

EEG and BIOPAC Integration for Emotion Recognition

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Technology degree in Biomedical Engineering

by

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DEPARTMENT OF BIOMEDICAL ENGINEERING

SCHOOL OF BIO AND CHEMICAL ENGINEERING

SATHYABAMA

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

Accredited with Grade "A++" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Sushmitha S (40240041)** and **Angelin Winslet C (40240003)** who have done the project work as a team and carried out the project entitled "**EEG and BIOPAC Integration for Emotion Recognition**" under our supervision from June 2023 to April 2024.

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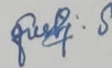
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ABSTRACT

This study presents a comprehensive methodology for analyzing emotional states based on EEG recordings. The data acquisition phase involves setting up the Biopac system and electrode placement to record physiological signals while participants are exposed to videos designed to evoke specific emotional responses. Preprocessing includes filtering to reduce noise interference, followed by feature extraction using various statistical measures such as mean, median, and standard deviation. These features aid in identifying discriminative properties of EEG signals associated with different emotions. Classification using machine learning in MATLAB ensures high accuracy, with superior models transferred to Python for inference. This integration enables the determination of emotional states corresponding to EEG signals, facilitating targeted emotional insights extraction. The structured approach from data acquisition to emotion classification leverages advanced signal processing and machine learning techniques, ensuring robustness and reliability in emotional state analysis.

Keywords: EEG, BIOPAC, Emotion recognition, Machine learning, MATLAB.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
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ANN	Artificial Neural Network
ACRNN	Attention-based Convolutional Recurrent Neural Network
Adaboost	Adaptive Boosting
BIOPAC	Biological Parameters Acquisition
BSL	BIOPAC Student Lab
BVP	Blood Volume Pulse
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
DDE	Dynamic Differential Entropy
DEAP	Dataset for Emotion Analysis using Physiological Signals
DECNN	Dynamic Empirical Convolutional Neural Network
ECG	Electrocardiogram
EDA	Exploratory Data Analysis
EEG	Electroencephalography
EMD	Empirical Mode Decomposition
EMG	Electromyography
EmotionDL	Emotion-aware Distribution Learning
ERP	Event-Related Potential
FBSE	Fourier-Bessel Series Expansion
FC	Functional Connectivity
FD	Fractal Dimension
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy

GBDT	Gradient Boost Decision Trees
GSR	Galvanic Skin Response
ICA	Independent Component Analysis
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LSTM	Long Short-Term Memory
MATLAB	Matrix Laboratory
MEG	Magnetoencephalography
MEMD	Multivariate Empirical Mode Decomposition
NB	Naïve bayes
NodeDAT	Node-wise Domain Adversarial Training
RBF	Radial Basis Function
RGNN	Regularized Graph Neural Network
RNN	Recurrent Neural Networks
SEED	SJTU Emotion EEG Dataset
sLORETA	Standardized Low-Resolution Electromagnetic Tomographic Analysis
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
WMD-DTW	Weighted Multidimensional Dynamic Time Warping
XGBoost	Extreme Gradient Boosting

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CHAPTER-1

INTRODUCTION

1.1 HUMAN EMOTIONS:

Emotions play a pivotal role in healthcare across various dimensions. Firstly, they significantly impact patient well-being and the healing process. Positive emotions like hope and optimism can bolster the immune system and aid in recovery, while negative emotions such as stress and anxiety may hinder healing and lead to complications. Anxiety and fear can exacerbate pain, while positive emotions and emotional support can alleviate pain perception, particularly in the context of chronic pain. Mental health care relies heavily on the understanding and management of emotions. Recognizing and addressing emotional issues like depression and anxiety is essential for effective mental health treatment. Effective communication in healthcare relies on recognizing that emotions can affect a patient's understanding and acceptance of medical information.

1.2 EEG:

Electroencephalography (EEG) is a non-invasive neuroimaging technique that records electrical activity in the brain through electrodes placed on the scalp. It's used to diagnose neurological disorders, study brain function, and monitor brain activity during tasks or sleep. EEG measures brain waves, helping researchers and healthcare professionals understand brain activity patterns. It involves placing scalp electrodes to detect electrical signals generated by neurons. These electrodes capture brain waves, providing valuable insights into brain function, diagnosing neurological conditions, and researching cognitive processes, making it a widely-used tool in neuroscience and clinical practice.

1.3 EMOTION RECOGNITION:

Emotion recognition, a growing field at the intersection of technology and psychology, focuses on the ability to identify and understand human emotions. It involves using various technologies such as facial recognition, voice analysis, and even brain activity monitoring to gauge emotional states. Emotion recognition has diverse applications, from enhancing human-computer interactions and virtual assistants to improving mental health diagnostics and treatment. It plays a crucial role in personalized marketing, healthcare, and education,

enabling more empathetic and responsive systems. As this field advances, it holds great promise for revolutionizing how we understand and interact with human emotions, with potential benefits spanning a wide range of industries and domains.

1.3.1 *RELATIONSHIP BETWEEN BIOPAC AND EEG:*

EEG (Electroencephalography) and BIOPAC systems work together seamlessly in emotion recognition. EEG involves the placement of electrodes on a person's scalp to record electrical brain activity, capturing neural responses associated with emotional states. BIOPAC systems serve as the hardware and software interface for data collection and analysis. These systems ensure the accurate acquisition of EEG signals, providing high-quality data for emotion recognition. The collected EEG data is then processed and analyzed using specialized software, which identifies distinct brain activity patterns linked to specific emotions. By integrating EEG with BIOPAC systems, researchers can more effectively detect and recognize real-time emotional responses. This collaboration between EEG and BIOPAC is crucial in fields like psychology and neuroscience, enabling a deeper understanding of human emotions and their applications in various domains, including healthcare, human-computer interaction, and mental health assessment.

CHAPTER-2

LITERATURE SURVEY

Xiangkun Yu et al. (2023) in this study, addressed real-time EEG emotion recognition by optimizing short time windows (≤ 3 seconds) with a 50-80% sliding step to capture fleeting emotions. Additive attention weighted relevant emotional data, particularly at the window's end, enhancing information extraction. The model combined EEG spatial, temporal, and frequency features, using LSTM for channel relationships and STFT for feature extraction. Achieving 85.40% and 74.26% accuracy on SEED and SEED-IV datasets, respectively, showed promising real-time performance.

Barjinder Kaur et al. (2018) presented an EEG-based emotion classification method, distinguishing between calmness, anger, and happiness. The study involved real-time experiments with ten participants exposed to emotion-inducing videos while recording EEG signals. The Higuchi technique was used to extract the fractal dimension (FD) feature from the EEG data. SVM classification achieved 60% accuracy with the RBF kernel, with happiness showing the most accurate brain activity classification.

Rupak Kumar Das et al. (2023) present 15 independent software modules for EEG signal analysis, including 7 MATLAB plugins and 31 EEGLAB. These modules serve as valuable tools for comparing EEG signal processing methods and guiding new researchers with use cases, definitions, and references. Researchers can select software based on hardware, data analysis needs, and programming proficiency. This paper offers a useful guide for EEG researchers to choose suitable software modules.

Chaofei Yu et al. (2022) proposed an adaptable EEG-based emotion recognition method, focusing on non-stationary and nonlinear EEG signals. It incorporates time-domain and nonlinear feature extraction techniques, favoring wavelet transform for non-stationary signals. Machine learning and deep learning, including SVMs, CNNs, RNNs, and LSTM networks, classify emotions. Datasets like DEAP, SEED-IV, and DREAMER are commonly used, and Python, TensorFlow, and MATLAB facilitate data processing. This evolving methodology aims to enhance accuracy and robustness in EEG-based emotion recognition].

Doma Vikrant et al. (2020) employed classic machine learning techniques like SVM, Naive Bayes, Decision Trees, Logistic Regression, KNN, and LDA to explore the neurophysiological mechanisms of emotions. These methods achieved accuracy rates from 55% to 75% and F1 scores from 70 to 86%. While KNN excelled in classifying "Liking," channel data from the back left hemisphere, segmented into 15-second intervals, improved accuracy. These findings demonstrate the suitability of traditional machine learning algorithms for emotional state identification.

Chunmei Qing et al. (2021) introduced a novel coefficients-based machine learning approach using EEG signals to better understand emotion activation mechanisms. It outperformed benchmark algorithms in accuracy and revealed insights into the temporal progression of emotion activation. The latter part of EEG signals showed stronger emotion correlation, and constructing correlation and entropy curves unveiled a progressive emotion activation pattern. Weight coefficients derived from these findings enhanced classification accuracy, supporting the theory of progressive emotion activation.

Liu et al. (2021) advocated for temporal brain networks to study dynamic functional connectivity (FC) in emotional states. SEED dataset was used, initially calculating multiband static networks with PLI. Discriminative connections for positive, neutral, and negative emotions were identified. The beta band yielded the highest accuracy (87.03%) in emotion recognition. Frontal and temporal lobes were key to emotion-related brain activity, and dynamic FC exhibited a small-world structure, particularly distinguishing positive emotions. These findings highlight dynamic FC's potential in exploring emotion-related brain function.

Seong-Eun Moon et al. (2020) developed a novel approach to EEG-based emotional video classification using Convolutional Neural Networks (CNNs). This method integrated brain connectivity into CNNs and demonstrated its effectiveness in recognizing user states. The study introduces data-driven techniques to enhance connectivity matrix construction, showing a correlation between emotional property-related brain connectivity and classification performance. This approach has potential applications in diverse emotional state classification tasks, and future work may explore its applicability in other brain imaging modalities like fMRI, MEG, and fNIRS.

Nalwaya A et al. (2022) in this research, explored emotion recognition using ECG and

EEG signals. Innovative entropy-based features in the Fourier-Bessel domain were introduced, offering improved frequency resolution for non-stationary signals. By employing Fourier-Bessel series expansion and the FBSE-based empirical wavelet transform, they decomposed the signals into narrow-band modes. Utilizing these features, their proposed algorithm achieved high accuracy (97.84%, 97.91%, and 97.86%) for arousal, valence, and dominance in the DREAMER dataset, demonstrating the effectiveness of entropy-based features in physiological signal-based emotion recognition.

Sharma R et al. (2020) developed a real-time emotion recognition system using EEG signals, which reflect emotional state changes. They employed a combination of nonlinear higher-order statistics and deep learning techniques, decomposing EEG signals into sub-bands through the discrete wavelet transform. To enhance accuracy, they utilized third-order cumulants and particle swarm optimization. The results, with an 82.01% average classification accuracy on the DEAP dataset, highlight the algorithm's potential for precise and rapid emotion recognition.

Jin L et al. (2020) introduced a novel approach for cross-subject emotion prediction using EEG data. The time-series analysis and spatial correlation to account for subject-specific variations in emotion recognition were combined. By defining channel-wise features through a symmetric matrix based on Pearson correlation coefficients, the spatial connections between brain regions were captured. These features were then fed into a two-layer stacked LSTM network, showcasing state-of-the-art classification rates on DEAP and SEED datasets: 98.93% and 99.10% for valence and arousal in DEAP, and 99.63% for three-class classification in SEED.

Stanisław Saganowski et al. (2022) collected data from 43 participants exposed to nine films designed to elicit specific emotions, capturing physiological responses and facial expressions. The dataset includes EEG, EDA and self-reports. It's suitable for exploring emotion recognition techniques, including multimodal approaches, comparing EEG and cardiovascular signals, discrete vs. dimensional emotion representations, and assessing wearables' effectiveness in BVP signal collection. The dataset is validated for inducing intended emotional states, enabling research on various emotion recognition aspects.

Joy et al. (2021) explored various machine learning methods for real-time emotion

recognition using physiological signals like EEG, ECG, and GSR. The study covered data collection, processing, and feature extraction, with high accuracy across approaches, often using the DEAP dataset. Key methods included Support Vector Machines (SVM) and various datasets like SJTU Emotion EEG and SEED datasets. Approaches included Weighted Multidimensional Dynamic Time Warping (WMD-DTW), decision trees, K-nearest neighbors (K-NN), and random forests. These methods exhibited commendable accuracy in emotion classification.

Guijun Chen et al. (2020) analyzed emotion-based reconstructed EEG sources and identified 26 specific Brodmann areas as regions of interest. They used these regions, along with various time- and frequency-domain data, to classify emotional states with support vector machines. Testing on the DEAP and TYUT 2.0 EEG-based datasets showed that features extracted from the selected source regions significantly improved emotion classification accuracy, emphasizing distinctions in active source regions and frequency bands. The study aimed to investigate these differences in emotion-related EEG signals using sLORETA.

Moon Inder Singh et al. (2021) categorized emotions into four distinct classes based on their positions on the arousal-valence plane, using ERP properties from the frontal region of 24 participants. They achieved an overall accuracy of 85%, surpassing previous ERP studies, highlighting the effectiveness of average ERP parameters in four-class classification. However, the one-versus-all classification technique, involving six classifiers, may affect overall accuracy.

Gisela Pinto et al. (2020) constructed a physiological model of emotions using electrodermal activity, ECG, and EMG data. They found that while ECG was the most informative for emotion classification, optimal performance occurred when all signals were integrated. The study emphasized the relevance of physiological signals in understanding and intervening in emotional processing, particularly when applied to fear, happiness, and neutral contexts. Monitoring multiple facial muscles proved essential for accurate emotion detection.

Lin Shu et al. (2020) demonstrated that a wearable smart wristband can collect heart rate data for emotion identification. Participants viewed videos designed to elicit neutral,

happy, and sad emotions, with heart rate data collected. Features extracted from heart rate data standardized against neutral states, and Adaboost and GBDT classifiers were applied. This approach holds potential for wearable technology to accurately monitor and assess emotional states, especially in static or nearly static scenarios.

Wei-Long Zheng et al. (2018) introduced the EmotionMeter, a framework for emotion recognition that combines eye and brain activity. The six electrodes above the ears to capture EEG signals were utilized, enhancing practicality and wearability. The fusion of EEG data and eye movement information using deep neural networks significantly improved performance, achieving a mean accuracy of 85.11% in recognizing happiness, sadness, fear, and neutrality, emphasizing the complementary nature of EEG and eye movements in representing emotional states and cognitive processes.

Peixiang Zhong et al. (2020) introduced the Regularized Graph Neural Network (RGNN) for capturing local and global relationships among EEG channels, inspired by the human brain's architecture. RGNN employs an adjacency matrix within a graph neural network. It also incorporates two regularization techniques: node-wise domain adversarial training (NodeDAT) and emotion-aware distribution learning (EmotionDL). Extensive testing on SEED and SEED-IV datasets demonstrated RGNN's superior performance compared to existing models, highlighting the effectiveness of the adjacency matrix and regularization techniques.

Md. Rabiul Islam et al. (2021) conducted a comprehensive review of emotion recognition systems, categorizing studies into deep learning and shallow machine learning approaches. The techniques, classifiers, recognized emotions, accuracy rates, and datasets were analyzed. The review provides educational insights and outlines future research directions, offering a comprehensive overview of features, feature extraction methods, system performance metrics, and algorithms in emotion recognition.

Shuaiqi Liu et al. (2020) introduced the Dynamic Empirical Convolutional Neural Network (DECNN) for emotion recognition, employing EMD and DDE to extract EEG features. The study used SEED and SJTU Emotion EEG Dataset, optimizing electrode placement for efficiency. The algorithm achieved a 3.53% accuracy improvement over state-of-the-art techniques, contributing to the design of wearable EEG devices.

Sricheta Parui et al. (2019) enhanced human emotion categorization precision through EEG signal features optimization using the XGBoost algorithm. This improved accuracy and outperformed other methods like Naive Bayes, KNN, C4.5, Decision Tree, and Random Forest when tested on the DEAP dataset.

Xie Weilun and Xue Wanli (2021) stated that the K-nearest neighbor (KNN) method, commonly used for emotion recognition based on physiological signals, has limitations in handling complex class distributions and boundary issues. This paper introduces an improved algorithm called WB-KNN. It uses a novel weighting method to improve voting accuracy, incorporates feature weighting in distance calculations, and employs a voting classifier to address class boundary challenges. The results show promising accuracy of 94.22% for recognizing four emotions in physiological data with skewed class distribution.

Wei Tao et al. (2020) introduces ACRNN, an end-to-end deep learning method for EEG emotion recognition. ACRNN considers spatial, temporal, and attentive aspects of EEG signals, using channel-wise attention for spatial features and extended self-attention for sample importance. It achieved high accuracies in valence, arousal, and dominance classification tasks in DEAP and DREAMER databases, outperforming existing methods.

Ahmet Mert and Aydin Akan (2016) addressed about the empirical mode decomposition (EMD) and its multivariate extension (MEMD) for EEG-based emotion recognition. EMD, known for handling nonstationary time series, is employed to analyze multichannel EEG signals. Various features are extracted and compared to benchmark results using the DEAP emotional EEG dataset.

Ke Zhang et al. (2022) in this paper, introduces a novel multimodal emotion recognition model using reinforcement learning and domain knowledge for video conversations. This approach combines real-time recognition with emotion-pair-based revisions, achieving state-of-the-art results across various emotion categories. Future work aims to enhance recognition across all emotion classifications by optimizing the reinforcement learning module and domain knowledge extraction.

Alex C. Nyquist and Aaron M. Luebbe (2019) in this review synthesized the current literature on adolescent depression, focusing on emotion recognition and awareness within

the ASC framework. Limited studies prevent definitive conclusions about recognition-awareness vulnerability to depression. More culturally sensitive research is needed to understand how these processes differ for one's own and others' emotions, requiring longitudinal studies before and after major depressive episodes to test vulnerability hypotheses.

Sarah Adel Bargal *et al.* (2016) outlined the implementation of a solution for the 2016 Emotion Recognition in the Wild Challenge, specifically in the video-based emotion recognition category. The approach processes audio-video clips to assign an emotion label from seven classes (including basic emotions like happiness, sad, disgust, surprise anger etc. and Neutral). The system comprises several interconnected modules: face detection, image preprocessing, deep feature extraction, feature encoding, and SVM classification. It attains a validation accuracy of 59.42% (surpassing the baseline of 38.81%) and a test recognition rate of 56.66% (better than the baseline of 40.47%).

Xi Ouyang *et al.* (2021) details the contribution to the Emotion Recognition in the Wild video-based sub-challenge, which aims to classify basic emotions and neutral expressions. The solution employs three cutting-edge techniques: deep network transfer learning for feature extraction, spatial-temporal model fusion for network integration, and semi-auto reinforcement learning for fusion strategy optimization. The approach achieves an overall accuracy of 57.2% on the challenge test dataset, surpassing the 40.47% baseline.

Aayush Bhardwaj *et al.* (2015) applied Independent Component Analysis (ICA) and machine learning techniques like Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) to categorize EEG signals into seven distinct emotions. This achieved average overall accuracies of 74.13% with SVM and 66.50% with LDA using a 4-fold cross-validation. The study indicates that accuracy improves with more training samples, with SVM performing better, especially in recognizing happy and sad emotions. Happy and sad emotions were identified with SVM at 87.5% accuracy each, compared to 82.5% with LDA.

CHAPTER-3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

3.1 AIM:

- Integrating EEG and BIOPAC systems is crucial for understanding and treating mental health disorders like depression and anxiety.
- Facial expressions can conceal emotions, requiring a deeper neural understanding.
- Real-time brain activity feedback empowers individuals for self-regulation and enhancing mental well-being, especially in meditation.
- It's valuable for bedridden patients who struggle to express emotions physically.
- Inaccurate emotion detection can lead to misunderstandings and unsatisfactory user experiences.
- The goal is to create a versatile tool for individuals, healthcare providers, and researchers to understand, monitor, and improve emotional well-being across diverse applications.

3.2 EXISTING SYSTEMS:

Emotiv EEG Headsets: Emotiv offers EEG headsets with built-in sensors capable of detecting emotions based on brainwave patterns. These headsets come with accompanying software for emotion analysis and interpretation.

Muse EEG Headband: The Muse headband is another EEG device designed for consumer use. While primarily marketed for meditation and mindfulness applications, it can also be utilized for emotion detection through EEG signals.

NeuroSky MindWave: The MindWave headset by NeuroSky is used for various EEG-based applications, including emotion detection. It interprets brainwave patterns to recognize emotional states and provides real-time feedback.

BrainBit EEG Headset: BrainBit offers a portable EEG headset designed for research and personal use. It includes software for emotion analysis, allowing users to monitor and interpret their emotional states based on EEG data.

OpenBCI: OpenBCI provides open-source EEG hardware and software for research and development purposes. Researchers and developers can use OpenBCI's platform to build custom solutions for emotion detection using EEG signals.

These systems vary in terms of their features, accuracy, and intended applications, but they all leverage EEG technology for emotion detection and analysis.

3.2.1 DISADVANTAGES OF EXISTING SYSTEMS:

Limited spatial resolution: EEG measures electrical activity on the scalp, which lacks spatial resolution compared to other neuroimaging techniques like fMRI or PET scans. This limitation may result in difficulty pinpointing the exact brain regions associated with specific emotions.

Susceptibility to noise: EEG signals can be easily influenced by external noise sources such as muscle movements, environmental factors, and electrode artifacts. Filtering out this noise can be challenging and may affect the accuracy of emotion detection.

Invasive electrode placement: Some EEG systems require the placement of electrodes directly on the scalp, which can be uncomfortable for users, especially over extended periods. This invasiveness may deter widespread adoption, particularly in consumer applications.

Limited emotion recognition accuracy: While EEG can detect general patterns associated with certain emotions, its accuracy in precisely identifying discrete emotional states may be limited. Emotions are complex and subjective, making it challenging to develop algorithms that accurately classify them based solely on EEG data.

Training and calibration requirements: Many EEG-based emotion detection systems require initial training and calibration sessions to personalize the algorithm for each user. This process can be time-consuming and may not always yield consistent results across different individuals.

Cost and accessibility: High-quality EEG hardware and software can be costly, limiting accessibility to researchers and developers with adequate funding. Additionally, consumer-grade EEG devices may offer lower accuracy and fewer features compared to professional-grade systems.

Ethical and privacy concerns: Emotion detection technologies raise ethical concerns regarding privacy, consent, and potential misuse of personal data. Users may be wary of devices that claim to infer their emotional states, especially if data collection and analysis methods are not transparent or well-regulated.

3.3 PROPOSED SYSTEM:

The proposed approach involves gathering data from a diverse range of individuals through the use of different video recordings designed to stimulate brain signals. These videos are presented to the participants to evoke their emotional responses and corresponding brain signal frequencies. Utilizing BIOPAC, the system assesses frequency and emotional fluctuations by capturing EEG-based brain signal values. This method enhances the quality of data acquisition while mitigating potential issues. In contrast to MRI scans, it offers greater reliability, non-invasiveness, and safety.

Proposed system advantages

- *Accurate Emotion Recognition:* EEG and BIOPAC integration ensures precise identification of happiness, sadness, and disgust.
- *Real-life Data:* Utilizes EEG signals from real individuals, enhancing authenticity.
- *MATLAB Machine Learning:* Enables robust emotion analysis through sophisticated algorithms.
- *Non-invasive:* Collects data with electrodes, avoiding invasive procedures.
- *Efficient Processing:* Streamlines data analysis for practical implementation.

3.4 APPLICATIONS:

- Real-Time Emotion Monitoring: EEG and BIOPAC integration captures brain signals from individuals, enabling continuous tracking of happiness, sadness, and disgust in real-life scenarios.
- Individualized Emotion Profiling: Utilizing EEG electrodes and BIOPAC, personalized emotion recognition models are developed in MATLAB, enhancing accuracy based on unique brain responses.
- Biofeedback Therapy Enhancement: Integrated EEG-BIOPAC systems in MATLAB facilitate biofeedback interventions tailored to individual emotional states, aiding in managing and alleviating mood disorders.
- Behavioral Research Advancements: MATLAB's machine learning algorithms analyze EEG data from BIOPAC to uncover nuanced patterns in emotions, contributing to advancements in psychological and neuroscientific research.
- Assistive Technology Development: EEG-BIOPAC integration, coupled with MATLAB's machine learning capabilities, fosters the creation of emotion-aware assistive technologies, promoting empathetic human-computer interactions.

3.5 SCOPE:

- The scope of EEG and BIOPAC emotion recognition is extensive. Applications include healthcare, mental well-being, and human-computer interaction.
- It can aid in mental health diagnostics and personalized interventions.
- Empowers individuals for stress management.
- Benefits marketing, education, entertainment, and technology.
- Promises a multidimensional enhancement of human experiences and well-being.

CHAPTER-4

MATERIALS AND METHODOLOGY, ALGORITHM USED

4.1 MATERIALS:

Emotion recognition typically requires a combination of hardware and software components. For the hardware, the needed tools are EEG (Electroencephalography) systems and BIOPAC systems to collect physiological data i.e., brain activity, Electrodes or sensors are used to capture these physiological signals accurately. The software component includes data processing and analysis tools for extracting relevant features from physiological data, such as MATLAB and EEG signal processing techniques. Machine learning algorithms, including classifiers like Support Vector Machines, KNN models are used for emotion classification. The integration of these hardware and software components allows for comprehensive emotion recognition, often used in fields like psychology, healthcare, human-computer interaction, and more.

4.1.1. HARDWARE USED:

BIOPAC:

BIOPAC, short for "Biological Parameters Acquisition," is a renowned and versatile system used in the field of physiological data collection and analysis. It offers a comprehensive and user-friendly platform for researchers, healthcare professionals, and educators to acquire and monitor various physiological parameters. BIOPAC systems are designed to measure a wide range of biological signals, including but not limited to, EEG, ECG, EMG and more. BIOPAC systems consist of hardware components like sensors, electrodes, and amplifiers, which are applied to individuals to capture physiological data. These signals are then transmitted to a computer interface, where specialized software is used for data analysis, visualization, and interpretation. BIOPAC finds applications in various fields, including healthcare, psychology, sports science, and education, enabling researchers and professionals to study and understand the human body's responses in different contexts. Its versatility and accuracy make it a valuable tool for physiological research and data collection, aiding in the advancement of knowledge and applications across multiple domains. BIOPAC systems aid in emotion recognition by capturing and analyzing

physiological responses associated with emotions. These systems collect data such as heart rate, skin conductance, and muscle activity, which can serve as indicators of emotional states. By synchronizing this physiological data with other information like video recordings or self-reported emotional responses, researchers can discern patterns and correlations. BIOPAC's customization and real-time monitoring capabilities enable tailored data collection and immediate observation of emotional changes. This data is crucial for both research and clinical applications, offering insights into emotional well-being, aiding diagnosis, and informing therapy in therapeutic and medical contexts.



Fig:4.1: BIOPAC hardware

LEAD SELECTION CIRCUIT:

The lead selection circuit, a vital component of BIOPAC EEG systems, connects electrodes to the device via a cable, with channel 1 and channel 2 available as connectors labeled SS2L. Placed behind the sample's earlobe, electrodes are linked via this isolated cable for recording physiological data. This circuit allows users to choose active electrodes and filter out unwanted signals through switches or relays operated by software. Filters within the circuit eliminate interference, ensuring only desired EEG signal frequencies pass through, enhancing data precision and quality. Specifications may vary by model, with typical features including multiple channels (8 to 64+), high input impedance (100 Megaohms to 10 Giga ohms), high CMRR (80 to 120 dB+), wide bandwidth (0.1 Hz to 100 Hz+), and fast switching speed.



Fig:4.2: Set up of Lead selection circuit and BIOPAC

EEG ELECTRODES:

Surface electrodes, alternatively referred to as disposable medical or adhesive electrodes, consist of a disc made of semi-rigid plastic material featuring a central recessed embossment, illustrated in Figure 4.3. Positioned within this embossed area is a metallic electrical contact, flanked by components on each side.



Fig:4.3: Surface Electrodes

The connection to the BIOPAC system is typically established through USB or other suitable interfaces as shown in fig:4.3. Furthermore, the data collected is processed and analyzed using specialized software, such as BSL (BIOPAC Student Lab) software, which

allows for visualization, interpretation, and further study of the EEG signals. Overall, EEG electrodes and leads, in conjunction with proper positioning, conductive mediums, grounding, and data acquisition systems, form a comprehensive setup that enables the accurate measurement and analysis of brain activity. The block diagram of this can be seen in the fig:4.4. This technology is widely used in neuroscience research, clinical diagnostics, and various applications related to understanding the brain's functions and responses.

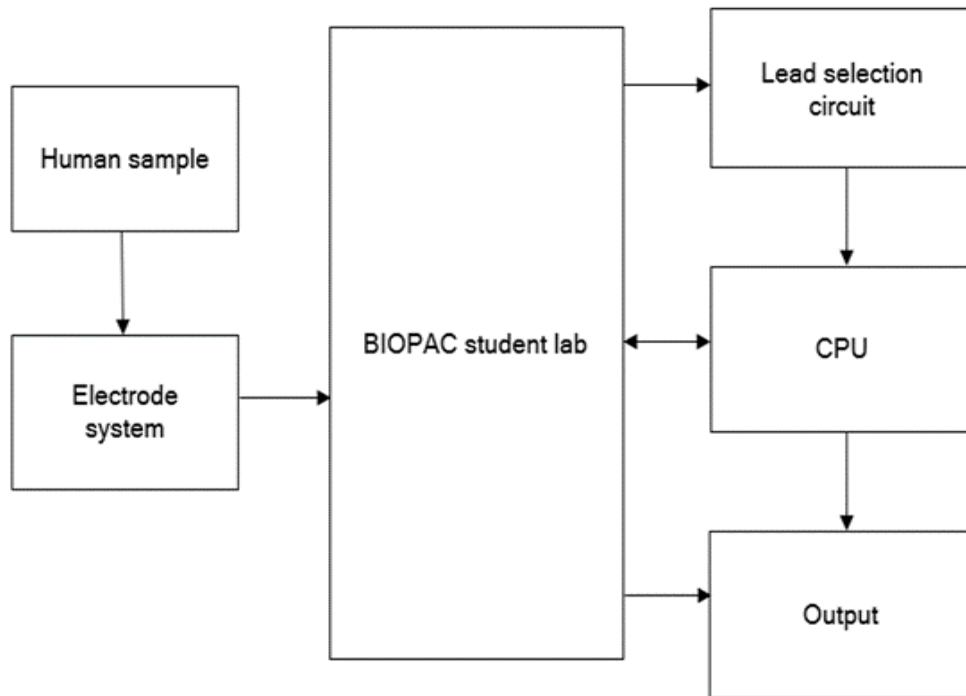


Fig:4.4: Block diagram of EEG and BIOPAC Integration

4.1.2 SOFTWARE USED:

MATLAB serves as a robust tool for implementing machine learning techniques within software development workflows. Leveraging MATLAB's extensive capabilities, models undergo efficient training and testing procedures, ensuring the attainment of high levels of predictive accuracy. Through MATLAB, algorithms undergo meticulous fine-tuning, and models are meticulously optimized to meet project-specific requirements. Upon achieving high-accuracy models within the MATLAB environment, seamless integration into Python

facilitates the extraction of precise emotional insights. Python's versatility, augmented by libraries such as TensorFlow and sci-kit-learn, further refine analyses, enabling the extraction of nuanced emotional patterns from the data. This iterative approach, synergizing the strengths of MATLAB and Python, not only ensures superior model accuracy but also facilitates a comprehensive exploration of the emotional context embedded within the data. Through the synthesis of these advanced methodologies, valuable insights are unearthed, empowering informed decision-making processes and enriching the overall user experience of software applications.

4.2 METHODOLOGY:

The data acquisition phase entails the establishment of the BIOPAC system alongside electrode placement for the recording of physiological signals. Participants are exposed to a series of three distinct videos, each designed to elicit a specific emotional response, while EEG signals are captured concurrently. Preprocessing steps involve the application of filters to mitigate noise interference within the recorded signals. Subsequently, the processed signals are exported to an Excel format for further analysis, where feature extraction techniques are employed. This entails the utilization of various statistical formulas such as mean, median, average deviation, standard deviation, mode, variance, skewness, and interquartile range. These statistical measures serve to characterize the underlying properties of the EEG signals, facilitating the identification of discriminative features associated with different emotional states. Following feature extraction, the dataset is subjected to classification using machine learning methodologies, specifically within the MATLAB environment. Here, models are trained and tested rigorously to attain high levels of accuracy in emotion classification tasks. Models exhibiting superior performance metrics are then transferred to Python for subsequent inference tasks. Within Python, the specific emotional states corresponding to the recorded EEG signals are determined using the trained models. This integration allows for the extraction of targeted emotional insights from the physiological data, enabling a comprehensive understanding of the participants' emotional responses to the stimuli. This comprehensive methodology encompasses a structured approach from data acquisition to emotion classification, leveraging advanced techniques from signal processing to machine learning. Such a

methodological framework ensures robustness and reliability in the analysis of emotional states based on EEG recordings.

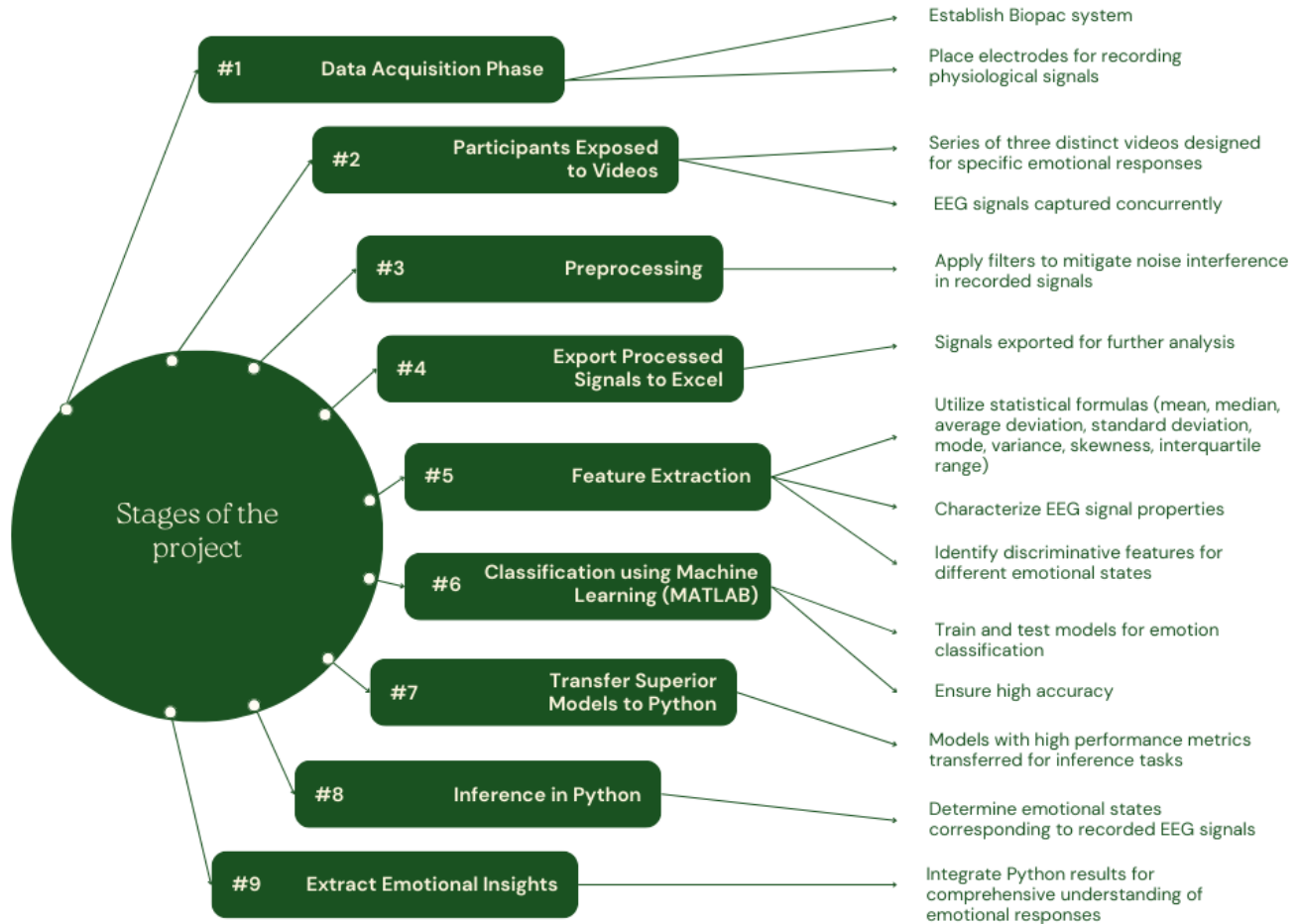


Fig:4.5: Diagrammatic representation of the stages involved in Emotion Recognition

4.2.1 DATA COLLECTION:

We initiated the experimental setup by connecting the electrodes to each participant and integrating them with the BIOPAC system. Subsequently, we presented a series of three videos, strategically chosen to elicit varying emotional responses including happiness, sadness, and disgust. Throughout the viewing process, we recorded the EEG signals of

the participants. This process yielded a comprehensive dataset consisting of 70 individual readings from distinct individuals. These data were compiled and converted into text files, prepared for subsequent phases of data analysis and classification.



Fig 4.6 (a),(b),(c): Video clips used for evoking Happy, Sad and Disgust emotions in participants respectively

Participants were exposed to 30-second videos stimuli aimed at evoking the emotions of happiness, sadness, and disgust, while their EEG brain wave patterns were recorded for subsequent emotion analysis. In Fig 4.7(a) a video depicting a heartwarming moment between a mother, father, and their baby as she takes her first steps is used. The mother beams with joy and excitement as she watches her child's milestone, while the father enthusiastically records the precious moment. The atmosphere is filled with warmth and encouragement as the parents cheer on their baby, motivating her to walk towards her father. This tender scene is carefully chosen to evoke feelings of happiness and delight in participants, capturing the universal joy of witnessing a child's developmental milestone and the supportive bond within a family. The video as seen in Fig 4.7(b) portrays a deeply distressing scene of a child in shock following a bomb attack. The child's overwhelming emotions are palpable as he cries in the aftermath of the devastation. This poignant moment is selected to evoke profound feelings of sadness in viewers, as the harrowing reality of the child's trauma unfolds. The EEG emotion detection aims to capture the raw emotional response elicited by witnessing such heartbreaking events, offering insight into the neural correlates of sadness in the human brain. The video as shown in Fig 4.7(c) is

designed to elicit a visceral reaction of disgust from participants by showcasing footage of worms. As viewers observe the wriggling and squirming of the worms, they may experience a strong aversion and revulsion. This deliberate choice aims to evoke a primal, instinctual response associated with disgust.

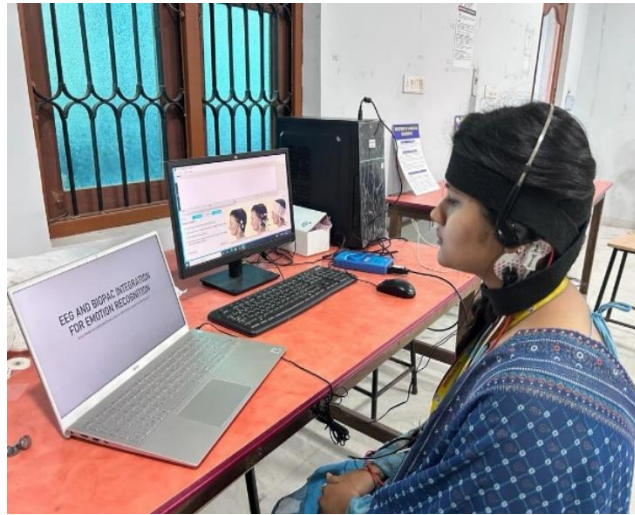


Fig 4.7: EEG signals being recorded as the participant views the videos

4.2.2 RECORDED DATA:

The signals showcased in Fig 4.8, Fig 4.9, Fig 4.10 denote the physiological responses garnered from participants through the BIOPAC instrument and their brain waves i.e. Alpha, Beta, Delta, Theta waves.

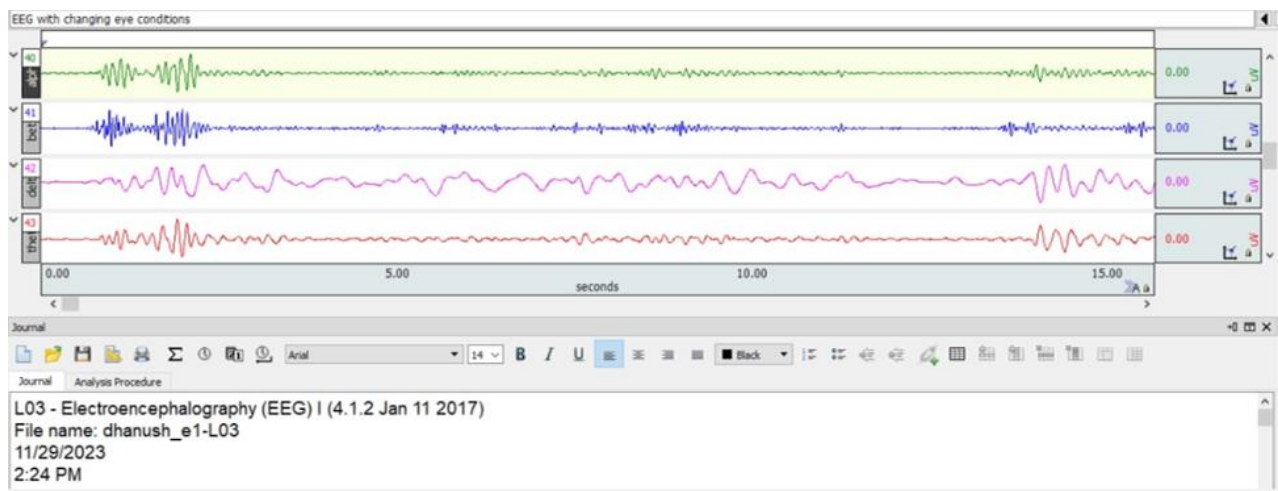


Fig 4.8: Recorded EEG waveform of sad emotion

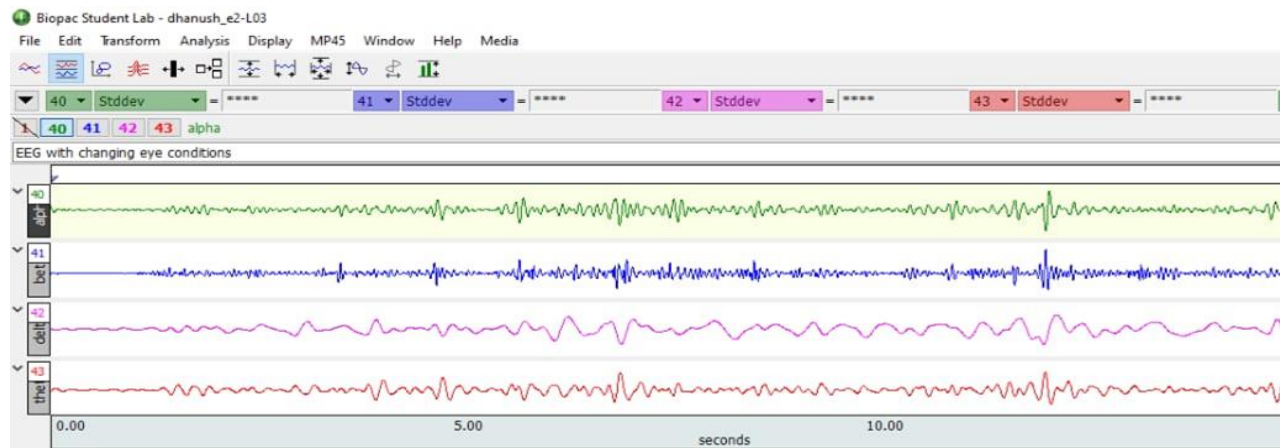


Fig 4.9: Recorded EEG waveform of disgust emotion



Fig 4.10: Recorded EEG waveform of happy emotion

4.2.3 FEATURE EXTRACTION IN EXCEL:

The dataset comprised EEG readings from 70 participants, resulting in a total of 210 files representing three emotions for each participant. These files were converted into text format and imported into Excel for further analysis. Feature extraction involved categorizing statistical features for four distinct EEG waveforms - Alpha, Beta, Delta, and Theta. These features encompassed a range of essential statistical metrics including mean, median, average deviation, standard deviation, mode, variance, interquartile range, and skewness, each computed using specific formulas. Through an analysis of these features, we obtained thorough insights into the distinctive traits and patterns displayed by each EEG waveform.

4.2.4 FORMULAE USED FOR FEATURE EXTRACTION:

$$\text{Mean} = \frac{\sum x_i}{n}$$

$$\text{Median} = l + \frac{\left(\frac{N}{2} - m\right)}{f} \times c$$

$$\text{Variance} = \frac{\sum (x_i - \bar{x})^2}{N}$$

$$\text{Average deviation} = \frac{\sum (X - \bar{X})}{N}$$

$$\text{Mode} = L + \left(\frac{f_1 - f_m}{2f_1 - f_m - f_2} \right) \times h$$

$$\text{Standard deviation} = \sqrt{\frac{\sum (X - \bar{X})^2}{n - 1}}$$

$$\text{Inter Quartile Range} = \frac{\text{upper quartile} - \text{lower quartile}}{Q_3 - Q_1}$$

Fig 4.11: Formulae used for feature extraction

4.3 ALGORITHM USED:

The algorithm of this project harnesses the power of machine learning algorithms, initially utilizing MATLAB and subsequently integrating Python for emotion-specific analysis. Through the utilization of these algorithms, the EEG signals undergoes training and testing processes with various models, resulting in enhanced accuracy in emotion classification. This approach not only ensures robustness in the analysis but also enables the extraction of nuanced emotional states from the data. Furthermore, by leveraging the capabilities of both MATLAB and Python, we can capitalize on the strengths of each platform, thus optimizing the overall performance and effectiveness of the classification process.

We individually imported datasets for each participant into MATLAB. Utilizing the Classification Learner app, we conducted classification, training, and testing processes. This involved training various models on the datasets to determine their effectiveness in accurately categorizing emotions based on EEG readings. Following training, we rigorously tested these models to assess their performance and refine their accuracy. The models we used to train and test are Tree, KNN, Neural network, Kernel, SVM, Ensemble, Linear regression, Naïve Bayes and Label propagation algorithm.

After identifying the models that demonstrate notable accuracy levels, we proceed to integrate them into Python for further refinement. This iterative process involves selecting the models that exhibit superior performance, thereby enhancing the precision of emotion classification. The output generated from this phase furnishes insights into the specific emotions experienced by individuals, alongside identifying the waveform that attains the highest accuracy. Through this meticulous approach, we not only discern the nuanced emotional states but also pinpoint the most reliable indicators within the EEG signals, facilitating a deeper understanding of the underlying emotional responses.

CHAPTER-5

RESULTS AND DISCUSSION, PERFORMANCE ANALYSIS

5.1 RESULTS AND DISCUSSION:

The experiment utilized BIOPAC to capture EEG signals as participants viewed emotion-inducing videos. These signals were then exported to text files and analyzed in Excel for feature classification. MATLAB was employed to process these features, training and testing various models to ensure accuracy. The most effective model was then implemented in Collab to accurately identify emotions based on EEG readings. MATLAB's confusion matrix was utilized to assess the accuracy of each model. This matrix provides a concise overview of the model's performance by delineating accurate and erroneous predictions across multiple classes, aiding in the swift evaluation of performance and identification of prevalent error trends.

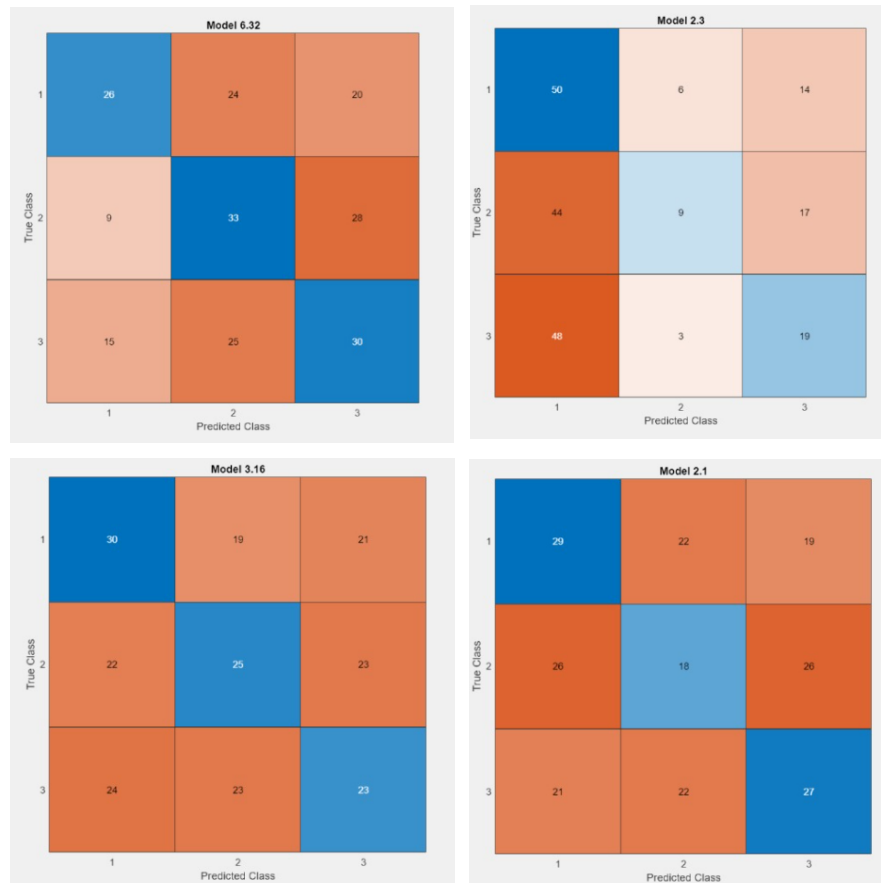


Fig 5.1 Confusion matrices of unprocessed Alpha, Beta, Delta and Theta signals

The confusion matrices offer comprehensive evaluations of kernel models trained on various raw EEG signals. For instance, one model trained on raw alpha signals achieves an accuracy of 42.4%, providing insights into its classification performance across three distinct classes. However, this accuracy also underscores areas for improvement, suggesting the necessity for further refinement. Similarly, another model, employing the Tree algorithm on raw beta signals, yields an accuracy of 37.1%, reflecting its effectiveness in classifying instances within a 3x3 grid. Meanwhile, a K-Nearest Neighbors (KNN) model trained on raw delta signals achieves a similar accuracy of 37.1%, demonstrating its capability in accurately categorizing instances based on these signals. Additionally, the classification of raw theta signals into three categories reveals a modest accuracy of 35.2%, suggesting potential complexities in accurately classifying these signals. These evaluations highlight both the strengths and limitations of each model, guiding future efforts in refining classification methodologies for EEG signal analysis.

Table 5.1: Accuracies of the four waves achieved using ML models in MATLAB

WAVES	ML MODEL	ACCURACIES
ALPHA	KERNAL	42.4%
BETA	TREE	37.1%
DELTA	KNN	37.1%
THETA	TREE	35.2%

5.1.1 FINAL ACCURACIES ACHIEVED:

To enhance the accuracy of our analysis of raw EEG signals in MATLAB, we embarked on a rigorous exploration of various modeling techniques. Despite initially achieving a maximum accuracy rate of 42%, we recognized the need for further refinement to unlock

the full potential of our classification models. Our strategy encompassed the utilization of sophisticated tools within MATLAB's expansive toolkit. Principal Component Analysis (PCA) emerged as a cornerstone in our approach, offering a robust means of reducing the dimensionality of the raw EEG signals. By extracting the most salient features while mitigating noise, PCA enabled us to uncover subtle patterns within the data, thereby bolstering the discriminative power of our models. Moreover, we harnessed the capabilities of MATLAB to implement tailored cost functions and optimizers. These components played a pivotal role in our pursuit of optimal model configurations and parameter settings. Through meticulous experimentation and optimization procedures, we endeavored to strike a delicate balance between maximizing accuracy and minimizing computational overhead, ensuring the efficiency and effectiveness of our classification algorithms.

Table 5.2: Final Accuracies achieved after processing signals in MATLAB

WAVES	ML MODEL	ACCURACIES
ALPHA	SVM	82.9%
BETA	SVM	91.0%
DELTA	KNN	85.2%
THETA	ENSEMBLE	75.8%

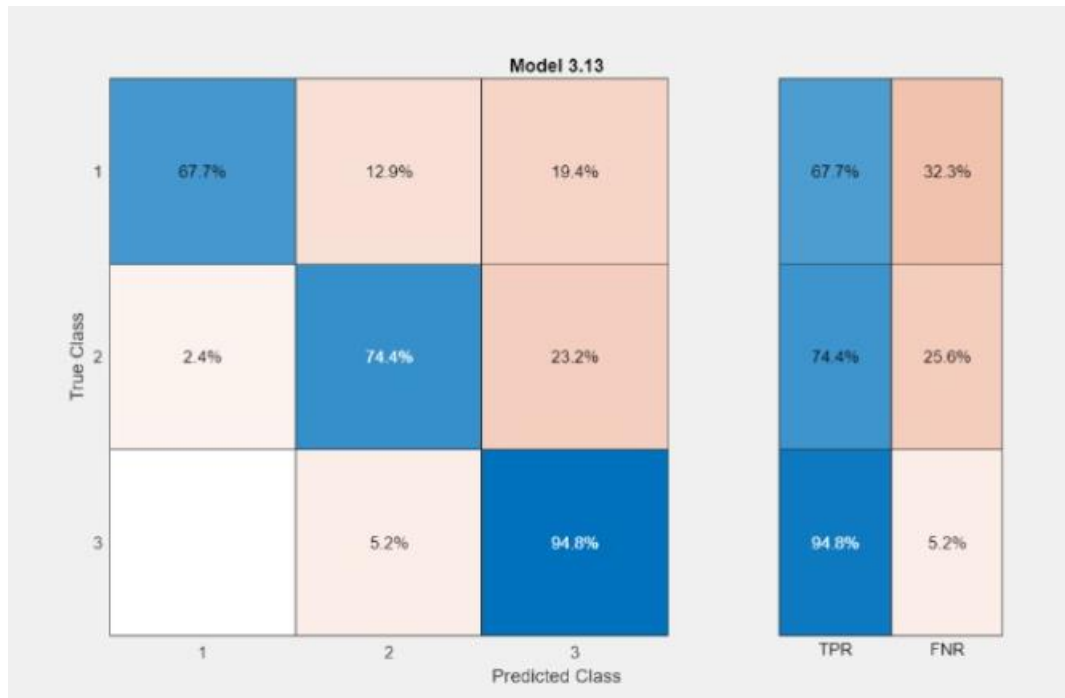


Fig 5.2: Final accuracy of alpha wave

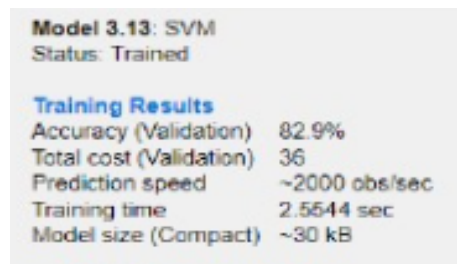


Fig 5.3: Training results of alpha wave

The confusion matrix seen in Fig 5.2 represents the culmination of the performance evaluation for the Alpha signal Support Vector Machine (SVM) model, boasting an impressive accuracy of 82.9%. This indicates that the model successfully predicted the correct class for the majority of instances within its dataset. Notably, the model's accuracy signifies its robustness in discerning distinct patterns inherent in the Alpha signal data. Beyond accuracy, the comprehensive assessment of the model extends to other crucial metrics. The total cost, totaling 36, reflects the combined expenses incurred during the model's development and deployment phases. Moreover, the model's prediction speed of 2000 observations per second underscores its efficiency in processing real-time data streams, particularly vital in dynamic environments. Delving into the model's training phase

seen In fig 5.3, it required a mere 2.5544 seconds to converge, showcasing its computational efficiency and rapid deployment potential. Altogether, these metrics illuminate the Alpha signal SVM model's prowess in achieving high accuracy while exhibiting efficiency, speed, and compactness, thereby affirming its suitability for real-world applications requiring timely and precise signal classification.

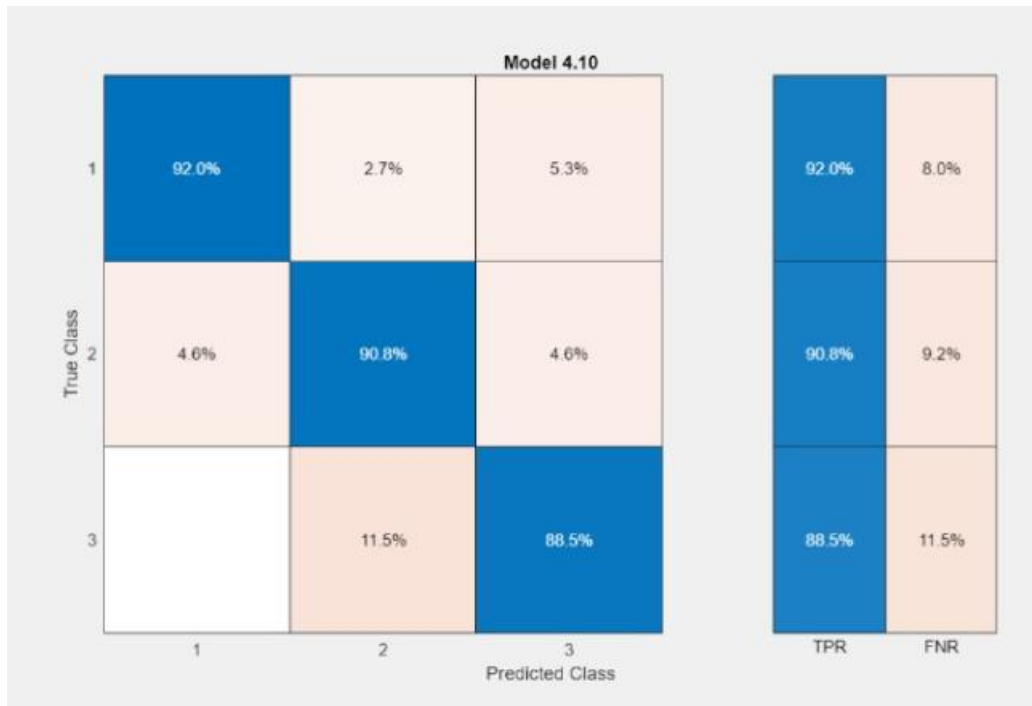


Fig 5.4: Final accuracy of beta wave

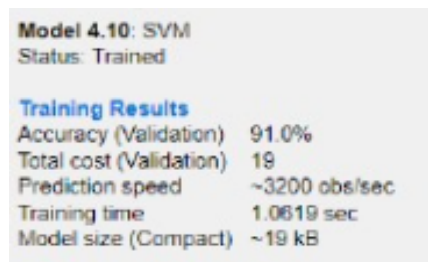


Fig 5.5: training results of beta wave

The confusion matrix presented in Fig 5.4 encapsulates the performance evaluation of a Support Vector Machine (SVM) model trained on beta signal data, yielding an impressive accuracy of 91.0%. Beyond accuracy, crucial metrics such as total cost, prediction speed, and training time underscore the efficiency and effectiveness of the model. The low total cost signifies economical resource allocation, while a high prediction speed of 3200

observations per second indicates swift real-time processing capabilities. Notably, the SVM model was trained expediently, with a training time of 1.0619 seconds, showcasing rapid model development. Furthermore, the model's compact size, at a mere 19 KB, reflects optimized memory utilization without compromising performance. This comprehensive evaluation not only highlights the model's high accuracy but also underscores its efficiency, speed, and compactness, rendering it a robust solution for classification tasks.

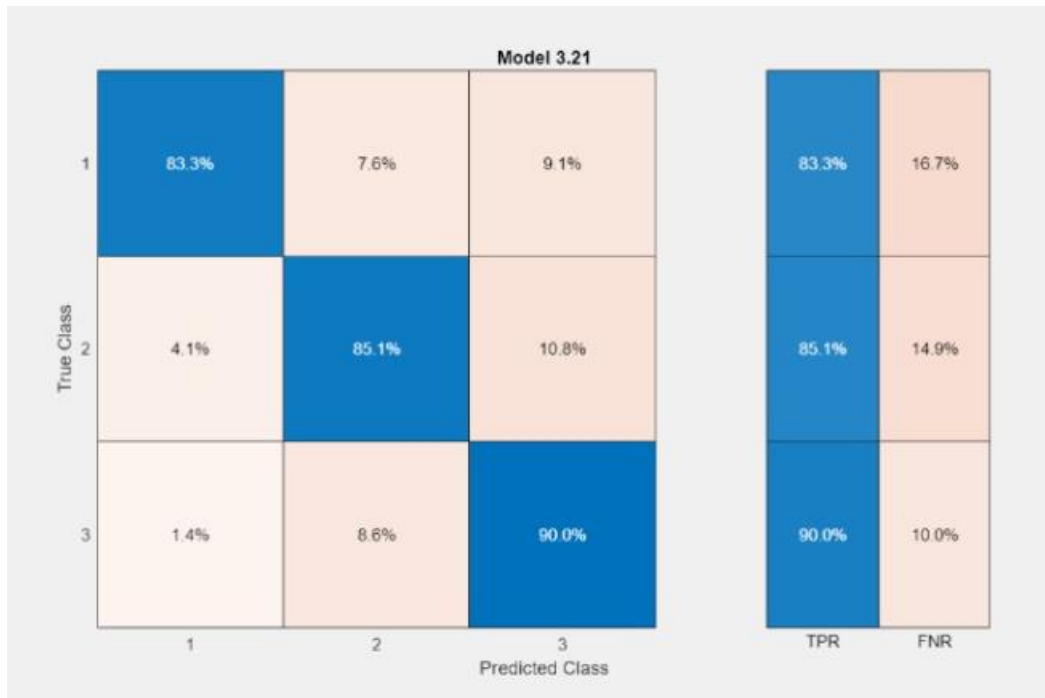


Fig 5.6: final accuracy of delta wave



Fig 5.7: training results of delta waves

The confusion matrix in Fig 5.6 illustrates the performance evaluation of a KNN (K-Nearest Neighbors) model trained on delta signal data, achieving an impressive accuracy of 85.2%. This metric signifies the proportion of correctly classified instances out of the total predictions made by the model. Alongside accuracy, various additional metrics contribute

to the comprehensive assessment of the model's efficacy. Notably, the total cost, calculated based on factors such as computational resources and time investment, amounts to 31 units. Furthermore, the model's prediction speed stands at a remarkable 12,000 observations per second, indicating its efficiency in processing data streams. During the training phase, the model required a mere 0.55991 seconds to converge, underscoring its agility in learning from the provided dataset. Moreover, the compact nature of the model is highlighted by its size of 28 KB, making it easily deployable across diverse computing environments. Together, these performance metrics paint a detailed picture of the KNN model's capabilities, showcasing its robustness, efficiency, and scalability for real-world applications.



Fig 5.8: Final accuracy of theta wave

Model 2.23: Ensemble	
Status: Trained	
Training Results	
Accuracy (Validation)	75.8%
Total cost (Validation)	51
Prediction speed	~2200 obs/sec
Training time	4.0022 sec
Model size (Compact)	~357 kB

Fig 5.9: training results of theta wave

The confusion matrix in Fig 5.8 offers a comprehensive snapshot of the performance of the Theta Signal Ensemble Model, showcasing its accuracy of 75.8%. This accuracy metric denotes the proportion of correctly predicted instances out of the total predictions made by the model. Beyond accuracy, the model's overall performance is further delineated by additional metrics. Notably, the total cost, which encapsulates the resources expended in developing and deploying the model, is recorded at 51. This cost factor encompasses various aspects such as computational resources, labor, and any associated expenses. Moreover, the prediction speed of the model is outlined at 2200 observations per second, highlighting the efficiency with which the model can process incoming data streams. This rapid prediction speed is instrumental in real-time applications where timely decision-making is crucial. Delving deeper into performance metrics, the training time required to develop the model is detailed, standing at 4.0022 seconds. This metric signifies the efficiency of the model training process, wherein shorter training times denote faster model development cycles. Additionally, the model size is specified at 357 KB, indicating the storage space required to store the model parameters and configurations. Efficient model size is essential for deployment in resource-constrained environments such as mobile devices or embedded systems. Overall, this detailed breakdown of performance metrics provides a comprehensive understanding of the Theta Signal Ensemble Model's capabilities and efficiency in handling classification tasks.

5.1.2. EMOTION CLASSIFICATION IN PYTHON:

After identifying the most accurate models, we integrate them into Python to identify specific emotional responses. We use Python's powerful libraries to extract detailed emotional insights tailored to our project needs. These chosen models undergo thorough evaluation and adjustments to ensure they can accurately determine precise emotional states. Once in Python, these refined models use advanced algorithms to uncover complex patterns in the data, resulting in targeted emotional classifications. This method not only builds on the accuracy achieved in MATLAB but also takes advantage of Python's capabilities. By combining these approaches, we gain valuable insights that inform decision-making and improve the overall user experience of our software applications.

Table 5.3: Accuracies acquired after training the datasets in python

ML Models	Accuracy Achieved
Linear Regression	80.42%
Label Propagation Algorithm	80.38%
K-Nearest Neighbor	80.50%
Classification and Regression Tree	80.25%
Naïve Bayes	80.30%
Support Vector Machine	88.43%

After running our Python code for emotion detection using various classification methods, we have obtained insightful results regarding the accuracy achieved by each machine learning model. Our analysis reveals that the Support Vector Machine (SVM) outperformed other models, attaining an impressive accuracy of 88.43%. This signifies the SVM's robustness in effectively classifying emotional states based on the input data.

Furthermore, other models such as Linear Regression, Label Propagation Algorithm, K-Nearest Neighbor, Classification and Regression Tree, and Naïve Bayes also demonstrated notable accuracy rates, ranging from 80.25% to 80.50%. These results indicate the competence of these models in accurately predicting emotional states, albeit with slight variations in performance.

Overall, our findings showcase the efficacy of machine learning approaches in emotion detection tasks, with SVM emerging as the top-performing model in terms of accuracy. These results provide valuable insights for future research and practical applications aimed at enhancing emotion recognition systems.

5.2 PERFORMANCE ANALYSIS:

5.2.1. OUTPUTS OF EMOTION CLASSIFICATION:

The Python code utilized six machine learning models to classify emotions based on a single participant's data encompassing three emotional states: happiness, sadness, and disgust after training the datasets. Upon inputting the data for four participants into the code, predictions for their respective emotions were generated. The outcome is determined by the predominant emotion detected across the models. For instance, if the models predict emotions as "happy, happy, happy, sad, sad, happy," the final result would be categorized as "happy" since it appears most frequently. This methodology ensures that the predicted emotion reflects the consensus among the employed machine learning models, providing a reliable assessment of the participant's emotional state.

```
LR Predicted Emotion Label: HAPPY  
LDA Predicted Emotion Label: HAPPY  
KNN Predicted Emotion Label: HAPPY  
CART Predicted Emotion Label: SAD  
NB Predicted Emotion Label: HAPPY  
SVM Predicted Emotion Label: HAPPY
```

Fig 5.10: Predicted output of participant 1

```
LR Predicted Emotion Label: SAD  
LDA Predicted Emotion Label: SAD  
KNN Predicted Emotion Label: SAD  
CART Predicted Emotion Label: HAPPY  
NB Predicted Emotion Label: SAD  
SVM Predicted Emotion Label: SAD
```

Fig 5.11: Predicted output of participant 2

```
LR Predicted Emotion Label: DISGUST  
LDA Predicted Emotion Label: HAPPY  
KNN Predicted Emotion Label: HAPPY  
CART Predicted Emotion Label: HAPPY  
NB Predicted Emotion Label: HAPPY  
SVM Predicted Emotion Label: HAPPY
```

Fig 5.12: Predicted output of participant 3

```

LR Predicted Emotion Label: HAPPY
LDA Predicted Emotion Label: HAPPY
KNN Predicted Emotion Label: HAPPY
CART Predicted Emotion Label: HAPPY
NB Predicted Emotion Label: HAPPY
SVM Predicted Emotion Label: HAPPY

```

Fig 5.13: Predicted output of participant 4

5.2.2 CONFUSION MATRICES FOR PARTICIPANT 4'S PREDICTED OUTPUT:

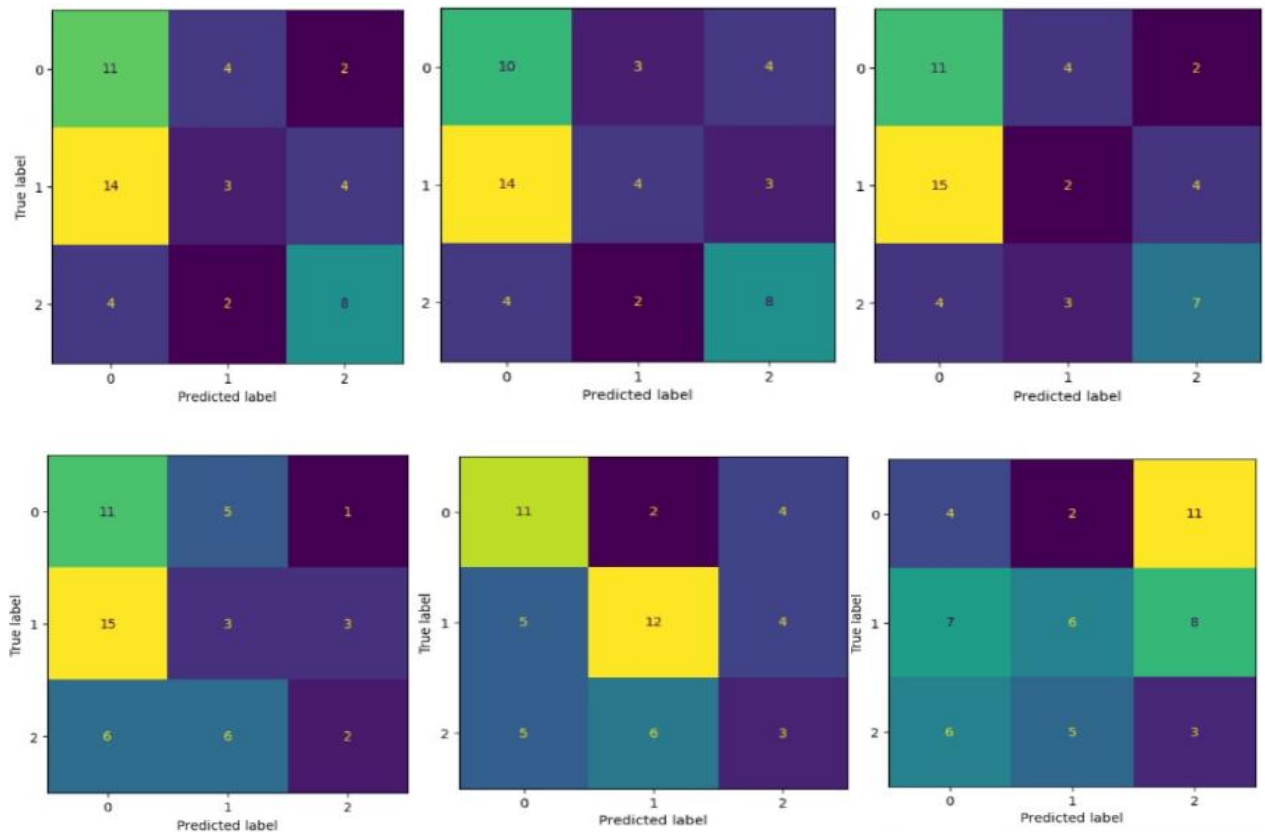


Fig 5.14: Participant 4's ML models confusion matrices.

After analyzing the confusion matrices generated by the LR, LDA, KNN, CART, NB, and SVM machine learning models for the classification and detection of emotions, several key observations emerge. The LR model exhibits a moderate performance with relatively balanced prediction across the three emotion classes. However, it tends to misclassify a notable portion of samples, particularly in distinguishing between emotions such as sadness and disgust. Similarly, the LDA model demonstrates similar trends to LR in terms of misclassifications, particularly between sadness and disgust. However, it shows slightly

improved performance in accurately categorizing happy emotions. Moving to the KNN model, it displays a comparable performance to LR and LDA, with relatively balanced confusion matrix values. However, it struggles slightly more in distinguishing between sadness and disgust. The CART model exhibits a mixed performance, with some confusion between sadness and disgust, as well as between happy and disgust emotions. It demonstrates relatively balanced predictions across the three emotion classes. In contrast, the NB model showcases a tendency towards misclassifying sadness and disgust emotions, particularly mistaking sadness for disgust. It struggles with balanced prediction across all classes, with notable misclassifications in differentiating between sadness and disgust. Finally, SVM emerges as the top-performing model, with the most balanced predictions across all emotion classes. It demonstrates the highest accuracy in distinguishing between the three emotions, with fewer misclassifications compared to other models.

In conclusion, while all models show varying degrees of success in emotion classification, SVM stands out as the most effective model, offering the most reliable predictions with the least misclassifications.

CHAPTER-6

SUMMARY AND CONCLUSION

6.1 SUMMARY:

The project focuses on detecting emotions from EEG signals captured using BIOPAC while users view videos designed to elicit three distinct emotional responses. Following data acquisition, features are extracted from the EEG readings. These features are then subjected to training and testing in MATLAB, utilizing various machine learning models to enhance accuracy. Models demonstrating high accuracy are subsequently transferred to Python for precise emotion detection. Leveraging Python's capabilities, the refined models discern specific emotional states from the EEG data. This comprehensive approach amalgamates signal processing, machine learning, and data analysis techniques to deliver robust emotion detection results. By synthesizing methodologies across MATLAB and Python, the project aims to provide valuable insights into human emotional responses, with implications for diverse applications such as mental health monitoring and user experience enhancement in interactive systems.

6.2 CONCLUSION:

In conclusion, this project represents a significant advancement in the field of emotion detection through EEG signals. By integrating sophisticated methodologies spanning data acquisition, feature extraction, machine learning model training, and precise emotion detection, we have achieved robust results. The collaborative utilization of MATLAB and Python showcases the synergy between signal processing and data analysis techniques, resulting in accurate emotion classification. These findings not only offer valuable insights into human emotional responses but also hold promising implications for diverse applications, including mental health monitoring and user experience enhancement in interactive systems. Moving forward, continued exploration and refinement of these methodologies promise to further advance our understanding and utilization of EEG-based emotion detection in various real-world scenarios.

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