EPILEPTIC SEIZURE DETECTION: LEVERAGING EEG DATA WITH DEEP LEARNING TECHNIQUES

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

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

Under the esteemed guidance of

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CERTIFICATE

This is to certify that the B. Tech Major Project report entitled **“Epileptic Seizure Detection: Leveraging EEG Data With Deep Learning Techniques”** is a bonafide work done by **G. Sreehitha (21R11A05N0), P. Mary Niharika (21R11A05Q2), P. Harsha Vardhan (21R11A05Q4)** in partial fulfillment of the requirement of the award for the degree of Bachelor of Technology in “**Computer Science and Engineering**” from Jawaharlal Nehru Technological University, Hyderabad during the year 2024-2025.

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We, **G. Sreehitha, P. Mary Niharika**, **P. Harsha Vardhan,** bearing Roll No's **21R11A05N0, 21R11A05Q2, 21R11A05Q4**, hereby declare that the project report entitled **"Epileptic Seizure Detection: Leveraging EEG Data with Deep Learning Techniques"** is done under the guidance of **Dr. S. Vishwanath Reddy**, **Associate Professor**, Department of Computer Science and Engineering, Geethanjali College of Engineering and Technology, is submitted in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering**.

This is a record of Bonafide work carried out by us and the results embodied in this project have not been reproduced or copied from any source. The results embodied in this project report have not been submitted to any other University or Institute for the award of any other degree or diploma.

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With warm regards,
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ABSTRACT

Epilepsy, which affects nearly 50 million people worldwide, is a significant neurological disorder, and EEG (electroencephalogram) data are extremely useful in detecting epileptic seizures by capturing the electrical activity of the brain. But seizure detection is generally inconvenient and requires expertise, and therefore it is necessary to automate. To counter this limitation, machine learning (ML) and deep learning (DL) techniques have been increasingly utilized to mechanize the detection process in order to make both effective and precise. Deep learning models, such as Long Short-Term Memory (LSTM) networks, have performed exceptionally well by learning features and fine-tuning performance metrics automatically Despite these advancements, issues do still emerge, e.g., scaling up models for multiclass classification and how to cope with limitations in available datasets. The system built here brings together ML and DL methods in conjunction to provide stronger, more reliable, and more autonomous seizure detection, potentially yielding improved clinical outcomes and a significant influence on the management of epilepsy.

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LIST OF ABBREVIATIONS

S. No	Acronym	Abbreviations
1	EEG	Electroencephalogram
2	LSTM	Long Short-Term Memory
3	LR	Logistic Regression
4	SVM	Support Vector Machine
5	DL	Deep Learning
6	ML	Machine Learning
7	CNN	Convolutional Neural Network

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1. INTRODUCTION

1.1 Overview of the Project

Epilepsy is a chronic neurological disorder that affects approximately 50 million people globally, making it one of the most prevalent neurological conditions worldwide. It is characterized by recurrent, unprovoked seizures resulting from abnormal and excessive electrical discharges in the brain. These seizures vary significantly in their type, duration, severity, and the regions of the brain they affect, leading to a broad spectrum of clinical manifestations—from mild sensory disturbances to full-body convulsions and loss of consciousness. Due to this unpredictability and severity, epilepsy severely impacts the quality of life of patients, often resulting in physical injuries, social stigma, and psychological distress.

Early diagnosis and continuous monitoring of seizures are essential for effective epilepsy management. Accurate detection not only assists in classifying the type of epilepsy but also helps in determining appropriate treatment strategies such as medication adjustments or surgical interventions. In this context, Electroencephalogram (EEG) plays a pivotal role. EEG captures the brain's electrical activity through electrodes placed on the scalp, enabling clinicians to observe patterns that indicate the presence of seizures. However, raw EEG signals are often contaminated with noise and artifacts, such as those caused by muscle movement or eye blinking. Therefore, preprocessing techniques like filtering and artifact removal are critical for enhancing the quality of the signals before further analysis. Following preprocessing, feature extraction is performed to identify specific characteristics or patterns in the EEG signals that are indicative of seizure.

1.2 Problem Statement

The study involves the development of an efficient and precise automated seizure detection system for epilepsy patients based on machine learning (ML) and deep learning (DL) methods. An epileptic seizure refers to a transient and temporary disruption in the usual brain functioning with abnormal and excess electrical activity. This electrical activity can have several physical and mental manifestations varying from mild to convulsions and loss of consciousness, and in certain cases can be followed by sudden and unanticipated death. Seizure detection in these epilepsy patients is very critical for the diagnosis and preparation of treatment strategies for them based on their specific needs. Early detection and then continuous surveillance of seizure will guarantee improved quality of life with minimized risk to life.

1.3 Objectives of the Project

The task involves training and applying a Long Short-Term Memory (LSTM) model for epileptic seizure detection from EEG signals to increase detection accuracy and reliability. Raw EEG signal preprocessing is necessary to eliminate noise and irrelevant information using techniques such as filtering, removal of artifacts, and baseline correction. Feature extraction and selection are central to the improvement of classification accuracy by providing more discriminative information. Extension of the model to multiclass classification is also explored in this work to predict multiple types of seizures. Classification and feature extraction are carried out using machine learning and LSTM deep learning methods that have immense possibilities of application for epilepsy diagnosis.

1.4 Scope of the Project

The goal of this project is to develop a seizure detection system that diagnoses epileptic seizures from EEG signals based on machine learning and deep learning. It starts with data acquisition and preprocessing utilizing datasets such as the UCI Epileptic Seizure Recognition dataset, which are divided into time-series data to be analyzed. Feature extraction follows, where filtering and artifact removal provide quality data. Training of models like SVM, Logistic Regression, and LSTM form the crux of the project, in terms of performance measures like accuracy, sensitivity, and precision to identify the best strategy. One of the aims is the real-time setup of a detection system that can be deployed in hospitals on a local server. Lastly, the system is properly tested by means of compatibility testing and accuracy check to make it reliable. In conclusion, the project seeks to provide a secure, accurate, and automatic system to assist medical practitioners in early diagnosis and continuous epilepsy monitoring using EEG analysis.

1.5 Methodology

The project utilizes EEG data from open sources like the UCI dataset, which is preprocessed and divided into short time segments. Machine learning and deep learning algorithms like SVM, Logistic Regression, and LSTM are trained on the data. They are evaluated in terms of accuracy and sensitivity. A working system is then built that can process EEG data and detect seizures in local server. The system is optimized and trained for speed and accuracy and is tested under a range of conditions to offer reliability for clinical purposes.

1.6 Organization of the Report

This project report is structured to provide a comprehensive overview of the epileptic seizure system, from conception to implementation.

Chapter 1 introduces the project, outlining its objectives, problem statement, scope, and the development methodology adopted.

Chapter 2 presents a literature survey reviewing the limitations of 4 existing systems, the need for improvement, and how seizure detection stands apart through a comparative study.

Chapter 3 covers system analysis, including a feasibility study, functional and non- functional requirements, and a detailed Software Requirements Specification (SRS).

Chapter 4 focuses on system design, highlighting architecture diagrams, use case modeling, and database schemas.

Chapter 5 discusses the implementation process, tools used, and code level descriptions of key modules.

Chapter 6 details the testing strategy and results.

Chapter 7 provides a conclusion, summarizes the project's achievements, and outlines potential future enhancements. Each chapter builds upon the previous to give the reader a clear understanding of the system's development journey and final outcome.

2. LITERATURE SURVEY

2.1 Review of Existing System

[1] **Kunekar, Pankaj, Mukesh Kumar Gupta, and Pramod Gaur. "Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques." Journal of Engineering and Applied Science 71.1 (2024): 21**

This studyfocuses on detecting epileptic seizures using EEG signals with machine learning (ML) and deep learning (DL) techniques. Using the UCI Epileptic Seizure Recognition dataset, it compares models like Logistic Regression, SVM, KNN, ANN, and a proposed LSTM-based model. The LSTM model achieved the highest accuracy (80%) and outperformed others in classification performance. It highlights the potential of DL for precise and automated seizure detection and suggests further research on multiclass classification and diverse datasets

[2] **Chaddad A, Wu Y, Kateb R, Bouridane A. Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques. Sensors (Basel). 2023 Jul 16; 23(14):6434. doi: 10.3390/s23146434. PMID: 37514728; PMCID: PMC10385593**

Developing an advanced epileptic seizure detection system using machine learning and deep learning techniques, with a primary focus on analyzing EEG signals. EEG data, known for its complexity and susceptibility to noise, is processed through various denoising methods and feature extraction techniques to ensure meaningful patterns are captured. The project leverages algorithms such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for classification, aiming to achieve high accuracy in detecting seizures.

Inspired by personal experience, this project is designed to provide an effective and reliable solution for epilepsy monitoring, potentially improving healthcare outcomes for individuals affected by this condition

[3] Zhou et al. (2018): Epileptic Seizure Detection Using EEG Signals and CNN - Frontiers in Neuro informatics, 12:95

The project used convolutional neural networks (CNNs) to automate epileptic seizure detection from EEG signals, eliminating manual feature extraction. Tested on the Freiburg (intracranial EEG) and CHB-MIT (scalp EEG) datasets achieved high accuracy, especially with frequency domain signals, reaching up to 85% for binary classification. This approach shows great promise for real-time clinical applications and seizure forecasting.

2.2 Limitations of Existing Approaches

1. **Excessive dependence on human intervention and analysis:**

   Most traditional security solutions utilized by online banks are based on human analysts for identifying, inspecting, and reacting to attacks. Manual intervention involves:

- Security system-generated logs and alert review.
- Manual event correlation to identify malicious activity patterns. Firewall policy or rule set update based on newly learned threats. Faults of this method:
- Labor-intensive: Time-consuming repetitive manual steps that have the potential to cause delay of threat detection.
- Scalability issues: With an increasing number of transactions and data, it becomes difficult for man to manage.

- Slow response: Slow response has the potential to cause massive damage in high-speed attacks such as phishing or DDoS before anything is deployed.

2. Inconsistent Accuracy Due to Human Error

Human professionals, as capable as they may be, are not flawless. In cybersecurity life:

- Missed detections are made through failure to notice subtle cues for threat or wrong interpretation of information.
- False positives (indicating legitimate behavior as malicious) and false negatives.
- Alert fatigue can affect security teams so that the large number of alerts means that important ones are overlooked.

3. Lack of Real-Time Monitoring Capabilities

Legacy systems tend to work on batch processing or scheduled scans, not continuous real-
Time

- Zero-day attacks, which take advantage of undiscovered vulnerabilities, can evade defenses ahead of detection
- Malware or unauthorized access may go undetected for extended periods.
- There is minimal situational awareness, which cannot react immediately

Impact:

- Delays in identifying threats allow attackers to shift laterally between systems.
- Extends the vulnerability window through which sensitive information is vulnerable.

- Restrict the bank from reacting pre-emptively or limiting harm early.

2.3 Need for the Proposed System

It would attempt to be more accurate and dependable in detecting epileptic seizures using LSTM-based deep learning architecture that would be more capable of learning temporal relationships in EEG signals compared to traditional methods. Furthermore, multiclass classification in detecting different forms of seizures would be explored to solve the problem of existing binary classification systems. Additionally, signal quality will be enhanced with preprocessing steps such as filtering and feature extraction. This combination of LSTM networks with multiclass classification is also expected to improve detection accuracy, demonstrate more generalization across subjects, and enable real-time detection, enabling timely interventions for patient's temporal pattern recognition for more accurate seizure detection using LSTMs.

1. Temporal pattern recognition for better seizure detection with LSTMs.
2. Multiclass classification feature to detect various kinds of seizures.
3. Improved generalization to other patients and seizure types.

2.4 Comparative Study

A comparison between conventional machine learning methods and deep learning techniques—specifically, Long Short-Term Memory (LSTM) networks—is presented with emphasis placed on enhanced performance of deep learning in handling intricate patterns in eeg data.

Traditional Standard ML algorithms like Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors are significantly feature-dependent on hand-crafted feature extraction and are unable to model temporal relations. They usually work well in the laboratory environment but break down under noisy or real EEG signals. On the other hand, LSTM networks learn features automatically from raw input and are tailor-made to handle sequential patterns. As such, they are extremely effective in EEG-based applications, as they can capture delicate, time-dependent signals that other models usually ignore.

2.5 Summary

The analysis of current seizure detection systems reveals certain inherent limitations, including overdependence on human intervention, inconsistent accuracy due to human error, and inability to carry out real-time monitoring. These limitations essentially bar timely and accurate diagnosis. To overcome these challenges, there is an increasing need for the creation of automated, intelligent, and real-time seizure detection systems. These systems should be able to monitor EEG data continuously, detect abnormal patterns with high accuracy, and alert them instantly. This would not only increase patient safety by allowing quicker medical response but also enhance clinical outcomes by giving neurologists more accurate and timely information. By utilizing advanced technology like deep learning, especially LSTM networks, next-generation systems will be able to learn sophisticated temporal patterns within EEG signals, eliminate false positives, and function with minimal human intervention. This transformation from manual to automated smart systems is a breakthrough in the field of neurological care and monitoring.

3. System Analysis

3.1 Feasibility Study

A feasibility study is important in project planning since it assesses the project's viability from multiple viewpoints to ensure that resources are properly allocated and that the project has a genuine opportunity to succeed.

- **Technical Feasibility**: This criterion determines if the technology suggested would be able to fulfill the needs of the project. It consists of analyzing the existing technological situation, hardware and software availability, and the expertise of the technical team. For the project in detecting epileptic seizures through EEG signals, technical feasibility would check the performance of machine learning models such as LSTM and SVM in analyzing and processing EEG signals. It would also consider whether the existing infrastructure can support the computational intensiveness of deep learning models.

- **Economic Feasibility**: Economic feasibility considers the cost-effectiveness of the project. It entails estimating the financial resources needed for development, implementation, and maintenance. Cost-benefit analysis is conducted to guarantee that the expected benefits, for example, enhanced patient outcomes and lower healthcare costs by ensuring precise detection of seizures, are more than the costs involved in the project. This research guarantees that the project is economically viable and offers a return on investment.

- **Operational Feasibility**: This aspect looks at how the project fits into current organizational structure and processes. It evaluates if the stakeholders are change-ready and if the system can be integrated into existing workflows. For seizure detection systems, operational feasibility would look at user acceptance by healthcare personnel, protocol changes that might be required, and the effect on patient care.

- **Time & Cost Estimation**: This component of the feasibility study entails thorough planning of the timeline and budget for the project. Correct estimation of time guarantees realistic timelines and ensures that resources are distributed effectively across various stages of development. Estimation of cost gives a detailed breakdown of expected costs, such as initial setup fees, ongoing maintenance costs, staff training, and user support, ensuring the project stays within budgetary limits throughout its life cycle**.**

3.2 Software Requirements Specification

3.2.1 System Features

- EEG data upload and preprocessing
- Feature extraction (e.g., PSD, wavelet)
- Seizure classification using ML/DL (LSTM, SVM, etc.)
- Real-time alerts for seizure detection
- Dashboard for results and history

3.2.2 User Classes and Characteristics

- **Clinicians**: View and analyzing seizure reports
- **Patients**: Receive alerts and monitor seizure history
- **Admin**: Manage users and system configuration

3.2.3 Assumptions and Dependencies

- Uses UCI EEG dataset (pre-segmented, labeled)
- Python, Flask, and ML libraries must be installed
- Internet/browser access required for web interface

- Database (e.g., SQLite) must be available for storage

3.3 Functional and Non-Functional Requirements

Functional Requirements:

1. EEG Data Processing: Capture and preprocess real-time EEG data from sensors to remove noise
2. Real-Time Seizure Detection: Process EEG signals using deep learning models (e.g., LSTM) continuously to detect seizures accurately and in a timely manner
3. Data Logging and Reporting: Detect and record detection events with rich logs and visual summaries for clinical review.
4. User Interface: Complement an intuitive interface for real-time data display, parameter setting, and reporting display.

Non-Functional Requirements

1. Usability: Simple and intuitive for clinicians as well as non-professionals.
2. Performance: Minimum latency to provide real-time detection and response.
3. Reliability: Minimum downtime with consistent and steady performance.
4. Security: Strong data protection practices via encryption, access controls, and privacy.

4. SYSTEM DESIGN

4.1 System Architecture

A system architecture or systems architecture is the abstract model that specifies the structure, behavior, and more views of a system. An architecture description is a formal representation and description of a system.

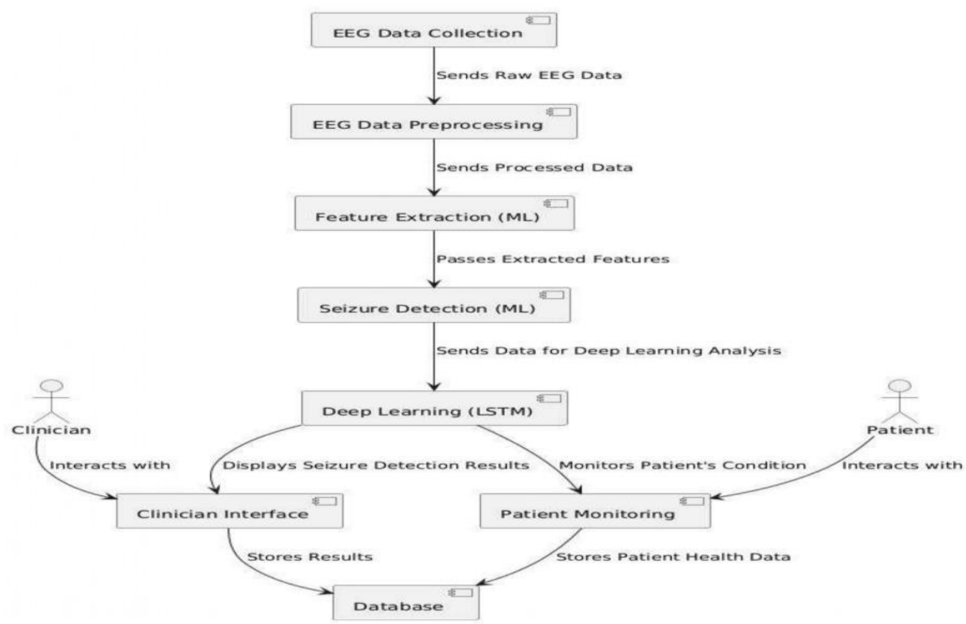


Fig 4.1 System Architecture

This is an epilepsy seizure detection and patient monitoring system based on EEG data. It starts with raw EEG signal acquisition, and the signals are preprocessed for noise removal. Key features from the filtered data are extracted with machine learning techniques, and those results are filtered further with a deep learning algorithm (LSTM) to provide high accuracy. The system displays seizure detection outcomes via a clinician interface and continuously monitors the patient's condition. All data are stored in a central database, enabling clinicians to make informed decisions and monitor long-term patient health. The system provides effective monitoring.

4.2 Database Design

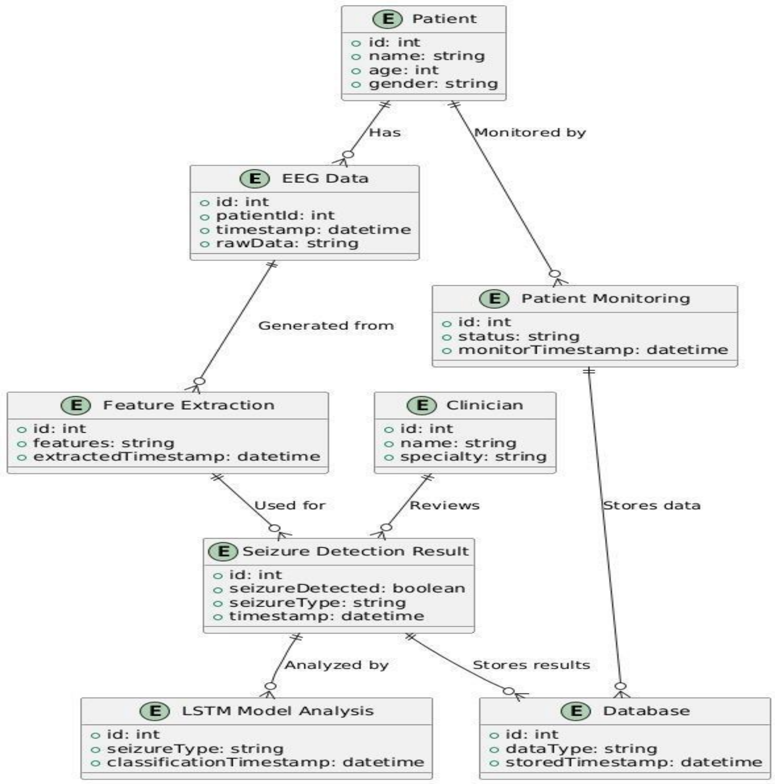


Fig 4.2 Entity- Relationship Diagram

The graph demonstrates an EEG data-based seizure detection system. It starts with the patient, the brain signals from whom are obtained as EEG data. They carry raw data as well as have the association of the identity and timestamp of the patient. Feature extraction occurs with the raw EEG data when essential patterns are labeled and assigned the timestamp. These characteristics are then utilized for seizure detection to give a result whether the seizure has happened or not, its nature, and the time. Clinicians interpret the results of seizure detection for medical assessment. The patient is continuously monitored while this is going on, and their condition is noted down. The detection results are also analyzed using an LSTM (Long Short-Term Memory) model to better classify the nature of the seizure. All information, such as monitoring, detection, and classification results, are saved in a central database.

4.2.1 Physical Data Flow Diagram

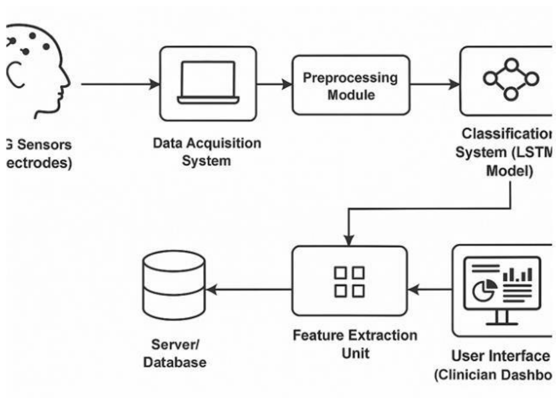


Fig 4.2.1 Physical Data Flow

4.3 UML Diagrams

4.3.1 Class Diagram

The UML class diagram outlines a modular Epileptic Seizure Detection System. It starts with the Data Preprocessing class, which cleans and normalizes raw EEG data. The processed data is passed to the Feature Extraction class to extract and select key features that indicate seizure patterns.

These features are then sent to two model classes: ML Model, which uses traditional algorithms like SVM and Logistic Regression, and DL Model, which focuses on LSTM-based deep learning. Both models support training, prediction, and evaluation.

At the core is the Seizure Detection System class, which manages the workflow—initializing the system, processing input data, detecting seizures, and displaying results to clinicians or users. This structure ensures accurate, efficient, and interpretable seizure detection.

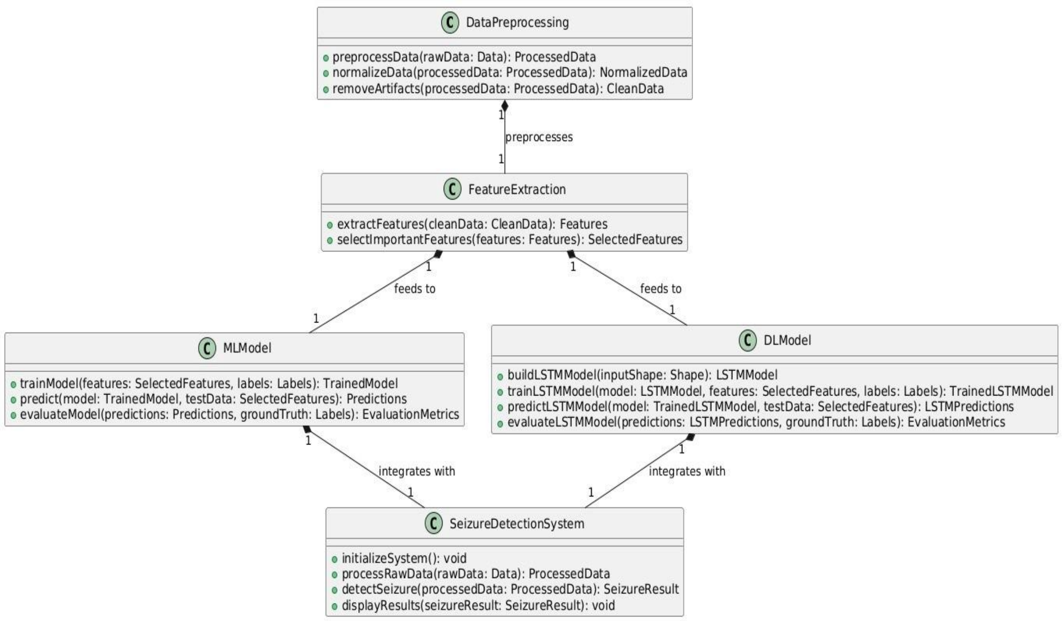


Fig 4.3.1 Class Diagram

4.3.2 Use case Diagram

The Epileptic Seizure Detection System is a comprehensive web-based application designed to facilitate the detection of epileptic seizures using EEG (electroencephalogram) data through machine learning. The process starts when the user, typically a medical professional or researcher, accesses and runs the web application on their local or remote server. Upon launching the application, the user logs in securely to gain access to the system's functionalities. The next step involves the user uploading or inputting an EEG dataset, which contains brainwave recordings potentially indicative of seizure activity. Once the dataset is provided, the system loads it into memory for processing. This dataset may contain raw signals which need to be cleaned and formatted before use. Hence, a preprocessing step is performed by the system, which includes handling missing or noisy data, normalizing values, segmenting time-series signals, and converting them into a suitable structure for model training or inference. After preprocessing, the system offers the option to train a machine learning model—commonly a Long Short-Term Memory (LSTM) network—on the EEG data. LSTM models are particularly effective for time-series data like EEG signals due to their ability to retain long-term dependencies and recognize temporal patterns. Once the model is trained, it is ready to perform predictions on new or existing EEG data to identify whether it shows signs of an epileptic seizure. Finally, the system generates and displays the prediction results through the web interface, allowing the user to interpret the outcomes. The result can indicate whether a seizure is detected or not, providing vital information that can support diagnosis and treatment planning.

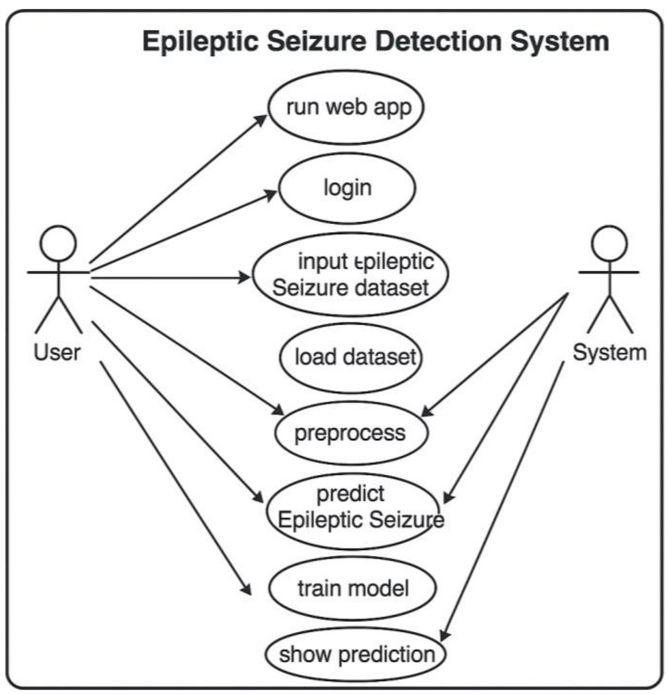


Fig 4.3.2 Use case Diagram

4.3.3 Sequence Diagram

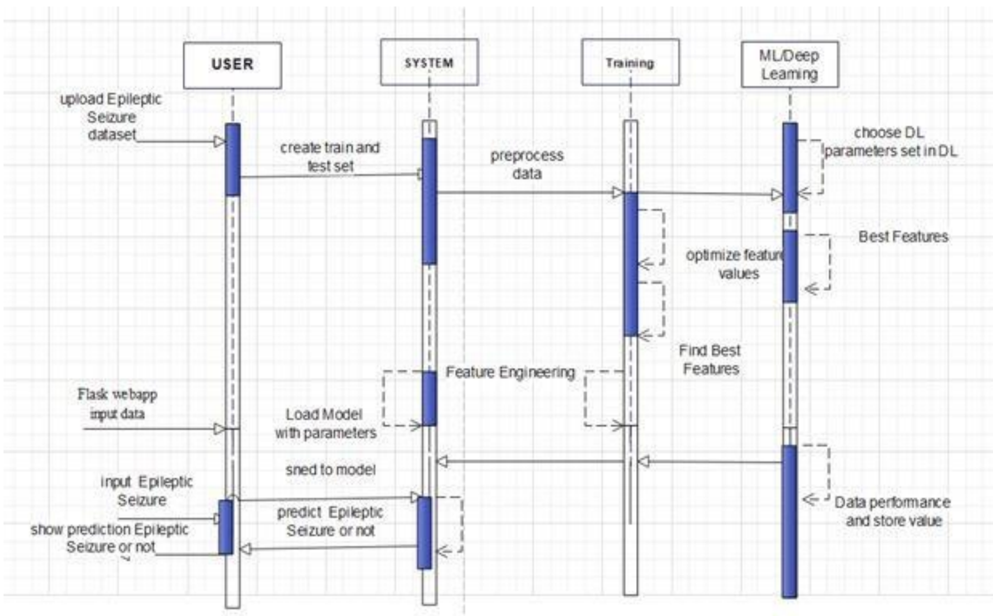
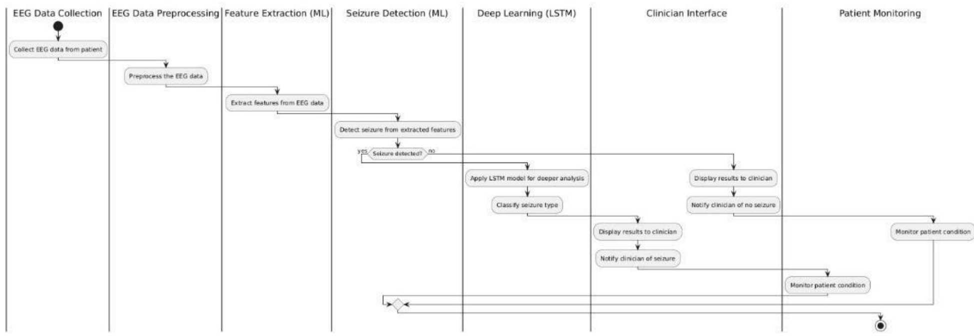


Fig 4.3.3 Sequence Diagram

The sequence diagram of the Epileptic Seizure Detection System illustrates the step-by-step interaction between the user, the web interface, the server backend, and the machine learning model during the process of seizure detection. The process begins when the user runs the web application and logs in through the interface using their credentials. Once authenticated, the user uploads an EEG dataset containing brainwave signals. The web interface forwards this dataset to the server backend, which is responsible for loading and storing the data in memory. The backend then preprocesses the dataset by cleaning, normalizing, and transforming it into a suitable format for analysis. After preprocessing, the user can choose to train the machine learning model, typically an LSTM network, on the processed data. This command is sent from the interface to the backend, which passes the data to the ML model for training. Once training is complete, the trained model is stored and ready for prediction.

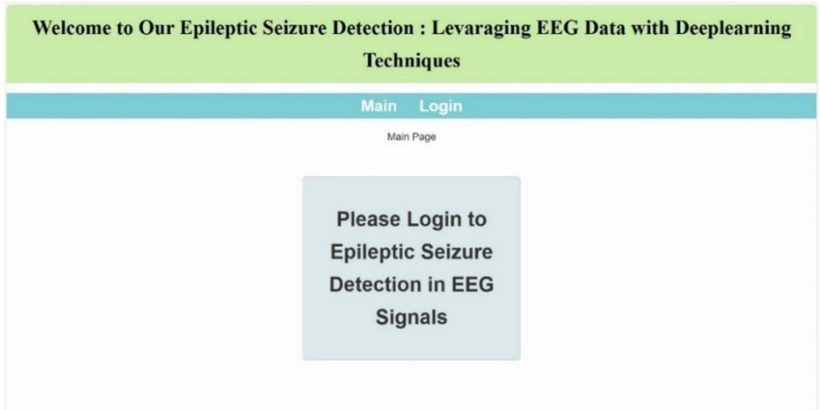
4.3.4 Activity Diagram



4.3.4 Activity Diagram

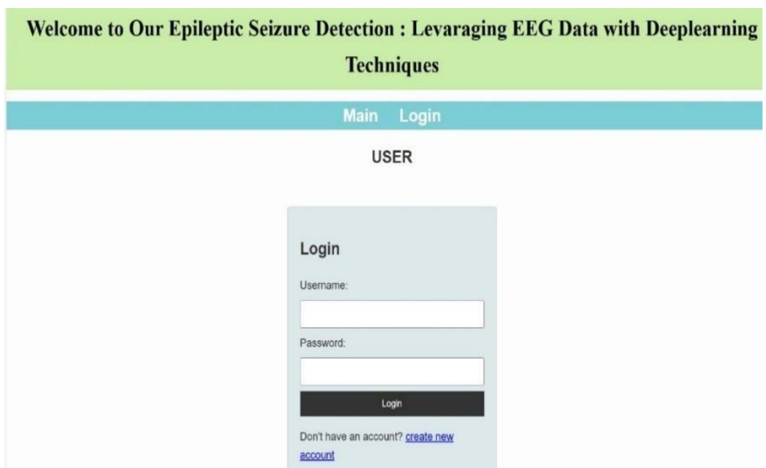
This activity diagram describes the overall view of an epileptic seizure detection system's process from EEG data and advanced AI techniques. The process begins with the collection of EEG signals from the patient, preprocessed for elimination of noise and artifacts. Once the data is cleaned, machine learning techniques are employed to extract significant features that are indicative of seizures. A decision node checks whether a seizure is detected—if yes, then the data is further processed using a Long Short-Term Memory (LSTM) deep learning model to identify the seizure type. The clinician then presents the findings, who is notified of whether a seizure exists. In either event, the condition of the patient is checked. This formal approach guarantees accuracy, immediate analysis, and clinical response to improve the quality of care for epilepsy patients.

4.4 User Interface Design



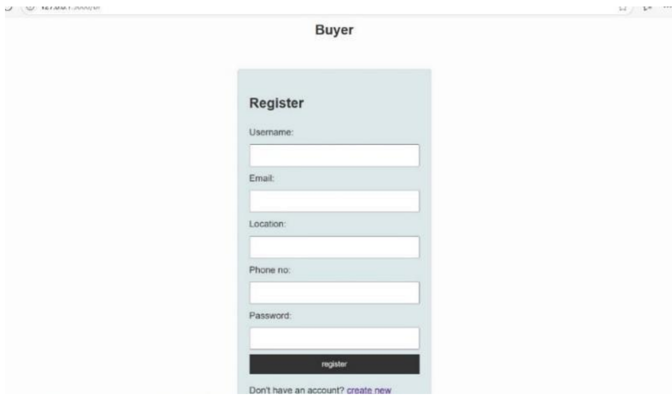
4.4.1 Main Page

Flask Web Interface



4.4.2 Login Page

Login with correct username and password



4.4.3 Registration Page

4.5 Design Standards Followed (IEEE, ISO, etc.)

Compliance with standard procedure is of supreme concern while designing the seizure detection software for quality maintenance, safety, and following industry's best practices. IEEE (Institute of Electrical and Electronics Engineers) and ISO (International Organization for Standardization) shall be followed by the project. IEEE 830 offers a software requirements specification writing guideline ensuring transparency and completeness allowing effective communication among stakeholders. In addition, ISO 9001 requirements will be applied to set up a quality management system with an emphasis on continuous improvement, customer satisfaction, and adherence to regulations. Development activities will also align with ISO/IEC 25010, defining software quality requirements and evaluation (SQuaRE) based on system properties such as usability, reliability, and performance. Integrating these requirements into the design and development phase not only enhances the overall quality of the software, but it gives stakeholders confidence that the software is dependable and in compliance with health-related legislation.

4.6 Safety & Risk Mitigation Measures

Safety and risk reduction are most essential in software development, especially software for use in health care environments where patient well-being relies on efficient and stable performance. Seizure detection software will have several safety precautions in place to reduce risks of incorrect classification of seizures or breakdown of the system. To begin with, a robust validation and verification procedure will be set up in place, involving extensive testing to ensure the accuracy of the machine learning models against well-defined benchmarks. Systems will also be provisioned for real-time monitoring to watch over system performance and identify potential anomalies in real-time. To secure data, encryption tools will be implemented to protect sensitive patient information, with the ability to meet compliance with regulations such as HIPAA. In addition, user training sessions will be provided to educate healthcare personnel on how to use the system.

5. IMPLEMENTATION

5.1 Technology Stack

1. Frontend Technologies

These technologies are used for building the user interface (UI) that allows users (clinicians/patients) to interact with the system:

- **HTML5 & CSS3**:
  Used for structuring and styling web pages.

2. Backend Technologies

This layer handles the core logic, APIs, and interactions between the user interface and the models/database:

- **Python 3.x**:
  The main programming language for development. It supports robust libraries for ML, data science, and web applications.
- **Flask Framework**:
  A lightweight Python web framework used to create RESTful APIs and serve model predictions through a web interface.
- **Flask Routes**:
  Used to define endpoints such as /upload, /predict, and /results.

3. Machine Learning / Deep Learning

For EEG signal classification and seizure prediction:

- **NumPy & Pandas**:
  Used for numerical computations and structured data manipulation.
- **Scikit-learn**:
  For ML algorithms like:

- Logistic Regression
- Support Vector Machine (SVM)
- **TensorFlow / Keras**:

  Deep learning framework used to build and train the LSTM (Long Short-Term Memory) network, ideal for time-series EEG data.
- **Joblib / Pickle**:

  Used to save and load trained models (model.pkl) for deployment and inference without retraining.

4. Data and Storage

Data handling and persistent storage:

- **Dataset**:
- UCI Epileptic Seizure Recognition Dataset (preprocessed from Bonn dataset)
- Each EEG segment consists of 178 data points (1-second window) and a class label (1–5)
- **SQLite / MySQL**:

  Stores:
- User information
- Prediction results
- Seizure history and logs for patients

5.2 Module-wise Implementation

1. **Data Collection Module:** Loads EEG data from the UCI dataset, where each instance has 178 data points and a class label (1–5).
2. **Preprocessing Module:** Cleans data by normalizing, segmenting into 1-second intervals, and splitting into training and test sets.
3. **Feature Extraction Module:** Statistical extracts (mean, variance) and

frequency features (PSD). LSTM uses raw time-series data directly.

4. **Model Training Module:** Trains ML models (SVM, LR, k-NN, etc.) and LSTM using TensorFlow/Keras. Models are saved using Pickle.
5. **Prediction and Evaluation Module:** Make predictions on new data and evaluate performance using accuracy, precision, recall, and F1-score.
6. **Web Interface Module:** Flask-based interface lets users upload EEG files, run predictions, and view results on a dashboard.
7. **Database Module:** Stores user data, predictions, and seizure history using SQLite/MySQL for tracking and future analysis.

5.3 Code Integration Strategy

1. Data Services Layer:

- Handles all MySQL interactions for user registration and login.
- Functions like Buyer-reg and Buyer-login act are imported from database.py and invoked directly in the corresponding routes for user management.
- Stores results related to user actions and predictions in a MySQL database.

2. Model Services Layer:

- Pre-trained models (LSTM and scaler) are loaded once at the application start using load-model and joblib-load.
- Models are stored in global variables (model, scaler, clf) for efficient, repeated access without reloading on each prediction request.

- Predictions are made using .predict () for the input data in the /pre and /pre1 routes.

3. Presentation Layer:

- Flask Jinja2 templates (e.g., main.html, result.html) render the frontend UI.
- Routes like /bhome, /blogin, /bregister, etc., return the appropriate templates after processing data and model predictions.
- Data (e.g., prediction results) is passed to templates for display.

4. File Handling:

- File uploads are handled securely using werkzeug. utils.secure_filename.
- Uploaded files are stored in the static/upload's directory.

5. Session Management:

- Flask's session is used to maintain user login status across different routes, leveraging a secret key (app. Secret-key).

6. Separation of Concerns:

- The application is modular, with separate layers for data access, model inference, and UI rendering.
- This design allows for easier maintenance, testing, and future expansions (e.g., swapping models or adding new routes).

5.4 Sample Code Snippets

```
import os  import MySQLdb
from flask import Flask, session, url_for, redirect, render_template, request, abort,
flash
import tensorflow as tf
import base64
import matplotlib.pyplot as plt
from werkzeug.utils import secure_filename
import numpy as np
import joblib import numpy as np
from flask import Flask, redirect, url_for, request, render_template
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from PIL import Image
from database import *
from pathlib import Path
import pandas as pd
import joblib import pickle
from tensorflow.keras.models import load_model
from sklearn.preprocessing import StandardScaler
model_filename = 'lstm_model.pkl'
with open(model_filename, 'rb') as file:  clf = pickle.load(file)
app = Flask(_name_)
```

```
app.secret_key = os.urandom(24)
model = load_model('epileptic_seizure_model.h5')
scaler = joblib.load('scaler.pkl')
app.config['UPLOAD_FOLDER'] = 'static/uploads'
@app.route("/")
def home():return render_template("main.html")
@app.route("/bhome")
def bhome():return render_template("bhome.html")
@app.route("/bl")
def bl():return render_template("blogin.html")
@app.route("/br")
def br():return render_template("breg.html")
@app.route("/log")
def ll():return render_template("main.html")
@app.route("/p")
def p(): return render_template("p.html")
@app.route("/bregister",methods=['POST','GET'])
def signup(): if request.method=='POST': username=request.form['username']
    email=request.form['email']
    password=request.form['password']
    add=request.form['Location']
    ph=request.form['Phone no']
    status = Buyer_reg(username,email,password,add,ph)
    if status == 1: return render_template("blogin.html")
    else: return render_template("breg.html",m1="failed")
@app.route("/blogin",methods=['POST','GET'])
def login():if request.method=='POST':
    username=request.form['username']
    password=request.form['password']
```

```
        status = Buyer_loginact(request.form['username'], request.form['password'])
        print(status)
        if status == 1: session['username'] = request.form['username']
            return render_template("bhome.html", m1="sucess")
        else:return render_template("blogin.html", m1="Login Failed")
@app.route("/pre",methods=['POST','GET'])
def pre():features=request.form['inputData']
    features_list = [float(x) for x in features.split()]
    features_array = np.array([features_list])
    prediction = clf.predict(features_array)
    print(prediction) result="
    if prediction[0] == 1:result="Epileptic Seizure Not Detected From EEG
Signals"
    if prediction[0] == 2:result="Epileptic Seizure Frist Stage Detected From EEG
Signals"
    if prediction[0] == 3: result="Epileptic Seizure Second Stage Detected From
EEG Signals"
    if prediction[0] == 4: result="Epileptic Seizure Third Stage Detected From EEG
Signals"
    if prediction[0] == 5: result="Epileptic Seizure Fourth Stage Detected From
EEG Signals"
    return render_template("result.html", text=result)
@app.route("/pre1",methods=['POST','GET'])
def pre1():features = request.form['inputData']# Input data as a space-separated
string
    features_list = [float(x) for x in features.split()]
    features_scaled = scaler.transform([features_list])
    features_reshaped = features_scaled.reshape (1, 1, len(features_list))
    prediction = model.predict(features_reshaped)
```

```
    print("ppppppppppppppppppppppppppppppppppp")     print(prediction)
    predicted_class = np.argmax(prediction)
    print("dddddddddddddddddddddddddddddddddddddddddddd")
print(predicted_class)
    result=''
    if prediction[0] == 1: result="Epileptic Seizure Not Detected From EEG
Signals"
    if prediction[0] == 2: result="Epileptic Seizure Frist Stage Detected From EEG
Signals"
    if prediction[0] == 3: result="Epileptic Seizure Second Stage Detected From
EEG Signals"
    if prediction[0] == 4: result="Epileptic Seizure Third Stage Detected From EEG
Signals"
    if prediction[0] == 5: result="Epileptic Seizure Fourth Stage Detected From
EEG Signals"
    return render_template("result.html", text=result)
if _name_ == "_main_": app.run(debug=True)
```

6. TESTING

6.1 Testing Strategy

Testing is the debugging program is one of the most critical aspects of the computer programming triggers, without programming that works, the system would never produce an output of which it was designed. Testing is best performed when user development is asked to assist in identifying all errors and bugs. The sample data are used for testing. It is not quantity, but quality of the data used the matters of testing. Testing is aimed at ensuring that the system was accurate and efficient before live operation commands.

Testing objectives:

The main objective of testing is to uncover a host of errors systematically and with minimum effort and time. Starting formally, we can say, testing is a process of executing a program with the intent of finding an error.

1. A successful test is one that uncovers a yet undiscovered error.
2. A good test case is one that has probability of finding an error, if it exists.
3. The test is inadequate to detect possibly present errors.
4. The software confirms the quality and reliable standards.

6.2 Unit Testing

The test cases help ensure that the seizure detection system operates correctly, providing accurate classifications and maintaining compatibility across different environments. Further test cases could be developed to evaluate different aspects such as the sensitivity and specificity of the algorithms, response times, and system behaviour under various loading conditions.

6.3 Integration Testing

Once individual units have passed unit testing, integration testing is performed to ensure that the modules interact correctly when combined.

- Verifies data flow between components, such as from EEG acquisition to preprocessing, and then to the detection engine.
- Checks whether interfaces between different layers (data, logic, and presentation)
- Help identify mismatches in data format, improper function calls, or timing issues in real-time processing.

6.4 System Testing

System testing involves evaluating the entire application as a complete, unified system to ensure it behaves as intended.

- Tests are conducted in an environment that closely replicates real-world usage.
- Includes end-to-end testing of features like real-time EEG signal processing, seizure detection accuracy, alert notifications, and data logging.
- Validates performance under normal and extreme load conditions to assess stability and responsiveness.

6.5 Test Cases and Results

Test cases are formally documented with the following elements:

- Test ID, Description, Input, Expected Output, Actual Output, Status (Pass/Fail).
- Test cases are grouped by module and testing phase (unit, integration, or system).
- Results are compiled and reviewed to ensure all functionalities meet

design expectations and any deviations are tracked and corrected.

Test case	Expected Output	Actual Output	Status
Load dataset	Dataset loads correctly with proper shape	Dataset loaded with shape(11500, 179)	Pass
Split data	Data is divided into 2 parts	Based on given test size data is divided and stored in train and test sets	Pass
Model trains correctly	Fit is performed	Training is done and accuracy is displayed	Pass
Accuracy calculation	Accuracy of each algorithm	Accuracy of each model	Pass
Plot training metrics	Training and validation graphs are displayed	Graphs rendered as expected	Pass
System testing in various versions of OS	Performance is better in windows-7	Same as expected output, performance is better inwindows-7	Pass

6.6 Bug Reporting and Tracking

All bugs identified during testing are systematically recorded using bug tracking tools such as JIRA, Bugzilla, or GitHub Issues.

- Each bug entry includes a unique ID, severity level, description, reproduction steps, screenshots (if applicable), and assigned team members.
- Bugs are prioritized based on impact and urgency, tracked through statuses like Open, In Progress, Resolved, and Closed.
- Ensures an organized and accountable approach to managing defects and improving the software over time.

6.7 Quality Assurance Standards

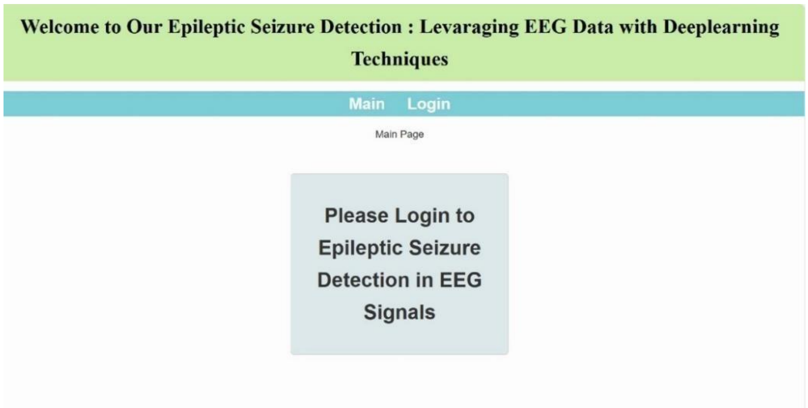
Quality Assurance (QA) is maintained throughout development using recognized standards and practices:

- The system may follow ISO/IEC 25010 standards, focusing on aspects like functionality, reliability, usability, performance efficiency, and maintainability.
- Adopts Agile testing practices, where testing is integrated continuously during development cycles (e.g., with sprints or iterations).
- Code reviews, automated test coverage reports, and continuous integration pipelines are also employed to maintain code quality.

7. RESULTS AND DISCUSSUION

7.1 Output Screenshots

The following screenshots showcase the key interfaces and functionalities of Seizure Detection System

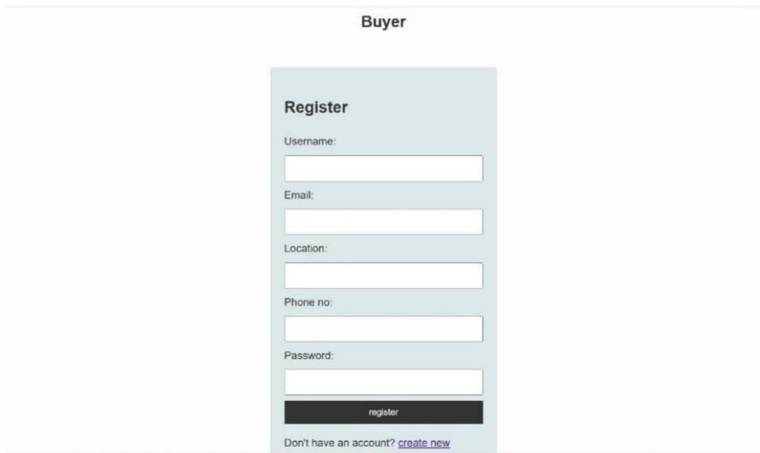


Screenshot 7.1.1 Main Page Output

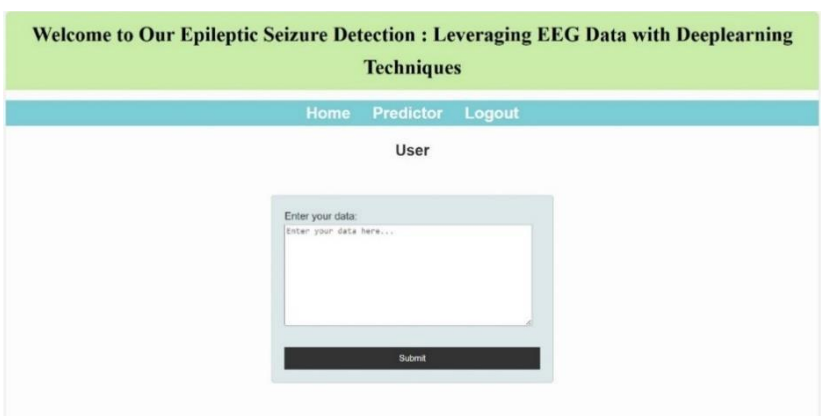
Login and Authentication: The login and signup interfaces provide secure authentication with options for email registration with mail id. The clean design uses flask web interface ensures better user experience.

Screenshot 7.1.2 Login Output

A user registration form for buyers, collecting basic details like username, email, location, phone, and password.

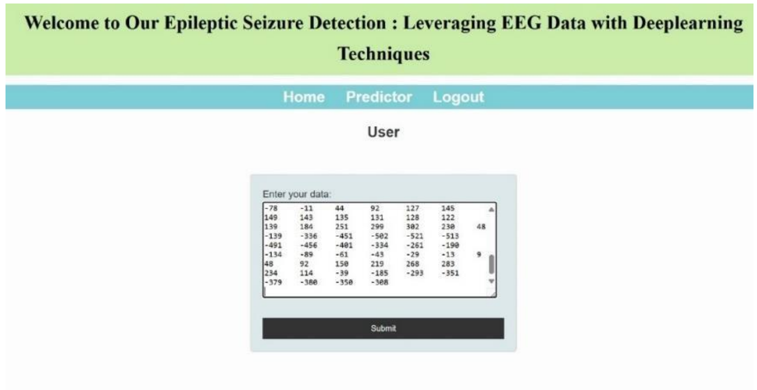


Screenshot 7.1.3 Registration Page Output

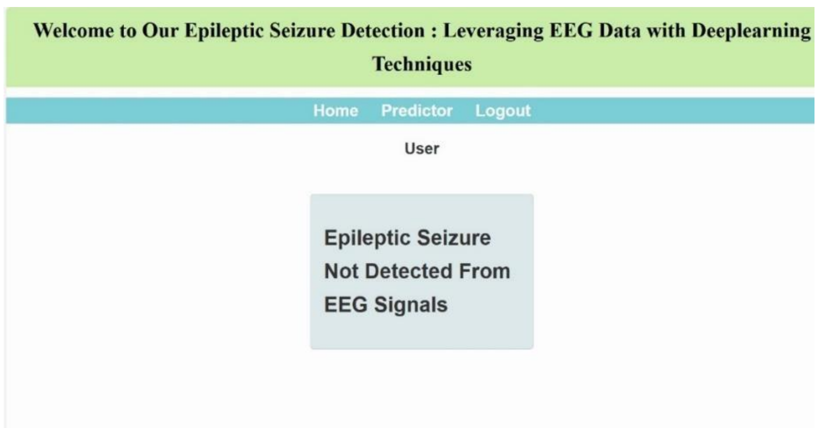


Screenshot 7.1.4 Upload EEG Data Output

Users can upload EEG signal files



Screenshot 7.1.5 Uploaded EEG Data Output



Screenshot 7.1.6 Classification Result Page

Displays seizure detection output with different seizure stages

7.2 Results Interpretation

The results show that among the tested models—Logistic Regression, Linear SVM, and LSTM—the LSTM model performed the best in detecting epileptic seizures from EEG data. LSTM achieved the highest classification accuracy, slightly exceeding the performance of the other two models. This demonstrates its ability to effectively capture temporal dependencies in sequential EEG signals, which are critical for accurate seizure detection. The consistent classification across various seizure stages confirms the LSTM model's reliability for medical diagnostic purposes.

7.3 Performance Evaluation

The LSTM model achieved an accuracy of 86.47%, surpassing Logistic Regression (82.49%) and Linear SVM (82.16%). It also reported higher F1-scores and recall, particularly for the seizure-related classes. These metrics indicate the model's strong ability to minimize false positives and false negatives. The deep learning structure of LSTM allows it to automatically learn and extract features from EEG signals, unlike traditional ML models which require manual feature engineering. Based on these metrics—accuracy, precision, recall, and F1-score—LSTM is proven to be the most effective and dependable model for epileptic seizure detection in this study.

7.4 Comparative Results

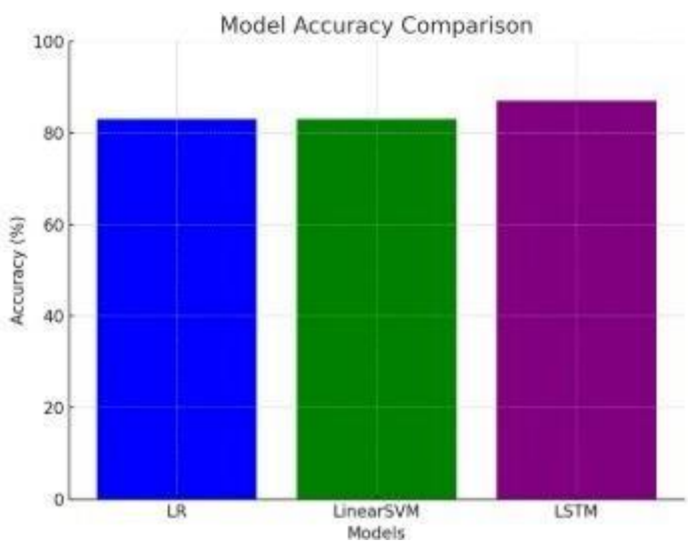


Fig 7.4 Model Accuracy Comparison

The bar chart titled "Model Accuracy Comparison" illustrates the performance of three classification models—Logistic Regression (LR), Linear SVM, and LSTM—based on their accuracy in detecting epileptic seizures. Among the models, LSTM achieves the highest accuracy, slightly outperforming both LR and Linear SVM, demonstrating its superior ability to learn temporal patterns from EEG data, making it the most effective model for this task.

8. CONCLUSION AND FUTURE SCOPE

8.1 Summary of the Work done

This project presents an effective and user-friendly Flask-based web application for automated epileptic seizure detection using EEG data. The system integrates a complete pipeline—starting from EEG signal preprocessing and feature extraction to seizure detection and classification. We implemented and compared multiple models, including Logistic Regression, Linear SVM, and LSTM. Based on accuracy and classification metrics, the LSTM model outperformed the others, thanks to its strength in modeling temporal dependencies in EEG signals, making it highly suitable for this medical application. The web interface built using Flask allows clinicians to upload EEG data, view detection results in real time, and receive immediate alerts in case of a detected seizure. This not only speeds up the diagnosis process but also supports continuous patient monitoring and timely clinical intervention. Overall, the system is a scalable and intelligent solution aimed at improving the efficiency, accuracy, and accessibility of epileptic seizure diagnosis in real-world healthcare settings.

8.2 Limitations

1. **Data Dependency:** The performance of the LSTM model heavily relies on the quality and quantity of the EEG data used for training. Limited datasets may lead to overfitting or under fitting, adversely affecting the model's ability to generalize new, unseen data.
2. **Variability in EEG Signals:** EEG signals can vary significantly between patients and even within the same patient over time. This variability can complicate the model's ability to accurately detect seizures and differentiate between seizure and non-seizure states.

3. **Model Interpretability**: Deep learning models, including LSTMs, are often seen as "black boxes." Their complex nature can make it challenging for healthcare professionals to understand the decision-making processes behind seizure detections, potentially reducing trust in the system.
4. **Integration with Existing Systems**: Integrating the proposed detection system with existing clinical workflows and electronic health records may present technical and logistical challenges. Ensuring compatibility, data sharing, and user adaptation needs careful consideration.
5. **Privacy and Data Security**: Handling sensitive health data raises significant concerns regarding privacy and data security. Compliance with regulations like HIPAA or GDPR is essential but can present additional implementation challenges.
6. **Clinical Validation**: The system's clinical effectiveness needs thorough validation through extensive clinical trials before it can be considered reliable for practical use in healthcare settings.
7. **User Interface Usability**: The system's user interface must be intuitive for clinicians to ensure effective interaction. Poor usability can lead to misuse and hinder the system's effectiveness in clinical environments.

8.3 Challenges Faced

1. **Noise and Artifacts in EEG Signals:** EEG data is susceptible to noise and artifacts from various sources, such as muscle activity, eye movements, or electrical interference. Successfully filtering out this noise without losing critical seizure-related information presents a major obstacle.
2. **Model Complexity and Tuning:** Designing and tuning deep learning models like LSTMs involves many hyper parameters, which can be difficult to optimize. Balancing model complexity to avoid overfitting while achieving good performance can be a cumbersome process.

3. **Integration with Healthcare Systems**: There may be challenges in integrating the seizure detection system with existing healthcare technologies and workflows, such as electronic health records (EHR) or patient monitoring systems. Ensuring seamless data flow and communication with existing platforms requires careful planning.
4. **Regulatory and Compliance Issues**: Navigating the regulatory landscape for medical devices and software can be complex. Ensuring that the system complies with medical standards and regulations (e.g., FDA approval) is critical but challenging.
5. **Real World Testing and Validation**: Validating the performance and effectiveness of the model in real-world clinical settings presents significant challenges. Conducting extensive clinical studies to prove the system's reliability and efficacy is necessary but resource demanding.

8.4 Further Enhancements

Although the current system performs effectively in detecting and classifying epileptic seizures, there is potential for further improvement. One key enhancement would be the integration of real-time deployment using wearable EEG devices, enabling continuous monitoring and timely intervention even outside clinical settings. Additionally, adopting a cloud-based infrastructure could improve data storage, accessibility, and facilitate remote alerts for clinicians. Expanding the model to support multi-class seizure classification would make it more clinically useful by identifying different types of seizures with greater precision. Future versions could also explore hybrid approaches, such as combining CNN with LSTM, to improve both spatial and temporal feature extraction. Lastly, incorporating patient-specific models could allow for personalized seizure prediction, increasing the system’s accuracy and adaptability to individual variations in EEG patterns.

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10. APPENDICES

A. Software Development Lifecycle Forms

1. Software Requirements Specification (SRS)

- EEG Data Upload: Users (clinicians or researchers) can upload EEG data files in .csv format.
- Data Preprocessing: Automated removal of unnecessary columns, normalization using Standard Scaler, and reshaping for LSTM compatibility.
- Feature Extraction: Statistical and signal-based features implicitly captured through LSTM layers. Logistic Regression was also explored for comparison.
- Classification: Both traditional ML (e.g., Logistic Regression) and deep learning (e.g., LSTM) models were integrated to classify seizure types (classes 1–5).
- Result Interpretation: Final output provides class prediction in a clear, understandable format for clinicians.
- Interface Design: A lightweight Flask-based web interface allowed end-users to interact with the model in a simple and intuitive way.
- Non-functional requirements such as usability, scalability, security, and performance were also addressed.

2. Feasibility Report

This report validated the project's practicality and sustainability from three core perspectives:

- Technical Feasibility: Utilized widely supported technologies including Python, TensorFlow/Keras, Scikit-learn, and Flask. The UCI EEG dataset provided a reliable data source.
- Operational Feasibility: Designed for use by clinicians with minimal

Technical expertise. Easy-to-use interface and clear outputs support operational use.

- Economic Feasibility: No expensive hardware or software was needed. Entirely built using open-source libraries and frameworks, reducing development and deployment costs.

3. Test Report Summary

The LSTM model achieved the highest accuracy (~86%–90%) compared to other models

B. Gantt chart

Project Schedule Summary

The Epileptic Seizure detection project was executed over a 4-month period with the following major phases:

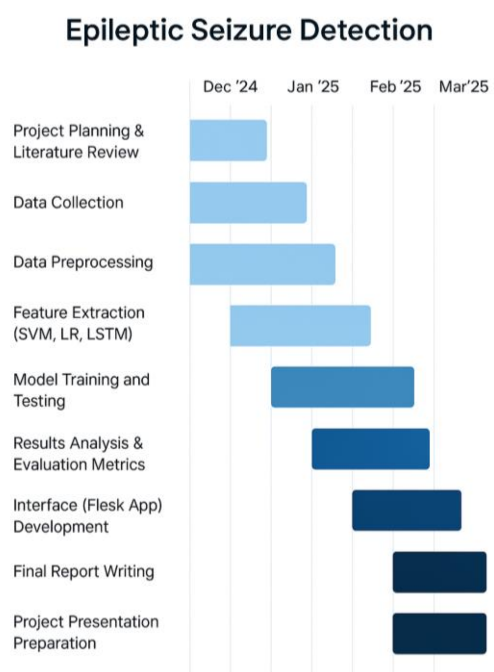
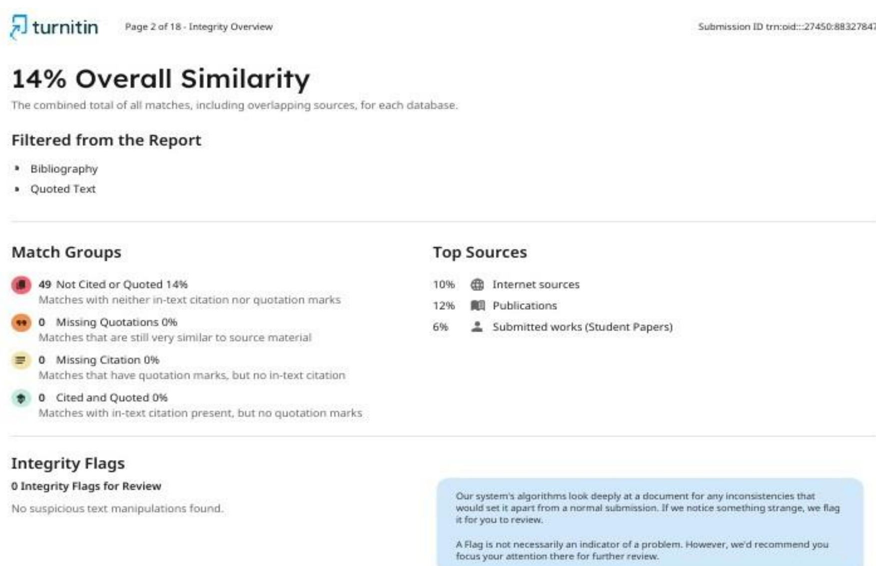


Fig 10.2 Gantt chart

C. Ethical Considerations & Consent

When designing an epileptic seizure detection system, ethical considerations must prioritize informed consent, ensuring patients understand how their data will be used and that participation is voluntary. Data privacy is critical, requiring anonymization, secure storage, and compliance with regulations like HIPAA or GDPR. The system must be designed to avoid bias and provide explainable AI outputs, enabling clinicians to trust and interpret the results. Clinical oversight is essential, with healthcare professionals reviewing predictions before any intervention. Furthermore, liability must be clearly defined for false predictions, and ongoing consent renewal and audit trails should be maintained to ensure accountability, transparency, and continuous ethical compliance throughout the system's use.

D. Plagiarism Report



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E. Source Code Repository

The complete source code for the project titled **“Epileptic Seizure Detection using EEG and Deep Learning”** is available on GitHub. It includes all relevant modules such as data preprocessing, model training, evaluation scripts, and the Flask-based web interface.

GitHub Repository:

https://github.com/pniharika18/Epileptic-Seizure-Detection

F. Conference paper published on project

Holy Mary Institute of Technology & Science

An UGC Autonomous Institution, (Approved by AICTE, New Delhi & Affiliated to JNTUH, Hyderabad).
Accredited by NAAC with 'A' Grade
Bogaram (V) Keesara (M), Medchal Malkajgiri (D), Hyderabad, Telangana 501301

ICCSCE 2025

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(ICCSCE-2025)

This is to certify that, Dr./Mr./Ms.. G. Sreehitha

Geethanjali college of engineering and technology has presented a paper in the International Conference on Computer Science and Communication Engineering (ICCSCE-2025) organized at Holy Mary Institute of Technology & Science, Hyderabad, Telangana, India held on 25 & 26 April 2025.

Paper Title : Epileptic Seizure Detection: Leveraging EEG Data with Deep Learning Techniques

Dr. Y DAVID SOLOMON RAJU
CONVENER

Dr. J B V SUBRAHMANYAM
PRINCIPAL, HITSCOE

Holy Mary Institute of Technology & Science

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Bogaram (V) Keesara (M), Medchal Malkajgiri (D), Hyderabad, Telangana 501301

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This is to certify that, Dr./Mr./Ms.. **P. Mary Niharika**

Geethanjali college of engineering and technology has presented a paper in the International Conference on Computer Science and Communication Engineering (ICCSCE-2025) organized at Holy Mary Institute of Technology & Science, Hyderabad, Telangana, India held on 25 & 26 April 2025.

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ICCSCE 2025

INTERNATIONAL CONFERENCE ON COMPUTER SCIENCE AND COMMUNICATION ENGINEERING (ICCSCE-2025)

This is to certify that, Dr./Mr./Ms..

P. Harsha Vardhan has presented a paper in the International Conference on Computer Science and Communication Engineering (ICCSCE-2025) organized at Holy Mary Institute of Technology & Science, Hyderabad, Telangana, India held on 25 & 26 April 2025.

Paper Title : **Epileptic Seizure Detection: Leveraging EEG Data with Deep Learning Techniques**

Dr. Y DAVID SOLOMON RAJU
CONVENER

Dr. J B V SUBRAHMANYAM
PRINCIPAL, HITSCOE

G. DVD With All Related Files

In the below link we have attached the ppts of our Project.
https://drive.google.com/drive/folders/1ZlGfVRwzDXXLZWWqUqTJwGo8BAUtM akN?usp=sharing

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