded by the EEG. Due to action of stimulus a change in the EEG pattern is observed which distinguishes it from the rest of the EEG signal.

1.3.3 Frequency Bands of EEG Signal

The EEG signal consists of different frequency components. The rhythmic activity is a specialised feature of the EEG signal. Bands of frequency are segregated based on this rhythmic activity [9]. Based on the type of frequency component, the EEG signal is divided into five different bands.

Table 1.2: Different frequency bands of EEG signal

Frequency Band	Frequency Range (Hz)	Functions
Delta (δ)	0.5 – 4	Sleep
Theta (θ)	4 – 8	Relaxed, Random thoughts
Alpha (α)	8 – 13	Passive attention
Beta (β)	13 – 30	Anxiety dominant, High focus
Gamma (γ)	>30	Concentration, Multi tasking

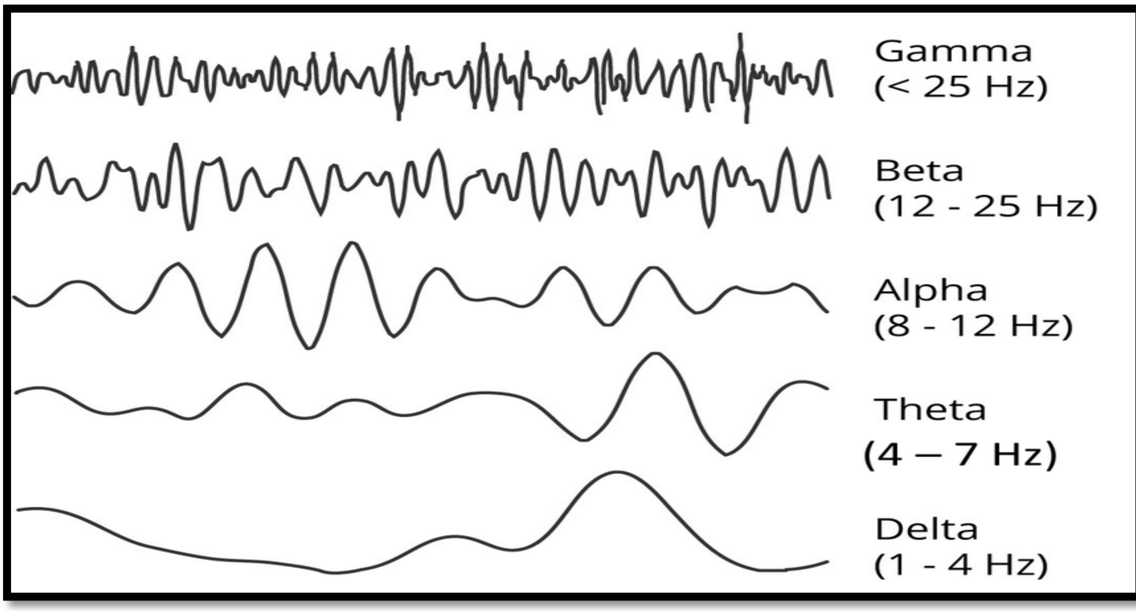


Fig. 1.5: Different Frequency Bands of EEG Signal [10]

Delta Band

The delta band belongs to the frequency range of o.5 Hz to 4 Hz. It is located in the frontal region in adults and in the posterior region in children. The amplitude of such waves is high and these are regarded as the slowest wave.

Theta Band

The theta band belongs to the frequency range of 4 Hz to 8 Hz. It is found in such regions of brain where actions related to hand are not present.

Alpha Band

The alpha band belongs to the frequency range of 8 Hz to 13 Hz. It is situated at the posterior part of the brain. These eaves are characterised by high amplitudes. These waves are very crucial in determining the level of anaesthesia during surgeries. It is also responsible to predict how much the brain is alert.

Beta Band

The beta band belongs to the frequency range of 13 Hz to 30 Hz. These are low amplitude waves present in the frontal region.

Gamma Band

The gamma band belongs to the frequency range of above 30 Hz. It is located in the somato-sensory cortex.

1.3.4 Acquisition of brain waves by EEG machine

The EEG machine contains scalp electrodes for picking up of the brain signals. When the ions present in the brain wave, reach these electrodes, they generates push and pull force on the electrons present on the metal surface of the electrodes. A voltage is created as pull and push of electrons are conducted easily by metal. This generated voltage can be measured by voltmeter. By proper recording of this voltage over period of time generates the EEG signal.

It is impossible to pick up the potential generated by a single neuron as it is quite low. The coordinated activity of various neurons having same spatial orientation generates the wave which is recorded in the EEG signal. The maintenance of same spatial orientation is essential as waves would not be generated if ions do not line up.

EEG is recorded by calculating the difference of voltages between an active electrode which is positioned on the scalp and the other one, a reference electrode which is positioned mainly on the earlobe. The reference electrode can be placed on any body part except the scalp. This method of acquisition of EEG is known as monopolar acquisition [11]. The most popular method is the bipolar recording in which the voltage difference of two active electrodes is used.

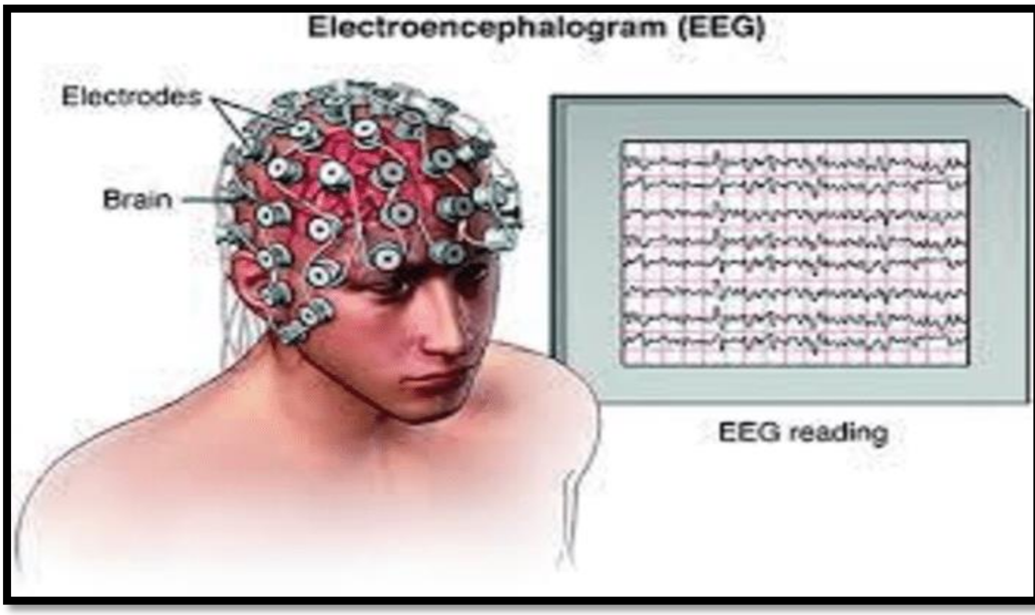


Fig 1.6: Recording of the EEG Signal placing electrodes on the skull of the subject [12]

Montage: The placement of electrodes on the scalp and their connection through channels form a symmetrical pattern which is referred to as the montage. Usually, the reference electrode is placed on a site which is not active like earlobe or fore-head. Following the 10/20 system [13], the EEG electrodes are positioned on scalp. In 10/20 system, there are locations of 21 electrodes. The methodology used in this system is that the electrodes are placed at a 10% and 20% of the distance in between the markings of the cranium by measuring sagittal, coronal and circumferential arcs.

The identification of the electrodes are done based on their position on the head, such as Fp - frontal-polar, C - central, P - parietal, T - temporal and O - occipital.

Electrodes on the left part of the scalp are denoted by odd numbers and on the right part of the head are denoted by even numbers. The electrode on the midline is denoted by Z. One electrode is labelled iso-ground and is placed on the neutral site of the head.

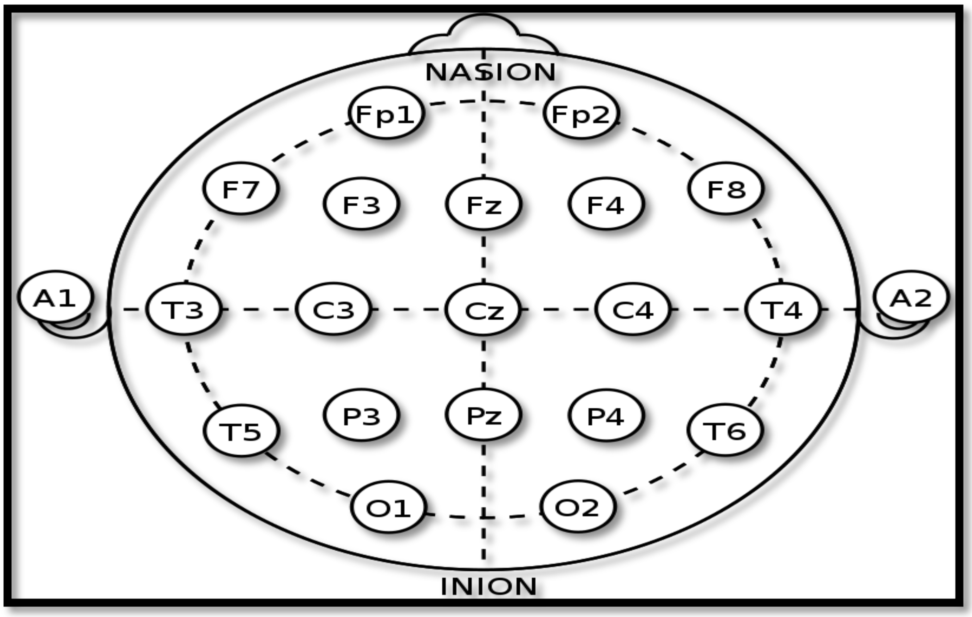


Fig. 1.7: 10/20 System of Electrode Placement [14]

Montages Selection: Both referential and bipolar montages are used for optimum EEG recording. According to the American EEG Society, each laboratory should utilize one of the numerous options from each main category, such as longitudinal-referential, longitudinal-bipolar and transverse-bipolar montages.

By connecting left and right temporal or left and right para-sagittal connections, a paired set of electrodes from homogeneous regions of the scalp may be created. This is known as the montages created by paired group. As the brain lacks functional or anatomical symmetry [15] in the coronal direction, paired group montages are only applicable to longitudinal montages.

Left and right pairings of paired channels from homologous brain regions are clustered together in longitudinal lines, temporal and para-sagittal pairs. Midline electrodes are not compatible with each other. In most cases, transverse paired channels are not employed. This approach works well for comparing symmetric electrode locations, but it makes accessing regional longitudinal relationships more challenging. Unpaired montage has the least amount of distortion, followed by paired group. The paired channel has the best recording symmetry, followed by the paired group. Unpaired montage has the drawback of poor symmetry, whereas paired channel has the problem of distortion.

1.3.5 Artifacts in EEG Signal

Artifacts are non-cerebral origin impulses that are recorded while recording of the EEG signal. EEG artifacts are ubiquitous [15]. These are unwanted in the actual signal as they impair the EEG signal so it is critical that they are identified and eradicated. The main dissimilarity between the original EEG signal of subject and the recorded artifact in it is that the amplitude of the artifacts are higher than that of the EEG signal There may be several types of artifacts in a single EEG recording. Of them the two most common types are the biological or physiological artifacts and the artifacts originated from the environment.

The biological artifacts contain the following:-

- Electromyogram (EMG) artifacts which are induced from activation of muscles during recording of the EEG signal.
- Electrooculogram (EOG) artifacts which are induced due to the blinking of eye, movement of eye balls during the recording of the EEG signal.
- Electrocardiogram (ECG) artifacts contaminating the EEG signal.
- Skull–defect artifacts

The environmental artifacts are of the following types:-

- 50Hz or 60 Hz frequency artifact corrupts the original EEG signal due to improper grounding of the EEG electrodes.
- Uneven positioning of the electrodes.
- Movement of the subject while recording of the EEG signal
- Sometimes there are inter–venous drips connected to the patients’ body which interfere while recording of the EEG signal.

1.4 Motivation and Objective

With the advancement of machine learning algorithm, brain–computer interfacing and non-invasive techniques of recording of the EEG signals, the research of cognitive neuroscience and cognitive psychology has been developed. From the early ages there have been lot of approaches to know about the true emotions of persons. With the advancement of brain computer interfacing technique, this has become quite easier. For analyzing the activity of human brain EEG is considered as a powerful tool which records various brain signals with the help of electrodes placed on the scalp.

Humour is recognized as a powerful tool that can invoke an emotion of joy or happiness in the reader reading the humorous contents. If a person feels depressed or sad, then after reading certain comic strips, the person's mood will change and he/she will start feeling happy. It is very rare that a person's emotion does not change after reading comic strips. In various fields of research like health, education and safety, estimating, interpreting and processing of human emotions and extracting various features from it is widely used. In the field of BCI studies based on EEG signals dealing with emotion have gained a lot of importance.

Emotion is comprised by the thinking of a person. When a person responds to the external stimulus, the outcome that occurs is designated as emotion. Emotion plays a crucial role in determining the behavioural aspect of a person .Under the action of a particular stimulus, different people respond differently. Thus emotion is described as a subjective phenomenon. Human emotion is divided into six different classes. These classes consist of happy, joy, relax, angry, disgust and sadness. Various works are done on classifying and recognising these emotions by using machine learning and deep learning approaches.

This work is targeted on one emotion – happy emotion. Only the happy emotion is studied in this study. Studies show that at present, most of the population is suffering from mental illness specially depression. The cause of this depression cannot be said with certainty. The cause of depression can be loss of job, job dissatisfaction or can also be related to family and friends. Sometimes this depression can be fatal if the person commits suicide. Studies reveal that most people are not genuinely happy nowadays instead they pretend to be happy. The objective of this work is to understand the brain dynamics when a person reads comic strips or jokes by analyzing the brain dynamics like before, after and during reading jokes. In this work, certain features based on happy emotions are extracted which can be beneficial for the researchers in the field of psychology to help people come out of the depression and be happy and content.

The happy emotion comes out of when a person experiences some humours content. Humour is regarded as a boon to the mankind as it serves as a coping strategy for persons when they are not in a good mental state. In this study comic strips are given as a humorous stimulus so the knowledge of linguistics is essential for the processing of humour [17]. The processing of humour involves two things like comprehension of humour and appreciation of humour. In this study while the subjects were going through the comic strips, the subjects comprehended the humour present in the comic strips and during the post application of the stimulus the subjects appreciated the humour present in the comic strips [18].

Vital requirement before choosing an effective machine learning algorithm is its prediction accuracy, adaptability to understand different features. In recent years, a lot of research has been done for predicting emotions based on proper machine learning model. The works dealt with the analysis of a person's facial expressions after reading some articles or hearing some audio or viewing some video and also conversations with other people. All of these arouse a sense of emotion in the subjects under test. Another approach was based on physiological signals. Studies show that change in physiological signals cause emotional change as changes occur in nervous system. The next approach which has gained a lot of importance and studies are still going on in this field deals with the brain signals generated by electroencephalogram.

Machine learning is used to identify the relation between the pre, during and post application of the stimulus. The study suggests a method of differentiating between the above mentioned three states based on two machine learning algorithms namely Logistic Regression and Support Vector Machine algorithms. Various statistical features like mean, standard deviation, different band powers of the EEG signals and fractal dimensions of the three states like the pre, during and post application of the stimulus is given as the input to training module of the algorithm and then based on these trained data, accuracy results of test data is generated.

2. Tools and Techniques

2.1 Analysis of time and frequency

2.1.1 Signal Power Analysis

The square of the RMS value of the signal gives the power of it. In simple terms, it can be said that it is evaluated by summing the absolute squares of signal's time–domain samples.

The placement of the electrodes on the different regions of the scalp during the various phases of recording of the EEG signal gives its average power. The placement of the electrodes can be frontal, parietal, frontal–polar, central and occipital. From the electrodes of these regions, the power is calculated and averaged.

2.1.2 Analysis of the power of brain waves

The EEG signal consists of six bands belonging to different frequency range and used in different activities. So there power is also different. Also upon subjected to stimulus the powers of these bands will vary which can give a clear insight of the changes happening in the brain structure due to the effect of the stimulus.

2.1.3 PSD Analysis

The power of the EEG signals can be analyzed using the power spectral density (PSD) of the said signals. One of the most powerful tools used for PSD estimation is by Welch periodogram method. Although this method does not provide consistency in estimation of the PSD of wide stationary process still this technique is fruitful in reducing the periodogram by segmenting time series which are overlapping. For each of these segments, periodogram is computed and then averaged to provide the value of the PSD. The frequency components can be analyzed from the PSD of the signal. As this method produces the PSD estimation of the various time–series segments the periodogram of each segment approximately represents uncorrelated values of the actual PSD but by performing the average the variability is lowered. The multiplication of these segments with window function produces average periodogram. As these segments are quite overlapping so values of the data at the initial and ending point of these segments are tapered with the help of the window and are removed from the adjoining segments. This also prohibitates the loss of data or information present in the signal.

2.1.4 Correlation Analysis

For checking how much strong the linearity of the relationship is correlation technique is used. When two data are correlated, it means that change in one variable will be reflected in the second variable, that is, if one data is increased the other data will also increase in the same amount. If no correlation exists between two data then change in one data will not be reflected in the other data. It is not necessary that two uncorrelated data do not share any relationship or are not dependent on each other instead it can be such that those data share a non–linear relation. If the value of correlation of two data is near to 0.9 then these data are called highly correlated and if the value is near to 0 then these data are highly uncorrelated.

In case of EEG signals, as the signal is recording by placing the electrodes on different areas of the scalp so there is a tendency that the recorded value can be correlated.

2.1.5 Necessity of Wavelet Transform

For removing the artifacts from signals, Fourier Transform plays a major role. It is very much useful for stationary signal as in such type of signal the frequency component does not change with time. All frequencies exist at all times. In case of Fourier Transform, one cannot tell at which moment of time, which event occurred as the time information is lost when the signal converts from time domain to frequency domain. In case of Fourier Transform, the signal's graph when plotted consists of only frequency and magnitude. No time information is present. So, if there is any discontinuity in the signal at which moment it has occurred cannot be determined. As in case of stationary signals, such problem at which time interval which frequency component exist does not occur, so, Fourier Transform can be used easily.

However there is another type of signal present which is known as non–stationary signal in which frequency components present in the signal change with time. The properties which make the signal non–stationary are variable event beginning time, variable event ending time, an abrupt shift present in the signal and also drifts. These are often the most crucial components of the signal and mostly used in the analysis of non–stationary signals. So, eliminating those or not considering those will give a faulty analysis. Hence, Fourier Transform is not a good choice for non–stationary signals [19].

But contamination of artifacts occurs in non–stationary signals as well, so, there is a need for the development of other methods which can overcome the drawbacks of Fourier Transform and also remove the artifacts.

The first development in this regard was the introduction the windowing technique in the required signal. This was developed by Denis Gabor (1946) and name of this method was given as Short Time Fourier Transform (STFT). As the name suggests, STFT is mainly based on the Fourier Transform but with the application of windowing. The windowing of the signal is achieved by selecting a small section of the signal at a certain time over which window of certain length is passed. The segment chosen was assumed to be stationary. This method eliminates the drawback of the Fourier Transform to a great extent as it converts the signals into a three dimensional function of frequency, time and magnitude. So, one can easily identify at which time interval, which frequency component exists. But this method also has a major drawback as the window length is fixed for all the frequency components present in the signal and cannot be varied for different frequencies. Often in case of physiological signals there is need for flexible window length where one can change the window length for various frequency components Also, if narrow window is chosen then the time resolution is better than frequency resolution. If wide window is chosen then the frequency resolution is better than time resolution. So, modification of STFT should be done for eliminating its drawbacks.

The next major development in this field was the introduction of Wavelet Transform. In this method, variable window length can be selected according to the requirement. Major change in this method was that this method is based on Time–Scale region rather than Time–Frequency region.

The various analysis methods working on various regions are listed in Table.

Table 2.1: Various Analysis Methods for Various Regions

Region	Analysis Method
Time–Amplitude	Shannon
Frequency–Amplitude	Fourier
Time–Frequency	Short Time Fourier Transform
Time–Scale	Wavelet

2.1.6 Time Scaling

To overcome the drawback of Short Time Fourier Transform, the scaling concept was introduced. The scaling feature removed the use of fixed window length for all frequencies present in the signal [20].

The concept of scaling is discussed below.

Suppose there is a signal x (t).

This signal can be scaled by multiplying a factor alpha to the time of the signal. The scaling factor is sometimes multiplied with the amplitude of the signal. The equation (1) represents the original signal and equation (2) represents the scaled signal.

$y(t) = x(t)$ -------- [eq.1]

$y(t) = x(t/\alpha)$ -------- [eq. 2]

So, this is a two dimensional signal. The y–axis is kept constant in the above two equations. The change in the x–axis will directly increase or decrease the magnitude of the original signal following the sign of the scaling factor α. Thus scaling of the original signal can be either positive or negative. This gives rise to two categories of time scaling.

- **Time Compression**

When the value of the scaling factor α is more than 0, then the amplitude of the signal is divided by the value of α keeping the value of the y–axis constant. This phenomenon is known as time compression.

The above signal x (t) can be compressed to x (2t). Here the scaling factor α is ½.The figure (2.1) depicts the time compression of the signal x (t), where the amplitude has reduced from 4 to 2, keeping the y–axis constant.

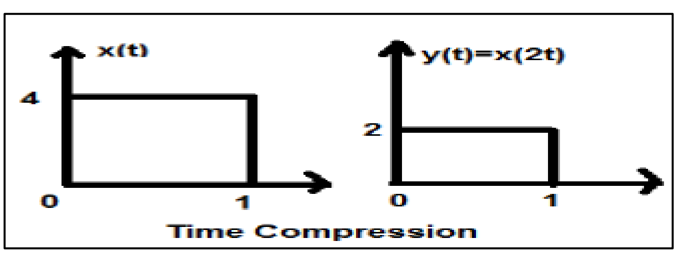


Fig.2.1: Time Compression [21]

- **Time Expansion**

If the time is divided by the scaling factor α then the magnitude of the signal in the y–axis gets multiplied by the value of α. This phenomenon is known as time expansion of the signal. In the above signal y (t) = x (t), if the value of α is 3, then after scaling, the expanded signal becomes y (t) = x (t/3). From the figure (2.2), it is clear that the amplitude of the signal is expanded by 3 times.

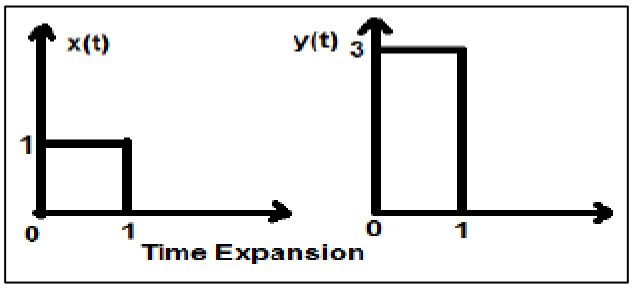


Fig. 2.2: Time Expansion [22]

2.1.7 Relationship between Scaling and Frequency in Wavelet Analysis

Frequency and scaling factor shares an inverse relationship. In case of Wavelet Analysis, a term called Centre Frequency is used which gives the concept of relationship between scaling and frequency [23].

The relation between frequencies, scaling factor and centre frequency is given in equation (3).

$Fa=Fc/\alpha$ ----- [eq. 3]

where,

Fa = Frequency

Fc = Centre Frequency

α = Scaling Factor

For a specified wavelet type, Fc computes the centre frequency. It is clear from the above equation that there is an inverse proportionality between frequency and scaling factor. As the scaling factor increases, the wavelet becomes more spread out resulting in lower frequencies. The centre frequency actually finds out the main frequency component in the wavelet.

The figure 2.3 shows how the centre frequency denoted by red colour captures the main wavelet oscillation or frequency given in blue colour.

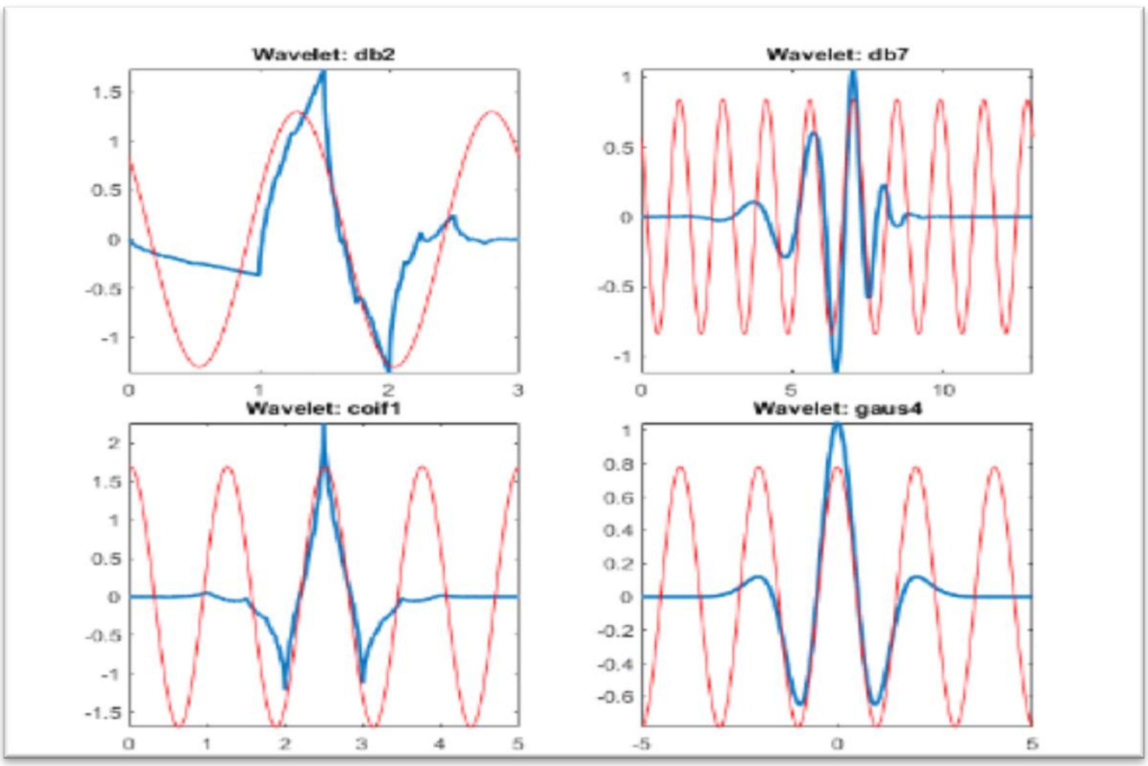


Fig.2.3: The centre frequency denoted by red colour captures the main wavelet oscillation or frequency given in blue colour [24]

Thus the increased values or higher values of scaling are related to the expanded wavelets and low frequency regions for finding out the coarser changes in the signal.

The lower values or the decreased values of the scaling factor are related to compressed wavelets and high frequency regions for finding out the rapid changes in the signal.

2.1.8 Scaling Function in Wavelet Analysis

The scale space ranges from 0 to infinity $0 < s < \infty$.This scale is required to be separated for the purpose of analysis and interpretation. "s" signifies the scale space. The scale of the mother wave corresponds to the value of $s = 1$. The two separations made from the scale space are $0 < s \leq 1$ and $1 \leq s < \infty$. The value 1 is present in both the separations as it denotes the scale of mother wave. Using the whole range of the space scale signifies the using of the total frequency range from the lowest frequency to the highest frequency considering the cut off frequency (ωc). The function of the cut off frequency is to separate between low and high frequencies. In the same manner, the scale s separates the space into detail and approximate space. The space between scales = 0 to s = 1 is treated as detail space and the space between $s > 1$ to $s = \infty$ is treated as approximate space.

2.1.9 Wavelet Theory

Wavelet is nothing but a waveform of limited duration having an average value of zero [25].

It is defined by equation 4.

$\varphi_{a,b}(t) = 1/\sqrt{a}\ \varphi((t-b)/a)$ ----- [eq. 4]

where,

a,b € R

a = Scale or Dilation Parameter

b = Position or Translation Parameter

'a' helps in stretching or compressing the wavelet while 'b' slide the wavelet along the time axis.

In case of Fourier Transform, all waveforms are transformed into harmonics of sine or cosine functions of different frequencies and in case of Wavelet Transform a waveform is converted into wavelets of different positions and scales.

Wavelet Transform is of two types:-

- Continuous Wavelet Transform (CWT)
- Discrete Wavelet Transform (DWT)

2.1.10 Continuous Wavelet Transform

CWT of a signal f (t) is given by equation 5 [26].

$CWT\ (a,b) = < f, \varphi a, b > = 1/\sqrt{a} \int f\ (t). \varphi((t-b)/a)dt$ ----- [eq. 5]

where,

$$< f, \varphi a, b > is\ the\ square\ integral\ inner\ product$$

By changing the values of 'a' and 'b', different wavelet coefficients are obtained.

With larger values of the scale parameter, 'a', the function $\varphi a, b$becomes a stretched form of the mother wavelet. This is very much essential for analysing the low frequency components present in the signal. If the value of scale parameter 'a' is small then the function $\varphi a, b$ is compressed which is useful for estimating the high frequency components present in the signal. The shape of the function $\varphi a, b$ will remain the same. Continuous wavelet transform generates wavelet coefficients that are position and scale dependent.

Scalogram of CWT

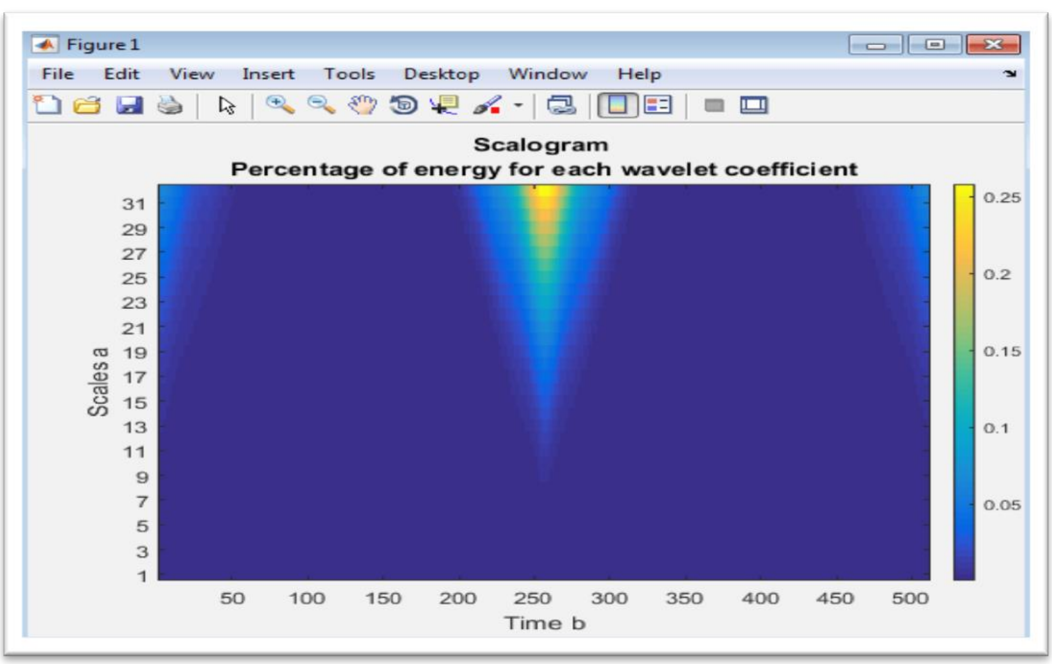


Fig. 2.4 Scalogram of CWT [27]

The scalogram of CWT is shown in figure 2.4. It is evident from the figure that at lower scale, fast varying components or high frequency components are captured. Fine frequency components are obtained. At higher scale, slow varying components or low frequency components are captured.

2.1.11 Discrete Wavelet Transform

In case of CWT, wavelet coefficients are calculated at every possible scale. It is tedious and produces a lot of data. But if the values of scales and positions are chosen to be discrete then the analysis will made be easier and generate huge data [28].

DWT can be expressed mathematically as equation 6.

$\varphi m, n\ (k) = a0^{\wedge(-m}/2)\varphi\ (a0^{m}(k - nb0a0\wedge m))$ ---- [eq. 6]

where,

m,n € Z

This can be achieved in two ways:-

- Redundant Wavelet Transform (Frames)
- Multi Resolution Analysis (MRA)

Redundant Wavelet Transform

$a = ao\wedge m$------ [eq.7]

where,

$a_0 > 1$and always have a fixed value

The scale parameter ‘a’ = an integer of one fixed dilation parameter

Values of ‘m’ vary which corresponds to different widths of wavelets.

The position parameter $b = nb_0a_o^m$ ---- [eq. 8]

where,

$b_0 > 0$ and always fixed value

n € Z

Narrow wavelets are shifted by small steps and larger wavelets are shifted by larger steps and wider wavelets are shifted by larger steps.

Multi Resolution Analysis

It is a more efficient method than redundant wavelet transform. It is widely used form of DWT. This method is known as Dyadic scales and positions as the values of scales and positions are based on the powers of 2. In this method, reduction of the amount of data is done by down sampling.

If the values of a_0 = 2 and b_0 = 1are chosen then from equation 6, MRA equation can be derived as shown in equation 9.

$\varphi m, n\ (k) = \ 2\ \text{^}(-\frac{m}{2})\varphi\ (2^{-m}(k - n))$ ----- [eq. 9]

Scalogram of DWT

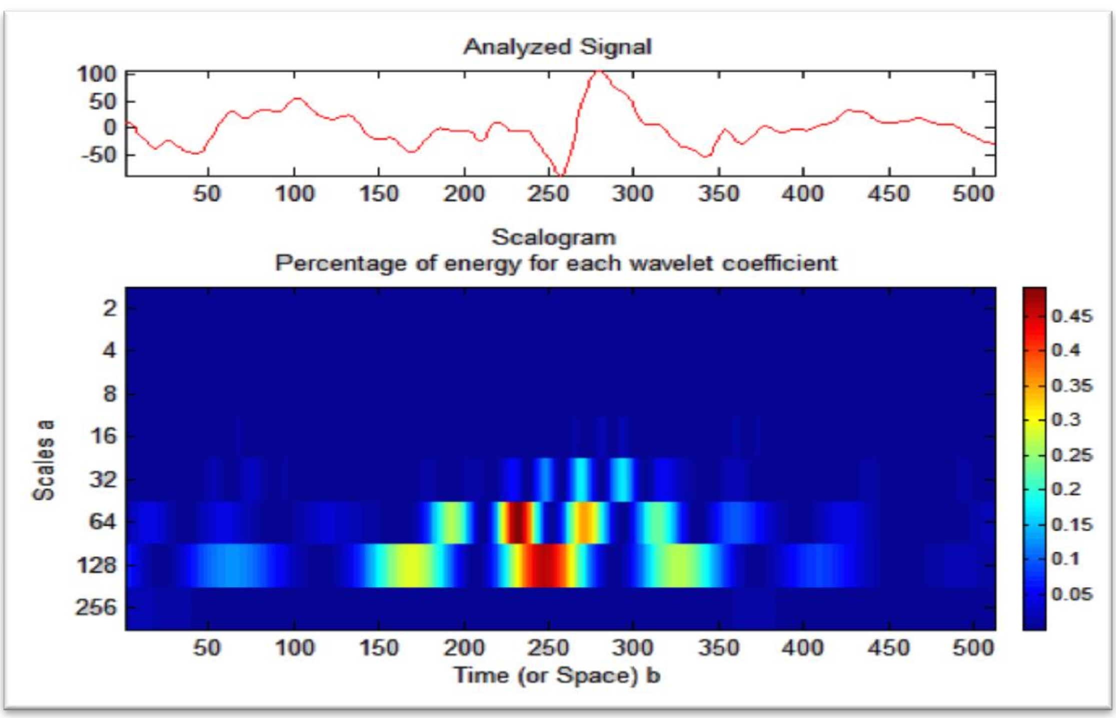


Fig. 2.5: Scalogram of DWT [29]

Figure 2.5 shows the scalogram of discrete wavelet transform. At lower scales the original signal is compressed and consists of high frequency components but at higher scales, the signal is stretched containing the frequency components.

Comparing the scalogram of DWT in figure 2.5 with CWT in figure 2.4, it can be observed that in case of CWT a smooth view of scalogram is obtained while in case of DWT a discrete view of scalogram is obtained as the scale and parameter values are discrete.

2.1.12 Wavelet Decomposition

The wavelet decomposition of a signal is mainly based on multi resolution theory using digital filters like high pass filter and low pass filter.

Wavelet Decomposition of a signal can be done in two different ways. These are:-

- One Level Decomposition
- Multi Level Decomposition

One Level Decomposition

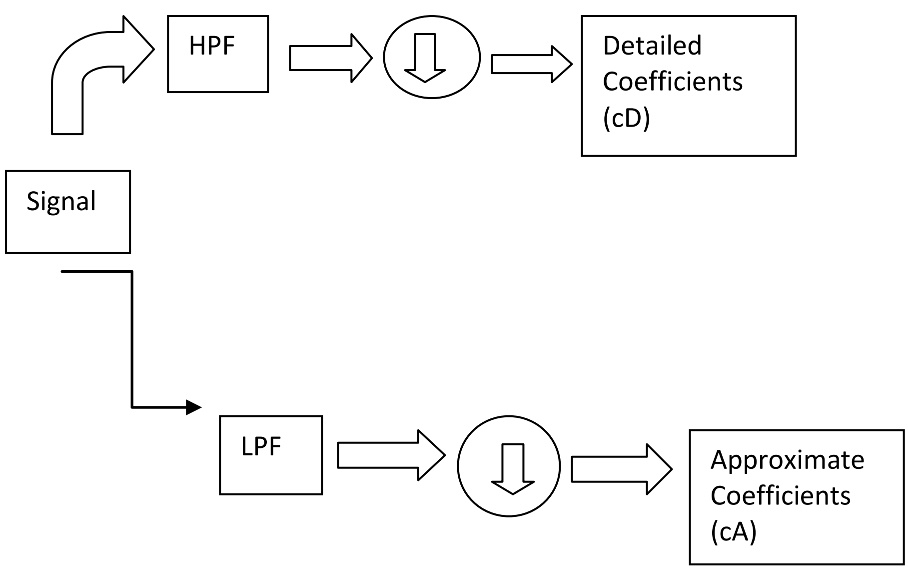


Fig. 2.6 One level decomposition

Figure 2.6 shows one level wavelet decomposition of signal.

Suppose the signal is s(t) contains 1000 points. In the first stage, it is passed through two filters – HPF and LPF. The signal from the output of HPF is labelled as $s(t_1)$ and the signal from the output of LPF is labelled as s(t2). Both $s(t_1)$ and $s(t_2)$ are down sampled by 2, that is the original number of points are halved as followed by MRA. After down sampling of $s(t_1)$, it contains 500 points which are the high frequency components present in the signal s(t).These are known as detailed coefficients (cD). After down sampling of $s(t_2)$, it also contains 500 points which are the low frequency components present in the signal s(t).These are known as approximate coefficients (cA).

Multi Level Decomposition

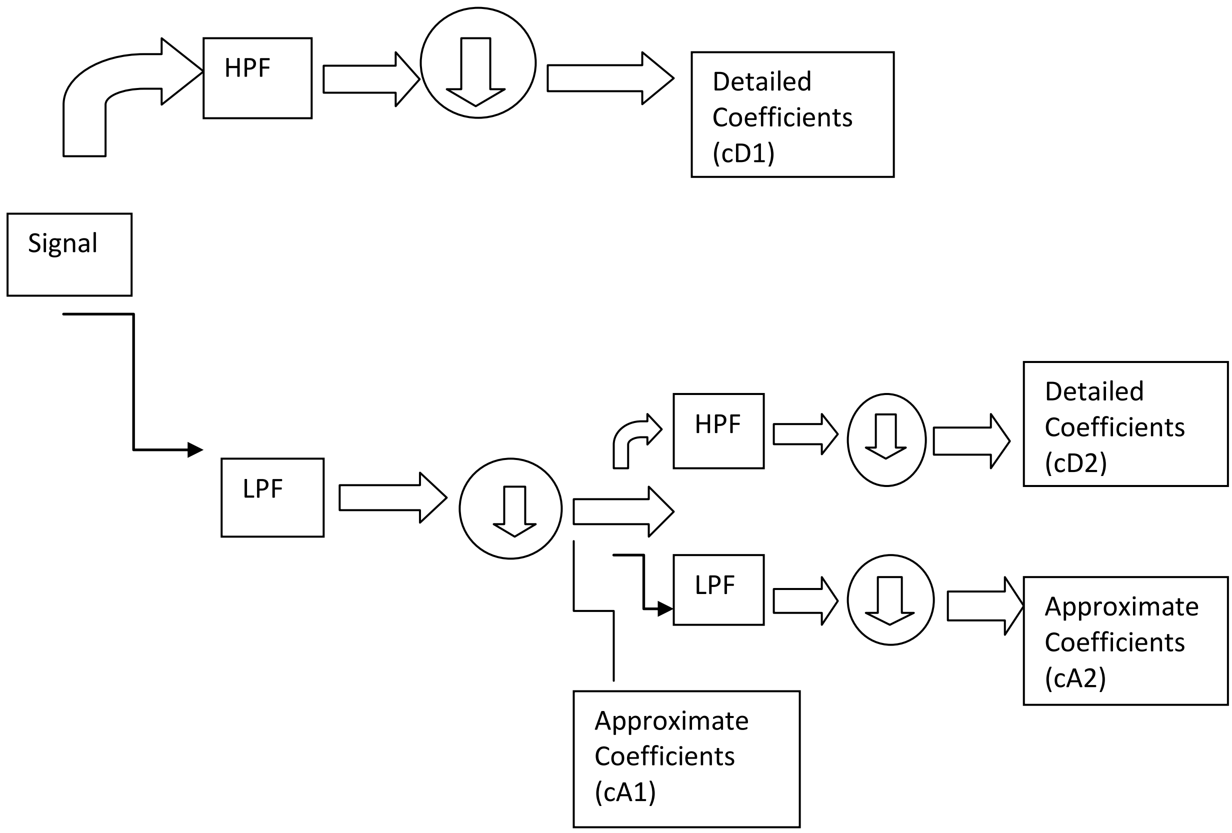


Fig. 2.7 Multi Level Decomposition

Figure 2.7 shows the multi level wavelet decomposition method. This type of decomposition is same as the previous one only the number of stages is more. In this method, the approximate coefficients of first stage are again decomposed in the next stage and the process continues. Maximum number of decomposition levels followed in this method is calculated by the formulalog N. The base of this logarithmic function is taken as 2 following the MRA technique.

From figure 2.7,

cD1 = Detailed Coefficients in Stage 1

cA1 = Approximate Coefficients in Stage 1

cD2 = Detailed Coefficients in Stage 2

cA2 = Approximate Coefficients in Stage 2

This form of wavelet decomposition using multi stages gives a wavelet transform tree.

2.1.13 Inverse Discrete Wavelet Transform (IDWT)

IDWT is required to reconstruct the original signal after decomposing the signal.

This is done in two ways. Which method is to be followed is dependent on the type of decomposition level used.

One Level Reconstruction

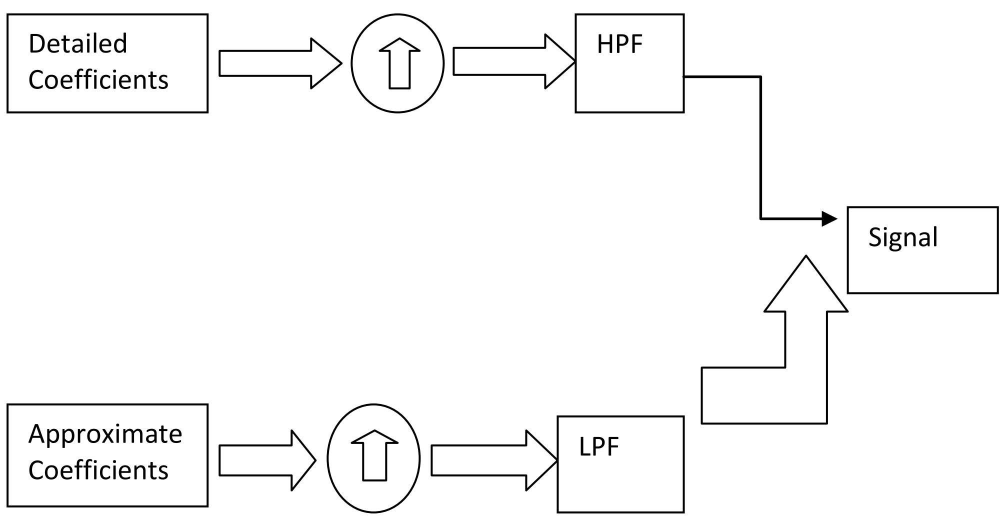


Fig.2.8 One Level Reconstruction

Figure 2.8 shows one level reconstruction. This method is only followed if signal is decomposed in 1 level. The up sampling of the signal should be done by the same value as the original signal was down sampled during decomposition. The HPF and the LPF here are known as reconstruction HPF and reconstruction LPF respectively.

Multi Level Reconstruction

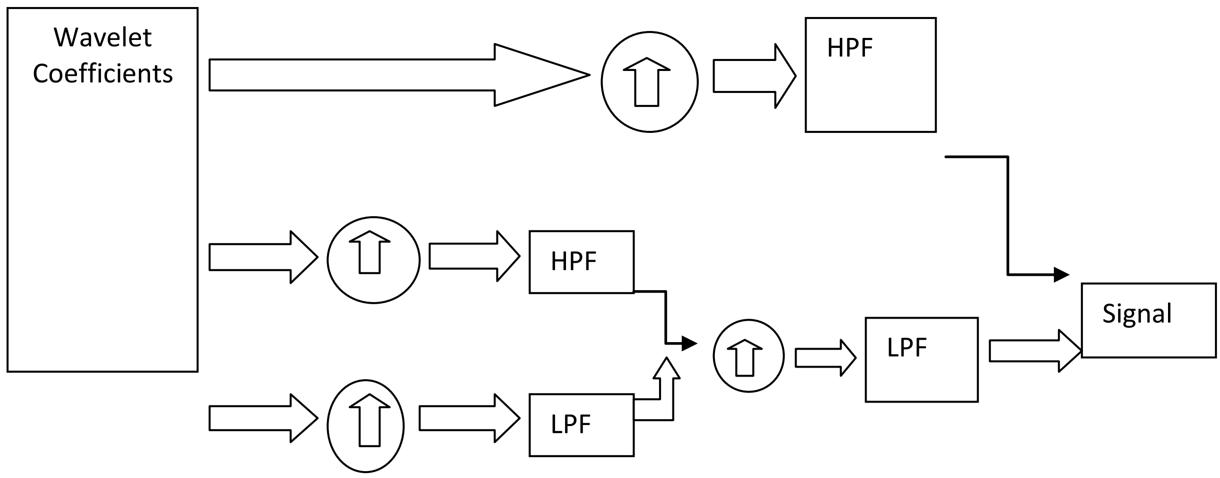


Fig. 2.9 Multi Level Reconstruction

Figure 2.9 shows the multi level reconstruction of the decomposed signal. This method is used only when decomposing of the original signal is done by multi level decomposition.

2.1.14 Types of Wavelets

There are different types of wavelets. The names of the types are mentioned below [30].

- Haar
- Daubechies
- Symlets
- Coiflets
- Bi–orthogonal
- Meyer
- Discrete Meyer
- Balttle &Lemarie
- Gaussian
- Mexican Hat
- Morlet
- Complex Gaussian

- Complex Shannon
- Complex B–spline Frequency
- Complex Morlet

The figure 2.10 shows some of the wavelet patterns.

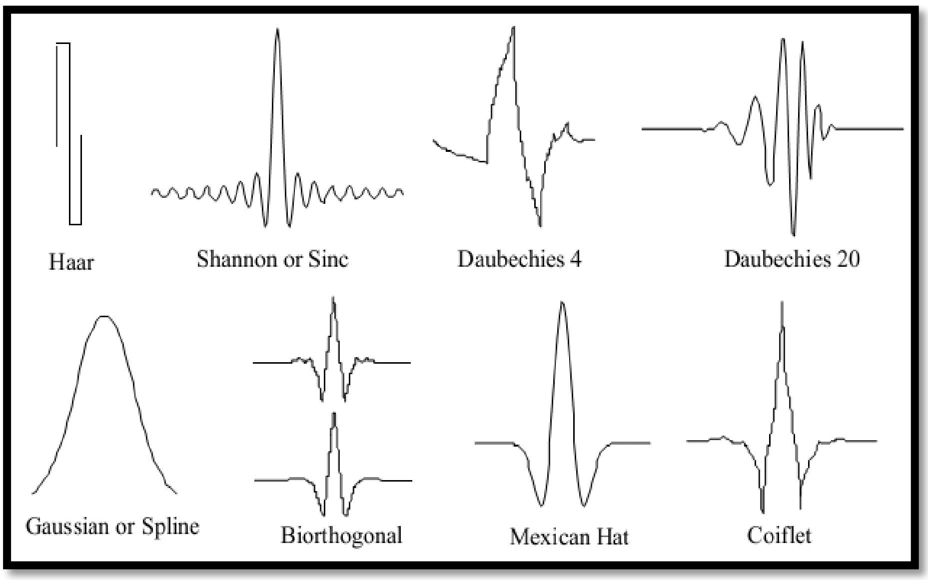


Fig. 2.10 Wavelet Patterns [31]

2.1.15 Applications of Wavelet Transform

Wavelet transforms have immense application in signal and image processing.

Application in Signal Processing

- Compression
- De–noising
- Discontinuity Detection
- Audio Enhancements and Effects

Application in Image Processing

- Compression
- De–noising
- Edge detection
- Image Fusion
- Image Enhancement

Other Application of Wavelet Transform

- Audio, Video, Image Watermarking
- Feature Extraction
- Face Recognition
- Optical Character Recognition
- Image Retrieval
- Data Analysis and Prediction
- Voice Recognition
- Numerical Analysis

2.2 Analysis of Non-linear Features

2.2.1 Fractal Geometry

The classical geometry or Euclidean concept of geometry deals with the objects created by mankind by applying the common theorems and concepts like Pythagoras' theorem, surface area, volume, perimeter, circumference, etc. This conventional method of geometry is applicable to only regular objects which can be drawn on plane surfaces. Such objects are lines, curves, points, square, rhombus, rectangle, parallelogram, sphere, cone, etc. The regular objects may be one–dimensional, two–dimensional, and three–dimensional and so on. The dimensions of regular objects have integer values. So, finding any feature of such shapes are easy. But in real world, nature consists of rough objects. Thus another type of objects is present other than the regular objects which are known as the irregular objects. Such objects cannot be drawn on plane surfaces and the dimension of such objects does not have an integer value. If we take the example of cloud, waterfalls, mountains, hills, lighting, etc, these do not have a proper integral dimension. Such as lighting doe not propagate in a linear path, the dimension of cloud cannot be considered as spherical, mountains and hills do not fall under the category of symmetrical cones [32]. As these objects do not contain a proper integer valued dimension, so, extracting features of such objects is quite impossible by applying the Euclidean concept. But extracting features of these objects are a must. This led to the emergence of the concept of fractal geometry. With the help of fractal geometry concept solving the features of irregular and rough surfaces can be done mathematically. Instead of dealing with regular objects having proper integral dimension, fractal concept of geometry deals with fractured or broken surfaces and objects present in the nature.

2.2.2 Fractals

The fragmented or fractured or broken or rough geometric shapes that can be further sub divided into smaller fragments where each fragment is a similar copy of the complete object are known as fractals. Fractal dimension is often a non–integer value. Fractals are measured only with the help of fractal dimension value. The degree of irregularity or fragmentation over multiple scales is known as fractal boundary which is determined with the concept of fractal dimension.

2.2.3 Features of Fractals

The fractals have two distinguishing features which are self–similarity and non–integer dimension.

If we carefully look at a leaf of a tree, then we will observe that each little portion of the leaf is similar to the whole leaf. That is we a fragment is teared out from the leaf then it will have the same features and same shape as that of the complete leaf. So we can conclude that the leaf is self–similar in nature. This same concept is applied to the fractals or fractured objects. If the fragmented portion is magnified numerous times, then after each step, the same shape of the fragment with the original object will be observed which proves the self–similar feature of the fractals [33].

Another feature of the fractals is the non–integer dimension value of the fragmented objects. This is complicated to explain. In the concept of conventional geometry, the regular objects have integer valued dimension like point having zero–dimension, lines and curves having one–dimensions, circles, rectangles, squares having two–dimension, spheres, cubes having three–dimension and so on. But in nature, there are various objects which are rough having dimension between two integer values. Hills do not have a regular surface so it belongs to the category of fractals and the dimension of this falls between two and three. Hence if a surface consists of large hills with small mounds then it will have second dimension and a surface consisting of many small mounds then it falls under third dimension.

2.2.4 Fractal Dimension with Euclidean Concept

A set of fractals can be defined as

$Nn = c/mD$ ------------------ (eq. 10)

Where N_n denotes the number of broken portions having a dimension which is linear in nature
m is the linear dimension
D is the dimension of the fractal
C is the constant

By applying simple concept of algebra to the equation 10, the above equation can be represented as

$D = ln(N_n + 1/N_n)/ ln(m/m+1)$ ------------------------- (eq.11)

Suppose a line of unit length is divided into many segments. Let the line is segmented into two parts. The segments are labelled as r_1 and r_2 where r is the segmentation length. r_1 = ½ and r_2 = ½. One of the lengths is taken and the other is discarded. Let the length r_1 is taken. So, now the value of N_1 = 1. The r_1 segment is further subdivided into two segments r_3 and r_4, where the r_3 segment is considered while the r_4 segment is discarded. Now the value of r_3 =1/4.So, the value of N_2 = 1. This is following an iterative process and upon multiple divisions of the segments the value of D turns out to be zero. This signifies that the fractal dimension is having value zero which is similar to the point in Euclidean concept. The main criteria for D to be zero is that irrespective of the number of iterations, the value of N_n = 1 in all cases. Thus if a line segment is continuously divided and only one part is kept, then the length of the segment will become zero as the order tends to infinity.

Let a line and divide it into two segments. In this case we consider both the segments. Here r_1 = ½ and N_1 = 2. If it is further divided, then r_2 = ½ and N_2 = 4. So D = ln(2) / ln (2) = 1. Thus the dimension is one.

Now we will discuss about a fractal dimension of line that lies between 0 and 1. Suppose a line is divided into three segments. We keep only the two end parts and discard the remaining part. After first division, the values of r_1 = 1/3 and N_1 = 2. After dividing it further the values of r_2 = 1/9 and N_2 = 4. Now calculating the value of D = ln(2) / ln(3) = 0.6309. Thus the dimension of such line segment lies between zero and one.

If again the line is divided into five parts and only the terminal two portions along with the central portion is kept then r1 =1/5 and N_1 = 3. Again if further segmentation occurs by following the previous method, then r2 = 1/25 and N_2 = 9. The value of D will be ln(3) / ln (5) = 0.6826. Thus in this case also the fractal dimension lies between zero and one irrespective of the number of fragments. But fractal dimension value is not only restricted between zero and one. The fractal dimension of a square lies between zero and two.

2.2.5 Fractal Dimension Concept in the field of Bio–medical Engineering

Fractal dimensional analysis has proved its application in the field of healthcare. If we carefully inspect the various physiological systems in the human body, then we will observe some patterns which are similar to the fractals. Previously Euclidean concept was used for observing various characteristics of physiological signals as these were represented by conventional geometry. But later it was observed that everything cannot be explained in this manner. With the advancement of fractal geometry, explanation of various physiological signals became easier.

Previously it was thought that the beating of the human heart is in a linear regular manner but with the advancement of fractal dimension, it is observed that there is a fluctuation pattern in the beating of the heart and this patter is similar to the fractal pattern. The nature of blood flow is fractal. Fractal parameters of blood are observed using ultrasound imaging. Detecting the cancer cells quickly is done by estimating the fractal nature of blood flow with use of mathematical tools. This is quite helpful in the field of healthcare as instead of using fine medical instruments, advanced machineries and microscopes only mathematics and fractal dimension is used to diagnose cancerous cell growths.

Another use of fractal dimension is evaluating the brain signals. The structure of the brain is complex in nature and EEG signal is used to measure it. Fractal dimension provides a quantitative description of this complexity of the EEG signal. The detail of the use of fractal dimension analysis in EEG signal is given in the next section.

2.2.6 Higuchi's Fractal Dimension

Human brain is a complex structure. The signals produced from the human brain are non–linear and non–stationary in nature. To get a wide amount of information about the signals of human brain, these signals are processed with non–linear signal processing techniques. Evaluating the fractal dimension of human brain is such an approach. Estimating the fractal dimension by Higuchi's method has proved to be the most efficient method among the other algorithms used for fractal dimension analysis like R–S, Katz. In this approach the complexity of the signal is measured with period of time. Since its discovery HFD is used in various fields for estimating the fractal dimensions. HFD is applied for analysis of bio-signals, magneto-encephalogram signals, and fMRI data. Also, it can be used for analyzing different stages of sleep, cognition, anaesthesia, epilepsy, and Alzheimer's.

2.2.7 Mathematical Explanation of Higuchi's Fractal Dimension

In HFD method a given time series X(t) is converted into a new time series , X_k^m; Where X_k^m is X(m), X(m + k), X(m + 2k),……. X(m + [(N - m)/ k]k) (m = 1,2,3,…k) [34]

Here [(N- m)/k] denotes Gauss's notation, m and k are integers, which indicates the initial time and interval time respectively. [6]

Therefore for a time interval, any k, we get k sets of new time series.

The following equation-1 gives the length of the curve formed by X_k^m.

$$L_m(k) = \{\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} |X(m+ik) - X(m+(i-1)k)|\right)(N-1)/\left[\frac{N-m}{k}\right]k\} / k \text{-------- (eq. 12)}$$

The normalized factor for curve length of subset time series is represented by the term $[(N-k)/\left[\frac{N-m}{k}\right] k]$. [7]

Now, the length of the curve for the time interval k is calculated as the average value of k sets of $L_m(k)$ given $<L_m(k)>$. Now if the curve is the curve of factor then it will follow the relation given in equation in 13

$<L_m(k)> \alpha K^{-D}$ [8] ------- (eq.13)

The fractal dimension derived by Higuchi's approach, often known as Higuchi's fractal dimension, is represented by the exponent D.

The K_{max} value is to be selected correctly for finding the accurate result of HFD. The best way to find the appropriate value of K_{max}, is by looking at which point the saturation point comes in the graph. That value is considered as K_{max}.

2.3 Machine Learning

2.3.1 Use of Machine Learning Classifiers

Machine Learning (ML) is a field of study in artificial intelligence where computers can learn or can be trained without the usage of complicated programming codes. In simple terms, Machine Learning is an automated tool which improvises the learning process of computers without the usage of complex coding that is the actual intervention of human beings. Machines especially computers can perform this based on training or experiences from training data [35]. The approach followed in machine learning is by using large set of data and then training the computers by building suitable machine learning model. The machine learning consists of various algorithms. The choice of algorithm depends on the underlying data type and the work to be performed. So, choosing an appropriate machine learning algorithm is of crucial importance.

Machine Learning has found great importance in various fields of research like healthcare. It is useful in detecting various critical diseases like cancer. Previously by looking at the cell images, doctors had to detect whether there is any cancerous growth. This used to take a lot of time and in case of such life threatening disease timely diagnosis of the patient is of utmost importance. With the advancement of machine learning, detecting cancer has become simpler for the doctors. The procedure used in machine learning approach for detecting cancer is very simple. The requisites for this are a high computation computer (machine), a huge quantity of image data (the quality of the image data should have to be good), building a suitable machine learning model with appropriate machine learning algorithm. This will generate an accurate result and doctors just have to make an assurance call.

2.3.2 Types of Machine Learning Model Approach

There are two different approaches for building a machine learning model. These two approaches are:-

- Supervised Learning
- Unsupervised Learning

Supervised Learning

From the name "Supervised Learning", it is easily understandable that this type of machine learning takes place in presence of a supervisor. In this type of learning, the data provided to the machine contains labels. The machine is trained according to that labelled data. The labels indicate correct answer for the data [36]. After training the machine with the labelled trained data, a new set of data (test data) is provided to the machine. The machine then produces correct answer for the test data by applying the training of the labelled data. Thus in this method of learning the machine learns from the labelled data [37].

Suppose a basket containing different fruits is given. For using supervised learning method, the below steps are followed:-

Suppose the example is training the machine with different fruits present in the basket one by one. The training should be done in the following manner.

- If the shape of the item is round and the colour is yellow, then it is labelled as lemon.
- If the shape of the item is cylindrical and the end part is curved having colour either green or yellow then it is labelled as banana.

After training the machine with the above mentioned labelled data, a test item is given and the machine is asked to identify that item. Suppose the given test item is a lemon.

As the machine has already learned from the trained labelled data, it will use it to identify the test item. Firstly the machine will classify the test item based on its colour and shape and then it will confirm the name of the test item and put it in the category of lemon. Thus by learning from the trained data, the machine applies its gathered knowledge to the test data.

Supervised learning is divided into following types [38].

- Classification
- Regression
- Logistic Regression
- Naive Bayes Classifiers
- K–NN (k nearest neighbours)
- Support Vector Machine
- Decision Tree

Advantages of Supervised Learning

- Learns from trained data and the output of the test data is produced from the previous knowledge.
- Optimizes performance with the use of previous experience.
- Is useful in solving various real world computation problems.

Disadvantages of Supervised Learning

- Training of data requires a lot of time. So computation time is high.

2.3.3 Logistic Regression

Logistic Regression (LR) is a type of ML algorithm. It belongs to the class of supervised learning that means it has labelled data associated with it. It consists of two categories of variables - dependent variables and independent variables. In this type of machine learning algorithm, the value of the dependent variable is predicted accurately by learning from the independent variable. The independent variable is also known as the target variable [39].

Suppose an image of a tumour is given to the machine. The tumour has various features. The features are associated with labels malignant and benign. The machine learns from the features along with their labels and when a test sample (image of another tumour) is given to the machine, it will predict whether it is malignant or benign. Here the dependent variable is the test tumour and the independent variable is the tumour image given during the training set.

As logistic regression is a supervised learning, labelled data is provided to the machine (computers) for the training purpose. The benefit of such labelled data is that answers are provided with the features. These features and their corresponding answers are learnt by the machine efficiently and are applied to detect the outcome from the test data.

On the basis of classification done by logistic regression, it is divided into three types:-

- Binary
- Multinomial
- Ordinal

Table 2.2: Binary vs Multinomial Regression

Binary	Multinomial
Target Variable is associated with two possible outcomes.	Target Variable is associated with three or more possible outcomes
Example: Condition of a tumour can be malignant or benign.	Example: Image of a chest x–ray can detect four possibilities of the condition of the lungs like not diseased, affected by SARS COV-2, affected by tuberculosis and affected by pneumonia.

Ordinal Logistic Regression consists of target value is associated with a category having quantitative importance. Example: The grades of a student in a specific subject can be A, B, C, D, E and F. Each of these grades has its own significance.

2.3.4 Logistic Regression Vs Linear Regression

Table 2.3: Difference between Logistic and Linear Regression

Logistic Regression	Linear Regression
Used for classification.	Used for regression.
Independent Variables have continuous values.	Independent Variables have discrete values.
Example: Age of a person.	Example: Condition of a tumour to be benign and malignant.

2.3.5 Support Vector Machine

Support Vector Machine (SVM) is a simple ML algorithm. It is a type of supervised learning. Although it is applicable for classification and regression but it is mainly used for classification related problems. Since SVM uses less computation time and produce result with a high rate of accuracy, so, it is used for solving different types of classification problems. SVM deals with two fundamental concepts – Hyperplane and Support Vectors [40].

Hyperplanes

These help in classifying the data points so they are known as decision boundaries. As the name suggests, hyperplane can be imagined as a plane surface or a line and the data points fall on either side of this plane. The data points falling on either side of the hyperplane belong to different classes. As SVM is a type of supervised learning, it consists of both features and labels. The features are useful for determining the dimension of the above mentioned hyperplane. If the dataset contains two features, then the hyperplane is just a line and if the hyperplane contains three features, then it is considered as a two–dimensional plane surface. If the number of features is greater than three then it is hard to imagine about the structure of the hyperplane.

To separate the classes of the data points, the choice of the hyperplane varies. The main objective used in SVM is that there should be maximum distance between the support vectors of the different classes. This will be done by choosing a hyperplane having maximum margin. The main motive of the SVM algorithm is selection of the hyperplane. The hyperplane chosen should be such that it segregates the N–dimensional space into classes and new or test data points are put in the correct category.

Support Vectors

Data points are regarded as support vectors. Theses support vectors lie closer to the hyperplane regardless of the number of features. These support vectors are also known as extreme points. The orientation and placement of the hyperplane is determined by these support vectors. The classifier margin is enhanced by these support vectors and if the support vectors are reduced, then the placement of the hyperplane varies. Margin is the distance between the hyperplane and the vectors. The margin needs to be enhanced. Optimal hyperplane is the hyperplane with largest margin. As this machine learning algorithm is based on support vectors so this algorithm is known as Support Vector Machine.

Figure 2.11 shows the hyperplane and support vectors of SVM.

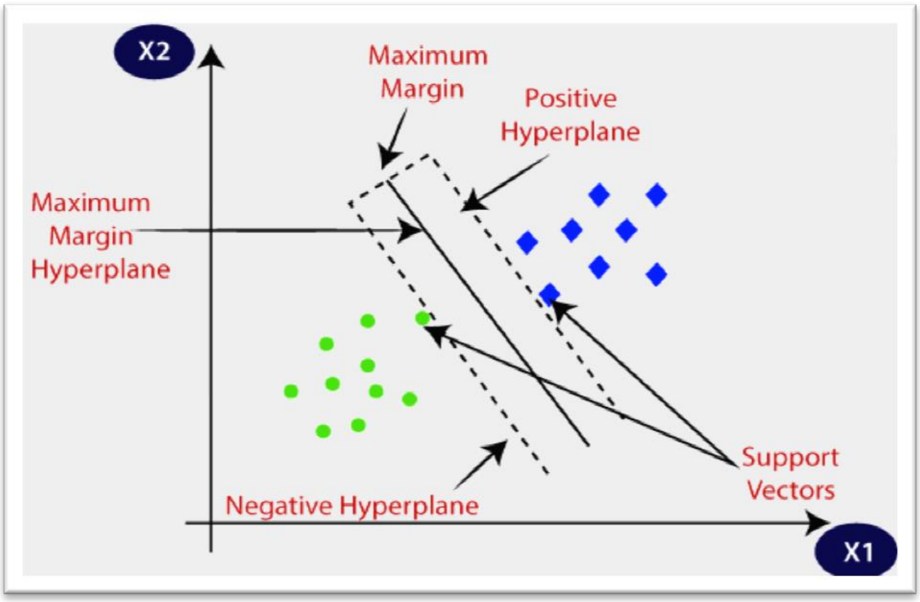


Fig. 2.11: Hyperplane and Support Vectors in SVM [41]

Suppose there are images of two fruits orange and lemon. Some of the features of these two are same like both of them are circular in shape. So, a model should be created such that the machine can correctly identify whether the image is of a cat or a dog. Such a model can be created by SVM algorithm. Firstly the model will be given various images of oranges and lemons. Using those images the machine will be trained. The machine will learn from the various features of oranges and lemons and will build a hyperplane or boundary line between the data points that is the oranges and lemons and choose extreme cases of these two classes. With the help of the support vectors, the machine will easily identify a test sample as an orange or lemon.

2.3.6 Types of Support Vector Machine

On the basis of classifying the data with the help of a straight line, SVM can be classified into two categories [42].

- Linear Support Vector Machine – When the dataset imported into the machine can be separated into two types of classes with the help of a one linear plane or straight line. Such data are known as linearly separable data. For classifying such type of data the classifier used is known as Linear SVM.

- Non Linear Support Vector Machine – When the dataset imported into the machine cannot be separated with the help of a straight line then it is known as non linear data. The classifier used for classifying such data is known as Non Linear SVM.

2.3.7 Unsupervised Learning

In this type of learning, the machine is trained with data which are not labelled, that is no guidance is provided to the machine while training. The machine trains itself according to some similarities or differences in pattern of the given data [43].

Suppose the machine is given an image containing two types of fruits such as lemon and banana which it had never seen before.

So, it has no previous idea of the features (shape and colour) of the fruits. It will train itself based on the similarities and differences of the patterns of the various fruits. The machine will classify the image into two parts. One part will contain the images of only lemons and the other part will contain the images of bananas. This categorisation is done based on the colour and shape of the two fruits. Thus no means of supervising was provided beforehand the machine had to train itself by self paced learning.

2.3.8 Differences between Supervised Learning and Unsupervised Learning

Table 2.4 Differences between Supervised and Unsupervised Learning [44]

Supervised	Unsupervised
The machine is trained using labelled data.	No labelled data is provided for training.
Computational method is simple.	Computational method is complex.
The accuracy rate of the test result is high.	The accuracy rate of the test result is high.

2.3.9 Working Model of Machine Learning

- Importing large data sets.
- The quality of the data should be in proper condition for accurate processing.
- Classifying the data into features and labels.
- Splitting the data into training and test sets.
- Building a model with suitable machine learning algorithm like Logistic Regression, Support Vector Machine.
- Feed appropriate amount of data into training model.
- Train the data with the chosen model.
- Use the remaining data for testing the accuracy of the chosen model with parameters like precision, recall and F1 score.

Figure 2.12 represents the block diagram of the working principle of machine learning.

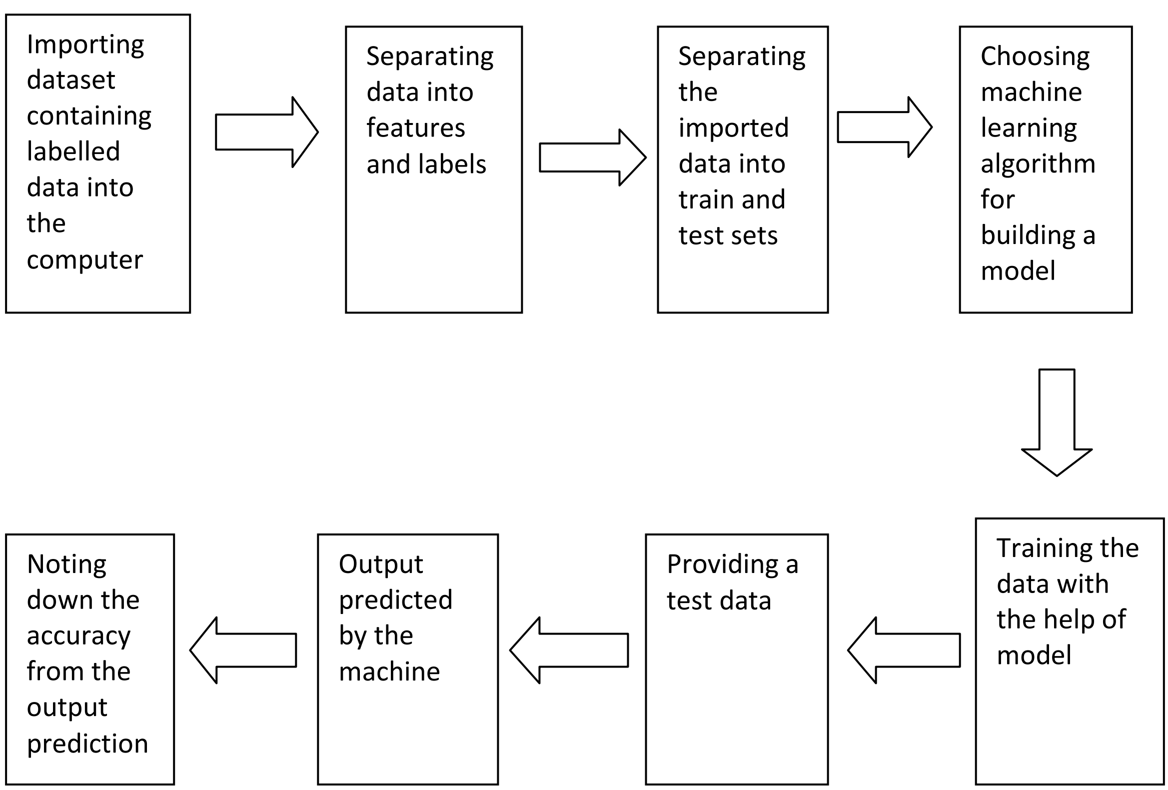


Fig.2.12 Working Principle of Machine Learning

2.3.10 Confusion Matrix

The accuracy of the machine learning model built is checked with the help of the output of the test data predicted by the machine. The matrix used for checking the accuracy is known as confusion matrix. Such accuracy can only be tested if the real or true values of the test data are known beforehand. This matrix is also termed as error matrix as it represents the error values also inside the matrix. The error values are the errors in the performance of the underlying model [45].

The characteristics of the confusion matrix are given below:-

- The dimension of the matrix is based upon the number of classes present in the classifier.
- The matrix consists of total number of predictions, predicted values and actual values.
- Predicted values are the values predicted by the machine and the actual values are the true values of the observations.

This is shown in table 2.5.

Table 2.5: Confusion Matrix

Total Number of Predictions	**Actual Value – No**	**Actual Value - Yes**
Predicted Value - No	True Negative (TN)	False Positive (FP)
Predicted Value - Yes	False Negative (FN)	True Positive (TP)

True Negative Values are obtained when the model has predicted No and the actual value of the observation is No.
True Positive Values are obtained when the predicted value is Yes and the true value is No.
False Negative Values are obtained when the model has predicted value No but the true value is Yes.
False Positive Values are obtained when the model has predicted value is Yes and the true value is No.

The factors determining the accuracy from the confusion matrix are given below:-

Classification Accuracy = It is the ratio of correct predictions to the total number of predictions.

(TP + TN) / (TP + FP + FN + TN)

Error Rate =It is the ratio of incorrect predictions to the total number of predictions.

(FP + FN) / (TP + FP + FN + TN)

Precision = It is the ratio of the true positive or correct value out of all the positive values.

TP / (TP + FP)

Recall = It is the ratio of correct values to the total number of true positive and false negative values.

TP / (TP + FN)

F–measure – While comparing two underlying models if the both the precision values are low and recall values are high or vice–versa, then the comparison becomes difficult. In such cases the F–measure value is considered as it evaluates the recall and precision simultaneously. The maximum value of this is obtained when the recall value is equal to the precision value.

F–measure = (2 + Recall + Precision) / (Recall + Precision)

2.3.11 Cross Validation

There is always a necessity to check the functionality of the designed machine learning model. The train/test split works efficiently in this regards but there is further more need of the checking of the model to get a better accuracy of the working of the model designed. For this the cross validation is used. It is slightly different from the normal train/test split.

The cross validation consists of three stages:-

- A subset is reserved as validation set.
- The model is trained with the help of training dataset.
- With the help of validation set, the performance of the underlying model is determined.

- If the accuracy of the model is good with the validation set, then the test data can be given to the model and if the accuracy of the model is not up to the mark, then the model should be further checked.

2.3.12 Methods for Cross Validation

There are various methods of cross validation [46]. These are:-

- Validation Set
- Leave P - out
- Leave one - out
- K - fold
- Stratified K - fold
- Holdout

➢ **Validation Set**

The input dataset is divided into training and validation set. These two subsets are equally paced that is both contain 50% of the data present in the dataset.
As only 50% of the data of the dataset is used for training the model, so, there is a chance of missing some important features.

➢ **Leave P - out**

Suppose a dataset has n data points and p data points are used validation set. So in the training dataset n–p data points are used. The whole process is used for each sample. The average error value is noted down to show the efficacy of the model.
But this method has a disadvantage that it efficiency decreases for large value of p.

- **Leave one - out**

This is similar to the above mentioned method. But the only difference is that instead of p only one dataset is chosen from the training set as validation set. It is repeated for each sample. The execution time is more.

- **K - fold**

In this approach, the imported dataset is divided into groups of similar sized samples. The number of groups is K. The samples are known as folds. Just like the previous method, only one dataset is chosen as the test or validation set and the remaining, that is, k–1 datasets are used as training set. It is the most popularly used cross validation method.

- **Stratified K - fold**

This method is similar to the above mentioned method. Only the concept of stratification is used here. In this method, the data is rearranged so that each group gives a better representation of the whole dataset.

- **Holdout**

In this method, a subset is removed from the training data and trained on the remaining part of the data to get the test results. The error obtained during this procedure gives the idea about the accuracy of the underlying model. It is the simplest approach of cross validation.

2.3.13 Train/Test Split Vs Cross Validation

- **Train/Test Split**

  The data that is imported is divided into two segments ─ training set and test set. The division is done on the basis of a ration like training set : test set = 70:30 or 80:20. The training set is the set which trains the data based on the model designed and the test set contains some data from the dataset which were not present in the training set to test the accuracy of the model. The test data gives the data based on the training set.

This provides a huge variance which is its delimitation.

- **Cross Validation**

It splits dataset into groups of train/test split. The result obtained from each group is averaged. It overcomes the delimitation of train/test split as each observation is used for both training and testing.

2.3.14 Disadvantages of Cross Validation

- For consistent data, the output produced has high accuracy but for inconsistent data the output varies significantly. In machine learning there is no consistency of data used so this delimitation of cross validation is of huge trouble.

- In some cases, data evolves with time. In such cases, the difference between training and test set is huge and the accuracy of the designed model will be low.

3. Literature Survey

In this chapter the studies and researches related to electroencephalograph signal acquisition, processing and analysis is discussed along with the relation of emotions with electroencephalograph. With the advancement of human–computer interaction techniques various works have been carried out for detection of emotion from the underlying EEG signal.

Comprehension and Interpretation of the brain signals has been the centre of attraction for scientists for ages. With the introduction of brain computer interfacing approach, the scientists have breathed a sigh of relief in this field of research. After this advancement various works have been carried out to detect human emotion correctly from the underlying brain signal acquired by electroencephalograph.

J Satheesh Kumar et al [47] in their work acquired the EEG signal from diseased brain in two different states where in one state the eyes of the subjects were open and in the second state the eyes of the subjects were closed. They categorized the EEG signals based on these two states.

Xiao Jiang et al [48] proposed in their work the various properties featuring the EEG signal and also the numerous kinds of artifacts degrading the nature of the acquired EEG signal. They discussed in their work the various techniques adopted for the removal of these artifacts and lastly they made a comparative study amongst these techniques to choose the best method. They concluded that Wavelet technique along with BSS method performs better than the high complex oriented computational methods.

Saleha Khatun et al [49] in their work removed ocular artifact obtained during recording of EEG through wavelet transform method. They compared between four wavelet kinds namely bior4.4, sym3, coif3 and haar. They used DWT. They concluded that bior4.4 and ciof3 proved better removal of ocular artifacts than the other methods.

Dr. Suhas S. Patil et al [50] used the previously gathered concept of de–noising of EEG signals by WT. But in their work they obtained the EEG signal while the subjects were performing some activities like counting, multiplication, composing letters and rotation. Five different wavelet types were used in each of these activities to de–noise the signal and a comparative study was made. It was observed that different types of wavelet works better for different activities like coif works better in baseline state, composing letters and counting activities while for multiplication task Dmey works better.

Noor Kamal Al-Qazzaz et al [51] in their work used three wavelets namely db, sym, coif of 45 different orders with four different thresholding functions like sqtwolog, heursure, minimax and rigrsure for de–noising of the EEG signal acquired using 19 channels from one normal and one diseased patient suffering from stroke. They evaluated SNR, PSNR, xcorr and MSE. It was observed that sym9 proved better than other methods.

Edson Estrada et al [52] wavelet method was used to de–noise EEG signals which were acquired during different stages of sleep. The main aim of this work was to find out the ideal threshold value and rule for de–noising. It was observed that soft thresholding on the detailed coefficients proved better results for de-noising.

Didar Dadebayev et al. [53] in their study discussed about different EEG devices used in emotion recognition and also the main areas of emotion recognition like feature extraction and using ML classifier. Lastly they made a study on the performance of different ML algorithms and discussed about the challenges faced during building an appropriate ML model.

Ms .Cynthia Joesph et al. [54] used various physiological signals like GSR, EMG and BVP for classifying emotions using SVM, NB and regression classifiers with five emotions namely anger, hatred, joy, reverence and grief. Different cross validation methods were used to verify the results obtained from the classifiers. Amongst the classifier performance, SVM proved better than others and in cross validation the k – fold leave one – out gave better accuracy score.

Jianhua Zhang et al. [55] showed in their work that electrodes placed in the frontal regions of the scalp were ideal for identifying emotional states of the subjects with great amount of accuracy. This proved that the frontal part of the brain deals with the emotional states of the persons.

Mehmet Bilal Er et al. [56] in their work used emotion of the subjects which was determined based on music stimulus. Different varieties of music were played to the subjects under test in an environment having no noise. Different channels of the electroencephalograph machine were used to acquire the EEG signal and from those spectrograms were generated which served as the input to the deep learning network. They used four different emotions for classification like the angry, sad, relax and happy. They developed a new method for recognising emotions using deep learning algorithms which proved to yield good results.

As the nature of the bio–medical signals are non–stationary and non–linear, so good technique of analysis of these signals is mainly done by analyzing the non-linear features [57]. The non–linear features of the EEG signals are evaluated. Such features are fractal dimension analysis, calculating LLE and entropy [58]. A unique property of such signals is self–similarity, which is iterating a structure of tiny scale forming structures of large scales [59]. Fractal dimensions analyze the signals possessing self–similarity which provide distinctive characteristics of the signals [60]. The fractional or non–integral dimensions of geometric shapes are referred to as fractals [61] which are used widely for measuring irregular nature of the signals [62]. There are many methods for calculating the fractal dimensions [63] of which the most effective is the Higuchi method [64].

Classification is an important or rather ultimate stage of processing of EEG signal. The aim of classification is to distinguish between the different phases. The function of classifier is evaluating some threshold or sometimes using ML algorithms. Most common techniques used for classification are SVM, LR, ANN, KNN, LDA, GMM, DT, and VG [65].

Evi Septiana Pane et al. [66] used two types of filtering techniques namely Chebyshev and IIR to extract the different frequency bands of the EEG signal and different features of the time and frequency domain were extracted to generate the dataset to be imported in the machine learning classifiers. They used four emotions for classifying which were angry, sad, relax and happy. They used RIPPER, SVM and decision tree algorithms where the accuracy of RIPPER algorithm proved better than others.

Jungryul Seo et al [67] used the concept of classifying boredom and non boredom from EEG signal. It is known that boredom is also a kind of emotion. Previously there was very less number researches on boredom. They used video stimulus for classification. From the acquired EEG signal the features that they extracted were band power normalisation, entropy and asymmetry which were imported to three types of machine learning classifiers namely k–NN, SVM and random forest in which ten-fold cross validation technique was used to verify the results. From this study the k–NN approach proved better performance than others.

Prashant Lahane et al [68] in their work followed a unique approach to determine the emotion of subjects. They gave different types of stimuli to the subjects during the acquisition of the EEG signals. The features from those EEG signals were evaluated using proposed kernel density. The artificial neural (ANN) classifier was used to recognise the emotion. The kernel density was modified by them and this proved to yield good results.

Sneha Lukose et al [69] used a very interesting approach in their study. They build a system which will recognise the emotion of the subject using their speech and based on the emotion identified, music which were already stored in the database will be played for cheering up the subject. They used five different types of emotions namely happy, anger, sad, boredom and anxiety. The SVM classifier was used in this approach which gave quite an acceptable result.

Regina W.Y. Wang et al [70] in their work processed humour based on some manipulated artistic drawings. In this work, the stimulus that was given contained some face–cutting of celebrities. The face–cutting was deformed deliberately to invoke the sense of humour in the subjects. The overall work was divided into three stages – determining the deformation, comprehending about the deformation and describing about the humour experienced by each of the subjects. For this the spectral and temporal responses were measured from the acquired EEG signal. From the analysis of these features it was concluded that the theta wave changed significantly in the cortical and parietal regions while the beta and alpha waves varied in the motor regions.

Oswald Barral et al [71] in their work followed a different approach of identifying the appraisal of humorous content through different physiological signals. In this study, the subjects were asked to browse humorous contents in a particular website and while they were going through the semantics, different physiological signals like ECG and EEG were recorded. Models were built for predicting the appraisal of the humour of different subjects which concluded that significant changes occur during the comprehension of the semantics. It was also observed that the EEG signals corresponding to the higher bands of frequency and heart rate changes during this stage. Also the prediction accuracy was more when all the physiological signals were taken into consideration than the single ECG signal.

Elisabeth Ruiz Padial et al [72] embedded the concept of fractal dimension with emotion. In their work both good and bad emotions were extracted from EEG signals after making the subjects watch some video clips containing neutral, humorous fear and disgust emotions. Fractal Dimension feature was extracted from the acquired signals using Higuchi's method. They also extracted HRV from ECG taken while watching the videos. They concluded that there is a keen relation between brain and cardiac in maintaining emotion as high fractal dimension values were obtained during humour state along with high HRV.

Tian Chen et al [73] used both EEG and ECG signals for recognising emotions. In their work they used two distinct classifiers – one for EEG and another for ECG to recognise emotions with accuracy. For EEG they used SVM classifier and for ECG they used two directional long and short–term–memory networks. They also fused these two classifiers and tried to find out the emotion. In the fusion combination, the accuracy was better than each of the classifier when used alone.

Rania Alhalaseh et al [74] used in their work EMD and VMD for processing of the EEG signal. Previously these two methods were not in use for processing of signal dealing with emotions. Non – linear parameters like fractal dimension by Higuchi method and entropy calculation was done. Finally four different classifiers were used for classification. These were CNN, DT, k – NN, naive Bayes in which the performance of CNN proved better than others.

Jianhua Zhang et al [75] in their work after acquisition of EEG signals de–noised the signal with WT extracted non–linear features. Four ML classifiers namely NB, SVM, RF and k–NN were used and a comparative study was made amongst them.

4. Methodology and Results

For accurately detecting the humour classification of the subjects using EEG signal, this paper uses statistical and non linear time series analysis method along with machine learning algorithms. Signal processing is followed in every step starting from experimental design to data collection and data analysis for modelling of humour classification of human brain.

4.1 Stimulus

Stimulus is something which arouses a specific reaction in the body of a person by acting from outside the body environment and changes the normal activities of the person for a short period of time. In this study, stimulus is given in the form of comic strips browsed from various sources in different languages to the subjects under consideration. The main motive of this study was to identify how the subjects can detect or appraise humour after reading the comic strips or in other words, the main aim of this experiment was to classify humour.

4.2 Description of the EEG machine

EEG recording machine manufactured by RMS India Pvt. Ltd was used for recording of the EEG data of the subjects. The name of the model is MAXIMUS 24. It is a hospital grade EEG recording machine consisting of 24 channels or electrodes. Out of these 24 channels, two channels is for ECG, two channels is for EMG, one channel is signified as ground electrode, another is considered as the reference electrode. Two electrodes are used for EEG recording from the mastoid region that is the region just behind the ear known as auricle electrodes are abbreviated as A1and A2. The electrodes are symbolized clearly so that one can easily identify the actual location of the electrode placement for accurately taking up the EEG data. The pre-frontal electrodes are abbreviated as Fp, the frontal electrodes are abbreviated as F, the parietal electrodes are abbreviated as P, temporal electrodes are abbreviated as T, the electrodes intended for occipital region are labelled as O and the cortical electrodes are labelled as C. The electrodes to be put in the middle line of the skull are symbolized with the letter Z. The electrodes to be put in the right side of the brain are signified by even numbers and the electrodes to be put in the left side of the brain are signified by odd numbers. There are two pre-frontal electrodes and two occipital electrodes.

There are five frontal electrodes, three central or cortical electrodes, three parietal electrodes and four temporal electrodes. The placement of the electrodes on the subjects' brain was done following the internationally accepted 10/20 system for EEG recording. The EEG recording machine was provided with two softwares. One of them was as used for acquiring of the EEG signal known as "Acquire" and the other was used for analyzing of the recorded EEG signal known as "Analysis". Before acquisition of the EEG signal, the selection of montage, filters, sweep and sensitivity was done in the "Acquire" software and the same settings was done in the "Analysis" software after acquisition for analysing the EEG signal. This machine has Electromyogram (EMG) and Electrocardiogram (ECG) filters to remove the interference of these two signals with the original EEG signal during the recording of EEG signal. Before placement of electrodes on a person's scalp, the places of putting those electrodes were cleaned with ethyl alcohol to remove the oil, dust and impurities. The electrodes used for this experiment are Ag / AgCl electrodes and those are put on the scalps of the subjects by using conduction paste to increase the conductivity and smooth acquisition of the signal.

4.3 Design of experiment

For classifying humour based on comic strips, there are various challenges. This experiment was designed wisely keeping those in mind. A total of eight subjects were taken out of which one is female and seven others are male. None of the subjects has any previous medical history of mental illness or disorders like anxiety disorder, depression, etc. One-liner comic strips browsed from various sources like websites and books were chosen as the stimulus. These comic strips were in two different languages namely English and Bengali. Before giving the comic strips, the subjects were asked about the choice of language of the comics. According to that, four one-liner comic strips were given. The duration of reading of each of these comics were fifteen seconds. So the total duration of reading the four comics were one minute. Before starting the experiment, the subjects were informed about the protocol of the experiment. The subjects were asked to relax and reduce movements of limbs and eye blinks as much as possible so as to remove the artifacts contaminating the recorded EEG signal. The total recording of the EEG signal was divided into three phases – "PRE", "DURING" and "POST".

The "PRE" phase consists of the EEG signal which was recorded before the subjects were given the comic strips to read. The subjects relaxed in this phase. This phase is of the duration of one minute. Post one minute, the subjects were given the four comic strips altogether to read silently. This phase is denoted as “DURING”. The total duration of this phase is one minute. After this phase, the subjects were again asked to relax and think about the comics, they just read. This phase is denoted as the “POST” phase and the duration of this phase is of five minutes. The total duration of recording of the EEG signal is of seven minutes.

Out of the nineteen channels only six channels were selected for the acquisition of the EEG signals in each of the phases. The frontal electrodes ‘F’ was selected as for acquisition of the emotions from the EEG signal especially for humour classification, the frontal electrodes provide the best accuracy in detecting the humour emotion. Six referential electrodes and one differential electrode were used for the recording of the EEG signals. The referential electrodes used are – ‘F7 - REF’, ‘F3 - REF’, ‘FZ – REF’, ‘F4 - REF’ and ‘F8 - REF’. By following the electrode placement convention the odd numbered electrodes namely ‘F7’and ‘F3 ’were placed on the left side of the scalp and the even numbered electrodes namely ‘F8’ and ‘F4’were placed on the right side of the scalp. The ‘FZ’ electrode was placed in the midline part of the scalp. Along with these two auricular electrodes (A1 and A2), ground and referential electrodes were also placed for proper recording of the EEG signals. This convention was followed in all the subjects under test.

The time distribution of recording of EEG signal is given in Table 4.1.

Table 4.1: Time distribution of the recording of the EEG signal of different subjects in the Pre, During and Post application of the stimulus

PHASE	**TIME (minutes)**
PRE	1
DURING	1
POST	5

4.4 EEG Signal Acquisitions

Surface electrodes made of silver or silver chloride was placed on the scalp of the subjects for the purpose of recording of the EEG signal. The placement of the electrodes on the subjects' scalp was done following the internally accept 10/20 system of EEG electrode placement. Since this work is based on humour classification so for reducing the dimension only the frontal electrodes (FZ, F3, F4, F7, F8) along with the ground, reference and auricular (A1, A2) electrodes were used. Thus all total nine electrodes were placed on the subjects. Five referential montages and one differential montage were used for the recording of the EEG signal. F3–REF, F4–REF, FZ–REF, F7–REF, F8–REF were used as the referential montages and F3–F4 were used as the differential montage.

The recording of the EEG signal was done using the above mentioned RMS MAXIMUS® computer based EEG machine. The recorded EEG signal was stored at a sampling frequency of 256 Hertz (Hz). While the EEG signal acquisition was done, the impedance of the scalp of the subjects and the electrodes placed on them was maintained to be less than 50 kilo ohm (Ω). This was done to ensure that there is very less interference of the artifacts with the actual EEG signal. The subjects were asked to relax and restrict the movement of limbs and eye blinking as much as possible for reducing artifacts. The sensitivity was adjusted at a point where the visualisation of the EEG signal was mostly accurate. The low pass and high pas filters were adjusted according to the frequency range of the EEG signal. The following settings of the "Acquire" and "Analysis" software were maintained to maintain a good level of accuracy.

1. Montage Selection – Reference – Channel (5), Channel – Channel (1)
2. Low Pass Filter (LPF) – 0.5Hz
3. High Pass Filter (HPF) – 35Hz
4. Notch Filter – ON
5. EMG Filter – ON
6. ECG Filter – ON
7. Sensitivity – 20μV/s
8. Sweep – 30mm/s

After recording of the EEG signal was complete then it was exported into .CSV file from the "Analysis" software into local storage.

The acquired EEG data of different subjects in the three phases in the .CSV file was then imported in the MATLAB Simulator software for plotting the data into a signal form.

4.5 De–noising of EEG Signal

After acquisition of the EEG signal from different subjects, the raw EEG signal needs to be de–noised as it contains artifacts. The acquired EEG signal is contaminated with various external noises. Although the machine used for acquiring of the EEG signal eliminates most of the noise still some noise persists in the signal. This noise needs to be eradicated in order to get accurate results during the data analysis of the EEG signal.

The de–noising of the EEG signals are done using Wavelet Transform. This is done so as EEG signals are non–stationary in nature and as discussed previously in this study Wavelet Transform is the most powerful tool for de–noising of such non–stationary signals.

The EEG signal is decomposed into multi level using Wavelet Transform. This decomposition is done using 10 levels of decomposition by db6 wavelet. The detailed coefficients are present in d1, d2, d3, d4, d5, d6, d7, d8, d9, d10 and approximation coefficients are obtained in a10. The high frequency components are present in detailed coefficients which are removed from stage 1 to stage 10. The noise components are mostly present in the high frequency region which is thus removed in the ten levels. After removal of the high frequency components from the signal, the approximate coefficients are obtained which is the actual de – noised signal. The threshold setting was done manually. The de–noised signal of the "PRE", "DURING" and "POST" phases of one of the subjects is given below.

The original and the de–noised EEG signals plotted in the MATLAB Simulator of one of the subjects in the three phases are given below along with an original and a de–noised EEG signal.

Signal Plots

➢ **Original EEG Signal and De–noised EEG Signals**

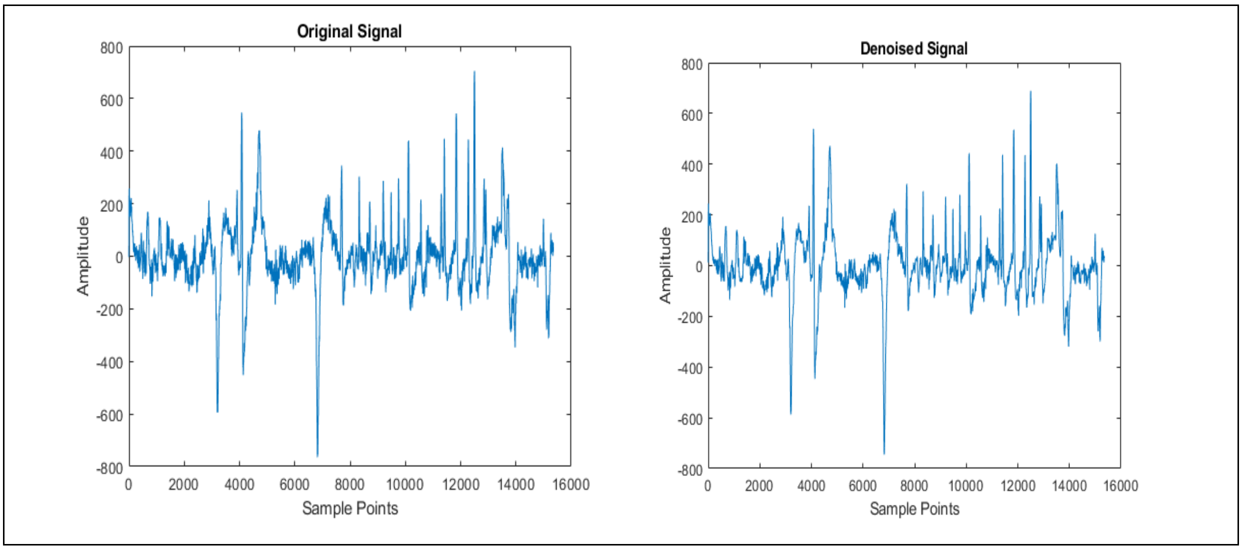


Fig. 4.1: The original and de–noised EEG Signal

The graphs of the EEG signals recorded before the action of the stimulus in all the subjects from all the channels plotted using MATLAB Simulator software are given below in the **"PRE PHASE"**.

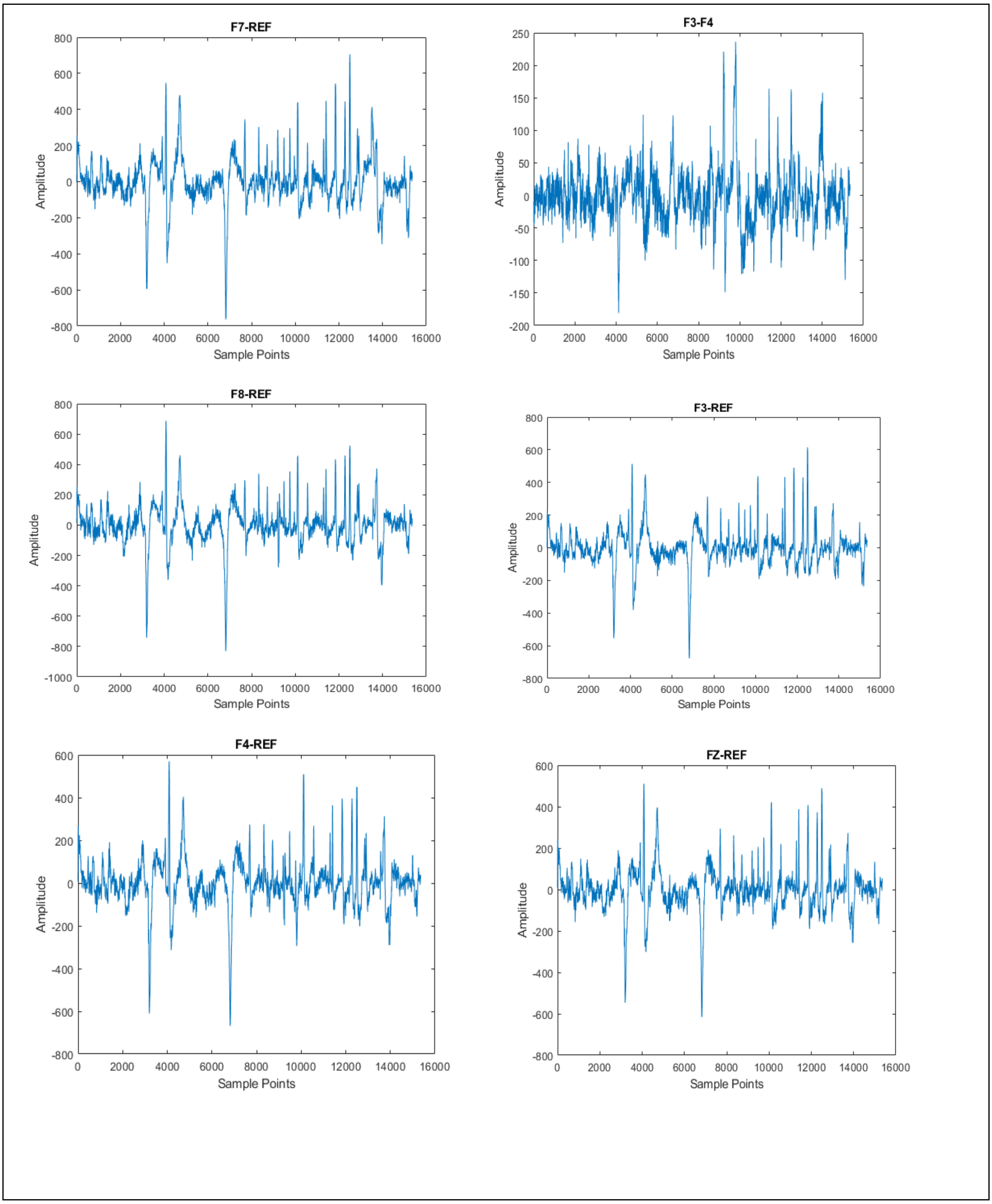


Fig. 4.2: EEG signals recorded in the PRE phase in all the leads

The graphs of the EEG signals generated using MATLAB Simulator software from all the channels in all the subjects while reading of the comic strips are given below in the **"DURING PHASE"**.

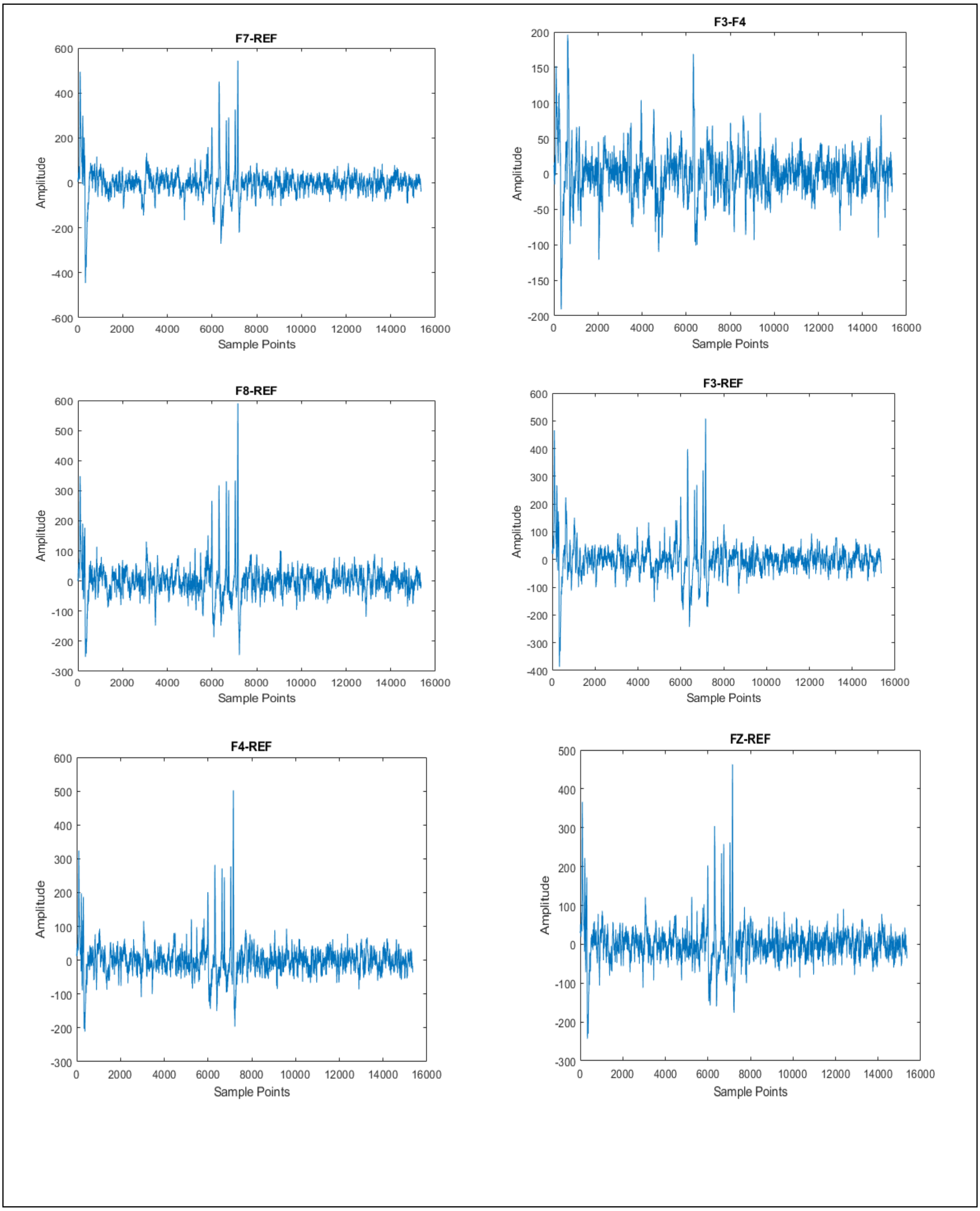


Fig. 4.3: EEG signals recorded in the DURING phase in all the leads

The graphs of the EEG signals in all the channels for all the subjects plotted in MATLAB Simulator software while they were interpreting about the content read from the comic strips is given below in the **"POST PHASE"**.

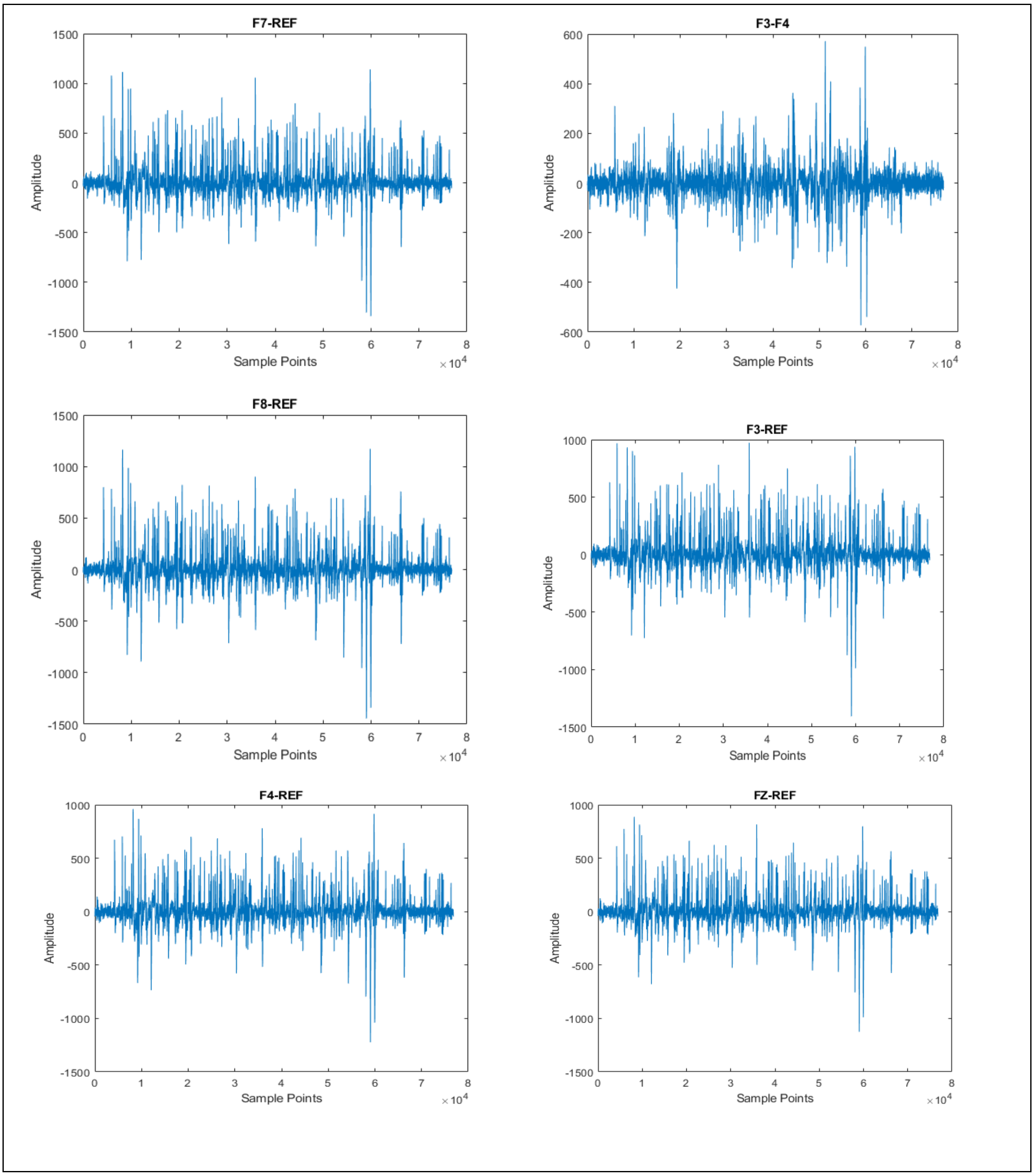


Fig. 4.4: EEG signals recorded in the POST phase in all the leads

4.6 Power Spectral Density

EEG signal contains power. Power Spectral Density (PSD) is estimating that power in the frequency domain. This work can be further extended for visualising the PSD of different frequency bands of the EEG signal.

In this experiment, the PSD of the EEG signal was estimated using Welch's periodogram technique.

The PSD of the Acquired and De–noised EEG signal is given below.

PSD Signal Plots

- **PSD Plot of Original and De-noised EEG Signal**

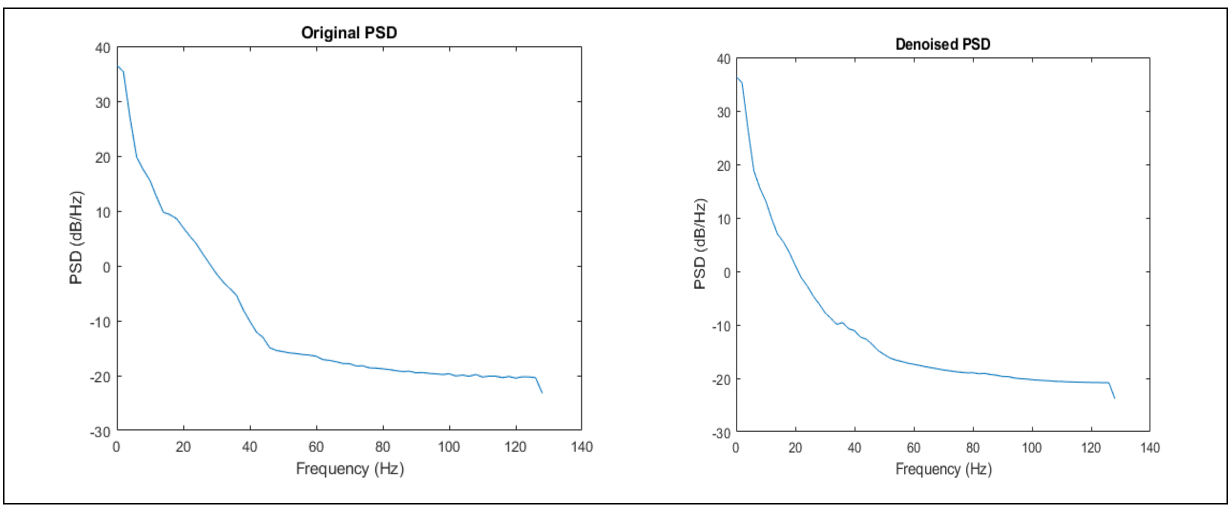


Fig.4.5: PSD of Original and De-noised EEG Signal

The PSD plots in the **“PRE PHASE”** of Subject 1 are given below:-

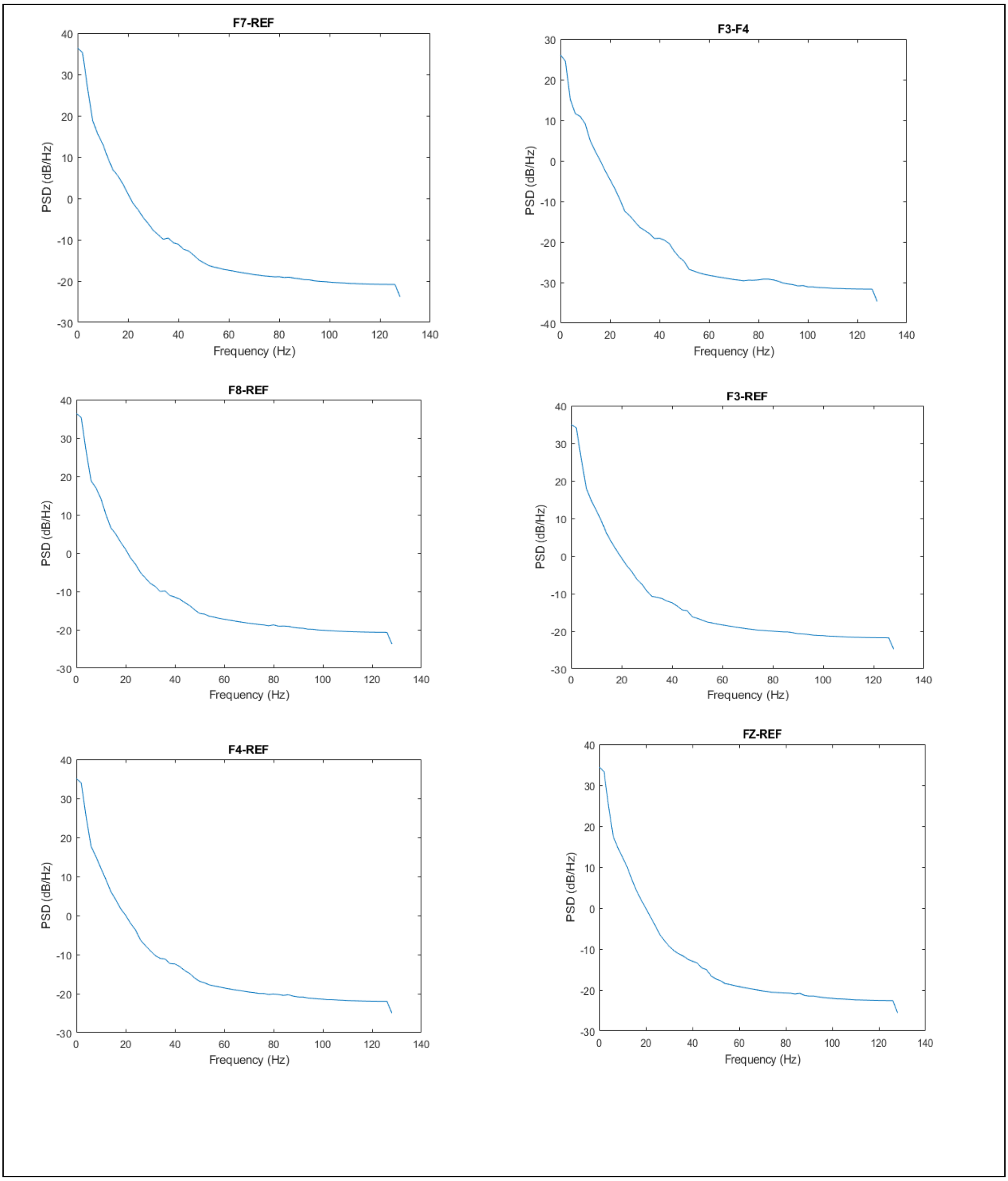


Fig.4.6: PSD of EEG Signal of Subject 1 in all the leads in the pre phase

The PSD of the EEG signals while reading the comic strips is given in the **"DURING PHASE"**.

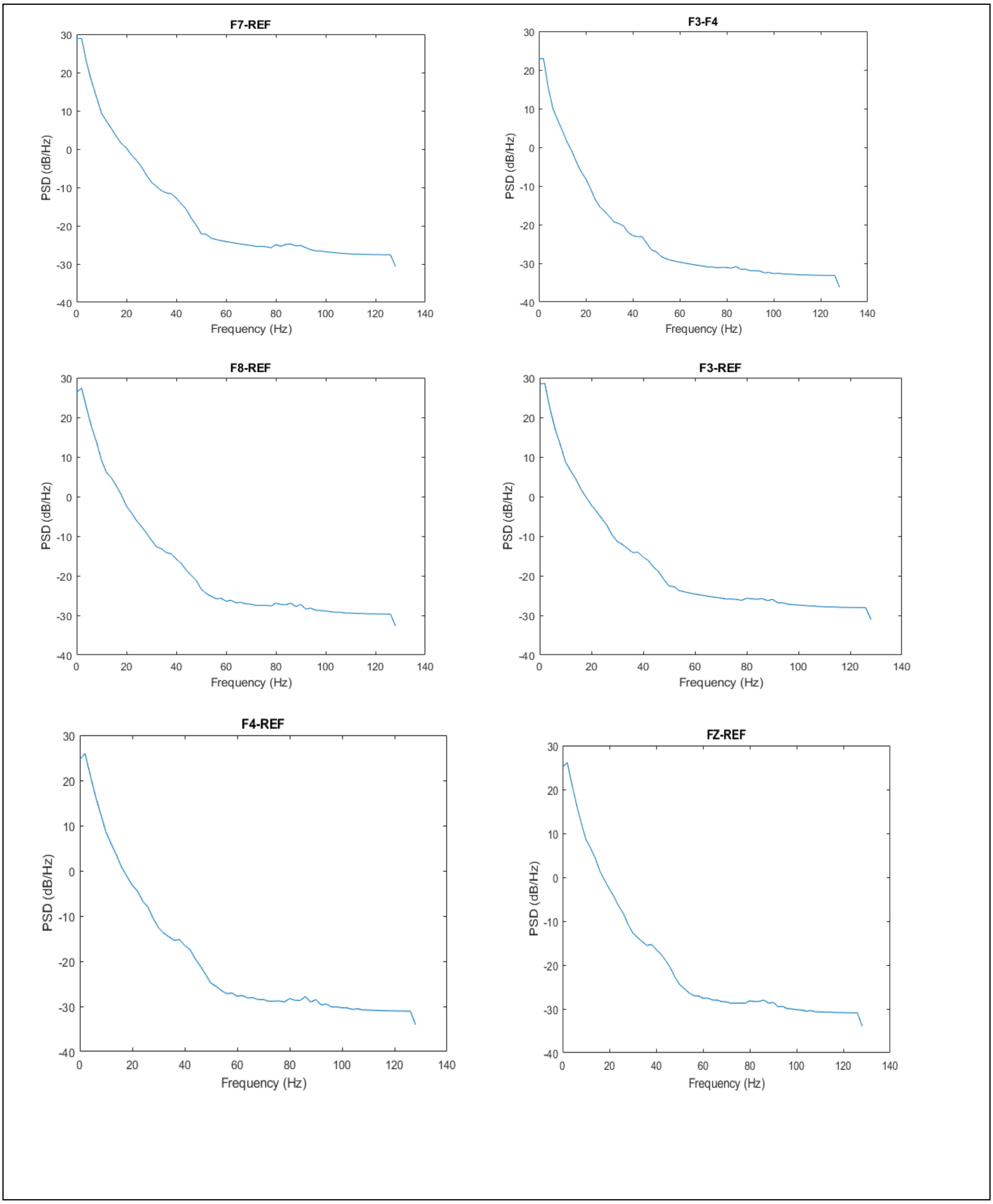


Fig.4.7: PSD of EEG Signal of Subject 1 in all the leads in the during phase

The PSD plots of the EEG signals recorded after the removal of the comic strips is given in the **“POST PHASE”**.

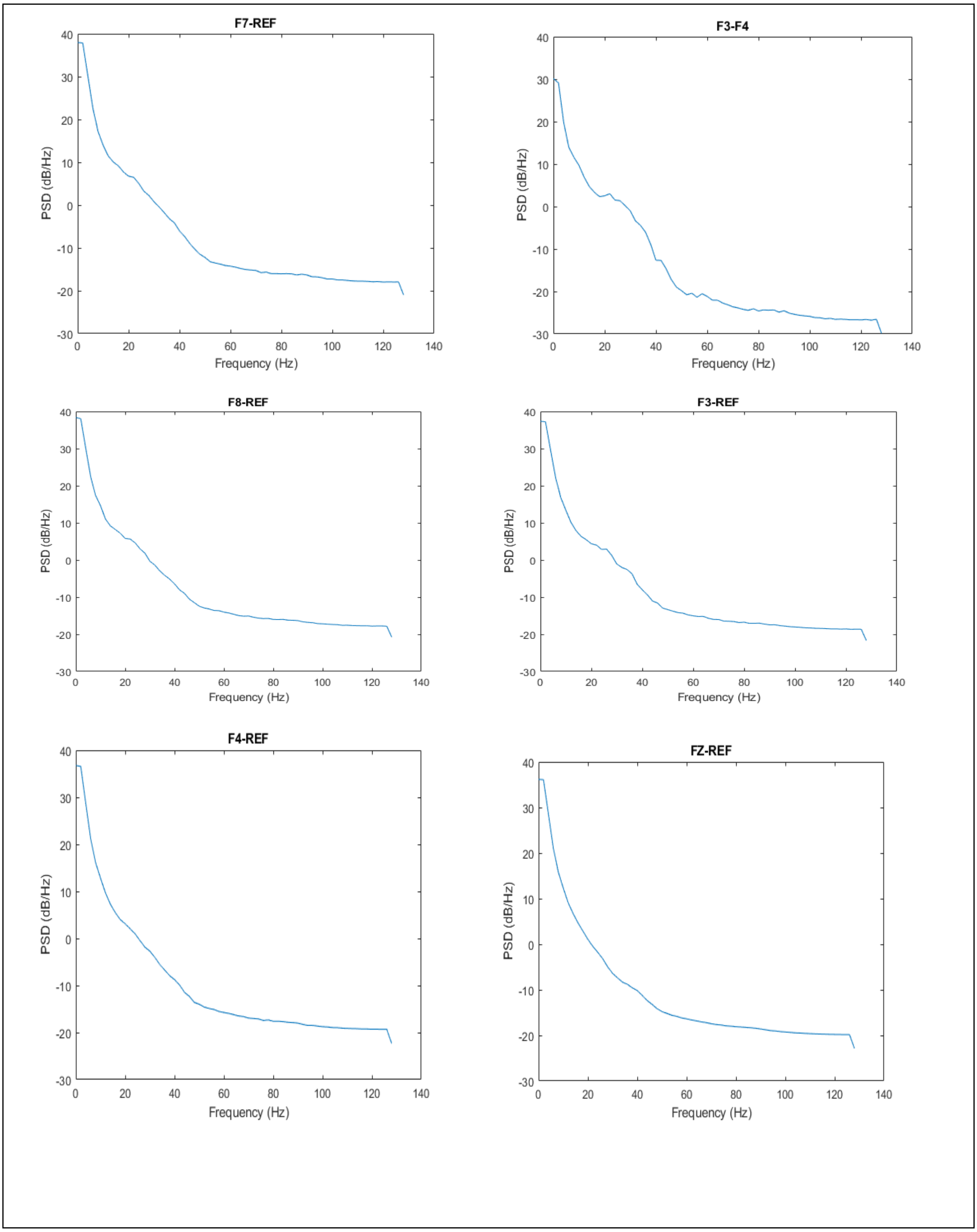


Fig.4.8: PSD of EEG Signal of Subject 1 in all the leads in the post phase

Some interesting findings from the PSD plots are given below:-

- The graphs of PSD of the signals before and after application of de–noising technique are plotted.
- It can be observed that by using the Welch method for finding the PSD of both the original and de–noised signals, some high frequency components present in the original EG signal has been removed.
- Most of the frequency bands of the EEG signal fall in the lower frequency region which is clear from their frequency range like delta band fall in the range between 0.5 Hz to 4 Hz; theta band fall in the frequency range between 4 Hz to 8 HZ and alpha band fall in the range between 8 Hz to 13 Hz.
- So most of the information contained in the EEG signal fall in the lower frequency range.
- From the PSD plot obtained after de–noising the signal, it is observed that the sharp edges present in the PSD plot of the original EEG signal has been smoothened which indicates that proper de-noising of the signal has been done by eliminating various unwanted components affecting the quality of the EEG signal.

4.7 Estimating the powers of different frequency bands of the Acquired EEG signals

EEG signal consists of different frequency bands like alpha, beta, theta, and delta. These bands work in different frequency ranges. They have specific power values under normal or resting condition. These values change when a stimulus acts on the human brain. This is so because when a certain stimulus is given to a subject, the brain of that subjects focuses on that stimulus and his brain makes these frequency bands function according to that target stimulus. So the power of the different bands change under a stimulus and when again the stimulus is removed the power change but at that moment also it is not same as in the normal or resting stage. It need some time to be same with the normal stage.

In this experiment comic strips served the purpose of stimulus and three phases of EEG signals were recorded as discussed earlier. So the powers of the different EEG frequency bands were different in the three phases such as “PRE”, “DURING” and “POST”.

The powers were indeed different in all the subjects in the three phases. But for all the subjects, the change was not significant enough to be reflected in ANOVA. The p–value was not significant to show that indeed change was happening in the three phases. The change in the band powers was not similar in all the subjects. For some of the subjects, the p–value was significant in some bands but that consistency was not maintained for all the subjects in all the bands. So a concrete conclusion cannot be drawn from these results.

The powers of the different frequency bands comprised in the recorded EEG signals in all the leads for Subject 1 in the three different phases are given below:-

The power of different bands in Subject 1 calculated in the Pre, During and Post phases:-

Table 4.2: Band power in Subject 1

LEAD	BAND	PRE	DURING	POST
F7 – REF	ALPHA	161.75	80.68	990.17
F3 – F4	ALPHA	81.93	41.07	90.51
F8 - REF	ALPHA	185.42	84.09	204.31
F3 - REF	ALPHA	134.73	74.90	170.09
F4 - REF	ALPHA	128.49	78.93	160.57
FZ - REF	ALPHA	142.31	80.91	143.58
F7 – REF	BETA	63.25	52.76	161.10
F3 – F4	BETA	34.45	19.75	52.93
F8 - REF	BETA	61.70	43.55	135.19
F3 - REF	BETA	48.91	42.01	81.61
F4 - REF	BETA	59.68	35.18	74.70
FZ - REF	BETA	59.38	39.57	64.30
F7 – REF	DELTA	9103.23	4030.20	19207.61
F3 – F4	DELTA	1029.72	707.51	3312.33
F8 - REF	DELTA	8989.25	3269.21	19670.90
F3 - REF	DELTA	7634.74	3707.33	16800.17
F4 - REF	DELTA	6599.39	2315.14	14310.43
FZ - REF	DELTA	6042.45	2364.59	13036.79
F7 – REF	THETA	400.00	515.02	990.17
F3 – F4	THETA	107.66	74.73	173.31
F8 - REF	THETA	428.22	543.79	953.93
F3 - REF	THETA	344.24	431.39	886.99
F4 - REF	THETA	319.01	423.37	724.71
FZ - REF	THETA	316.84	407.01	694.25

The average band power calculated considering all the leads in all the eight subjects is given below:-

Table 4.3: Average Band Power off all frequency bands in all the leads

LEAD	BAND	Average Pre	Average During	Average Post
F7-REF	ALPHA	782.79	622.00	1676.94
F3-F4	ALPHA	1292.32	776.49	1311.69
F8-REF	ALPHA	814.05	642.67	1632.21
F3-REF	ALPHA	1095.54	907.25	2596.12
F4-REF	ALPHA	2091.73	1478.29	2891.83
FZ-REF	ALPHA	676.83	546.31	1412.37
F7-REF	BETA	610.51	552.83	1136.05
F3-F4	BETA	1878.36	1159.85	1880.81
F8-REF	BETA	709.41	545.53	1176.19
F3-REF	BETA	1168.83	1056.07	3047.16
F4-REF	BETA	2686.03	1901.34	3259.76
FZ-REF	BETA	559.59	472.39	1039.15
F7-REF	DELTA	48549.93	11666.28	71032.73
F3-F4	DELTA	1855.07	1719.36	2433.64
F8-REF	DELTA	47438.58	11325.48	72736.56
F3-REF	DELTA	40870.00	9580.88	62825.67
F4-REF	DELTA	40179.98	9872.89	64676.66
FZ-REF	DELTA	35356.34	8339.94	58872.66
F7-REF	THETA	4363.03	1642.10	5967.07
F3-F4	THETA	1040.74	555.11	960.44
F8-REF	THETA	4469.88	1709.19	6097.08
F3-REF	THETA	4048.30	1634.70	6108.45
F4-REF	THETA	4900.23	2075.73	6469.98
FZ-REF	THETA	3428.55	1362.26	5037.96

Below are the graphs signifying the variation of the different band powers in the three phases.

The variation in the alpha band power in Subject 1 is reflected in the following graph.

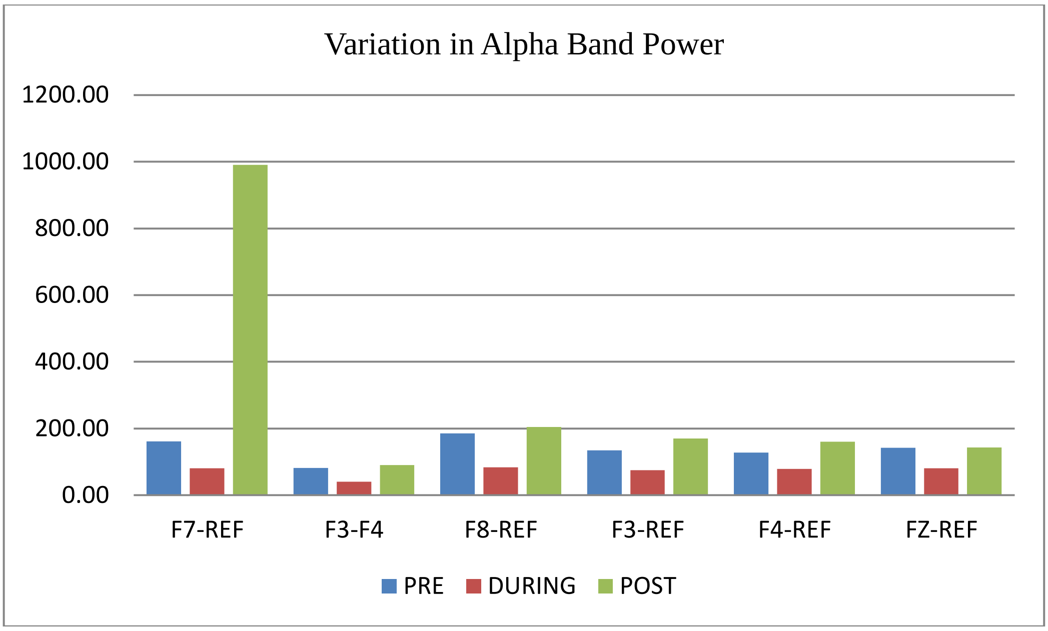


Fig. 4.9: Variation of Alpha Band Power in Subject 1

The variation in the beta band power in Subject 1 is reflected in the following graph.

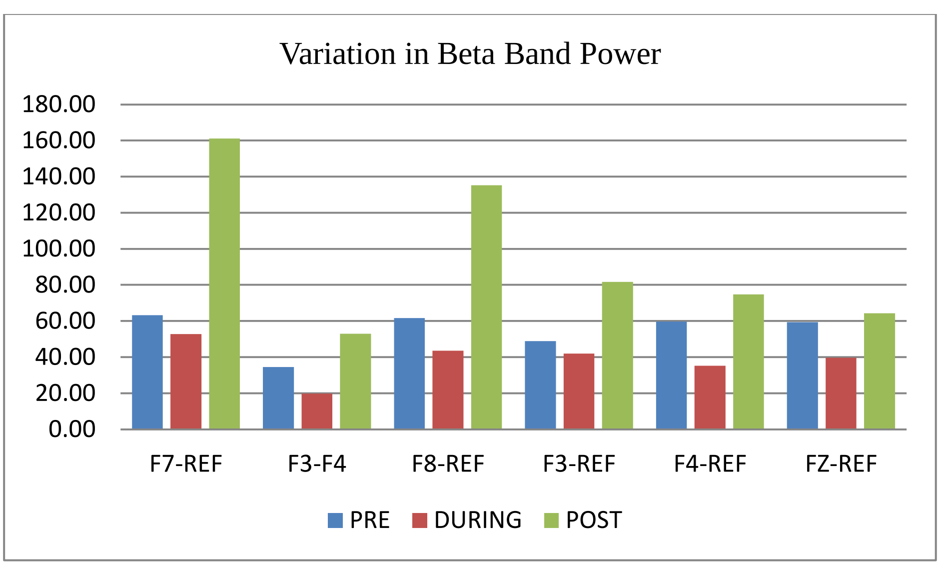


Fig. 4.10: Variation of Beta Band Power in Subject 1

The variation in the delta band power in Subject 1 is reflected in the following graph.

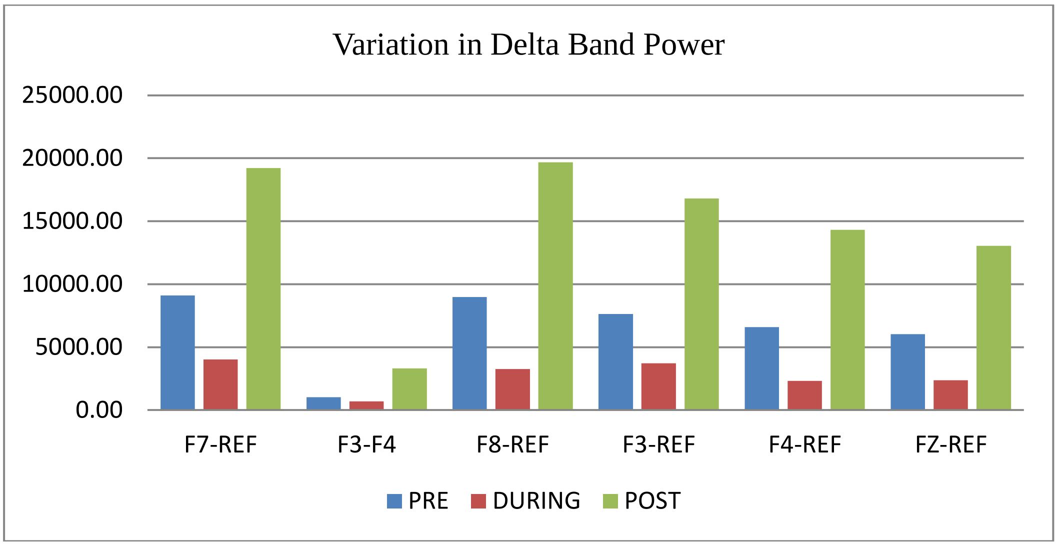


Fig. 4.11: Variation of Delta Band Power in Subject 1

The variation in the theta band power in Subject 1 is reflected in the following graph.

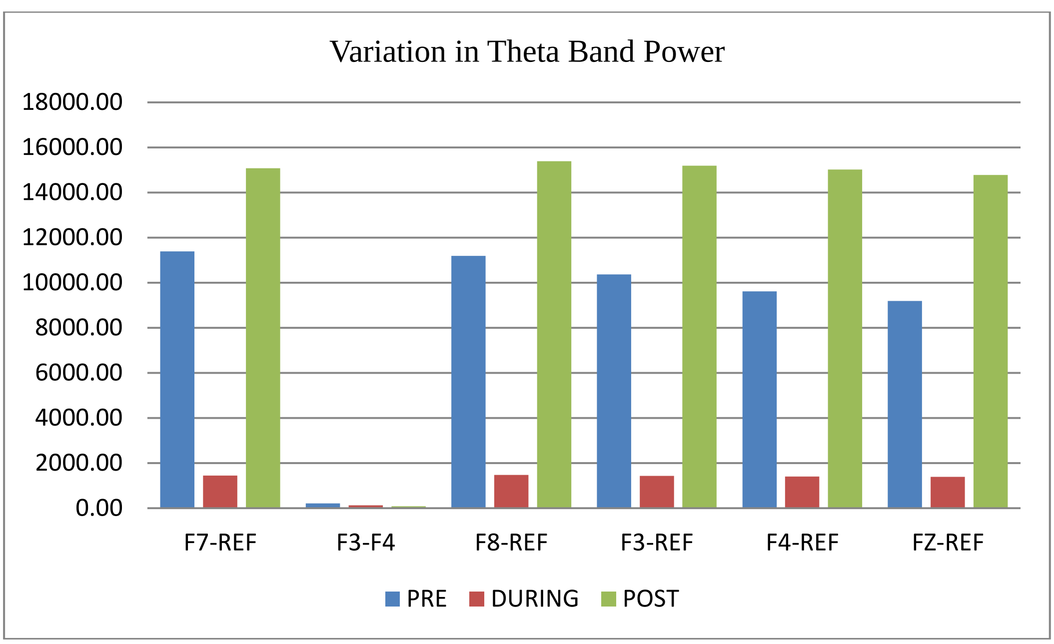


Fig. 4.12: Variation of Theta Band Power in Subject 1

The variation in the average alpha power is reflected in the following graph.

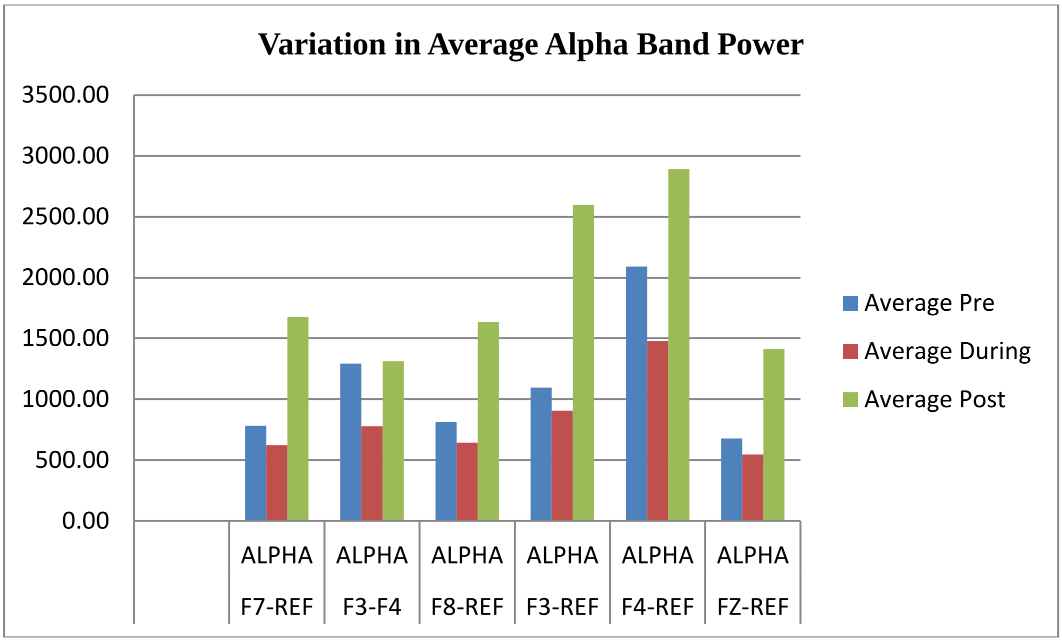


Fig. 4.13: Variation of Average Alpha Band Power

The variation in the average band power is reflected in the following graph.

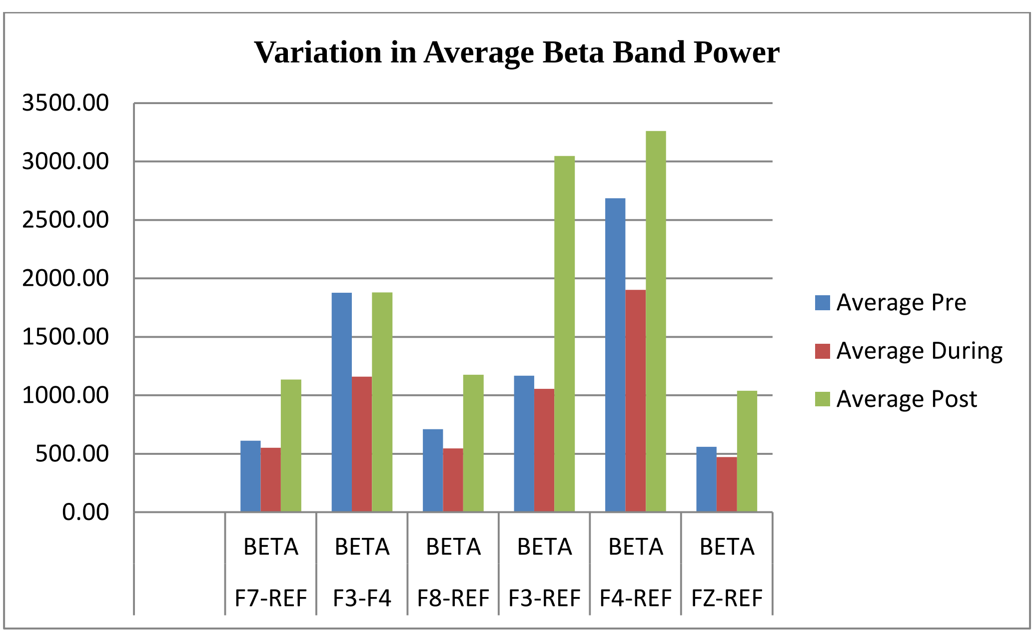


Fig. 4.14: Variation of Average Beta Band Power

The variation in the average delta power is reflected in the following graph.

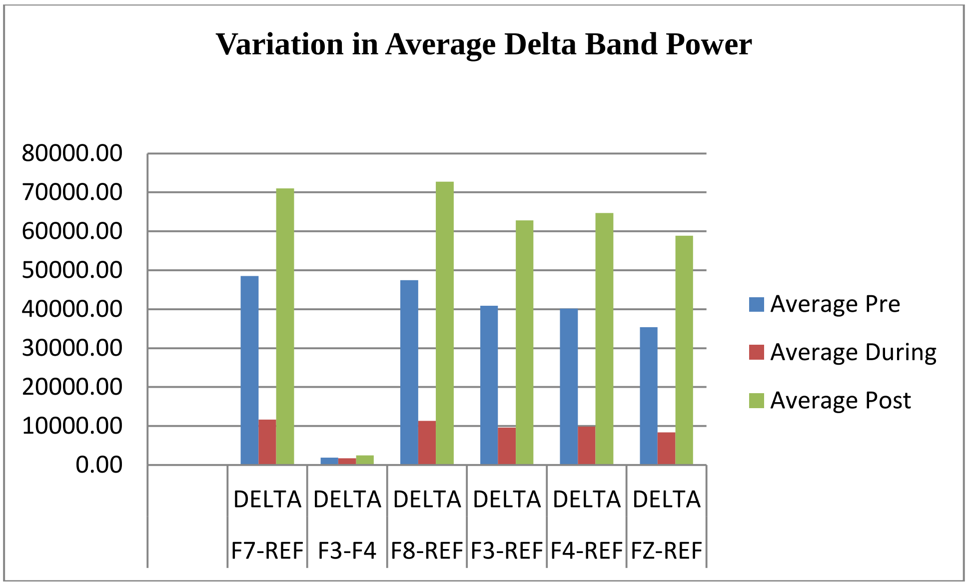


Fig. 4.15: Variation of Average Delta Band Power

The variation in the average theta power is reflected in the following graph.

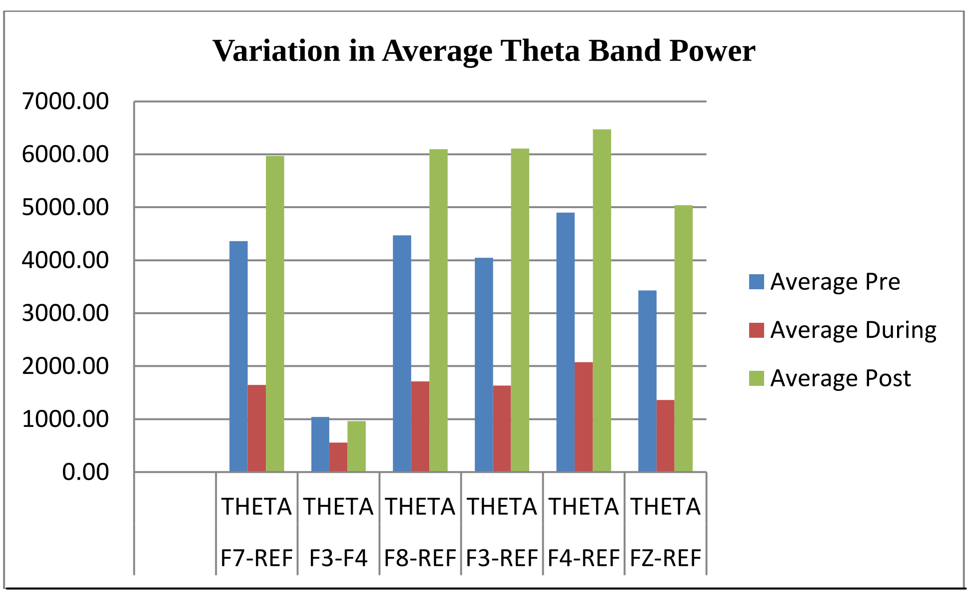


Fig. 4.16: Variation of Average Theta Band Power

Some of the interesting findings observed from the variation in powers of the different bands in the three phases are given below:-

- A sharp decrease in the power of all the frequency bands is observed in the during phase, that is when the subjects were reading the comic strips. This can be due to the fact that the contents of the comic strips were comprehended while the subjects were reading those.

- This decrement in the powers of the different bands varies from subject to subject. Thus, it can be said that comprehension of humour is subjective in nature.

- After the comic strips were removed from the subjects, the powers of the different bands increased than the powers calculated in the resting phase. This shows that the subjects were interpreting the humour content in those comic strips after reading those and a significant reduction of stress have induced in them.

- A sharp dip in the average alpha power while reading the comic strips was observed in all the subjects. Alpha wave marks the resting phase of the brain. Decrease in this alpha power means there is an increase in the activity of the cortex. This signifies that the subjects were reading the content of the comic strips were attentively. After the comic strips were taken away from the subjects, an increase in the alpha power is observed. This suggests that there was a decrease in the activity of the cortex and the subjects were easily able to interpret the humour from the contents given to them.

- A sharp decrease in the beta power observed while reading the contents of the comic strips indicates that the subjects were not anxious while reading the comic strips. The variation is not same for all the subjects. As the perception of humour is different for various subjects thus it can be said variation in the beta power is highly subjective. An increase in the beta power is observed after the comic strips were removed from the subjects. As beta power deals with the cognitive result of an activity, so a rise in the beta power is expected while the subjects were interpreting the contents of humour.

This can be attributed that the recognition or interpretation of humour from the comic strips was done with equal amount of proficiency in all the subjects.

- The theta power correlates with subconscious and emotional states of persons. As emotional perception is different for different subjects, so the theta is also highly subject dependent. A dip in the theta power observed in while the subjects were reading the comic strips indicates that the subjects were not just sitting relaxed holding the comic strips instead they were reading the contents and trying to comprehend from it. An increase in the theta power is observed after the comic strips were taken from the subjects. This indicates after reading the humour contents, the mood of the subjects changed and they were feeling happy and relaxing.

- A sharp decrease in the delta band power observed while the subjects were reading the comic strips signifies that the subjects were not feeling sleepy while reading the contents of the comic strips. The decrease in the delta power while comprehending from the comic strips indicates that there was some arousal effect from the humorous contents. An increase in the delta power is observed after the comic strips were taken from the subjects. This indicates after reading the humour contents, the mood of the subjects changed and they were feeling relaxed.

To determine the magnitude of variation in the powers of all the bands as seen from the above charts in the three different phases both in the average of the band powers and in a single subject, a more efficient statistical tool, ANOVA is used. The findings from the above mentioned method is given below:-

The ANOVA performed on the Alpha Band for Subject 1 is given below:-

Table 4.4: ANOVA Result for Alpha Band in Subject 1

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	5	672.8787	134.5757			
DURING	5	359.9014	71.98028			
POST	5	769.0527	153.8105			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	18307.27	2	9153.634	8.038709	0.006095	3.885294
Within Groups	13664.33	12	1138.695			
Total	31971.6	14				

Here the p-value is less than 0.05 which signifies that the variation in the alpha power in subject 1 is significant.

The ANOVA performed on the Beta Band for Subject 1 is given below:-

Table 4.5: ANOVA Result for Beta Band in Subject 1

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	5	264.1175	52.82349			
DURING	5	180.0642	36.01283			
POST	5	408.7224	81.74448			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	5350.676	2	2675.338	6.507299	0.012188	3.885294
Within Groups	4933.546	12	411.1288			
Total	10284.22	14				

Here the p-value is more than 0.05 which signifies that the acceptance of the null hypothesis.

The ANOVA performed on the Delta Band for Subject 1 is given below:-

Table 4.6: ANOVA Result for Delta Band in Subject 1

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	5	30295.55	6059.11			
DURING	5	12363.78	2472.757			
POST	5	67130.61	13426.12			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	311851721	2	155925860	9.567456	0.003278	3.885294
Within Groups	195570302	12	16297525			
Total	507422022	14				

Here the p–value is less than 0.05 which signifies that the variation in the delta power in subject 1 is significant.

The ANOVA performed on the Theta Band for Subject 1 is given below:-

Table 4.7: ANOVA Result for Theta Band in Subject 1

ANOVA SINGLE FACTOR			
SUMMARY			
Groups	**Count**	**Sum**	**Average**
PRE	5	1515.966	303.1933
DURING	5	1880.29	376.0579
POST	5	3433.191	686.6383

ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	414665.791	2	207332.9	4.460526	0.035611	3.885294
Within Groups	557780.591	12	46481.72			
Total	972446.383	14				

Here the p–value is less than 0.05 which signifies that the variation in the theta power in subject 1 is significant.

The ANOVA performed on the Alpha Band for average power in all subjects is given below:-

Table 4.8: ANOVA Result for Alpha Band for Average Power in all Subjects

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	6	6753.245	1125.541			
DURING	6	4973.001	828.8334			
POST	6	11521.15	1920.192			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	3821142	2	1910571	6.926964	0.007399	3.68232
Within Groups	4137247	15	275816.5			
Total	7958389	17				

Here the p–value is less than 0.05 which signifies that the variation in the average alpha power of all the subjects is significant.

The ANOVA performed on the Beta Band for average power in all subjects is given below:-

Table 4.9: ANOVA Result for Beta Band for Average Power in all Subjects

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	6	7612.74	1268.79			
DURING	6	5688.018	948.0029			
POST	6	11539.13	1923.188			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	2964256	2	1482128	2.188228	0.146598	3.68232
Within Groups	10159779	15	677318.6			
Total	13124035	17				

Here the p–value is more than 0.05 which signifies acceptance of null hypothesis.

The ANOVA performed on the Delta Band for average power in all the subjects is given below:-

Table 4.10: ANOVA Result for Delta Band for Average Power in all Subjects

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**			
PRE	6	214249.9	35708.31651			
DURING	6	52504.83	8750.805702			
POST	6	332577.9	55429.65446			
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	6589106961.55	2	3294553480.78	9.755620608	0.001932	3.68232
Within Groups	5065623624	15	337708241.6			
Total	11654730585	17				

Here the p–value is more than 0.05 which signifies that the variation in the average delta power of all the subjects is significant.

The ANOVA performed on the Theta Band for average power in all subjects is given below:-

Table 4.11: ANOVA Result for Theta Band for Average Power in all Subjects

ANOVA SINGLE FACTOR			
SUMMARY			
Groups	**Count**	**Sum**	**Average**
PRE	6	22250.73	3708.455
DURING	6	8979.085	1496.514
POST	6	30640.97	5106.828

ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	39764990	2	19882495	9.080508	0.002606	3.68232
Within Groups	32843694	15	2189580			
Total	72608684	17				

Here the p–value is less than 0.05 which signifies that the variation in the average theta power of all the subjects is significant.

From the ANOVA performance as given above the following findings can be listed:-

- The p–value observed in the average band power estimate of all subjects is less than 0.05 for alpha, delta and theta bands. This fulfils the alternative hypothesis and rejects the null hypothesis. This indicates that there is a significance variation between the powers of the three phases in the alpha, delta and theta bands of all the subjects.

- The p-value observed in the average band estimate of all subjects is more than 0.05 for beta. This fulfils the null hypothesis and rejects the alternative hypothesis. This indicates that although the power is changing in the three phases in the beta band in all the subjects still the magnitude of change is not significant.

4.8 Finding Correlation between the different leads of the Acquired EEG signal

The EEG signals of the eight subjects were taken in six leads as mentioned earlier. The values in the leads were different for each of the subjects. But there has to be some similarity between these values as all were taken from the same subject under same conditions and at the same point of time. To prove this a statistical tool, correlation was used. Two of the leads were taken at the same time to see the correlation. In this way the correlation was checked between all the leads and the value was noted. In all the cases, a positive correlation was reflected and the leads ere highly correlated.

The correlated values between all the leads for all the subjects considering two leads simultaneously are given below:-

Table 4.12: Correlation between all the leads in the three phases

LEAD	SUBJECT	PRE	DURING	POST
F7-REF & F8-REF	Subject 1	0.90149359	0.84542503	0.91854329
F7-REF & F8-REF	Subject 2	0.93661189	0.94035904	0.95605714
F7-REF & F8-REF	Subject 3	0.83659656	0.84159057	0.75098889
F7-REF & F8-REF	Subject 4	0.97161816	0.92617745	0.96822888
F7-REF & F8-REF	Subject 5	0.98202112	0.94051492	0.98603391
F7-REF & F8-REF	Subject 6	0.96774636	0.94101072	0.99417257
F7-REF & F8-REF	Subject 7	0.97926935	0.939138	0.97284536
F7-REF & F8-REF	Subject 8	0.92395021	0.8417615	0.87597179
F7-REF & F3-REF	Subject 1	0.9511727	0.924574	0.930847
F7-REF & F3-REF	Subject 2	0.97214761	0.978416	0.985742
F7-REF & F3-REF	Subject 3	0.8177746	0.895525	0.807802
F7-REF & F3-REF	Subject 4	0.95193196	0.926469	0.86454
F7-REF & F3-REF	Subject 5	0.98844292	0.940515	0.99579
F7-REF & F3-REF	Subject 6	0.98972216	0.985982	0.997017
F7-REF & F3-REF	Subject 7	0.99416294	0.982177	0.990634
F7-REF & F3-REF	Subject 8	0.9670258	0.902764	0.863893
F7-REF & F4-REF	Subject 1	0.890399	0.833811	0.927982
F7-REF & F4-REF	Subject 2	0.926383	0.933263	0.960996
F7-REF & F4-REF	Subject 3	0.834832	0.857061	0.756008
F7-REF & F4-REF	Subject 4	0.95212	0.901035	0.929997
F7-REF & F4-REF	Subject 5	0.979348	0.970787	0.9893
F7-REF & F4-REF	Subject 6	0.965123	0.949626	0.99401
F7-REF & F4-REF	Subject 7	0.972427	0.879973	0.967691
F7-REF & F4-REF	Subject 8	0.52663	0.364959	0.496954
F7-REF & FZ-REF	Subject 1	0.927867	0.87371	0.956396
F7-REF & FZ-REF	Subject 2	0.936283	0.954124	0.970833
F7-REF & FZ-REF	Subject 3	0.65883	0.828239	0.729274
F7-REF & FZ-REF	Subject 4	0.976577	0.957222	0.977455

F7-REF & FZ-REF	Subject 5	0.988328	0.981246	0.991018
F7-REF & FZ-REF	Subject 6	0.975622	0.968888	0.994273
F7-REF & FZ-REF	Subject 7	0.986931	0.968369	0.984358
F7-REF & FZ-REF	Subject 8	0.930636	0.523781	0.673632
F8-REF & F3-REF	Subject 1	0.925367	0.81241	0.876495
F8-REF & F3-REF	Subject 2	0.934758	0.947571	0.959339
F8-REF & F3-REF	Subject 3	0.872393	0.960749	0.958415
F8-REF & F3-REF	Subject 4	0.934702	0.877738	0.855665
F8-REF & F3-REF	Subject 5	0.976716	0.946194	0.986938
F8-REF & F3-REF	Subject 6	0.961223	0.949092	0.994994
F8-REF & F3-REF	Subject 7	0.98276	0.947172	0.978652
F8-REF & F3-REF	Subject 8	0.942424	0.849821	0.836824
F8-REF & F4-REF	Subject 1	0.962969	0.92345	0.972539
F8-REF & F4-REF	Subject 2	0.97578	0.980536	0.982055
F8-REF & F4-REF	Subject 3	0.904308	0.977974	0.979196
F8-REF & F4-REF	Subject 4	0.985077	0.974898	0.96383
F8-REF & F4-REF	Subject 5	0.980392	0.973332	0.994715
F8-REF & F4-REF	Subject 6	0.990735	0.975923	0.997612
F8-REF & F4-REF	Subject 7	0.985113	0.911098	0.964048
F8-REF & F4-REF	Subject 8	0.678954	0.620685	0.640213
F8-REF & FZ-REF	Subject 1	0.954612	0.862378	0.958009
F8-REF & FZ-REF	Subject 2	0.943317	0.954438	0.965626
F8-REF & FZ-REF	Subject 3	0.642526	0.944218	0.949597
F8-REF & FZ-REF	Subject 4	0.99405	0.989941	0.994953
F8-REF & FZ-REF	Subject 5	0.983836	0.957329	0.989306
F8-REF & FZ-REF	Subject 6	0.979901	0.966304	0.995693
F8-REF & FZ-REF	Subject 7	0.986857	0.951632	0.980616
F8-REF & FZ-REF	Subject 8	0.932466	0.544834	0.671016
F3-REF & F4-REF	Subject 1	0.929757	0.848191	0.90666
F3-REF & F4-REF	Subject 2	0.950804	0.961268	0.97618
F3-REF & F4-REF	Subject 3	0.868426	0.971691	0.973918
F3-REF & F4-REF	Subject 4	0.9622	0.932077	0.948202

F3-REF & F4-REF	Subject 5	0.982085	0.977668	0.991012
F3-REF & F4-REF	Subject 6	0.965378	0.96188	0.996958
F3-REF & F4-REF	Subject 7	0.978335	0.887685	0.964354
F3-REF & F4-REF	Subject 8	0.577764	0.457376	0.578859
F3-REF & FZ-REF	Subject 1	0.973683	0.899388	0.932717
F3-REF & FZ-REF	Subject 2	0.971051	0.983563	0.989572
F3-REF & FZ-REF	Subject 3	0.617157	0.937867	0.956673
F3-REF & FZ-REF	Subject 4	0.940191	0.900914	0.853528
F3-REF & FZ-REF	Subject 5	0.994487	0.987157	0.993611
F3-REF & FZ-REF	Subject 6	0.981205	0.984531	0.998095
F3-REF & FZ-REF	Subject 7	0.995943	0.985856	0.996591
F3-REF & FZ-REF	Subject 8	0.965047	0.769639	0.887262
F4-REF & FZ-REF	Subject 1	0.968857	0.959206	0.984942
F4-REF & FZ-REF	Subject 2	0.964114	0.97283	0.983713
F4-REF & FZ-REF	Subject 3	0.779134	0.94479	0.961436
F4-REF & FZ-REF	Subject 4	0.98371	0.967227	0.957342
F4-REF & FZ-REF	Subject 5	0.989466	0.98898	0.994522
F4-REF & FZ-REF	Subject 6	0.991897	0.985188	0.998846
F4-REF & FZ-REF	Subject 7	0.980215	0.897872	0.966375
F4-REF & FZ-REF	Subject 8	0.552639	0.356191	0.542417

The average correlation values between the leads in all the subjects in each of the three phases - pre, during and post is given in table 4.13.

Table 4.13: Average Correlation Values between all the leads in all the subjects in three phases

LEAD	Pre	During	Post
F7-REF & F8-REF	0.9374134	0.901997	0.927855
F7-REF & F3-REF	0.9540476	0.942053	0.929533
F7-REF & F4-REF	0.8809078	0.836314	0.877867
F7-REF & FZ-REF	0.9226343	0.881947	0.909655
F8-REF & F3-REF	0.941293	0.911343	0.930915
F8-REF & F4-REF	0.9329161	0.917237	0.936776
F8-REF & FZ-REF	0.9271955	0.896384	0.938102
F3-REF & F4-REF	0.9018437	0.874729	0.917018
F3-REF & FZ-REF	0.9247814	0.895251	0.920965
F4-REF & FZ-REF	0.901254	0.884036	0.923699

The variation in the average correlation value amongst all the leads in the three phases is denoted by the figure below:-

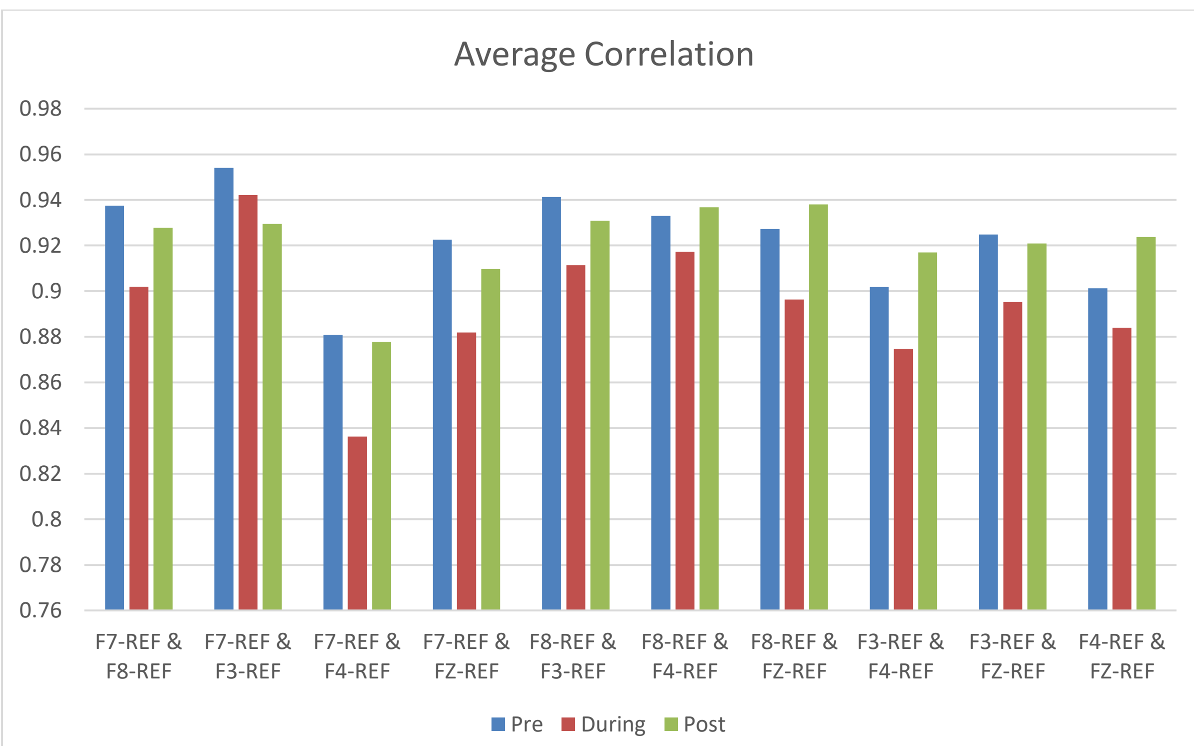


Fig. 4.17: Variation in the average correlation values in the three phases

The magnitude of variation in the average correlation values between all the leads in all the subjects in the three phases is performed using the statistical tool ANOVA.

Table: 4.14: ANOVA Result of Average Correlation between all the leads in all the subjects in the three phases

ANOVA SINGLE FACTOR						
SUMMARY						
Groups	**Count**	**Sum**	**Average**	**Variance**		
PRE	10	9.224287	0.922429	0.000479		
DURING	10	8.941292	0.894129	0.000796		
POST	10	9.212386	0.921239	0.000308		
ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	0.005124	2	0.002562	4.854252	0.015815	3.354131
Within Groups	0.01425	27	0.000528			
Total	0.019374	29				

The observations from the above correlation results are:-

- The correlation values observed in between the leads in each of the three phases for all the subjects are near to 0.9, which signifies that the leads are highly correlated. This symbolizes to the fact that although the leads which correspond to the placement of electrodes, were located at various portions of the scalp of the subjects, still the underlying brain dynamics were behaving in a co–ordinate manner irrespective of whether the subject was under resting condition or reading the comic strips or interpreting the humorous contents from the strips given.

- Although the leads were highly correlated, still the values were varying in the three phases. This can be attributed to the effect of stimulus. The variation is seen from the chart provided in figure 4.17. To estimate the extent of variation, statistical tool ANOVA was utilised in which the p–value was less than 0.05 signifying acceptance of alternative hypothesis. This indicates that under the effect of humour stimulus the brain was behaving differently than the resting condition. The correlated values of the leads in the post phase did not return back to the values obtained in the resting phase. This depicts that the effect of stimulus was still persistent after the subjects stopped reading the comic strips.

4.9 Fractal Dimension Analysis

The dynamics of the human brain is highly complex. To understand about this complexity, non–linear feature like the analysis of the fractal dimension of the human brain is quite necessary. This will help to observe the effect of a stimulus in the human brain. The most useful method for computing the fractal dimension of the human brain is by HFD method. For this the fractal dimensional analysis was performed and the results with the variation of the fractals in the three phases for one subject and also for the average HFD values considering all the subjects in all the leads are given below.

For finding the fractal dimension the main criteria is proper selection of the value of K_{max}. The method used for determining the value of K_{max} is by carefully inspecting the saturation point in the graph. In this study, after looking minutely into various graphs, it was observed that the saturation point is around 50 and so the value of K_{max} was set to 50.

The change in the fractal dimension values of the EEG signal in the pre, during and post phases in Subject 1 are given below:-

Table 4.15: HFD variation in Subject 1

LEAD	HFD		
	Pre	During	Post
F7-REF	1.87385	1.938043	1.910535
F3-F4	1.916673	1.955541	1.913666
F8-REF	1.882175	1.941816	1.905965
F3-REF	1.876576	1.941314	1.908458
F4-REF	1.878584	1.949117	1.907152
FZ-REF	1.882395	1.94877	1.910202

The variation in the average HFD values of the EEG signal in the pre, during and post phases are given below:-

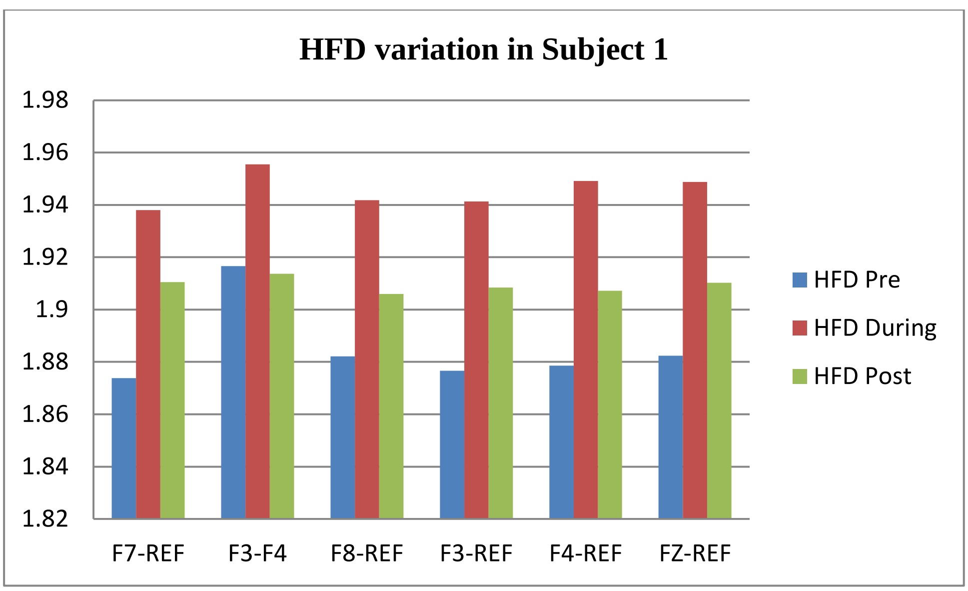


Fig. 4.18: HFD variation in the three phases in Subject 1

The change in the fractal dimension values of the EEG signal in the pre, during and post phases for average HFD values taking all the subjects under consideration are given below:-

Table 4.16: Average HFD Variation

LEAD	HFD		
	Pre	During	Post
F7-REF	1.91925	1.92281	1.91283
F3-F4	1.93778	1.93885	1.94101
F8-REF	1.92253	1.93428	1.91769
F3-REF	1.92396	1.93712	1.92144
F4-REF	1.93226	1.94172	1.92345
FZ-REF	1.91198	1.93622	1.91737

The variation in the average HFD values of the EEG signal in the pre, during and post phases are given below:-

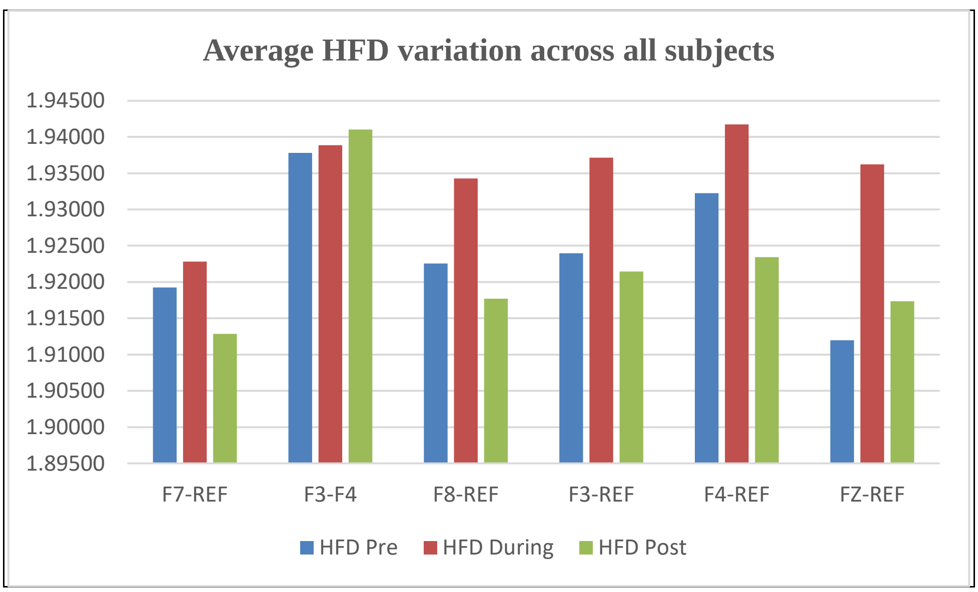


Fig 4.19: Average HFD variation in the three phases in all the Subjects

The observations from the HFD variation shown above are listed below.

- From the above figure 4.19, it is observed that the when the subjects were under the influence of the stimulus, that is when the subjects were reading the contents of the comic strips, the value of the fractal were increasing then the resting phase.

- After the removal of the comic strips from the subjects, the fractal values were not equal to the resting phase. This suggests that the subjects were feeling relaxed after interpreting the humorous contents from the comic strips.

- The variation of the fractal values observed in the different leads is different. This can be attributed to the fact that the perception of humour is highly subjective in nature.

4.10 Need for windowing of the EEG signal

For the need of emotion classification, dataset needs to be created. The datasets should have some features of the acquired EEG signals and labels. The labels are required to distinguish which feature belongs to which phase of the acquisition. The dataset should be large enough that is it should have large amount of features. This is required as the dataset will be given to the machine learning classifiers. The classifier will be trained on the basis of the features, that is which feature value belongs to which phase. The window length is chosen same as sampling frequency and the window time is taken as one second. This gives sixty data points of the whole signal. The window is passed through the whole signal in one second time to obtain the values of the features required. The sampling frequency of 256 Hz is used. After the values are obtained, the labels are put for clear distinction. Different types of features were used for creating the dataset. The features used for creating the dataset are some statistical features like mean, standard deviation and also other features like estimating different frequency band powers and non–linear feature like analysis of fractal dimension by Higuchi’s method. The mean computes the average value of the input signal. When the window of 1 second time frame at sampling frequency is passed through the EEG signals of different subjects, the men value is obtained. The K_{max} value selection is of utmost importance. The value of K_{max} is selected by carefully observing the saturation point in the graph. The value of K_{max} is chosen to be 50 in this study.

The values of the different features evaluated after windowing the signals along with the label numbers of each phase is given underneath. Since the dataset is quite large so a part of it is given below:-

Table 4.17: Extraction features through windowing

Mean F7-REF	**Mean F3-F4**	**Mean F8-REF**	**Mean F3-REF**	**Mean F4-REF**	**Mean FZ-REF**
104.8242	-9.24609	100.6367	92.20313	100.9141	93.875
1.398438	-3.84766	12.5625	1.242188	4.578125	2.546875
28.16016	-0.04297	24.81641	23.75391	23.30859	27.37109
-40.4531	-1.35938	-47.3516	-41.5313	-40.6641	-42.8828
Std F7-REF	**Std F3-F4**	**Std F8-REF**	**Std F3-REF**	**Std F4-REF**	**Std FZ-REF**
79.65403	14.6209	77.48379	69.33797	75.31654	67.13282
35.55274	18.24271	52.57089	35.24263	39.46318	36.09462
71.42138	17.38813	66.90046	63.24696	57.54005	56.36553
38.44667	17.86078	37.15576	34.54828	34.71413	37.40717
Alpha F7-REF	**Alpha F3-F4**	**Alpha F8-REF**	**Alpha F3-REF**	**Alpha F4-REF**	**Alpha FZ-REF**
34.20454	33.36098	156.6154	30.27627	71.03255	52.20148
343.6659	103.6998	755.4458	208.4861	109.7366	81.42342
155.7712	35.21128	336.623	169.2581	198.3474	182.5876
281.4117	96.30047	520.2059	319.0114	496.1348	415.6448
Beta F7-REF	**Beta F3-F4**	**Beta F8-REF**	**Beta F3-REF**	**Beta F4-REF**	**Beta FZ-REF**
55.7382	11.80684	46.44975	35.51451	51.24652	54.99305
68.42063	26.65068	81.74866	27.44927	28.14089	18.92474
61.99284	21.57001	92.22496	25.95179	21.20568	12.09094
37.12189	10.09788	55.57871	38.29884	45.91356	52.85339
Theta F7-REF	**Theta F3-F4**	**Theta F8-REF**	**Theta F3-REF**	**Theta F4-REF**	**Theta FZ-REF**
74.06296	77.08871	270.7974	68.30105	160.1698	115.952
149.3141	70.02217	611.9596	93.40498	155.7602	144.3341

456.8317	69.16791	901.7535	459.4742	523.7092	537.0735
438.293	250.0417	640.907	443.3118	726.5189	567.4392
Delta F7-REF	**Delta F3-F4**	**Delta F8-REF**	**Delta F3-REF**	**Delta F4-REF**	**Delta FZ-REF**
15530.33	36.1923	13685.26	12193.09	12830.78	11401.85
555.1554	87.65285	1251.917	497.8894	764.4486	500.7707
8020.28	176.9219	6269.983	6365.025	4842.672	5494.425
1627.206	139.2503	2591.391	1583.255	1331.814	1784.764
Gamma F7-REF	**Gamma F3-F4**	**Gamma F8-REF**	**Gamma F3-REF**	**Gamma F4-REF**	**Gamma FZ-REF**
6.618205	4.618668	14.457	4.979327	8.163405	6.073902972
13.67056	4.810297	16.34019	3.169751	4.711311	5.152353797
10.33035	8.9092	8.603087	5.299896	9.506139	6.637542773
21.48308	8.377474	11.65967	11.29524	14.74244	17.44425244
HFD F7-REF	**HFD F3-F4**	**HFD F8-REF**	**HFD F3-REF**	**HFD F4-REF**	**HFD FZ-REF**
1.372326	1.771629	1.473726	1.407479	1.46502	1.474051
1.729992	1.733715	1.636081	1.695742	1.62374	1.705225
1.363669	1.696514	1.439757	1.390938	1.416233	1.433722
1.687461	1.734425	1.855677	1.678122	1.724042	1.700202

4.11 Classification of different phases with Machine Learning approach

After extracting the features from the three different phases using the windowing technique, the features of the three phases are labelled accordingly. The features belonging to the **"PRE"** phase was labelled as **0**, the features belonging to the **"DURING"** phase was labelled as **1** and the features belonging the **"POST"** phase was labelled as **2**. This labelling is done as it helps in building the model with machine learning algorithm. The data used is labelled data. Three different .CSV files are created One file contains the features of "PRE" and "DURING" phases along with their corresponding labels, another consists of the features of "DURING" and "POST" phases with their labels and the third file contains features of the "PRE" and "POST" phases with their labels. This is done to create their different datasets.

Two different types of strategy are used in this experiment. In one approach the three datasets contain features of Higuchi's Fractal Dimension, Mean, Standard Deviation, different band powers of the EEG signals of the three phases along with their labels and in the second approach the datasets contain features only Mean, Standard Deviation, different band powers of the EEG signals of the three phases. Using these two different approaches the accuracy of the two different approaches are checked.

The aim for building the machine learning model is to test whether the machine can identify which feature belongs to which phase. This is done by training the model using appropriate machine learning algorithms. The algorithms used for this are Logistic Regression and Support Vector Machine. The accuracy of these algorithms was further verified with the help of cross validation technique. The classification process with the help of machine learning approach was done using Python.

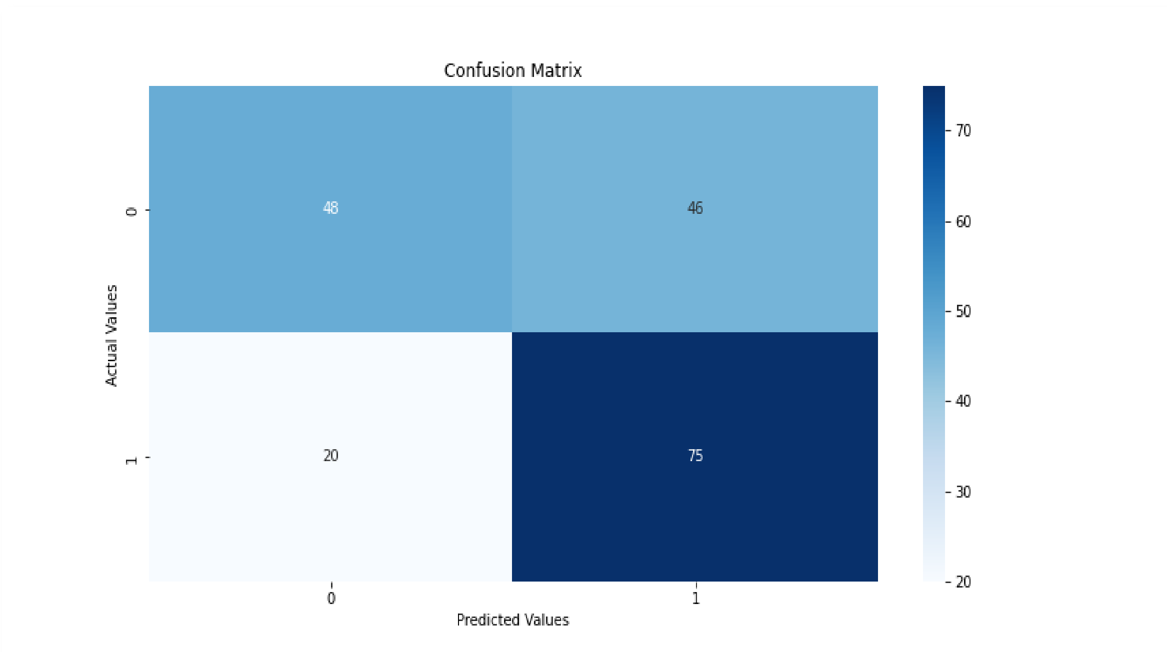
The workflow of the classification using machine learning algorithm is given below:-

- Importing the datasets
- Importing the required library functions in Python
- Stratifying the data so that training and test set get sufficient amount of data of the different phases present in the dataset
- Segregating the features and labels
- Splitting data into training and test set in the ratio 75:25
- Importing machine learning algorithms like Logistic Regression and Support Vector Machine
- Training the training dataset according to the machine learning algorithm chosen
- Applying the training on the test data
- Checking the accuracy from the test result with the help of confusion matrix

The Confusion matrices for the different datasets are given below:-

- **The Confusion matrix using Logistic Regression without the HFD feature is given below:-**

<u>Table 4.18: Confusion Matrix for the dataset containing Pre & During Features and Labels using LR (without HFD)</u>



Accuracy – 65.07936508

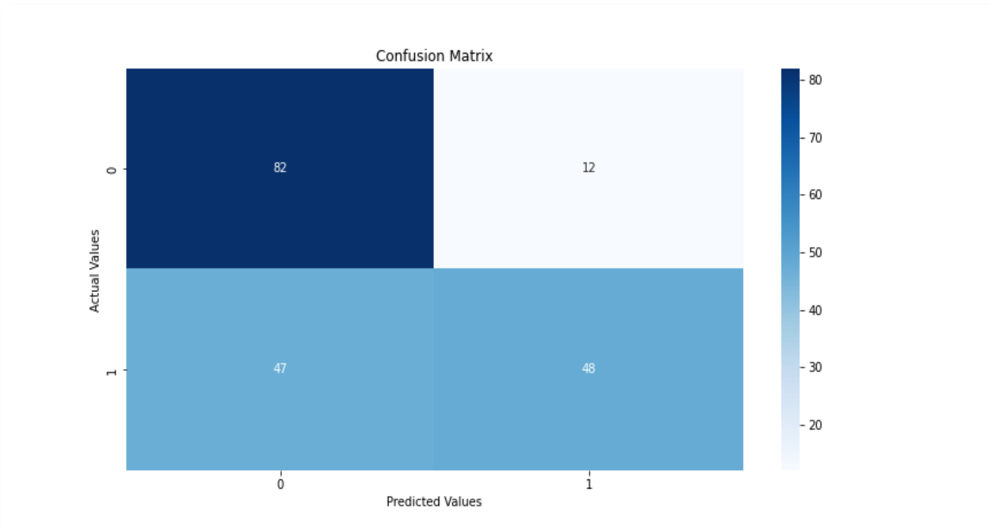
TP value – 75

TN value –48

FP value – 46

FN value - 20

Table 4.19: Confusion Matrix of the dataset containing During & Post Features and Labels using LR (without HFD)



Accuracy – 68.78306878

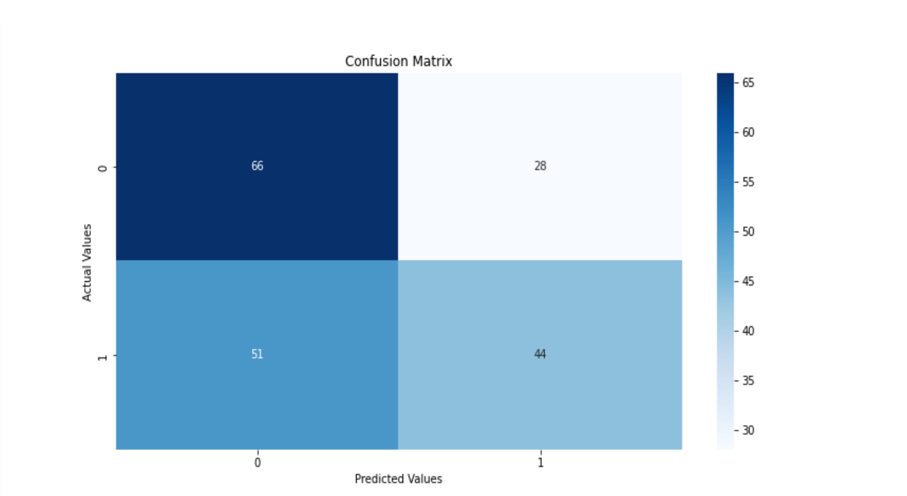
TP value –48

TN value –82

FP value – 12

FN value - 47

Table 4.20: Confusion Matrix of the dataset containing Pre & Post Features and Labels using LR (without HFD)



Accuracy – 58.2010582010581

TP value – 44

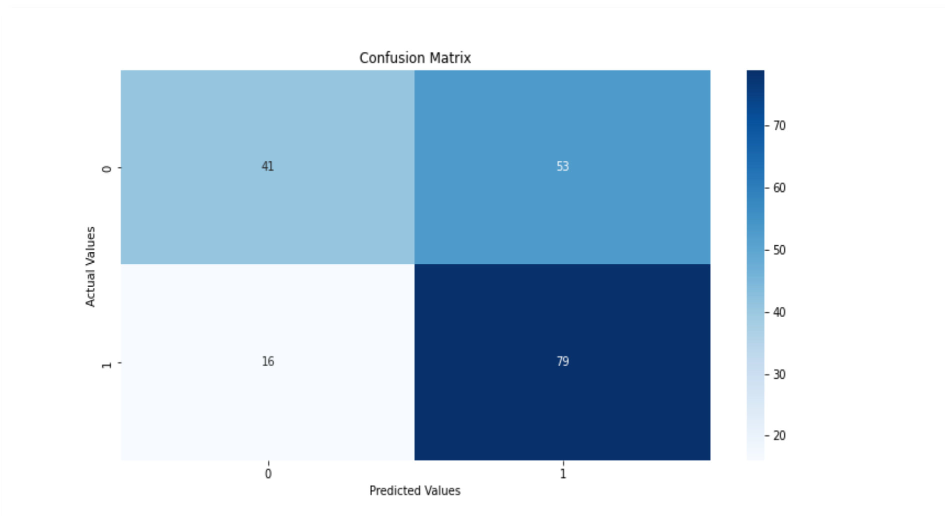
TN value – 66

FP value – 28

FN value - 51

➢ **The Confusion matrix using SVM without the HFD feature is given below:-**

<u>Table 4.21: Confusion Matrix of the dataset containing Pre &During Features and Labels using SVM (without HFD)</u>



Accuracy – 63.4920634920634

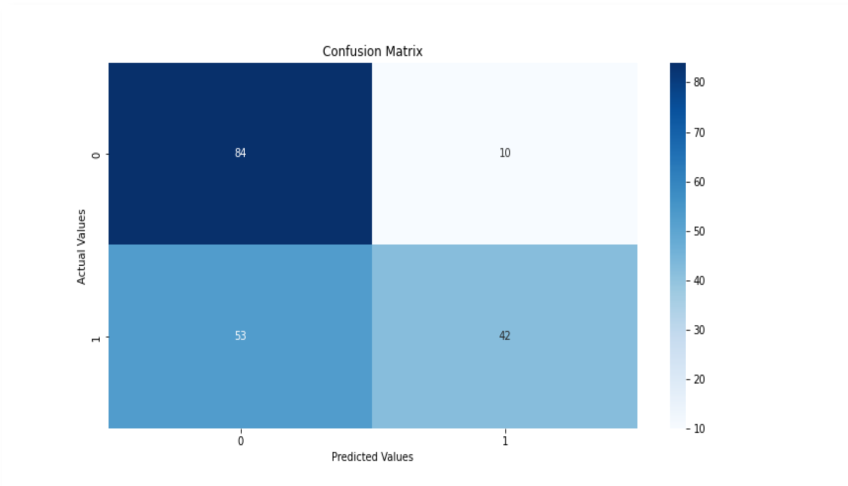
TP value –79

TN value –41

FP value – 53

FN value - 16

Table 4.22: Confusion Matrix of the dataset containing During & Post Features and Labels using SVM (without HFD)



Accuracy – 66.6666666666666

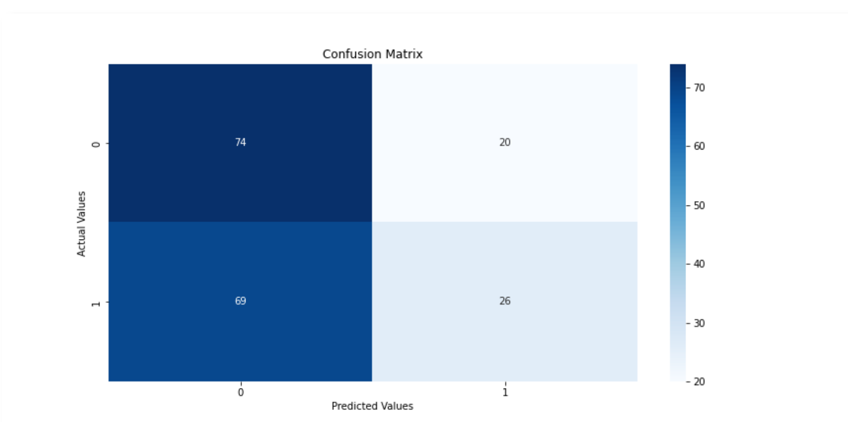
TP value –42

TN value –84

FP value –10

FN value - 53

Table 4.23: Confusion Matrix of the dataset containing Pre & Post Features and Labels using SVM (without HFD)



Accuracy – 52.9100529100529

TP value –26

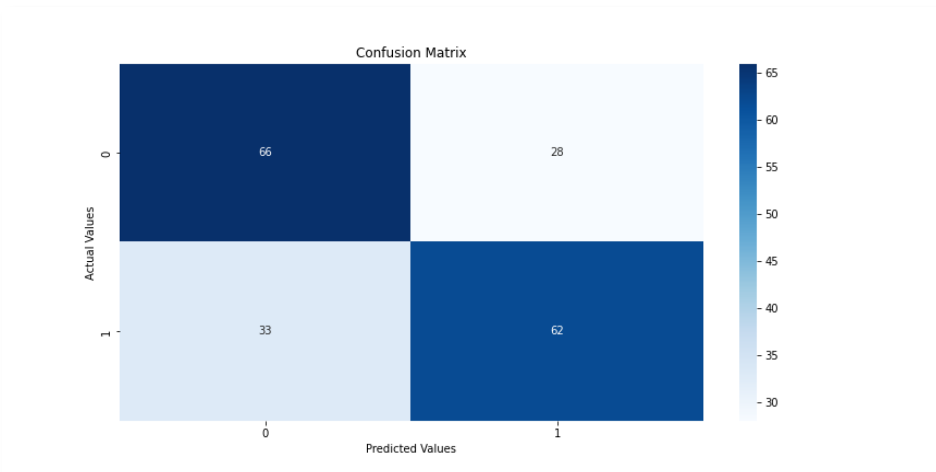
TN value –74

FP value – 20

FN value - 69

- **The Confusion matrix using Logistic Regression with the HFD feature is given below:-**

Table 4.24: Confusion Matrix of the dataset containing Pre &During Features and Labels using LR (with HFD)



Accuracy – 67.7248677248677

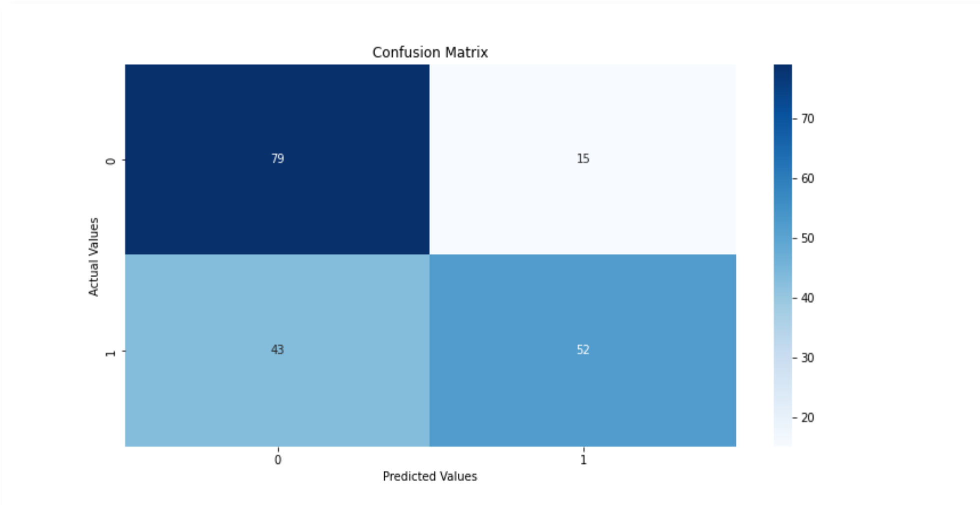
TP value –62

TN value –66

FP value – 28

FN value – 33

Table 4.25: Confusion Matrix of the dataset containing During & Post Features and Labels using LR (with HFD)



Accuracy – 69.3121693121693

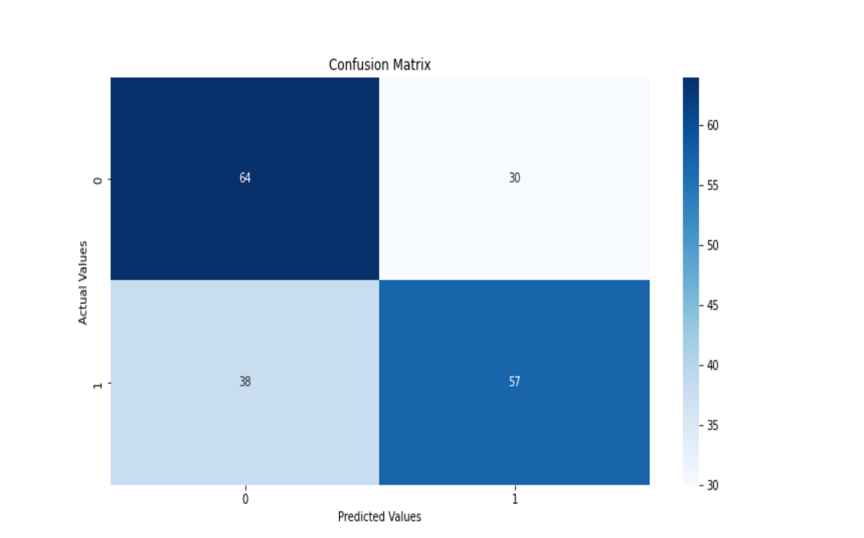
TP value –52

TN value –79

FP value – 15

FN value - 43

Table 4.26: Confusion Matrix of the dataset containing Pre & Post Features and Labels using LR (with HFD)



Accuracy – 64.021164021164

TP value –57

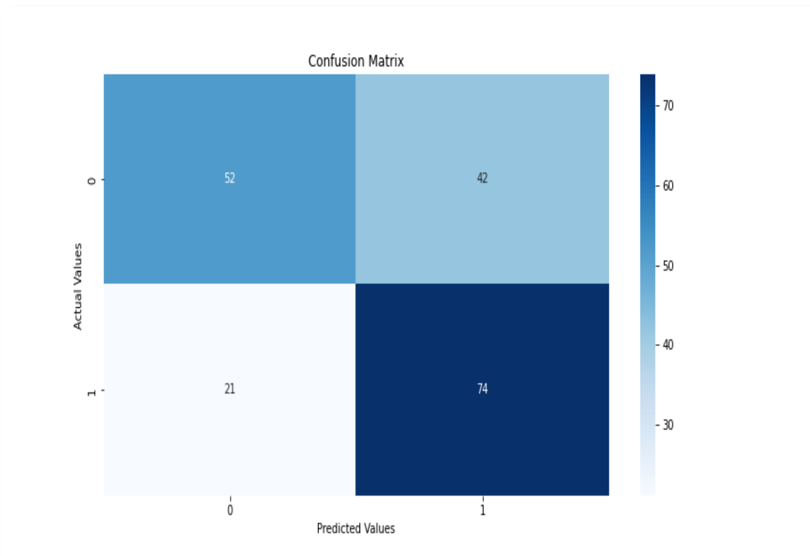
TN value –64

FP value – 30

FN value - 38

➢ **The Confusion matrix using SVM without the HFD feature is given below:-**

Table 4.27: Confusion Matrix of the dataset containing Pre & During Features and Labels using SVM (with HFD)



Accuracy – 66.66666666666666

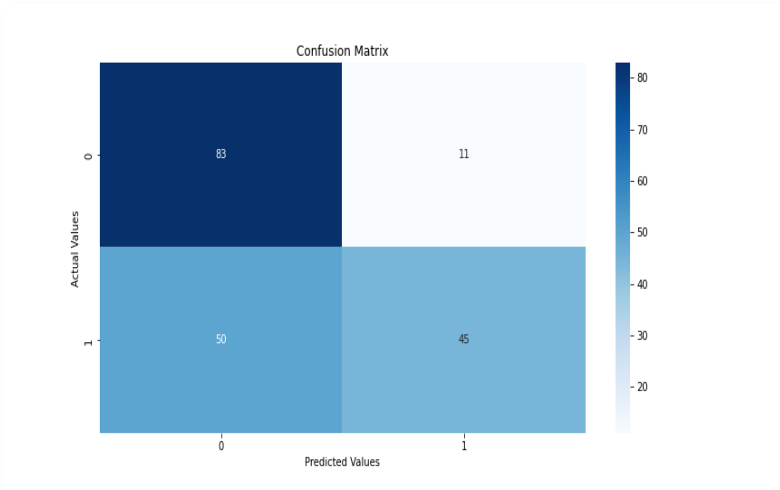
TP value –74

TN value –52

FP value – 42

FN value - 21

Table 4.28: Confusion Matrix of the dataset containing During & Post Features and Labels using SVM (with HFD)



Accuracy – 67.7248677248677

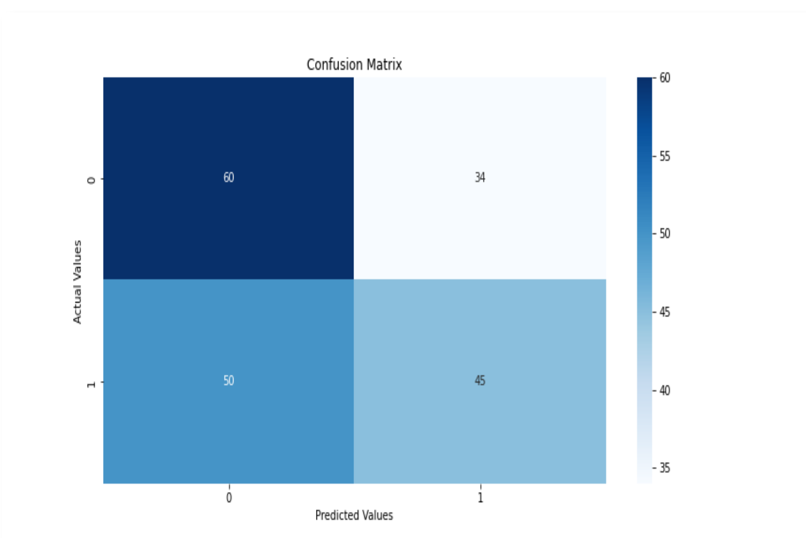
TP value –45

TN value –83

FP value –11

FN value - 50

Table 4.29: Confusion Matrix of the dataset containing Pre & Post Features and Labels using SVM (with HFD)



Accuracy – 55.5555555555555

TP value –45

TN value –60

FP value – 34

FN value - 50

The accuracy of the Logistic Regression and Support Vector Machine in case of using both HFD feature and without using HFD feature along with other characteristics of machine learning algorithms like precision, recall, F – measure are given below:-

Accuracy Score of the sets containing training as well the test data without HFD feature is given below:-

Table 4.30: Training and Test Set Accuracy Score for LR and SVM (without HFD)

ML Algorithm	**Type of Dataset**	**Test Accuracy Score**	**Train Accuracy Score**
LR	Pre & During	65.07936508	67.42
LR	During & Post	68.78306878	73.11
LR	Pre & Post	58.2010582	63.97
SVM	Pre & During	63.49206349	71.13
SVM	During & Post	66.66666667	73.51
SVM	Pre & Post	52.91005291	64.24

The classification reports obtained using LR and SVM algorithms excluding HFD feature are provided below:-

Table 4.31: Classification Report containing Precision, Recall and F – measure for both LR and SVM (without HFD)

ML Algorithm	Dataset			Precision	Recall	f1-score	Support
LR	Pre & During		0	0.71	0.51	0.59	94
			1	0.62	0.79	0.69	95
		Accuracy				0.65	189
		Macro - avg		0.66	0.65	0.64	189
		Weighted - avg		0.66	0.65	0.64	189
LR	During & Post		1	0.64	0.87	0.74	94
			2	0.8	0.51	0.62	95
		Accuracy				0.69	189
		Macro - avg		0.72	0.69	0.68	189
		Weighted - avg		0.72	0.69	0.68	189
LR	Pre & Post		0	0.56	0.7	0.63	94
			2	0.61	0.46	0.53	95
		Accuracy				0.58	189
		Macro - avg		0.59	0.58	0.58	189
		Weighted - avg		0.59	0.58	0.58	189
SVM	Pre & During		0	0.72	0.44	0.54	94

			1	0.6	0.83	0.7	95
		Accuracy				0.63	189
		Macro - avg		0.66	0.63	0.62	189
		Weighted - avg		0.66	0.63	0.62	189
SVM	During & Post		1	0.61	0.89	0.73	94
			2	0.81	0.44	0.57	95
		Accuracy				0.67	189
		Macro - avg		0.71	0.67	0.65	189
		Weighted - avg		0.71	0.67	0.65	189
SVM	Pre & Post		0	0.52	0.79	0.62	94
			2	0.57	0.27	0.37	95
		Accuracy				0.53	189
		Macro - avg		0.54	0.53	0.5	189
		Weighted - avg		0.54	0.53	0.5	189

Cross validation result for LR and SVM without the HFD feature is given below:-

Table 4.32: Cross Validation of LR and SVM (without HFD)

ML Algorithm	Type of Dataset	Average Cross Validation Score
LR	Pre & During	60.2113
LR	During & Post	63.9085
LR	Pre & Post	51.8486
SVM	Pre & During	59.507
SVM	During & Post	63.6444
SVM	Pre & Post	50.088

Accuracy Score with HFD feature

Table 4.33: Training and Test Set Accuracy Score for LR and SVM (with HFD)

ML Algorithm	Type of Dataset	Test Accuracy Score	Train Accuracy Score
LR	Pre & During	67.72486772	75.63
LR	During & Post	69.31216931	73.51
LR	Pre & Post	64.02116402	65.96
SVM	Pre & During	66.66666667	77.88
SVM	During & Post	67.72486772	74.97
SVM	Pre & Post	55.55555556	68.08

The classification reports obtained using LR and SVM algorithms including HFD feature are provided below:-

Table 4.34: Classification Report containing Precision, Recall and F – measure for both LR and SVM (with HFD)

ML Algorithm	Dataset			Precision	Recall	f1-score	Support
LR	Pre &During		0	0.67	0.7	0.68	94
			1	0.69	0.65	0.67	95
		Accuracy				0.68	189
		Macro - avg		0.68	0.68	0.68	189
		Weighted - avg		0.68	0.68	0.68	189
LR	During & Post		1	0.65	0.84	0.73	94
			2	0.78	0.55	0.64	95
		Accuracy				0.69	189
		Macro - avg		0.71	0.69	0.69	189
		Weighted - avg		0.71	0.69	0.69	189
LR	Pre & Post		0	0.63	0.68	0.65	94
			2	0.66	0.6	0.63	95
		Accuracy				0.64	189
		Macro - avg		0.64	0.64	0.64	189
		Weighted - avg		0.64	0.64	0.64	189
SVM	Pre & During		0	0.71	0.55	0.62	94

			1	0.64	0.78	0.7	95
		Accuracy				0.67	189
		Macro - avg		0.68	0.67	0.66	189
		Weighted - avg		0.67	0.67	0.66	189
SVM	During & Post		1	0.62	0.88	0.73	94
			2	0.8	0.47	0.6	95
		Accuracy				0.68	189
		Macro - avg		0.71	0.68	0.66	189
		Weighted - avg		0.71	0.68	0.66	189
SVM	Pre & Post		0	0.55	0.64	0.59	94
			2	0.57	0.47	0.52	95
		Accuracy				0.56	189
		Macro - avg		0.56	0.56	0.55	189
		Weighted - avg		0.56	0.56	0.55	189

Cross validation result for LR and SVM with the HFD feature is given below:-

Table 4.35: Cross Validation of LR and SVM (with HFD)

ML Algorithm	Type of Dataset	Average Cross Validation Score
LR	Pre & During	57.4824
LR	During & Post	62.412
LR	Pre & Post	55.2817
SVM	Pre & During	59.5951
SVM	During & Post	63.5563
SVM	Pre & Post	51.4085

The findings from the datasets after applying the ML algorithms are listed below:-

- The test accuracy result for the algorithms, logistic regression and support vector machine lies in between 50% to 70% for both types of datasets namely datasets containing HFD feature and datasets without using the HFD feature.

- The cross validation result for the same lies in between 50% to 70%. For cross validation the accuracy result has decreased which is true for application of cross validation.

- In case of using the HFD feature in the dataset for the three phases “PRE”, “DURING” and “POST”, the test accuracy is more than when the feature is not used. This shows that the fractal dimension analysis play a crucial role while classifying the results of the three phases by the computer. This is due to the fact that with the application of the stimulus the fractal dimension of the human brain changes from the resting state.

5. Discussion

The classification of features of emotion by using ML algorithm based on EEG signals acquired from different subjects has shown some important findings upon response of human brain to humour stimulus. The observations are discussed below.

- **Analysis of Humour in present lifestyle**

This study was started with an aim of analysing the variations in the brain dynamics of human beings with the effect of humour stimulus. By looking at the present busy and workaholic life–style, the stimulus was chosen to be humour as it will help one to relax and reduce stress. Due to the pandemic situation all around the globe in the last two years, people have faced restrictions in going out and enjoying, some has suffered even more by losing their close ones and some have been affected financially. These lay the foundation of depressing mood. People nowadays do not have the time to take care of their mental health. There is a need of taking care of the mental health otherwise not only the person himself but also his work and family will be affected. The foremost approach towards this mental relaxation and stress relief can be achieved only by humour. Watching comedy video clips or movies related to comedy is time consuming and there is a lack of time in each and everyone's life at present. So the old concept of reading comic strips can prove more efficient as it hardly takes time. Reading the contents from the comic strips and comprehending and interpreting the humour from the contents lighten one's mood. Mood is related to emotion and emotion is a function of the human brain. Thus perception of humour changes the dynamics of the underlying brain. These variations observed from different analytical approaches performed in this study are discussed in the next part.

- **Protocol set–up for this experiment**

An experimental procedure was designed which involved recording of the EEG signal from eight different subjects including male and female. The EEG signals were then pre-processed, de-noised and then analysed using various time-frequency domain tools, non-linear methods, and in order to quantify and validate our work, machine learning classifiers were used on the acquired datasets.

The EEG recording protocol was divided into three phases namely pre, during and post phase. Pre phase refers to the time interval before the subject read the jokes or when the subjects were under a resting condition. The time for recording the EEG signal is one minute. During phase refers to the time interval when the subjects were reading the comic strips. The time duration of EEG recording for this phase is one minute. The post phase refers to the time interval when the subjects were interpreting the humorous contents from the comic strips read in during phase and in this phase the comic strips were taken away from the subjects. The time duration for this phase is five minutes. The EEG signal recording phase is designed in such a way so that the effect of reading of the jokes can be compared with periods before and after it.

- **Observation of the acquired EEG signal**

The plots of the EEG signal in the three phases are different from each other which can be seen from the plots given in the methodology and results section. This can be the cause of the effect of the stimulus. Thus it can be confirmed that the stimulus is causing some changes in the dynamics of the brain of the subjects. Also as the six electrodes used in this study were placed in different parts of the scalp, so the signal plot obtained from each of these electrodes are different from each other. This indicates that different portions of the brain act differently under same condition or even under the effect of the same stimulus. The EEG plots in the three phases of the eight different subjects are different which implies that the perception of humour stimulus is subjective in nature. As EEG is a non-stationary wave without any distinctive or predictable characteristic form, hence, by visual inspection of the EEG signal plots no particular attribute which can be the cause of the variation in the signal between the three phases of recording cannot be analysed. This can be confirmed by looking into the EEG signal plots obtained from MATLAB simulator given in methodology and results section.

- **Observation on the de–noised EEG signal**

After acquisition of the EEG signal, a basic pre-processing stage of the signal analysis is necessary which is done by the signal de–noising. By de–noising the signal the unwanted elements affecting the quality of the signals are eradicated. In this study for the purpose of de–noising of the signal the wavelet transform tool is applied. There are various methods for de–noising of signals like FIR, IIR filters and also Fourier Transform. As Fourier Transform is mainly works for frequency domain signals so this technique is discarded as EEG signal contains both time and frequency domain components. EEG signal is 1D signal and FIR and IIR filters do not produce good SNR values for such signals. Thus these techniques are avoided. As wavelet transform works both for time and frequency domain signals and are provide good SNR values for 1D signal, so from these observations the wavelet based methods prove to be an efficient tool in de–noising the EEG signals and is used in this experiment. For this in this study, wavelet was chosen to be Daubechis 6 (db6) form of the wavelet is used for de–noising of the signal. Ten levels of decomposition are applied. Trial and error method is adopted for choosing the threshold value. The threshold value was set by careful inspection of the signal. Hence soft thresholding is applied. The threshold value is set such that the high frequency components are removed and only the significant trends remain in the signal. For all the levels of decomposition, the same threshold value was set to retain the significant features only. The EEG signals after de-noising have been plotted.

- **Observation from the PSD plots of both original and de–noised EEG signals**

For checking whether proper de–noising is done or not, the PSD plots using the Welch method for both the original and de–noised signals are plotted. It can be seen that in PSD plots, after de-noising, some high frequency components have been removed. Most of the information of the EEG signal is present in the low frequency region, which is up to 20 Hz. The different bands of the EEG signal namely the delta (0.5 Hz to 4 Hz), theta (4 Hz to 8 Hz) and alpha (8 Hz to 13 Hz) bands comprise the low frequency region of the signal. In the original signal plot, it can be observed that there are some sharp ridges within 0 Hz to 20 Hz. But after de–noising of the signals, those sharp ridges have been smoothened. Hence we can confirm that wavelet de-noising has improved the quality of the EEG signals. Also, this can be visually confirmed by the looking at the PSD plots given in the methodology and results section, that the EEG wave is free from high frequency noise after application of wavelet based de–noising technique.

- **Observation from the variation in the different band powers of the EEG signals in the three phases**

Alpha, beta, theta, delta waves are important sub bands of the EEG signal, carrying essential information regarding underlying dynamics of the brain. After de–noising of the signal, the alpha, beta, delta and theta bands are extracted from the signal by using MATLAB simulator. The results were tabulated and inspected. The powers of these bands are determined for each of the three phases in all the leads for all the subjects and an estimate of the average power fluctuation considering all the subjects in all the leads is determined. The power variation of one subject and the average power fluctuation are given in the methodology and results section. From both above mentioned cases, the tables of power fluctuation it is observed that for all the leads the alpha, beta, delta and theta band powers are decreasing than the powers in the resting condition while the subjects are reading and comprehending the jokes from the comic strips. Again after the removal of the stimulus from the subjects, the powers of the different bands did not come back to the resting phase. This suggests that while the subjects were reading the jokes the underlying brain dynamics were changing which were causing change in the band powers. Also when the stimulus was removed and the persons were interpreting the humour from the contents of the comic strips, their brains were still under the effect of the stimulus and so the power in the post phase was not equal to that in the pre phase although it increased from the during phase. The variations observed in the different bands are discussed in the part that follows.

- **Variation of alpha band power**

From the charts of variation in average alpha power given in the methodology and results section, consistent decrease in the power is observed while the subjects were reading the jokes. This reveals that the humour stimulus causes an arousal effect in the subjects. As alpha wave marks the resting condition of the brain, decrease in the alpha power denotes some rise in the cortical activity. This can be attributed to the fact that the subjects were quite attentive while reading the comic strips. Even after the removal of the stimulus, the power did not return back to the original state. This signifies that the effect of stimulus was still persistent.

- **Variation of beta band power**

The beta power in during phase, that is when the subjects were reading the comic strips, a significant decrease is observed. As beta wave mainly deals with the reasoning of the contents present in the comic strips given to them, so decrease in the beta power in the during phase implies that the ability of reasoning varies in different subjects. This is reflected from the results. After removal of the comic strips, there is significant rise in the beta power but it is not equal to the power in the pre phase which indicated to the fact that the persons were interpreting the humorous contents from the jokes and their stressful moods were relaxing. Thus it can be observed that although the reasoning ability was low in the subjects still the interpretation of the humour was significantly in them signifying that interpretation was done after reading the strips. This can also be attributed to the condition that some subjects recognised the humour from reasoning while others familiarised it with some of the events that had previously occurred in their life.

- **Variation of delta band power**

The delta band power can be seen from the variation charts are having a significant dip while the persons were reading the comic strips than the power in the resting phase. Delta power is predominant when a person is sleeping. This decrease in the power implies that when the persons were reading the comic strips, they were not feeling sleepy at all. Instead some arousal effect was observed in the subjects reading the humorous contents. Again a rise in the power is reflected in the post phase, which indicates that after perceiving the humour the mood of the subjects became less stressful.

- **Variation of theta band power**

From the charts dealing with the variation of theta power, a decrease in the theta power is visualised while the subjects were reading the comic strips. As theta power mainly deals with the subconscious minds of persons, so a decrease in the theta power indicates that the persons were very much conscious and concentrated while reading the comic strips. Again the rise of the theta power in the post phase is observed and the magnitude of this increase is not equal to the power captured in the resting condition. This signifies that after the removal of the comic strips from the subjects, the effect of stimulus was still pertaining in their minds. After removal of these comic strips, the subjects' brain again went back to the subconscious state but in the subconscious state also the persons were thinking about the humorous contents of the jokes just read.

- **Statistical Analysis of band power fluctuation**

Observing from the tables and charts of power variation of the different bands of the EEG signal, it can be said that the average power of the brains of the subjects decreased significantly. But this magnitude of decrement is varying from subject to subject. This indicates that the perception (comprehension and interpretation) of humour is highly subjective. The decrement in the average power of all the bands implies that the subjects were relieved from stress after perceiving the humour. Also another important observation was visualised after removal of the comic strips that the power did not rise back to its resting back indicating that the effect of stimulus was still predominant in the brain of the subjects.

As the magnitude of variation in the average powers of the different bands is varying from subject to subject as visualised from the tables and charts given in the methodology and results section, so a tool or technique must be utilised to find out about the significance of variation. In order to validate our inferences from the tabulated band powers for each subject, we used ANOVA, a reliable statistical analysis tool. The use of this tool indicated that the variation of the alpha, delta and theta band powers in the three phases were quite significant. This can be said as in each of these bands' variation, the p–value is less than the significant value, 0.05 and the F–critical value are more than the F–value indicating the change is highly significant. Thus the observations predicted from the tabulated data and the charts are justified by this finding for each of the alpha, delta and theta bands. For the variation in the average beta band power when this statistical method was applied, it was observed that the F-critical value was higher than the F–value and the p-value is higher than the significant value, 0.05 which rejects the alternative hypothesis and accepts the null hypothesis. The alternative hypothesis states that the observed variation is significant while the null hypothesis states that the observed variation is not significant. This finding can be attributed to the effect of the cause that the reasoning capability varies in different persons. Thus this finding also justifies our observation of the fluctuation in the average beta power.

- **Observation on the correlation analysis of the six different leads used in the experiment**

The results from the analysis of correlation between the six different leads showed high degree of correlation in all the three phases of recording of the EEG signal. Also from this analysis of correlation of the different leads, it was observed that these leads showed variation in the correlation values among the different phases, which means that the correlation value of a particular electrode pair is different in the three phases but the value of a lead is quite similar to another lead in the same phase. The high of correlation observed from the results, signifies that although the six different leads were positioned at different places on the scalp, still the dynamics of the underlying brain behaved similarly irrespective of whether the subject was under resting condition or subjected to the humour stimulus. The correlation value between the leads decreased when the subjects were reading the comic strips. This suggests that when the subjects were under the action of humour stimulus, a change occurs in the underlying physiological process which leads to the variation between the correlation values in the resting phase and the comprehending phase. Also when the comic strips were taken away from the subjects, the correlation value was not equal to that of the resting phase instead it was lower than the resting phase but greater than the during phase. This indicates that the effect of stimulus was still active in the subjects and also after interpreting the humour from the contents, the subjects were feeling relaxed.

From the tabulated results of correlation between the three phases given in methodology and results section, it is observed that there is a variation between the values of correlation of the leads in the three phases. To find out the magnitude of variation the reliable tool, ANOVA was performed. The results observed from this tool show that there is a significant variation between the leads in the three phases. The p-value was less than the significant level indicating the acceptance of alternative hypothesis. Thus it can be suggested that under the action of humour stimulus the brain dynamics of the subjects' were changing and also it can be said that there was a relaxing effect in the moods of the subjects.

- **Observation on the fractal dimensional changes of the EEG signal in the three phases**

From the fractal dimensional analysis of the EEG signal, a rise is observed in the complexity of the EEG signals while the subjects were reading the jokes. This signifies that when the subjects were under the effect of the stimulus the underlying region of the brain stimulated the other regions to work in a synchronised manner for achieving the effect of the humour stimulus. While the subjects were interpreting the humorous content from the comic strips, the complexity of the fractal dimension decreased from its previous phase. This signifies that the only the humour-associated region of brain was functioning for perceiving the humour. When the subjects were reading the comic strips the fractal dimension increased from that in the resting phase and also when the comic strips were removed from the subjects, the fractal dimension did not return to the resting phase instead it was lesser than that of the resting phase. This signifies that when the subjects were under the effect of the humour stimulus the fractal dimension showed some increase and even after the removal of the stimulus the effect of humour was still persistent in the brain of the subjects.

- **Data preparation for ML Analysis**

The windowing of the signal was performed to divide the signal into small parts. A window of time frame of 1 sec was passed through the whole signal of each phase. Due to adoption of this technique large amount data was generated. The mean, standard deviation, different band–powers and fractal dimension of the signal of the three phases were estimated through the winnowing technique. With the help of windowing the whole signal, different features were extracted from the three phases of the recorded EEG signals. The data acquired from windowing the signals were labelled. The data of the pre phase was labelled 0, the data of during phase was labelled 1 and the data of the post phase was labelled 2. The objective for producing such large datasets and labelling those data was the application of machine-learning algorithms. From the tabulated results as seen from the methodology and results section, it is observed that the value of the mean, standard deviation and the different band powers are changing in each of the phase.

➢ Observation from the classification of features by ML algorithms

The aim of using machine learning in this study was to show whether the machine can identify the features by studying from the labelled data of the three phases – "PRE", "DURING", "POST". One dataset contained labelled data from "PRE and DURING", "DURING and POST", and "PRE and POST". Two different ML algorithms were used in this study namely Logistic Regression and Support Vector Machine. The model was trained individually with the two selected ML algorithms. The test data was provided after training and the accuracy score was found from the confusion matrix.
The observations from the confusion matrix are as follow:-

When the dataset named "PRE and DURING" excluding the fractal dimension feature was imported and Logistic Regression was applied, then true negative score was 48 and the true positive score was 75. The false positive result is 46 and false negative result is 20. The total number of correct predictions made from this dataset is 123.

When the dataset named "DURING and POST" excluding the fractal dimension feature was imported and Logistic Regression was applied, then true negative score was 82 and the true positive score was 48. The false positive result is 12 and false negative result is 47. The total number of correct predictions made from this dataset is 130.

When the dataset named "PRE and POST" excluding the fractal dimension feature was imported and Logistic Regression was applied, then true negative score was 66 and the true positive score was 44. The false positive result is 28 and false negative result is 51. The total number of correct predictions made from this dataset is 110.

When the dataset named "PRE and DURING" excluding the fractal dimension feature was imported and SVM was applied, then true negative score was 41 and the true positive score was 79. The false positive result is 53 and false negative result is 16. The total number of correct predictions made from this dataset is 120.

When the dataset named "DURING and POST" excluding the fractal dimension feature was imported and SVM was applied, then true negative score was 84 and the true positive score was 42. The false positive result is 10 and false negative result is 53. The total number of correct predictions made from this dataset is 126.

When the dataset named “PRE and POST” excluding the fractal dimension feature was imported and SVM was applied, then true negative score was 74 and the true positive score was 26. The false positive result is 20 and false negative result is 69. The total number of correct predictions made from this dataset is 100.

When the dataset named “PRE and DURING” including HFD was imported and LR was applied, then true negative score was 66 and the true positive score was 62. The false positive result is 28 and false negative result is 33. The total number of correct predictions made from this dataset is 128.

When the dataset named “DURING and POST” including HFD was imported and LR was applied, then true negative score was 79 and the true positive score was 52. The false positive result is 15 and false negative result is 43. The total number of correct predictions made from this dataset is 131.

When the dataset named “PRE and POST” including HFD was imported and LR was applied, then true negative score was 64 and the true positive score was 57. The false positive result is 30 and false negative result is 38. The total number of correct predictions made from this dataset is 121.

When the dataset named “PRE and DURING” including HFD was imported and SVM was applied, then true negative score was 52 and the true positive score was 74. The false positive result is 42 and false negative result is 21. The total number of correct predictions made from this dataset is 126.

When the dataset named “DURING and POST” including HFD was imported and SVM was applied, then true negative score was 83 and the true positive score was 45. The false positive result is 11 and false negative result is 50. The total number of correct predictions made from this dataset is 128.

When the dataset named “PRE and POST” including HFD excluding the imported and SVM was applied, then true negative score was 60 and the true positive score was 45. The false positive result is 34 and false negative result is 50. The total number of correct predictions made from this dataset is 105.

From the above results, it is observed that the maximum number of correct predications was made from the dataset “DURING and POST” excluding HFD and the same dataset including HFD and using LR algorithm. This suggests that the humour stimulus was very much effective in the subjects and the subjects comprehended and interpreted the humour from the contents of the comic strips efficiently.

After applying train test split technique on machine learning algorithms namely LR and SVM, in the data without the fractal feature, the test accuracy obtained was 52% to 65% and in the data with the fractal feature, the test accuracy obtained was 55% to 68%.

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The above mentioned score was further validated with cross validation technique. By applying cross validation method, the accuracy percentage scores obtained were in accordance to the train test split scores. After applying cross validation on ML algorithms namely logistic regression and support vector machine, in the data without the fractal feature, the test accuracy obtained was 50% to 60% and in the data with the fractal feature, the test accuracy obtained was 51% to 57%.

These scores indicate that the fractal dimension of the human brain varies quite a bit upon acting of the stimulus and so the datasets containing those features provided greater accuracy.

Thus by analyzing some key features like variation of EEG signal band power, correlation of the different leads used from recording of the signal from the subjects, fractal dimension estimation and applying algorithms of machine learning, it is evident that the subjects perceived the humour stimulus efficiently from the comic-strips and the purpose of this experiment of determining the changes of brain dynamics with humour stimulus was also successful.

6. Conclusion

The primary goal of this study was to analyze the effect of humour human brain. This study was performed to see how the dynamics of the human brain varies with humour stimulus. For this purpose, the EEG signal was analyzed in the three different phases of the application of stimulus like the “PRE”, “DURING”, “POST”. The time-domain, frequency-domain and the non–linear features like fractal dimension analysis were performed along with the use of ML algorithm for the purpose of classification of the emotional features.

The experimental set–up and the methods used for testing of the comprehension and interpretation of the humorous contents were fruitful as the subjects were successfully able to recognize the humour with high efficacy. Thus irrespective of the language of the jokes the perception of humour was successfully imparted into the brain of the subjects.

From the processing and analysis part significant effects of the brain dynamics with respect to the stimulus were observed. It is very much evident that some relaxing and stress relieving effects are observed in all of the subjects with the humour stimulus. The perception of humour is highly subjective in nature which is also reflected in the various charts and tables provided in the methodology and results section, but still the stress reducing effects are prominent from all the results.

The plots of the EEG signals signified that the brain of different persons act variably under resting condition, comprehension and interpretation phases. This can be visualised from the plots of the different phases of the EEG signal.

The usage of the wavelet feature for removing the artifacts from the recorded EEG signal is quite significant. With proper selection of mother wavelet, applying the appropriate type of wavelet transform and using optimized level of thresholding, proper de–noising of the EEG signal was performed. This is signified by looking at the PSD plots of both the original and de–noised signals where the ridges or the high frequency components present in the low frequency component region of the signal is removed.

The variations in the band powers of the EEG signal signified that the persons were reading the comic strips given to them attentively, consciously and the effect of the stimulus was persistent not only in when the subjects were reading the jokes but also when they were interpreting the humorous contents.

Further it can also be concluded that as the brain was subjected to the same condition during the recording of the signals of each of the phases, so, there is a high rate of correlation between all the leads at a particular phase.

Also the variation in the three phases whether in respect to band power or correlation of the leads is prominent from the value given by the reliable statistical tool, ANOVA.

The values of the dimension of fractals after calculated by Higuchi's method showed variations in the three phases symbolizing to the fact that the fractal dimensions of the brain were changing subjected to the humour stimulus.

From the accuracy scores after application of classification algorithms, it is evident that without the application of the fractal dimension feature of the EEG signals in the three phases, the test accuracy score obtained from the "PRE and DURING" phase is 65.08% for LR and 63.49% for SVM. For "DURING and POST" phase, it is 68.73% for LR and 66.66% for SVM and for "PRE and POST" phase it is 58.20% for LR and 52.91% for SVM. With the application of the fractal dimension feature of the EEG signals in the three phases, the test accuracy score obtained from the "PRE and DURING" phase is 67.72% for LR and 66.66% for SVM. For "DURING and POST" phase, it is 69.31% for LR and 67.72% for SVM and for "PRE and POST" phase it is 64.20% for LR and 55.55% for SVM.

From cross validation, in the datasets without the HFD feature, the accuracy score obtained in the "PRE and DURING" phase, for LR is 60.211%, and 59.51% for SVM. The accuracy score obtained in the "DURING and POST" phase is 63.91% for LR and 63.64% for SVM and for "PRE and POST" phase, it is 51.85% for LR and 50.08% for SVM. From cross validation, in the datasets with the HFD feature, the accuracy score obtained in the "PRE and DURING" phase, for LR is 57.55%, and 59.51% for SVM. The accuracy score obtained in the "DURING and POST" phase is 62.42% for LR and 63.55% for SVM and for "PRE and POST" phase, it is 55.28% for LR and 51.40% in SVM.

Thus from the test accuracy scores obtained after application of both the algorithms, it is evident that the identification of the various features done by Logistic Regression algorithm is better than Support Vector Machine algorithm. Also it can be concluded that the test accuracy scores is more when the fractal analysis feature was included in the dataset. This proves that the dimension of the fractal analysis of the EEG signal in the three different phases has changed quite a bit and also the human brain behaves differently when the subject reads the comic strips, that is, when a stimulus acts on the human brain.

Also from the classification of the features in the three phases by models build from algorithms of ML, it can be concluded that the values of each of the features change when the brain is subjected to a stimulus. It thus can be concluded that due to the significant variation the classifier can easily be trained by just putting the labels of each phase and good percentage value of prediction can be obtained from the testing set data of each dataset

It is clear from the above observations and analysis that the persistence of stimulus was effective when after removal of the stimulus. Thus it can be concluded that the effect of humour stimulus causes some stress reliving and relaxing effect in the subjects and also causes some arousal effect.

7. Future Scope of Work

Further analysis of the emotion using various other features of the EEG signal needs to be performed. Other non–linear features like Chaos analysis can be implemented. Other machine learning algorithms can be applied to find which algorithm suites better for the emotional analysis. The experiment can be further extended for diseased subjects like the subjects having anxiety disorders or suffering from depression. More importance should be given to design a machine learning algorithm which can identify the features more accurately with using less amount of time.

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