SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute under Visvesvaraya Technological University, Belagavi)

Project Report on

"AI Powered AR/VR for Analysing Study Behavior"

submitted in partial fulfillment of the requirement for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE & ENGINEERING

Submitted by

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

2024-25

SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that the project work entitled "AI Powered AR/VR for Analysing Study Behavior" is a bonafide work carried out by Arfath (1SI22CS401), Chethan Kumar H R (1SI22CS403), Namitha M (1SI22CS407) and Varun Kumar M S (1SI22AD405) in partial fulfillment for the award of degree of Bachelor of Engineering in Computer Science & Engineering from Siddaganga Institute of Technology, an autonomous institute under Visvesvaraya Technological University, Belagavi during the academic year 2024-25. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the department library. The Project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering degree.

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Course Outcomes

After successful completion of major project, graduates will be able to:

CO1: To identify a problem through literature survey and knowledge of contemporary engineering technology.

CO2: To consolidate the literature search to identify issues/gaps and formulate the engineering problem

CO3: To prepare project schedule for the identified design methodology and engage in budget analysis, and share responsibility for every member in the team

CO4: To provide sustainable engineering solution considering health, safety, legal, cultural issues and also demonstrate concern for environment

CO5: To identify and apply the mathematical concepts, science concepts, engineering and management concepts necessary to implement the identified engineering problem

CO6: To select the engineering tools/components required to implement the proposed solution for the identified engineering problem

CO7: To analyze, design, and implement optimal design solution, interpret results of experiments and draw valid conclusion

CO8: To demonstrate effective written communication through the project report, the one-page poster presentation, and preparation of the video about the project and the four page IEEE/Springer/ paper format of the work

CO9: To engage in effective oral communication through power point presentation and demonstration of the project work

CO10:To demonstrate compliance to the prescribed standards/ safety norms and abide by the norms of professional ethics

CO11: To perform in the team, contribute to the team and mentor/lead the team

CO-PO Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO-1											3			
CO-2		3												
CO-3										3				
CO-4						3								
CO-5	3	3												
CO-6					3						3			
CO-7			3	3										
CO-8									3					
CO-9									3					
CO-10							3							
CO-11								3						
Average	3	3	3	3	3	3	3	3	3	3	3			

PSO mapping to be done by respective Dept.

Attainment level: - 1: Slight (low) 2: Moderate (medium) 3: Substantial (high)

POs: PO1: Engineering knowledge, PO2: Problem analysis, PO3:Design of solutions, PO4:Conduct investigations of complex problems, PO5: Engineering tool usage, PO6:Engineer and the world, PO7:Ethics, PO8:Individual and collaborative work, PO9:communication, PO10:project management and finance,PO11: Life-long learning.

Abstract

Virtual Reality (VR) has become a promising innovation for immersive learning experiences. Despite ongoing research, the cognitive impact of VR-based learning remains unclear. A study that compares students' cognitive levels during VR-based and traditional learning sessions using Electroencephalography (EEG) and machine learning techniques is presented in this paper. This project utilized a mobile EEG system with 10 channels to collect ECG data from participants during both learning experiences. Machine learning models were able to use EEG signals as markers for cognitive state classification, with the ability to classify cognitive states and compare learning efficiency.

The study involved 30 students who were instructed using VR and traditional methods. Machine learning models were utilized to identify cognitive patterns, which was a result of their training and the ability for them to discriminate with great accuracy across different learning contexts. Cognitive engagement and attention levels were found to be significantly different in VR-based learning compared to traditional methods. Moreover, the level of workload varied with increasing learning tasks.

By utilizing EEG and machine learning, these results indicate that educational strategies can be evaluated and improved by adapting learning environments to match students' real-time cognitive states. Additionally, The research provides a roadmap to designing intelligent, adaptive learning systems that optimize educational outcomes by providing personalized learning experiences.

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Chapter 1

Introduction

This project explores the application of machine learning to assess and enhance students' cognitive thinking levels. By analyzing EEG (electroencephalogram) data, we aim to gauge cognitive functioning and provide tailored feedback that can support students in strengthening critical thinking skills. Cognitive performance can be challenging to evaluate and improve without detailed, objective data, so this project leverages EEG sensors to capture brain activity patterns, offering insights into how students process information, solve problems, and learn new concepts. This approach allows for an in-depth analysis of cognitive abilities and individualized feedback based on specific needs.

The project uses EEG-generated datasets to train machine learning models that identify patterns associated with cognitive processing levels. By doing so, it facilitates a continuous improvement loop, wherein students receive constructive, personalized feedback that can help them enhance their problem-solving and analytical skills. This data-driven approach not only provides immediate feedback but also contributes to longitudinal studies on cognitive development, opening doors for educators to incorporate science-backed strategies for fostering higher-order thinking in educational settings.

An EEG (electroencephalogram) device is a non-invasive tool used to measure electrical activity in the brain. It consists of electrodes placed on the scalp that detect tiny electrical impulses generated by neurons as they communicate. EEG devices are commonly used in medical and research settings to study brain functions, monitor brain disorders like epilepsy, and investigate mental states such as attention, relaxation, and cognitive processing. Because EEG provides real-time insight into brain activity, it is also used in neuroscience research, cognitive studies, and, increasingly, in fields like machine learning, where brain wave patterns can help analyze cognitive functions and inform adaptive educational and therapeutic applications.

1.1 Motivation

Enhanced Learning: Personalized feedback can improve students' cognitive and problem-solving skills.
Data-Driven Insights: EEG-based analysis offers objective measures of cognitive functioning.
Real-Time Feedback: Immediate brain activity monitoring enables adaptive learning adjustments.
Research Advancement: The project supports ongoing studies in cognitive development and educational psychology.
Educational Innovation: Integrating neuroscience and machine learning can transform traditional teaching methods

1.2 Objective of the project

- Evaluate the effectiveness of regular classes for learning.
- Evaluate the effectiveness of VR classes for learning.
- Finding Most effective method for learning among regular and VR classes.

1.3 Organisation of the report

This project report shall be presented in a number of chapters, starting with Introduction and ending with Summary and Conclusions. Each of the other chapters will have a precise title reflecting the contents of the chapter. A chapter can be subdivided into sections, subsections and sub subsection so as to present the content discretely and with due emphasis. When the work comprises two or more mutually independent investigations, the project report may be divided into two or more parts, each with an appropriate title. However, the numbering of chapters will be continuous right through. In this section make sure to mention in what chapter what is explained.

Chapter 2

Literature Survey

In this study [1] investigates the impact of posture yoga on the brain using EEG and employs a Deep Neural Network (DNN) to automatically discern mental states during real-time yoga practice and resting states. The DNN achieved a test accuracy of 100% in the gamma band, clearly demonstrating the difference between yoga and resting states. The application of this model could serve as a biomarker for identifying the effect of yoga on the brain, with potential uses in mental health and wellness, stress management, and performance optimization.

In this study [2] explores cognitive stress recognition during mathematical tasks and EEG changes following audio-visual stimuli for relaxation. EEG signals were recorded using the Enobio-8 device during math puzzle solving (stress state) and while watching funny videos (happy state). The Long Short-Term Memory (LSTM) deep learning model was used for classification, achieving an accuracy of 86% in the beta band. The application of this model could help in stress management, neurofeedback, and improving learning outcomes by identifying stress and relaxation states based on EEG data.

In [3], the authors used an EEG power spectral density-based metric to evaluate cognitive workload during operator training in the process industries. It shows that operators' mental models and decision-making capabilities are best measured through cognitive workload. Based on experiments with ten participants performing 438 tasks, the system metric quantitatively captures cognitive workload and enables investigation of the evolution of mental models as well as development of more efficient operator training systems.

In [4], the authors looked at cognitive load in multimedia learning tasks using EEG feature extraction and Partial Directed Coherence (PDC). Analysis of 34 participants' data revealed that cognitive load depended on learning states as well as associated EEG frequency bands. The study observed that reliable cognitive load assessment was possible with effective connectivity measures, such as PDC, on the optimization of multimedia learning processes.

Using multifractal detrended fluctuation analysis (MFDFA) on EEG signals, the authors classified the cognitive task states [5]. MFDFA features were able to distinguish cognitive states adjudicated from data of 38 participants who performed six tasks. Using support vector machine (SVM) and decision tree classifier (DTC) on a multinomial classification, accuracy of 96.84 % (SVM) and 92.49 % (DTC) are obtained respectively. It also suggested that nonlinear EEG analysis has good potential to be used to classify cognitive tasks.

In [6], the authors created a wearable EEG based system to record student engagement in Learning 4.0. The system was able to predict engagement using a signal processing pipeline in which Filter Bank, Common Spatial Pattern and SVM were used, achieving 77% accuracy. The study highlights the importance of active strategies and technology mediated learning in improving engagement and learning effectiveness in tech environments.

A comprehensive review of machine learning approaches for EEG cognitive workload recognition was presented in [7]. The EEG preprocessing, feature extraction, classification and evaluation methods were studied, and deep learning techniques are presented. It discussed open problems and new directions, laying a foundation for future research in operator state monitoring.

In [8], the authors monitored students' mental engagement during an interaction with a virtual learning environment by EEG signals. Especially the treatment identification phase, comprising more mental effort, the study identified trends in engagement. The study observed significant correlations between engagement measures and learner performance that inform effective tutoring interventions.

An Intelligent Tutoring System (ITS) with fuzzy neural networks for identifying and teaching of learning-disabled students was proposed in [9]. Learner profiling and adaptive content delivery were applied using FMNN classifiers. Results of 24 participants resulted in better accuracy in identifying learning disabilities, implying that ITS framework for personalized education is possible.

An EEG based tool for predicting the cognitive performance of university students under different learning modalities is presented in [10]. Video based learning performed better than text based learning, and there were correlations between cognitive states (ie, theta/alpha ratio, delta power) and performance. It achieved 85

An early detection of Mild Cognitive Impairment (MCI) based on sleep EEG was proposed by the authors in [11]. The system was able to classify given sleep features such as slow waves and spindles, achieving a classification accuracy of 93.46% with a GRU network. Sleep EEG was shown to be more powerful than awake EEG in discriminating MCI versus healthy control participants in order to facilitate early intervention and Alzheimer's disease prevention. neuroscience.

In [15], researchers examined EEG techniques to understand the neural processes underlying early social and cognitive development in infants and young children. The study focused on the roles of alpha, theta, and gamma frequency bands, using examples like the infant mu rhythm related to action processing, frontal alpha asymmetry associated with approach–withdrawal behaviors, and EEG power analysis in early psychosocial adversity. These findings showcase how EEG can be applied to study key aspects of developmental neuroscience.

Chapter 3

System Overview

EEG Data Collection: Brain activity is recorded using EEG devices during specific tasks or interactions. This involves placing electrodes on the scalp to measure electrical signals produced by neuronal activity.

Feature Extraction: Extracted EEG features, like frequency bands, are processed for meaningful analysis. This step involves identifying relevant patterns in the EEG data, such as alpha, beta, and theta waves, which correspond to different cognitive states.

Model Developing and Training: Machine learning models are trained to recognize patterns in the extracted EEG features. This involves feeding the models with labeled data to learn how to distinguish between different cognitive states or responses.

Model Evaluation and Validation: The models are tested for accuracy, and feedback systems are created based on their outputs. This step ensures that the models can reliably interpret EEG data and provide meaningful feedback to users.

System Testing and Deployment: The integrated system is implemented and tested in real-world environments for usability and effectiveness. This involves deploying the EEG-based system in practical settings, such as classrooms or workplaces, to evaluate its performance and user experience.

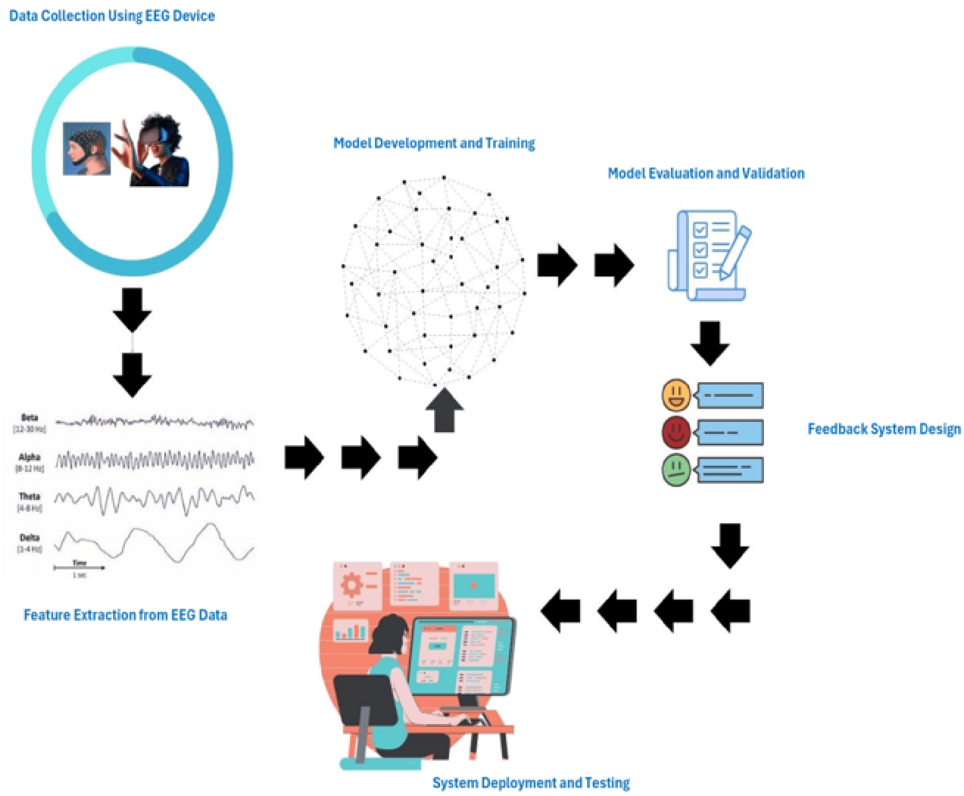

Figure 3.1: System Overview

Chapter 4

System Architecture and High Level Design

4.1 Jio Dive

The JioDive is a cutting-edge virtual reality headset introduced by Jio to deliver an immersive VR experience. Designed for use with compatible smartphones, it allows users to enjoy 360-degree videos, VR gaming, and live events in an engaging manner. Lightweight and user-friendly, JioDive brings entertainment and educational content to life, offering an affordable entry point into the world of virtual reality.

Figure 4.1: Jio Dive.

4.2 EEG

An **EEG (Electroencephalogram)** device is a non-invasive tool used to measure and record the electrical activity of the brain. It works by placing electrodes on the scalp, which detect and amplify the brain's electrical signals, providing valuable insights into brain function. EEG devices are commonly used in medical fields to diagnose conditions like epilepsy, sleep disorders, and brain injuries. Beyond healthcare, they are increasingly employed in neuroscience research, cognitive studies, and even brain-computer interface applications to explore brain activity and responses.

Figure 4.2: EEG Device.

4.3 Software Requirements

Programming Languages

- **Python**: For developing and integrating machine learning models, EEG data processing, and TensorFlow/CNN implementation.

Frameworks and Libraries

1. **Machine Learning and Deep Learning:**

   - **scikit-learn**:
     - StandardScaler: Standardizes features by removing the mean and scaling to unit variance.
     - train_test_split: Splits the dataset into training and testing sets.
     - confusion_matrix: Evaluates model performance.

   - **TensorFlow/Keras**:
     - Building and training a CNN-LSTM model for EEG cognitive load classification.
     - Layers Used:
       * Conv1D: For extracting spatial features from EEG data.
       * LSTM: For modeling sequential data patterns.
       * Dense: For classification.
     - Model compilation and training with metrics like accuracy and loss.

2. **EEG Data Processing:**

   - **Pandas**: Used for handling tabular EEG data loaded from CSV files $pd.read_csv$.
   - **Numpy**: Provides efficient numerical operations on arrays (np.sum, np.mean, etc.).
   - **SciPy**: scipy.stats.entropy is used for computing the signal entropy.

Development Environment

- **Jupyter Notebook**: For rapid prototyping and model experimentation. .

4.4 Functional Requirements

1. The system should collect EEG data from the participants during VR and non-VR conditions.
2. It should preprocess the EEG data using MNE signal processing libraries.
3. The AI model should analyze EEG data using CNN and classify student behavior patterns.
4. The VR environment should provide a seamless interface for interaction with participants during data collection.
5. The system should generate and store visualizations of EEG patterns and behavior analytics.

4.5 Non Functional Requirements

1. The system should process EEG data.
2. The VR experience should have high performance with no frame drops, ensuring a smooth user experience.
3. The EEG analysis pipeline should ensure accuracy and reliability in the classification of behavior patterns.
4. The platform should be scalable to accommodate more students or additional experiments in the future.
5. The system should be secure, protecting the collected data from unauthorized access.

Chapter 5

Software Architecture and Low Level Design

- **Low Level Design**

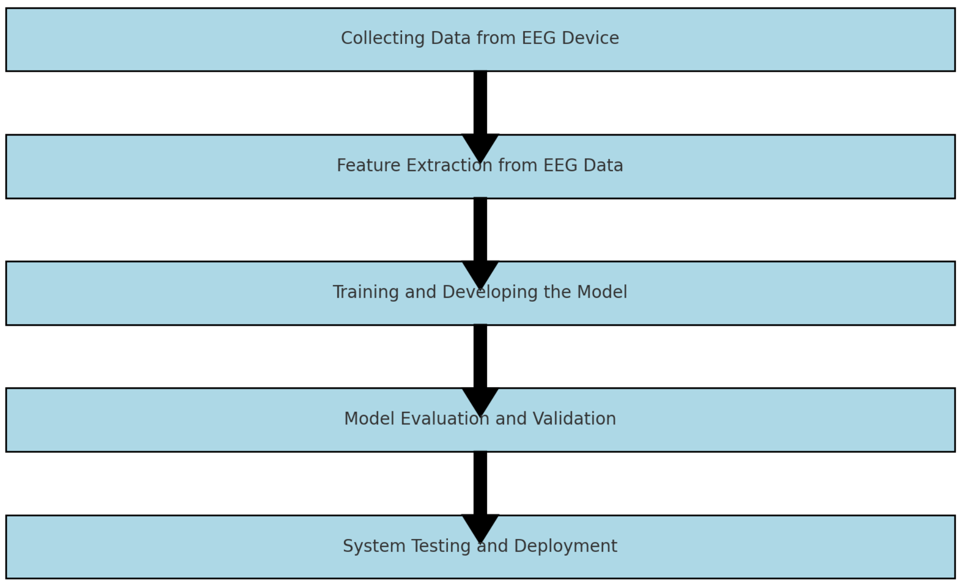

Figure 5.1: Low Level Design.

1. **Collecting Data from EEG Device**

   This module involves capturing real-time brainwave signals from the EEG device while the student interacts with the VR environment. It ensures proper synchronization and storage of raw EEG data.

2. **Feature Extraction from EEG Data**

   The raw EEG data is processed to extract meaningful features such as frequency bands, signal amplitude, or statistical patterns. These features serve as inputs for the model training phase.

3. **Training and Developing the Model**

   Using the extracted features, this module builds and trains machine learning or deep learning models to analyze student behavior, such as engagement or focus levels.

4. **Model Evaluation and Validation**

   The trained model is tested against validation datasets to evaluate its accuracy, precision, and overall effectiveness. Adjustments are made to improve performance as needed.

5. **System Testing and Deployment**

   This module tests the end-to-end system in real-world scenarios to ensure reliability and robustness before deploying it for actual use. It includes integrating hardware and software components seamlessly.

- **Deep learning architecture diagram**

Its model architecture is well-suited to time series data, including EEG, and includes layers of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM). To minimize dimensionality, the input data is pooled at maximum capacity in the CNN layer, where it is extracted to extract local features. The layers in the sequence are referred to as LSTM, and the dense layers at the end perform the ultimate classification. A hybrid model that incorporates both spatial and temporal features allows the data to be analyzed sequentially.

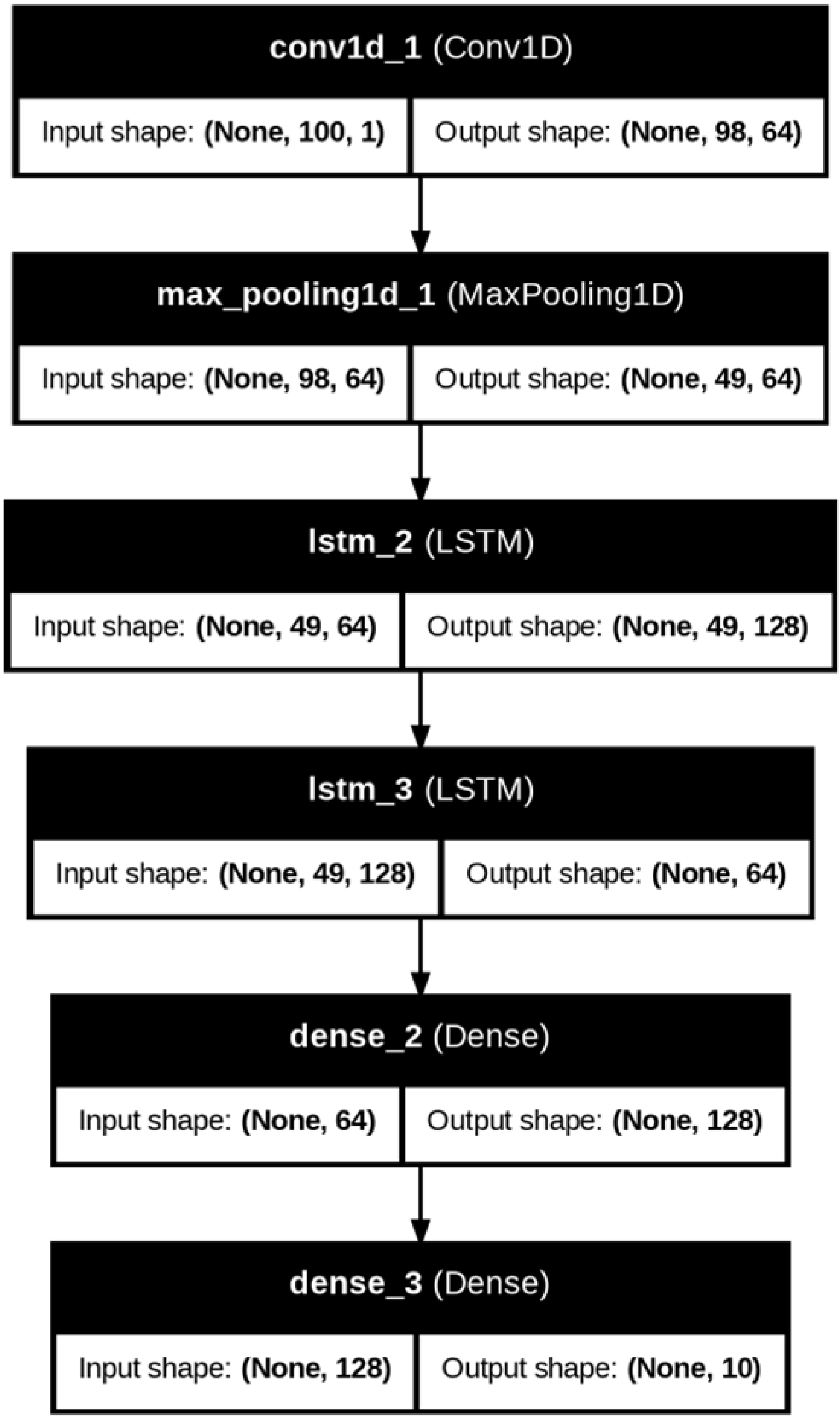

Figure 5.2: Deep learning architecture diagram

Chapter 6

Results

1) Model accuracy plot.

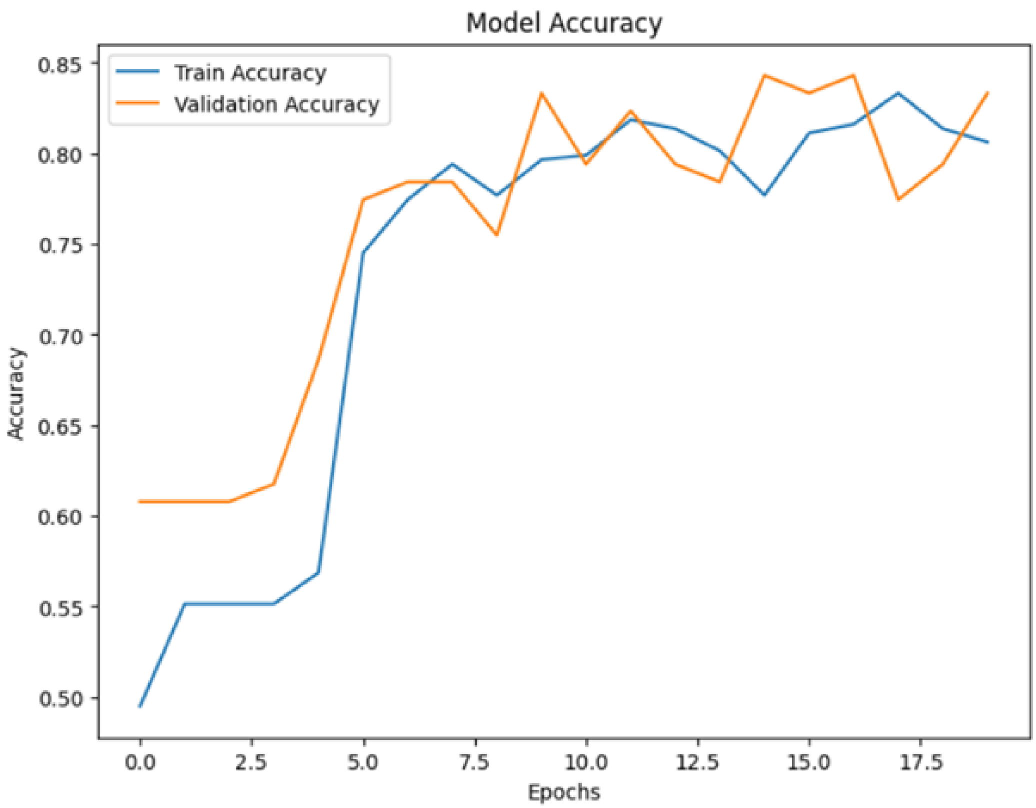

Figure 6.1: model accuracy plot

Shows training and validation accuracy over epochs, helping to assess model learning, convergence, and detect overfitting or underfitting.

2) classification report

Classification Report:

	precision	recall	f1-score	support
Slow	0.80	0.97	0.88	62
Fast	0.93	0.62	0.75	40
accuracy			0.83	102
macro avg	0.86	0.80	0.81	102
weighted avg	0.85	0.83	0.83	102

Figure 6.2: classification report

Provides precision, recall, and F1-score for each class, indicating model performance in correctly classifying slow and fast learners.

3) confusion matrix

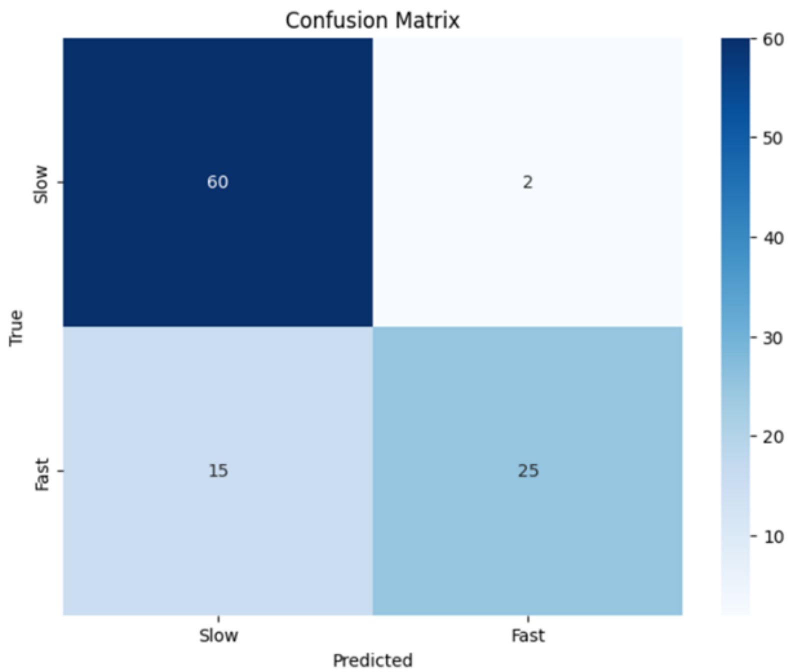

Figure 6.3: confusion matrix

A heatmap that displays the confusion matrix compares actual and predicted classes, indicating correctness of model when it shows classifications on each side as true or false to inference elsewhere and not so much because it helps identify areas for improvement.

4) User friendly design

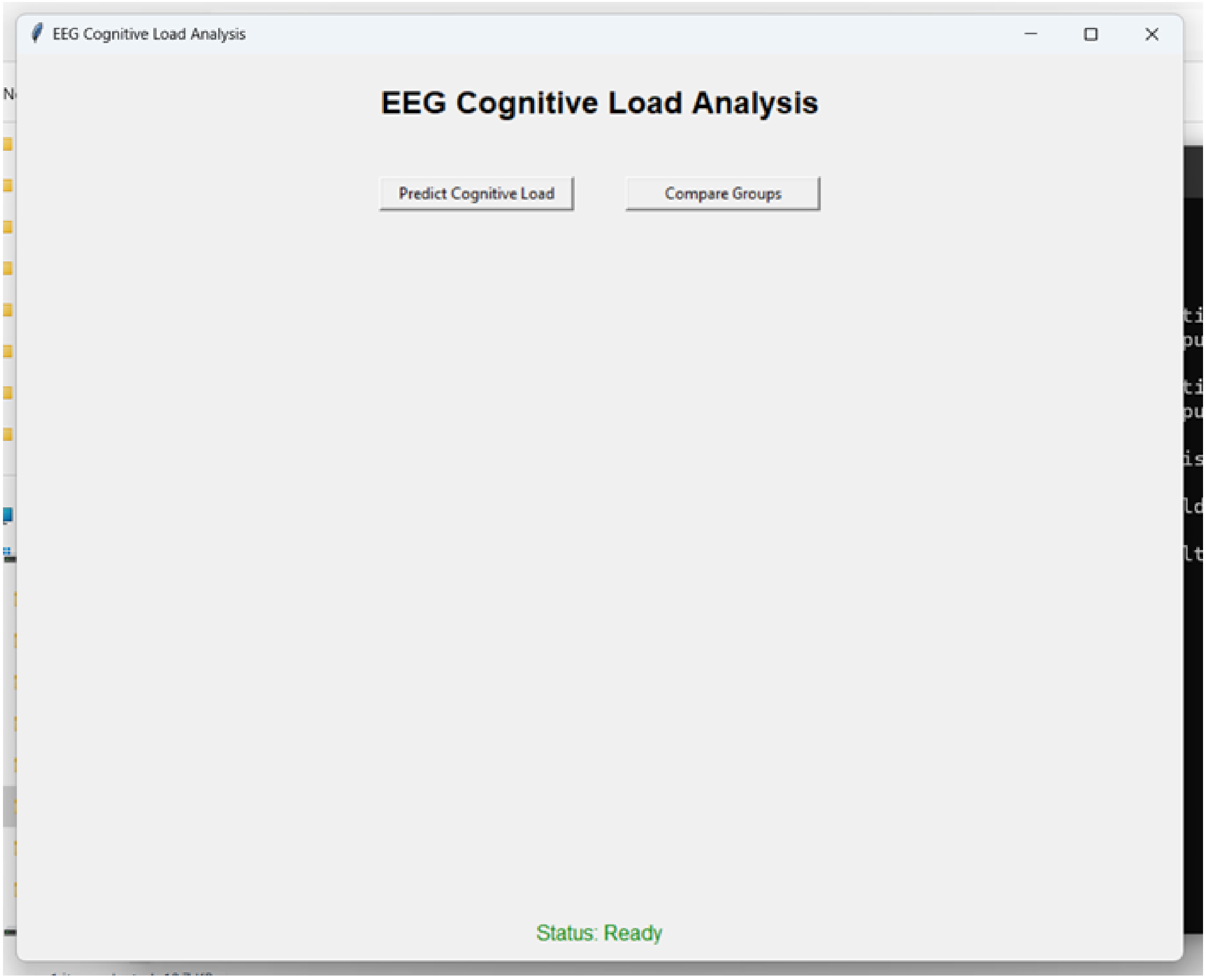

Figure 6.4: User friendly design

The EEG Cognitive Load Analysis application offers a user-friendly interface that allows for the interactive analysis and visualization of ECG data. The feature enables users to anticipate cognitive load, compare groups, and present results in interactive graphs with bar charts and confusion matrices. The design provides a user-friendly interface with buttons for keystrokes and graphical elements.

5) First graph predict individual student cognitive load

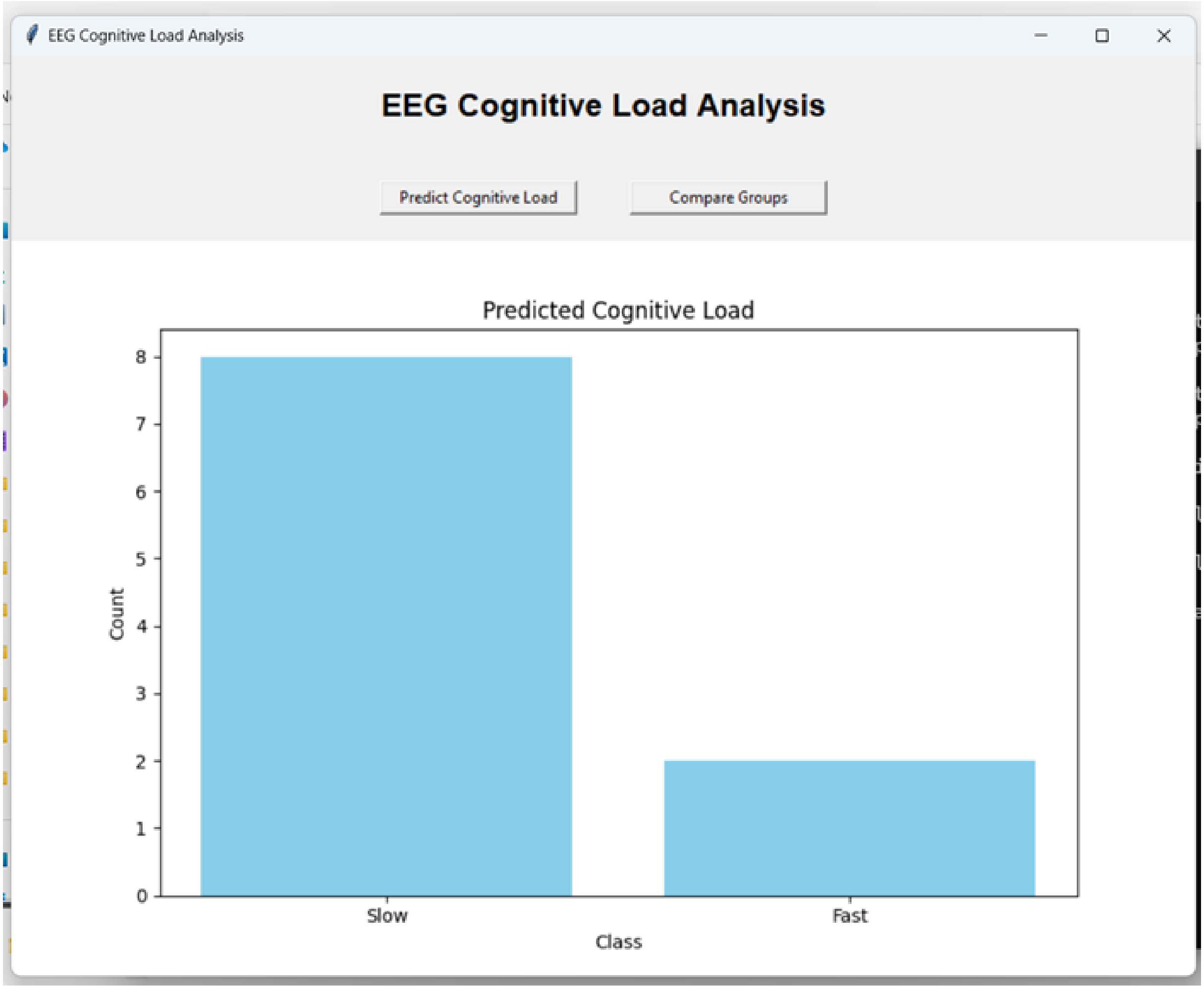

Figure 6.5: First graph predict individual student cognitive load

This bar chart illustrates the distribution of cognitive load predictions, which are categorized as "Slow" or "Fast." A brief overview of how this dataset is distributed across these two cognitive states provides insight into the model's overall predictions. The data sets exhibit one-to-one comparisons between the two categories.

6) Plot which compare two groups With ARVR and Without ARVR

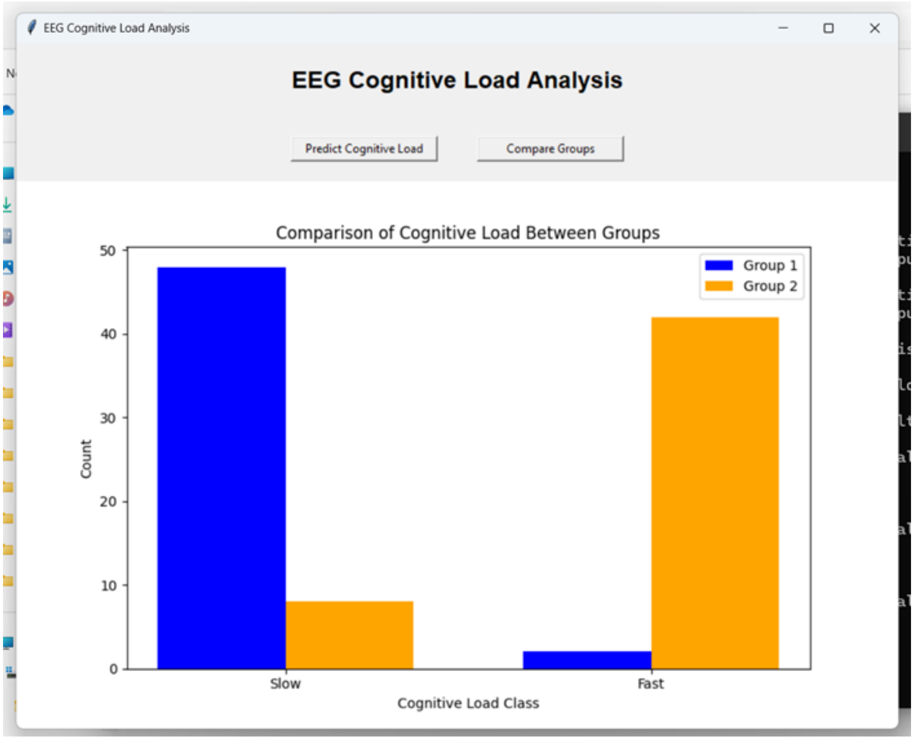

Figure 6.6: Plot which compare two groups With ARVR and Without ARVR

The counts of "Slow" prediction and "Fast" predictions are compared in descending order on this side-by-side bar chart. This is particularly useful for comparative analysis in experiments or studies because it shows clear variations in cognitive load.

7) Comparison with previous work

Ref	Accuracy	Technology Used	Application	NO. of Students	EEG Device
[1]	82%	DNN & LSTM	Healthcare	50	Enobio-8
[15]	77%	DL	Military	12	Mindlink Headset
[4]	80%	ML	Training purpous	60	EMOTIV Insight 2.0
[5]	83%	CNN & LSTM	Education	80	Enobio-8

Table 6.1: Comparison with previous work

This table provides a detailed comparison of research papers, highlighting the Accuracy, Technology used, and Applications and outcomes of each study.

8) ROC (Receiver Operating Characteristic) Graph

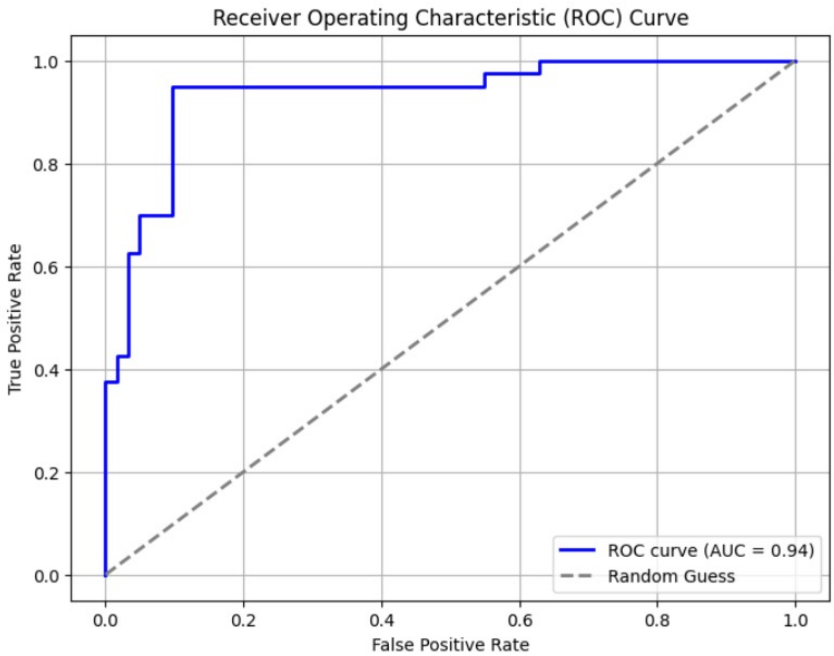

Figure 6.7: ROC (Receiver Operating Characteristic) Graph

A model's performance in binary classification is depicted by the ROC curve on a graph. A comparison between True Positive Rate (sensitivity) and False Positive Rat (1-specificity) is presented by plotting data for different classification thresholds. Measuring the model's ability to differentiate between classes is possible with the AUC, which indicates that a value closer to 1 would improve its performance.

Chapter 7

Conclusion

- The integration of EEG signals and machine learning in VR learning environments provides valuable insight into student cognitive levels in real-time.

- Real-time feedback based on EEG data can significantly enhance student engagement and optimize their learning experience.

- Machine learning models effectively identify cognitive patterns, offering personalized recommendations to support individual learning needs.

- This approach demonstrates the potential to transform traditional educational methods by making VR learning more adaptive and responsive to the cognitive states of the students.

7.1 Summary of the project work

This project compares the effectiveness of traditional and VR-based teaching methods using EEG data and AI models. Students are divided into two groups: one taught through traditional methods and the other using VR headsets with 3D videos. EEG devices capture the student's brain activity to measure cognitive thinking levels and learning effectiveness. The data collected are processed using TensorFlow, CNNs, and LSTM models to analyze attention, engagement, and cognitive performance. The project's goal is to identify the teaching method that best enhances cognitive abilities and to provide AI-driven feedback to improve learning experiences.

7.2 Scope for future work

- **Personalized Learning**: The system can adapt the content based on real-time EEG data to match each student's cognitive level and learning pace.
- **Emotion and Behavior Analysis**: It can be extended to analyze emotions such as stress, boredom, or excitement to improve teaching methods.
- **Scalable Classroom Integration**: The technology can be implemented in smart classrooms for real-time monitoring of students' engagement and attention levels.
- **Application in Special Education**: The project can help customize teaching for students with learning disabilities by identifying their cognitive challenges.
- **Mental Health and Cognitive Therapy**: The system can be used to track cognitive fatigue and stress, contributing to mental wellness programs.

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Appendices

Appendix A

Data Set Details

-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.2E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12
-4E+08	-4.1E+07	-4E+08	-4E+08	-4E+08	-4E+08	-1.1E+07	-9.8E+07	0	1.73E+12

Figure A.1: Data Set Sample.

The image shows a sample of EEG data output from an 8-electrode EEG device, represented in numerical form with scientific notation. Each column likely corresponds to the voltage signals recorded from different brain regions through the electrodes. The data includes large negative values, indicating fluctuations in brainwave activity across time. The presence of zero values and uniform readings suggests either a baseline or inactive phase during data collection. Additionally, the high values in some columns (e.g., around 1.73E+12) might indicate calibration offsets or noise in the signal that needs preprocessing. Proper filtering and normalization are necessary to clean the data for accurate analysis of cognitive states or brain activity patterns.

Appendix B

Configuration Details

GitHub Link: Click Here

Appendix C

Code Snippets

```
import os
import pandas as pd
import numpy as np
from scipy.signal import welch, coherence
from sklearn.preprocessing import StandardScaler
from tensorflow.keras import layers, models
from tensorflow.keras.models import load_model
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import tkinter as tk
from tkinter import messagebox, filedialog
from tkinter import ttk
from matplotlib.backends.backend_tkagg import FigureCanvasTkAgg
import matplotlib.pyplot as plt
import seaborn as sns

# Feature Extraction Functions
def calculate_band_power(data, fs, band, window_sec=2):
    if len(data) < window_sec * fs:
        nperseg = len(data)
    else:
        nperseg = window_sec * fs
    freqs, psd = welch(data, fs, nperseg=nperseg)
    band_freqs = (freqs >= band[0]) & (freqs <= band[1])
    return np.sum(psd[band_freqs])

def calculate_signal_entropy(data):
```

Figure C.1: code snapshot 1.

```python
def calculate_signal_entropy(data):
    from scipy.stats import entropy
    return entropy(data)

def calculate_channel_coherence(channel1, channel2, fs):
    freqs, coh = coherence(channel1, channel2, fs)
    return np.mean(coh)

def extract_features(student_data, fs, bands):
    band_power = []
    entropy_values = []
    coherence_values = []

    for channel in range(student_data.shape[1]):
        channel_band_power = {
            band_name: calculate_band_power(student_data.iloc[:, channel], fs, band_range)
            for band_name, band_range in bands.items()
        }
        band_power.append(channel_band_power)

        entropy_values.append(calculate_signal_entropy(student_data.iloc[:, channel]))
```

Figure C.2: code snapshot 2.

```python
# Load EEG Data
def load_eeg_data(folder_path):
    data = []
    for file in os.listdir(folder_path):
        if file.endswith('.csv'):
            file_path = os.path.join(folder_path, file)
            data.append(pd.read_csv(file_path, header=None))
    return data

# Prepare Features
def prepare_features(data, fs, bands, label_mapping=None):
    band_power_list = []
    features = []
    labels = []

    for student_data in data:
        band_power, _, _ = extract_features(student_data, fs, bands)
        band_power_list.append(band_power)

    for band_power in band_power_list:
        for channel_band_power in band_power:
            features.append(list(channel_band_power.values()))
            if label_mapping:
                labels.append(label_mapping.get(max(channel_band_power, key=channel_band_power.get), 'slow'))
```

Figure C.3: code snapshot 3.