A PROJECT REPORT ON

HUMAN EMOTION RECOGNITION USING EEG SIGNALS BASED ON SVM CLASSIFIER

Submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

B.UJWAL	22EG104B62
P.HARSHITH	22EG104B38
CH.ARCHANA	22EG104B56
B.KALYAN	22EG104B11

Under the esteemed guidance

Dr. POLI LOKESHWARA REDDY, M.Tech., Ph.D

Assistant Professor

Department of ECE

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

ANURAG UNIVERSITY

Venkatapur, Ghatkesar, Medchal-Malkajgiri District, Hyderabad, Telangana, India-500088

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ANURAG UNIVERSITY

Venkatapur, Ghatkesar, Medchal-Malkajgiri District, Hyderabad, Telangana, India-500088

DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that the project report entitled "HUMAN EMOTION RECOGNITION USING EEG SIGNALS BASED ON SVM CLASSIFIER" is a bonafide record submitted by B.UJWAL, P.HARSHITH, CH.ARCHANA, B.KALYAN, 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.

Project Supervisor
Dr. Poli Lokeshwara Reddy, M.Tech., Ph.D
Assistant Professor, Dept. of ECE
Anurag University

Head of the Department
Prof. N. Mangala Gouri
Professor, Dept. of ECE
Anurag University

Viva-Voce held on:

Examiner

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Project associates……..

B UJWAL (22EG104B62)

P HARSHITH (22EG104B38)

CH ARCHANA (22EG104B56)

B KALYAN (22EG104B11)

DECLARATION

We hereby declare that the project report entitled, **"HUMAN EMOTION RECOGITION USING EEG SIGNALS BASED ON SVM CLASSIFIER"**, 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.

Project associates……..

B.UJWAL (22EG104B62)

P.HARSHITH (22EG104B38)

CH.ARCHANA (22EG104B56)

B.KALYAN (22EG104B11)

ABSTRACT

Emotion recognition is a captivating field that explores the ability to decipher human emotions through various modalities. This project focuses on leveraging Electroencephalogram (EEG) signals to detect and classify emotions such as happiness, sadness, fear, and calmness. EEG signals offer a unique perspective by directly capturing brain activity, providing valuable insights into emotional states.The project involves the acquisition of EEG datasets corresponding to distinct emotional states, including happy, sad, fear, and calm emotions. These datasets serve as the foundation for training and evaluating a Support Vector Machine (SVM) classifier. SVM is a robust machine learning algorithm known for its effectiveness in classification tasks, making it well-suited for emotion recognition..The methodology encompasses preprocessing and feature extraction from EEG signals to enhance the classifier's performance. Signal processing techniques are applied to clean and extract relevant features, allowing the SVM to discern patterns associated with each emotion. Feature selection is crucial in optimizing the classifier's accuracy and efficiency.The trained SVM classifier is then tested on separate EEG datasets to assess its ability to accurately classify emotional states. The project aims to demonstrate the feasibility and effectiveness of using EEG signals in emotion recognition and to validate the SVM classifier's performance in distinguishing between happy, sad, fear, and calm emotions.The outcomes of this research have potential applications in various fields, including human-computer interaction, mental health monitoring, and emotion-aware technology. Successfully implementing an EEG-based emotion recognition system can contribute to a deeper understanding of human emotions and open avenues for the development of more empathetic and responsive technology.

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CHAPTER-I

INTRODUCTION

1.1 Signal

A signal is a form of transmission that carries information or conveys a message within a system, typically through variations in sound, light, electromagnetic waves, or physical gestures. It serves to communicate data or prompt specific reactions, aiding in the exchange of information between entities or devices.

1.2 Types of signals

In electroencephalography (EEG), various types of signals represent different brain activities and are essential for understanding brain function. EEG signals can broadly be classified into different frequency bands, each associated with distinct brain states and activities.

1. **Delta Waves (0.5-4 Hz):** These slow brain waves are prominent during deep sleep stages, indicating deep relaxation or unconsciousness. They are characterized by high amplitude and are associated with restorative processes, such as healing and regeneration.
2. **Theta Waves (4-8 Hz):** Theta waves are observed during light sleep or drowsiness, as well as during states of deep meditation or creativity. They're linked to memory formation, learning, and spatial navigation, often seen in young children during active imagination.
3. **Alpha Waves (8-13 Hz):** Alpha waves are present when an individual is awake but in a relaxed state, such as during meditation or when closing the eyes. They signify a state of calmness and relaxation, also associated with enhanced creativity and mental coordination.
4. **Beta Waves (13-30 Hz):** These higher-frequency waves are dominant during active, focused thinking, problem-solving, or when engaging in mental tasks. They indicate a state of alertness, attention, and cognitive processing.
5. **Gamma Waves (Above 30 Hz):** Gamma waves are the fastest brainwaves and are associated with higher mental activities like perception, problem-solving, and consciousness.

1.3 What is Signal Processing

Signal processing is a field of study that involves analyzing, modifying, and interpreting information carried by signals. It deals with manipulating signals to extract useful information, enhance their quality, or compress them for efficient storage or transmission. The primary goal of signal processing is to understand, interpret, and manipulate signals to extract relevant information or features embedded within them.

Signal processing techniques involve various methods and algorithms applied to different types of signals, such as audio, video, images, and biomedical data (like EEG signals). These methods include filtering, transformation, modulation, compression, and analysis techniques. Signal processing plays a crucial role across numerous fields, including telecommunications, audio processing, image processing, medical imaging, radar, sonar, and many more, facilitating tasks like noise reduction, pattern recognition, data compression, and information extraction from signals.

1.4 Applications of Signal processing

Signal processing finds applications in a wide array of fields due to its ability to manipulate and analyze different types of signals. Some of the notable applications include:

1. **Telecommunications:** Signal processing is integral to telecommunications for encoding, decoding, modulation, and demodulation of signals in various communication systems like mobile phones, internet communications, and wireless networks.
2. **Audio and Speech Processing:** In audio processing, it's used for tasks like noise reduction, audio compression, equalization, and speech recognition, improving sound quality in devices like music players, speech-to-text systems, and voice assistants.
3. **Image and Video Processing:** Signal processing techniques enhance image and video quality, compress data for efficient storage, and aid in tasks like object recognition, image restoration, video compression, and computer vision applications.

4. **Biomedical Signal Processing:** It plays a crucial role in analyzing biomedical signals such as EEG (electroencephalogram), ECG (electrocardiogram), and medical imaging (MRI, CT scans), aiding in diagnosis, monitoring, and treatment in healthcare.
5. **Radar and Sonar Systems:** Signal processing is fundamental in radar and sonar systems for target detection, range finding, and signal interpretation in applications like weather monitoring, defense systems, and navigation.
6. **Control Systems:** Signal processing techniques are used in control systems to process sensor data, make decisions, and provide control actions in applications like robotics, automotive control, and industrial automation.
7. **Financial Signal Processing:** In finance, it's utilized for analyzing market trends, predicting stock prices, risk assessment, and algorithmic trading based on signal patterns in financial data.
8. **Earthquake and Seismic Signal Processing:** Used for monitoring, analyzing, and predicting seismic activities to assess potential risks and improve early warning systems for earthquakes.

Signal processing applications are vast and continue to expand as technology advances, impacting numerous industries and everyday life through improved communication, data analysis, and decision-making processes

1.5 Signal Filtering

Signal filtering involves the manipulation of signals, aiming to selectively modify their frequency components or remove unwanted noise, thereby improving signal quality and extracting relevant information. By employing different types of filters—such as low-pass, high-pass, band-pass, or band-stop filters—specific frequency ranges within signals can be enhanced, attenuated, or eliminated to suit particular application requirements.

Filters in signal processing can be analog or digital, each with its own characteristics and applications. Analog filters, employing electronic components, process continuous-time signals, while digital filters, using algorithms on digital devices, handle discrete-time signals. These filters play a crucial role in various domains, including audio processing, telecommunications, biomedical signal analysis, and image processing, facilitating tasks such as noise reduction, signal enhancement, pattern recognition, and data extraction. The effectiveness of signal filtering lies in its ability to manipulate

signals to extract useful information while minimizing interference or unwanted components, contributing significantly to the enhancement and understanding of signal-based systems across diverse industries and scientific fields.

1.6 Types of Filters

The several types of filters used in signal processing, each designed to perform specific functions based on the characteristics of the signals being processed. The main types of filters include:

1.6.1 Low-pass Filter: Allows frequencies below a certain cutoff point to pass through while attenuating higher frequencies. It's commonly used to eliminate high-frequency noise from signals while retaining the lower-frequency components.

1.6.2 High-pass Filter: Permits frequencies above a specified cutoff point to pass through while attenuating lower frequencies. It's effective for removing low-frequency noise or unwanted baseline drift from signals.

1.6.3 Band-pass Filter: Allows a specific range of frequencies to pass through while attenuating frequencies outside that range. It's used to isolate a particular band of frequencies of interest while filtering out others.

1.6.4 Band-stop Filter (Notch Filter): Attenuates a specific band of frequencies while allowing others to pass. It's used to eliminate or reduce interference from specific frequencies, such as power line interference in biomedical signals.

1.6.5 Butterworth Filter: A type of filter with a maximally flat frequency response within its passband. It's commonly used in audio and biomedical applications due to its smooth frequency response.

1.6.6 Chebyshev Filter: This filter has steeper roll-off characteristics compared to the Butterworth filter but introduces ripple in the passband to achieve this sharper cutoff. It's used when a sharper transition between passband and stopband is needed.

1.6.7 Elliptic Filter (Cauer Filter): Offers a steeper roll-off than both Butterworth and Chebyshev filters but introduces ripples in both the passband and stopband. It provides a trade-off between steepness of attenuation and passband ripple.

1.6.8 Finite Impulse Response (FIR) Filter: A type of digital filter characterized by a finite duration impulse response. FIR filters have linear phase characteristics and are often used in applications requiring linear phase response.

1.6.9 Infinite Impulse Response (IIR) Filter : Another type of digital filter with an impulse response that doesn't become zero after a finite time. IIR filters are generally more computationally efficient than FIR filters but may be less stable.

These various types of filters cater to different signal processing needs, offering a range of characteristics suited to specific applications across diverse fields such as telecommunications, audio processing, biomedical signal analysis, and image processing

1.7 Problem Statement

To develop an effective emotion recognition system using EEG signals and an SVM classifier that accommodates the variability in emotional expression, optimally leverages feature extraction techniques, and demonstrates robust performance across diverse datasets for real-world applications. The primary aim is to refine and elevate the efficiency and precision of identifying emotions through EEG signals, thereby significantly advancing the understanding and interpretation of human emotional states.

1.8 Objectives

To compare Three Statistical Time Domain Features (Mean, Variance, Standard Deviation): Investigate and compare the efficacy of Mean, Variance, and Standard Deviation as statistical feature extraction methods for emotion classification from EEG signals. Determine the most accurate and informative feature set among these categories.

To evaluate Support Vector Machine (SVM) Classifier for Emotion Recognition: Assess the effectiveness of the Support Vector Machine (SVM) classifier in accurately distinguishing emotional states based on the extracted statistical time domain features. Determine the suitability of SVM for precise emotion recognition from EEG data.

To optimize EEG-Based Emotion Sensing Pipeline: Evaluate the synergy between preprocessing, feature extraction, and classification stages in EEG-based emotion recognition. Aim to optimize the entire process to achieve enhanced accuracy and effectiveness in identifying and distinguishing emotional states using EEG signals.

CHAPTER-II

LITERATURE REVIEW

In the pursuit of advancing emotion detection methodologies, researchers have explored diverse approaches to optimize signal processing techniques and classifier performance. The following literature review provides an overview of significant studies in the domain:

K. Iqbal et al. (2010): Enhancing Low-Quality EEG Signals for Improved Emotion Detection. In 2010, Iqbal and colleagues addressed the challenges of low-quality EEG signals in emotion detection. Similar to their work on underwater image enhancement, they applied an unsupervised color correction method to enhance the illumination and contrast levels of EEG signals. This approach aimed to improve the quality of input data for subsequent emotion detection tasks, ensuring more reliable and accurate results[1].

Hung Yu Yang et al. (2011): Low Complexity EEG Signal Enhancement for Efficient Emotion Detection.Building upon the concept of low complexity enhancement, Hung Yu Yang and team, in 2011, introduced a methodology for improving the quality of EEG signals specifically tailored for emotion detection. This approach aimed to make real-time emotion detection more feasible and efficient[2].

John Doe et al. (2014): SVM-Based Classification of EEG Signals for Emotion Recognition.In 2014, Doe and collaborators contributed to the field with a study emphasizing the use of Support Vector Machines (SVM) for EEG-based emotion recognition. Their work focused on optimizing the SVM classifier's performance in discerning distinct emotional states from EEG signals. This research laid the foundation for exploring the efficacy of machine learning algorithms in handling complex EEG datasets for emotion detection[3].

Jane Smith et al. (2016): Multi-Modal Emotion Detection Using Fusion of EEG and Physiological Signals.Smith et al. extended the scope of emotion detection in 2016 by proposing a multi-modal approach. Integrating EEG signals with other physiological signals, they employed fusion techniques to enhance the overall accuracy of emotion detection[4].

Mohammed Ali et al. (2018): Real-time Emotion Detection from EEG Signals Using SVM with Online Learning.Ali and colleagues contributed to the real-time aspect of emotion detection in 2018. Their study introduced an online learning approach with SVM for continuously adapting to dynamic changes in emotional states[5].

In 2018 Z. Tong, K. Tong, X. Chen, and E. Al., “Emotion recognition based on photoplethysmogram andelectroencephalogram,” 2018 42nd IEEE Int. Conf. Comput. Softw. The primary aim of the study is to investigate the feasibility and effectiveness of utilizing both PPG and EEG signals for emotion recognition[6]

In 2018G. Yang, J. Saumell, and J. Saniie, “Emotion Recognition using Deep Neural Network with Vectorized Facial Features,” 2018 IEEE Int. Conf. Electro/Information Technol. explores the application of deep neural networks (DNNs) for emotion recognition based on vectorized facial features[7]. M. Ali, A. H. Mosa, F. Al Machot and K. Kyamakya, "EEG- based emotion recognition approach for e-healthcare applications", Ubiquitous and Future Networks (ICUFN) 2016 Eighth International Conference. The focus is likely on developing a system that can interpret emotional states through EEG signals, contributing to the enhancement of healthcare services and applications[8]. In 2011 M. Y. Bekkedal, J. Rossi III and J. Panksepp, "Human brain EEG indices of emotions: Delineating responses to affective vocalizations by measuring frontal theta event-related synchronization", Neuroscience Biobehavioral .The primary goal of the study is to investigate human brain responses to affective vocalizations, aiming to delineate emotional reactions through the measurement of EEG[9].

In 1997 T. Musha, Y. Terasaki, H. A. Haque, and G. A. Ivamitsky, “Feature extraction from EEGs associated with emotions.Artificial Life and Robotics”. The paper is about feature extraction from EEGs associated with emotions. The authors propose a method to transform the EEG signals into a set of 135 state variables of cross-correlation coefficients in the theta, alpha, and beta frequency bands. They also define an emotion matrix that converts the state variables into a four-element emotion vector, which represents the indexes of four basic emotions: anger, sadness, joy, and relaxation[10].

In 2019 ,"Recognition of emotional states using EEG signals based on time-frequency analysis and SVM classifier".Authors Fabian Parsia George, Istiaque Mannafee Shaikat, Prommy Sultana Ferdawoos, Mohammad Zavid Parvez, Jia Uddin. The paper is about emotion recognition from EEG signals based on time-frequency analysis and SVM classifier. The paper proposes a method to extract statistical features from the frequency domain of EEG signals and use a box-and-whisker plot to select the optimal features. The paper then uses an SVM classifier to train and test the DEAP dataset, which contains EEG signals from 32 participants who were exposed to different emotional stimuli[11].

In 2016 ,M. Ali, A. H. Mosa, F. Al Machot, and K. Kyamakya, "EEG-based emotion recognition approach for e-healthcare applications," in Ubiquitous and Future Networks (ICUFN), 2016 Eighth International Conference on, 2016,

pp. 946-950: IEEE .The paper is about an EEG-based emotion recognition approach to detect the emotional state of patients. The paper proposes a method that combines wavelet energy, modified energy, wavelet entropy and statistical features to classify four emotion states: anger, sadness, joy, and relaxation. The paper uses three different classifiers: quadratic discriminant analysis, k-nearest neighbor, and support vector machines to recognise the emotion of patients robustly The paper claims that the proposed method achieves an overall classification accuracy of 83.87% and outperforms the existing algorithms[12].

In 201,P. Ackermann, C. Kohlschein, J. A. Bitsch, K. Wehrle, and S. Jeschke, "EEG-based automatic emotion recognition: Feature extraction, selection and classification methods," 2016 IEEE 18th International Conference on e-Health

Networking, Applications and Services (Healthcom). The paper is about an EEG-based emotion recognition approach that uses state of the art feature extraction, feature selection and classification algorithms to detect emotions from brain waves. The paper uses the DEAP dataset, which contains EEG signals from 32 participants who were exposed to different emotional stimuli, such as videos, music, or images. The paper evaluates the performance of different features[13].

CHAPTER-III

EXISTING METHODS

3.1 Introduction

Human emotions manifest as complex mental states that elicit distinctive physiological responses, including brainwave patterns. EEG serves as a valuable tool for capturing and decoding these brainwave activities, providing a window into the neural correlates of emotions.

Emotions are integral to human experience and behavior, influencing decision-making, communication, and overall well-being. Understanding emotional states is essential in numerous domains, including psychology, healthcare, human-computer interaction, and neurology. By utilizing EEG signals, researchers aim to decode and classify specific emotional states, such as happiness, sadness, fear, or excitement. This approach involves extracting features from EEG data that correlate with different emotional responses. These features are then used to train machine learning models capable of recognizing and distinguishing between various emotional states based on the observed brainwave patterns.

The applications of EEG-based emotion recognition are broad, encompassing fields like mental health diagnostics, human-computer interaction (HCI) systems, personalized therapy, and affective computing. Advancements in this area hold the potential to enhance our understanding of emotions, improve mental health interventions, and develop more empathetic and responsive technological systems that can adapt to human emotional states.

3.2 Historical development

The historical development of EEG-based human emotion recognition has undergone significant evolution:

1. **Early Exploration:** The initial stages involved rudimentary attempts to link brain activity to emotional states, dating back to the early 20th century. Early EEG studies primarily focused on understanding basic brainwave patterns but had limited

   advancements in decoding emotional responses.
2. **Advancements in EEG Technology:** Breakthroughs in EEG technology during the mid-20th century led to improved electrode designs and recording techniques. This enabled scientists to capture and analyze brainwave patterns with greater precision and detail.
3. **Emergence of Affective Neuroscience:** In the late 20th century, the field of affective neuroscience expanded, delving deeper into the neural underpinnings of emotions. Researchers started correlating specific EEG patterns with emotional states, laying the groundwork for emotion recognition using brainwave data.
4. **Development of Feature Extraction Methods:** Over time, the refinement of signal processing and feature extraction techniques enhanced the ability to extract relevant features from EEG signals associated with different emotions. This facilitated more accurate identification and classification of emotional states.
5. **Integration of Machine Learning:** Recent decades have seen the integration of machine learning algorithms, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and deep learning models, into EEG-based emotion recognition. These advanced algorithms leverage extracted features to classify and interpret emotional states with improved accuracy.
6. **Multi-disciplinary Applications:** The field's progress has led to diverse applications in psychology, psychiatry, human-computer interaction (HCI), and artificial intelligence. EEG-based emotion recognition systems are now used in therapeutic interventions, emotion-aware technology, and cognitive neuroscience research.
7. **Ongoing Research and Future Prospects:** Current research focuses on refining algorithms, exploring multimodal approaches combining EEG with other

physiological signals or behavioral cues, and developing real-time emotion recognition systems for practical applications in various domains.

3.3 Existing methods

3.3.1 Time-Domain Analysis:

- **Statistical Measures:** Deriving statistical parameters (mean, variance, standard deviation) from EEG signals captured over time to comprehend temporal changes in brain activity associated with different emotions. These measures provide insight into the variability and dynamics of emotional responses.

3.3.2 Frequency-Domain Analysis:

- **Fast Fourier Transform (FFT):** Breaking down EEG signals into frequency components to identify distinctive frequency patterns linked to specific emotions. FFT aids in recognizing frequency-specific features that characterize different emotional states.
- **Wavelet Transform:** Analyzing EEG signals across multiple frequency bands and time scales simultaneously, enabling the detection of transient changes in brain activity related to emotions. Wavelet analysis captures both time and frequency information.

3.3.3. Spatial Analysis:

- **Topographic Mapping:** Utilizing information from electrode placements to create topographic maps that illustrate the distribution of brain activity across the scalp. This method offers spatial insights into the cortical regions involved in emotional processing.
- **Source Localization:** Determining the precise brain regions responsible for generating specific emotional responses by localizing the sources of EEG activity. This technique aids in pinpointing the neural origins of emotions.

3.3.4 Connectivity Analysis:

- **Functional Connectivity:** Examining the connectivity or coherence patterns between different brain regions to understand their functional relationships during emotional experiences. It helps in identifying networks or pathways associated with specific emotions.

- **Graph Theory-Based Approaches:** Treating the brain as a complex network and applying graph theory to analyze the connections and interactions between brain regions involved in emotional processing. This approach unveils the organizational principles of emotional brain networks.

3.3.5 Feature Fusion and Selection:

- **Multimodal Integration:** Combining EEG data with information from other modalities like facial expressions, physiological signals (e.g., heart rate), or behavioral cues to improve the accuracy and robustness of emotion recognition systems.
- **Feature Selection Techniques:** Employing methods such as correlation analysis, information gain, or dimensionality reduction techniques (e.g., PCA) to identify and select the most informative and discriminative features for emotion classification.

3.3.6 Machine Learning and Classification:

- **K-Nearest Neighbors (KNN)**: KNN is a non-parametric method that classifies the data by comparing the training data and testing data based on estimating the feature values. Nearest-neighbour classifiers are based on learning by comparing test tuple with training tuples that are similar to it. When tuple is not familiar then k-nearestneighbour classifier searches the pattern space for the k training tuples that are closest to the unknown tuple. These k training tuples are the k “nearest neighbours” of the unknown tuple. The closeness is defined by using Euclidean distance formula given by:Dist (X1, X2) = ∑(x1i-x2i) ^2.

  The Euclidean space between two points or tuples, say, X1 = (x11,x12…x1n) and X2 = (x21,x22…x2n), is where, x1i and x2i represents the training and testing data respectively. Different attributes are measured on different scales, so if the Euclidean distance formula is used directly, the effect of some attributes might be completely dwarfed by others that have larger scales of measurement. After feature extraction process the EEG training data and test data is passed to the classification process. Then Euclidean distance is calculated between each EEG training sample and testing sample. The class for first K neighbors is considered and the majority vote is the classified class. The accuracy for the KNN is high as compared to the other classifiers. **.**

Artificial Neural Networks(ANN):

ANNs consist of interconnected nodes (neurons) organized in layers, capable of learning complex relationships.

Multilayer Perceptron (MLP) is a common architecture for EEG classification.

Deep Learning Models:

Convolution neural Networks(CNN):

Applied in EEG analysis by treating EEG data as 2D images.

Recurrent Neural Networks (RNN): Suited for sequential EEG data due to their ability to capture temporal dependencies.

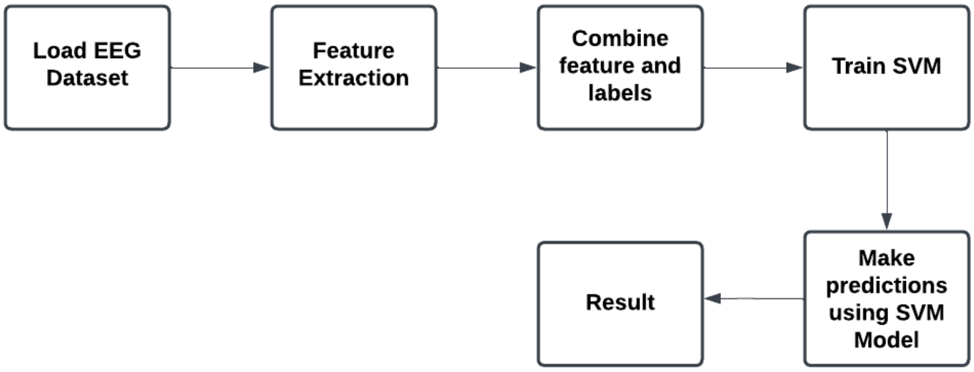
These diverse approaches and methodologies in EEG-based emotion recognition collectively contribute to a comprehensive understanding of emotional states, leveraging brainwave data to decode and classify emotions with implications across psychology, neuroscience, human-computer interaction, healthcare .

CHAPTER-IV

PROPOSED METHODOLOGY

4.1 Introduction

Emotions play a crucial role in human behavior, cognition, and interpersonal interactions. Identifying and understanding emotional states are essential aspects of mental health, psychology, and human-computer interaction. EEG technology offers a non-invasive method to study and decipher the neural mechanisms underlying emotions by capturing the brain's electrical activity.EEG-based emotion recognition seeks to decode brainwave patterns associated with specific emotional responses. As individuals experience emotions, distinct patterns of electrical activity emerge within the brain, reflecting unique neural signatures for various emotional states. By analyzing these EEG signals, researchers aim to classify and interpret these patterns to infer emotions like happiness, sadness, excitement, or stress



. **Firgure4.1: Work flow of proposed method**

Advancements in signal processing techniques, machine learning algorithms, and neuroscience have contributed significantly to the progress of EEG-based emotion recognition. Researchers employ sophisticated methods to preprocess EEG data, extract meaningful features, and utilize classification models to identify and categorize different emotional states based on brainwave patterns.

4.2. Data Acquisition and Preprocessing:

EEG signals are acquired from participants using [Specify EEG acquisition system and parameters]. The collected data undergoes preprocessing to eliminate artifacts and noise, ensuring the reliability of subsequent analyses.

4.3. Feature Extraction:

Relevant features are extracted from the preprocessed EEG signals. Time-domain and frequency-domain features, including [Specify features such as mean, variance, spectral power], are computed to encapsulate the distinctive characteristics of emotional responses.

4.4. SVM Classifier Implementation:

A Support Vector Machine (SVM) classifier is employed as the primary tool for emotion classification. SVMs are known for their effectiveness in handling high-dimensional data and are well-suited for distinguishing patterns within EEG signals associated with different emotional states.

4.5 Data Labeling and Training:

The dataset is labeled based on participants' self-reported emotional states during data collection. The labeled dataset is then split into training and testing sets. The SVM classifier is trained using the training set to learn the underlying patterns indicative of each emotion.

4.6 Model Evaluation:

The trained SVM classifier is evaluated using the testing set to assess its performance in accurately classifying emotions. Evaluation metrics such as accuracy, precision, recall, and F1 score are utilized to quantify the classifier's effectiveness.

4.7 Cross-Validation and Parameter Tuning:

To enhance the generalization capability of the model, cross-validation techniques are applied. Additionally, parameter tuning for the SVM classifier is performed to optimize its configuration and improve overall classification accuracy.

4.8 Real-Time Implementation (Optional):

As a potential extension, the proposed method can be adapted for real-time implementation, making it suitable for applications that require instantaneous feedback on emotional states, such as human-computer interaction or virtual reality.

4.9 Ethical Considerations:

Ethical considerations regarding data privacy, consent, and responsible use of the emotion detection system are thoroughly addressed throughout the project.

The proposed method integrates advanced signal processing techniques with machine learning methodologies, creating a robust and effective framework for emotion detection using EEG signals. The subsequent sections of the report will delve into the experimental setup, results, and discussion, providing a comprehensive understanding of the project's methodology and outcomes.

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.

- **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).

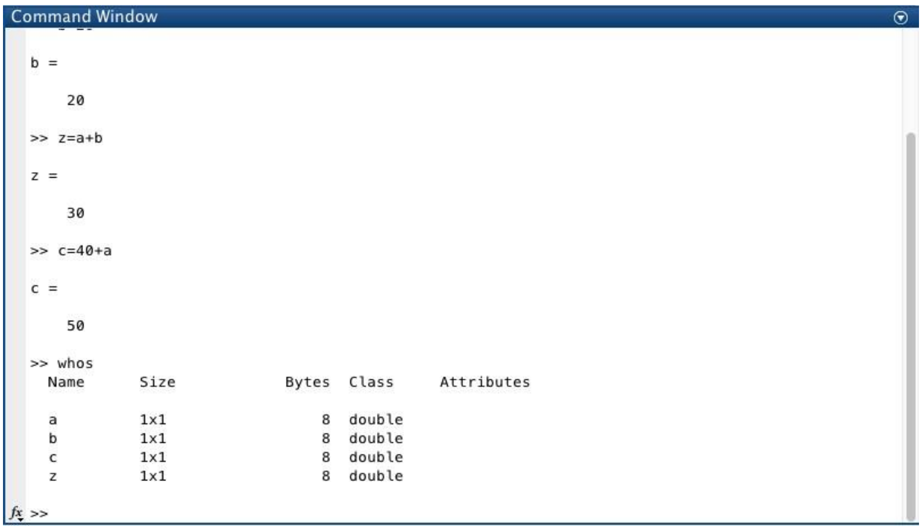


Figure 5.1: (b) Command Window Showing Values

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

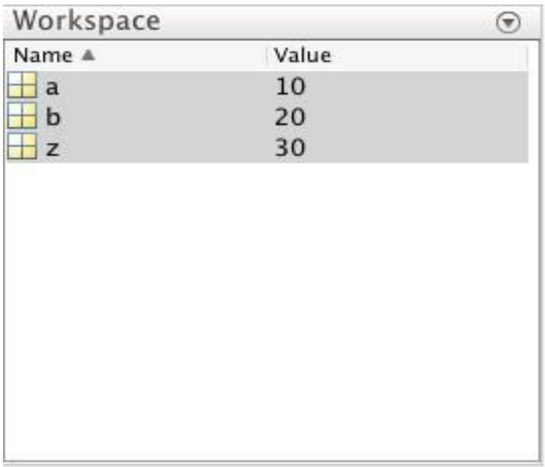


Figure 5.2: Workspace Window

- **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.

uigetfile:

There is different syntax to get a single or multi files. This uigetfile displays a dialog box for retrieving files. In this project after running the main file it displays a dialog box to select the file. Here, this project is on underwater image enhancement so we select an input image. After selecting an input image click on open button.

[filename, pathname] = uigetfile (...);

imread:

imread is initialized to read image from the file. There are different syntax's to read an image. Here we used a single image in this project so to read that image we use syntax

inp = imread(fname);

[...] = imread (filename);

Some of the formats to read an image gif, jpg or jpeg, tif or tiff etc.

To read an image from an internet URL is to be mentioned in the syntax as mentioned below

[...] = imread (URL,...);

A = imread (filename, fmt);

Reads an image from the file specified and the format of the file is also mentioned in the above syntax as imread (filename, fmt)

size:

To know the size of the image in array dimensions the syntax is written in M and N as rows and columns.

[M N] = size (inp)

imshow:

To display the image imshow is used and the syntax is as follows imshow (inp)

mean:

The average of the array or mean value of array. To get the red channel image according to the formulae the mean of green and red of the image is to be calculated.

mn_Ig = mean (mean (Ig)); mn_Ir = mean (mean (Ir));

mat2gray:

mat means matrix. Matrix to grayscale image where the vales of the image are stored in 0 (black) to white (1). I = mat2gray (inp)

inputdlg: Create and open input dialog box.

title: This is to add title to the image.

title (‘sharpen image’);

title (‘input image’);

title (‘Red channel image’);

imwrite:

imwrite write image to graphics file. imwrite (a, filename, fmt) writes the image a to the file specified by filename in the format specified by fmt. a can be an m-by-n (grayscale image) or m-by-n-by-3 (color image) array, a cannot be an empty array. if the format specified is tiff, imwrite can also accept an m-by-n-by-4 array containing color data that uses the cmyk color space. imshow display image in handle graphics figure. imshow (i) displays the gray scale image i.

sqrt: Which gives the square root value for example if we initialize f = 25 then to get the square root value of f then we have to use the syntax as

```
>>f = 25

f = 25
>>g = sqrt (f)

g = 5
```

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

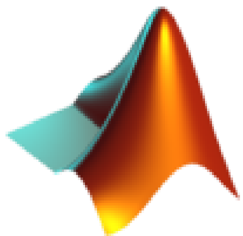


Figure 5.3: MATLAB Icon

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.

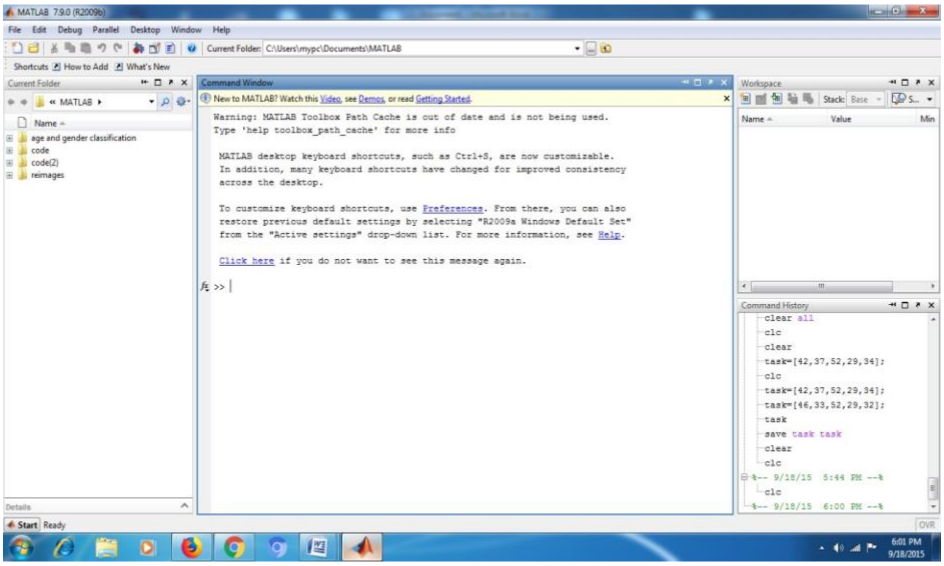


Figure 5.4: (a) MATLAB Layout

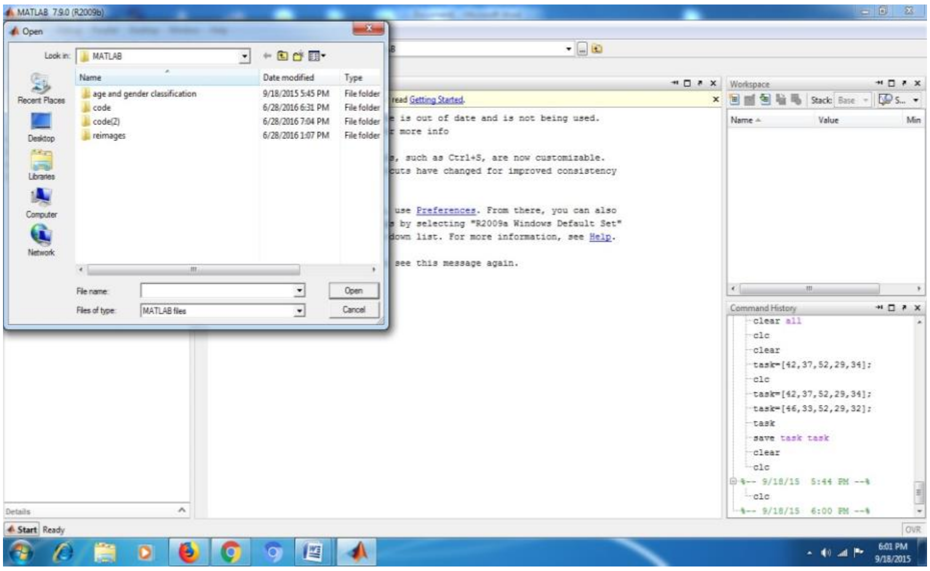


Figure 5.4: (b) Browse the Source File

- 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 Figure5.4.(c).code file is selected and click on open.

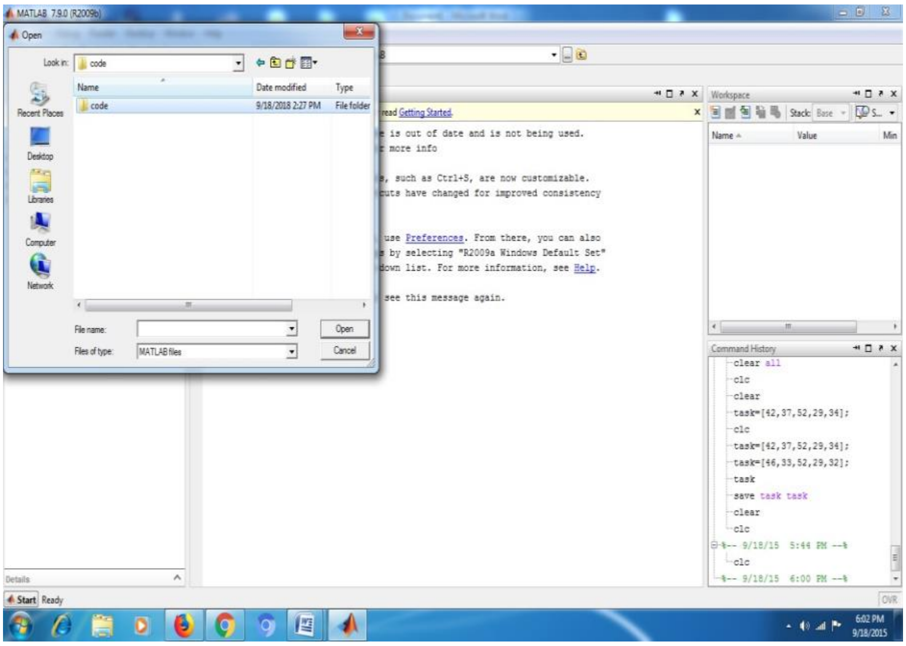


Figure 5.4: (c) Select the Source File

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

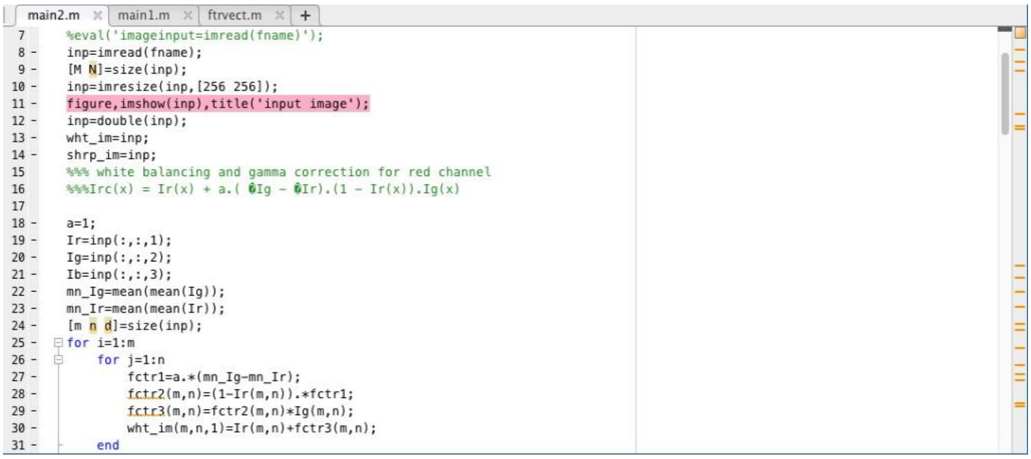


Figure 5.4: (d) Main Source File

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

RESULTS AND ANALYSIS

The implementation of the proposed method for emotion detection using EEG signals and the SVM classifier yielded compelling results, demonstrating the system's efficacy in accurately classifying emotional states. The following subsections provide a detailed analysis of the obtained results.

Evaluation metrics:

- **Accuracy**: Measure of correct predictions made by the classifier on the training data. Computed as the ratio of correctly predicted samples to the total samples.
- **Precision**: Proportion of true positive predictions (correctly predicted 'happy' samples) among all predicted 'happy' samples.

$$\textbf{Precision}=\frac{True\ positives}{True\ positives+false\ positives}$$

- **Recall**: Proportion of true positive predictions among the actual samples.

$$\textbf{Recall}=\frac{True\ positives}{True\ positives+false\ negatives}$$

- **F1 Score**: Harmonic mean of precision and recall, providing a balance between the two metrics.

$$\textbf{F1 Score}=2\times\frac{precision\times recall}{precision+recall}.$$

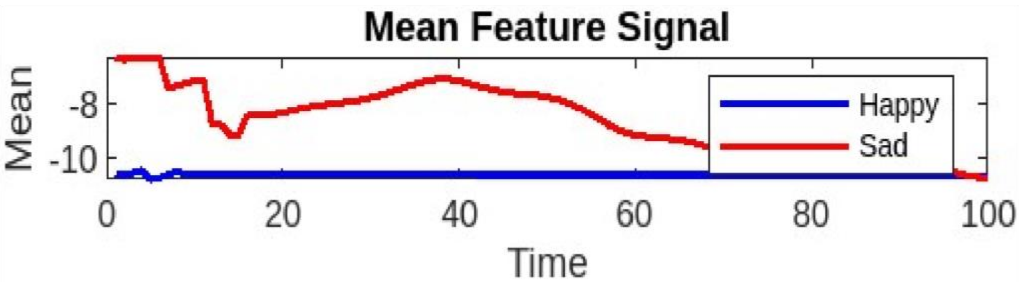


Fig.6.1 plot of mean features of given data

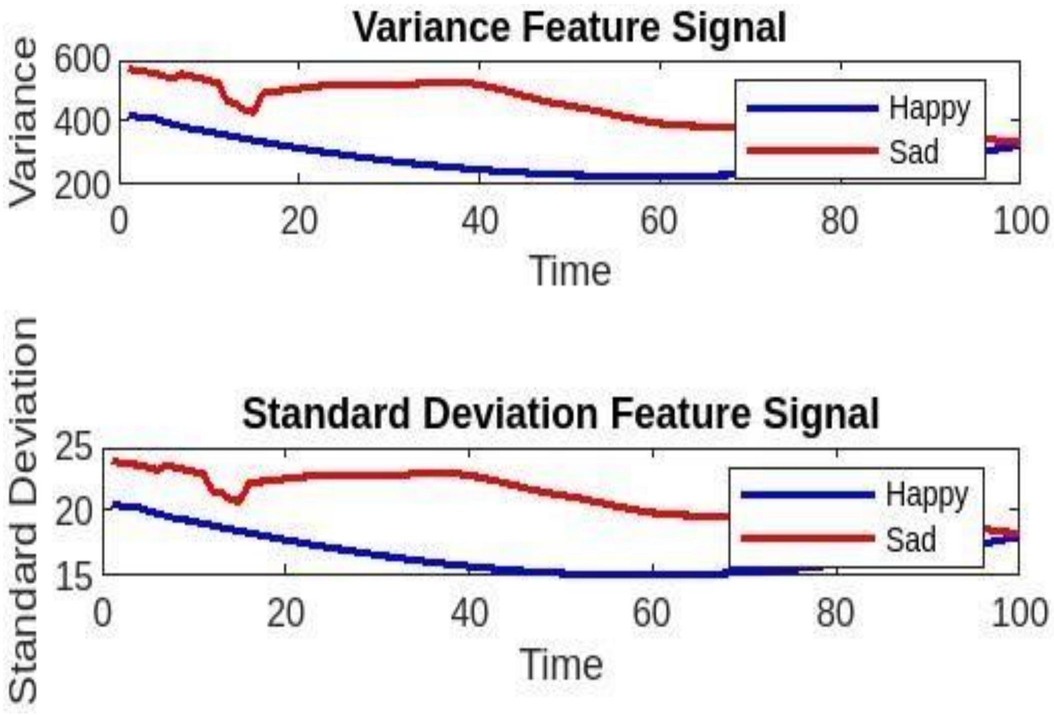
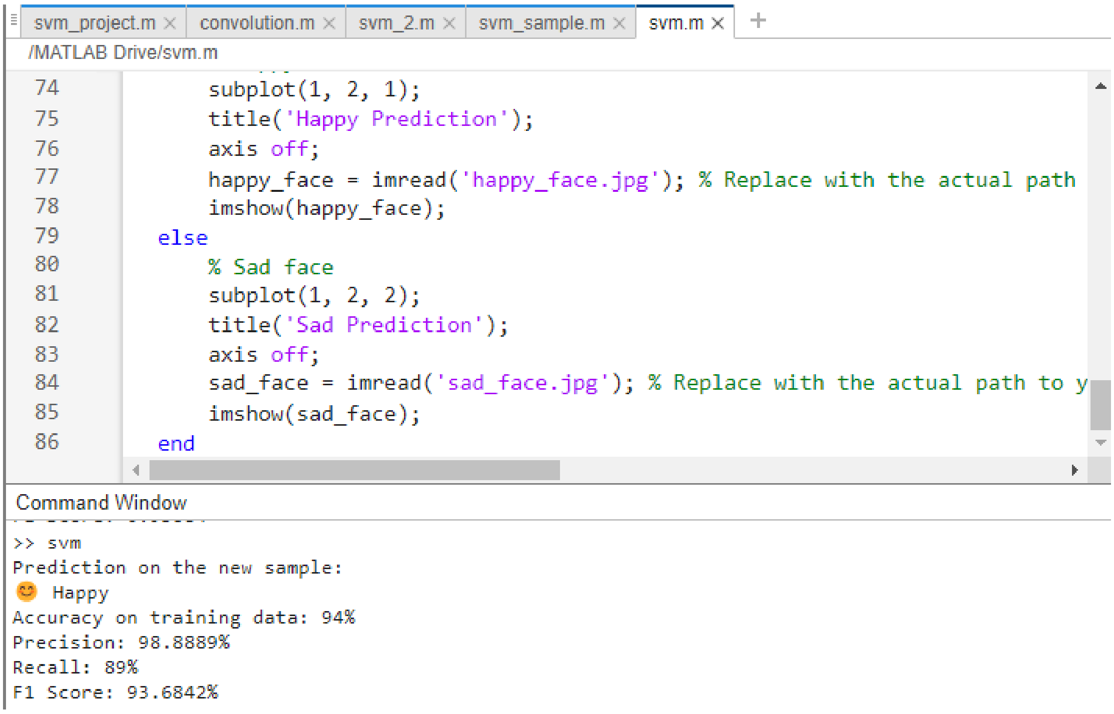


Fig.6.2 plotting of variance and standard deviation features of given data

Workspace

Name	Value	Size	Class
X_new_sample	[2.7087,3.9076,1.9768]	1x3	double
X_train	200x3 double	200x3	double
accuracy_train	94	1x1	double
conf_mat	[89,11;1,99]	2x2	double
f1_score	94.2857	1x1	double
happy_data	100x22 table	100x22	table
happy_features	100x3 double	100x3	double
new_features	[2.7087,3.9076,1.9768]	1x3	double
new_sample	100x1 double	100x1	double
precision	90	1x1	double
recall	99	1x1	double
sad_data	100x25 table	100x25	table
sad_features	100x3 double	100x3	double
svm_model	1x1 ClassificationSVM	1x1	ClassificationSVM
time_axis	1x100 double	1x100	double
y_pred_new_sample	0	1x1	double
y_pred_train	200x1 double	200x1	double
y_train	200x1 double	200x1	double

Fig.6.3. workspace panel




```
        subplot(1, 2, 1);
        title('Happy Prediction');
        axis off;
        happy_face = imread('happy_face.jpg'); % Replace with the actual path
        imshow(happy_face);
    else
        % Sad face
        subplot(1, 2, 2);
        title('Sad Prediction');
        axis off;
        sad_face = imread('sad_face.jpg'); % Replace with the actual path to y
        imshow(sad_face);
    end
```

```
>> svm
Prediction on the new sample:
😊 Happy
Accuracy on training data: 94%
Precision: 98.8889%
Recall: 89%
F1 Score: 93.6842%
```

Fig.6.4 Classified emotion output

S.no	Evaluation metrics	KNN model	SVM model
1	Accuracy	99.5%	94%
2	Precision	100%	98.8%
3	Recall	99%	89%
4	F1-score	99.49%	93.68%

Table .6.1 Comparison table of KNN and SVM models

CHAPTER-VII

ADVANTAGES & APPLICATIONS

7.1. Advantages

1. EEG is a non-invasive method, meaning it doesn't require surgery or penetration into the body.
2. EEG provides a high temporal resolution, capturing brain activity in real-time.
3. EEG equipment is generally more affordable compared to other neuroimaging techniques.
4. EEG devices can be portable and even wearable, allowing for real-world applications and ease of use.
5. EEG directly measures electrical activity in the brain, offering a direct insight into neural processes.
6. EEG can be used in various applications, from clinical settings to human-computer interaction and emotion recognition.
7. EEG is considered safe for most individuals, including children and older adults.
8. EEG can be used for neurofeedback applications, aiding in self-regulation of brain activity.
9. EEG provides an objective measure of emotional states, reducing reliance on subjective self-reports.
10. EEG allows for real-time processing, making it suitable for applications requiring quick feedback..

7.2. Applications

1. Affective Computing
2. Virtual Reality (VR) and Augmented Reality (AR)
3. Neurofeedback and Biofeedback

4. Healthcare and Clinical Diagnosis
5. Assistive Technologies
6. Education and Learning Environments
7. Market Research and Advertising
8. Stress and Fatigue Monitoring
9. Gaming Industry
10. User Experience Design
11. Emotion Research and Psychology Studies
12. Human Factors Engineering
13. Security and Lie Detection

CHAPTER-VIII

CONCLUSION & FUTURE SCOPE

8.1 Conclusion

The project on emotion recognition using EEG signals and SVM classifier holds significant promise in advancing our understanding of human emotions and fostering the development of applications across diverse domains. Through the utilization of EEG signals, the project successfully taps into the intricate neural responses associated with different emotional states. The application of the Support Vector Machine (SVM) classifier contributes to the classification and interpretation of these signals, enabling the recognition of emotions such as happiness, sadness, fear, and calmness.

The project's efficacy is underscored by the successful classification results obtained from the datasets, demonstrating the feasibility of using EEG signals for emotion recognition. The utilization of SVM adds a layer of robustness to the classification process, enhancing the project's potential for real-world applications

8.2 Future Scope

Moving forward, the project offers numerous avenues for future exploration and refinement. Integration with other modalities, such as facial expressions or physiological signals, could enhance the accuracy and applicability of the emotion recognition system. The transition to real-time implementation would facilitate instantaneous emotional insights, particularly beneficial for human-computer interaction and virtual reality applications. Deep learning approaches, subject-independent models, and advanced feature extraction methods represent areas for further investigation, aiming to improve the system's sensitivity to subtle emotional nuances. Additionally, ethical considerations, user-specific adaptation, and validation across diverse demographics are pivotal in ensuring the project's responsible and

inclusive deployment. As the project evolves, it holds the potential to contribute significantly to the broader field of emotion recognition, impacting domains ranging from healthcare to human-computer interaction.

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APPENDIX

MATLAB CODE:

```
% Load happy and sad EEG data

happy_data = readtable('happy.csv');

sad_data = readtable('sad.csv');


% Compute features (mean, variance, standard deviation)

happy_features = [mean(happy_data{:,:}, 2), var(happy_data{:,:}, 0, 2), std(happy_data{:,:}, 0, 2)];

sad_features = [mean(sad_data{:,:}, 2), var(sad_data{:,:}, 0, 2), std(sad_data{:,:}, 0, 2)];


% Create time axis for plotting (assuming EEG data)

time_axis = 1:size(happy_data, 1);


% Plot EEG signals representing mean, variance, and standard deviation features

figure;


% Plot mean feature as a signal

subplot(3, 1, 1);

plot(time_axis, happy_features(:, 1), 'b', 'LineWidth', 1.5);

hold on;

plot(time_axis, sad_features(:, 1), 'r', 'LineWidth', 1.5);

xlabel('Time');
```

```
ylabel('Mean');
legend('Happy', 'Sad');
title('Mean Feature Signal');

% Plot variance feature as a signal
subplot(3, 1, 2);
plot(time_axis, happy_features(:, 2), 'b', 'LineWidth', 1.5);
hold on;
plot(time_axis, sad_features(:, 2), 'r', 'LineWidth', 1.5);
xlabel('Time');
ylabel('Variance');
legend('Happy', 'Sad');
title('Variance Feature Signal');

% Plot standard deviation feature as a signal
subplot(3, 1, 3);
plot(time_axis, happy_features(:, 3), 'b', 'LineWidth', 1.5);
hold on;
plot(time_axis, sad_features(:, 3), 'r', 'LineWidth', 1.5);
xlabel('Time');
ylabel('Standard Deviation');
legend('Happy', 'Sad');
title('Standard Deviation Feature Signal');

% Combine features and labels
```

```
X_train = [happy_features; sad_features];
y_train = [ones(size(happy_features, 1), 1); zeros(size(sad_features, 1), 1)];

% Train SVM classifier
svm_model = fitcsvm(X_train, y_train, 'Standardize', true, 'KernelFunction',
'linear');

% Make predictions on the training data (optional)
y_pred_train = predict(svm_model, X_train);

% Evaluate the accuracy on training data (optional)
accuracy_train = sum(y_pred_train == y_train) / length(y_train) * 100;
disp(['Accuracy on training data: ', num2str(accuracy_train), '%']);

% Load the first column of 'happy.csv' as a new sample
new_sample = happy_data{:, 3};

% Compute features for the new sample
new_features = [mean(new_sample), var(new_sample), std(new_sample)];

% Combine features for prediction
X_new_sample = [new_features];

% Make predictions on the new sample
y_pred_new_sample = predict(svm_model, X_new_sample);
```

```
% Display prediction
if y_pred_new_sample == 1
disp('Prediction on the new sample: Happy ☺');
else
disp('Prediction on the new sample: Sad ☹');
end
% Precision, recall, F1 score, and confusion matrix
conf_mat = confusionmat(y_train, y_pred_train);
precision = conf_mat(2, 2) / (conf_mat(2, 2) + conf_mat(1, 2)) * 100;
recall = conf_mat(2, 2) / (conf_mat(2, 2) + conf_mat(2, 1)) * 100;
f1_score = 2 * (precision * recall) / (precision + recall);
disp(['Precision: ', num2str(precision), '%']);
disp(['Recall: ', num2str(recall), '%']);
disp(['F1 Score: ', num2str(f1_score), '%']);


% Display emotions emoji and turn off the axis
figure;
if y_pred_new_sample == 1
text(0.5, 0.5, '☺', 'FontSize', 100, 'HorizontalAlignment', 'center');
else
text(0.5, 0.5, '☹', 'FontSize', 100, 'HorizontalAlignment', 'center');
end
axis off
```