AI based Brain State Recognition

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Declaration

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DEDICATION

We dedicate this study first and foremost to Allah, the Almighty for giving us strength, health, and guidance.

To our respected parents and family for having trust in us.

To our institute Comsats University Islamabad, Abbottabad campus.

And finally, to our respected supervisor and co-supervisor for guiding, leading and mentoring us.

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ABSTRACT

AI based Brain State Recognition

Our work explores the convergence of Brain-Computer Interface (BCI) and artificial intelligence to forecast eye states (open/closed) using electroencephalogram (EEG) signals. We employ advanced feature extraction methods like Discrete Wavelet Transform and statistical features to enhance the analysis of EEG signals. Classifiers such as Convolutional Neural Network (CNN) and Random Forest contribute to our system's capability to discern patterns in EEG signals.

This work focuses on diverse applications, particularly in healthcare, where the system aids communication for individuals in pseudo coma and detects neurological disorders. Additionally, it addresses the crucial aspect of road safety by monitoring driver fatigue through EEG analysis. Our work demonstrates promising results, emphasizing the potential for an efficient and user-friendly computer-human interaction paradigm.

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Chapter 1

Introduction

Our project aims to change how we interact with computers by using brain activity instead of traditional methods like keyboards and mice. We're tapping into Electroencephalogram (EEG) technology, capturing the brain's electrical signals with special sensors on the scalp. These signals are then translated into computer commands using smart techniques, creating a Brain-Computer Interface (BCI). This interface allows device control without any physical movement.

In our exploration, we're not only diving into BCI but also combining it with artificial intelligence to understand different brain states using EEG. This mix has the potential to enhance computer-human interaction significantly. Our specific focus is on predicting whether eyes are open or closed directly from EEG signals. The EEG, like listening to the brain's electrical activity with specialized head sensors, offers a non-intrusive way to grasp how the brain works. Our goal is to make computer control easy for users through their thoughts, eliminating the need for pressing buttons or moving physically.

1.1. A BCI System

In our work, we are developing an EEG-based system designed for the classification of eye states, specifically discerning between open and closed eyes. This work holds immense relevance for various applications, particularly in the realm of healthcare, where understanding cognitive states is critical.

Our chosen framework for this significant undertaking is Anaconda3, a versatile and robust platform that ensures an efficient and streamlined development process. Anaconda3 is a Python 3.x distribution with a focus on streamlined package management and deployment. It utilizes the Conda package manager for efficient dependency handling and supports the creation of isolated virtual environments. Pre-loaded with data science and machine learning libraries, Anaconda3 integrates the Spyder IDE and Jupyter Notebooks for development and collaboration. The user-friendly Anaconda Navigator GUI makes environment and package management simple across different operating systems. It's a versatile choice for Python-based projects, especially in data science and scientific computing, backed by a strong community and educational resources.

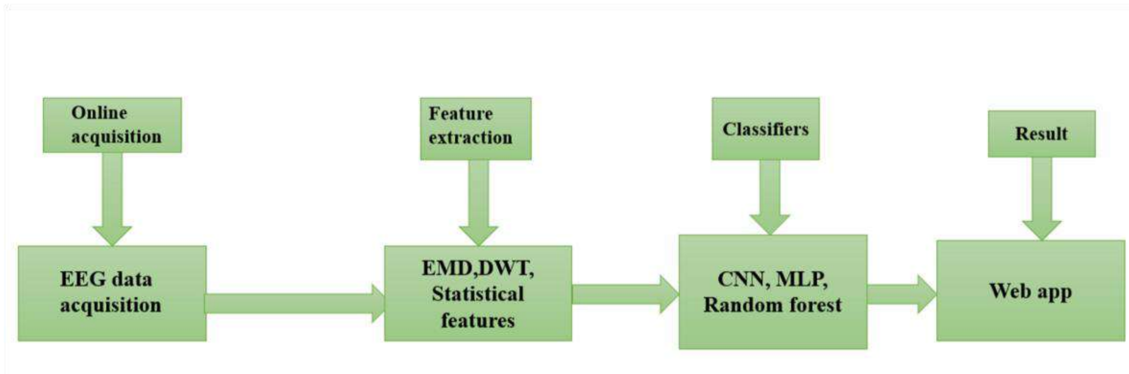

Figure 1.1 BCI system workflow

To initiate our work, we collected dataset from the UCI Machine Learning Repository, tailored for eye state classification. This dataset serves as a foundational resource, enabling the training and validation of our system to accurately distinguish between open and closed eye states. All data is from one continuous EEG measurement with the Emotiv EEG Neuroheadset. The duration of the measurement was 117 seconds. The eye state was detected via a camera during the EEG measurement and added later manually to the file after analysing the video frames. '1' indicates the eye-closed and '0' the eye-open state.

The feature extraction phase incorporates advanced methodologies, including Discrete Wavelet Transform (DWT), statistical features, and Empirical Mode Decomposition. These techniques enable us to extract meaningful information from the EEG signals, capturing essential characteristics indicative of eye states.

The extracted features then serve as input for our classification stage, where we deploy state-of-the-art classifiers such as Convolutional Neural Network (CNN), Random Forest, and Multi-Layer Perceptron (MLP). These classifiers excel at discerning patterns and relationships within the features, allowing our system to make precise distinctions between open and closed eye states.

1.2. Problem Statement

We aim to develop an efficient and user-friendly system capable of accurately predicting and categorizing the state of human eyes as either open or closed based on recorded electroencephalography (EEG) signals. This system has the potential to significantly enhance human-computer interaction, finding applications in various areas, including medical care and daily life chores.

Within the medical domain, our system can be helpful in several applications. For instance, it can offer a valuable means of communication for individuals in pseudo coma, where patients experience complete loss of voluntary muscle movement except for eye control. By analyzing EEG signals related to eye states, our system can facilitate effective communication for these patients. Additionally, the classification of eye states has implications for neurological disorder detection, providing insights into conditions such as epilepsy and sleep disorders. Furthermore, our system can contribute to monitoring and predicting driver fatigue, a crucial aspect of road safety. By offering insights into the driver's alertness level through EEG analysis, our system aims to contribute to reducing the risk of accidents caused by drowsy driving.

Chapter 2

Literature Review

2.1. BCI-An Insight into Neural Interfaces

In relation to BCI, this chapter aims to provide background information on neurophysiology and its fundamental principles. Understanding the intricacies of neurophysiology is essential for grasping the foundations of Brain-Computer Interfaces (BCIs). By delving into the functions of the nervous system, including the electrical activities within neurons and the communication between them, we can gain insights into the neural processes that form the basis for the operation of BCIs.

2.1.1. The Human Brain

The human brain is divided into different regions based on their location and functions. The brain has an outer layer called cerebral cortex, which is responsible for higher cognitive functions. This layer is divided into lobes where electrodes are placed noninvasively for EEG recordings. Refer to fig 2.1, for different lobes, their functions and their influence on EEG which are briefly described as follows:

2.1.1.1. Frontal Lobe

- **Function**: Associated with motor function, problem solving, spontaneity, memory, language, initiation, judgement, impulse control, and social and sexual behavior.
- **EEG Influence**: Activity in the frontal lobe can be reflected in the frontopolar and frontocentral regions of the EEG. Abnormalities may indicate issues with executive functions and emotional regulation.

2.1.1.2. Parietal Lobe

- **Function**: Processes sensory information it receives from the outside world, mainly relating to spatial sense and navigation (proprioception), the main sensory receptive area for the sense of touch.

- **EEG Influence**: Parietal lobe activity can be observed in the parietal and parietooccipital regions of the EEG. It plays a role in sensory integration and spatial awareness.

2.1.1.3. Temporal Lobe

- **Function**: Involved in processing auditory information and is also important for the processing of semantics in both speech and vision. The hippocampus, a part of the temporal lobe, is critical for the formation of new memories.
- **EEG Influence**: Temporal lobe activity is reflected in the temporal regions of the EEG. Abnormalities in this region may be associated with auditory processing disorders or memory issues.

2.1.1.4. Occipital Lobe

- **Function**: Main center for visual processing. It contains most of the anatomical region of the visual cortex.
- **EEG Influence**: Visual stimuli and processing are reflected in the occipital regions of the EEG. Certain patterns in this area can be indicative of visual processing abnormalities or epileptic activity. [8]

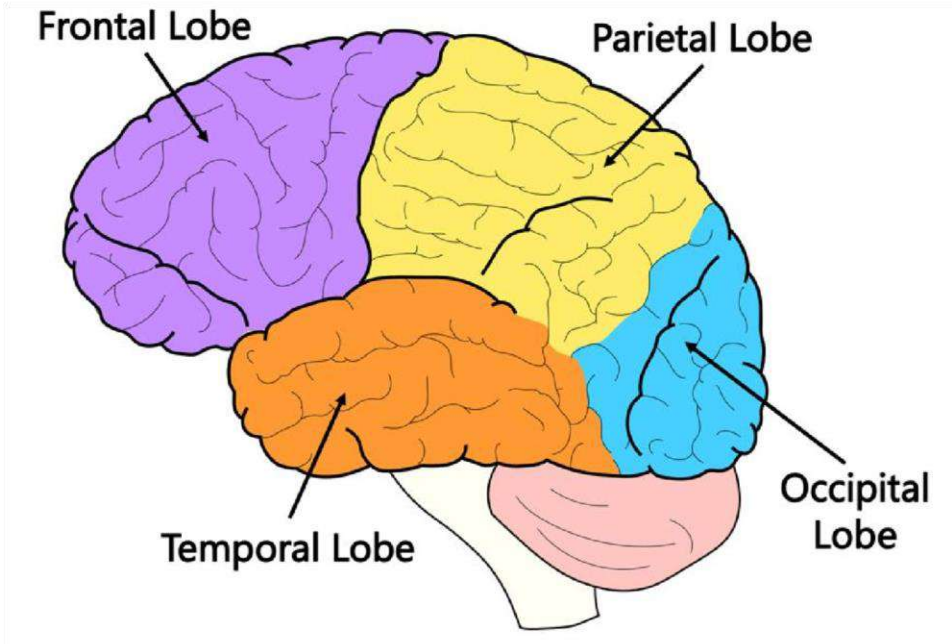

Figure 2.1 Lobes of brain *[9]*

2.1.2. Electrode Placement

2.1.2.1. The 10-20 Electrode System

The 10-20 electrode system is an internationally recognized method [10] to describe and apply the location of scalp electrodes for EEG recordings. It is commonly used in neuroscience and medicine to map the locations of electrodes on the scalp.

2.1.1.1. Key Electrode Locations

The following codes represent a specific location on the scalp where electrodes are placed to measure brain activity. These codes represent positions on the left and right sides of the brain, with prefixes indicating different regions (e.g., frontal, temporal, parietal, occipital) and numbers indicating relative positions (odd numbers for left hemisphere and even numbers for the right hemisphere).

Frontal Region

- AF3

- F7
- F3
- F4
- F8
- AF4

Central Region

- FC5
- FC6

Parietal Region

- P7
- P8

Occipital Region

- O1
- O2

Temporal Region:

- T7
- T8

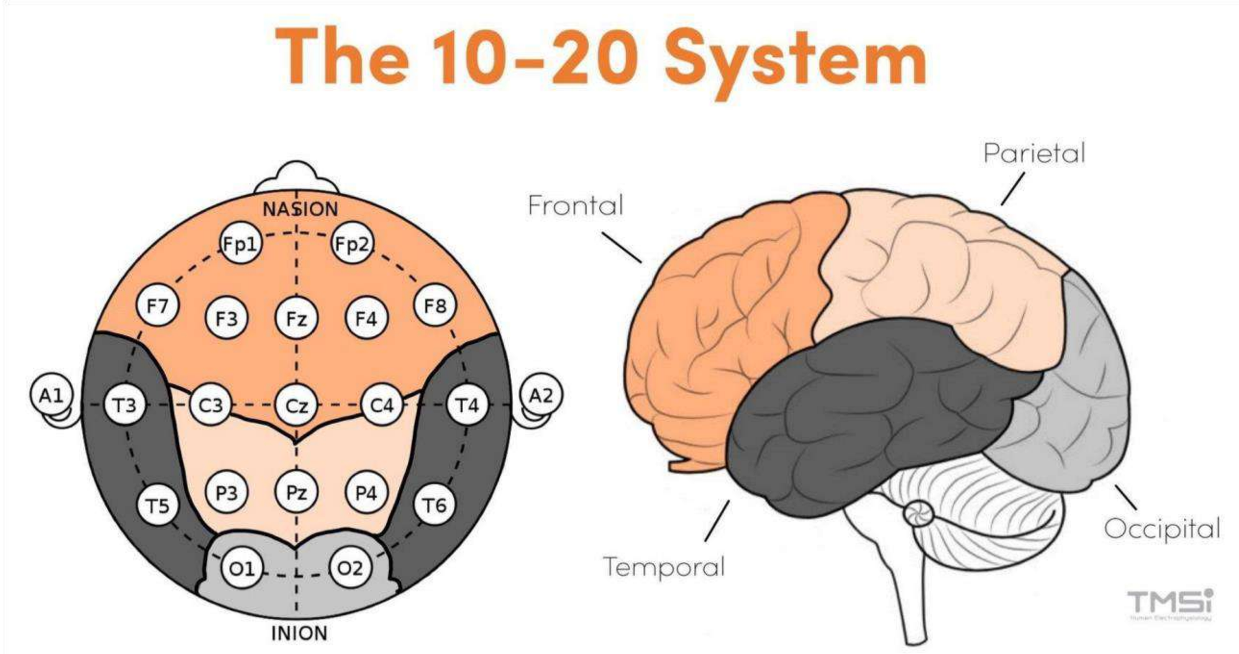

Figure 2.2 10-20 electrode system [11]

2.2. The Eye: Mechanisms of Eye movement and EEG Correlates

The eye, a marvel of sensory perception, plays a pivotal role in our daily interactions with the environment. Understanding the intricate mechanisms of eye movement is crucial for deciphering EEG signals associated with motor activities. In the realm of eye movement and its classification, understanding the intricate process of motor function is essential. Even seemingly simple actions, such as shifting one's gaze or blinking, involve the orchestration of various anatomical regions, with the motor cortex playing a pivotal role.

Six muscles known as the extraocular muscles play a crucial role in facilitating the movement of the eye. Emerging from the common tendinous ring, also referred to as the annulus of Zinn, within the eye cavity, these muscles form attachments to the eyeball. Specifically, the six muscles include the lateral, medial, inferior, and superior recti muscles, along with the inferior and superior oblique muscles. When these muscles contract, they induce movement in the eyeball by exerting tension and pulling it in the direction of the contracting muscle.

To illustrate, consider the lateral rectus situated on the outer side of the eyeball. Upon contraction, it prompts the eyeball to move outward, directing the pupil in that direction. Conversely, the medial rectus initiates inward movement of the eyeball, the inferior rectus causes a downward and outward gaze, and the superior rectus induces an upward and outward gaze. The superior oblique and inferior oblique muscles attach to the eyeball at angles. The superior oblique muscle contributes to moving the eye downward and inward, while the inferior oblique muscle facilitates upward and inward eye movement. This intricate interplay of muscles orchestrates the precise control and coordination of eye movements.

2.2.1. Types of Eye Movements

Different types of eye movements include Saccades (Rapid, voluntary eye movement), Smooth Pursuit (Tracking moving objects), Vergence (Coordinated movement of both eyes for depth perception), Blinking (Rapid closure and opening of the eyelids) and Nystagmus (Involuntary rhythmic eye movements). [12]

2.2.2. Neural Control of Eye Movements

The intricate control of eye movements is orchestrated by a network of brain regions, including the frontal eye fields, superior colliculus, cerebellum, and brainstem nuclei. These areas work in harmony to execute precise and coordinated eye movements, reflecting the integration of motor commands with sensory feedback.

2.2.3. EEG Signatures of Eye Movement

Electroencephalography (EEG) serves as a valuable tool for monitoring brain activity associated with eye movements. During eye movement tasks, distinct EEG patterns emerge, providing insights into the underlying neural processes. Understanding these patterns is instrumental in developing an AI-based model for brain state recognition, particularly in distinguishing between different types of eye movements.

2.2.3.1. Motor Cortex and Eye Movements

The voluntary eye movements are initiated by cerebral cortical activity and involve more ocular motor control structures than simple ocular reflexes. The cortical areas initiate eye movements and work through brainstem ocular motor centers to produce a response, i.e., there are *no* direct connections between the cerebral cortex and the extraocular motor nuclei. [13]

The motor cortex, situated in the frontal lobe, is a central hub for generating impulses that govern movement. Signals originating from the primary motor cortex traverse the body's midline, activating skeletal muscles on the opposite side. This means that the left hemisphere controls the right side of the body, and vice versa. The primary motor cortex boasts a meticulous organization, with different body parts represented in a specific order, akin to a neural map. The extent of representation corresponds to the level of control; intricate movements like those of the hand and fingers claim more significant cortical real estate than larger body regions.

In the context of eye state classification using EEG, these neural pathways and regions contribute to the generation of distinct electroencephalographic patterns associated with eye movements and states. The interplay between cortical and subcortical structures underscores the complexity of understanding and classifying eye states based on EEG signals, offering a fascinating intersection of neuroscience and technology.

2.3. Eye state and EEG

The practical applications of deciphering human intentions through neural activity are diverse. Various neuroimaging methods, including magneto encephalography, electroencephalography, functional near-infrared spectroscopy, and functional magnetic resonance imaging, have played pivotal roles in developing decoding applications based on neural activity. Specifically, electroencephalography (EEG) has found widespread use in different identification systems.

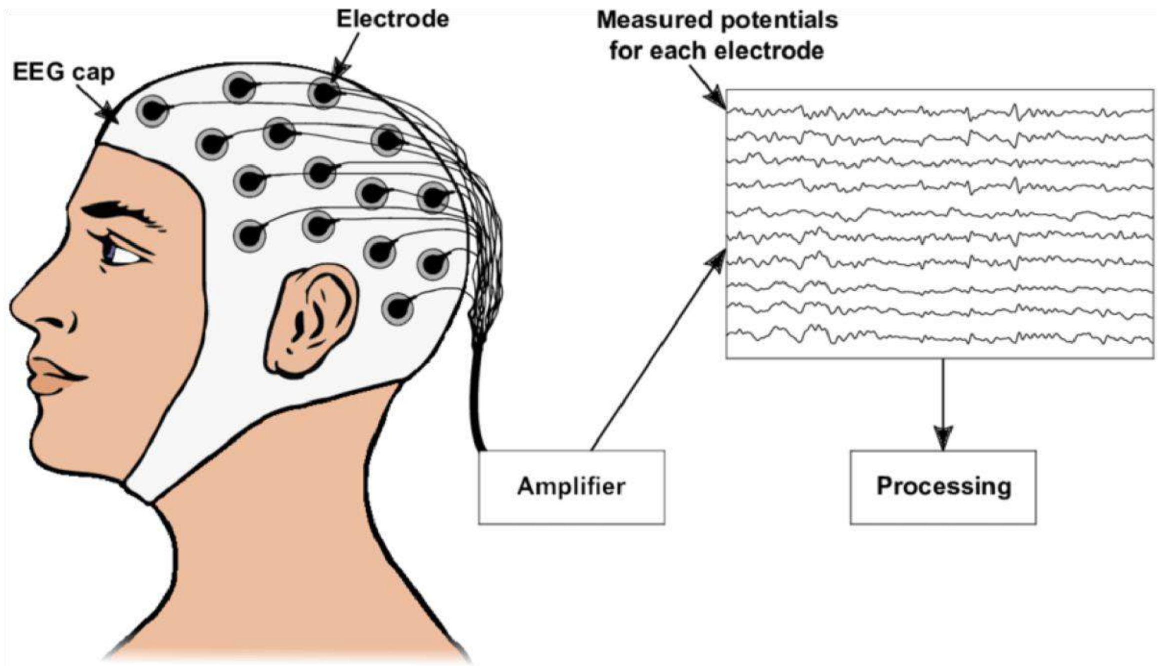

Figure 2.3 EEG recording process [14]

One noteworthy application of EEG lies in the realm of eye state identification. Tackling the challenging research goal of distinguishing between open and closed states of the eyes in real-life scenarios using EEG signals holds significant importance for both medical care and daily life tasks. Eye state identification, considered a common time-series classification problem, has garnered considerable attention within the research community. EEG, a technique frequently employed in eye state classification, serves to discern a human's cognitive state. Notably, the literature showcases successful applications of EEG eye state classification across diverse domains, including driving drowsiness detection, infant sleepwaking state identification, emotional arousal detection, personal authentication, and driver alertness monitoring. [16]

2.4. EOG

Electrooculography (EOG) is a technique used to measure the electrical potential generated by eye movements. Unlike EEG, which primarily captures brain activity, EOG focuses on detecting changes in the electrical fields around the eyes caused by eye movements and changes in gaze direction. EOG relies on the fact that the eye is a dipole, meaning it has a positive charge at the cornea and a negative charge at the retina. When the eyes move, the orientation of this dipole changes, leading to alterations in the electrical potential recorded by electrodes placed around the eyes.

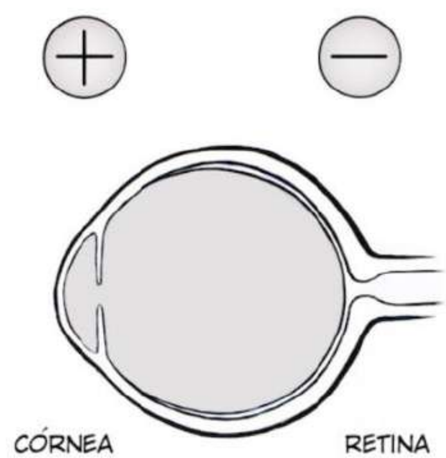

Figure 2.4 corneo-retinal standing [15]

An EOG records eye movement because of a voltage difference between the cornea and the retina (Figure 4.2). As the eye moves, the vector of this electric field changes with respect to recording electrodes placed on the skin at fixed points.

2.5. Related Work

Historically, brain-computer interfaces (BCIs), also known as brain-machine interfaces (BMIs), have primarily served individuals with disabilities, aiding in communication and prosthetic control. They empower users to engage with their environment, bypassing the need for peripheral nerves and muscles by utilizing control signals derived from electroencephalographic activity.

These systems, encompassing both hardware and software components, can be broadly categorized based on the placement of electrodes for the detection and measurement of neuronal activity in the brain. In invasive approaches, electrodes are directly inserted into the cortex, while in non-invasive systems, such as ours, they are placed on the scalp and use EEG to detect neuron activity.

The story of brain-computer interfaces (BCIs) started with Hans Berger discovering how the human brain's electrical activity works, leading to the development of electroencephalography (EEG). In 1924, Berger recorded brain activity using EEG, identifying patterns like the alpha wave. Over time, EEG recording methods improved from simple silver wires to more advanced setups.

In the 1970s, BCI research at UCLA marked a crucial period, introducing the term "brain-computer interface." The focus shifted to helping people with impaired hearing, sight, and movement. EEG, being non-invasive and detecting brain signals from the scalp, played a key role. By the mid-1990s, there were significant developments in both invasive and noninvasive EEG-based BCIs. Researchers like Phillip Kennedy and teams led by Richard Andersen, John Donoghue, Miguel Nicolelis, and Andrew Schwartz made important progress. Kennedy's team achieved the first intracortical BCI using invasive EEG, while non-invasive EEG methods were used to decode images seen by cats.

The work of Nicolelis, Donoghue, Schwartz, and Andersen demonstrated the versatility of EEG-based BCIs. They showed real-time control of movements, from tracking visual targets to navigating virtual reality. The historical journey concludes with EEG-based BCIs contributing to advanced neuroprosthetics, exploring ways to restore mobility in paralyzed limbs. [1]

In recent years, the field of brain-computer interfaces (BCIs) has witnessed remarkable advancements, building upon the historical foundations laid by pioneers like Hans Berger. Contemporary research, as exemplified by a 2018 study on epileptic seizure detection utilizing EEG signals and Convolutional Neural Networks (CNN) [2], showcases the integration of cutting-edge technologies. This study, which garnered 167 citations, employed intracranial EEG (iEEG) data obtained through invasive presurgical epilepsy monitoring. The high-density EEG data, collected from 21 patients, provided detailed insights into the brain's electrical activity, particularly during epileptic events. Moreover, the utilization of advanced machine learning techniques, such as CNN, demonstrated the potential for accurate seizure detection. The Freiburg dataset, sourced from the Epilepsy Center at the University Hospital of Freiburg, Germany, presented a wealth of information, including recordings of 87 seizures from 21 patients. The study marked a shift toward leveraging deep learning architectures, reflecting the evolution of BCI research beyond traditional EEG applications.

In another notable 2019 study, researchers focused on leveraging EEG data and machine learning algorithms to detect epilepsy [3]. They compared three classification algorithms— naive Bayes, random forest, and K-nearest neighbor (KNN)—following the pre-processing of raw EEG data and feature extraction. The standout performer was the KNN classifier, achieving an impressive accuracy of 92.7% and demonstrating superior precision (82.5%) compared to naive Bayes and random forest. Despite naive Bayes exhibiting the highest sensitivity at 80.3%, KNN's balanced performance across metrics positioned it as the preferred classifier. The study emphasized the potential of machine learning in EEG-based epilepsy detection, showcasing advancements in medical diagnostics through brain-computer interfaces.

In late 2020, a study revolutionized emotion recognition through EEG signals [4]. The automated model employed novel techniques like empirical mode decomposition and variational mode decomposition for signal processing, departing from traditional methods. Unique features like entropy and Higuchi's fractal dimension were incorporated, highlighting innovation in EEG signal handling. The classification stage utilized diverse algorithms—naïve Bayes, k-nearest neighbor, convolutional neural network, and decision tree. Impressively, the CNN-based method achieved an outstanding accuracy of 95.20%, representing a major leap in emotion recognition via EEG signals.

In a prior study from 2018, researchers utilized advanced computer models like Stacked Autoencoder (SAE) for the classification of eye states as open or closed [5]. The SAE model achieved an impressive accuracy of 98.9%, showcasing its effectiveness in discerning between these states. Continuing the exploration of EEG-based eye state classification, a study published in 2020 [6] introduced an innovative approach using Long Short-Term Memory (LSTM) networks. This model aimed to detect whether the eyes are open or closed with an accuracy of 89.23%. The UCI machine learning repository provided the dataset, recorded from 14 electrodes strategically placed on the scalp. Data preprocessing involved converting eye state labels to numeric classifications, visualizing data using MATLAB, and removing outliers to ensure representative behaviour. After rescaling and partitioning the dataset, LSTM was applied, utilizing 70% of the data for training. The LSTM layer, with 200 units, addressed the vanishing gradient problem, crucial for capturing long-term dependencies in sequential data. The model's output layer used SoftMax activation for classification, achieving compelling results in predicting eye states.

Recent research of 2023 proposes a hybrid method for EEG based eye state classification [7] employing supervised and unsupervised learning for fast and accurate classification. The approach combines Learning Vector Quantization (LVQ) and bagged tree techniques, aiming to handle multivariate signals and non-linearities. Evaluated on a real-world EEG dataset with 14,976 instances, the method yielded promising results. LVQ combined with the bagged tree outperformed other classifiers, achieving an accuracy of 94.31% and demonstrating effectiveness in ensemble learning and clustering approaches in EEG signals analysis.

Chapter 3

Methodology

3.1. Signal Acquisition

In this section, the process of acquiring raw data for brain state recognition is elaborated upon. Various components and software utilized for capturing EOG signals are discussed along with the methodology for electrode placement.

The acquisition of raw EOG signals involves the following components and processes:

Body Surface Electrodes:

Surface electrodes are positioned strategically on the scalp to capture electrical activity generated by the brain.

Conductor Electrode Cable:

A specialized cable is used to connect the electrodes to the data acquisition system, ensuring reliable signal transmission.

Electrode Leads:

Leads connect the electrodes to the electrode cable, facilitating the transfer of electrical signals to the measurement system.

KL-710 Software:

The KL-710 software serves as the interface for data acquisition, allowing for real-time monitoring and recording of EOG signals.

KL-74001 x1:

This component likely refers to a specific model or version of the data acquisition hardware, providing the necessary functionality for signal capture and processing.

Conductive Gel for Electrode Conductivity:

Conductive gel is applied to the electrode-skin interface to reduce impedance and improve signal quality.

Acquired Data on Excel:

Recorded EEG data is stored and managed using Excel or similar spreadsheet software for subsequent analysis and processing.

Electrode Placement:

The placement of electrodes on the scalp is crucial for accurate signal acquisition:

Positive Electrode:

Positioned below the right eye, this positive electrode captures electrical signals relative to the reference electrode.

Negative Electrode:

Placed above the left eye, the negative electrode captures electrical signals relative to the reference electrode.

Ground Electrode:

Located in the middle of the forehead, the ground electrode provides a stable reference point for measuring EEG signals.

This comprehensive setup ensures the reliable acquisition of EEG data necessary for subsequent analysis and interpretation in brain state recognition experiments.

3.2. Acquired Signal Analysis

Following the setup phase, the acquired signals underwent testing for various movements, including left, right, up, down, rotation, and blinking. However, for the subsequent analysis, focus was narrowed down to two specific movements: rotation and blinking. These movements were selected based on their relevance to the research objectives and their potential for distinguishing between different brain states.

3.2.1. Analysis of Selected Movements: Rotation and Blinking

Rotation:

This movement involves the rotation of the eyes in different directions, which induces distinct patterns of electrical activity in the brain. The acquired EEG signals during rotation were analyzed to identify characteristic features associated with this movement.

Blinking:

Blinking, a common eye movement, also elicits specific electrical patterns in the brain. By examining the acquired EEG signals during blinking, unique markers indicative of this movement were sought.

3.2.2. Inter-Subject Variance Analysis

To understand the variability in the acquired signals across different subjects, an analysis of inter-subject variance was conducted. This analysis aimed to assess how the EOG signals varied among individuals during the selected movements.

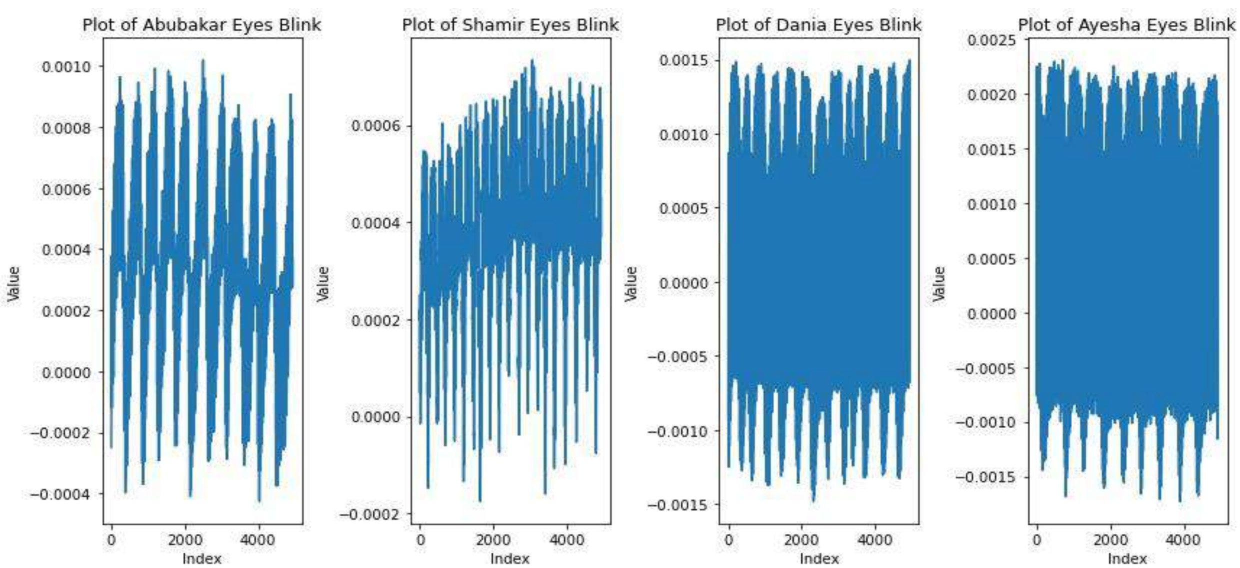

Figure 3.1 Subjects 5 seconds blink bv result comparison

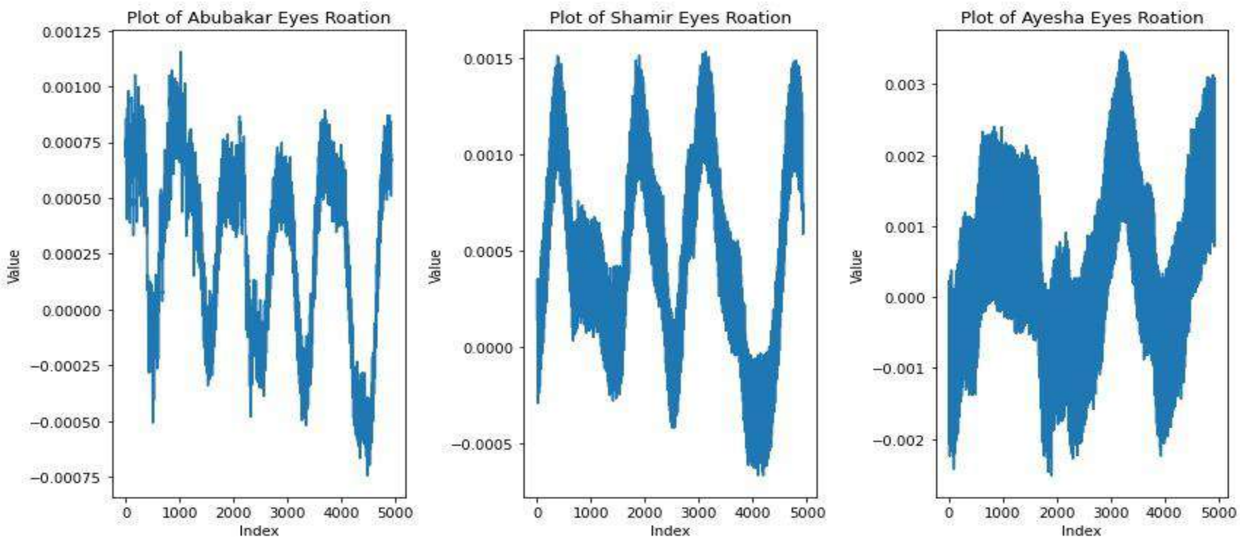

Figure 3.2 Subjects 5 seconds rotation result comparison

Graphical representations were generated to visualize the inter-subject variance in the acquired EOG signals. These plots provide insights into the consistency or variability of brain activity patterns across subjects during rotation and blinking movements.

3.3. Feature extraction:

In our ongoing project, we focus on extracting meaningful features from EOG signals to analyze eye rotations and blinks. EOG signals were collected under two distinct conditions—during a continuous 5-second period and a shorter 2.5-second interval. For each dataset, specific statistical features were calculated to summarize the underlying characteristics of the signals.

- The 5-second EOG recordings captured eye rotations and blinks, resulting in a total of 145 samples.
- The 2.5-second EOG recordings, aimed at capturing more transient eye rotations and quicker blinks, yielded 290 samples.

3.3.1. Statistical Feature Extraction:

For both datasets with different time durations, we computed the following statistical features:

Mean: The average value, providing a central tendency of the signal.

$$\textbf{Formula: } \mu = \frac{1}{N}\sum_{i=1}^{N} xi$$

N = no. of data points

xi = data points

Standard deviation: Standard deviation is a statistical measure that quantifies the amount of variability or dispersion in a set of data values. It is widely used in statistics, research, and various scientific disciplines to determine how spread out the numbers in a data set are from the mean (average) value.

$$\textbf{Formula: } \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

μ = mean

N = no. of data points

xi = data points

Kurtosis: Measures the 'tailedness' of the distribution, useful for identifying outliers or extreme deviations in the signal.

$$\textbf{Formula: } \mathrm{k} = \frac{1}{N}\sum_{i=0}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 - 3$$

μ = mean

N = no. of data points

xi = data points

σ = standard deviation

These features were selected to capture basic yet informative characteristics of the EOG signals, providing initial insights into the behavior and dynamics of eye movements.

Next Steps – Advanced Feature Extraction:

- Moving forward, we plan to employ the Fourier Transform and other advanced feature extraction methods. This approach will allow us to analyze the frequency components of the EOG signals, offering a deeper understanding of the periodic nature and frequency-related phenomena inherent in eye movements and blinks.
- Applying the Fourier Transform will enable us to distinguish between different types of eye movements (such as rapid saccadic movements versus slower tracking movements) and various blinking patterns, based on their frequency spectra.

Objective:

- The objective of incorporating advanced features such as those derived from the Fourier Transform is to enhance the accuracy and effectiveness of our analysis. By transitioning to frequency-domain analysis, we aim to refine our ability to classify different types of eye activities and potentially improve the applications of our findings in areas such as user interface accessibility, neurological research, and clinical diagnostics.

3.4. Classification:

In our study, we employed various classification techniques to analyze both our locally acquired dataset and an online dataset. Each dataset was subjected to different classifiers to evaluate their effectiveness in distinguishing between types of eye movements and blinks.

3.4.1. Classifiers for Our Acquired Dataset:

1. **Support Vector Machine (SVM):** Known for its effectiveness in high-dimensional spaces and cases where the number of dimensions exceeds the number of samples.
2. **Random Forest:** A robust ensemble technique that uses multiple decision trees to reduce over fitting and improve generalization.
3. **Logistic Regression:** A simple yet powerful linear classifier that estimates probabilities

using a logistic function, widely used for binary classification tasks.

4. **Multilayer Perceptron (MLP):** A type of neural network suitable for capturing complex relationships in the data through multiple layers and non-linear activations.

3.4.2. Classifiers for the Online Dataset:

1. **Random Forest:** Again, utilized for its robustness and effectiveness in handling diverse datasets.
2. **Multilayer Perceptron (MLP):** Employed to leverage its deep learning capabilities in detecting nuanced patterns in the data.
3. **Convolutional Neural Network (CNN):** Specifically chosen for the online dataset to take advantage of its strength in spatial data analysis, which is typical in image and signal processing.
4. **Logistic Regression:** Used for its efficiency and effectiveness in binary classification scenarios.

Future plans to enhance classification accuracy: As we continue to refine our approach and seek higher accuracy in classifying EOG signals, we plan to explore additional classifiers and techniques, including:

1. **Linear Discriminant Analysis (LDA):** To be tested for its ability to find a linear combination of features that characterizes or separates two or more classes of objects or events.
2. **K-Nearest Neighbors (KNN):** This method will be considered for its simplicity and effectiveness, particularly in scenarios where the decision boundary is very irregular.
3. **Other Advanced Techniques:** We are also open to experimenting with other advanced machine learning and statistical methods based on the evolving needs of our analysis and the characteristics of the datasets.

Our objective is to continuously improve the predictive performance of our models. By integrating these diverse classifiers, we aim to develop a robust framework that accommodates the complexities of EOG signal data, ultimately enhancing our ability to interpret and utilize this data effectively in practical applications.

Chapter 4

Results

4.1. Online dataset:

The performance of the classifiers used on the online dataset is quantitatively assessed based on their accuracy metrics. Each classifier was trained and tested on the dataset to understand their effectiveness in classifying EOG signal data. Here are the detailed results:

Logistic Regression: Achieved an accuracy of 64%. This relatively lower performance might be due to the linear nature of logistic regression, which could struggle with the more complex patterns in the data that require capturing non-linear interactions.

Multilayer Perceptron (MLP): This model demonstrated a high accuracy of 96%, suggesting that its deep learning capabilities are highly effective in handling the intricate structures and relationships within the EOG signal data.

Convolutional Neural Network (CNN): Exhibited a robust performance with an accuracy of 91%. The success of the CNN model underscores its strength in processing spatially structured data like signals, benefiting from its ability to capture local dependencies through convolution operations.

Random Forest: Delivered a strong accuracy of 89%. The ensemble method, which operates by building multiple decision trees and merging their outputs, showed great efficacy, likely due to its ability to reduce overfitting and handle variance effectively in complex datasets.

4.2. Offline dataset:

Our study analyzed the performance of several classifiers on an offline dataset consisting of EOG signals collected over two different durations: 5 seconds and 2.5 seconds. Each duration was intended to capture distinct eye rotations and blinking patterns. The classification results are summarized below:

5-second duration (Eye Rotation and Blinking:

> **Random Forest (RF)**: Achieved an accuracy of 83%, demonstrating its robustness in handling the complexity of the data.

Support Vector Machine (SVM): Recorded a lower accuracy of 60%, indicating potential challenges in capturing the variability with linear boundaries.

Logistic Regression (LR): Had an accuracy of 52%, suggesting limitations in dealing with the dataset's complexity through linear methods.

Multilayer Perceptron (MLP): Excelled with an accuracy of 86%, showcasing its capability in learning nonlinear relationships effectively.

2.5-second duration (Eye Rotation and Blinking):

Random Forest (RF): Maintained a consistent accuracy of 83%, affirming its effectiveness across different time scales.

Support Vector Machine (SVM): Improved to 71%, possibly benefiting from a more dynamic representation of quicker eye rotations.

Logistic Regression (LR): Increased to 61%, showing some improvement but still underperforming relative to more complex models.

Multilayer Perceptron (MLP): Showed a decrease to 76%, which could reflect challenges in adapting to the shorter duration of signal data.

Discussion: The variation in performance across different classifiers and signal durations highlights the need for tailored approaches depending on the temporal characteristics of the data. The superior performance of the MLP and RF in both durations underscores their potential in capturing and analyzing complex, time sensitive EOG signals.

Future Directions: As we continue our research, our goals are to:

Enhance the accuracy of existing models through refined preprocessing, feature engineering, and more sophisticated modeling techniques.

Explore additional classifiers and machine learning techniques that might be better suited for the specific challenges presented by the different durations and complexities of EOG signals.

Expand our research to include the analysis of other brain states using electroencephalography (EEG). This will involve developing and adapting our current methodologies to accommodate the distinct characteristics of EEG data, which may also contribute to a more comprehensive understanding of brain functions and states.

Our ongoing work on this project aims not only to improve the performance of classifiers detecting and interpreting EOG signals but also to extend our findings to broader applications in brain state analysis, enhancing both the theoretical and practical implications of our research.

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