International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Identification of Appropriate Channels and Feature Types That Differentiate the Normal and Stress Data of EEG Signals

[1]Mrs. Nikita R. Hatwar, [2]Dr. Ujwalla G. Gawande, [3]Ms. Chetana B. Thaokar, [4]Mr. Rajendra F. Hatwar

Submitted: 28/05/2023 **Revised**: 16/07/2023 **Accepted**: 30/07/2023

Abstract: Mental stress is proving to be a cause for functional impairment of daily activities and it is on increase. Further, continual stress should implicate numerous disorders of mind and body. Stress increases the chances of despair, stroke, coronary failure, and cardiopulmonary arrest. Human brain is a major target of psychological pressure because it determines the context of the human mind in a threatening and demanding circumstances as shown by latest neuroscience. The objective method of determining the level of stress, taking into account the human brain, greatly increases the associated dangerous effects. Therefore, the system proposed in this paper performs electroencephalography (EEG) signal analysis. Data for stressed individuals is recorded and the signal is filtered with time domain and frequency domain-based filters. Fast Fourier Transform (FFT) algorithm is used to transform the data from time domain to frequency domain. Features namely Normalized Absolute Power, Relative Power, Normalized Peak Power and Change in Power are extracted and paired t-test is used for feature selection. Features having confidence value above 95% are chosen. Within the experimental setting, stress is induced through Mental Arithmetic Task Tool (MATT) which is popular experimental pattern found on the concept of Montreal Imaging Stress Test (MIST). When performance was evaluated of all the subjects it was observed that in normal condition the average performance is 73.71% and in stress condition it is 60.18%. So, it is evident that MATT is inducing stress as performance is reduced by average 13.53% from normal to stress. The proposed system involves EEG feature extraction and feature selection using paired t-test to various brain locations across six frequency bands for stress detection. In this paper, our aim is to compare the different types of feature values of appropriate channels and frequency band to find the confidence percentage (above threshold percentage) of feature values that helps to differentiate the normal and stress classes. The results of proposed system find the correct frequency band of appropriate channel of feature types that differentiate the normal and stress data.

Keywords*: EEG, paired t-test, FFT, PSD, MIST, MATT, Frequency Band, Stress.*

1. Introduction

Stress is a situation where an individual cannot meet his daily demands. It can also be stated as lack of energy to satisfy the needs. Demands can be social or psychological in nature. Psychological and social stresses present in daily life led to poor quality of life that affects the people's behavior, performance of job, mental and physical health. [1]. In daily life Psychosocial stress exists which leads to many psychophysiological diseases. It increases the probability of coronary failure, and cardiopulmonary arrest [2-4], stroke [5] and depression [6].

[1]*Research Scholar, Information Technology, Yeshwantrao Chavan College of Engineering, Hingna Road Wanadongri,*
Nagpur, Maharashtra 441110, India
npvanjari@gmail.com
[2]*Associate Professor and Dean R & D, Information Technology, Yeshwantrao Chavan College of Engineering, Hingna Road Wanadongri,*
Nagpur, Maharashtra 441110, India
ujwallgawande@yahoo.co.in
[3]*Assistant Professor, Information Technology, Ramdeobaba College of Engineering,*
Nagpur, Maharashtra 440013, India.
thaokarcb@rknec.edu
[4]*Joint Director (IT) / Scientist-D, NIC- IVFRT, Collector Office, National Informatics Centre, Civil Lines, Nagpur - 440001, Maharashtra, India.*
r.hatwar@nic.in

To reduce stress, it needs to be quantified to various levels. Clinical methods available for detecting stress are subjective. Stress is detected through various surveys such as Stress Response Inventory (SRI) [7], the Life Events and Coping Inventory (LECI) [8] and the Perceived Stress Scale (PSS) [9]. It delays treatment as it identifies stress after a person gets stressed. Cognitive damage cannot be disclosed using subjective solutions. Alternatively, it can be individual's reluctance to admit that he or she are under stress. There is a need of some neuroimaging modalities to quantify stress and it should be an objective method and guarantee an accurate diagnosis.

According to recent development in neuroscience mental stress directly affects human brain [10] because it perceives whether a situation is threatening and stressful.

Electroencephalography (EEG) is a noninvasive and inexpensive modality used to widely measure brain activity. Human brain neural dynamics are observed by EEG and it is clinically approved standard neuroimaging modality. How information is processed in brain is revealed by EEG signals. With recent advances in technology EEG recording has been greatly improved.

Two types of noise signals are present in EEG signals they are intrinsic and extrinsic. Intrinsic noise is created by physiology such as facial muscle activity, eye blinking and movement. On the other hand, extrinsic noise is produced by physical or environmental factors such as environmental noise, high impedance, electrode popping and noise in wiring, in the EEG device.

Intrinsic noise can be eliminated using Wavelet Transform, Adaptive noise cancellation (ANC) and Independent Component Analysis (ICA). Extrinsic noise can be eliminated by applying various filters such as 0.5 Hz to 30 Hz Bandpass filter [11], 0.1 Hz filter to remove the DC artifacts using Savitzky-Golay lowpass filter [12], cut-off frequencies of 1 and 15 Hz 4th order Butterworth band-pass filter [13], Band pass filters (Lower frequency range of 0.5Hz and Higher 65Hz) [14], line noise is removed using a 50-Hz notch filter [15] and Infinite Impulse Response (IIR) filter [16].

Features are of two categories Time domain and Frequency domain, as a result, for the detection of mental stress using EEG data, the best analysis techniques are required. EEG features that reflect the full dataset can be extracted using analysis. Time domain analysis, such as the use of the Hjorth parameter [17], entropy [18], frequency domain analysis, which includes power analysis in various frequency bands [19], and time–frequency analysis, which involves the use of the wavelet transform [20], are among these techniques.

Stress affects prefrontal brain region [25]. For stress detection, the signals are acquired from FP1, FP2, AF7, AF8, F7 and F8 data are used. Signals from these locations are recorded for 3 minutes which accounts to lakhs of signals. Two types of filters are applied i.e., Time and frequency-based. Sequence of filters is 1) Trim filter (Time based filter) 2) Air Filter (Time based filter) and 3) Harmonic Filter (Frequency based filter). Fast Fourier Transform (FFT) algorithm is used to transform the data from time domain to frequency domain. Data Analysis will be performed on the frequency domain data that helps to extract features to classify stress and normal data. It is also important to extract data in various frequency bands i.e., delta (0.5–4 Hz), theta (4–8 Hz), alpha (8– 12 Hz), beta (12–30 Hz), and gamma (30–100 Hz). Power Spectral Density (PSD) is used to convert each complex value of frequency bin into power of amplitude of that particular frequency.

After all these processing features are extracted, mainly four features are extracted Normalized Absolute Power, Normalized Peak Power, Relative Power and Change in Power. Approximately thousands of feature values are extracted; an efficient feature selection procedure is required to choose features that can differentiate the signal data into two classes i.e., Stress and Normal.

2. Methodology

2.1. Subject Selection

Twenty-one healthy male and female subjects (mean age of 21.67 years) were selected from different background. The system is designed to perform experiment in both conditions (i.e., Stress and Control). During experiment, it is required that subject should be in productive mode and therefore we selected the productive time frame between 9:00 am to 12:00pm and 4:00pm to 7:00pm for the experiment.

2.2. EEG Device Selection

The acquired EEG device is a made in India NEOSOCH having 6+1 channels [30]. Locations of channels are not predefined we can place any channel at any required brain locations. All six electrodes are silver coated and passive electrodes. The sampling rate of selected device is 250 Hertz's i.e., it reads signals at the rate of 250 samples per second. The maximum sampling rate 250Hz of EEG device is sufficient to detect the data of all frequency bands as it is 2.5 times greater than our required highest frequency band. Specification of device is as follows:

- Compatible to USB 2.0 and 3.0
- 6 Channels and 1 reference electrode Maximum Voltage = 5 volts.
- Electrode Length: 4 feets
- Maximum Input Current: 200mA.
- Low power consumption: 1 watt.
- Battery: Not required.
- Source of Input power: PC/Laptop.
- 7 feet long Input wire.
- Compatible with Windows and Linux.
- **Weight:** 750gm (Device and Electrodes).
- **Dimensions**: 29cm x 20cm x 70cm

Fig 1: Selected EEG Device

2.3. EEG Placement

Electrodes of EEG device are placed according to 10–20 montage. There is total 62 locations on the scalp where EEG electrode can be placed as shown in fig 2, but we have chosen following locations Fp1, Fp2, F7, F8, AF7 and AF8. These locations are non-hairy locations due to which we do not require wet electrodes therefore we have used dry electrodes. The reference electrode is placed on either of the ear lobes (A1 or A2).

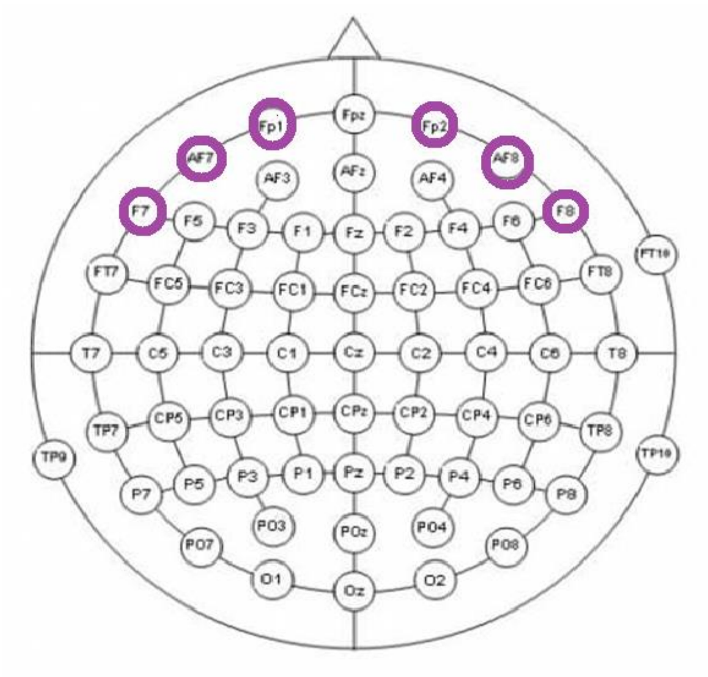

Fig 2: Locations of Brain 10-20 Montage

2.4. Experimental Design

2.4.1. *Mental Arithmetic Task Tool (MATT)*

As shown in Figure 4, the experimental paradigm supported by MIST [21] helps to assess and induce mild psychological stress associated with brain activation and physiology using EEG. Mental Arithmetic Task Tool (MATT) is a computer-based tool as shown in Fig. 3a and 3b. This tool is used to induce mild psychological stress associated with physiology and brain activation, usually aimed at explicitly assessing the response to stress and control condition. In this case, both stress and control conditions were simulated in two separate sessions at least one day gap to reduce the training effect on performance and reduce hypothalamic-pituitary-adrenal axis activation [24]. Each session consisted of four consecutive blocks: The session is divided into four consecutive processes: familiarization process, rest process, performing mental arithmetic tasks and relaxation process.

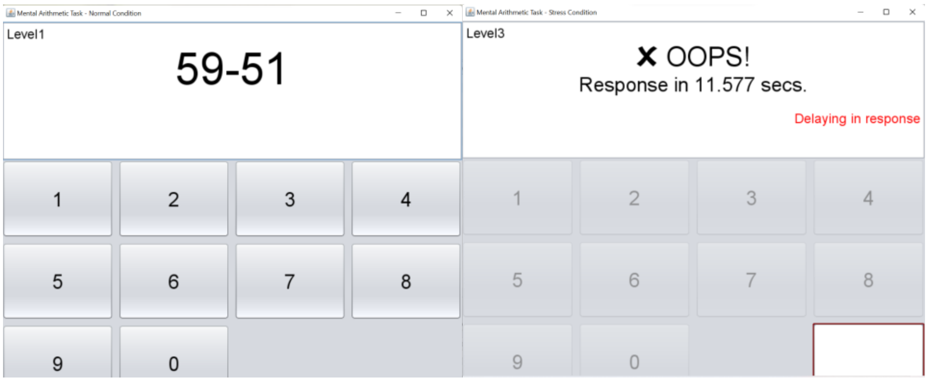

Fig 3 a: MATT Normal Condition **Fig 3** b: MATT Stress Condition

Subjects were made familiar with experimental settings in first block which is habituation block. In this block EEG signals are not recorded. It starts with arrival of subject and briefing them with experiment. Meanwhile, the subject is given sample arithmetic tasks. A single digit is an answer to every sample arithmetic task. Appropriate key is pressed to minimize eye movement. For three minutes EEG signals were recorded in rest condition. Subject must be seated comfortably, hands on knees, palms open, upper teeth separated from lower teeth, tongue protruding in mouth, feet not touching ground with foot slippers or shoes. A circle appears in front of subject on screen which he needs to focus on. Unwanted artifacts can be minimized by taking all these measures have been taken to reduce the subject's ability to move, such unwanted artifacts can also be minimized. At the heart of the experimental design is the block of mental arithmetic tasks. Tasks were performed differently under stress and control conditions in separate sessions. Similar arithmetic tasks were given in both conditions. For example, an arithmetic task involving four numbers (up to 99) uses four operands (addition (+), subtraction (-), multiplication (×) and division (/)), 5 + (2 × 30) / 12. In both the stress and control conditions consists of four distinct levels (L1 – L4). Addition between only two numbers is given in Level 1, addition and subtraction between three numbers is given as arithmetic tasks in level 2, multiplication along with addition, and subtraction is given in level 3 for four numbers, and all four operations between four numbers are given in level 4. Subject has to respond by pressing correct key on the screen as answer to each arithmetic task is a single digit number. Each level duration is for three minutes. Under stressful conditions, computerized mental arithmetic tasks with deadlines are given to subjects, i.e., time is limited for each task, so that subject's accuracy is reduced. Each task has the deadline with an additional text message such as "Delaying in response", "Speed Up", "TOO SLOW!!", and "Do Fast Calculation!!" is displayed to distract subjects. Depending on the attempt response appears on the screen showing the response time and true/false/no response after each task. In addition, stress feedback on commands appears on the screen, after a number of attempts. The procedure for the control is equivalent to the stress condition but has no time limit and no stress feedback. Any brain activation caused by mental arithmetic task is matched with control condition. Due to this it is convenient in declaring the activation caused by mental stress in stress conditions with greater accuracy. In the control condition the feedback display ("correct" or "incorrect") remained after each task. In this condition, details of EEG are recorded for three minutes.

Performance is calculated of the MATT in normal and stress condition. In normal condition the average performance is 73.71% and in stress condition it is 60.18%. So, it is evident that MATT is inducing stress as performance is reduced by average 13.53% from normal to stress.

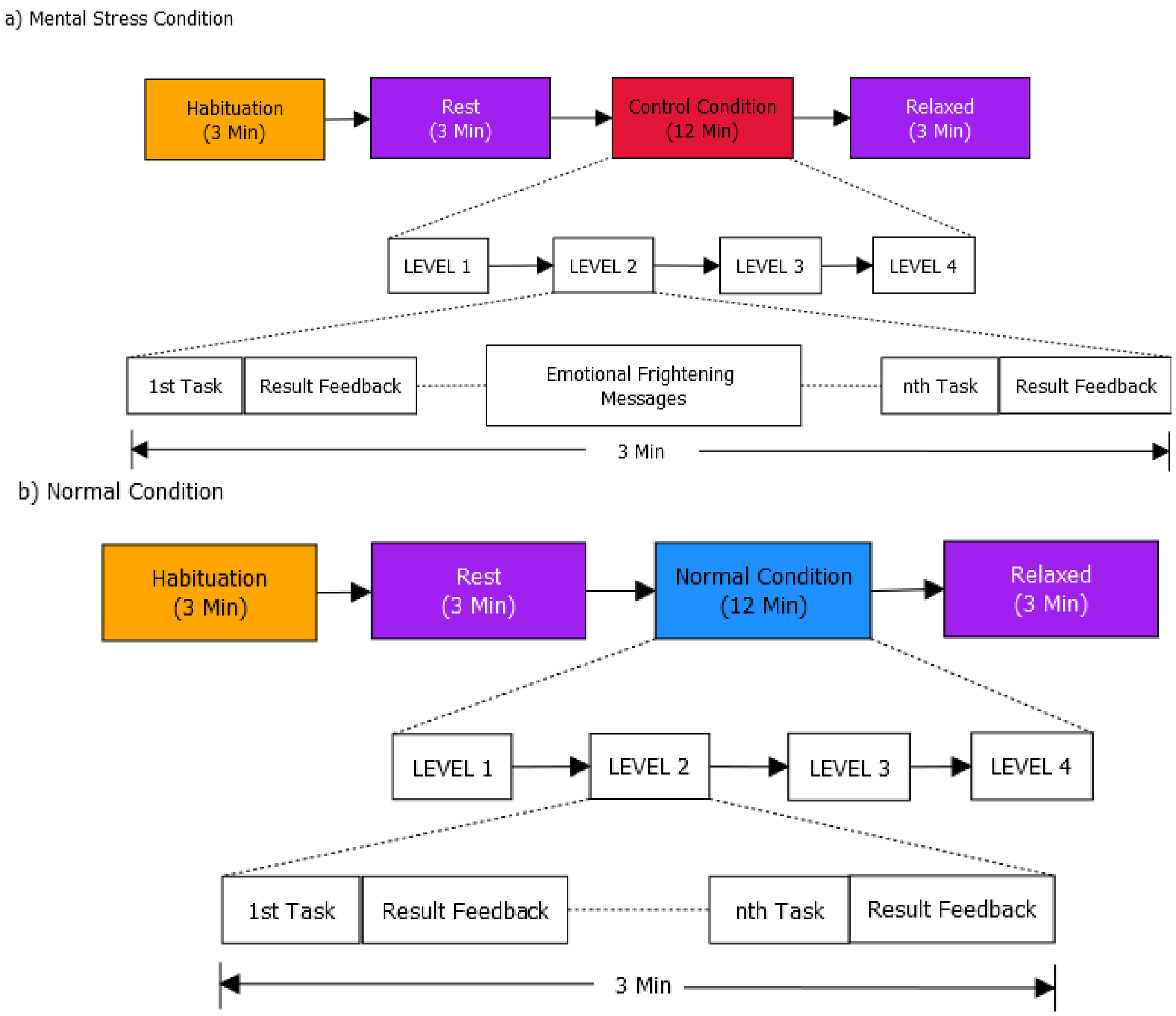

Fig 4: Experiment flow

2.5 Filters

The EEG signal has been cleaned up to remove artifacts using trimming filters, harmonic filters, and bandpass filters. Trim filter is applied on time domain signals, harmonic and band filters are applied on frequency domain signals.

Filters are categorized into two types i.e.

1. Time based data filters

2. Frequency based data filters

2.5.1 Time based data Filters

Two filters are implemented in Time domain they are:

a) Air filter

b) Trim filter

a) Air filter: While recording the EEG data, it is necessary to properly place the electrodes of EEG device on different sensing locations of brain as well as reference electrode should be placed at the ear. If one or more than one electrode is not properly placed or loosely placed, then that electrode will not sense the correct EEG signal instead it generates air signal. So, to minimize this problem, we need to check the signal values of all connected electrodes and to differentiate the signal as AIR or EEG. A filter is created that checks the signal values of electrodes as AIR or EEG as shown in fig. 3a & fig. 3b. To check whether it is Air or EEG signals amplitude of signal is checked if it greater than threshold (>200 mV) it is air signal otherwise EEG signals.

Electrode ID	Channel	Status
1	FP1	EEG SIGNAL
2	FP2	EEG SIGNAL
3	AF7	EEG SIGNAL
4	AF8	EEG SIGNAL
5	F7	EEG SIGNAL
6	F8	EEG SIGNAL

Fig 3a: EEG Signal

Electrode ID	Channel	Status
1	FP1	AIR SIGNAL
2	FP2	AIR SIGNAL
3	AF7	AIR SIGNAL
4	AF8	AIR SIGNAL
5	F7	AIR SIGNAL
6	F8	AIR SIGNAL

Fig 3b: Air Signal

b) Trim filter: This type of filter is applicable on time domain data to remove unwanted or noisy signals from the recorded data. A Trim Filter designed to perform filtering of noisy signal of time-based recorded data. Recorded data of EEG device is a time-based data i.e., signal values are stored against time where signal value is in millivolt and time is in seconds. After doing analysis of recorded signals, it is found that in some of the cases, there is sudden rise in signal value just at the starting and stopping time of recording, these signals are noisy signals, duration of such noisy signals varies from 0.1 to 2 seconds. To remove such noisy signals, Trim filter is designed.

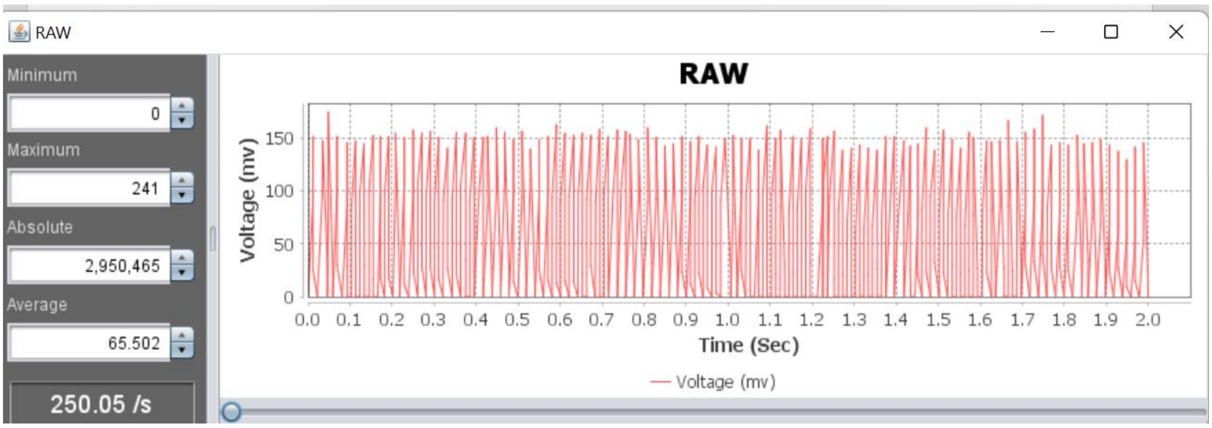

Fig 4: Time Based Recorded Data

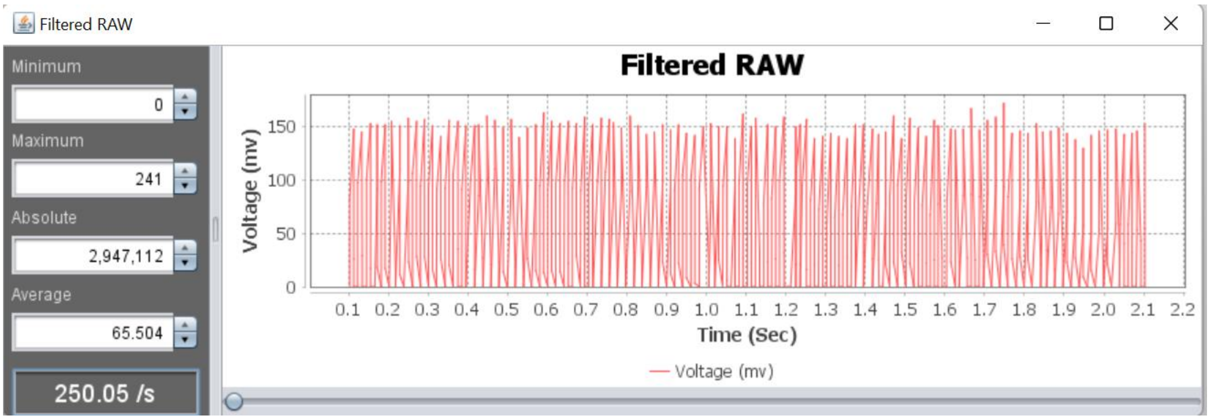

Fig 5: Time based filtered data

Fig. 4 shows sudden rise in signal from 0 to 0.1 seconds and in fig. 5. Shows the remaining signals after trimming the noisy signals by trim filter.

2.5.2 Frequency based data filters

Filters performs filtering operation on the frequency-based data are known as frequency-based data filters. A Harmonics Filter is designed which filters the noisy signals from the frequency-based data. Fast Fourier transform algorithm is used to transform time-based data into frequency-based data. X-axis of frequency-based data is frequency in hertz and Y-axis represents the PSD (Power spectrum density) value. Noise due to harmonics are generated due to electrical signals or DC signals, since the frequency of electrical signals in India is 50Hz therefore harmonics generated in multiple of 50Hz i.e., harmonics noisy signals are generated around 50Hz,100Hz,150Hz,200Hz and so on.

Frequency of electrical signals is not accurate and therefore due to fluctuation in the frequency of electrical signals around +3 to -3 Hz, some ranges of harmonics frequency are defined.

Consider fluctuation offset = +3 to -3

Harmonics Ranges = {47 to 53 Hz, 97 to 103Hz, 147 to 153Hz}

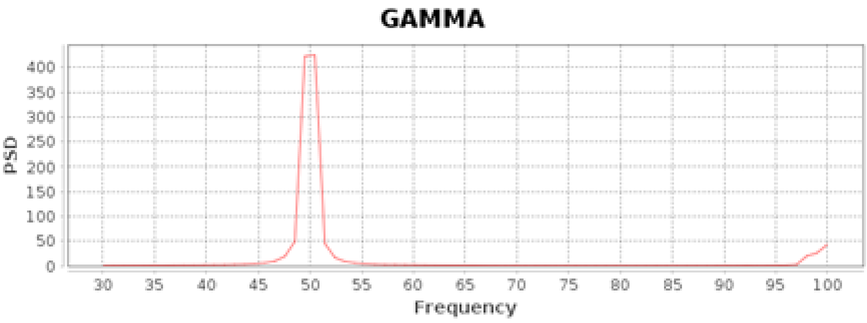

Fig 6 a: Noise Signals at 50Hz

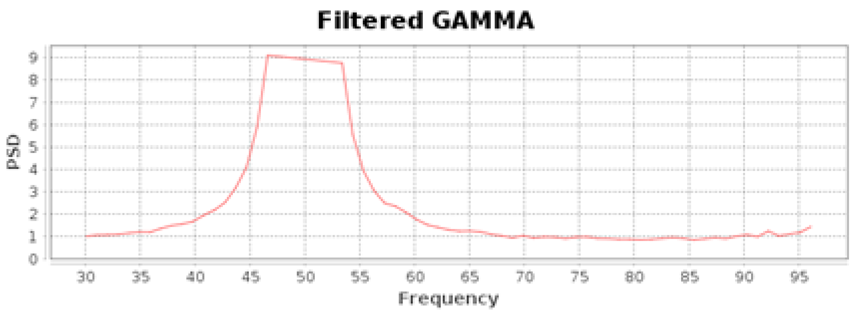

Fig 6 b: Noise Signals Removed by Harmonic Filter

It was observed before applying harmonic filter, absolute power is 1,177.604 and after applying it reduces to 109.491 which indicates large amount of sound is eliminated.

2.6 Time Domain to Frequency Domain Conversion

2.6.1. Frequency Domain Data

To perform the detail analysis of EEG data only time domain data is not sufficient, instead frequency-based data is also required to be studied. Frequency based data helps to analyze the amplitude of signal on different frequencies. While recording the signals from EEG device through multiple channels, the recorded data is always in time domain format i.e., amplitude (millivolt) of signal with respect to time (milliseconds). The next step is to convert signal data of time domain format into frequency domain format (amplitude vs frequency).

Frequency based data is obtained from time-based data using standard mathematical concept known as Fourier Transform. Fourier transform helps to decompose the data into its constituent frequencies. Fourier transform is used in various applications such as image analysis, data compression, audio processing, signal processing etc. Mainly there are two major algorithms used to implement Fourier transform i.e., DFT (Discrete Fourier Transform) and FFT (Fast Fourier Transform). Initially many researchers preferred to implement DFT for Fourier transform but later on FFT was developed which is faster than DFT. FFT is nothing but implementation of DFT having significant time complexity.

Time complexity of DFT is O(N^2) while that of FFT is O (N log N) and therefore FFT is faster than DFT.

An FFT algorithm is implemented to convert the time domain data of recorded signal into frequency domain data. There are some important points to be noted down while implementing the FFT algorithm.

- Number of samples or signal values (N) input to the FFT should be in power of 2 i.e., 2,4,8,16,32,64,128,256,512,1024 etc.

- Input sample values should be complex values consisting of real and imaginary part.

It is necessary to convert all the signal values into complex form (real & imaginary part) before transforming the time domain data into frequency domain. After applying FFT on input complex values as shown in Fig 8., the output values will be in the form of vector of complex values but these output complex values are in frequency domain. Plotting such complex values is not possible thus power of amplitude is calculated of each frequency bin and to find the power of amplitude, concept of PSD i.e., power spectral density is used.

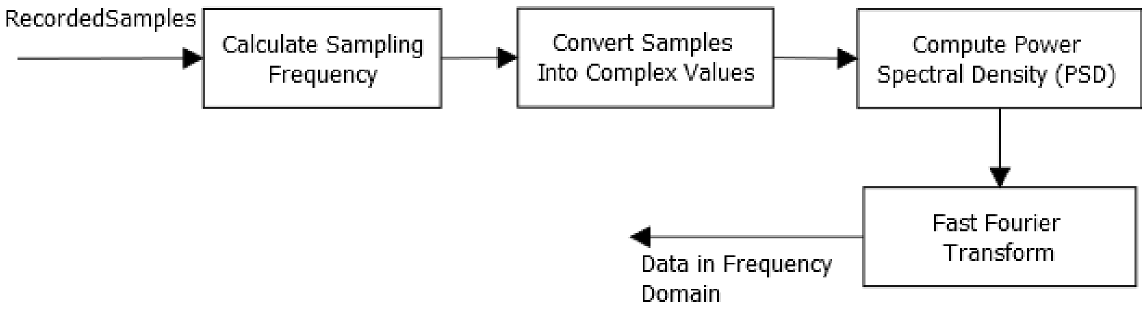

Fig 7: Process to Convert Time Domain Data into Frequency Domain

2.6.3 Fast Fourier Transform

The most commonly used FFT is the Cooley-Tukey algorithm. It is a divide and conquer algorithm that recursively decomposes a DFT of any aggregate size N = N1N2 into a large number of smaller DFTs of sizes N1 and N2. The most famous use of the Cooley-Tukey algorithm is to split the transformation into two parts of size N/2 at each step. It is therefore limited to powers of two magnitudes.

Formula

$$Ce = Te + Wk * Te \quad (1)$$

$$Co = To - Wk * To \quad (2)$$

Where

Ce = Frequency domain data of even term

Co = Frequency domain data of odd term

Te = Even complex term

To = Odd complex term

Wk =real + imaginary

real = cos (Kth)

imaginary = sin (Kth)

Kth = (-2 * k * PI)/N

k = index of complex term

N = Number of samples

Let,

Tc = {C0, C1, C2, C3}

Tc = Complete set of time domain data

C0, C1, C2 & C3 are complex values

.

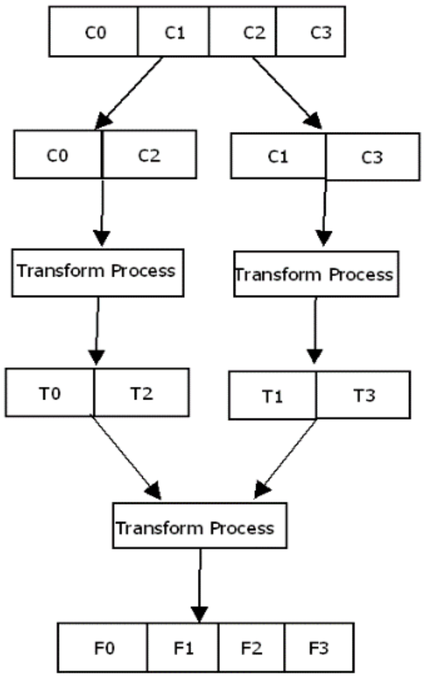

Fig 8: Process to Find FFT

F0, F1, F2 and F3 are transformed values in frequency domain

Output of FFT is an array of frequency bins where each bin represents a complex value against a particular frequency but each bin value is a complex value, so output is in frequency domain. But this is not sufficient to plot complex values against frequency as the values are in complex format so a method needs to be devised that helps us for plotting the graph for different frequency band. Here the role of PSD i.e., power spectral density comes in, that converts each complex value of frequency bin into power of amplitude of that particular frequency. PSD represents the normalized power density of amplitude at particular frequency we can say power spectral density is the normalized integral power at particular frequency.

2.7 *Power Spectral Density*

Formula of PSD is given below:

$$PSD = (M * M)/ (Fs * N) \qquad (3)$$

Where

M = Magnitude of complex value

Fs = Sampling Frequency

N = Number of Samples

Parameters considered for PSD calculation of frequency bands

Window Size = 1024

Overlapping = 75%

2.8 *EEG Feature Extraction*

Feature extraction is an important and complex process used for finding the important features from the time and frequency based recorded EEG data.

2.8.1 Normalized Absolute Power

Absolute Power is the sum of power spectrum density detected in particular frequency band for the given phase.

EEG signal are low frequency signals and therefore we are considering low frequency bands as given below.

Delta Band (0.5 to 4 Hz)

Theta Band (4 to 8 Hz)

Alpha Band (8 to 13 Hz)

Beta Band (13 to 30 Hz)

Gamma Band (30 Hz to 100 Hz)

EEG Band (0.5 to 100Hz)

Total number of frequency bands i.e., fb = 6

Phases = {REST, LEVEL1, LEVEL2, LEVEL3, LEVEL4, RELAXED}

Total number of phases i.e., pn=6

Absolute power is calculated for each frequency band of 6 phases, so total number of values of absolute power in each channel are 6 x 6 = 36 values per channel.

Formula for absolute power is given below.

$$Pa = \sum_{i=fs}^{fe} psd_i \qquad (4)$$

Where ***Pa*** = Absolute power

psd = power spectrum density of ith frequency

fs = Start frequency of frequency band

fe =End frequency of frequency band

$PA_{[fb \times pn]}$ = Matrix of Absolute Power of size fb x pn containing elements of absolute power (***Pa***).

Where

pn = Number of Phases

fb = Number of frequency bands

Normalized Absolute Power

$$PAnij = PAij / Max (PAi) \qquad (5)$$

Where

pn =6

fb =6

$PA_{[fb \times pn]}$ = Matrix of Absolute Power

$PAn_{[fb \times pn]}$ = Feature Matrix of Normalized Absolute Power

Following data shows the Feature Value Matrix of Normalized Absolute Power of FP1 Channel under Normal Condition

NORMAL - FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	0.973	1.000	0.867	0.784	0.787	0.846
ALPHA	0.945	1.000	0.890	0.826	0.904	0.791
BETA	0.886	1.000	0.815	0.770	0.783	0.772
THETA	0.896	1.000	0.805	0.725	0.731	0.771
DELTA	0.856	1.000	0.942	0.909	0.916	0.809
GAMMA	0.709	0.773	0.848	0.922	1.000	0.663

Table 1: Matrix of Normalized Absolute Power for FP1 in Normal Condition

Following data shows the Feature Value Matrix of Normalized Absolute Power of FP1 Channel under Stress Condition

STRESS - FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	0.990	0.914	0.926	1.000	0.979	0.814
ALPHA	0.807	0.731	0.793	1.000	0.937	0.778
BETA	0.810	0.749	0.806	0.944	1.000	0.775
THETA	0.800	0.773	0.894	0.963	1.000	0.890
DELTA	0.998	1.000	0.766	0.603	0.591	0.574
GAMMA	0.994	0.910	0.927	1.000	0.964	0.803

Table 2: Matrix of Normalized Absolute Power for FP1 in Stress Condition

2.8.2 Normalized Peak Power

Peak Power

Peak Power is the maximum power spectrum density detected in particular frequency band for the given phase.

Pp = Max (psdi)

$PP_{[fb \times pn]} =$ Matrix of Peak Power (***Pp***)

Normalized Peak Power

PPnij = PPij / Max (PPi) (6)

Following data shows the Feature Value Matrix of Normalized Peak Power of FP1 Channel under Normal Condition

NORMAL - FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	1.000	0.904	0.784	0.610	0.584	0.751
ALPHA	0.972	1.000	0.886	0.816	0.886	0.774
BETA	0.806	1.000	0.783	0.730	0.731	0.767
THETA	0.868	1.000	0.769	0.640	0.658	0.822
DELTA	0.804	0.870	0.847	0.939	1.000	0.738

GAMMA	1.000	0.904	0.784	0.610	0.584	0.751

Table 3: Matrix of Normalized Peak Power for FP1 in Normal Condition

Following data shows the Feature Value Matrix of Normalized Peak Power of FP1 Channel under Stress Condition

STRESS - FP1

	REST	**Level1**	**Level2**	**Level3**	**Level4**	**RELAXED**
EEG	0.962	0.888	1.000	0.885	0.789	0.635
ALPHA	0.675	0.687	0.718	1.000	0.818	0.683
BETA	0.801	0.820	0.760	0.983	1.000	0.743
THETA	0.684	0.673	0.859	1.000	0.848	0.919
DELTA	0.954	1.000	0.440	0.320	0.305	0.308
GAMMA	0.962	0.769	1.000	0.885	0.789	0.635

Table 4: Matrix of Normalized Peak Power for FP1 in Stress Condition

2.8.3 Relative Power

Relative power is calculated from the absolute power of frequency bands as given below.

Pr = Pa / Pt (7)

Where

Pr = Relative power of frequency band

Pa = Absolute power of frequency band

Pt = Total power of all frequency bands

To calculate the total power (***Pt***) of all frequency bands, we derived one more frequency band known as EEG band (0 to 100Hz) that includes all five frequency bands. Absolute power of this band is known as ***Pt*** (Total Power).

Relative power is calculated for each frequency band of 6 phases, so total number of values of relative power in each channel are 6 x 6 = 36 values per channel.

PR $_{[fb\ x\ pn]}$ = Matrix of Relative Power of size fb x pn containing elements of relative power (***Pr***)

Following data shows the Feature Value Matrix of Relative Power of FP1 Channel under Normal Condition

NORMAL – FP1

	REST	**Level1**	**Level2**	**Level3**	**Level4**	**RELAXED**
EEG	1.000	1.000	1.000	1.000	1.000	1.000
ALPHA	0.027	0.027	0.028	0.029	0.032	0.026
BETA	0.092	0.101	0.095	0.099	0.100	0.092
THETA	0.024	0.027	0.025	0.025	0.025	0.024
DELTA	0.033	0.037	0.040	0.043	0.043	0.036
GAMMA	0.824	0.808	0.812	0.805	0.801	0.823

Table 5: Matrix of Relative Power for FP1 in Normal Condition

Following data shows the Feature Value Matrix of Relative Power of FP1 Channel under Stress Condition

STRESS – FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	1.000	1.000	1.000	1.000	1.000	1.000
ALPHA	0.034	0.034	0.036	0.042	0.040	0.040
BETA	0.120	0.120	0.127	0.138	0.149	0.139
THETA	0.027	0.028	0.032	0.032	0.034	0.037
DELTA	0.069	0.075	0.057	0.041	0.041	0.048
GAMMA	0.750	0.743	0.748	0.746	0.735	0.736

Table 6: Matrix of Relative Power for FP1 in Stress Condition

2.8.4 Change in Power

Change in Power is the ratio of difference between power of phase with respect to the power value at rest phase to the power value at rest phase of particular frequency band.

$$Pc = (Pa - Pr)/Pr \qquad (8)$$

Where

Pa = Absolute power of phase

Pr = Absolute power of rest phase

Pc = Change in power

Since change in power is calculated with respect to the power value of rest phase therefore the change in power of rest phase is always 0. It is calculated for 6 phases of 6 frequency bands.

$PC_{[fb \times fn]}$ = Feature Matrix of change in power of size $fb \times fn$.

Following data shows the Feature Value Matrix of Relative Power of FP1 Channel under Normal Condition

NORMAL - FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	0.000	0.028	-0.109	-0.194	-0.190	-0.130
ALPHA	0.000	0.059	-0.058	-0.125	-0.042	-0.163
BETA	0.000	0.129	-0.080	-0.131	-0.117	-0.129
THETA	0.000	0.116	-0.101	-0.191	-0.184	-0.139
DELTA	0.000	0.169	0.101	0.062	0.070	-0.055
GAMMA	0.000	0.090	0.195	0.299	0.410	-0.065

+ve value indicates power increases and -ve value indicates power decreases.

Table 7: Matrix of Change in Power for FP1 in Normal Condition

Following data shows the Feature Value Matrix of Relative Power of FP1 Channel under Stress Condition

STRESS - FP1

	REST	Level1	Level2	Level3	Level4	RELAXED
EEG	0.000	-0.077	-0.065	0.010	-0.010	-0.177
ALPHA	0.000	-0.094	-0.017	0.240	0.162	-0.036

BETA	0.000	-0.076	-0.005	0.164	0.234	-0.043
THETA	0.000	-0.033	0.118	0.204	0.250	0.113
DELTA	0.000	0.002	-0.233	-0.396	-0.408	-0.425
GAMMA	0.000	-0.085	-0.067	0.006	-0.030	-0.193

+ve value indicates power increases and -ve value indicates power decreases

Table 8: Matrix of Change in Power for FP1 in Stress Condition

2.9 EEG Feature Selection

Paired-t test is a method that shows correlation between two vector-based sample data. The calculated value of paired t- test is then compared with the values of t-distribution table that gives the cumulative probability, this cumulative probability (cp) value indicates the confidence value to differentiate two classes. For finding the cumulative probability, the degree of freedom is taken as n-1, where n represents number of samples. Feature with maximum cp values indicates high correlation with the class variable. Minimum threshold of cp could be 0.95 (95%) for the selection of features.

$$t = \frac{\mu 1 - \mu 2}{\sqrt{\frac{\sigma 1^2}{n1} - \frac{\sigma 2^2}{n2}}} \quad (9)$$

Where

μ- Mean

σ- Standard Deviation

n - Number of Samples

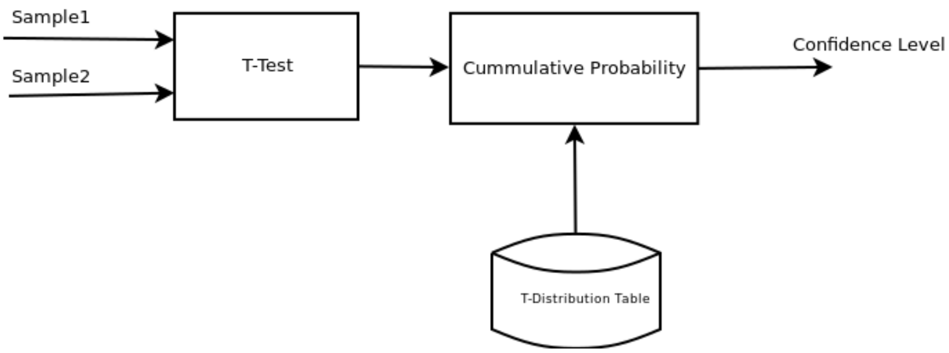

Fig 9: Process to Find Confidence Level using Paired T-Test

After extracting feature values of different types of features, number of elements in each type of feature are 6 x 36 =216 and therefore total number of feature values will be 216 x 4 (as four types of features) = 864. Now to select the features that shows proper change to differentiate the two classes i.e., Normal and Stress, it is necessary to apply some statistical technique. Here for the feature selection a paired-t test method is applied as shown in Table 9. A subset of features from the extracted features is selected which is the objective of the feature selection method.

Following cumulative probability (confidence) generated using the feature - Normalized Absolute Power through FP1 channel of Normal & Stress Phase.

Channel = FP1

Sr. No.	**Label**	**Confidence %**
1.	EEG	93%
2.	ALPHA	93%
3.	BETA	97%
4.	THETA	93%

5.	DELTA	99%
6.	GAMMA	88%

Table 9: Features with 95% Confidence Value is Selected

3. Results and Discussion

Number of Feature values extracted

Name of Channel	Normal#	Stress#
FP1	36	36
FP2	36	36
F7	36	36
F8	36	36
AF7	36	36
AF8	36	36
Total	216	216

Table 10: Total Feature Values Extracted

Since four features are extracted therefore total features are (216 + 216) * 4 = 432 * 4 = **1728 Feature values**

Results of paired t-test can be summarized as:

Table 11 shows the EEG channels and frequency bands having confidence value greater than or equal to 95%. From the results it is observed that channels AF7, F8, F7, FP2 and FP1 plays an important role along with the frequency bands DELTA, GAMMA, BETA, ALPHA and EEG for differentiating between stress and normal condition of a subject.

Feature	Channel	Band	Confidence Value
Normalized Absolute Power	AF7	DELTA	99.1615438
	F8	GAMMA	95.7653381
	F8	BETA	95.1792454
	F8	ALPHA	96.4803178
	F8	DELTA	96.3658337
	F8	EEG	97.1119451
	F7	DELTA	96.1449168
	FP2	DELTA	95.1889387
	FP1	DELTA	98.4485527

Table 11: Channel and Frequency Band Having Confidence Value Above 95% for Normalized Absolute Power

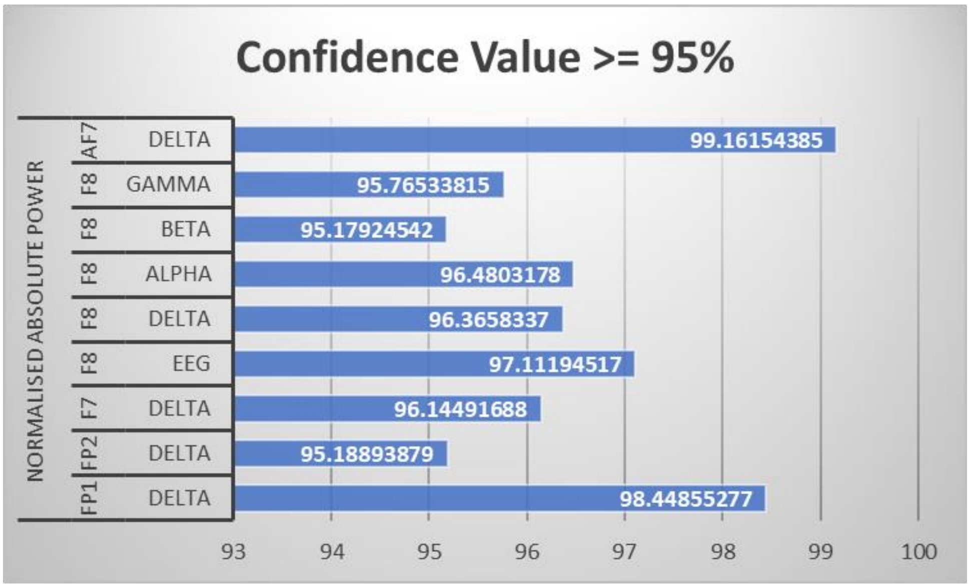

Fig 10: Diagrammatic Representation of Channel and Frequency Band Having Confidence Value Above 95% for Normalized Absolute Power

Fig. 10 above represents the data of normalized absolute power graphically. Where Y-axis represents EEG channels, frequency bands and X-axis represents the confidence value.

Table 12 below shows data for relative power here we get better results for EEG channels AF7, FP2 and FP1 with EEG frequency bands BETA and ALPHA.

Feature	Channel	Band	Confidence Value
Relative Power	AF7	BETA	96.67947125
	FP2	BETA	99.1448999
	FP1	ALPHA	96.51965722

Table 12: Channel and Frequency Band Having Confidence Value Above 95% for Relative Power

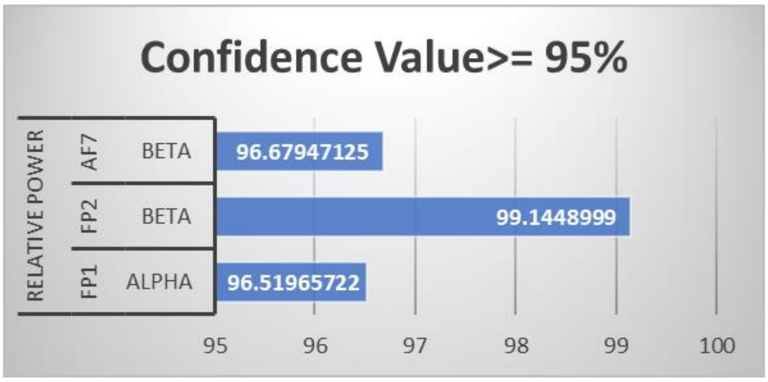

Fig 11: Diagrammatic Representation of Channel and Frequency Band Having Confidence Value Above 95% for Relative Power

Fig. 11 above represents the data of relative power graphically. Where Y-axis represents EEG channels, frequency bands and X-axis represents the confidence value.

Table 13 below shows data for normalized peak power here it is observed that EEG channels AF7, F8, F7, FP2 and FP1 with EEG frequency bands DELTA.

Feature	Channel	Band	Confidence Value
Normalized Peak Power	AF7	DELTA	98.4461691
	F8	DELTA	97.3193558
	F7	DELTA	97.5210535
	FP2	DELTA	95.7568269
	FP1	DELTA	98.2196975

Table 13: Channel and Frequency Band Having Confidence Value Above 95% for Normalized Peak Power

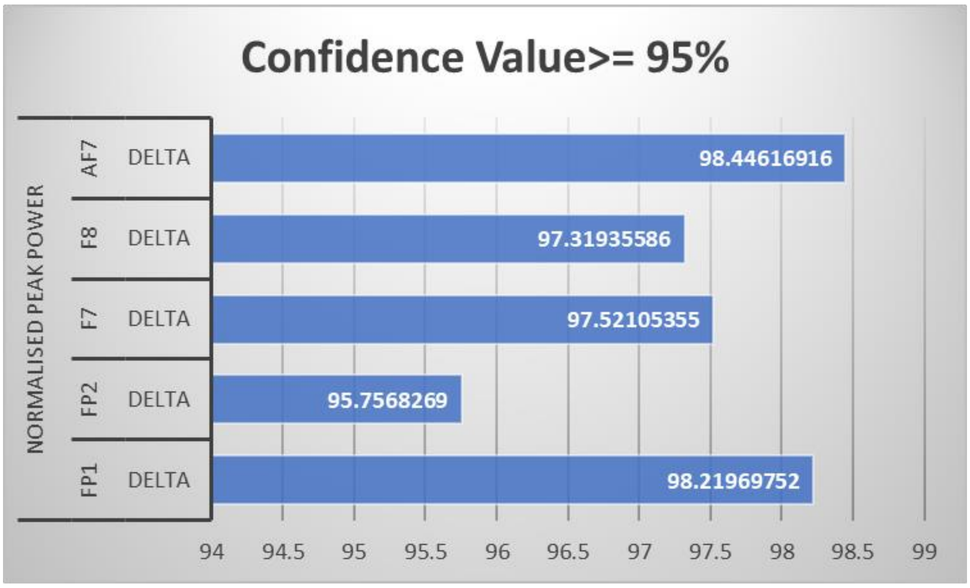

Fig 12: Diagrammatic Representation of Channel and Frequency Band Having Confidence Value Above 95% for Normalized Peak Power

Fig. 12 above represents the data of normalized peak power graphically. Where Y-axis represents EEG channels, frequency bands and X-axis represents the confidence value.

Table 14 below shows data for change in power here it is observed that EEG channels FP2 and FP1 with EEG frequency bands DELTA, EEG, GAMMA, ALPHA, and THETA.

Feature	Channel	Band	Confidence Value
Change in Power	FP2	DELTA	97.53302836
		EEG	96.59861002
	FP1	GAMMA	95.76594779
		ALPHA	96.20723063
		THETA	97.35041215
		DELTA	97.11481323
		EEG	98.07624849

Table 14: Channel and Frequency Band Having Confidence Value Above 95% for Change in Power

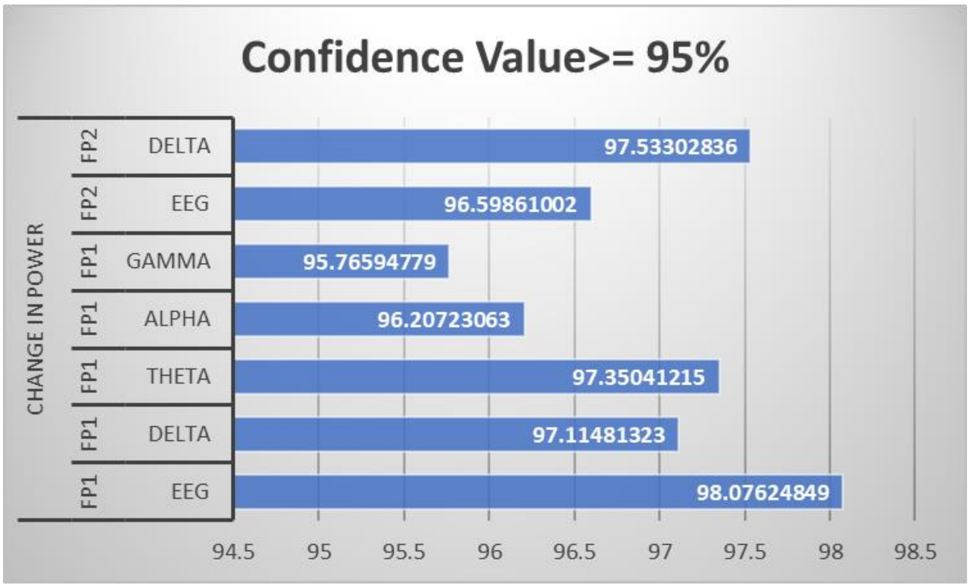

Fig 13: Diagrammatic Representation of Channel and Frequency Band Having Confidence Value Above 95% for Change in Power

Fig. 13 above represents the data of change in power graphically. Where Y-axis represents EEG channels, frequency bands and X-axis represents the confidence value.

This paper provides analysis of which frequency band, channel and feature type helps in discriminating the stress and normal EEG data. In order to do this, a MIST-based experimental paradigm with four levels of stress based on time constraint, distraction, and evaluative pressure was created to imitate social pressure. Four identical control conditions with tasks of a matching difficulty were available for the comparison of the four stress levels. The task's nature was the same, and that's what we mean when we state that it was of the same task difficulty. The findings, confirm the experimental paradigm to create stress based on task performance and response time.

EEG was not considered in earlier studies as one of the biomarkers of stress [26] despite it can more effectively represent stress. Because stress ultimately triggers responses in the ANS after beginning in the amygdala, exposure to physiological indicators other than EEG is likely seen [27]. Numerous experimental tasks, such as an arithmetic task or a Stroop task, have been utilized in research to induce stress in the experimental conditions. However, a number of these studies did not validate or evaluate whether these tasks led to stress. For instance, in addition to the rest condition serving as no stress, the Stroop task and the arithmetic task were used to inflict high and low degrees of stress [28]. By adhering to particular paradigms, the tasks that essentially result in a cognitive burden can be exploited to create stress. For instance, the arithmetic task was presented under time constraint in the Montreal imaging stress task (MIST) [21] and the Stroop task, as well as under social evaluative pressure in the Trier social stress task [29].

EEG signals are highly susceptible to artifacts. In this research three filters have been designed, two are applied on time domain data and one on frequency domain data. Time domain filters are trim and air filters. Trim filter trims initial and end signal of 0.1 sec, whereas air filter helps to sense whether electrode is properly connected or not. Paired t-test is applied to choose appropriate features that differentiates between stress and normal condition.

The extracted features are normalized absolute power, normalized peak power, relative power and change in power. Out of these three features Normalized Absolute Power, Normalized Peak Power and Change in Power are newly introduced features. Total feature values extracted are 1728. Paired t-test is used for feature selection, feature values having 95 % confidence value are chosen. From the above results, it is clear that FP1 and FP2 channels are giving good confidence values in all feature types through ALPHA, BETA and DELTA Bands. The confidence values of DELTA band for FP1, FP2, AF7, F7 & F8 of feature -Normalized Peak Power are above the threshold value.

4. Conclusion

EEG is a low-cost workable alternative that is suitable for use in medical centers and health facilities for remote applications. In contrast, the current clinical diagnostic approach involves well-structured questionnaires and interviews with subjects experiencing mental stress. The main contribution of this work is three new features are introduced Normalized Absolute Power, Normalized Peak Power and Change in Power. From the above results, it is clear that FP1 and FP2 channels are giving good confidence values in all feature types through

ALPHA, BETA and DELTA Bands. The confidence values of DELTA band for FP1, FP2, AF7, F7 & F8 of feature -Normalized Peak Power are above the threshold value.

5. Acknowledgement

We would like to thank all those who voluntarily accepted to be part of our study. We are rigid to our commitment of not to use this study for any unethical purpose.

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