A PROJECT REPORT ON

ANALYSIS OF EEG SIGNALS USING WELCH'S POWER SPECTRAL DENSITY

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In

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CERTIFICATE

This is to certify that the project report entitled "ANALYSIS OF EEG SIGNALS USING WELCH'S POWER SPECTRAL DENSITY" is a bonafide record submitted by SANJANA MAURYA, NAGALAGAYA NITHIN, MD ABBUBAKAR, RAHUL KOPPULA, Department of Electronics and communication Engineering, Anurag University and is submitted in partial fulfillment for the award of Degree of Bachelor of Technology in "Electronics and Communication Engineering" for the year 2023-2024. The work reported herein does not form part of any other thesis on which a degree has been awarded earlier.

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DECLARATION

We hereby declare that the project report entitled, **"ANALYSIS OF EEG SIGNALS USING WELCH'S POWER SPECTRAL DENSITY"**, is the work done by us and submitted for the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering, under the guidance of **Dr. Poli Lokeshwara Reddy, M.Tech., Ph.D,** Assistant Professor, Department of Electronics and Communication Engineering, Anurag University.

We further declare that this project report has not been previously submitted before either in part or full for the award of any degree or any diploma by any organization or any universities.

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ABSTRACT

Electroencephalograph (EEG) is an electrical field that generated by our brain incessantly. The EEG signal released by the brain is different when a people is performing different activities in their daily life. And such EEG signals consist complicated information that can be interpreted.

The aim of this project is to conduct a comprehensive analysis of Electroencephalogram (EEG) signals by employing the Welch method for Power Spectral Density (PSD) estimation, alongside bandpass filtering techniques. This study utilizes Support Vector Machine (SVM) classification to discern distinctive patterns within the EEG data. The performance of the classification model is evaluated using crucial metrics such as accuracy, precision, recall, and F1-score. This integrated approach of signal processing methodologies, spectral analysis, and machine learning classification aims to provide a robust framework for interpreting EEG signals. The ultimate goal is to offer valuable insights into cognitive patterns or abnormalities present within EEG data, thereby contributing to advancements in neuroscience and clinical diagnostics.

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CHAPTER-I
INTRODUCTION

1.1 What is Signal?

A signal is a fluctuating quantity that conveys information about a phenomenon. It can be analog or digital, representing continuous or discrete data. Signals are fundamental in various fields like telecommunications, electronics, and neuroscience. They can be categorized as deterministic or random, depending on their predictability. In communication systems, signals transmit data over a medium, carrying information through modulation and encoding. In electronics, signals can be voltage variations in circuits, conveying information through changes in amplitude, frequency, or phase. Signal processing involves manipulating signals to extract relevant information or enhance specific characteristics. In the context of biology, neural signals transmit information in the form of electrical impulses between neurons. Signals are characterized by parameters such as amplitude, frequency, and duration. They can be periodic, representing repeating patterns, or aperiodic, with no fixed repetition. Noise in signals refers to unwanted interference that can degrade the quality of information. Signal-to-noise ratio measures the quality of a signal relative to background noise. Filters are used to modify signals by attenuating or amplifying specific frequencies. Fourier analysis decomposes complex signals into simpler sinusoidal components. In control systems, signals are crucial for feedback mechanisms, enabling adjustments based on system responses. Signals play a pivotal role in modern technologies such as wireless communication, audio processing, and image recognition. Understanding signal characteristics is essential for designing efficient and reliable systems across diverse applications.

1.2 Types of Signals

Electric signals (in electronics)-different voltages and currents in the electric network called electric "circuit "or "device, which can be further described as the process of changes a certain physical quantity or state of a physical object over certain period of time. They are used for the purpose of visualization, registration and transmission of messages (information). Signal can be a carrier of different information e.g. electric, magnetic and acoustic signals and contains the information parameter e.g. amplitude, frequency or pulse width. In electronics, the most important signals are the changes in electric charge, current, voltage and electromagnetic field. They are used to analyse the behaviour of electronic circuits or to measure the changing electrical values.

1.2.1 Analog

Analog signal processing is for signals that have not been digitized, as in most 20th-century radio, telephone, and television systems. This involves linear electronic circuits as well as nonlinear ones. The former are, for instance, passive filters, active filters, additive mixers, integrators, and delay lines. Nonlinear circuits include compandors, multipliers (frequency mixers, voltage-controlled amplifiers), voltage-controlled filters, voltage-controlled oscillators, and phase-lockedloops.

1.2.2 Continuous time

Continuous-time signal processing is for signals that vary with the change of continuous domain (without considering some individual interrupted points). The methods of signal processing include time domain, frequency domain, and complex frequency domain. This technology mainly discusses the modelling of a linear time- invariant continuous system, integral of the system's zero-state response, setting up system function and the continuous time filtering of deterministic signals

1.2.3 Discrete time

Discrete-time signal processing is for sampled signals, defined only at discrete points in time, and as such are quantized in time, but not in magnitude. Analog discrete-time signal processing is a technology based on electronic devices such as sample andhold circuits, analog time-division multiplexers, analog delay lines and analog feedback shift registers. This technology was a predecessor of digital signal processing(see below), and is still used in advanced processing of gigahertz signals. The conceptof discrete-time signal processing also refers to a theoretical discipline that establishesa mathematical basis for digital signal processing, without taking quantization error into consideration.

1.2.4. Digital

Digital signal processing is the processing of digitized discrete-time sampled signals. Processing is done by general-purpose computers or by digital circuits such as ASICs, field-programmable gate arrays or specialized digital signal processors (DSP chips).Typical arithmetical operations include fixed- point and floating-point real-valued and complex-valued, multiplication and addition. Other typical operations supported by the hardware are circular buffers and lookup tables. Examples of algorithms are the fast Fourier transform (FFT), finite impulse response (FIR) filter, Infinite impulse response (IIR) filter, and adaptive filters such as the Wiener and Kalman filters.

1.2.5 Nonlinear

Nonlinear signal processing involves the analysis and processing of signals produced from nonlinear systems and can be in the time, frequency,or spatiotemporal domains. Nonlinear systems can produce highly complex behaviours including bifurcations, chaos, harmonics, and subharmonics which cannot be producedor analysed using linear methods. Polynomial signal processing is a type of non-linear signal processing, where polynomial systems may be interpreted as conceptually straightforward extensions of linear systems to the non-linear case.

1.2.6 Statistical

Statistical signal processing is an approach which treats signals as stochastic processes, utilizing their statistical properties to perform signal processing tasks.[10] Statistical techniques are widely used in signal processing applications. For example, one can model the probability distribution of noise incurred when photographing an image, and construct techniques based on this model to reduce the noise in the resulting image.

1.3 Signal Processing

Signal processing is a field that involves manipulating, analysing, and interpreting signals to extract useful information. It encompasses both analog and digital signals across various applications. In analog signal processing, continuous signals are modified, while digital signal processing involves discrete data in a digital format. Common operations include filtering, modulation, and transformation. Fourier Transform is a fundamental tool in signal processing, decomposing signals into frequency components. Signal processing is vital in telecommunications for encoding, decoding, and transmission. In audio processing, it is used for tasks like filtering out noise or enhancing specific frequencies. Image processing relies on signal processing techniques for tasks like image enhancement and recognition. Signal processing plays a crucial role in biomedical applications, such as analysing electrocardiograms (ECGs) or electroencephalograms (EEGs). Adaptive signal processing allows systems to adjust to changing conditions. Applications range from speech recognition to seismic signal analysis. Signal processing techniques are integral in modern technologies, including wireless communication, radar systems, and medical imaging. The field continues to evolve with advancements in algorithms, machine learning, and computational power. Understanding signal processing principles is essential for engineers and researchers across diverse domains.

1.4 Applications of Signal Processing

Signal processing techniques are used in a wide range of applications, including:

1.4.1 Telecommunications: Signal processing techniques are used in telecommunications to transmit, receive, and process signals over communication channels. This includes tasks such as modulation, demodulation, error correction, and signal amplification.

1.4.2 Audio and video processing: Signal processing techniques are used to enhance the quality and clarity of audio and video signals, as well as to extract features such as speech, music, and moving objects.

1.4.3 Image processing: Signal processing techniques are used to improve the quality and resolution of images, as well as to extract features such as edges, shapes, and textures.

1.4.4 Speech recognition: Signal processing techniques are used to analyse and interpret speech signals, enabling the development of systems that can transcribe speech or recognize spoken commands.

1.4.5 Control systems: Signal processing techniques are used in control systems to stabilize and optimize the performance of systems by processing feedback signals from sensors and actuators.

1.4.6 Biomedical engineering: Signal processing techniques are used in biomedical engineering to analyse and interpret signals from medical devices such as electrocardiograms (ECGs) and magnetic resonance imaging (MRI) scanners.

1.4.7 Financial engineering: Signal processing techniques are used in financial engineering to analyse and interpret financial data and to develop predictive models for financial markets.

1.5 Electroencephalography

An EEG is a test that detects abnormalities in your brain waves, or in the electrical activity of your brain. During the procedure, electrodes consisting of small metal discs with thin wires are pasted onto your scalp. The electrodes detect tiny electrical charges that result from the activity of your brain cells. The charges are amplified and appear as a graph on a computer screen, or as a recording that may be printed out on paper. Your healthcare provider then interprets the reading.

1.5.1 Electrode positions

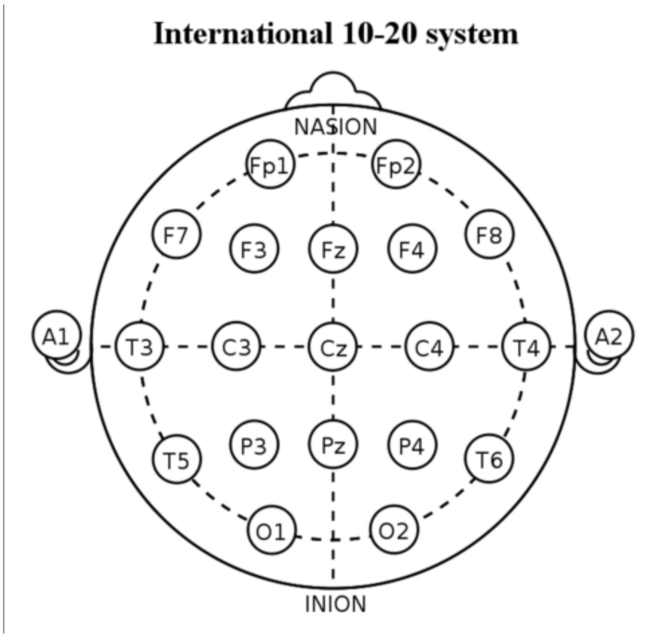

Fig 1.5.1(a) Placement of the 19 scalp electrodes

10-20 System: This system divides the scalp into regions where electrodes are placed at specific locations. Electrodes are named based on the region and the specific position.

1.6 Power Spectral Density Analysis

The power spectral density (PSD) or power spectrum provides a way of representing the distribution of signal frequency components which is easier to interpret visually than the complex DFT. As the term suggests, it represents the proportion of the total signal power contributed by each frequency component of a voltage signal (P = V2IR). It is computed from the DFT as the mean squared amplitude of each frequency component, averaged over the n samples in the digitised record. However, since only n/2 frequency components are unique, the two halves of the DFT are combined (doubling the power of each component) and plotted as the lower k = 1 … n/2+1 components,

$$\mathrm{PSD(k)} = \frac{2di}{n^2}((Y\,real_k)^2 + (Y\,imag_k)^2)$$

Each element PSD(k) is a measure of the signal power contributed by frequencies within a band of width df centred on the frequency $k\ df$. One immediate advantage of the PSD is that it is a real, not a complex, quantity, expressed in terms of squared signal units per frequency units (e.g. $V^2\ Hz^{-1}$, $mmHg^2\ Hz^{-1}$), and can be plotted as a single graph. One consequence of this is that some information contained in the full DFT (the phase information) has been discarded from the PSD. Another, more general, way of looking at the PSD is as the frequency distribution of the signal variance. In fact the variance of the original digitised record can be computed from the integral of the PSD,

$$\sigma^2 = \sum_{k=0}^{n/2} PSD(k)$$

1.7 Problem Statement

Power Spectral Density (PSD) analysis of Electroencephalography (EEG) signals presents a pivotal approach in understanding the relationship between brain activity and frequency distributions associated with cognitive and emotional states. The complexity arises from interpreting the diverse frequency bands (delta, theta, alpha, beta, gamma) extracted from PSD and their correlation with cognitive processing and emotional responses. Overcoming challenges related to noise, artifacts, and individual variability, the research seeks to advance the comprehension of PSD patterns' alignment with cognitive and emotional states, fostering prospects for enhanced diagnostic tools and innovations in neuroscientific applications.

1.8 Objectives of proposed work

- To develop methodologies to extract relevant features from EEG signals that encapsulate distinctive emotional patterns.
- To determine the significant features contributing to emotion classification and interpret their relevance.
- To achieve high classification accuracy for different emotional states using suitable evaluation metrics such as accuracy, precision, recall, and F1-score.

1.9 Organization of Report

Chapter 1 presents the overview on signals and signal processing. It mainly focused on the Electroencephalography and the electrode positioning on brain. Power Spectra Density is also mentioned.

Chapter 2 examines the existing literature relevant to the addressed problem statement of analysis of EEG signals using Welch's power spectral density. This review aims to previous information to provide the foundation for the current project.

Chapter 3 presents the previously existing traditional methodologies for the analysis of EEG signals and mentioned their individual limitations in obtaining an effective solution.

Chapter 4 provides the proposed methodology of the project and explains the pre-processing, feature extraction and classifier used in detail.

Chapter 5 gives a description of the MATLAB software which is utilized to perform this simulation. It introduces the basic commands and the codes of MATLAB that are generally used.

Chapter 6 presents the simulation results by evaluating performance metrics and comparing with respect to different electrodes. The plots of the implemented codes are also displayed in this chapter.

Chapter 7 discusses the advantages and applications of the proposed methodology in various fields. It is proven effective by mentioning its unique features in the advantages.

Chapter 8 concludes on the implementation of the algorithms for the analysis of EEG signals using Welch's power spectral density and explains how this work can be developed in the future.

CHAPTER- II

LITERATURE REVIEW

Sofien Gannouni et al. [1] Recognizing emotions using biological brain signals requires accurate and efficient signal processing and feature extraction methods. Existing methods use several techniques to extract useful features from a fixed number of electroencephalography (EEG) channels. The primary objective of this study was to improve the performance of emotion recognition using brain signals by applying a novel and adaptive channel selection method that acknowledges that brain activity has a unique behaviour that differs from one person to another and one emotional state to another. Moreover, we propose identifying epochs, which are the instants at which excitation is maximum, during the emotion to improve the system's accuracy. We used the zero-time windowing method to extract instantaneous spectral information using the numerator group-delay function to accurately detect the epochs in each emotional state. Different classification scheme were defined using QDC and RNN and evaluated using the DEAP database. The experimental results showed that the proposed method is highly competitive compared with existing studies of multi-class emotion recognition. The average accuracy rate exceeded 89%. Compared with existing algorithms dealing with 9 emotions, the proposed method enhanced the accuracy rate by 8%. Moreover, experiment shows that the proposed system outperforms similar approaches discriminating between 3 and 4 emotions only. We also found that the proposed method works well, even when applying conventional classification algorithms.

Ahmad Chadda et al. [2] The electroencephalography (EEG) signal is a non-invasive and complex signal that has numerous applications in biomedical fields, including sleep and the brain-computer interface. Given its complexity, researchers have proposed several advanced preprocessing and feature extraction methods to analyse EEG signals. In this study, we analyse a comprehensive review of numerous articles related to EEG signal processing. We searched the major scientific and engineering databases and summarized the results of our findings. Our survey encompassed the entire process of EEG signal processing, from acquisition and pretreatment (denoising) to feature extraction, classification, and application. We present a detailed discussion and comparison of various methods and techniques used for EEG signal processing.

Additionally, we identify the current limitations of these techniques and analyse their future development trends. We conclude by offering some suggestions for future research in the field of EEG signal processing.

Tran Y et al. [3] Electroencephalography (EEG) signals are used widely in clinical and research settings. Electrical activity generated from large populations of neurons in the brain is measured using scalp-mounted EEG sensors. As a result, we can obtain information regarding brain activity in various cognitive and emotional states. Due to their ability to provide this type of information, EEG signals are used in applications such as monitoring levels of alertness and mental engagement, investigating chronic conditions, and as signals for biofeedback or assistive devices. Innovations in this field have led to advancements in signal processing methods and the development of novel applications ranging from brain–computer interfaces (BCIs) to neuromarketing. EEG signals can be processed in time, frequency, or spatial domains, providing multi-dimensional means to interpret brain activities. Aside from providing invaluable information, EEG signals also have the advantage of capturing complex neural patterns at a high rate of speed. As a reliable, portable, and non-invasive way to measure the electrical activity in the brain, EEG is a central methodology for affordable and practical research and a promising clinical healthcare tool. This Special Issue focuses on EEG signal processing for biomedical engineering applications with original research, communication, and review papers demonstrating broad methodologies and applications.

Liu Junxi et al. [4] Emotion classification based on brain–computer interface (BCI) systems is an appealing research topic. Recently, deep learning has been employed for the emotion classifications of BCI systems and compared to traditional classification methods improved results have been obtained. In this paper, a novel deep neural network is proposed for emotion classification using EEG systems, which combines the Convolutional Neural Network (CNN), Sparse Autoencoder (SAE), and Deep Neural Network (DNN) together. In the proposed network, the features extracted by the CNN are first sent to SAE for encoding and decoding. Then the data with reduced redundancy are used as the input features of a DNN for classification task. The public datasets of DEAP and SEED are used for testing. Experimental results show that the proposed network is more effective than conventional CNN methods on the emotion recognitions. For the DEAP dataset, the highest recognition accuracies of 89.49% and 92.86% are achieved for valence and arousal, respectively. For the SEED dataset, however, the best recognition accuracy reaches 96.77%. By combining the CNN, SAE, and DNN and training them separately, the proposed network is shown as an efficient method with a faster convergence than the conventional CNN.

Jinru Yang et al. [5] Emotion recognition can be achieved by speech recognition, the judgment of limb movements, analysis of Electrooculogram (EOG) or capturing of facial expressions. However, those types of emotion recognition methods cannot detect human emotion well, because humankind can use fake body movement and words to hide real emotions. In this paper, we proposed an EEG-based emotion classification method based on Bidirectional Long Short-Term Memory Network (BiLSTM). Electroencephalogram (EEG) signal can detect human emotion correctly because human represent their real emotions in their mind and cannot hide emotions there. Meanwhile, EEG is a time sequence signal which needs a model which can deal with this type of data. Therefore, we chose Long Short-term Memory Network to process the EEG signal. In particular, we used an improvement version of LSTM model BiLSTM to manage the signals. BiLSTM can processes input data from front to back and back to front. Meanwhile, BiLSTM can store important information and forget unnecessary information; therefore, this process increases the accuracy of the model. Our method classifies four discrete classifications (happy, sad, fear, and neutral) for emotion classification, which achieves competitive performance compared with other conventional emotion classification methods. The final experimental results show that we can achieve an accuracy of 84.21% for four emotional states classification by using our method.

Mohd Maroof Siddiqui et al. [6] Insomnia is a sleep disorder in which the subject encounters problems in sleeping. The aim of this study is to identify insomnia events from normal or effected person using time frequency analysis of PSD approach applied on EEG signals using channel ROC-LOC. In this research article, attributes and waveform of EEG signals of Human being are examined. The aim of this study is to draw the result in the form of signal spectral analysis of the changes in the domain of different stages of sleep. The analysis and calculation is performed in all stages of sleep of PSD of each EEG segment. Results indicate the possibility of recognizing insomnia events based on delta, theta, alpha and beta segments of EEG signals.

M. Alsolamy et al. [7] Emotions play an important role in our thinking and behaviour and hence contribute in shaping up of our personality. Many theoretical and experimental researches have been conducted to recognize the emotions from verbal or non-verbal behaviours. It is well known that the electroencephalogram (EEG) signals contain rich information about the activities of the brain and they can reliably enable us to estimate the emotions if they are properly interpreted. In this paper, we propose a model to discriminate the emotional state of a person by analysing his brain signals recorded during listening to the Quran and using a machine learning approach. It is assumed that listening to the Quran brings reverence, and hence two types of emotions emerge which are distinguished as happy and unhappy. In our analysis, we used the Power Spectral Density (PSD) of different bands as features and the Support Vector Machine (SVM) as a classifier. Experiments were conducted by 14 participants and they gave a classification accuracy rate 85.86%.

Siuly et al. [8] EEG is becoming increasingly important in the diagnosis and treatment of mental and brain neuro-degenerative diseases and abnormalities. The role of the EEG is to help physicians for establishing an accurate diagnosis. In neurology, a main diagnostic application of EEGs is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study. In this chapter, we provide a brief discussion of various uses and the significance of EEGs in brain disorder diagnosis and also in brain-computer interface (BCI) systems. In this chapter, we also discuss why EEG signal analysis and classification are required for medical and health practice and research. Then, we provide the key concepts of EEG signal classification and a brief description of computer-aided diagnostic (CAD) systems.

Harsh Dabas et al. [9] This paper proposes a 3D emotional model for classifying emotions of a user while watching a musical video. A standard dataset DEAP (Database for Emotion Analysis using Physiological Signals) Dataset is used for studying and analysing the human emotions using EEG signals. Participants are shown various videos across multiple trials and their corresponding EEG signals are recorded. The emotional states are classified on the basis of various parameters such as arousal, valence, dominance, and liking for a particular set of video. After relevant pre-processing and noise removal a 3D Emotional model is constructed. The 3D Emotional

Model comprising of 8 octants within a Valence-Arousal-Dominance space gives rises to 8 different emotional states namely relaxed, peaceful, bored, disgust, nervous, sad, surprised and excited. The resultant emotional state obtained provides useful insight into the thinking and behaviour of participants in certain scenarios. The EEG based emotional classification can aid the developers to provide relevant recommendations to the user on the basis of his emotional state. Machine learning algorithms like Naïve Bayes, Support Vector Machine (SVM) when applied to the proposed 3D Emotional model classifies the emotion aptly with an accuracy of 78.06% and 58.90% respectively.

Jiang Wang et al. [10] As a subjectively psychological and physiological response to external stimuli, emotion is ubiquitous in our daily life. With the continuous development of the artificial intelligence and brain science, emotion recognition rapidly becomes a multiple discipline research field through EEG signals. This paper investigates the relevantly scientific literature in the past five years and reviews the emotional feature extraction methods and the classification methods using EEG signals. Commonly used feature extraction analysis methods include time domain analysis, frequency domain analysis, and time-frequency domain analysis. The widely used classification methods include machine learning algorithms based on Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Naive Bayes (NB), etc., and their classification accuracy ranges from 57.50% to 95.70%. The classification accuracy of the deep learning algorithms based on Neural Network (NN), Long and Short-Term Memory (LSTM), and Deep Belief Network (DBN) ranges from 63.38% to 97.56%.

Arijit Nandi et al. [11] In face-to-face and online learning, emotions and emotional intelligence have an influence and play an essential role. Learners' emotions are crucial for e-learning system because they promote or restrain the learning. Many researchers have investigated the impacts of emotions in enhancing and maximizing e-learning outcomes. Several machine learning and deep learning approaches have also been proposed to achieve this goal. All such approaches are suitable for an offline mode, where the data for emotion classification are stored and can be accessed infinitely. However, these offline mode approaches are inappropriate for real-time emotion classification when the data are coming in a continuous stream and data can be seen to the model at once only. We also need real-time responses according to the emotional state. For this, we propose a real-time emotion classification system (RECS)-based Logistic Regression (LR) trained in an online fashion using the Stochastic Gradient Descent (SGD) algorithm. The proposed RECS is capable of classifying emotions in real-time by training the model in an online fashion using an EEG signal stream. To validate the performance of RECS, we have used the DEAP data set, which is the most widely used benchmark data set for emotion classification. The results show that the proposed approach can effectively classify emotions in real-time from the EEG data stream, which achieved a better accuracy and *F1-score* than other offline and online approaches. The developed real-time emotion classification system is analysed in an e-learning context scenario.

H.Ullah et al.[12] Among various physiological signal acquisition methods for the study of the human brain, EEG (Electroencephalography) is more effective. EEG provides a convenient, non-intrusive, and accurate way of capturing brain signals in multiple channels at fine temporal resolution. We propose an ensemble learning algorithm for automatically computing the most discriminative subset of EEG channels for internal emotion recognition. Our method describes an EEG channel using kernel-based representations computed from the training EEG recordings. For ensemble learning, we formulate a graph embedding linear discriminant objective function using the kernel representations. The objective function is efficiently solved via sparse non-negative principal component analysis and the final classifier is learned using the sparse projection coefficients. Our algorithm is useful in reducing the amount of data while improving computational efficiency and classification accuracy at the same time. The experiments on publicly available EEG dataset demonstrate the superiority of the proposed algorithm over the compared methods.

Md.Mustafizur et al. [13] Assessment of the cognitive functions and state of clinical subjects is an important aspect of e-health care delivery, and in the development of novel human-machine interfaces. A subject can display a range of emotions that significantly influence cognition, and emotion classification through the analysis of physiological signals is a key means of detecting emotion. Electroencephalography (EEG) signals have become a common focus of such development compared to other physiological signals because EEG employs simple and subject-acceptable methods for obtaining data that can be used for emotion analysis. We have therefore reviewed published studies that have used EEG signal data to identify possible interconnections between emotion and brain activity. We then describe theoretical conceptualization of basic emotions, and interpret the prevailing techniques that have been adopted for feature extraction, selection, and classification. Finally, we have compared the outcomes of these recent studies and discussed the likely future directions and main challenges for researchers developing EEG-based emotion analysis methods.

Acharya et al. [14] Assessment of the cognitive functions and state of clinical subjects is an important aspect of e-health care delivery, and in the development of novel human-machine interfaces. A subject can display a range of emotions that significantly influence cognition, and emotion classification through the analysis of physiological signals is a key means of detecting emotion. Electroencephalography (EEG) signals have become a common focus of such development compared to other physiological signals because EEG employs simple and subject-acceptable methods for obtaining data that can be used for emotion analysis. We have therefore reviewed published studies that have used EEG signal data to identify possible interconnections between emotion and brain activity. We then describe theoretical conceptualization of basic emotions, and interpret the prevailing techniques that have been adopted for feature extraction, selection, and classification. Finally, we have compared the outcomes of these recent studies and discussed the likely future directions and main challenges for researchers developing EEG-based emotion analysis methods.

Sakalle et al. [15] The COVID-19 has resulted in one of the worlds most significant worldwide lock-downs, affecting human mental health. Therefore, emotion recognition is becoming one of the essential research areas among various world researchers. Treatment that is efficacious and diagnosed early for negative emotions is the only way to save people from mental health problems. Genetic programming, a very important research area of artificial intelligence, proves its potential in almost every field. Therefore, in this study, a genetic program-based feature selection (FSGP) technique is proposed. A fourteen-channel EEG device gives 70 features for the input brain signal; with the help of GP, all the irrelevant and redundant features are separated, and 32 relevant features are selected. The proposed model achieves a classification accuracy of 85% that outmatches other prior works.

TABLE:

S.No	Journal Name/ Vol./Page No./Year	Title	Method	Advantages	Limitations
1.	Scientific Reports,**11**, Article number: 7071 (2021) 29 March 2021	Emotion detection using EEG signals and a zero-time windowing-based epoch estimation and relevant electrode identification	Emotion recognition using brain signals by applying a novel and adaptive channel selection method	adaptability, accuracy, and competitiveness	complexity, generalizability, Interpretability & sensitivity to emotion set sizes
2.	Sensors **2023**,23(14), 6434 ,16 July 2023.	EEG Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques	Higher-order Spectral Analysis And deep learning	Provide real-time feedback, aiding individuals in self-regulating their brain activity for therapeutic purposes.	EEG is most sensitive to neural activity within a specific frequency range, limiting its ability to capture certain types of brain activity, such as fast oscillations or very slow processes.
3.	Sensors (Basel), vol 22(24),9754, 2022 Dec 13.	Signal Processing for Biomedical Applications.	Non-invasive Measurement, Temporal Precision.	EEG data can be analysed in time, frequency, and spatial domains, providing rich multi-dimensional information for studying brain activities.	The frequency range of EEG signals is limited, potentially restricting the information available for analysis.

4.	Frontiers in Systems Neuroscience Volume 14,2020.	EEG-Based Emotion Classification Using a Deep Neural Network and Sparse Autoencoder.	Deep neural network combines with CNN and SAE.	The proposed network is more effective than conventional CNN methods on the emotion recognitions	Integration of multiple networks might increase computational complexity and resource demands.
5.	Procedia Computer Science, volume 174,2020.	EEG-based emotion classification based on Bidirectional Long Short-Term Memory Network	EEG's temporal nature suits models like BiLSTM.	Classification using BiLSTM offers authentic emotion detection and competitive performance	It faces challenges related to data quality, emotional granularity, generalization, interpretability, and computational demands, impacting its broader applicability and ease of interpretation.
6.	Sleep Science, Volume 9, Issue 3, 2016, Pages 186-191.	Diagnosis of insomnia sleep disorder using short time frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC	PSD-based time-frequency analysis on EEG signals	Potentially identifying insomnia events through spectral analysis of specific EEG frequency segments.	Generalizability, clinical correlation, and methodology might impact the accuracy and broader applicability of the findings in clinical practice.

7.	7th International Conference on Computer Science and Information Technology (CSIT),2016.	Emotion estimation from EEG signals during listening to Quran using PSD features	Employs Support Vector Machine (SVM) as a classifier, leveraging its robustness in discerning emotional patterns from PSD features.	Explores the distinct emotional responses (happy and unhappy) triggered by listening to the Quran, providing insights into emotional states linked to specific stimuli.	Conducted experiments with 14 participants, which might limit the generalizability of results to broader populations.
8.	Springer, Cham,04 January 2017.	Significance of EEG Signals in Medical and Health Research.	Brain-Computer Interface (BCI) Systems, Computer-Aided Diagnosis (CAD) Systems.	Integrating technological advancements to assist healthcare professionals in diagnosing brain disorders more efficiently.	Signal resolution or speed might restrict their applications or real-time responsiveness.
9.	International Conference on Computer Science and Artificial Intelligence (CSAI '18),2018.	Emotion Classification Using EEG Signals.	Introduces a comprehensive model for classifying emotions based on EEG signals, capturing nuances of arousal, valence, dominance, and liking, offering a multi-dimensional understanding.	The proposed 3D Emotional Model demonstrates promise in capturing multi-dimensional emotions from EEG signals, offering insights into human behavior and potential for personalized recommendations	Accuracy might be influenced by noise in EEG signals or individual differences in interpreting emotional experiences, impacting classification reliability.

10.	Cognitive Robotics, Volume 1, 2021, Pages 29-40.	Review of the emotional feature extraction and classification using EEG signals	Machine learning algorithms (SVM, KNN, NB) and deep learning algorithms (NN, LSTM, DBN).	Diverse Feature Extraction Methods,Varied Classification Accuracy.	Challenges in interpretability and computational demands compared to traditional methods.
11.	Sensors. 2021; 21(5):1589	Real-Time Emotion Classification Using EEG Data Stream in E-Learning Contexts	real-time emotion classification system (RECS), Utilizes Stochastic Gradient Descent (SGD) for online training.	Demonstrates better accuracy and F1-score compared to both offline and online approaches, indicating the effectiveness of the proposed real-time classification system.	The performance and applicability of the proposed system might vary based on specific contexts and datasets beyond the DEAP dataset
12.	IEEE Access, vol. 7, pp. 40144-40153, 2019.	Internal Emotion Classification Using EEG Signal With Sparse Discriminative Ensemble	Efficient EEG Channel Selection, Kernel-Based Representations, Graph Embedding Objective Function.	Reduces data volume, improving computational efficiency, while simultaneously enhancing classification accuracy.	Complex algorithms might lack interpretability, hindering the understanding of the underlying EEG channel selection process.
13.	Computers in Biology and Medicine, Volume 136, 2021	Recognition of human emotions using EEG signals	Assessing cognitive functions and clinical states in e-healthcare and human-machine interface development	In-depth Analysis of Methodologies, Significance of emotions in cognition.	Identifies future directions and challenges but might not comprehensively cover the full spectrum of potential.

14.	Communications in Computer and Information Science, vol 1367, 2020.	Multi-class Emotion Classification Using EEG Signals	Brain-Computer Interface systems, and Machine Learning, focusing on deep learning architectures for emotion analysis.	Comparative analysis between Long Short-term Memory (LSTM) and Convolutional Neural Network (CNN) models, using different Train-Test splits.	Solely relying on accuracy might overlook nuances in model performance; other metrics like precision, recall, or F1-score could offer a more comprehensive assessment.
15.	Journal of Healthcare Engineering, vol. 2022, Article ID 8362091, 6 pages, 2022.	Genetic Programming-Based Feature Selection for Emotion Classification Using EEG Signal.	Genetic Program-based Feature Selection (FSGP) technique, leveraging Artificial Intelligence's	FSGP contributes to enhancing the model's accuracy, potentially outperforming previous approaches.	Genetic programming-based models could lack interpretability, potentially hindering a clear understanding of how specific features contribute to emotion recognition.

CHAPTER-III
EXISTING METHODS

The recognition of emotional states is a crucial step in the development of a brain-computer interface (BCI) system. This framework proposes a two-stage CIF-based filtering method to classify emotion EEG signals. At the first stage, the raw EEG signal is decomposed into IMFs by EMD and noisy-IMFs are filtered using the correlation-criterion. At the second stage, the denoised-EEG signal is decomposed into band-limited modes using VMD and frequency-components filtering is performed by the IF-based criterion. After, processing raw EEG signals from CIF-stages, the denoised and desired frequency range EEG signals.

3.1 Brain-Computer Interface

Brain-Computer Interface (BCI) is a technology that establishes a direct communication pathway between the brain and an external device, such as a computer or a machine, bypassing the need for traditional pathways like muscle movements or speech. BCIs interpret neural signals to control external devices or to gather information from the brain. These interfaces can work in various ways, often involving sensors placed on the scalp (non-invasive) or implanted directly into the brain (invasive). Non-invasive BCIs, like EEG (electroencephalography), detect electrical activity in the brain, while invasive BCIs use implanted devices to directly interface with neurons.

BCIs have diverse applications, from assisting individuals with disabilities to controlling prosthetic limbs, aiding in rehabilitation, enabling communication for those with speech impairments, and even enhancing human capabilities in various fields. They represent a cutting-edge field with promising potential for both medical and non-medical applications.

A Brain-Computer Interface (BCI) system refers to the entire setup designed to enable communication between the brain and an external device, typically a computer or a machine. It encompasses several components:

1. **Sensors or Electrodes:** These are used to detect and record brain activity. They can be non-invasive (placed on the scalp) or invasive (implanted directly into the brain).

2. **Signal Processing Unit:** This unit interprets the neural signals received from the sensors. It involves advanced algorithms and signal processing techniques to extract meaningful information from the raw brain signals.
3. **Decoder or Interface Software:** This software interprets the processed signals and translates them into commands or actions for the external device to perform.
4. **External Device:** This could be a computer, a robotic limb, a wheelchair, or any device that can be controlled or influenced by the brain's signals.
5. **Feedback Mechanism:** Some systems incorporate a feedback loop, providing information back to the user. For example, visual or auditory feedback to confirm that a command has been successfully executed.

3.2 Common Independent Features (CIF) based Filtering

CIF (Common Independent Features) filtering is a method used in Brain-Computer Interface (BCI) systems for processing and extracting relevant information from EEG (Electroencephalography) signals. The two-stage CIF-based filtering are:

1. Common Spatial Patterns (CSP)
2. Independent Component Analysis (ICA) filtering

3.2.1 Common Spatial Patterns (CSP)

CSP is a technique used to enhance the discriminative information in EEG (Electroencephalography) data. It aims to find spatial filters that maximize the variance of one class while minimizing the variance of another. For example, in a motor imagery task for a BCI, CSP might be used to enhance the brain signals associated with imagining moving the left hand while suppressing signals related to imagining moving the right hand.

The method of common spatial patterns (CSP) designs spatial filters in such a way that the variances in the filtered time series data are optimal (in the least squares sense) for discrimination (Koles, 1991; Müller-Gerking et al., 1999; Guger et al., 2000; Romoser et al., 2000).

We are given input data $S_{c}^{i}{}_{i=1}^{k}$ denoting EEG/ECoG data from trial i for class $c \in \{1,2\}$

(e.g., hand versus foot motor imagery). Each S_c^i is an $N \times T$ matrix, where N is the number of EEG channels and T the number of samples in time per channel. We assume that the S_c^i are centered and scaled.

The goal of CSP is to find M spatial filters, given by an $N \times M$ matrix W(each column is a spatial filter), that linearly transform the input signals according to

$$s_{csp}(\mathrm{t}) = W^T \mathrm{s}(\mathrm{t})$$

Where s(t) is the vector of input signals at time t from all the channels.

$$R = \frac{1}{} \sum S^i (S^i)^T$$

for $c \in \{1,2\}$. The CSP technique involves determining a matrix W such that

$$W^T R_1 W = \Lambda_1$$

$$W^T R_2 W = \Lambda_2$$

where the Λ_i are diagonal matrices and $\Lambda 1 + \Lambda 2 = I$ (I is the identity matrix). This can be done by solving a generalized eigenvalue problem given by

$$R_1 w = \lambda R_2 w$$

The generalized eigenvectors w_j that satisfy the above equation form the columns of W and represent the CSP spatial filters. Spatial filtering with such filters can thu₁s significantly enhance discrimination ability. Typically, a small number of eigenvectors (e.g., six) areused as CSP filters in BCI applications. A more detailed overview of the CSP method can be found in Blankertz et al. (2008), and various enhancements to boost robustnessand applicability are given in Lemm et al. (2005), Dornhege et al. (2006), and Grosse-Wentrup and Buss (2008).

3.2.2 Independent Component Analysis (ICA)

ICA is used to separate a multivariate signal into additive subcomponents, assuming that the signals are generated by different independent sources. In the context of EEG signals, ICA can help separate the brain signals from noise or artifacts, which can significantly improve the quality of the extracted features used for classification or control purposes in BCIs.

Mathematically, ICA can be represented as follows:

Assume we have n observed signals or measurements, represented as a vector

$$\mathbf{x}(t)=[x1(t),x2(t),\ldots,xn(t)]T \text{ at time } t.$$

These observed signals are assumed to be linear combinations of n independent source signals, denoted as

$$\mathbf{s}(t)=[s1(t),s2(t),\ldots,sn(t)]T, \text{ and a mixing matrix } \mathbf{A}:$$

$$\mathbf{x}(t)=\mathbf{A}\cdot\mathbf{s}(t)$$

Where $\mathbf{x}(t)$ is the observed signal vector, $\mathbf{s}(t)$ is the vector of independent source signals, $\mathbf{A}$ is the mixing matrix, where each row represents the weights or coefficients applied to the source signals to create the observed signals.

The goal of ICA is to estimate the original independent source signals $\mathbf{s}(t)$ by finding a demixing matrix $\mathbf{W}$ such that:

$$\mathbf{y}(t)=\mathbf{W}\cdot\mathbf{x}(t)$$

Where $\mathbf{y}(t)$ is the estimated source signal vector. The demixing matrix $\mathbf{W}$ is computed to minimize the statistical dependence or maximize the statistical independence between the elements of $\mathbf{y}(t)$. This is usually achieved by maximizing some measure of non-Gaussianity or statistical independence, often based on measures such as negentropy or kurtosis.

The estimated source signals are obtained by applying the demixing matrix $\mathbf{W}$ to the observed signals $\mathbf{x}(t)$. The resulting signals $\mathbf{y}(t)$ ideally represent the original independent sources, separated from each other as much as possible.

ICA is a powerful technique used in various fields such as signal processing, neuroscience, and machine learning for blindly separating mixed signals into their original independent components, assuming certain statistical properties of the sources.

3.3.3 Two-stage CIF based filtering

1. **First Stage** - IMF Decomposition with EMD and Correlation-Criterion Filtering:

    - EMD (Empirical Mode Decomposition): The raw EEG signal is decomposed into Intrinsic Mode Functions (IMFs) using EMD. IMFs represent different oscillatory modes within the signal.
    - Correlation-Criterion Filtering: Noisy IMFs are identified and filtered out using a correlation-based criterion. This step aims to remove unwanted noise or artifacts from the EEG signal.

2. **Second Stage** - VMD Decomposition and IF-Based Criterion Filtering:
    - VMD (Variational Mode Decomposition): The denoised EEG signal from the first stage is further decomposed into band-limited modes using VMD. VMD decomposes the signal into components with specific frequency bands.
    - IF-Based Criterion Filtering: Frequency components are filtered based on an Instantaneous Frequency (IF)-based criterion. This step aims to isolate and extract desired frequency components related to the emotional states under study.
3. **Resulting Denoised and Desired Frequency Range EEG Signals:**
    - After these processing stages, the framework yields denoised EEG signals that have undergone noise reduction through IMF and frequency-based filtering.
    - The final output comprises EEG signals within the desired frequency range relevant to the classification of emotional states.

The two-stage CIF (Common Independent Features) filtering method, while effective in extracting relevant information from EEG (Electroencephalography) signals for emotional state classification within Brain-Computer Interface (BCI) systems, poses potential challenges. Its complexity in signal processing and multiple filtering stages introduces computational overhead, the risk of information loss or distortion, sensitivity to parameter tuning, reduced interpretability of extracted features, increased potential for overfitting, and the delicate balance between noise removal and preserving crucial signal components, underscoring the need for careful optimization and validation to mitigate these disadvantages.

CHAPTER-IV

PROPOSED METHODOLOGY

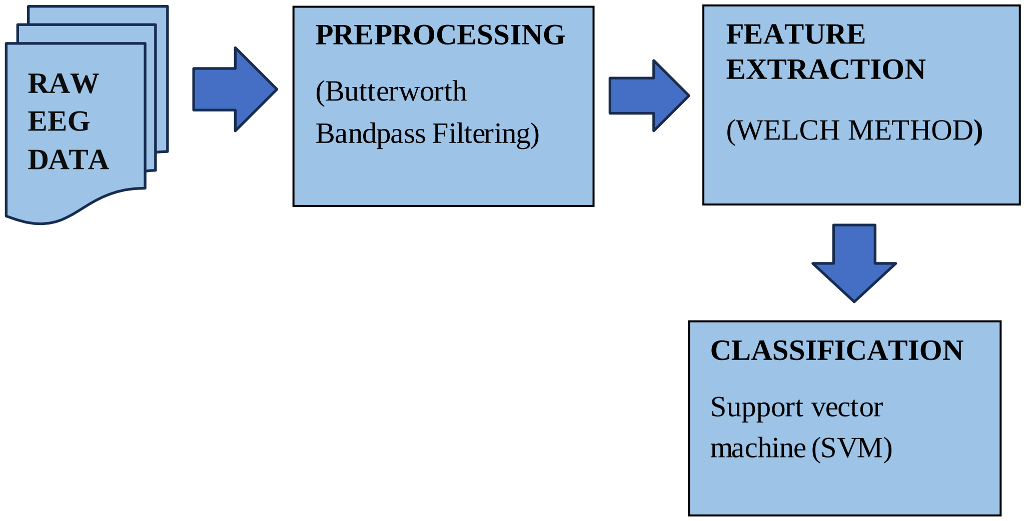

Fig 5.1: Block Diagram of proposed methodology

4.1 Data Set

The DEAP dataset consists of two parts:

The ratings from an online self-assessment where 120 one-minute extracts of music videos were each rated by 14-16 volunteers based on arousal, valence and dominance. The participant ratings, physiological recordings and face video of an experiment where 32 volunteers watched a subset of 40 of the above music videos. EEG and physiological signals were recorded and each participant also rated the videos as above. In this assignment, labels are extracted into separate file and data of each channel is extracted into separate file. Data from each channel is stored in row wise versus time in column for each trail, per person. Then, EEG signal processing will be applied to extract most informative features from the raw data.

4.2 EEG Signal Processing

The collected EEG signals were converted to the ASCII form which can be readable easily by the MATLAB software. Basically, the EEG signal processing consists of 3 stages which is pre-processing, feature extraction and classifier.

In this research the F7,F8,Fp1,Fp2,P7,P8,O1and O2 channel is selected.

F7 and F8 electrodes are positioned at the frontal sites on the left and right sides, respectively, around the temporal regions of the head. Monitoring F7 and F8 activity helps in understanding brain dynamics related to cognitive functions, emotional processing, and language.

4.2.1 Pre-Processing

The Butterworth bandpass filter was implemented during the pre-processing stage. The butterworth filter provides a response that is no ripple and maximally flat in the passband and stopband . It provide good average transient characteristics and expense wide transition region from band pass to band stop thus enable a good compromise between amplitude response selectivity [5]. In fact, the collected EEG raw data consist of all frequency band such as Delta, theta, alpha, beta, and gamma. It is then pre-processing with the Butterworth bandpass filter to separate the signal accordingly. The frequency band chosen is the alpha which is 8 Hz to 13 Hz, beta that are from 13 Hz to 30 Hz. In this paper, the raw EEG signals from frontal channel F7,F8,Fp1,Fp2, parietal channel P7,P8 and occipital channel O1 and O2 is electrode location which is extracted for EEG signal processing. This electrode position of the brain was taken because it is exclusively related to the emotion regulation, decision-making, social-cognition.

4.2.2 Feature Extraction

The power spectral density (PSD) was used as the feature extraction method in this study. PSD is a good tool for stationary signal processing and suitable for narrowband signal. It is a common signal processing technique that distributes the signal power over frequency and show the strength of the energy as function of frequency. Under the PSD, the Welch method is adopted in this study.

Welch method

Welch's method, named after Peter D. Welch, is an approach for spectral density estimation. It is used in physics, engineering, and applied mathematics for estimating the power of a signal at different frequencies. The method is based on the concept of using periodogram spectrum estimates, which are the result of converting a signal from the time domain to the frequency domain. Welch's method is an improvement on the standard periodogram spectrum estimating method and on Bartlett's method, in that it reduces noise in the estimated power spectra in exchange for reducing the frequency resolution. Due to the noise caused by imperfect and finite data, the noise reduction from Welch's method is often desired.

The Welch method is based on Bartlett's method and differs in two ways:

The signal is split up into overlapping segments: the original data segment is split up into L data segments of length M, overlapping by D points.

If D = M / 2, the overlap is said to be 50%

If D = 0, the overlap is said to be 0%. This is the same situation as in the Bartlett's method.

The overlapping segments are then windowed: After the data is split up into overlapping segments, the individual L data segments have a window applied to them (in the time domain).Most window functions afford more influence to the data at the center of the set than to data at the edges, which represents a loss of information. To mitigate that loss, the individual data sets are commonly overlapped in time (as in the above step).The windowing of the segments is what makes the Welch method a "modified" periodogram.After doing the above, the periodogram is calculated by computing the discrete Fourier transform, and then computing the squared magnitude of the result. The individual periodograms are then averaged, which reduces the variance of the individual power measurements.

4.2.3 Classifier

Support Vector Machines (SVMs) are supervised learning models used for classification and regression tasks. In the context of classification, SVMs are effective in finding the optimal hyperplane that best separates different classes in a dataset. The main goal is to create a decision boundary that maximizes the margin, which is the distance between the hyperplane and the nearest data points of each class, known as support vectors. SVMs work well in both linearly separable and non-linearly separable datasets through the use of kernel functions that map data into higher-dimensional spaces where separation is possible. SVMs are robust, effective in high-dimensional spaces, and have a regularization parameter that helps prevent overfitting, making them widely used in various domains, including image classification, text classification, and biological sciences. The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible.

The dimension of the hyperplane depends upon the number of features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three.

Let's consider two independent variables x1, x2, and one dependent variable which is either a blue circle or a red circle.

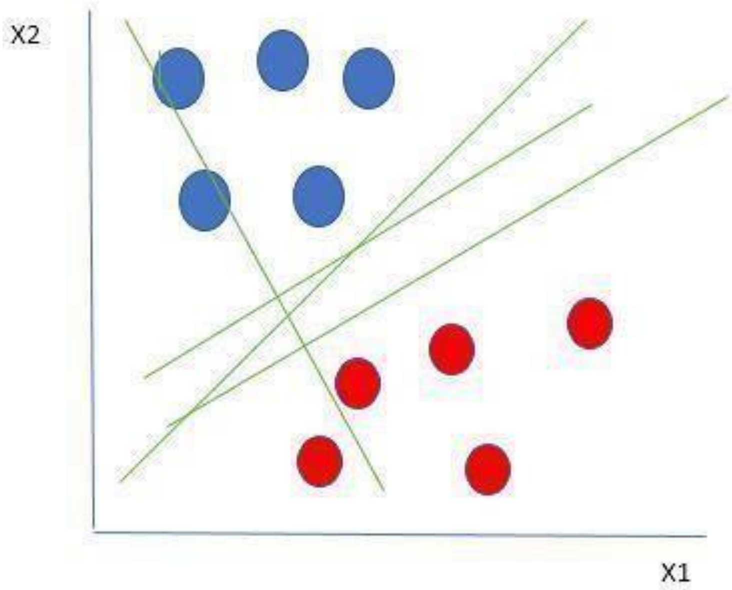

Fig 4.2.3(a) Linearly Separable Data Points

From the figure above it's very clear that there are multiple lines (our hyperplane here is a line because we are considering only two input features x1, x2) that segregate our data points or do a classification between red and blue circles.

Mathematical intuition of Support Vector Machine

Consider a binary classification problem with two classes, labeled as +1 and -1. We have a training dataset consisting of input feature vectors X and their corresponding class labels Y.

The equation for the linear hyperplane can be written as:

$$w^T x + b = 0$$

The vector W represents the normal vector to the hyperplane. i.e the direction perpendicular to the hyperplane. The parameter b in the equation represents the offset or distance of the hyperplane from the origin along the normal vector w.

The distance between a data point x_i and the decision boundary can be calculated as:

$$d_i = \frac{w^T x_i + b}{||w||}$$

where ||w|| represents the Euclidean norm of the weight vector w. Euclidean norm of the normal vector W.

4.3 Performance metrics

To evaluate the performance of machine learning models the common metrics used is as follows:

4.3.1 Accuracy

It measures the proportion of correctly predicted instances among the totalinstances in the dataset. It's calculated as the ratio of the number of correctpredictions to the total number of predictions. While accuracy is a straightforward measure, it might not be the best metric, especially if the classes in the dataset are imbalanced.

4.3.2 Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It indicates the accuracy of positive predictions. It's calculated as TP / (TP + FP), where TP is the number of true positives (correctly predicted positive instances) and FP is the numberof false positives (incorrectly predicted as positive).

4.3.3 Recall

Recall measures the ratio of correctly predicted positive observations to the all observations in the actual class. It's calculated as TP / (TP + FN), whereFN is the number of false negatives (actual positives incorrectly predicted as negative. It signifies the model's ability to find all the relevant cases within a dataset.

4.3.4 F1-Score

The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall. It's calculated as 2 * (Precision * Recall) / (Precision + Recall). The F1 score considers both false positives and false negatives and is a good measure of a model's accuracy in cases where the classes are imbalanced.

4.4 Mean Value

In signal processing, the Welch method is used to estimate the power spectral density (PSD) of a signal. It's essentially a method for obtaining a smoothed and more accurate estimate of the PSD by dividing the signal into segments, computing the periodogram for each segment, and then averaging those periodograms. The mean value associated with the Welch method typically refers to the averaging process it employs. After segmenting the signal and computing the periodograms for each segment, these periodograms are averaged together to obtain a more robust estimate of the PSD. The mean value, in this context, represents the average or mean of these individual periodograms calculated from the signal segments. This averaging process helps reduce variance and provides a more stable estimation of the PSD compared to using a single periodogram calculated over the entire signal.

CHAPTER-V

SOFTWARE DESCRIPTION

5.1 Introduction

In this project, we use the software MATLAB to execute the required results. MATLAB (matrix laboratory) is a fourth-generation high-level programming language and interactive for numerical, visual and programming.

Matrix laboratory is developed by Math Works. This MATLAB allows

- Matrix manipulations
- Plotting of functions and data
- Implementing of algorithms
- Creation of user interface
- It has built-in commands and math functions which help in mathematical calculations, numerical methods and generating plots. MATLAB has many advantages compared to conventional computer languages (e.g., C, FORTRAN) for solving technical problems. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning.

5.2 Basics of Software

5.2.1 Basic Building Blocks of MATLAB

The basic building block of MATLAB is MATRIX. The fundamental data type is the array. Vectors, scalars, real matrices and complex matrix are handled as specific class of this basic data type. The built in functions are optimized for vector operations. No dimension statements are required for vectors or arrays.

Ø **MATLAB Window:** The MATLAB works based on five windows: Command window, Workspace window, Current directory window, Command history window, Editor Window, Graphics window and Online-help window. **Command Window:** In this command window it displays a command prompt ">>" and the cursor starts blinking where the commands can be entered and executed for example we try some arithmetic expressions.

Example 1 >> 20+

(3*6) ans =

38

Example 2 >>50/50*10

ans =

10

Figure 5.1: (a) Command Window

Work Space Window: Let us consider one example by initializing value to two variables as shown in the Figure 5.1. (b).

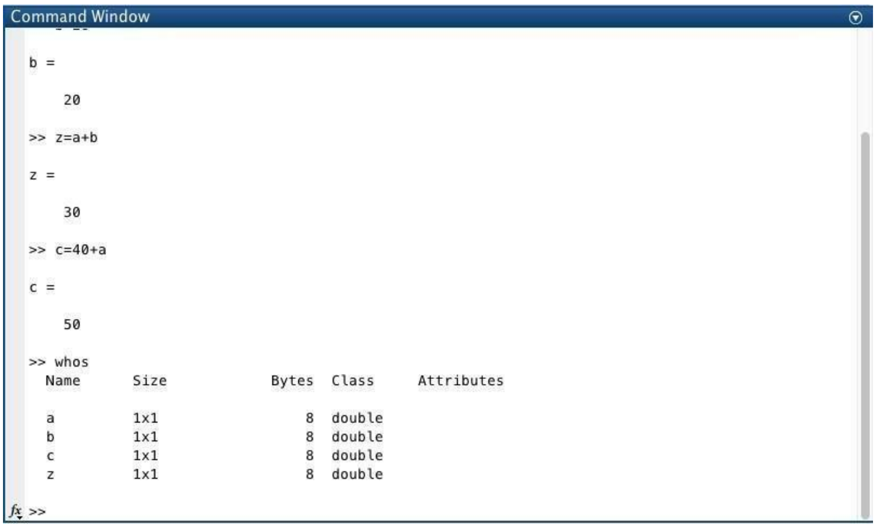

Figure 5.1: (b) Command Window Showing Values

As shown in the Figure 5.1 (b). a is initialized one value and b also with some value. z is having the value of a +b. Workspace is a collection of all variables.

a = 10 and b =20 z = a+b =30

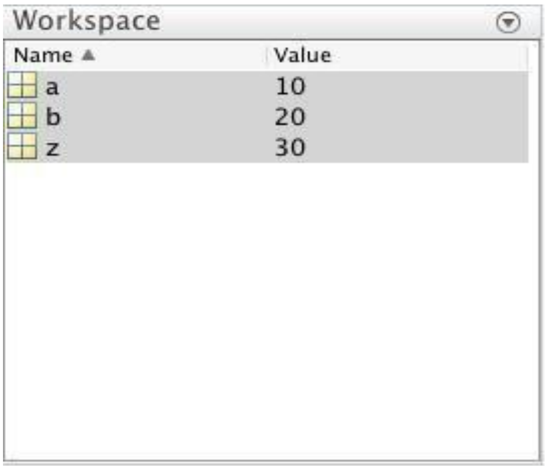

Figure 5.2: Workspace Window

- **Current Directory Window:** The current Directory tab shows the contents of the current directory, whose path is shown in the current directory window. For example, in the windows operating system the path might be as follows: C:\MATLAB\Work, indicating that directory "work" is a subdirectory of the main directory "MATLAB"; which is installed in drive C.
- **Command History Window:** The Command History Window contains a record of the commands a user has entered in the command window, including both current and previous MATLAB sessions. Previously entered MATLAB commands can be selected and re-executed from the command history window by right clicking on a command or sequence of commands. This is useful to select various options in addition to executing the commands and is useful feature when experimenting with various commands in a work session.
- **Editor Window:** Editor Window is to create a new file and to edit the saved page. We can create a new file and can also open an existing file here the files are saved with .m extension are called as M-files.

- **Graphics or Figure Window:** The output of all graphic commands typed in the command window is seen in this window.
- **Online Help Window**: MATLAB provides online help for all it's built in functions and programming language constructs. To know about any function or the command click on the help icon so that we can easily find out the command description. To check the proper command or function at a particular line click on the help command and look for command

5.2.2 MATLAB Files

M-Files

These are standard text file with 'm' extension to the file name and creating own matrices using M-files, which are text files containing MATLAB code. MATLAB editor or another text editor is used to create a file containing the same statements which are typed at the MATLAB command line and save the file under a name that ends in .m. There are two types of M-files:

- **Script Files**

It is an M-file with a set of MATLAB commands in it and is executed by typing name of file on the command line. These files work on global variables currently present in that environment.

- **Function Files**

A function file is also an M-file except that the variables in a function file are all local.

This type of files begins with a function definition line.

5.2.3 MATLAB Commands Required

clc:

(Clear Command Window) This syntax clears all the text displaying in the Command Window which clears the entire screen.

clear:

Here clear it removes all the variables and functions from the workspace. For example, if we consider three variables of x, y, z initializing some values as

p = 1;

q= 2;

r = 3;

clear p;

Only one variable p is cleared from the workspace and the remaining two variables q and r displays in the workspace.

load:

load(filename) loads data from filename into the MATLAB® workspace. If filename is a MAT-file, then load(filename) loads variables from the file; if filename is an ASCII file, then load(filename) loads a double-precision array containing data from the file.

plot:

plot(X,Y) creates a 2-D line plot of the data in Y versus the corresponding values in X. To plot a set of coordinates connected by line segments, specify X and Y as vectors of the same length. To plot multiple sets of coordinates on the same set of axes, specify at least one of X or Y as a matrix.

Pwelch :

The function is used to estimate the Power Spectral Density (PSD) of a signal using Welch's method. This method divides the signal into overlapping segments, computes the periodogram (which represents the power spectrum of each segment), and then averages these periodograms to get a smoother estimate of the PSD**.**

end:

To terminate any block of the code then the end is used. If we use any of these for, while, switch, if, and try then we end the block by using end syntax. Generally, the loops are used to check any conditions according to program. To terminate the block and go to the next line we close the block with end.

5.3 Starting the MATLAB

- Double click on MATLAB software

Figure 5.3: MATLAB Icon

5.3.1 Creating a New Project:

- To create a new file go to the Toolbar >>File>>New
- A window appears on the screen to create a new file name.
- Here all the files are stored with .m extension

Open the MATLAB layout here the top of the layout a toolbar is present which have many tools to create files, run the program, help, window, desktop, edit and debug. To the left current folder is present which stores the present running files. To the top right corner a workspace which is to display all defined variables with memory allocation. Right bottom command history which records all commands and in the middle of this command window is present which is used to generate the small programs.

Advantages

- It is a case sensitive language
- MATLAB does not require compiler to execute.
- It is object oriented language.

Disadvantages

- It is very costly the user has to buy each and every module.
- It is very difficult during cross compiling.
- It uses a large amount of memory.

5.4 Method of Implementation

- Double click on the MATLAB icon after displaying the MATLAB layout on the screen at the top of the layout toolbar is present. Go for new or if the file has to be selected from the drive go to the file drive. Open the file in the current folder displays at the left of the MATLAB layout. The MATLAB layout is displayed in the Figure 5.3. (a).as shown.

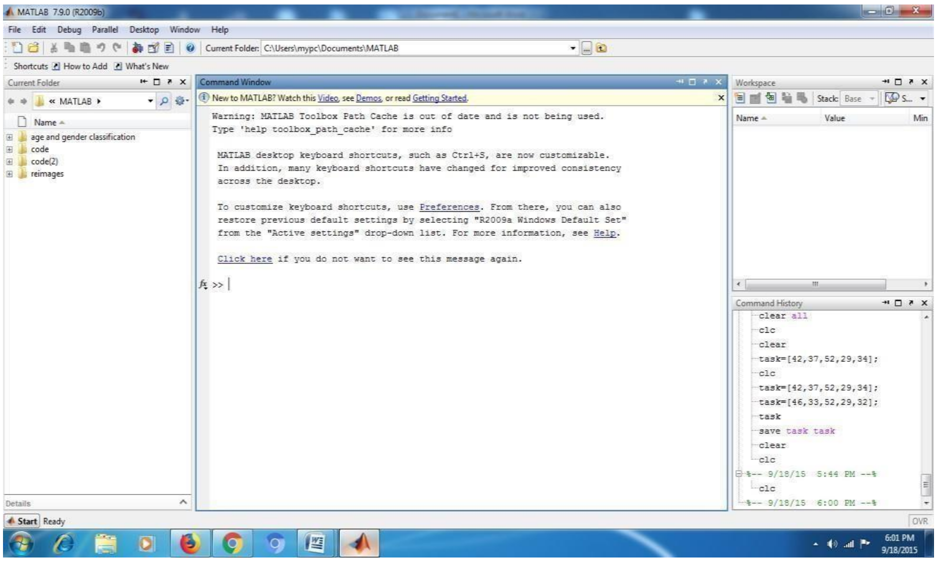

Figure 5.4: (a) MATLAB Layout

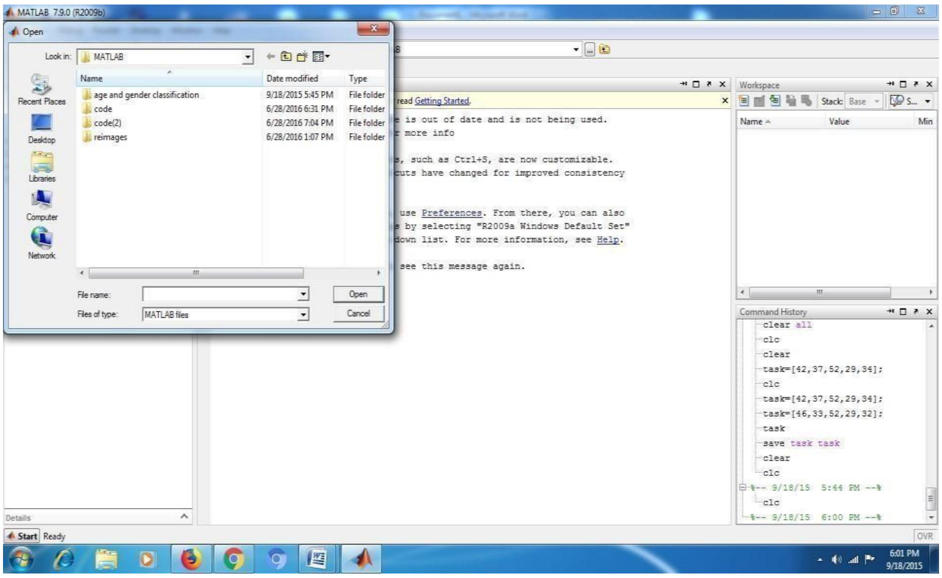

Figure 5.4: (b) Browse the Source File

➢ Click on open and select the source file from the drive. Select the source file and click on open button then the source files opens in the current folder. Click on + sign to see the files present in the folder. If a source file is to be selected or to be added to the current folder click on file in the tool bar present at the top.

➢ Select the source file and click on open button. As shown in the Figure 5.4.(c).code file is selected and click on open.

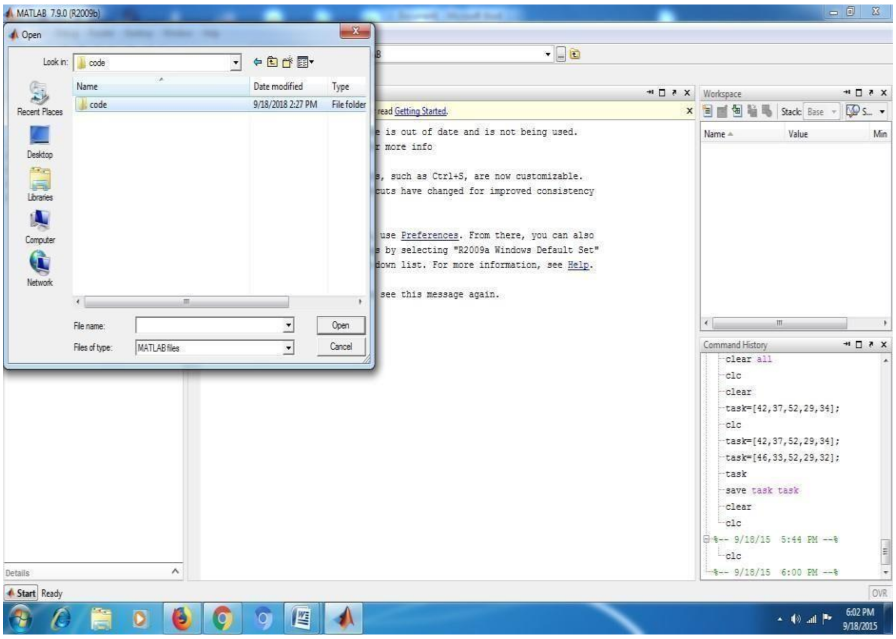

Figure 5.4: (c) Select the Source File

- After clicking on code file the file is going display in the current folder list.

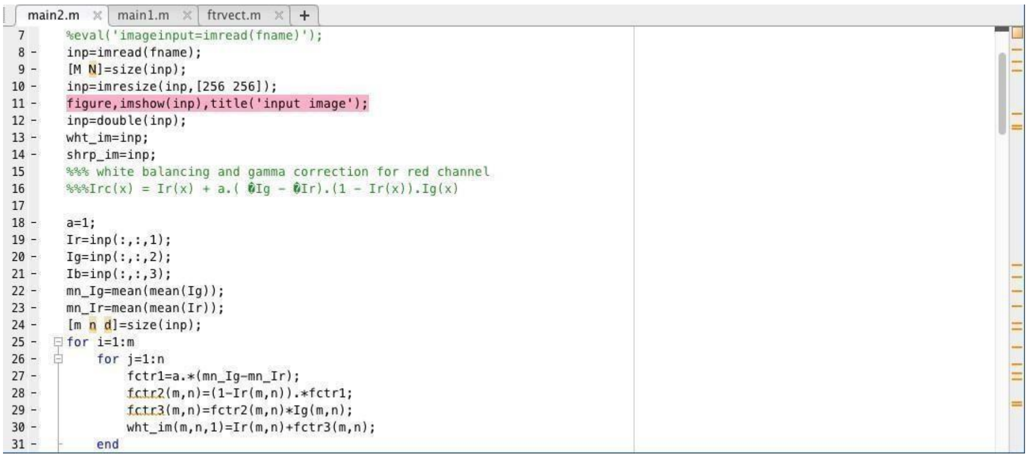

Figure 5.4: (d) Main Source File

In current folder it displays our code source file. Double click on the file it displays the main file and the image which is going to be our input image.

- Click on main file as shown in the Figure 5.3. (d).

  Run the main file it displays a dialog box to select the input file.

CHAPTER-VI

RESULT AND ANALYSIS

6.1 Filtering Result

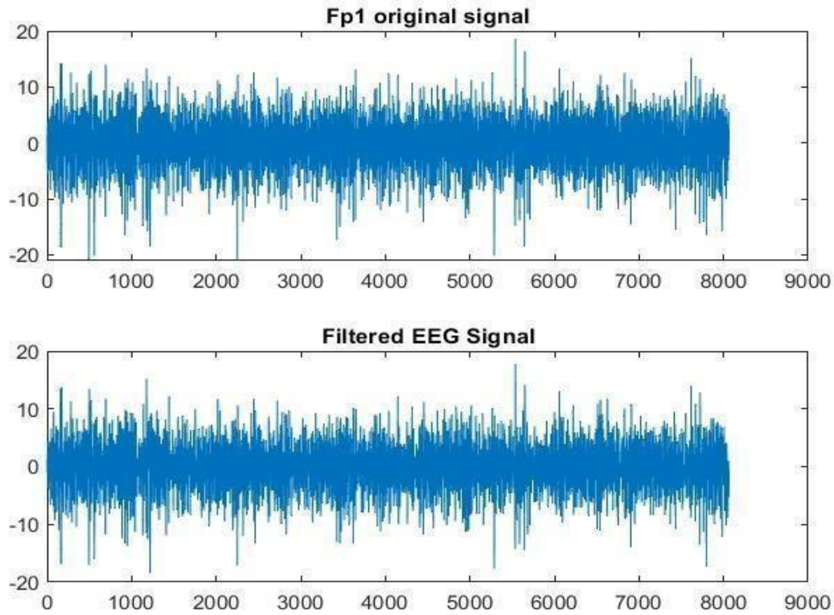

Fig 6.1(a) Fp1 filtered signal

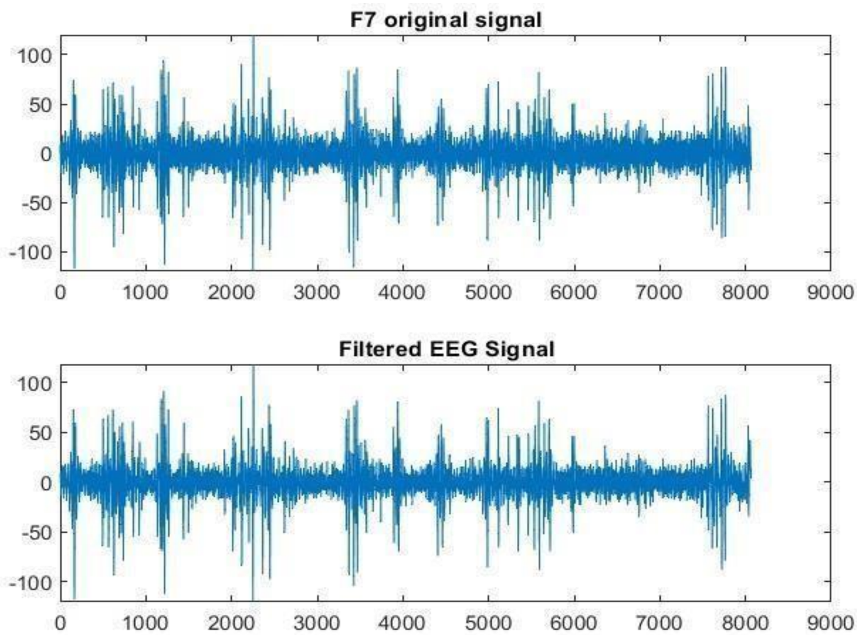

Fig 6.1(b) F7 filtered signal

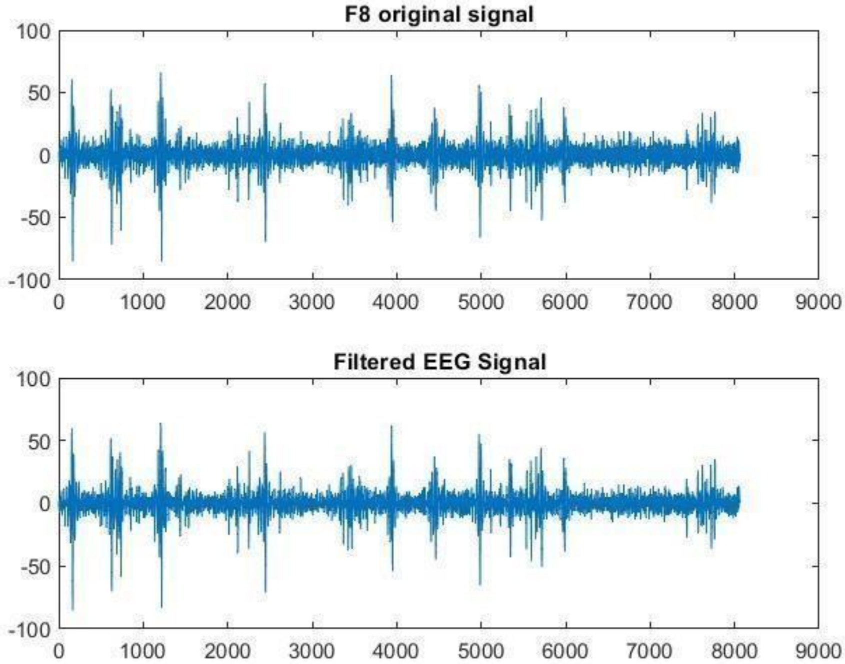

Fig 6.1(c) F8 filtered signal

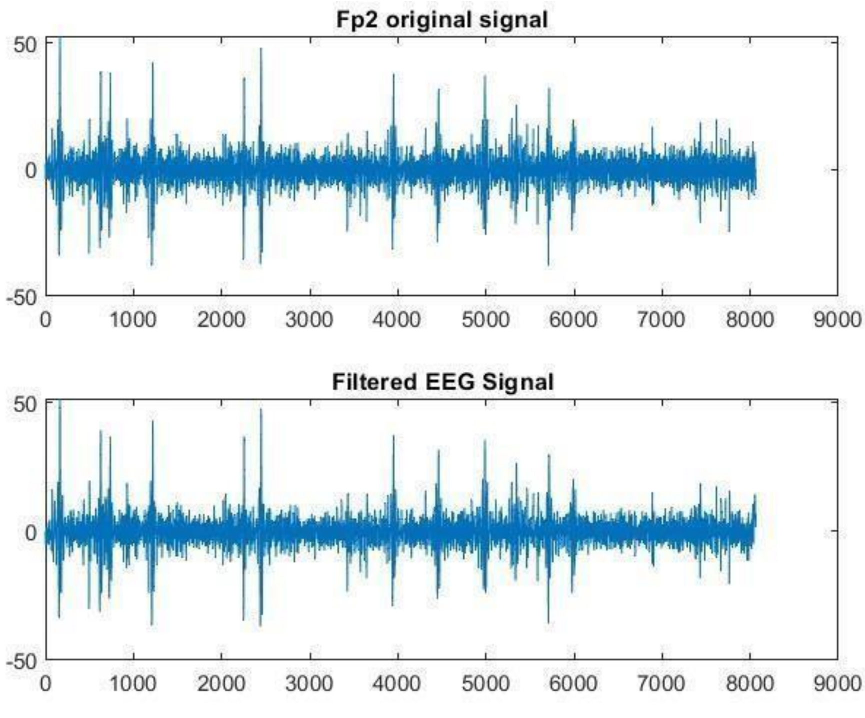

Fig 6.1(d) Fp2 filtered signal

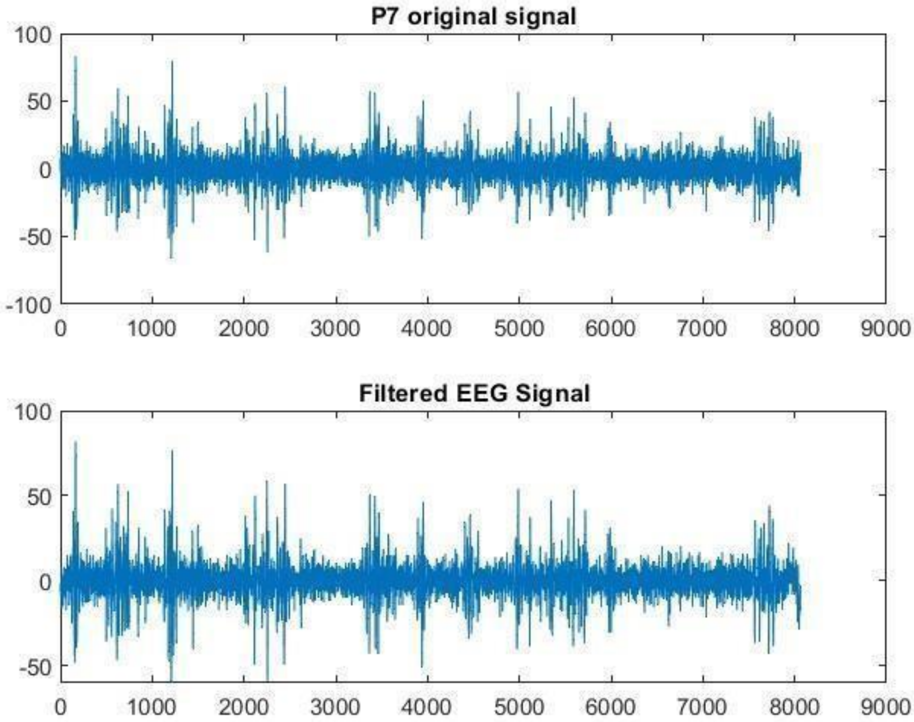

Fig 6.1(e) P7 filtered signal

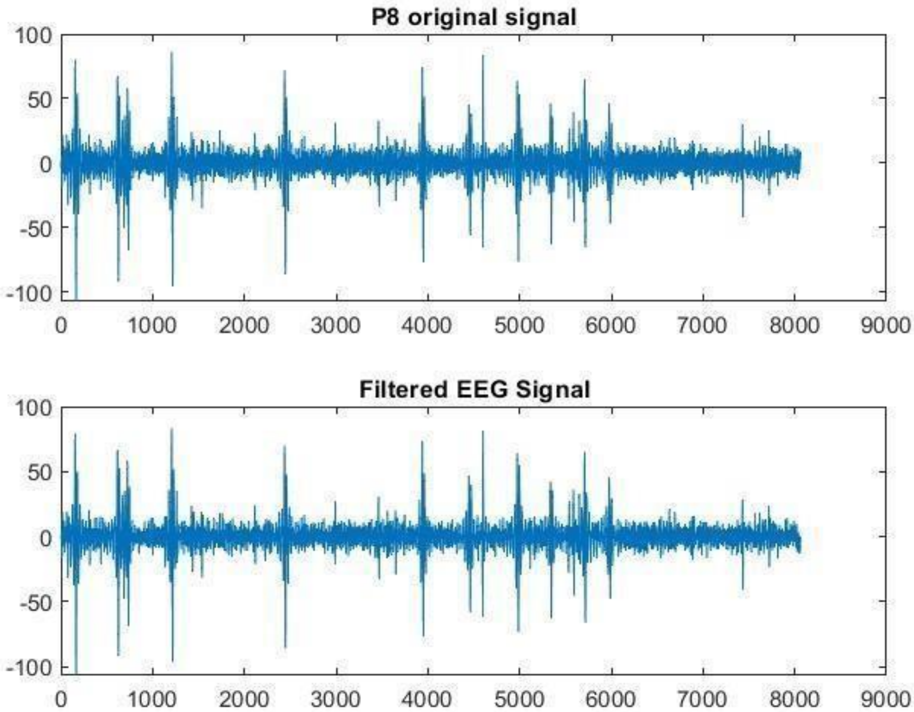

Fig 6.1(f) P8 filtered signal

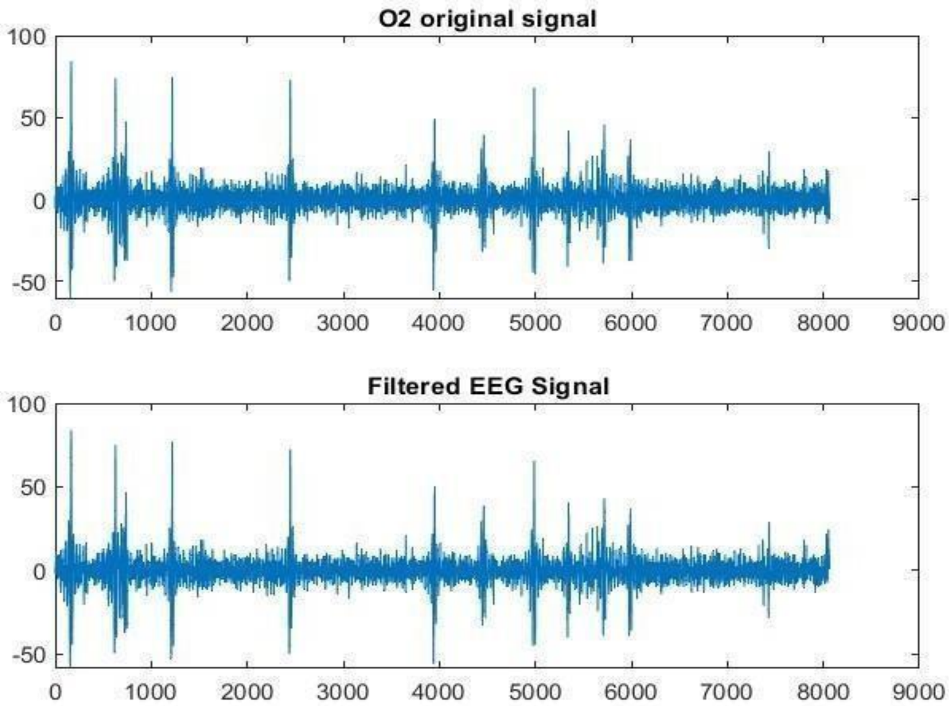

Fig 6.1(g) O2 filtered signal

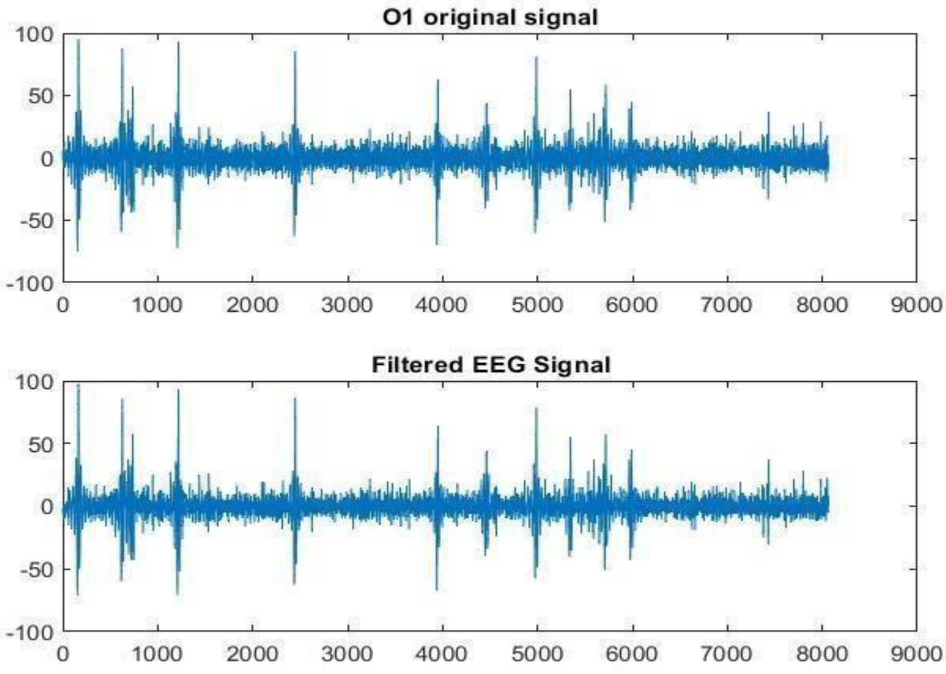

Fig 6.1(h) O1 filtered signal

6.2 Welch power spectral Estimation

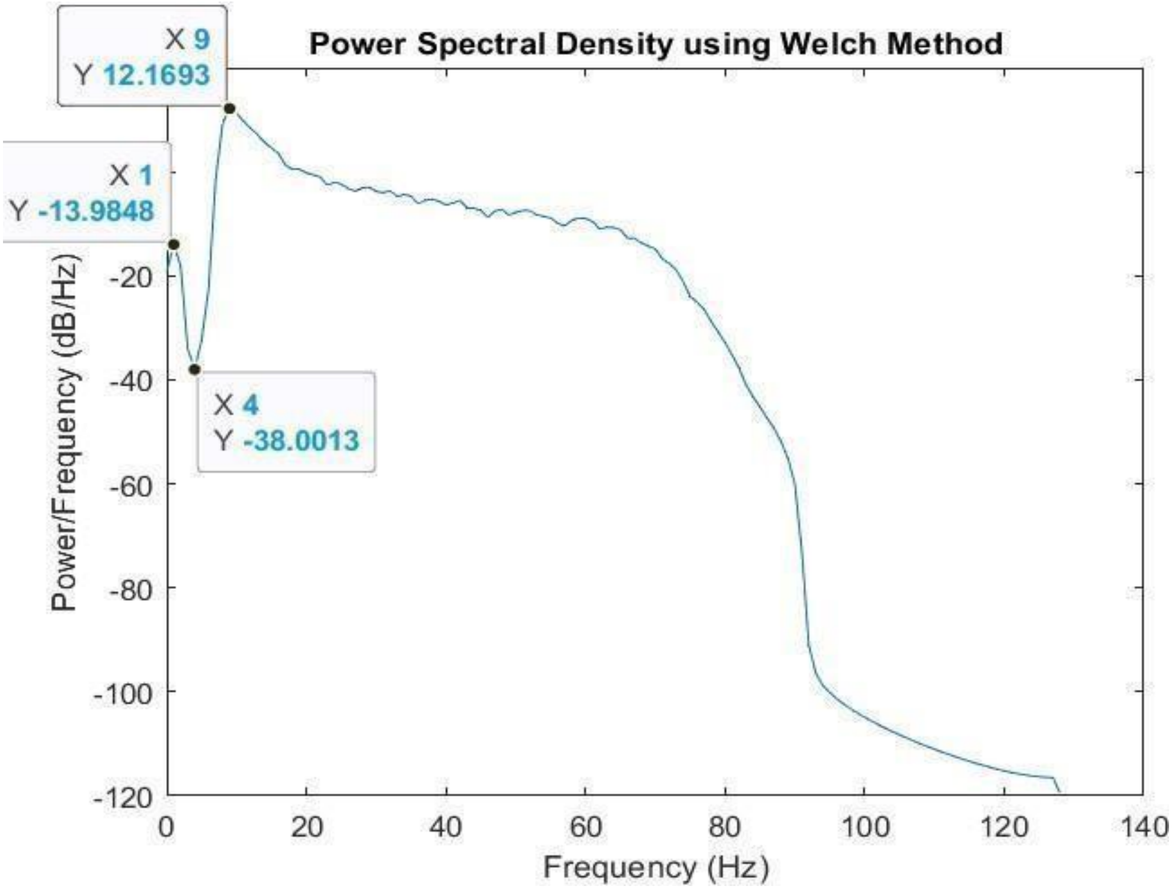

Figure:6.2 Power spectral density graph

The highest peak in the alpha i.e. (8-13 Hz) range in power spectral analysis indicates a prominent peak in the alpha range indicates a relaxed mental state. It's associated with relaxation, calmness, and a lack of activecognitive engagement.

Whereas Beta waves (13-30 Hz) are associated with active, focused, and alert mental states. Higher beta frequencies often correspond to more intense cognitive engagement, such as problem-solving, decision-making, and active thinking.

Gamma waves (30-100Hz) are the fastest brainwaves and are associated with high-level cognitive processing, perception, and consciousness. They are linked to moments of insight, high focus, and are often seen during peak cognitive activity.

6.3 Mean Value Result

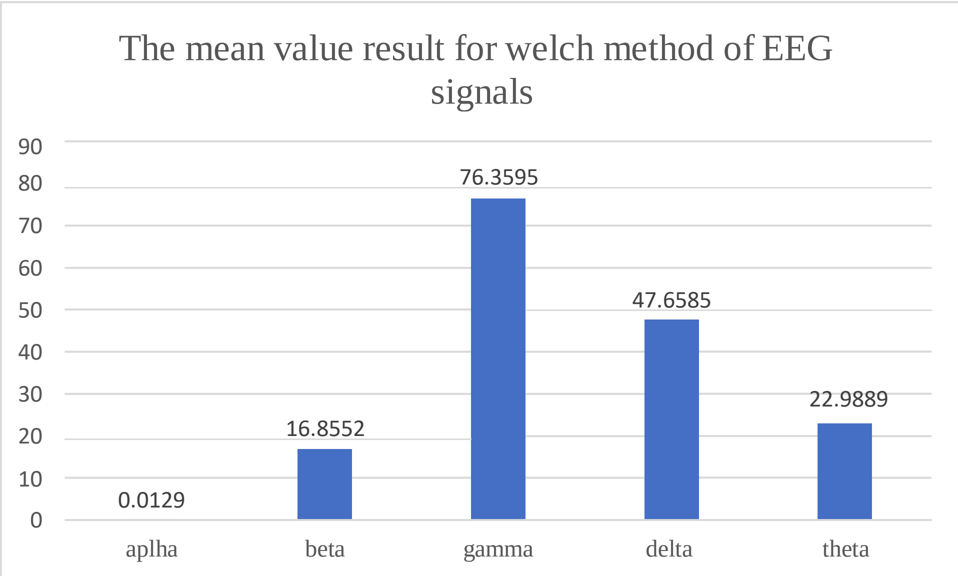

Fig 6.3: The mean value result for welch method of EEG signal

A noticeable rise in Gamma band power might indicate heightened cognitive processing or engagement in tasks requiring increased mental effort or focus

Overall Mean Value ≈ 32.174

It implies a balanced contribution from these bands to the overall electrical activity observed in the dataset. Relative to individual band power values, this mean provides a benchmark for understanding how each frequency band contributes to the overall electrical activity.

6.4 Classification Result

Channel	Accuracy	Precision	Recall	F1-score
F7	0%	-	-	-
F8	100%	1	1	1
Fp1	50%	-	-	-
Fp2	50%	0.5	-	-
P7	0%	-	-	-
P8	50%	-	-	-
O1	0%	-	-	-
O2	0%	0	0	0

Table 6.4.: Classification result for Welch method EEG signal

Overall, these results signify a model with flawless performance specifically tailored to identify and categorize F8 channel instances with absolute precision and recall. A 50% accuracy suggests that out of the total instances classified, only half were correct for these channels, while the other half were misclassified. Aresult of 0 across these metrics implies that the model did not make any correct predictions for these channels.

CHAPTER-VII

ADVANTAGES & APPLICATIONS

7.1 Advantages

- Precise Insights: Flawless classification offers precise understanding of specific brain region activities, aiding focused neuroscientific research.
- Robust BCIs: High accuracy enhances Brain-Computer Interfaces, enabling reliable interpretation of brain signals for diverse applications.
- Personalized Therapy: Accurate localization supports tailored interventions for neurological disorders, improving treatment outcomes.
- Rehabilitation Support: Accurate neural patterns aid neurofeedback therapies for rehabilitation post-brain injuries.
- Advancements in Psychology: Localization contributes to understanding memory, attention, and emotional processing.
- Clinical Trials Optimization: Precise characterization assists in evaluating drug effects and optimizing neuroscience trials.
- Potential for Precision Medicine: Accurate neural signatures enable personalized therapeutic approaches.
- Insights into Brain Connectivity: Aid in understanding brain network dynamics and communication.

7.2 Applications

- Neurological Research: Understanding localized brain functions in studies related to cognitive disorders and brain development.
- Brain-Computer Interfaces: Enhancing BCIs for controlling devices and aiding paralysis patients.
- Clinical Diagnostics: Precise diagnosis of conditions like epilepsy, sleep disorders, and strokes.
- Neurorehabilitation: Supporting therapies for stroke recovery and cognitive rehabilitation.
- Psychological Studies: Exploring emotions, behavior, and mental health through precise brain activity understanding.

- Precision Medicine: Guiding personalized treatments and drug interventions based on neural patterns.
- Brain Mapping: Understanding brain networks and connectivity for broader neuroscience insights.
- Stress Management: Supporting biofeedback techniques for stress reduction and emotional regulation.
- Educational Interventions: Optimizing learning interventions based on brain activity understanding.
- Technological Innovations: Inspiring advancements in neuro-inspired computing and brain imaging technologies.

CHAPTER-VIII

CONCLUSION & FUTURE SCOPE

In study unveils, the PSD is used as feature extraction and the Welch method is used. The analysis of band power values revealed varying performance in channel classification.The overall mean value provided an aggregate insight into signal strength across frequency bands. Flawless classification in certain channels like F8 showcased exceptional accuracy, precision, recall, and F1-scores, indicating precise identification. However, for channels F7, P7, O1, and O2, as well as FP2, FP1, and P8, the model's performance was either entirely incorrect or inconsistent, with accuracy and all other metrics at 0 or 50%. Improvements in PSD feature extraction, refinement of spectral analysis techniques, or the incorporation of domain-specific knowledge into models could contribute to better understanding and more accurate classification of EEG channels based on their PSD characteristics. Overall, PSD obtained through the Welch method serves as a fundamental feature representation in EEG signal analysis.

REFERENCES:

[1] Gannouni, S.,Aledaily, A.,Belwafi, K. *et al.* Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification. *Sci Rep* **11**, 7071 (2021).

[2] Chaddad, A., Wu, Y., Kateb, R., & Bouridane, A. (2023). Electroencephalography Signal Pro cessing: A Comprehensive Review and Analysis of Methods and Techniques. *Sensors (Basel, Switzerland)*, *23*(14), 6434.

[3] Tran Y. EEG Signal Processing for Biomedical Applications. Sensors (Basel). 2022 Dec 13;22(24):9754.

[4] Liu Junxiu, Wu Guopei, Luo Yuling, Qiu Senhui, Yang Su, Li Wei, Bi Yifei. EEG-Based Emotion Classification Using a Deep Neural Network and Sparse Autoencoder. Frontiers in Systems Neuroscience.Volume 14,2020.

[5] Jinru Yang, Xiaofan Huang, Hongkai Wu, Xingtong Yang, EEG-based emotion classification based on Bidirectional Long Short-Term Memory Network, Procedia Computer Science,Volume 174,2020

[6] Mohd Maroof Siddiqui, Geetika Srivastava, Syed Hasan Saeed, Diagnosis of insomnia sleep disorder using short time frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC, Sleep Science, Volume 9, Issue 3, 2016, Pages 186-191.

[7] M. Alsolamy and A. Fattouh, "Emotion estimation from EEG signals during listening to Quran using PSD features," 2016 7th International Conference on Computer Science and Information Technology (CSIT), Amman, Jordan, 2016.

[8] Siuly, S., Li, Y., Zhang, Y. (2016). Significance of EEG Signals in Medical and Health Research. In: EEG Signal Analysis and Classification. Health Information Science. Springer, Cham. 04 January 2017.

[9] Harsh Dabas, Chaitanya Sethi, Chirag Dua, Mohit Dalawat, and Divyashikha Sethia. 2018. Emotion Classification Using EEG Signals. In Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence (CSAI '18).

[10] Jiang Wang, Mei Wang, Review of the emotional feature extraction and classification using EEG signals, Cognitive Robotics, Volume 1, 2021, Pages 29-40, ISSN 2667-2413.

[11] Nandi A, Xhafa F, Subirats L, Fort S. Real-Time Emotion Classification Using EEG Data Stream in E-Learning Contexts. *Sensors*. 2021; 21(5):1589.

[12] H. Ullah, M. Uzair, A. Mahmood, M. Ullah, S. D. Khan and F. A. Cheikh, "Internal Emotion Classification Using EEG Signal With Sparse Discriminative Ensemble," in *IEEE Access*, vol. 7, pp. 40144-40153, 2019.

[13] Md. Mustafizur Rahman, Ajay Krishno Sarkar, Md. Amzad Hossain, Md. Selim Hossain, Md. Rabiul Islam, Md. Biplob Hossain, Julian M.W. Quinn, Mohammad Ali Moni, Recognition of human emotions using EEG signals: A review, Computers in Biology and Medicine, Volume 136, 2021, 104696, ISSN 0010-4825.

[14] Acharya, D. *et al.* (2021). Multi-class Emotion Classification Using EEG Signals. In: Garg, D., Wong, K., Sarangapani, J., Gupta, S.K. (eds) Advanced Computing. IACC 2020. Communications in Computer and Information Science, vol 1367.

[15] Aditi Sakalle, Pradeep Tomar, Harshit Bhardwaj, Asif Iqbal, Maneesha Sakalle, Arpit Bhardwaj, Wubshet Ibrahim, "Genetic Programming-Based Feature Selection for Emotion Classification Using EEG Signal", *Journal of Healthcare Engineering*, vol. 2022, Article ID 8362091, 6 pages, 2022.

[16] Sachin Taran, Varun Bajaj, Emotion recognition from single-channel EEG signals using a two-stage correlation and instantaneous frequency-based filtering method, Computer Methods and Programs in Biomedicine ,Volume 173,2019,Pages 157-165

[17] Rajesh P.N. Rao, Reinhold Scherer, Chapter 10 - Statistical Pattern Recognition and Machine Learning in Brain–Computer Interfaces, Editor(s): Karim G. Oweiss , Statistical Signal Processing for Neuroscience and Neurotechnology, Academic Press,2010, Pages 335-367,ISBN 9780123750273, https://doi.org/10.1016/B978-0-12-375027-3.00010-7.

APPENDIX:

SOURCE CODE

```
clc;
clear;
close all;
load dataset2.mat;
%% preprocessing
data = featuresraw(:,30);
sampling_rate = 256;
low_freq = 1;
high_freq = 70;
order = 5;
[b, a] = butter(order, [low_freq, high_freq] / (sampling_rate / 2), 'bandpass');
filtered_data = filtfilt(b, a, data);
 time = 0:(length(data)-1);
 Snr = snr(data);Snr
 figure;
 subplot(2,1,1);
plot(time,data);
title("Fp1");
Snr=snr(filtered_data);Snr
subplot(2,1,2);
plot(time, filtered_data);
title('Filtered EEG Signal');
%% segmentation
% Assuming preprocessed_data contains EEG data from multiple electrodes (each
column represents a different electrode)
% Define parameters for segmentation
epoch_length = 2; % Length of each epoch in seconds
sampling_rate = 256; % Sampling rate of the EEG data in Hz
samples_per_epoch = epoch_length * sampling_rate;
total_epochs = floor(size(data, 1) / samples_per_epoch);
segmented_epochs = cell(total_epochs, size(data, 2)); % Cell array to store segmented
epochs for each electrode
for i = 1:total_epochs
    start_idx = (i - 1) * samples_per_epoch + 1;
    end_idx = i * samples_per_epoch;

    for j = 1:size(data, 2)
        segmented_epochs{i, j} = data(start_idx:end_idx, j);
    end
end
% Assuming 'segmented_epochs' contains segmented EEG data for each electrode
% Define frequency ranges for each band (adjust as needed)
delta_band = [1, 4];  % Delta band (1-4 Hz)
theta_band = [4, 8];  % Theta band (4-8 Hz)
alpha_band = [8, 13];  % Alpha band (8-13 Hz)
beta_band = [13, 30];  % Beta band (13-30 Hz)
gamma_band = [30, 100];% Gamma band (30-100 Hz)
```

```
% Initialize band power matrix to store band power values for each electrode
num_epochs = size(segmented_epochs, 1); % Number of epochs
num_electrodes = size(segmented_epochs{1}, 2); % Number of electrodes
band_power = zeros(num_epochs, num_electrodes, 5); % 5 columns for 5 frequency
bands
% Iterate through each electrode and compute band powers for each epoch
for electrode = 1:num_electrodes
   for epoch = 1:num_epochs
      epoch_data = segmented_epochs{epoch, electrode}; % EEG data for specific
epoch and electrode
      % Compute PSD for the epoch data
      fs = 256; % Replace with your actual sampling frequency
      [pxx, f] = pwelch(epoch_data, [], [], [], fs);
      % Find indices corresponding to each frequency band
      delta_indices = find(f >= delta_band(1) & f <= delta_band(2));
      theta_indices = find(f >= theta_band(1) & f <= theta_band(2));
      alpha_indices = find(f >= alpha_band(1) & f <= alpha_band(2));
      beta_indices = find(f >= beta_band(1) & f <= beta_band(2));
      gamma_indices = find(f >= gamma_band(1) & f <= gamma_band(2));
      % Calculate power within each frequency band using the PSD
      delta_power = sum(pxx(delta_indices));
      theta_power = sum(pxx(theta_indices));
      alpha_power = sum(pxx(alpha_indices));
      beta_power = sum(pxx(beta_indices));
      gamma_power = sum(pxx(gamma_indices));
      % Store band power values in the band_power matrix
      band_power(epoch,electrode,:) = [delta_power, theta_power, alpha_power,
beta_power, gamma_power];
   end
end
%%
% Assuming 'num_epochs' represents the total number of epochs in your data
% Assign labels to epochs based on the task or condition they represent
% Example: Creating labels for three different tasks (rest, cognitive task, relaxation)
task_labels = {'Rest', 'Cognitive Task', 'Relaxation'};
% Create labels corresponding to each epoch
% Replace this logic with your actual task/condition assignment for each epoch
labels = repelem(task_labels, ceil(num_epochs / numel(task_labels)));
labels = labels(1:num_epochs); % Trim excess labels if needed
% Assume 'band_power' contains band power values and 'labels' contains
corresponding labels
% Reshape band_power matrix for feature organization
[num_epochs, num_electrodes, num_bands] = size(band_power);
% Reshape band_power matrix into a feature matrix (each row represents an epoch,
each column represents a feature)
feature_matrix = reshape(band_power, [num_epochs, num_electrodes * num_bands]);
% Assuming 'labels' contains your class labels (make sure it corresponds to the
epochs)
% Here, 'labels' should have a length of 'num_epochs'
% Organize labels corresponding to each epoch
```

```
label_matrix = repmat(labels(:), 1, num_electrodes * num_bands);
% Now 'feature_matrix' contains band power features for each epoch
% 'label_matrix' contains corresponding labels for each epoch
% Display the sizes of feature_matrix and label_matrix
disp(['Size of feature_matrix: ', num2str(size(feature_matrix))]);
disp(['Size of label_matrix: ', num2str(size(label_matrix))]);
%% another method
% Assuming 'feature_matrix' contains extracted features and 'label_matrix' contains
corresponding labels
% Split the data into training and testing sets (80% for training, 20% for testing)
train_ratio = 0.8;
num_samples = size(feature_matrix, 1);
cv = cvpartition(num_samples, 'HoldOut', 1 - train_ratio);
train_indices = cv.training;
test_indices = cv.test;
% Split the data into training and testing sets
train_features = feature_matrix(train_indices, :);
train_labels = label_matrix(train_indices);
test_features = feature_matrix(test_indices, :);
test_labels = label_matrix(test_indices);
% Train the SVM classifier using fitcecoc (replace this with any other classifier)
svm_model = fitcecoc(train_features, train_labels);
% Predict labels for the test set
predicted_labels = predict(svm_model, test_features);
% Evaluate the accuracy of the classifier
accuracy = sum(strcmp(predicted_labels, test_labels)) / numel(test_labels);
fprintf('Accuracy SVM: %.2f%%\n', accuracy * 100);
%% confusion matrix
% Calculate confusion matrix
confMat = confusionmat(test_labels, predicted_labels);
% Calculate evaluation metrics: accuracy, precision, recall, and F1-score
accuracy = sum(diag(confMat)) / sum(confMat(:));
precision = diag(confMat) ./ sum(confMat, 1)';
recall = diag(confMat) ./ sum(confMat, 2);
f1_score = 2 * (precision .* recall) ./ (precision + recall);
% Display the metrics
fprintf('Accuracy: %.2f%%\n', accuracy * 100);
fprintf('Precision: %.2f\n', mean(precision));
fprintf('Recall: %.2f\n', mean(recall));
fprintf('F1-Score: %.2f\n', mean(f1_score));
%% mean value
% Assuming 'feature_matrix' contains the extracted features after feature extraction
% Calculate the mean value for each feature across all epochs
mean_features = mean(feature_matrix, 1);
% Reshape the mean_features array to organize means by electrodes and bands
[num_epochs, num_features] = size(feature_matrix); % Get the number of features
% Define the number of electrodes and bands used in band_power matrix
num_electrodes = size(band_power, 2);
num_bands = size(band_power, 3);
% Calculate the number of features per electrode and band
```

```
features_per_electrode_band = num_features / (num_electrodes * num_bands);
% Reshape mean_features based on electrodes and bands
mean_features_reshaped = reshape(mean_features, [features_per_electrode_band,
num_electrodes, num_bands]);
% Display the mean values for each electrode and band
disp('Mean values for each electrode and band:');
disp(mean_features_reshaped);
% Calculate the overall mean value for all features
overall_mean = mean(mean_features);
disp(['Overall mean value for all features: ', num2str(overall_mean)]);
```