

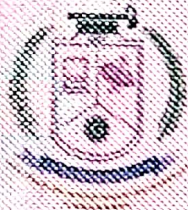
MENTAL STRESS ASSESSMENT METHODS USING EEG SIGNALS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in biomedical engineering

by

P. CATHERINE MELITA PRADHIKSHA (39240011)

R. DIVYA (39240016)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

POONJEE NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

APRIL - 2023

MENTAL STRESS ASSESSMENT METHODS USING EEG SIGNALS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in biomedical engineering

by

P. CATHERINE MELITA PRADHIKSHA (39240011)

R. DIVYA (39240016)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

APRIL- 2023



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited "A" Grade by NAAC | 12B Status by UGC | Approved by AICTE
www.sathyabama.ac.in

DEPARTMENT OF BIOMEDICAL ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of P. Catherine Melita Pradhiksha (39240011) and R. Divya (39240016) who carried out the project entitled "Mental stress assessment methods using EEG signals" under our supervision from October 2022 - April 2023.

INTERNAL GUIDE

Dr. P. GRACE KANMANI PRINCE, M.E, Ph.D.

HEAD OF THE DEPARTMENT

Dr. T. SUDHAKAR, M.Sc. Ph.D.

HEAD OF THE DEPARTMENT
DEPARTMENT OF BIOMEDICAL ENGINEERING
SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Kodambakkam Nagar, Rajiv Gandhi Salai
Chennai - 600 079

Submitted for Viva voce Examination held on 18.04.2023

Internal Examiner

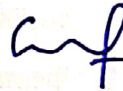
External Examiner

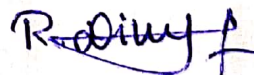
DECLARATION

We **P. Catherine Melita Pradhiksha (39240011)** and **R.Divya (39240016)** , hereby declare that the Project Report entitled "**Mental stress assessment methods using EEG signals**" done by me under the guidance of **Dr. P. Grace Kanmani Prince**, **Department of Biomedical Engineering (Internal)** at **Sathyabama Institute of Science and Technology** is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE: 18.04.2023

PLACE: Chennai

1. 

2. 

SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

We convey our thanks to **Dr. T. Sudhakar, M.Sc., Ph.D., Head of the Department, Department of Biomedical Engineering** for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my **Project Guide Dr. P. Grace Kanmani Prince, Department of Biomedical Engineering** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to **all Teaching and Non-teaching staff members of the Department of Biomedical Engineering** who were helpful in many ways for the completion of the project.

MENTAL STRESS ASSESSMENT METHODS USING EEG SIGNALS

ABSTRACT

Emotional stress can make health issues worse. It is a word used to describe how the sympathetic nervous system (SNS) and hypothalamus-pituitary-adrenocortical axis control how the human body responds to mental, physical, and emotional events (HPA axis). When referring to internal (personality structure) or exterior (problem resolution) problems that have a variety of negative physiological and emotional impacts, this expression may be employed. Electroencephalogram (EEG) signal is one important candidate because it contains rich information about mental states and condition. In this project used EEG data as input by following these steps were processed which is noise removal using non local means, feature extraction using LSSVM, LSTM, HJORTH ACTIVITY AND COMPLEXITY then classification using band analysis and power spectrum analysis then will get the output whether the stress detected is normal or abnormal .In this project also used deep learning approaches to improve the accuracy of mental stress level assessment.

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	i
	CONTENTS	ii
	LIST OF ABBREVIATIONS	iii
	LIST OF FIGURES	iv
1	INTRODUCTION	1
2	LITERATURE SURVEY	3
	AIM AND SCOPE	9
	3.1 Existing method	
3	3.1.1 Disadvantages of existing method	
	3.2 Proposed method	
	3.2.1 Advantages of proposed method	
	3.3 Typical uses include	
	METHODS AND ALGORITHM USED	11
	4.1 Domain Used	
4	4.2 Block Diagram	
	4.3 Methods	
	4.3.1 Input EEG data	
	4.3.2 Noise removal using NLM	
	4.3.3 Feature Extraction	

4.3.4 Classification

4. 4 Algorithms used

4.4.1 Least squares support vector machines

4.4.2 Wavelet transform

4.4.3 Data structure

4.4.4 Wiretap channel

4.4.5 Long short term memory

4.4.6 Neural network

4.4.7 Finite impulse response

4.4.8 Fast fourier transform

RESULT AND DISCUSSIO

5.1 input image

5.2 Decomposed image

5.3 Reconstruction level

5.3.1 1st level reconstruction level

5.3.2 2nd level reconstruction level

5.3.3 3rd level reconstruction level

5.3.4 4th level reconstruction level

5.4 Training observation 1

5.5 Sorted data

5.6 Algoritham comparison

5.6.1 LSSVM vs WT

- 5.6.2 DS vs WTC
- 5.6.3 LSTM vs NN
- 5.6.4 LSSVM vs LSTM
- 5.6.5 FIR vs LSTM
- 5.7 Power spectrum using FFT
- 5.8 Time frequency
- 5.9 Waveform for DELTA band
- 5.10 Single sided amplitude spectrum of DELTA
- 5.11 Waveform for THETA band
- 5.12 Single sided amplitude spectrum of THETA
- 5.13 Waveform for ALPHA band
- 5.14 Single sided amplitude spectrum of ALPHA
- 5.15 Waveform for BETA band
- 5.16 Feature Extraction
- 5.17 Training process
 - 5.17.1 MU
 - 5.17.2 Gradient
- 5.18 Output image

LIST OF ABBREVIATIONS

Abbreviation	Full form
DS	Data Structure
EDA	Electrodermal activity
EEG	Electroencephalogram
EMG	Electromyogram
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
HPA	Hypothalamus-pituitary-adrenocortical
HRV	Heart rate variability
LSSVM	Least squares support vector machine
LSTM	Long short term memory
NN	Neural Network
NLM	Non local means
SNS	sympathetic nervous system
WT	Wavelet Transform
WTC	Wiretap Channel

LIST OF FIGURES

Figure No.	Figure Name	Page No.
5.1	Input Image	17
5.2	Decomposed Image	18
5.3.1	1 st Level reconstruction	18
5.3.2	2 nd Level reconstruction	19
5.3.3	3 rd Level reconstruction	19
5.3.4	4 th Level reconstruction	20
5.4	Training Observation 1	20
5.5	Sorted Data	21
5.6.1	LSSVM vs WT	21
5.6.2	DS vs WTC	21
5.6.3	LSTM vs NN	22
5.6.4	LSSVM vs LSTM	23
5.6.5	FIR vs LSTM	23
5.7	Power spectrum using FFT	24
5.8	Time frequency	24
5.9	Waveform for DELTA band	25
5.10	Single sided amplitude spectrum of DELTA	25
5.11	Waveform for THETA band	26
5.12	Single sided amplitude spectrum of THETA	26
5.13	Waveform for ALPHA band	27
5.14	Single sided amplitude spectrum of ALPHA	27
5.15	Waveform for BETA band	28
5.16	Feature Extraction	28
5.17	Training process	29
5.18	Output image	30

CHAPTER 1

INTRODUCTION

Health problems can be exacerbated by mental stress, among other things. It is the term used to describe the way the human body reacts to mental, physical, and emotional stimuli under the guidance of the sympathetic nervous system (SNS) and hypothalamus-pituitary-adrenocortical axis (HPA axis). This statement can be used in reference to internal (personality structure) or external (handling problems) issues that cause various physiological and unfavorable emotional alterations. Acute, episodic, and chronic stress are the three types of stress that have been identified in literature. Short-term exposure is a factor in acute stress, which is not damaging when the stimulus is present more frequently for a brief period of time, episodic stress, which is brought on by ongoing stresses. Studies have shown that emotional stress has direct physiological impacts that contribute to a number of disorders, including stroke, cardiovascular disease, cognitive issues, speech uniqueness, and depression. Moreover, stress has an indirect impact on health on a variety of levels, including decisions made regarding eating, sleeping, and skin issues. In order to prevent harmful effects on performance and health, researchers have created a variety of methods to gauge stress levels early on. Since everyone reacts to stress differently, measuring mental stress can be difficult. In addition, assessment and analysis are crucial to the validity of evaluating mental stress. Subjective techniques are typically used to evaluate stress. The self-report questionnaires like the perceived stress scale are the most often utilized technique. The results of questionnaires, self-ratings, and interviews have been validated as reliable measures of mental stress in several research. Questionnaires, however, demand the user's complete attention and are subjective. Because of this, people are sometimes unaware of how much stress they actually are under. Thus, methods like self-report surveys could produce an unreliable stress level measurement. Moreover, they appear to be less informative than physiological assessments. Heart rate variability (HRV), electrodermal activity (EDA), electromyogram (EMG), blood pressure, pupil diameter, salivary cortisol, and

salivary alpha amylase are among the physiological markers that researchers have identified as stress indicators. Yet, a variety of circumstances, such as emotional stress, might affect physiological signs. Circadian rhythm has reportedly been linked to fluctuations in cortisol levels throughout the day. Furthermore, salivary alpha amylase levels are influenced by physical activity, and humidity and skin conditions might alter EDA. By directly or indirectly monitoring brain activity, many neuroimaging techniques have been utilized to evaluate mental stress.

CHAPTER 2

LITERATURE SURVEY

Weinstein, M.; Seeman, T.E.; Sloan, R.P. The interactive effect of change in perceived stress and trait anxiety on vagal recovery from cognitive challenge. *Int. J. Psychophysiol.* 2011, 82, 225–232. The goal of the current study was to explore the hypothesis that the link between trait anxiety and anger and vagal recovery from a cognitive challenge is moderated by changes in state negative affect (measured as perceived stress) after the task. A sample of 905 people from the Midlife in the United States Study had their heart rate variability and respiratory rate evaluated. The activities included Stroop colour-word matching and computerised mental arithmetic. Changes in perceived stress significantly moderated the relationship between trait anxiety and vagal recovery from cognitive challenges, according to multiple regression analyses that controlled for the effects of demographic, lifestyle, and medical factors influencing cardiac vagal control (Beta = .253, $p = .013$). After accounting for respiratory rate, this effect became hardly significant (Beta = .177, $p = .037$). The link between trait anger and vagal recovery, however, was not significant either before (Beta = .141, $p = .257$) or after (Beta = .186, $p = .072$) controlling for respiratory rate. Secondary analyses showed that greater decreases in perceived stress were related to bigger increases in cardiac vagal control following the challenge in people with higher levels of trait anxiety. Changes in perceived stress, however, showed no effect on vagal recovery in people with lower levels of trait anxiety. Therefore, the connection between trait anxiety and vagal recovery from cognitive difficulty is moderated by change in perceived stress but not by change in trait anger. (PsycInfo Database Record (c) 2021 APA, all rights reserved)

Garg, A.; Chren, M.-M.; Sands, L.P.; Matsui, M.S.; Marenus, K.D.; Feingold, K.R.; Elias, P.M. Psychological stress perturbs epidermal permeability barrier homeostasis: Implications for the pathogenesis of stress-associated skin disorders. *JAMA Dermatol.* 2001, 137, 53–59. Many skin conditions, including psoriasis and atopic dermatitis, seem to be brought on by or made worse by psychological stress. However, it is still unclear what particular pathogenic impact psychological stress plays. Recently, it was demonstrated in 3 separate mouse models of psychological stress that psychological stress has a deleterious impact on cutaneous permeability barrier function and that tranquillizer Coad ministration prevents this stress-related degradation in barrier function.

Giannakakis, G.; Grigoriadis, D.; Giannakaki, K.; Simantiraki, O.; Roniotis, A.; Tsiknakis, M. Review on psychological stress detection using biosignals. *IEEE. Affect. Comput. Comput.* 2019, 1–16. This review investigates the effects of psychological stress on the human body measured through biosignals. When a potentially threatening stimulus is perceived, a cascade of physiological processes occurs mobilizing the body and nervous system to confront the imminent threat and ensure effective adaptation. Bio signals that can be measured reliably in relation to such stressors include physiological (EEG, ECG, EDA, EMG) and physical measures (respiratory rate, speech, skin temperature, pupil size, eye activity). A fundamental objective in this area of psychophysiological research is to establish reliable biosignal indices that reveal the underlying physiological mechanisms of the stress response. Motivated by the lack of comprehensive guidelines on the relationship between the multitude of biosignal features used in the literature and their corresponding behaviour during stress, in this paper, the impact of stress to multiple bodily responses is surveyed. Emphasis is put on the efficiency, robustness and consistency of biosignal data features across the current state of knowledge in stress detection. It is also explored multimodal biosignal analysis and modelling methods for deriving accurate stress correlates. This paper aims to provide a comprehensive review on biosignal patterns caused during stress conditions and reliable practical guidelines towards more

Hanrahan, K.; McCarthy, A.M.; Kleiber, C.; Lutgendorf, S.; Tsalikian, E. Strategies for salivary cortisol collection and analysis in research with children. *Appl. Nurs. Res.* 2006, 19, 95–101. [In paediatric research, salivary cortisol has become a convenient, reasonably priced biologic stress marker. When using this measure in research on children, it is important to take into account that cortisol is extremely variable and susceptible to a wide range of stimuli. The following sample collection strategies are used: (1) standardising sample collection times, including baseline samples; (2) employing uniform collection tools and techniques; (3) adjusting for specific foods, drinks, medications, and diagnoses; and (4) developing procedures and protocols. Choosing the right assay and lab, specifying units of measurement and norms, and implementing quality controls are additional methods for laboratory analysis. These methods yield reliable and valid salivary cortisol readings by controlling extraneous factors

O'Connor, D.B.; Thayer, J.F.; Vedhara, K. Stress and health: A review of psychobiological processes. *Annu. Rev. Psychol.* 2021, 72, 663–688. The cumulative science linking stress to negative health outcomes is vast. Stress can affect health directly, through autonomic and neuroendocrine responses, but also indirectly, through changes in health behaviors. In this review, we present a brief overview of (a) why we should be interested in stress in the context of health; (b) the stress

response and allostatic load; (c) some of the key biological mechanisms through which stress impacts health, such as by influencing hypothalamic-pituitary-adrenal axis regulation and cortisol dynamics, the autonomic nervous system, and gene expression; and (d) evidence of the clinical relevance of stress, exemplified through the risk of infectious diseases. The studies reviewed in this article confirm that stress has an impact on multiple biological systems. Future work ought to consider further the importance of early-life adversity and continue to explore how different biological systems interact in the context of stress and health processes.

Zanetti, M.; Mizumoto, T.; Faes, L.; Fornaser, A.; De Cecco, M.; Maule, L.; Valente, M.; Nollo, G. Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices. *J. Ambient Intell. Humaniz. Comput.* 2019, 12, 4409–4418. Mental stress is a physiological condition that significantly lowers quality of life and negatively impacts both physical and mental health. For this reason, precise measures of stress levels can be useful in developing preventative and treatment strategies. This study suggests a method for categorising various mental stress levels using physiological signals provided by minimally intrusive wearable technology. There were 17 healthy volunteers that took part in this investigation. They were put into three different mental states: a relaxed state, a stressful cognitive state, and a sustained attention task. A one lead electrocardiogram (ECG), a respiratory signal, a blood volume pulse (BVP), and 14 channels of a 10-20 electroencephalogram made up the physiological signals that were obtained (EEG). The RR series, respiratory series, pulse arrival time (PAT) series, and delta, theta, alpha, and beta power series of the 14 EEG channels were all included in 59 time series of 300 samples each for all participants. Using the Network Physiology paradigm, various classifiers were constructed to determine the degree of mental stress starting from a pool of 3481 features computed from the aforementioned physiological parameters. The classifiers for logistic regression and random forest, which were cross-validated using a leave-one-person-out study, had the greatest accuracy of 84.6%. As cardio-respiratory signals are better suited for usage in real-life circumstances, a second analysis was done to assess the classification accuracy using only these signals. In this instance, the maximum accuracy of 76.5% was attained

Arrighi, J.A.; Burg, M.; Cohen, I.S.; Kao, A.H.; Pfau, S.; Caulin-Glaser, T.; Zaret, B.L.; Soufer, R. Myocardial blood-flow response during mental stress in patients with coronary artery disease. *Lancet* 2000, 356, 310–311. Myocardial ischemia, which results from emotional provocation, occurs in as many as 30–50% of patients with CAD during the discourse of their daily lives. This emotionally provoked or mental stress ischemia is associated with the poor prognosis, with emerging treatment strategies. This chapter will outline the conceptual constructs which support the pathophysiologic underpinnings, and biobehavioral aspects associated with this

mental stress ischemia. We will review a biobehavioral model where cognitive stress is transduced in the brain. The response of the brain to psychosocial stress is a highly sophisticated and integrated process by which sensory inputs are evaluated and appraised for its importance in relation to previous experience and current goals. The biologic consequences of such stress transduced in the CNS has its effect upon the cardiovascular flow and function through changes in autonomic balance, which result in various biologic processes that culminate in the perturbation of flow and function of the heart

Al-Shargie, F.; Tang, T.B.; Badruddin, N.; Kiguchi, M. Towards multilevel mental stress assessment using SVM with ECOC: An EEG approach. *Med Biol. Eng. Comput.* 2018, 56, 125–136. Mental stress has been identified as one of the major contributing factors that leads to various diseases such as heart attack, depression, and stroke. To avoid this, stress quantification is important for clinical intervention and disease prevention. This study aims to investigate the feasibility of exploiting electroencephalography (EEG) signals to discriminate between different stress levels. We propose a new assessment protocol whereby the stress level is represented by the complexity of mental arithmetic (MA) task for example, at three levels of difficulty, and the stressors are time pressure and negative feedback. Using 18-male subjects, the experimental results showed that there were significant differences in EEG response between the control and stress conditions at different levels of MA task with p values < 0.001 . Furthermore, we found a significant reduction in alpha rhythm power from one stress level to another level, p values < 0.05 . In comparison, results from self-reporting questionnaire NASA-TLX approach showed no significant differences between stress levels. In addition, we developed a discriminant analysis method based on multiclass support vector machine (SVM) with error-correcting output code (ECOC). Different stress levels were detected with an average classification accuracy of 94.79%. The lateral index (LI) results further showed dominant right prefrontal cortex (PFC) to mental stress (reduced alpha rhythm). The study demonstrated the feasibility of using EEG in classifying multilevel mental stress and reported alpha rhythm power at right prefrontal cortex as a suitable index.

Movahed, R.A.; Jahromi, G.P.; Shahyad, S.; Meftahi, G.H. A Major Depressive Disorder Classification Framework based on EEG Signals using Statistical, Spectral, Wavelet, Functional Connectivity, and Nonlinear Analysis. *J. Neurosci. Methods* 2021, 358, 109–209. The diagnosis of major depressive disorder (MDD), a common mental illness, is made using questionnaire-based techniques, however these may not produce an accurate result. In this line, numerous studies have concentrated on identifying MDD utilising electroencephalogram (EEG) data and machine learning methods.

Mumtaz, W.; Rasheed, S.; Irfan, A. Review of challenges associated with the EEG artifact removal methods. *Biomed. Signal Process. Control* 2021, 68, 1–13. Electroencephalography (EEG), as a non-invasive modality, enables the representation of the underlying neuronal activities as electrical signals with high temporal resolution. In general, the EEG artifact removal methods have been considered as a fundamental preliminary step during EEG analysis. However, the associated challenges of EEG artifact removal methods should be addressed carefully, to fully utilize the data. This manuscript is based on the notion that the full capacity of the EEG artifact removal methods can be achieved while addressing the associated challenges well. Because these methods could enhance the inferences deduced from the EEG data. The focus of this manuscript is to elaborate challenges (e.g., the algorithm-specific challenges and general challenges) of the EEG artifact removal methods. Considering the challenges, the manuscript has presented recommendations to address them. The manuscript also provides information on Matlab and Python-based toolboxes developed for EEG preprocessing. In addition, this manuscript provides a brief account of the EEG artifact types along with an overview of the EEG artifact removal methods. In short, this manuscript provides information on various EEG artifact removal methods and the recommendations provided serve as guidelines for the selection of suitable tools and methods for EEG artifact corrections.

Thatcher, R.; Krause, P.; Hrybyk, M. Cortico-cortical associations and EEG coherence: A two-compartmental model. *Electroencephalogr. Clin. Neurophysiol.* 1986, 64, 123–143. 189 youngsters between the ages of 5 and 16 had their EEG coherence calculated from 19 scalp sites. By contrasting EEG coherence as a function of various interelectrode distances in the anterior-to-posterior versus posterior-to-anterior directions, tests of spatial homogeneity of EEG coherence were done. Since there was more coherence in the anterior-to-posterior direction than in the posterior-to-anterior directions, quite significant inhomogeneities were detected. Additionally, frontal derivations showed more coherence than posterior derivations and were derived from the right hemisphere as opposed to the left. These findings suggest that there were at least two distinct sources of EEG coherence: coherence created by short-distance axonal connections and coherence produced by long-distance connections.

Xia, L.; Malik, A.S.; Subhani, A.R. A physiological signal-based method for early mental-stress detection. *Biomed. Signal Process. Control* 2018, 46, 18–32. For effective clinical treatment, the early identification of mental stress is essential. The

automatic methods described in the literature have demonstrated significance and effectiveness in terms of diagnosis speed when compared to conventional procedures. Unfortunately, most of them tend to place more emphasis on accuracy than on forecasts of treatment efficacy. This could lead to the creation of less reliable and accurate procedures, which are inappropriate for use in therapeutic settings. In this study, we analyse fluctuations in both electroencephalogram (EEG) and electrocardiogram (ECG) data from 22 male individuals (mean age: 22.54 ± 1.53 years), and we provide a comprehensive framework for the early diagnosis of mental stress. This research makes a substantial addition by demonstrating that the paradigm it uses can make predictions about treatment efficacy.

CHAPTER 3

AIM AND SCOPE

3.1. EXISTING METHOD

One of the significant causes of a number of health issues is mental stress. The degree of mental stress in its early phases can be measured using a variety of instruments established by scientists and medical professionals. The research has suggested a number of neuroimaging instruments to measure workplace mental stress. A strong candidate is the electroencephalogram (EEG) signal since it offers a wealth of data about the conditions and states of the mind. The approaches for assessing mental stress using EEG signals are reviewed in this article. The study emphasizes the significant variances between the research findings and makes the case that different approaches to data

3.1.1. Disadvantages of existing method

- Time consuming process
- Less accuracy

3.2. PROPOSED METHOD

- The process consists of feature selection and classification.
- The classification process uses the LSSVM, Entropy, Hjorth activity, complexity, LSTM
- Band analysis, power spectrum analysis

3.2.1 Advantages of proposed method:

- Improved performance than other algorithms
- Less computational cost
- Less time

3.3. TYPICAL USES INCLUDE

- Math and computation
- Algorithm development
- Modeling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics
- Application development, including graphical user interface building

CHAPTER 4

METHODS; ALGORITHMS USED

4.1. DOMAIN OVERVIEW

The process consists of feature selection and classification. The classification process uses the band analysis, Power spectrum analysis model. The amount of raw data required for classification is impractical for most machine learning algorithms. Hence we need to perform various feature extraction techniques for successful classification of data. Pre-processing of data includes transformation of EEG signals from time domain to frequency domain and removal of noise and artefacts. The typical extraction methods that exists are Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). The recorded EEG signals were made noise free in the pre-processing stage. Frontal and temporal alpha and beta asymmetries, and alpha asymmetry was calculated from these features. Once the EEG data has been collected we then need to classify the data using classifiers. MATLAB gives a lot of freedom to choose from a variety of classifiers namely band analysis, Power spectrum analysis to name a few. In our method, we proposed LSSVM, Entropy, Horthy activity, complexity and LSTM to provide better performance. Performance optimization may be done by evaluating all the parameters using DCNN. Extracted feature parameters are plotted such Contrast, Corers ,Energy ,Entropy , Homogeneity ,Mean , and SD to classify the mental stress from the EEG signal.

4.2. BLOCK DIAGRAM

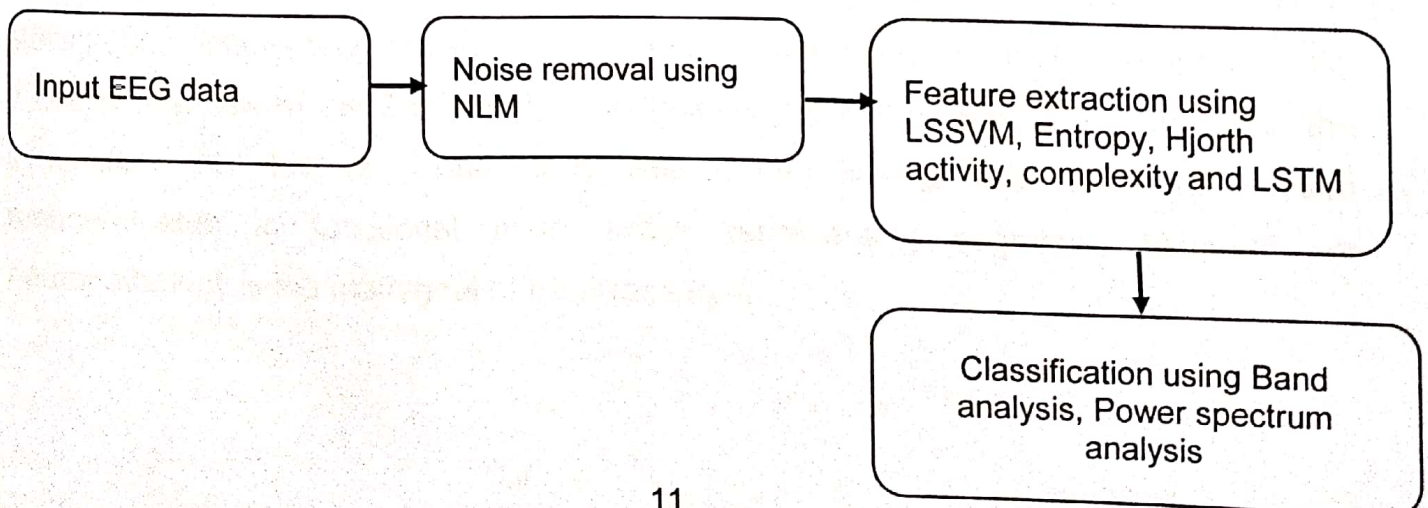


Fig: 4.2: Block Diagram

Fig 4.2 represents the block diagram of the project where the input image of EEG is given as the input data, for removing the noise using NLM. Then for feature extraction we are using LSSVM, Entropy, Hjorth activity, Complexity and LSTM and the classification is done by using Band analysis, Power spectrum analysis

4.3. METHODS

4.3.1. Input EEG data

Prior to using data analysis techniques, the EEG signal undergoes laborious preprocessing steps to eliminate noise and artefacts. In order to learn useful information about the signal, data preparation is crucial. Hence, in-depth familiarity with the many kinds of artefacts is necessary. The most frequent types of artefacts that impact EEG data, according to Jiang et al. , are physiological artefacts. Artifacts are yet another significant source of skewed knowledge. To visually detect and reject apparent artefacts, the digitised EEG data can be divided into epochs. Researchers have used a range of strategies to eliminate noise and distortions from EEG signals, including regression techniques, blind source separation (BSS), empirical-mode decomposition (EMD), and wavelet transform algorithms. Together with adaptive and Wiener filtering, high pass, band pass, notch filters, and independent component analysis (ICA), this is furthermore used. In fact, there is yet no universally accepted standard for EEG pre-processing that can be applied to all research projects. Data analysis is the process of evaluating, purging, manipulating, and modelling EEG signals in stress studies with the goal of uncovering relevant information, guiding conclusions, and supporting decision-making. In the literature, a number of data processing techniques have been described for using EEG signals to analyses mental stress. To reduce the cost of data processing as well as storage and dimensional space, it is crucial to choose a suitable analysis approach. An in-depth overview of the EEG analysis techniques for mental stress is provided in the subsection that follows. Connectivity Approaches linking various neural rhythm measurements to functional brain states representing cognition, behavior, or neuropathology is the main goal of EEG research.

4.3.2. Noise removal using NLM

Several kinds of noise frequently appear in digital photographs. Noise is a result of mistakes made during the picture acquisition process, which causes pixel values to not accurately represent the true intensities of the actual scene. Depending on how the image is produced, noise can be added to an image in a variety of ways. Film grain is a source of noise when an image is scanned from a film photograph. In addition, the film's condition or the scanner itself may have caused noise. When a picture is immediately converted to a digital format, noise may be introduced by the data collection method (such as a CCD). The toolbox offers the `imnoise` function, which you can use to add different kinds of noise to an image to replicate the consequences of some of the issues mentioned above. These examples make use of this function. Linear filtering reduces noise. Some kinds of noise can be eliminated using linear filtering. Certain filters, including averaging or Gaussian filters, are suitable for this use. For instance, reducing grain noise from a photo can be done with the help of an averaging filter. Local differences brought on by grit are lessened since each pixel is averaged out with the pixels around it. Further information on linear filtering with `imfilter` can be found in [What Is Image Filtering in the Spatial Domain? Detector](#)). Noise can be introduced during electronic image transmission.

4.3.3. Feature extraction

LSTMs are superior to RNN and traditional feed-forward neural networks in many aspects. This is due to their ability to remember certain patterns selectively over extended periods of time. This article's goal is to make LSTM understandable and practical for use in everyday situations.

Even though modern computers are incredibly powerful, people are still considerably superior at executing simple but difficult tasks like gripping an object or recognizing a picture. This dominance most likely results from the structure of the human brain. McCulloch and Pitts, who provided a model for the 'neuron,' the brain's fundamental building block, in 1943, were pioneers in the study of artificial analogues of the human brain's structure. The soma, the cell body of the neuron, and the 'axon,' its sole output fibre, can be seen as the neuron. To other neurons or other structures, such as muscles, the axon transmits electrical pulses. About 10 additional neurons provide the cell with

information. The junctions that receive input are referred to as "synapses." In addition to being a key idea in physics and chemistry, entropy also has applications in cosmology and economics. It belongs to thermodynamics in physics. It is a key idea in physical chemistry, a branch of science. The disorder of a system is measured by entropy. It is a thermodynamic system's extensive attribute, which means that the amount of matter in the system affects how much it is worth. Entropy is typically represented in equations by the letter S and has units of joules per kelvin (JK^{-1}) or kilogramme per meter squared per kelvin ($\text{kg/m}^2/\text{s}^2\text{K}^{-1}$). Low entropy describes a highly ordered system..

4.3.4. Classification

Compared to conventional approaches, neural networks exhibit self-study, self-organization, associational memory, parallel processing, and distributed storage. Identification models are stable and repeatable thanks to neural network technology's high fault tolerance. The fundamental building block of artificial neural networks is the artificial neuron, which is an arithmetic module and resembles the biological model. The basic elements of an artificial neurons are (1) a set of input nodes, indexed by I say, $1, 2, \dots, I$, that receives the corresponding input signal or pattern vector, say $x = (x_1, x_2, \dots, x_I)$; (2) a set of synaptic connections whose strengths are represented by a set of weights, here denoted by $w = (w_1, w_2, \dots, w_I)$; and (3) an activation function Y that relates the total synaptic input to the output (activation) of the neuron.

4.4 ALGORITHMS USED

4.4.1 Least-squares support-vector machines (LS-SVM)

For statistics and in statistical modeling, are least-squares versions of support-vector machines (SVM), which are a set of related supervised learning methods that analyze data and recognize patterns, and which are used for classification and regression analysis. In this version one finds the solution by solving a set of linear equations instead of a convex quadratic programming (QP) problem for classical SVMs. Least-squares SVM classifiers were proposed by Johan Suykens and Jobs Vandewalle.^[1] LS-SVMs are a class of kernel-based learning methods.

4.4.2 Wavelet transform (WT)

Mathematical algorithm designed to turn a waveform or signal in the time domain into a sequence of coefficients based on an orthogonal basis of small finite waves, or wavelets. The transform can be easily extended to multidimensional signals, such as images, where the time domain is replaced with the space domain. This algorithm was introduced in 1989 by Stéphane Mallat.^[1]

4.4.3 Data structure (DT)

Is a method of organizing data in a virtual system. Think of sequences of numbers, or tables of data: these are both well-defined data structures. An algorithm is a sequence of steps executed by a computer that takes an input and transforms it into a target output. Together, data structures and algorithms combine and allow programmers to build whatever computer programs they'd like. Deep study into data structures and algorithms ensures well-optimized and efficient code.

4.4.4 Wiretap channel (WC)

Is a setting where one aims to provide information-theoretic privacy of communicated data based solely on the assumption that the channel from sender to adversary is "noisier" than the channel from sender to receiver

4.4.5 Long short term memory (LSTM)

It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems. LSTM has feedback connections, i.e., it is capable of processing the entire sequence of data, apart from single data points such as images

4.4.6 Neural Network (NN)

A neural network is a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so the network

generates the best possible result without needing to redesign the output criteria. The concept of neural networks, which has its roots in artificial intelligence, is swiftly gaining popularity in the development of trading systems.

4.4.7 Finite Impulse Response (FIR)

In signal processing, a finite impulse response (FIR) filter is a filter whose impulse response (or response to any finite length input) is of finite duration because it settles to zero in finite time

4.4.8 Fast Fourier Transform (FFT)

As the name implies, the Fast Fourier Transform (FFT) is an algorithm that determines Discrete Fourier Transform of an input significantly faster than computing it directly. In computer science lingo, the FFT reduces the number of computations needed for a problem of size N from $O(N^2)$ to $O(N \log N)$

CHAPTER 5

RESULT AND DISCUSSION

As in input, an abnormal EEG signal data is given .The input data image is decomposed and got a clumsy image .The clumsy data is undergoes for 4 level of reconstruction. In 1st level of reconstruction the clumsy decomposed signal was further enhanced, same in 2nd level of reconstruction .In 3rd level of reconstruction single were enhanced and got clear signals .In 4th level it is further enhanced and the peaks were well defined .The reconstruction signal is then trained to see clear signals and it is not clumsy .The data is sorted and can see the sequence improving by the process of sorting. Algorithm comparison is done can visually see the difference. By using FFT for power spectrum can produce the signal in 100ks clumsy .In time frequency ,we can able to see the peaks clearly .Waveform of DELTA, ALPHA ,BETA and THETA have got separately for these signals were also seen clearly .Then the data is undergone for the process of feature extraction ,and training process takes place .Then we got the output whether it is normal or abnormal stress

5.1 INPUT IMAGE

In fig 5.1 Input image of the abnormal EEG signal data

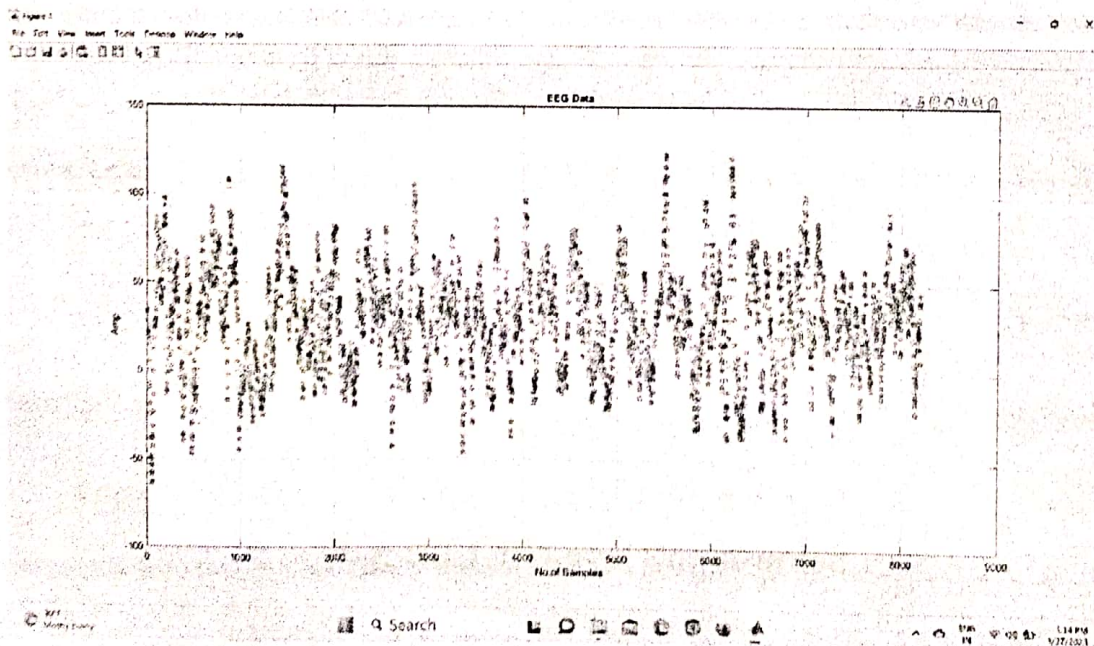


Fig: 5.1 Input Image

5.2. DECOMPOSED IMAGE

In fig 5.2 We got the decomposed signal but It looks clumsy

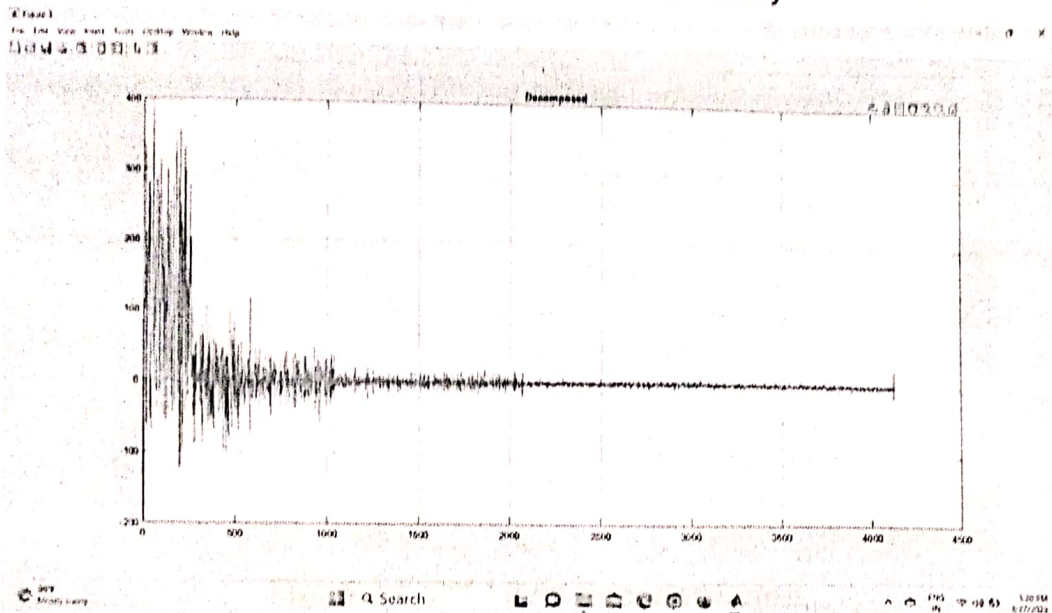


Fig: 5.2 Decomposed Image

5.3. RECONSTRUCTION LEVEL

5.3.1. 1st Level Reconstructed

In fig 5.3.1 The clumsy decomposed signal was further enhanced

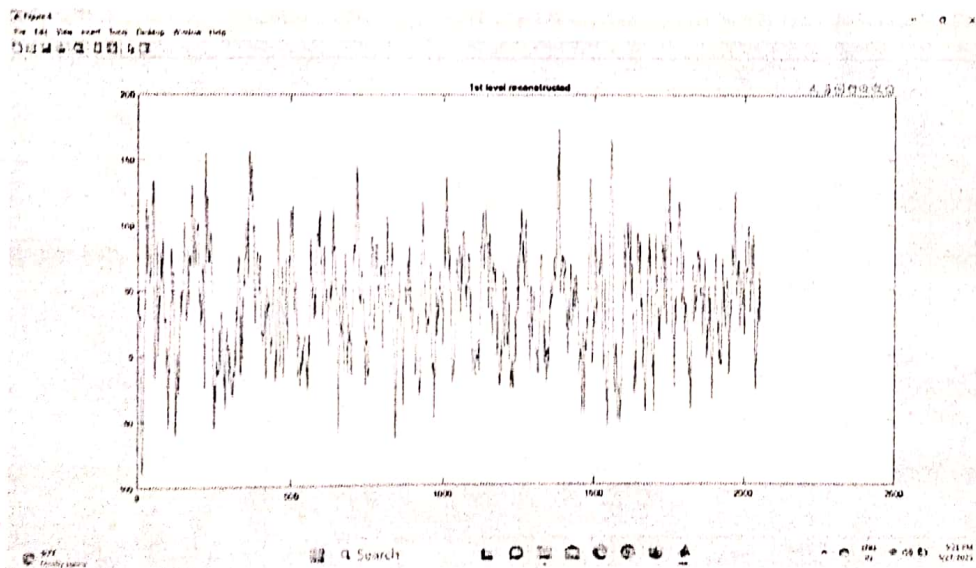


Fig: 5.3.1 1st Level Constructed

5.3.2. 2nd Level Reconstructed

In fig 5.3.2 The second level reconstruction signal was enhanced further

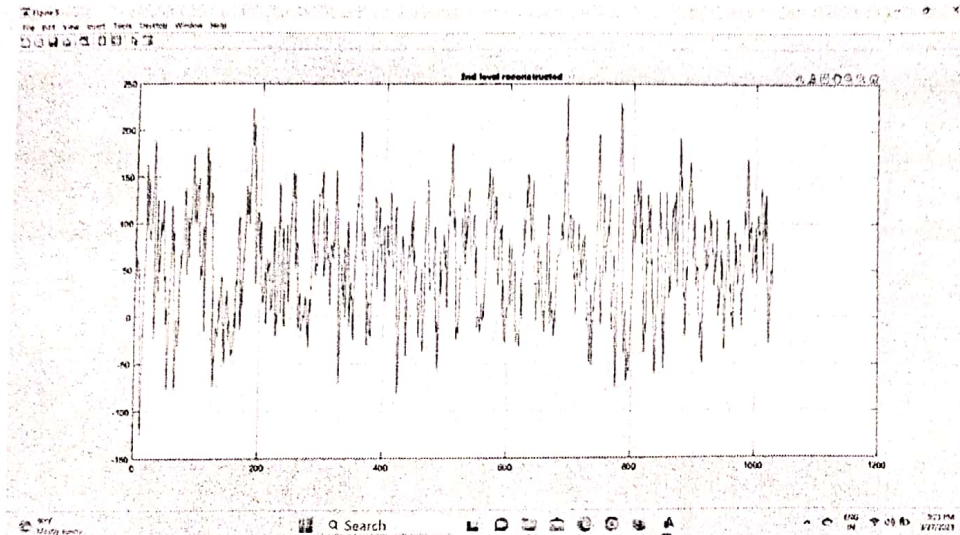


Fig: 5.3.2 2nd Level Reconstructed

5.3.3. 3rd Level Reconstructed

In fig 5.3.3 3rd level reconstruction signal were enhanced and we can clearly see the signals

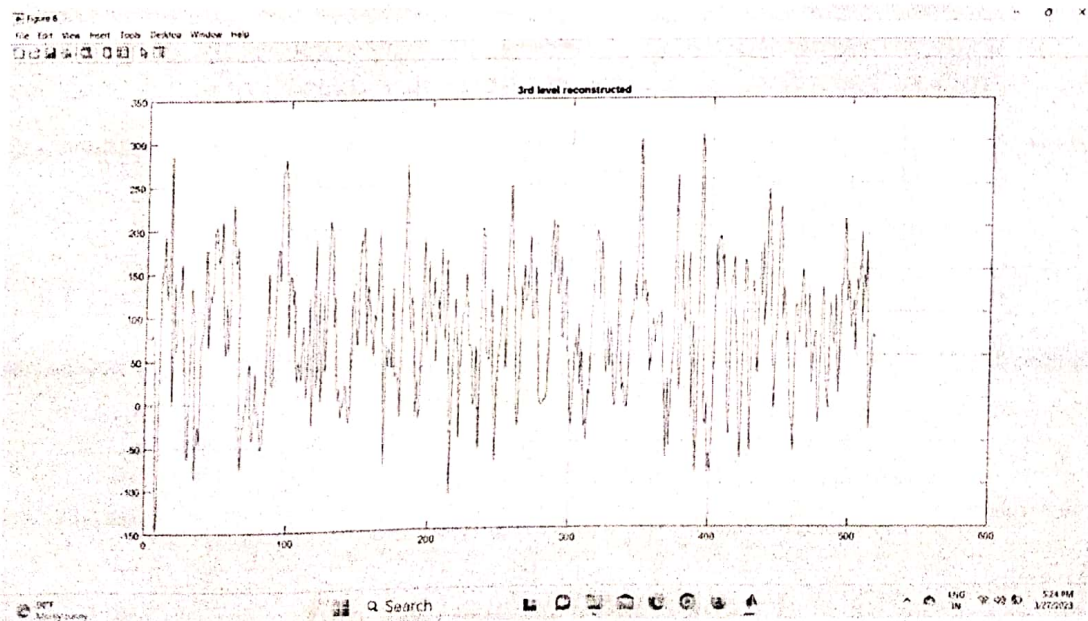


Fig: 5.3.3 3rd Level Reconstructed

5.3.4. 4th Level Reconstructed

In fig 5.3.4 The 4th level reconstruction signal were enhanced and the peaks were well defined

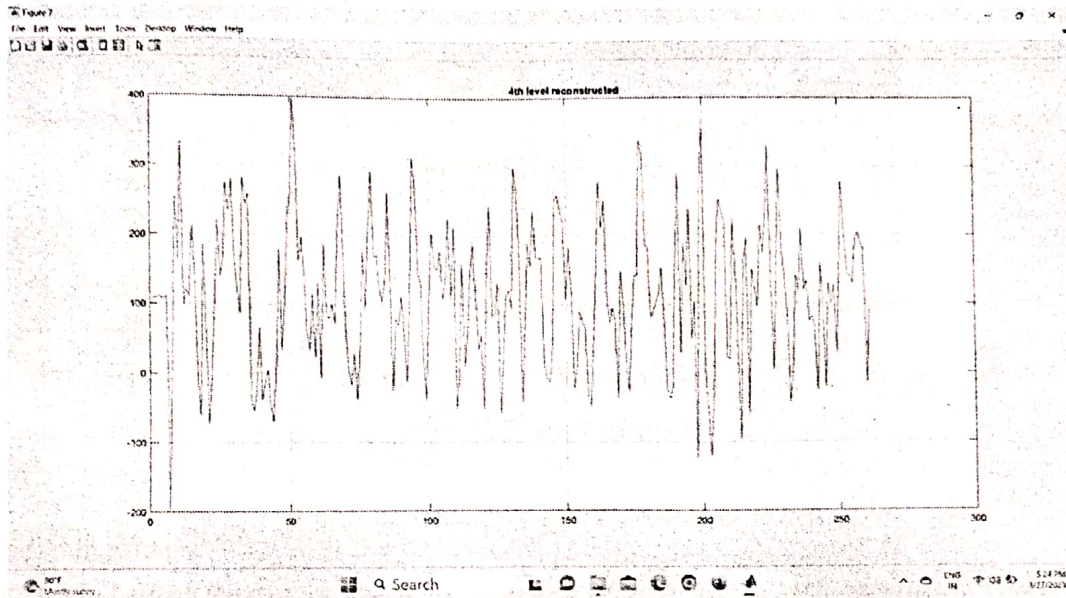


Fig: 5.3.4 4th Level Reconstructed

5.4. TRAINING OBSERVATION 1

In fig 5.4 in training observation we can clearly see the signals it is not clumsy

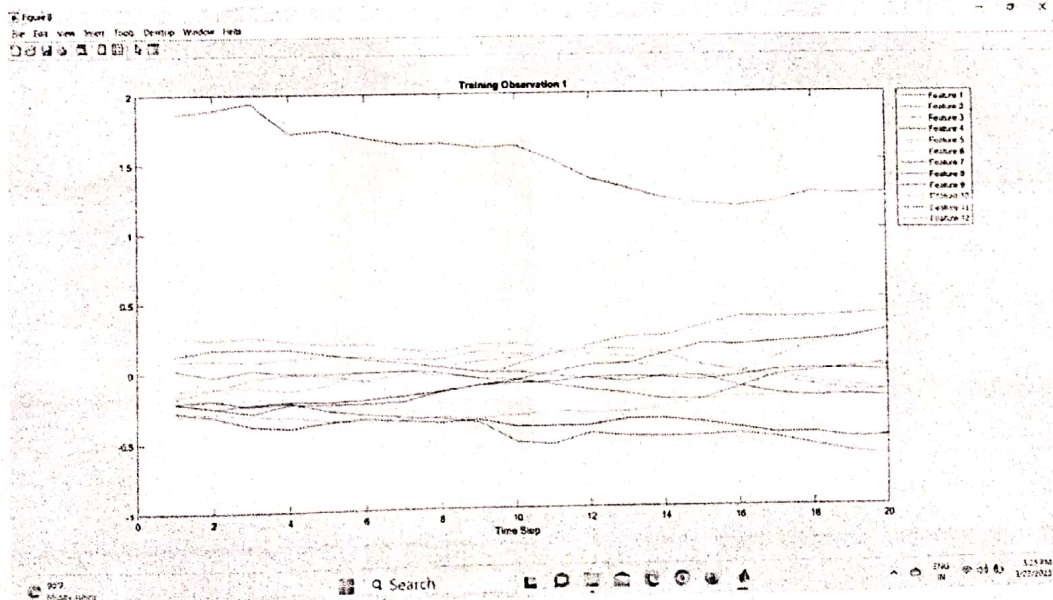


Fig: 5.4 Training Observation 1

5.5. SORTED DATA

In fig 5.5 In sorted data we can see the sequence improving by sorting

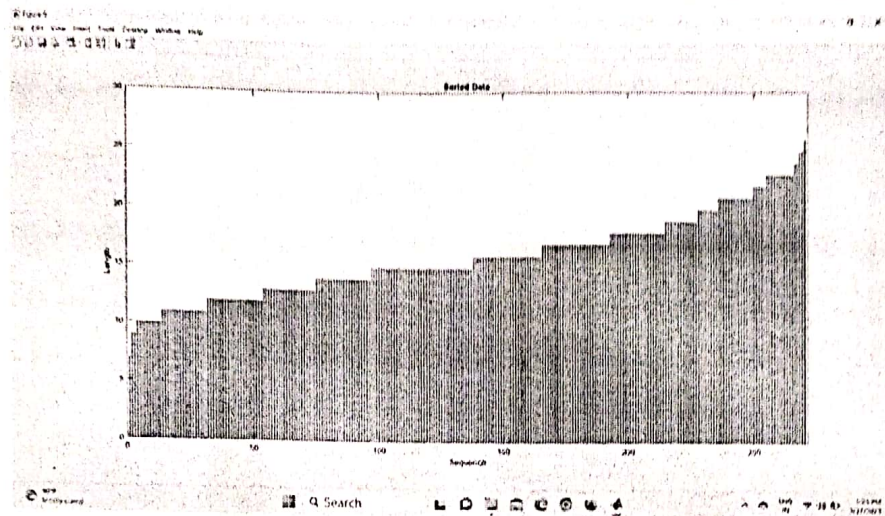


Fig: 5.5 Sorted data

5.6. ALGORITHM COMPARISON

5.6.1. LSSVM (Least Squares Support Vector Machine) vs WT (Wavelet Transform)

In fig 5.7.1 WT (Wavelet Transform) is 10% more than LSSVM(Least Squares Support Vector Machine)

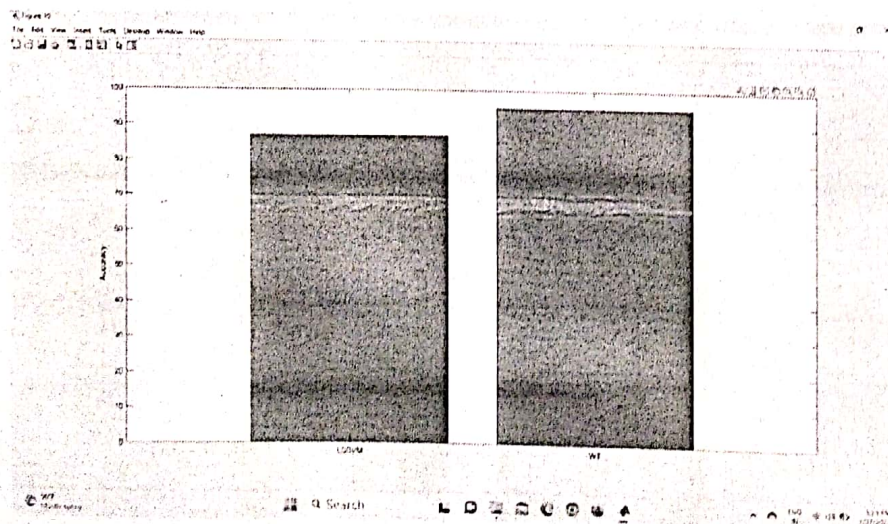


Fig: 5.6.1 LSSVM vs WT

5.6.2. DS (Data Structure) vs WTC (Wiretap Channel)

In fig 5.6.2 DS (Data Structure) is 15% more than WTC (Wiretap Channel)

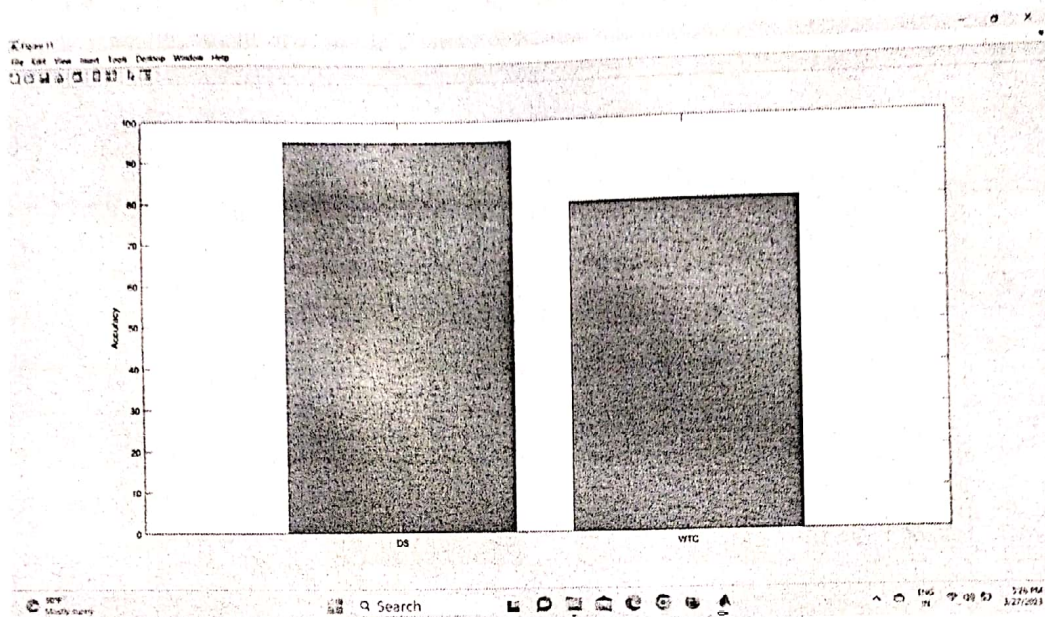


Fig: 5.6.2 DS vs WTC

5.6.3. LSTM (Long Short Term Memory) vs NN (Neural Network)

In fig 5.6.3 LSTM (Long Short Term Memory) is 18% more than NN (Neural Network)

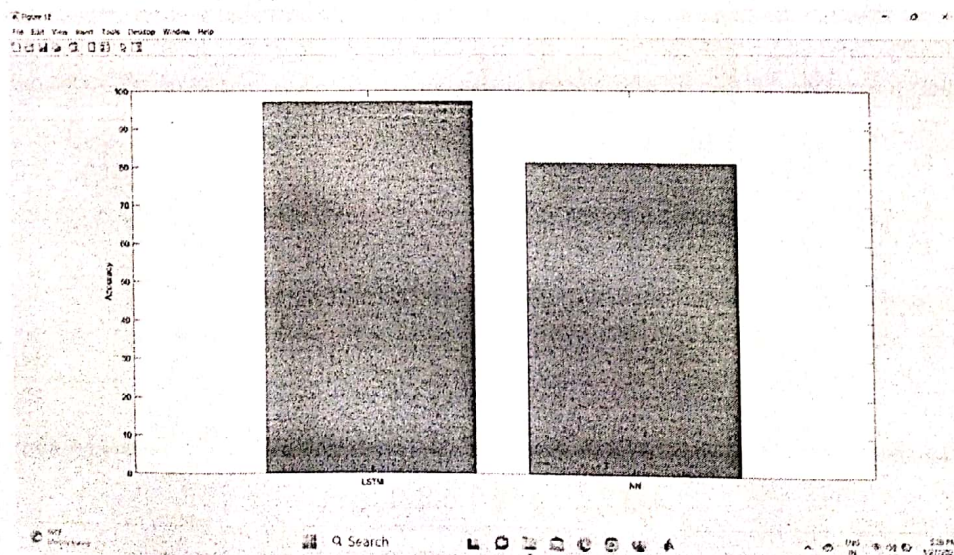


Fig: 5.6.3 LSTM vs NN

5.6.4. LSSVM (Least Squares Support Vector Machine) vs LSTM (Long Short Term Memory)

In fig 5.6.4 LSSVM (Least Squares Support Vector Machine) is 15% more than LSTM(Long Short Term Memory)

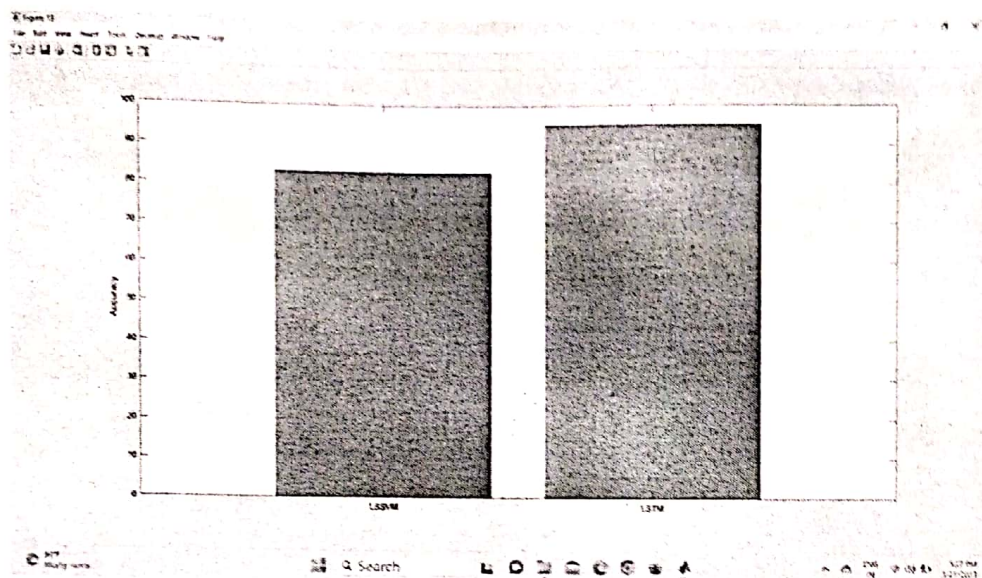


Fig: 5.6.4 LSSVM vs LSTM

5.6.5. FIR (Finite Impulse Response) vs LSTM (Long Short Term Memory)

In fig 5.6.5 LSTM (Long Short Term Memory) is 20% more than FIR (Finite Impulse Response)

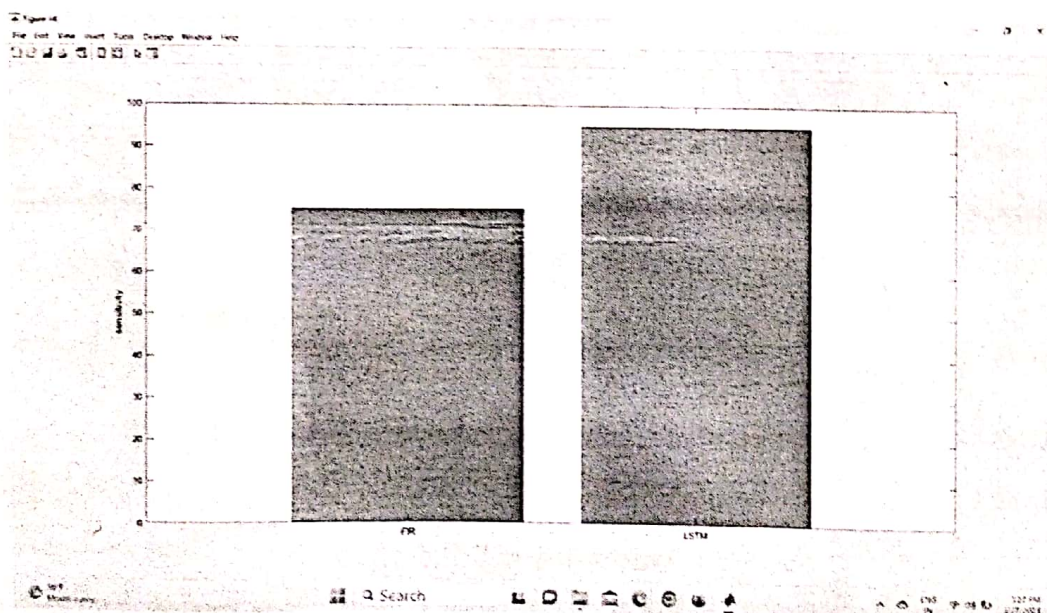


Fig: 5.6.5 FIR vs LSTM

5.7. POWER SPECTRUM USING FFT

In fig 5.7 the signal 100ks clumsy

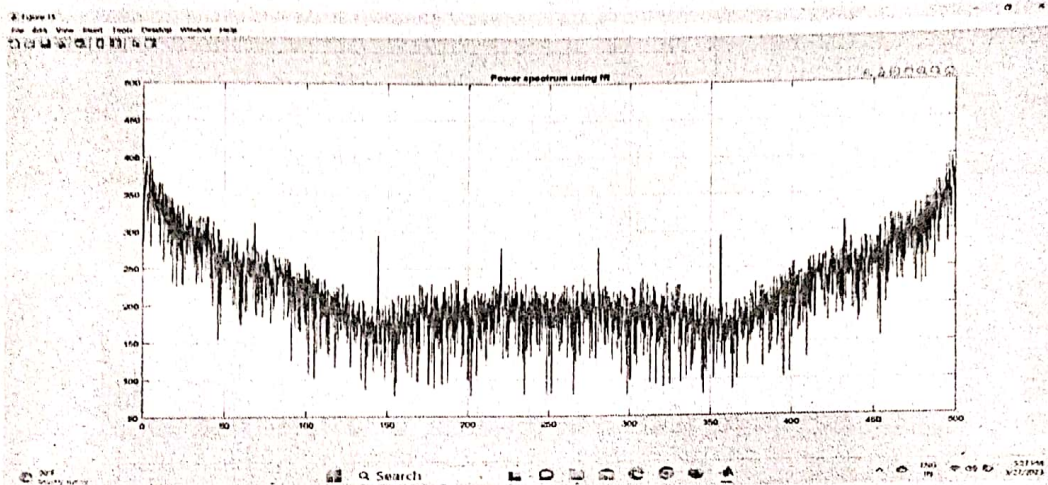


Fig: 5.7 Power spectrum using FFT

5.8. TIME FREQUENCY

In fig 5.8 in time frequency we can clearly see the peaks

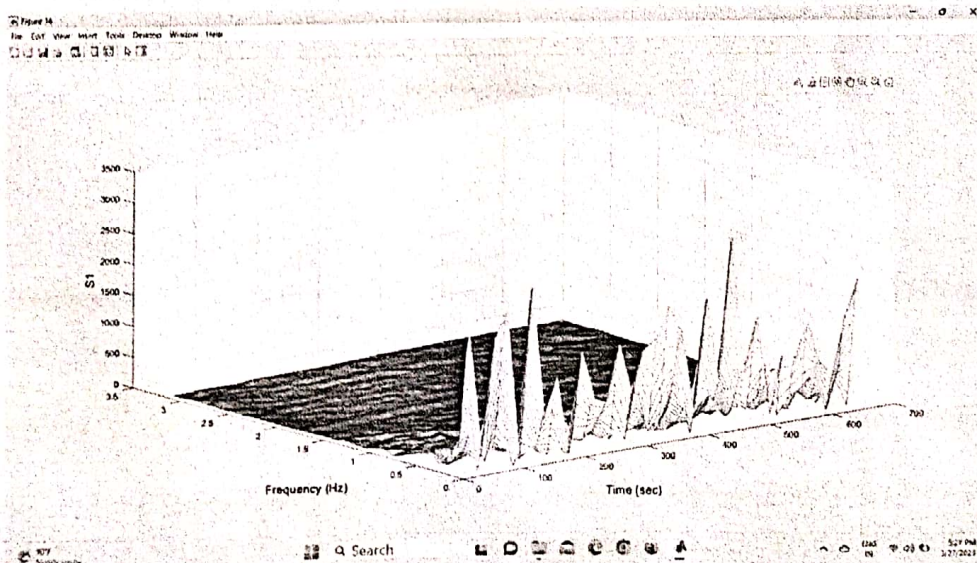


Fig: 5.8 Time frequency

5.9. WAVEFORM FOR DELTA

In fig 5.9 Band Delta waves are high amplitude neural oscillations with a frequency between 0.5 and 4 hertz. Delta waves, like other brain waves, can be recorded with electroencephalography^[1] (EEG) and are usually associated with the deep stage 3

of NREM sleep, also known as slow-wave sleep (SWS), and aid in characterizing the depth of sleep. Suppression of delta waves leads to inability of body rejuvenation,

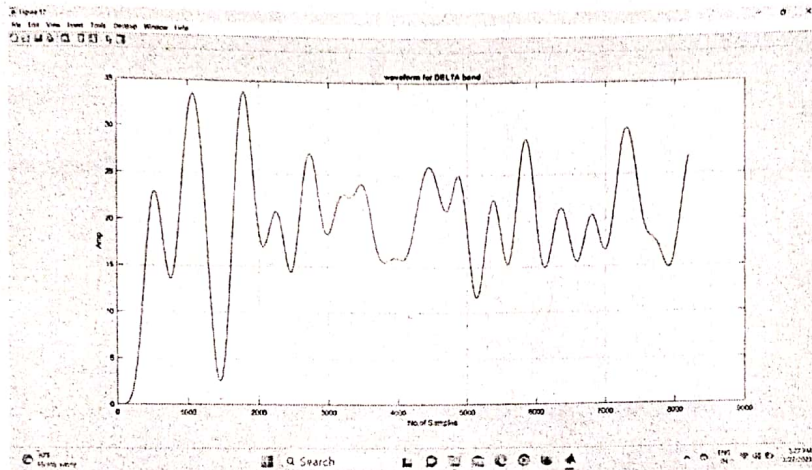


Fig: 5.9 Waveform for DELTA band

5.10. SINGLE – SIDED AMPLITUDE SPECTRUM OF DELTA

In fig 5.10 In 50 to 100 we can clearly see the signals

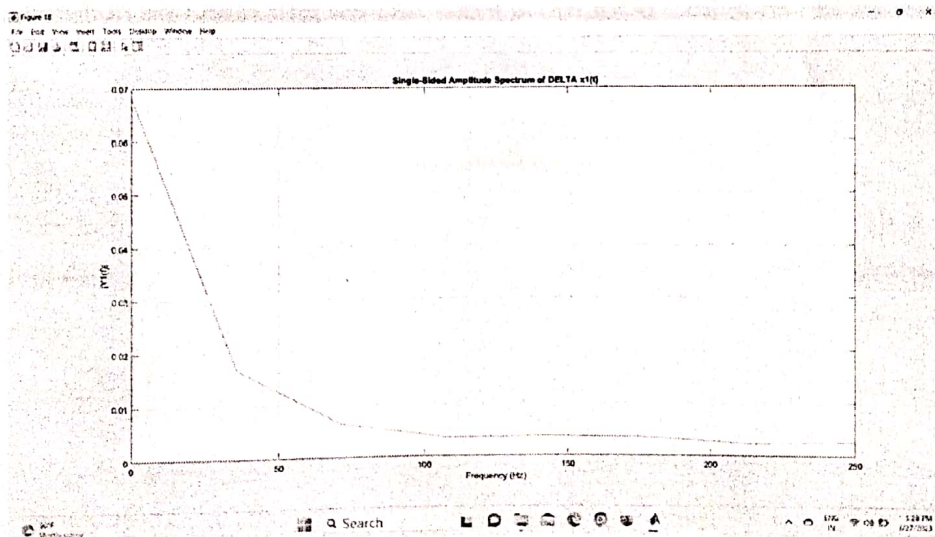


Fig: 5.10 Single – sided amplitude spectrum of delta

5.11. WAVEFORM OF THETA BAND

In fig 5.11 Theta waves generate the theta rhythm, a neural oscillation in the brain that underlies various aspects of cognition and behavior, including learning, memory, and

spatial navigation in many animals.^{[1][2]} It can be recorded using various electrophysiological methods, such as electroencephalogram (EEG), recorded either from inside the brain or from electrodes attached to the scalp.

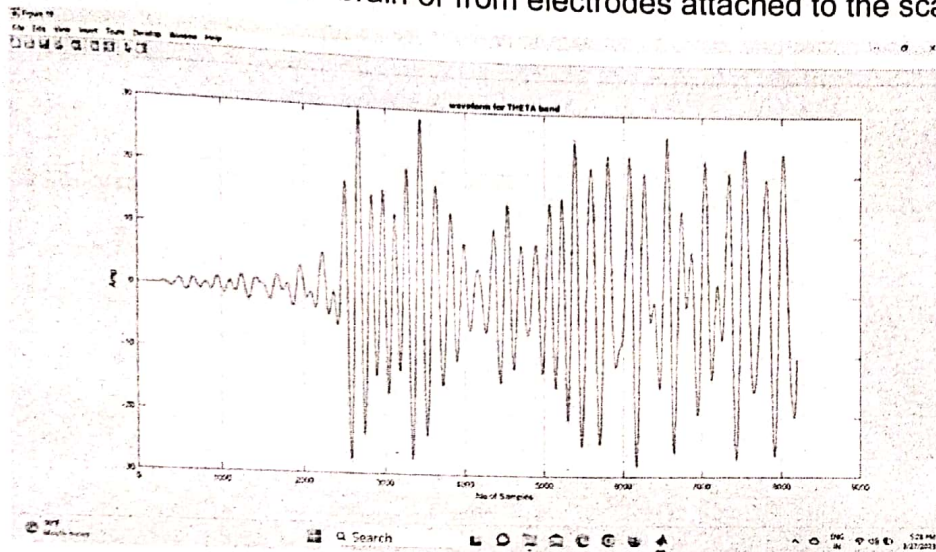


Fig: 5.11 Waveform of Theta band

5.12. SINGLE – SIDED AMPLITUDE SPECTRUM OF THETA

In fig 5.12 50 to 100 we can clearly see the EEG signals but some times it is constant there is no variation and after that we can see it is dropping

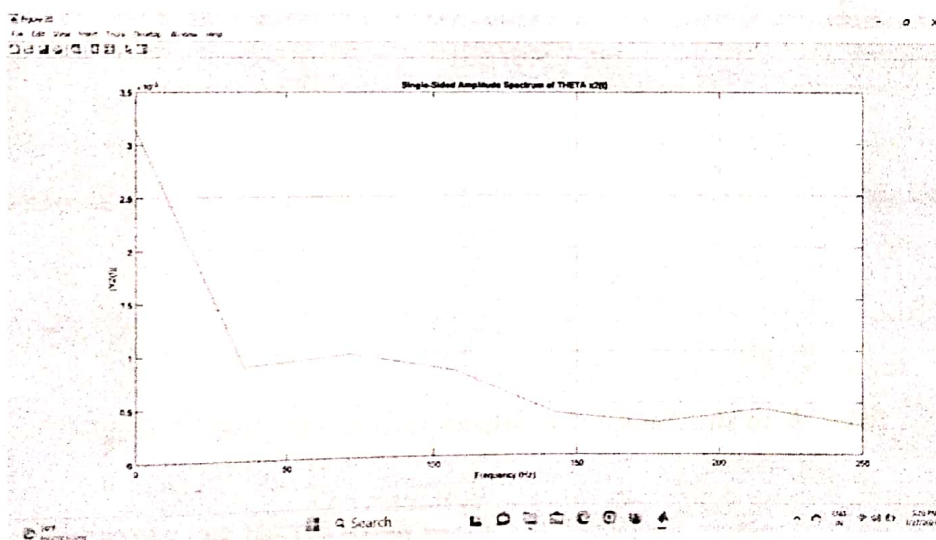


Fig: 5.12 Single – sided amplitude spectrum of THETA

5.13. WAVEFORM FOR ALPHA BAND

In fig 5.13 Alpha waves, or the alpha rhythm, are neural oscillations in the frequency

range of 8-12 Hz^[1] likely originating from the synchronous and coherent (in phase or constructive) electrical activity of thalamic pacemaker cells in humans. Historically, they are also called "Berger's waves" after Hans Berger, who first described them when he invented the EEG in 1924.^[2]

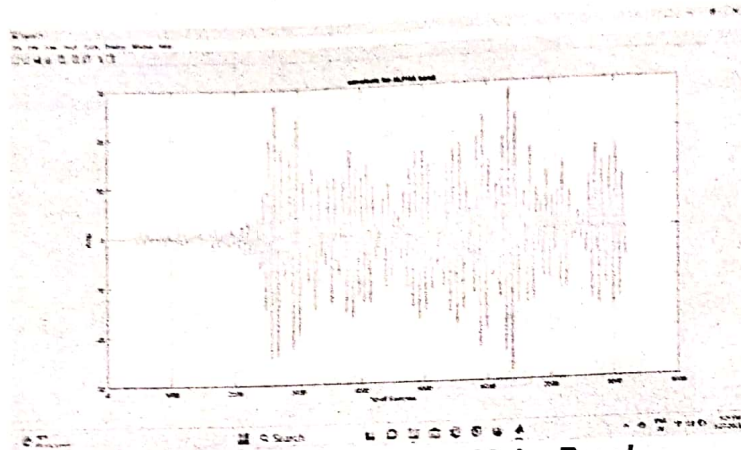


Fig: 5.13 Waveform for Alpha Band

5.14. SINGLE – SIDED AMPLITUDE SPECTRUM OF ALPHA

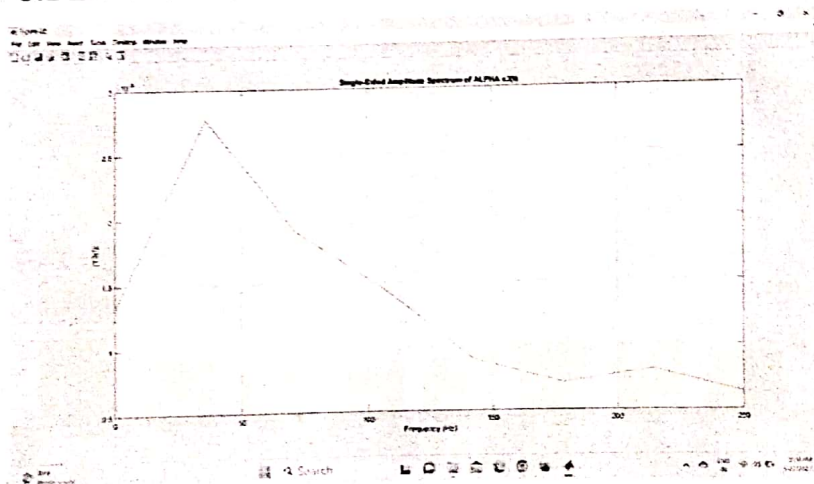


Fig: 5.14 Single – sided amplitude spectrum of ALPHA

5.15. WAVEFORM FOR BETA BAND

In fig 5.15 Beta waves, or beta rhythm, are a neural oscillation (brainwave) in the brain with a frequency range of between 12.5 and 30 Hz (12.5 to 30 cycles per second). Beta waves can be split into three sections: Low Beta Waves (12.5–16 Hz,

"Beta 1"); Beta Waves (16.5–20 Hz, "Beta 2"); and High Beta Waves (20.5–28 Hz, "Beta 3").^[1] Beta states are the states associated with normal waking consciousness.

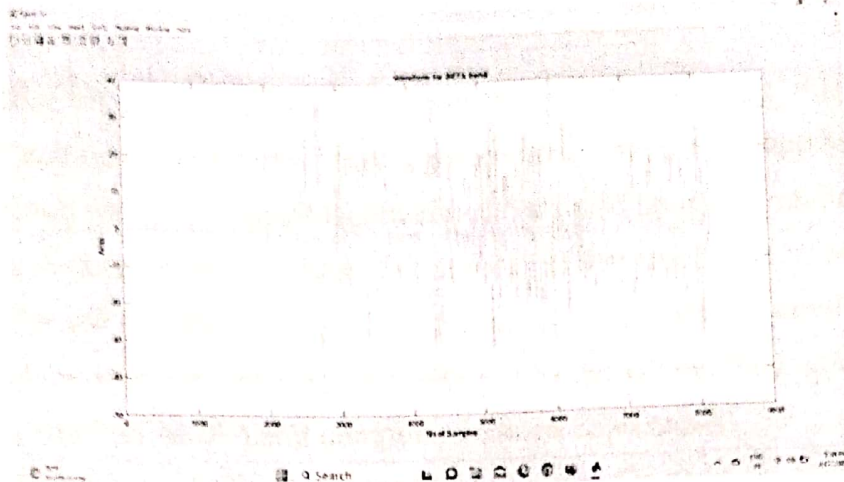


Fig: 5.15 Waveform for Beta band

5.16. FEATURE EXTRACTION

In fig 5.16 Contrast 0.8;corre 0.7;RMS 0.6;energy 0.7;entropy 0.8;homogeneity 0.9;mean 0.9;SD 0.8

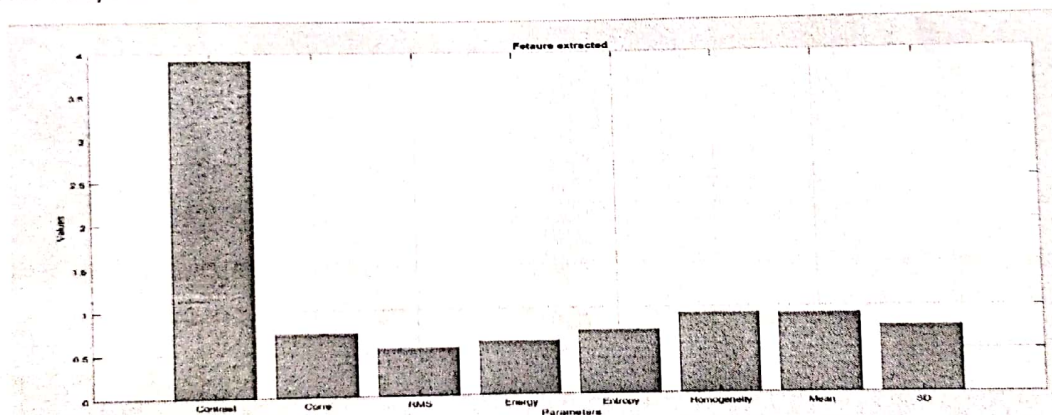


Fig: 5.16 Feature Extraction

5.17. TRAINING PROCESS

5.17.1 MU

The μ -law algorithm (sometimes written mu-law, often approximated as u-law) is a compressing algorithm, primarily used in 8-bit PCM digital telecommunication systems

in North America and Japan. It is one of two versions of the G. 711 standard from ITU-T, the other version being the similar A-law.

5.17.2 Gradient

Gradient descent is an optimization algorithm which is commonly-used to train machine learning models and neural networks. Training data helps these models learn over time, and the cost function within gradient descent specifically acts as a barometer, gauging its accuracy with each iteration of parameter updates. Until the function is close to or equal to zero, the model will continue to adjust its parameters to yield the smallest possible error. Once machine learning models are optimized for accuracy, they can be powerful tools for artificial intelligence (AI) and computer science applications.

In fig 5.1 MU gradient values are increasing gradually

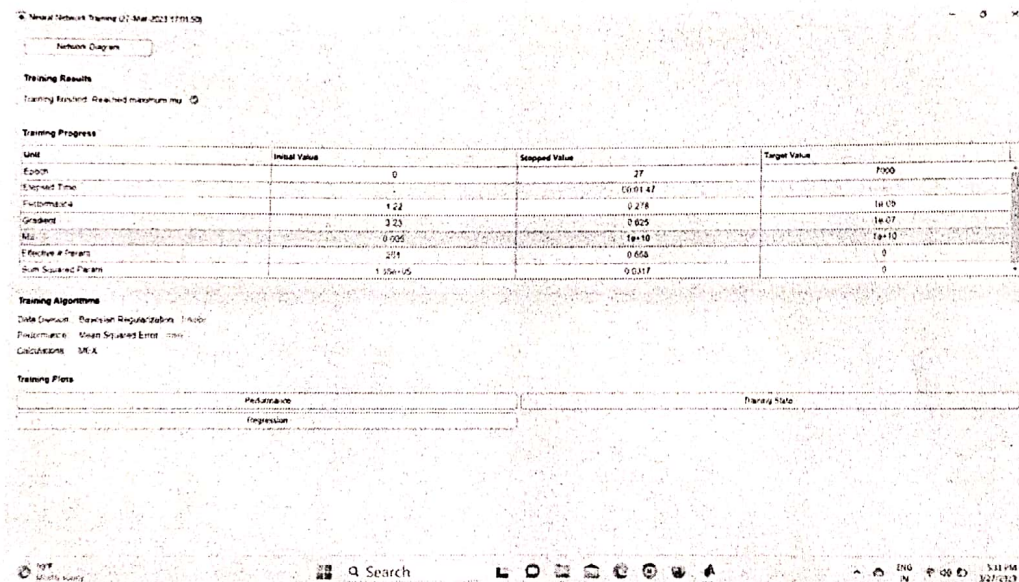


Fig: 5.17 Training Process

5.18. OUTPUT IMAGE

In fig 5.18 Neural networks are a series of algorithms that mimic the operations of an animal brain to recognize relationships between vast amounts of data. As such, they tend to resemble the connections of neurons and synapses found in the brain

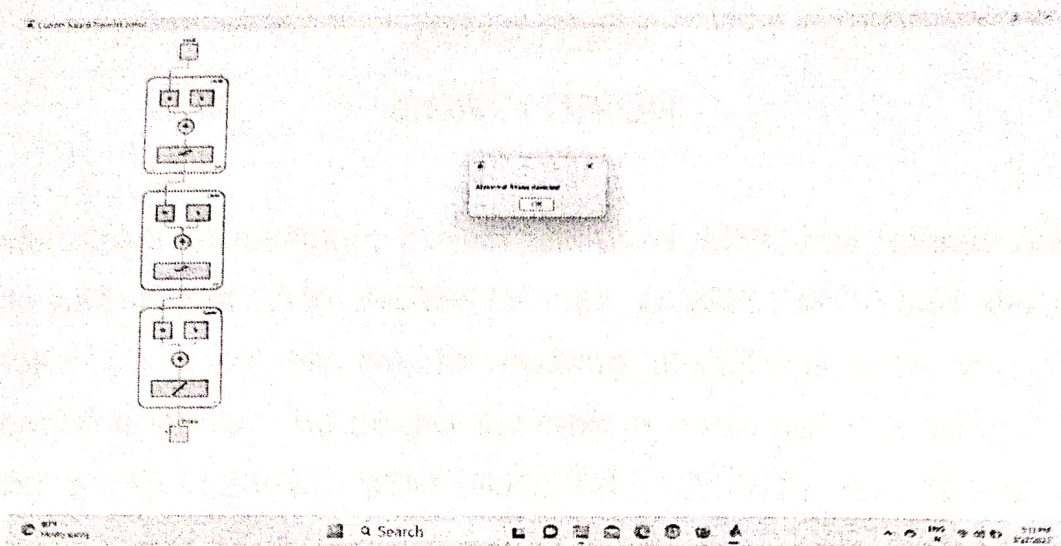


Fig: 5.18 Output image

CHAPTER 6.

CONCLUSION

In mental stress assessment project we used EEG data signals and algorithm LSSVM ,LSTM ,HJORTH ,ACTIVITY and COMPLEXITY and develop a less computational cost and less time for studying the EEG data and identifying normal or abnormal in stress .The project involves in noise removal using FFT ,feature extraction using LSSVM ,LSTM ,HJORTH ,ACTIVITY and COMPLEXITY and classification using band analysis ,power spectrum analysis . Used to extract the EEG signals' delta, theta, alpha, and beta sub frequencies. The result will be interpreted in the context of the potential to address. Experimental results show that lifting-based wavelets are both highly suitable and expedient for wavelet analysis of spike and wave EEG signals. In comparison to CWT, it requires less processing power. Using artificial neural networks, the signal is categorised based on feature values.

REFERENCE

1. Aright, J.A.; Burg, M.; Cohen, I.S.; Kao, A.H.; Pfau, S.; Caulin-Glaser, T.; Zaret, B.L.; Soufer, R. Myocardial blood-flow response during mental stress in patients with coronary artery disease. *issue* 2000, volume 356, page 20-25
2. Al-Shargie, F.; Tang, T.B.; Badruddin, N.; Kiguchi, M. Towards multilevel mental stress assessment using SVM with ECOC: An EEG approach. *Med Biol. Eng. Issue* 2018, volume 56, page 125–136
3. Garg, A.; Chren, M.-M.; Sands, L.P.; Matsui, M.S.; Marenus, K.D.; Feingold, K.R.; Elias, P.M. Psychological stress perturbs epidermal permeability barrier homeostasis: Implications for the pathogenesis of stress-associated skin disorders. *Issue* 2001, volume 137, page 53–59.
4. Giannakakis, G.; Grigoriadis, D.; Giannakaki, K.; Simantiraki, O.; Roniotis, A.; Tsiknakis, M. Review on psychological stress detection using biosignals. *IEEE. Affect. Issue* 2019, page 1–16
5. Hanrahan, K.; McCarthy, A.M.; Kleiber, C.; Lutgendorf, S.; Tsalikian, E. Strategies for salivary cortisol collection and analysis in research with children. *Appl. Issue* 2006, 19, volume 19, page 95–101
6. . Movahed, R.A.; Jahromi, G.P.; Shahyad, S.; Meftahi, G.H. A Major Depressive Disorder Classification Framework based on EEG Signals using Statistical, Spectral, Wavelet, Functional Connectivity, and Nonlinear Analysis. *J. Neurosci. Methods .issue* 2021, volume 358, page 109–209.
7. Mumtaz, W.; Rasheed, S.; Irfan, A. Review of challenges associated with the EEG artifact removal methods. *Biomed. Signal Process. Control. issue* 2021, volume 68 ,page 1–13.
8. O'Connor, D.B.; Thayer, J.F.; Vedhara, K. Stress and health: A review of psychobiological processes. *Annu. Rev. Psychol. Issue* 2021, volume 72, page 663–688

9. Thatcher, R.; Krause, P.; Hrybyk, M. Cortico-cortical associations and EEG coherence: A two-compartmental model. *Electroencephalogr. Clin. Neurophysiol.* Issue 1986, volume 64, page 123–143
10. Weinstein, M.; Seeman, T.E.; Sloan, R.P. The interactive effect of change in perceived stress and trait anxiety on vagal recovery from cognitive challenge. *Int. J. Psychophysiol.* 2011, volume 82, page 225–232
11. Xia, L.; Malik, A.S.; Subhani, A.R. A physiological signal-based method for early mental-stress detection. *Biomed. Signal Process Control.* Issue 2018, volume 46, page 18–32
12. Zanetti, M.; Mizumoto, T.; Faes, L.; Fornaser, A.; De Cecco, M.; Maule, L.; Valente, M.; Nollo, G. Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices. *J. Ambient Intell. Humaniz.* Issue 2019, volume 12, page 4409–4418

Appendix

```
clc
clear all;
close all;
[filename pathname]=uigetfile('*.txt','Select EEG ref Signal');
file=strcat(pathname,filename);
input_signals=load(file);

ts_seq=2;

cutoff_daq=500;

[n,m]=size(input_signals);

t=(1:n)*ts_seq;

h=figure

plot(t,input_signals,'p');
title('EEG Data')
xlabel('No.of Samples');
ylabel('Amp');
axis on;
grid on
h1=figure
plot(t,input_signals(:,1), 'b-')
daqq=input_signals(:,1);
[c,l]=wavedec(daqq,4,'db4');
ca1=appcoef(c,l,'db4',1);
ca2=appcoef(c,l,'db4',2);
ca3=appcoef(c,l,'db4',3);
ca4=appcoef(c,l,'db4',4);
figure;
plot(c),title('Decomposed'),grid on
figure;
% subplot(2,2,1)
plot(ca1);
title('1st level reconstructed'),grid on
% subplot(2,2,2)
figure;
plot(ca2);
title('2nd level reconstructed'),grid on
% subplot(2,2,3)
figure;
plot(ca3);
```

```

title('3rd level reconstructed'),grid on
% subplot(2,2,4)
figure;
plot(ca4);
title('4th level reconstructed'),grid on

```

```

load load_data.mat
figure
plot(XTrain{1})
xlabel("Time Step")
title("Training Observation 1")
numFeatures = size(XTrain{1},1);
legend("Feature " + string(1:numFeatures),Location="northeastoutside")
numObservations = numel(XTrain);
for i=1:numObservations
    sequence = XTrain{i};
    sequenceLengths(i) = size(sequence,2);
end
[sequenceLengths,idx] = sort(sequenceLengths);
XTrain = XTrain(idx);
YTrain = YTrain(idx);
figure
bar(sequenceLengths)
ylim([0 30])
xlabel("Sequence")
ylabel("Length")
title("Sorted Data")
miniBatchSize = 27;
inputSize = 12;
numHiddenUnits = 100;
numClasses = 9;

layers = [ ...
    sequenceInputLayer(inputSize)
    bilstmLayer(numHiddenUnits,OutputMode="last")
    fullyConnectedLayer(numClasses)
    softmaxLayer
    classificationLayer]
options = trainingOptions("adam", ...
    ExecutionEnvironment="cpu", ...
    GradientThreshold=1, ...
    MaxEpochs=50, ...
    MiniBatchSize=miniBatchSize, ...
    SequenceLength="longest", ...
    Shuffle="never", ...

```



```

Verbose=0, ...
Plots="training-progress");
net = trainNetwork(XTrain,YTrain,layers,options);

Accuracy =[ 87 95];

lyer = categorical({'LSSVM' 'WT'})
figure,bar(lyer,Accuracy)
ylabel('Accuracy')
Accuracy =[ 80 95];

lyer = categorical({'WTC' 'DS'})
figure,bar(lyer,Accuracy)
ylabel('Accuracy')
Accuracy =[ 81 97];

lyer = categorical({'NN' 'LSTM'})
figure,bar(lyer,Accuracy)
ylabel('Accuracy')
Accuracy =[ 83 95];

lyer = categorical({'LSSVM' 'LSTM'})
figure,bar(lyer,Accuracy)
ylabel('Accuracy')

sensitivity =[75 95];
lyer = categorical({'FIR' 'LSTM' })
figure,bar(lyer,sensitivity)
ylabel('sensitivity')

y=fft(input_signals);
power_spectrum=abs(y).^2;
frequency=(1:n)*cutoff_daq/n;
h2=figure
plot(frequency,20*log(power_spectrum),'b')
grid on;axis on;
title('Power spectrum using fft')

[S1,F,T] = spectrogram(input_signals(:,1),chebwin(128,100),0,cutoff_daq);

S1=abs(S1);
h4=figure
mesh(T,F,S1);
xlabel('Time (sec)','FontSize',14);

```

```

ylabel('Frequency (Hz)','FontSize',14);
zlabel('S1','FontSize',14);
grid on;axis on;
cutoff_daq = 500;
pass_band = 0;
ss_band = 4;
Dpass = 0.057501127785;

Dstop = 0.0001;
glcms = graycomatrix(daqq);
group_daq_seq = 20;
[n, fo, ao, w] = firpmord([pass_band, ss_band]/(cutoff_daq/2), [1 0], [Dpass, Dstop]);

b1 = firpm(n, fo, ao, w, {group_daq_seq});

Hd1 = dfilt.dffir(b1);
x1=filter(Hd1,input_signals);
h9=figure
plot(t,x1,'k')
title('waveform for DELTA band')
xlabel('No.of Samples');
ylabel('Amp');
grid on;axis on;
L=10;
cutoff_daq=500;
N_point_fft = 2^nextpow2(L);
y1 = fft(x1,N_point_fft)/L;
f = cutoff_daq/2*linspace(0,1,N_point_fft/2);
h10=figure
plot(f,2*abs(y1(1:N_point_fft/2)))
title('Single-Sided Amplitude Spectrum of DELTA x1(t)')
xlabel('Frequency (Hz)')
ylabel('|Y1(f)|')
grid on;axis on;
cutoff_daq = 500;
Fstop1 = 3.5;

Fpass1 = 4;

Fpass2 = 7;

Fstop2 = 7.5;

Dstop1 = 0.0001;

Dpass = 0.057501127785;

```



```

Dstop2 = 0.0001;

group_daq_seq = 20;
[n, fo, ao, w] = firpmord([Fstop1 Fpass1 Fpass2 Fstop2]/(cutoff_daq/2), [0 1 0], [Dstop1
Dpass Dstop2]);

b2 = firpm(n, fo, ao, w, {group_daq_seq});
Hd2 = dfilt.dffir(b2);
x2=filter(Hd2,input_signals);
h11=figure
plot(t,x2,'r')
title('waveform for THETA band')
xlabel('No.of Samples');
ylabel('Amp');
grid on;axis on;
L=10;
cutoff_daq=500;
N_point_fft = 2^nextpow2(L);
y2 = fft(x2,N_point_fft)/L;
f = cutoff_daq/2*linspace(0,1,N_point_fft/2);

h12=figure
plot(f,2*abs(y2(1:N_point_fft/2)))
title('Single-Sided Amplitude Spectrum of THETA x2(t)')
xlabel('Frequency (Hz)')
ylabel('|Y2(f)|')
grid on;axis on;

cutoff_daq = 500;

Fstop1 = 7.5;

Fpass1 = 8; Fpass2 = 12;
Fstop2 = 12.5;
Dstop1 = 0.0001;
Dpass = 0.057501127785;
Dstop2 = 0.0001;
group_daq_seq = 20;

[n, fo, ao, w] = firpmord([Fstop1 Fpass1 Fpass2 Fstop2]/(cutoff_daq/2), [0 1 0], [Dstop1
Dpass Dstop2]);

b3 = firpm(n, fo, ao, w, {group_daq_seq});
Hd3 = dfilt.dffir(b3);
x3=filter(Hd3,input_signals);

```

```

h13=figure
plot(t,x3,'g')
title('waveform for ALPHA band')
xlabel('No.of Samples');
ylabel('Amp');
grid on;axis on;
L=10;
cutoff_daq=500;
N_point_fft = 2^nextpow2(L);
y3 = fft(x3,N_point_fft)/L;
f = cutoff_daq/2* linspace(0,1,N_point_fft/2);

```

```

h14=figure
plot(f,2*abs(y3(1:N_point_fft/2)))
title('Single-Sided Amplitude Spectrum of ALPHA x3(t)')
xlabel('Frequency (Hz)')
ylabel('|Y3(f)|')
grid on;axis on;
cutoff_daq = 500;

```

```
Fstop1 = 11.5;
```

```
Fpass1 = 12;
```

```
Fpass2 = 30;
```

```
Fstop2 = 30.5;
```

```
Dstop1 = 0.0001;
```

```
Dpass = 0.057501127785;
```

```
Dstop2 = 0.0001;
```

```

group_daq_seq = 20;
[n, fo, ao, w] = firpmord([Fstop1 Fpass1 Fpass2 Fstop2]/(cutoff_daq/2), [0 1 0], [Dstop1
Dpass Dstop2]);

```

```
b4 = firpm(n, fo, ao, w, {group_daq_seq});
```

```
Hd4 = dfilt.dffir(b4);
```

```
x4=filter(Hd4,input_signals);
```

```
h15=figure
```

```
plot(t,x4,'y')
```

```
title('waveform for BETA band')
```

```
xlabel('No.of Samples');
```

```
ylabel('Amp');
```

```
grid on;axis on;
```



```

L=10;
cutoff_daq=500;
N_point_fft = 2^nextpow2(L);
y4 = fft(x4,N_point_fft)/L;
f = cutoff_daq/2*linspace(0,1,N_point_fft/2);

zzz=1;
GLCM_mat = graycomatrix(input_signals,'Offset',[2 0;0 2]);

GLCMstruct = Computefea(GLCM_mat,0);

v1=GLCMstruct.contr(1);

v2=GLCMstruct.corr(1);

v5=GLCMstruct.dissi(1);

v6=GLCMstruct.energ(1);

v7=GLCMstruct.entrop(1);

v8=GLCMstruct.homom1(1);

v9=GLCMstruct.homop(1);

v10=GLCMstruct.maxpr(1);

v11=GLCMstruct.sosvh(1);

v12=GLCMstruct.autoc(1);

magg1 = [v1,v2,v5,v6,v7,v8,v9,v10];
somenames={'Contrast','Corre','RMS','Energy','Entropy','Homogeneity','Mean','SD'};
figure;
bar(magg1);
set(gca,'xticklabel',somenames);
xlabel('Parameters');
ylabel('Values');
title('Fetaure extracted');
grid on;axis on;
magg1=y1+y2+y3+y4;
maggni1=sum(magg1);
maggnil = Dep_neurall(maggni1);
vall=real(maggni1)*10;
if vall<0

```

```
    msgbox('Normall signal');  
else  
    msgbox('Abnormal Stress detected');  
end
```