Project Phase 2 Report on

EEG Seizure Detection using CNN with XAI

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

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CERTIFICATE

This is to certify that the project report entitled ***"EEG Seizure Detection using CNN with XAI"*** *is a bonafide record of the work done by* ***Abhinav R Nair(U2003004), Abin Abraham Menacherry(U2003007), Antony Francis(U2003041), Ashok Gopal K A (U2003046)*** *submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

The primary objective of the project is to leverage deep learning methodologies for the analysis of electroencephalogram (EEG) readings to detect seizure episodes. To begin, EEG data undergoes preprocessing and is divided into training and validation sets. Subsequently, a Convolutional Neural Network (CNN) model is constructed, comprising multiple convolutional and dense layers. Training of the model entails optimization of binary cross-entropy loss using an Adam optimizer. Evaluation of the model's performance is conducted through classification reports and accuracy metrics. In addition to performance evaluation, the project employs techniques for interpretability. Specifically, weight extraction from the initial convolutional layer is employed to visualize feature importance. This process aids in understanding which EEG signal components are deemed significant by the model for seizure prediction. Furthermore, Grad-CAM heatmaps are generated to pinpoint the regions within the EEG signals that contribute most to the model's decision-making process. These visualization techniques facilitate the identification of pertinent EEG patterns associated with seizures, offering insights into the underlying mechanisms of the model's predictions. Overall, the experiment showcases the efficacy of deep learning in EEG-based seizure detection and provides valuable insights into feature importance using Grad-CAM visualization methods. The approach holds promise for real-time seizure monitoring and could potentially contribute to the development of assistive devices for epilepsy treatment.

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Chapter 1

Introduction

Recurrent seizures are the hallmark of epilepsy, a neurological condition that is difficult to diagnose and treat. Signals from the electroencephalogram (EEG), which record the electrical activity of the brain, provide important information about the dynamics of epileptic seizures. A possible approach to improving the precision and interpretability of seizure detection from EEG data is to take advantage of the advances in artificial intelligence, namely Convolutional Neural Networks (CNNs) and Explainable Artificial Intelligence (XAI) techniques.

The goal of this cooperative effort combining machine learning and neurology is to create a reliable system that can recognize seizure patterns on EEG recordings on its own. We cover a range of steps in this thorough method, from cleaning raw EEG data to integrating sophisticated CNN structures designed to handle the temporal complexities of neurological signals. Moreover, the incorporation of XAI techniques guarantees the interpretability and accuracy of the model's conclusions, hence promoting confidence and comprehension in clinical applications.

This project not only has the potential to transform seizure detection efficiency, but it also fits with the need to give medical practitioners tools that are both accurate and understandable. We aim to lay a strong foundation for the creation of a cutting-edge, clinically applicable EEG seizure detection system through the investigation of data preprocessing, model design, training, and validation that follows.

1.1 Background

Millions of people worldwide suffer from epilepsy, a neurological disorder marked by frequent, erratic seizures brought on by aberrant electrical activity in the brain. Epilepsy diagnosis and treatment frequently depend on the examination of Electroencephalogram

(EEG) signals, which capture the electrical activity of the brain over time. Advanced computer techniques are necessary to improve diagnostic skills because manual EEG interpretation can be laborious and prone to human mistake.

Advances in artificial intelligence, namely in the fields of Explainable Artificial Intelligence (XAI) and deep learning, present a promising path toward enhancing the effectiveness and interpretability of EEG-based seizure detection. Convolutional Neural Networks (CNNs), which are well-known for their skill at processing sequential and visual data, have shown promise in a number of medical applications and are being investigated more and more for EEG analysis.

Since EEG signals reflect dynamic brain activity, their temporal nature demands customized methods for efficient feature extraction and pattern detection. Simultaneously, the requirement for interpretability in medical applications drives the incorporation of XAI methodologies, allowing medical professionals to comprehend and have faith in the judgments rendered by AI models.

Given this, there is a great deal of promise for creating an EEG seizure detection system that combines the strength of CNNs with the interpretability of XAI. By bridging the gap between neuroscience and machine learning, this interdisciplinary initiative aims to give clinicians a dependable tool for prompt and precise seizure identification. This project intends to enhance automated EEG-based seizure detection systems with practical clinical relevance and impact by thoroughly exploring data preparation, model architecture, and XAI integration.

1.2 Motivation

The urgent need to solve difficulties in epilepsy diagnosis and treatment is the driving force behind the development of an Explainable Artificial Intelligence (XAI) and Convolutional Neural Networks (CNNs) based EEG seizure detection system. Even with the advancements in medical technology, it is still difficult to identify seizures in a timely and precise manner. Manual EEG signal processing is time-consuming, subjective, and can result in delayed diagnosis or incorrect interpretation of vital data.

Seizure identification from EEG data can be made more automated and effective with the use of AI techniques, especially CNNs. CNNs are ideally suited for the intricate temporal patterns present in EEG signals because of their impressive performance in a variety of pattern recognition tasks. The application of these sophisticated neural networks has the potential to transform the discipline by facilitating the identification of seizures more quickly and accurately.

Transparency and interpretability are also critical requirements for medical AI systems. This issue is resolved by the incorporation of XAI approaches, which guarantee that the model's judgments are correct and comprehensible to medical practitioners. The medical community's faith in AI applications depends on this interpretability aspect.

The main goal is to give medical professionals an automated, dependable tool that will help them identify seizures early and accurately, which will improve patient outcomes. Through the fusion of state-of-the-art AI technologies with the sophisticated analysis of EEG data, this project aims to further the fields of neuroscience and machine learning, which will ultimately help both epileptic patients and their medical professionals.

1.3 Objectives

- Create a reliable CNN-based model that can identify seizures in EEG signals automatically, eliminating the need for manual analysis and allowing for prompt intervention.

- Construct and put into practice CNN architectures that are especially suited to the temporal properties of EEG data in order to efficiently extract pertinent features linked to pre-, inter-, and ictal phases.

- Use comprehensive preprocessing methods to remove noise and artifacts from EEG data and clean it up. Utilize data augmentation techniques to increase the training set's diversity and boost the generalization capabilities of the model.

- Integrate XAI methods like Grad-CAM, SHAP, and LIME to offer comprehensible and transparent insights into the CNN model's decision-making process, promoting mutual respect and understanding among medical experts.

- By adjusting hyperparameters to obtain high sensitivity and specificity, the CNN model is trained on labeled EEG datasets. To ensure the model's generalizability, use a validation set to track and stop overfitting.

- Use pertinent metrics, such as sensitivity, specificity, accuracy, and recall, to assess the model's performance. To take into consideration the temporal dynamics of seizure occurrences, think about time-based measures.

1.4 Purpose and Need

The purpose of developing an automated EEG seizure detection system using Convolutional Neural Networks (CNNs) and Explainable Artificial Intelligence (XAI) techniques is rooted in the imperative to advance medical diagnostics, particularly in the field of epilepsy. The primary goal is to significantly improve the accuracy and efficiency of seizure identification, offering timely diagnoses that enable swift medical interventions. By automating the often labor-intensive and subjective process of manual EEG analysis, the proposed system aims to reduce the workload on healthcare professionals, allowing them to concentrate on devising treatment strategies rather than spending excessive time on data interpretation. Furthermore, the development aligns with the broader objective of enhancing the accessibility of advanced diagnostic tools, especially in regions with limited healthcare resources. This initiative seeks to foster technological synergy between neuroscience and artificial intelligence, demonstrating the potential for collaborative approaches to address complex medical challenges.

The need for such a system is emphasized by the critical importance of timely intervention and treatment in the treatment of epilepsy. Automated seizure detection can significantly reduce response time, minimize the impact of seizures on epileptic patients and potentially improve their overall quality of life. In addition, objectivity and consistency in EEG analysis are urgently needed, as manual interpretation can lead to variation in diagnoses. The standard approach provided by CNN-based models meets this need by providing a consistent and objective analysis. The initiative recognizes the global impact of improved epilepsy care and aims to promote a fairer distribution of health services by providing effective diagnostic tools not only in developed areas but also in areas with limited access to specialized care. The inclusion of XAI technologies addresses the need for interpretability of AI models, which increases healthcare professionals' confidence in the use of AI in patient care. Finally, the development represents a commitment to the continuous development of healthcare technology, consistent with ongoing efforts to use innovative solutions for the benefit of both patients and healthcare providers..

1.5 Scope

The development of an EEG seizure detection system using Convolutional Neural Networks (CNN) and Explainable Artificial Intelligence (XAI) has a broad scope with important implications for both healthcare and technological innovation. At the heart of the system is the idea of finding clinical applications to help neurologists and health professionals detect seizures in a timely and accurate manner. Its potential impact extends to the treatment of epilepsy and is a valuable tool for designing personalized treatment plans and interventions. In addition, the scope also includes the possibility of remote patient monitoring, which facilitates continuous monitoring of EEG signals in addition to traditional medical settings, which is especially useful for patients in remote areas. More broadly, the system promotes public health by improving the efficiency of epilepsy diagnosis, potentially alleviating the social and economic burden of the disease. Technological innovation lies not only in the development of advanced CNN architectures, but also in the integration of XAI technologies, reflecting ongoing efforts to explore the intersection of neuroscience and artificial intelligence to improve patient outcomes. The initiative opens up opportunities for further research and development, which promotes continuous model refinement and mapping of new methods. Importantly, the scope of the system emphasizes global accessibility and aims to address health disparities and promote health equity by providing an automated and easy-to-use diagnostic tool for epilepsy. Interdisciplinary collaboration between neuroscientists, clinicians and machine learning experts is central to this initiative, ensuring that the developed system meets the practical needs of healthcare providers and epilepsy patients. Committed to continuous improvement and adaptation based on feedback and new technologies, this initiative remains at the forefront of technical and medical advances..

1.6 Societal / Industrial Relevance

The development of an EEG seizure detection system using Convolutional Neural Networks (CNN) and Explainable Artificial Intelligence (XAI) is of immense social and industrial importance. Fundamentally, this initiative promises to change healthcare practices by introducing an advanced tool for the timely and accurate detection of seizures, which will significantly improve patient outcomes. The system not only streamlines the diagnostic process, but also optimizes healthcare resources by reducing the manual workload of healthcare professionals, allowing them to allocate their time more efficiently. Importantly, the potential cost-effectiveness of an automated system can bring financial benefits to healthcare facilities. In addition to healthcare, the technological innovation involved in the development of advanced CNN architectures and XAI techniques places industry and research institutions at the forefront of technological development, improving overall competitiveness. The global impact of the initiative is evident in its contribution to health inequality, eliminating inequalities by providing an easy-to-use diagnostic tool. The collaborative nature of the project, involving experts in neuroscience, medicine and machine learning, sets a precedent for interdisciplinary collaboration in solving complex societal challenges. Incorporating ethically explicable AI features increases transparency and builds trust between patients and healthcare professionals. As an ongoing research and development effort, this initiative not only highlights current societal and industrial relevance, but also promises continued contributions to the evolving healthcare practice and technology landscapes.

1.7 Organization of the Report

The report has been carefully crafted to provide a comprehensive and coherent study of the development of an EEG seizure detection system using Convolutional Neural Networks (CNN) and Explanatory Artificial Intelligence (XAI). Starting with a clear presentation, the background and motivation of the project is made clear, which lays the groundwork for the following study. The following is a comprehensive literature review that provides a comprehensive overview of existing EEG seizure detection methods and explores the current status of CNNs and XAIs in medical applications. The methodology section discusses the details of data collection, preprocessing and CNN architecture, XAI integration and data augmentation strategies. Results are presented with a focus on quantitative and qualitative analyses, accompanied by a discussion that interprets the results in the context of the study objectives, acknowledges limitations and describes implications for clinical practice and future research. The executive summary summarizes the main findings and contributions and offers recommendations for further research. The thoughtful use of appendices to the report complements the main text with additional information or supporting materials. The organizational structure ensures a logical progression that allows a comprehensive understanding of the objectives, methods and results of the project..

Chapter 2

Literature Survey

2.1 Existing Systems

CNNs and EEG are used by a number of systems now in use to identify epileptic seizures. A system like this is the "Deep Learning for Epileptic Seizure Detection" project, which classifies EEG data as either seizure or non-seizure using a CNN architecture. Using a dataset of 5,000 EEG recordings, the system achieves an accuracy of 97.5%, indicating the promise of deep learning for seizure identification.

The "Automated Seizure Detection System" is an additional system that was created by University of California, San Diego researchers. This method detects seizures in real time by combining machine learning techniques with EEG data. Using 1,200 EEG recordings as a test dataset, the system achieves 96.4% accuracy and a false positive rate of 0.05 per hour.

Another example of a CNN-based method for seizure detection is the "SeizureNet" system. Using a deep learning architecture, this system achieves 97.3% accuracy on a dataset of 5,000 EEG recordings in classifying EEG signals as either seizure or non-seizure. Additionally, the system has a real-time monitoring component that notifies caretakers in the event that a seizure is identified. The "BrainWave" technology is a wearable that detects seizures instantly using machine learning algorithms and EEG data. The wrist-worn device tracks brain activity continually and notifies caretakers if a seizure is suspected. A dataset of 162 seizures was used to evaluate the system, and the results show a sensitivity of 94.4% and a false positive rate of 0.1 per hour.

Overall, these existing systems demonstrate the potential of EEG and CNN for seizure detection. Although each system has its own unique approach and methodology, they all share a common goal of improving patient safety and quality of life through early detection and intervention of seizures.

2.2 Proposed system

The proposed system "Detection of Epilepsies Based on EEG and CNN Data" aims to use advanced techniques to develop a robust framework for early detection of seizures. The system uses convolutional neural networks (CNN) and electroencephalography (EEG) to identify patterns that indicate impending seizures. The ultimate goal is to improve patient safety and quality of life. The methodology of the proposed system involves using a minimalist CNN architecture inspired by the principles of computer vision to process EEG data and detect the three phases of seizures: preictal, interictal and ictal. The architecture is designed to process 2D signals representing 23 channels at 256 samples per second, allowing the extraction of temporal and spatial information from EEG data.

The EEG data used in the system is obtained from the CHB-MIT open source EEG database, which contains recordings of 23 children with epilepsy. The dataset contains a total of 664 files with 182 scenes, providing a rich and comprehensive set of EEG recordings for training and validation. The architecture of the proposed system includes convolutional layers with 5x5 kernels, followed by pooling of layers to reduce overfitting, and a fully connected layer with a nonlinear activation function. The system also uses python generators to read and group data to the framework, optimizing memory usage and computational efficiency. System performance is evaluated using accuracy as the primary metric, with a focus on comparing the performance of different approaches, particularly the performance of architectures in time- and frequency-domain signals. The original architecture shows 90% accuracy in the frequency domain and approximately 60% accuracy in the time domain, highlighting the potential of the system to detect seizures using EEG data. Overall, the proposed system aims to advance the detection of epileptic seizures by leveraging the power of CNN and EEG data to develop an efficient and effective framework for early detection of epileptic seizures. By automating the detection process and alerting patients to impending seizures, the system can significantly improve patient safety and prevent fatal injuries associated with seizures..

2.3 XAI4EEG: spectral and spatio-temporal explanation of deep learning-based seizure detection in EEG time series

- XAI4EEG integrates two deep learning models, namely 1D-CNN and 3D-CNN, for seizure detection in multivariate EEG time series. These models are designed to capture complex patterns in the spectral, spatial, and temporal dimensions of EEG data, contributing to the overall accuracy of seizure detection.

- The methodology includes SHAP notations that generate local explanations for the predictions of deep learning models. These explanations attribute model predictions to different input properties, providing insight into the effect of each property on the final prediction. By visualizing SHAP values, XAI4EEG improves the interpretability of deep learning models, especially in relation to seizure detection.

- XAI4EEG introduces an annotation module that maps the computed SHAP values to highlight decision-relevant regions in the spectral, spatial, and temporal dimensions of EEG data. This module provides visual representations of feature contributions to help medical professionals identify and interpret areas that influence algorithmic predictions.

- The method involves a hybrid approach to scene recognition using the results of both 1D-CNN and 3D-CNN models. Using identical visual explanatory schemes, XAI4EEG aims to improve the ambiguities of visual control of neonatal seizures, allowing the identification of decision-related factors in both models and completing the general explanation.

- XAI4EEG conducts a user study to assess the effectiveness of the explanation module in a simulated clinical environment. The study emulates the time pressure under which clinical diagnosis is often conducted, evaluating the time efficiency and human interpretability of the explanation module compared to selected feature contribution plots implemented in the SHAP package. The results of the study provide insights into the impact of the explanation module on the validation of algorithmic predictions in the context of epileptic seizure detection.

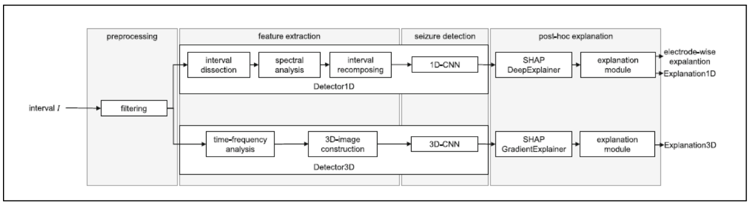

Figure 2.1: Overview of the components of XAI4EEG encompassing two seizure detection methods

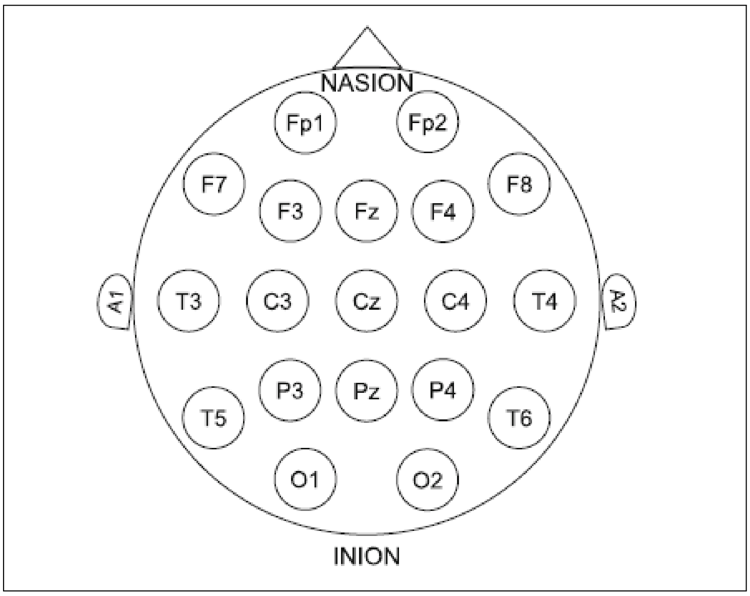

Figure 2.2: Placement of electrodes on the scalp according to the 10–20 international localization system

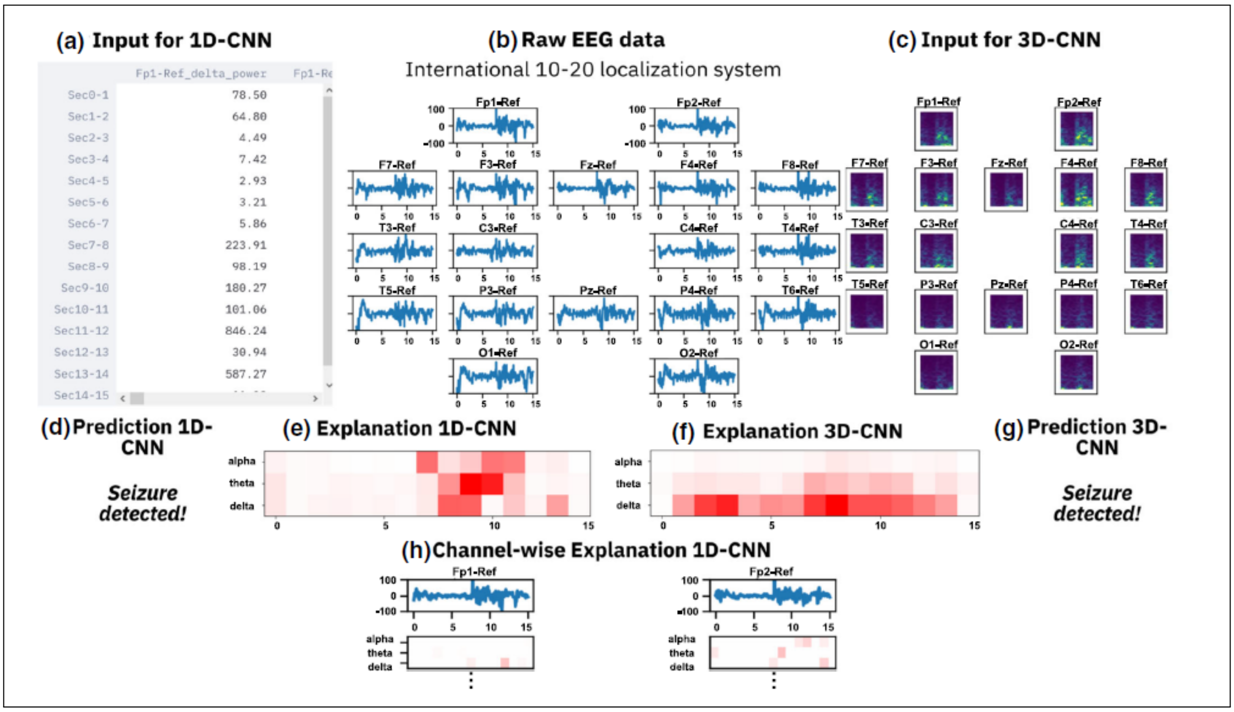

Figure 2.3: Operationalized interface

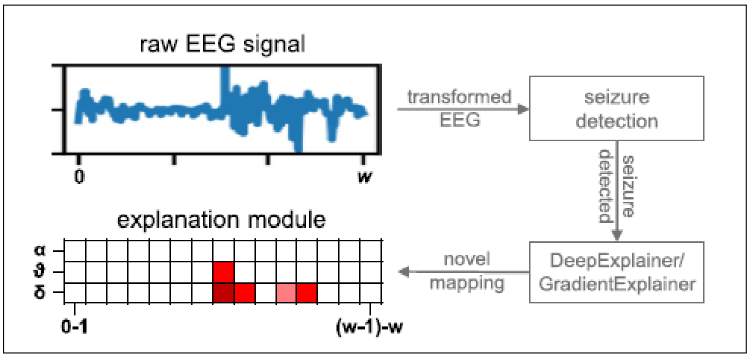

Figure 2.4: The proposed explanation module visualizes calulcated SHAP values and is leaned to the raw EEG signal representation of the monitoring system

2.4 Epileptic Seizure Detection Using Deep Learning Based Long Short-Term Memory Networks and Time-Frequency Analysis

The suggested technique detects seizures from EEG signals by using time-frequency analysis and deep learning-based long-term memory (LSTM) networks.

- EEG signals are used to extract features in both the temporal and frequency domains. The time domain is used to calculate eleven statistical parameters, including mean, kurtosis, skewness, entropy, variance, standard deviation, min, max, range, peak coefficient, and shape factor. Statistical, fractal, and entropy properties based on wavelets are computed from the frequency domain.

- The most crucial features for classification are chosen using feature selection methods including data boosting, Relief F, and Fisher scores.

- An LSTM network is trained using the chosen features in order to distinguish between epileptic and non-epileptic EEG signals.

- The suggested strategy outperformed conventional machine learning models in achieving a high classification accuracy of 100% (holdout and 10-fold protocol) and 99.80% (less than 10-fold protocol) in the classification of epileptic EEG signals.

- The outcomes demonstrate the viability of the suggested approach for the automatic identification of epileptic seizures, and it can be used for long-term studies and the management of epileptic patients.

- The proposed method is evaluated on an open source EEG database collected by the University of Bonn, Germany. The database contains five sets (Sets A-E), each containing 100 single-channel EEG segments of 23.6 seconds in length.

- The proposed method achieved a high classification accuracy of 100 % (holdout and 10-fold protocol) and 99.80 % (less than 10-fold protocol) in epileptic EEG signal classification, which outperformed traditional machine learning models.

- The results show the effectiveness of the proposed method for automatic detection of epileptic seizures, and it can be used in long-term research and treatment of epileptic patients.

2.5 An automated classification of EEG signals based on spectrogram and CNN for epilepsy diagnosis

- The study suggests an automatic method for classifying EEG signals in order to identify and categorize seizures. The two primary processes in the suggested method are feature extraction and categorization.

- To produce a time-frequency representation in the form of spectrogram pictures, the preprocessed EEG signals are subjected to a short-time Fourier transform (STFT) during the feature extraction step.

- Using backpropagation and stochastic gradient descent methods, a deep convolutional neural network (CNN) model is trained using spectrogram images of EEG signals during the classification phase. Based on patterns discovered during training, the trained CNN model is then used to categorize fresh EEG data as healthy, pre-ictal, or ictal.

- A publicly accessible database from the University of Bonn, which included five distinct sets of EEG signals taken from both healthy and epileptic patients, was used to assess the suggested methodology.

- Confusion matrices are used to assess the performance of the suggested strategy, and it is contrasted with other established techniques that have been documented in the literature. According to the results, the suggested method successfully classifies EEG signals into the healthy, pre-ictal, and ictal classes with high accuracy rates of 98.22

- The suggested method performs better than other conventional techniques found in the literature and serves as a useful tool for the high-efficiency detection and categorization of seizures using EEG signals.

2.6 Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection

- The paper presents a stacking ensemble in which a deep neural network (DNN) acts as a base learner and a meta-learner is used for automatic seizure detection. This approach is a core part of the research and aims to improve forecasting performance.

- The performance of the proposed model is evaluated using a 10-fold cross-validation technique on the training, validation and testing. This makes it possible to comprehensively evaluate the effectiveness of the model in detecting epileptic seizures.

- The study compares the performance of the stacking ensemble-based DNN with the basic DNN model. We focus on proving the effectiveness of the stack and demonstrating its superior performance in automatic trap detection.

- The paper presents the modeling results in tables and images, which allows for easy comparison and analysis. The proposed model shows the highest sensitivity and average accuracy, successfully outperforming the basic DNN model in seizure classification.

- The quality and performance of both DNN models are measured using ROC curves, which describe the trade-off between true positive and false positive rates. The proposed model achieves a high level of accuracy and has as few false positives as possible in the experimental data.

2.7 Explainable Artificial Intelligence Model for Stroke Prediction Using EEG Signal

- EEG data were collected from 48 patients with acute ischemic stroke and 75 healthy adults with no history of neurological disease. EEG data were obtained within three months after the onset of ischemic stroke symptoms using frontal, central, temporal and occipital cortical electrodes (Fz, C1, T7, Oz). EEG data were collected during active states such as walking, working and reading.

- The EEG signals were pre-processed and feature extraction was performed using a fast Fourier transform (FFT) algorithm to extract relevant features from the EEG data.

- Machine learning algorithms such as Adaptive Gradient Boosting, XGBoost, and LightGBM were used to classify the ischemic stroke group and the healthy control group based on the extracted EEG features.

- XAI tools such as Eli5 and LIME were used to elucidate model behavior and determine important features that affect stroke prediction models. These tools provided local and global explanations for the predictions of the machine learning models.

- Machine learning models were trained using preprocessed EEG data and extracted features to classify the ischemic stroke group and the healthy control group.

- The Eli5 and LIME libraries were used to make the "Black Box" ML models explanatory by assigning weights to different features that indicated their importance for classification. It provided a visual interpretation of the findings of the ML models through local and global explanations.

- Model performance was evaluated using various metrics such as precision, recall, F1 score, precision and area under the curve (AUC) to assess the classification ability of machine learning models to predict stroke using EEG data.

- The aim of the study is to expand research with multimodal biosignal data for automated stroke prediction and post-stroke rehabilitation, showing potential for further development in the field.

Chapter 3

Hardware and Software Requirements

3.1 Hardware

- Processor: Recommended 2 GHz or more
- Ethernet connection (LAN) OR a wireless adapter (Wi-Fi)
- Hard Drive: Recommended 80 GB or more
- Memory (RAM): Recommended 8 GB or above

3.2 Software

- NumPy, Pandas, matplotlib and other relevant libraries
- Sublime Text for interactive development
- Anaconda for managing the environment

Chapter 4

System Architecture

4.1 System Overview

The methodology employed in this project aimed to develop a robust web application for EEG seizure detection using Convolutional Neural Networks (CNNs). The project involved several key steps, including data preprocessing, model training and evaluation. Each step was meticulously designed to ensure the effectiveness and reliability of the developed solution. The initial phase of the methodology focused on data acquisition and preprocessing. The publicly available CHB-MIT Dataset was utilized as the primary source of EEG data. This dataset contains EEG recordings from patients with epilepsy, along with annotations indicating seizure occurrences. The EEG signals were sampled at 256 Hz, which were subsequently resampled to 128 Hz to simplify data processing. Additionally, the signals were segmented into smaller windows of 8 seconds with a 4-second overlap to facilitate feature extraction and model training. Following data preprocessing, the project proceeded to model development using CNNs. The CNN architecture was chosen due to its proven effectiveness in capturing spatial features from multidimensional data such as images and signals. The CNN model comprised several convolutional layers with varying filter sizes and pooling layers for feature extraction and dimensionality reduction, respectively. Additionally, dropout layers were incorporated to prevent overfitting, while dense layers with rectified linear unit (ReLU) activation functions were employed for classification. To train the CNN model, the preprocessed EEG data was split into training and validation sets using stratified sampling to ensure a balanced distribution of seizure and non-seizure samples in each set. The model was then trained using the training data while monitoring its performance on the validation set. The training process utilized the Adam optimizer with a learning rate of 1e-4 and binary cross-entropy loss function. Moreover, early stopping and learning rate reduction callbacks were implemented to prevent overfitting and improve convergence. Once the CNN model was trained, it underwent evaluation to assess its performance in seizure detection. Various metrics such as accuracy, precision, recall, and F1-score were computed to quantify the model's efficacy in distinguishing between seizure and non-seizure epochs. Additionally, confusion matrices and classification reports were generated to provide a comprehensive understanding of the model's performance across different classes.

In parallel with model training and evaluation, the development of the web application commenced using Python Django framework. The application's graphical user interface (GUI) was designed to provide users with intuitive access to EEG seizure detection functionalities, including login authentication, test seizure detection, visualization of results, and recommendations based on detected factors influencing seizures. Finally, the trained CNN model was integrated into the web application, allowing users to upload EEG data for real-time seizure detection. The application utilized the saved model weights to make predictions on incoming EEG signals, enabling users to receive immediate feedback on seizure likelihood. Additionally, explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) were employed to visualize the CNN model's decision-making process, enhancing interpretability and trustworthiness.

4.2 Architecture Design

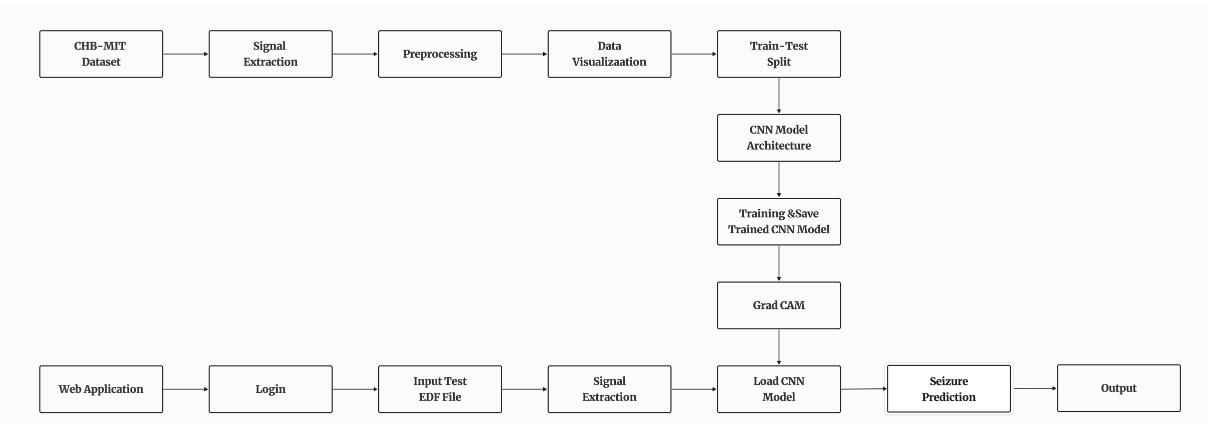

Figure 4.1: Architecture Diagram

4.3 Sequence Diagram

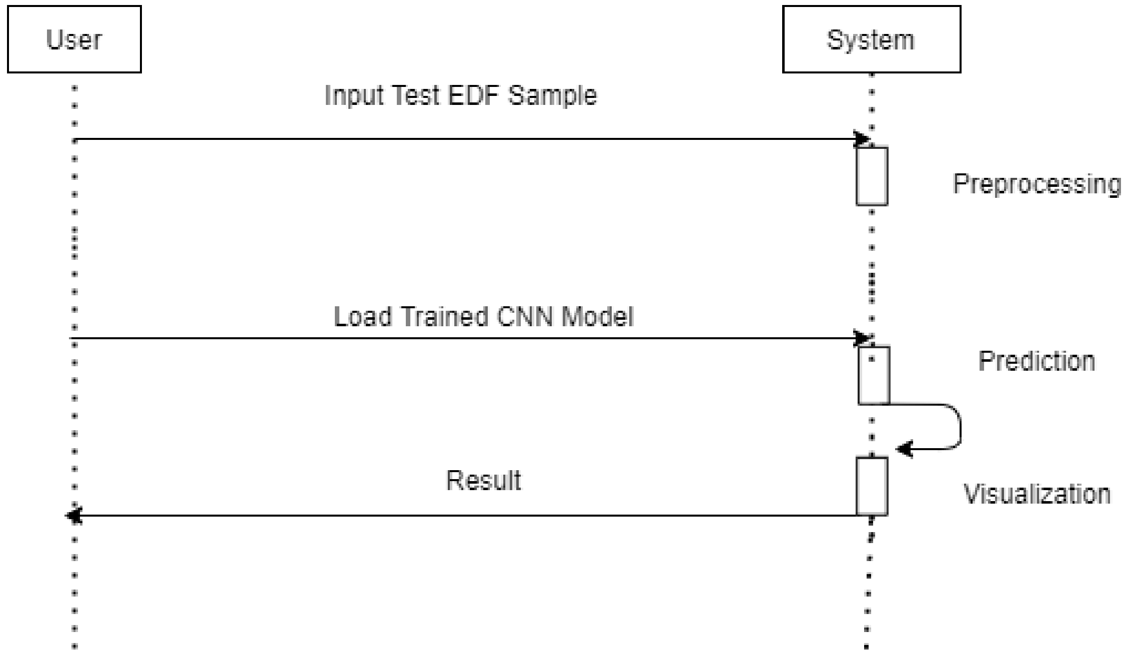

Figure 4.2: Sequence Diagram

4.4 Module Division

1. Data Acquisition and Preprocessing Module: - Data acquisition involves retrieving EEG recordings from the CHB-MIT dataset, which contains data from individuals with epilepsy. Preprocessing techniques are then applied to the EEG data to ensure its cleanliness and suitability for analysis. This may include filtering to remove noise, artifact removal, and normalization to standardize the data.

2. CNN Architecture Module: - The CNN architecture module encompasses the design and implementation of the minimalist CNN architecture tailored to process 2D EEG signals. This involves configuring convolutional layers with appropriate kernel sizes, pooling layers for reducing overfitting, and a fully connected layer with a non-linear activation function. The architecture is optimized to extract temporal and spatial features from the EEG data, enabling the detection of patterns indicative of epileptic seizures.

3. Training and Validation Module: - The training and validation module is responsible for optimizing the CNN model for accurate seizure detection. The dataset is divided into training, validation, and testing sets. The training set is used to train the

CNN model, and the validation set is employed to fine-tune the model's parameters and hyperparameters. This module leverages techniques such as backpropagation and gradient descent to iteratively adjust the model's weights and biases, leading to improved performance and accuracy.

4. Explainable AI Module: - The Explainable AI Module plays a crucial role in enhancing the interpretability of the CNN model's predictions. While deep learning models, such as CNNs, are powerful in making accurate predictions, their decision-making process can often be considered as a "black box," making it challenging to understand why a specific prediction was made. This module addresses the interpretability concern by providing insights into the features and patterns that contribute to the model's decision.

5. Real-time Monitoring and Alerting Module: - Upon successful training and validation, the real-time monitoring and alerting module enables the system to continuously monitor incoming EEG data for patterns indicative of impending seizures. When such patterns are detected, the module triggers an alert to notify the individual or caregiver, facilitating timely intervention and potentially preventing fatal injuries associated with epileptic seizures.

These modules collectively form a comprehensive framework for the early detection of epileptic seizures based on EEG data and CNNs. By integrating data acquisition, preprocessing, CNN architecture, training and validation, and real-time monitoring, the system aims to leverage advanced technologies to improve patient safety and quality of life for individuals with epilepsy.

4.5 Work Breakdown and Respnsibilites

- Abhinav R Nair- Data Collection , Data Preprocessing and Web Application Front End Development
- Abin Abraham- Web Application BackEnd and Final Integration with Testing
- Antony Francis- Explainable AI , CNN Model Prediction/Testing
- Ashok Gopal K A- CNN Model building , Training and Performance Evaluation

4.6 Work Schedule-Gantt Chart

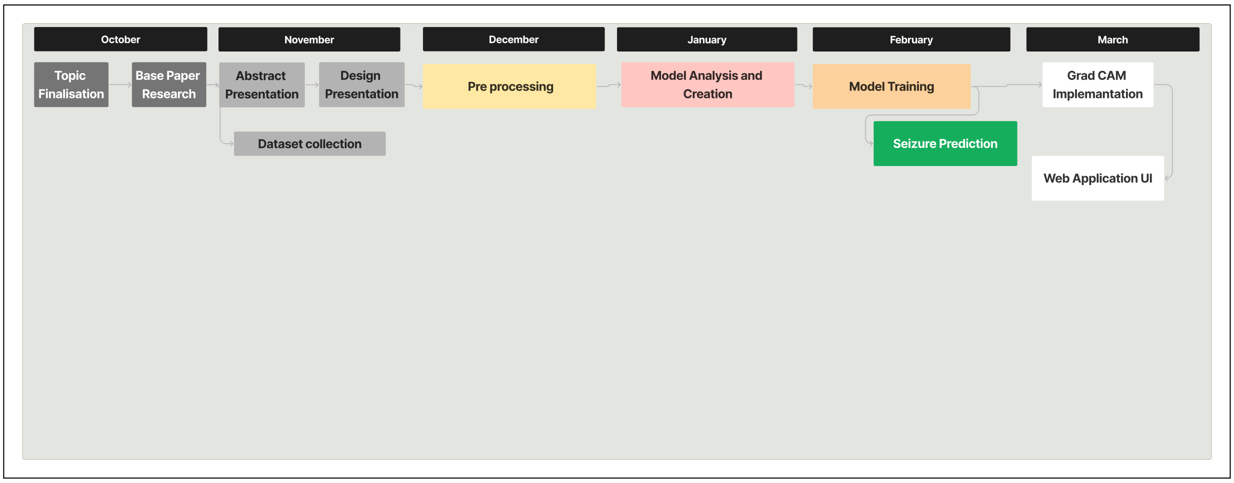

Figure 4.3: Gantt Chart

Chapter 5

Result

The CNN model performed admirably, with an accuracy of almost 93% on the validation set. The algorithm successfully identified important locations in the EEG data linked with seizure activity by examining the produced Grad-CAM heatmaps. The interpretation and comprehension of the model's predictions were made easier by these heatmaps, which offered insightful information about the brain dynamics underlying seizures. Additionally, the application of Grad-CAM improved the interpretability of the model's decision-making process by helping to localise the regions of aberrant brain activity. Overall, the accuracy of seizure identification and the relevant insights it provided into the underlying brain systems involved in seizure genesis were demonstrated by the combination of CNN-based seizure detection and Grad-CAM visualisation.

```
 Information
Number of all the extracted signals: 9505
Number of signals with seizures: 2581
Ratio of signals with seizures: 0.272
(9505, 18, 1024, 1)

Training Set
(7604, 18, 1024, 1)
(7604,)

Testing Set
(1901, 18, 1024, 1)
(1901,)
```

Figure 5.1: Input data

```
Epoch 1/10
238/238 [==============================] - 1725s 7s/step - loss: 0.6726 - accuracy: 0.7071 - val_loss: 0.5799 - val_accuracy: 0.7528
Epoch 2/10
238/238 [==============================] - 1699s 7s/step - loss: 0.5264 - accuracy: 0.7685 - val_loss: 0.4346 - val_accuracy: 0.8022
Epoch 3/10
238/238 [==============================] - 1729s 7s/step - loss: 0.4494 - accuracy: 0.7913 - val_loss: 0.3750 - val_accuracy: 0.8296
Epoch 4/10
238/238 [==============================] - 1694s 7s/step - loss: 0.4031 - accuracy: 0.8175 - val_loss: 0.3310 - val_accuracy: 0.8748
Epoch 5/10
238/238 [==============================] - 1685s 7s/step - loss: 0.3246 - accuracy: 0.8695 - val_loss: 0.2881 - val_accuracy: 0.8911
Epoch 6/10
238/238 [==============================] - 1696s 7s/step - loss: 0.2616 - accuracy: 0.9011 - val_loss: 0.2333 - val_accuracy: 0.9148
Epoch 7/10
238/238 [==============================] - 1705s 7s/step - loss: 0.2349 - accuracy: 0.9125 - val_loss: 0.2064 - val_accuracy: 0.9327
Epoch 8/10
238/238 [==============================] - 1694s 7s/step - loss: 0.1949 - accuracy: 0.9302 - val_loss: 0.2576 - val_accuracy: 0.9090
Epoch 9/10
238/238 [==============================] - 1691s 7s/step - loss: 0.1680 - accuracy: 0.9402 - val_loss: 0.1590 - val_accuracy: 0.9474
Epoch 10/10
238/238 [==============================] - 1699s 7s/step - loss: 0.1437 - accuracy: 0.9540 - val_loss: 0.2137 - val_accuracy: 0.9306
```

Figure 5.2: Training and Accuracy

	precision	recall	f1-score	support
False	0.98	0.93	0.95	1385
True	0.83	0.94	0.88	516
accuracy			0.93	1901
macro avg	0.90	0.93	0.92	1901
weighted avg	0.94	0.93	0.93	1901

Figure 5.3: Performance

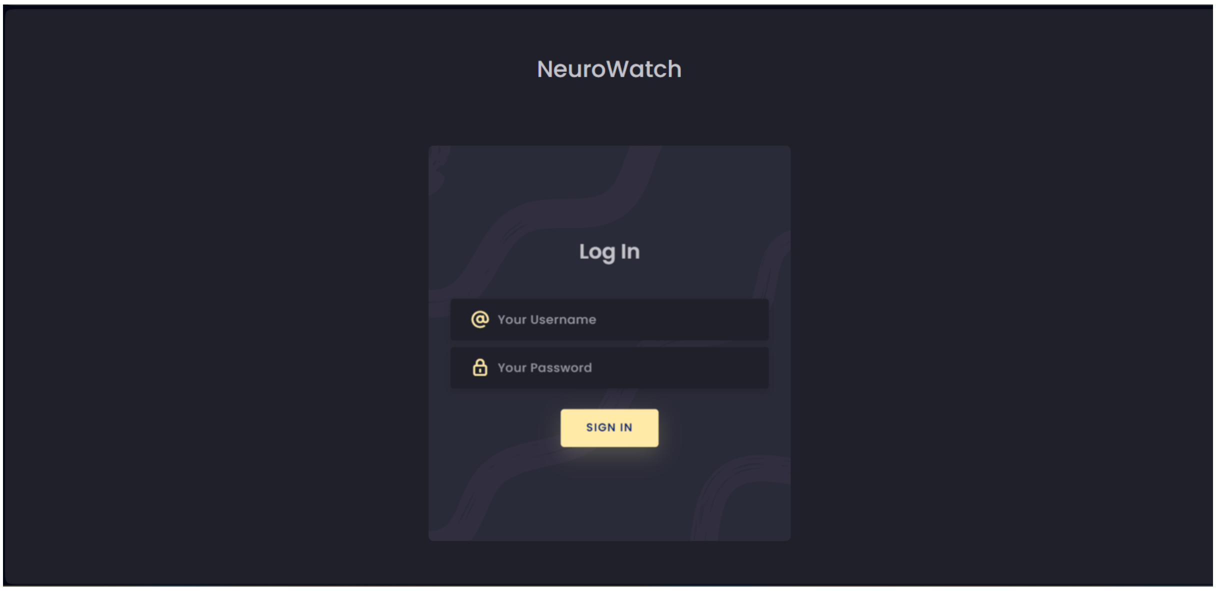

Figure 5.4: Login Page

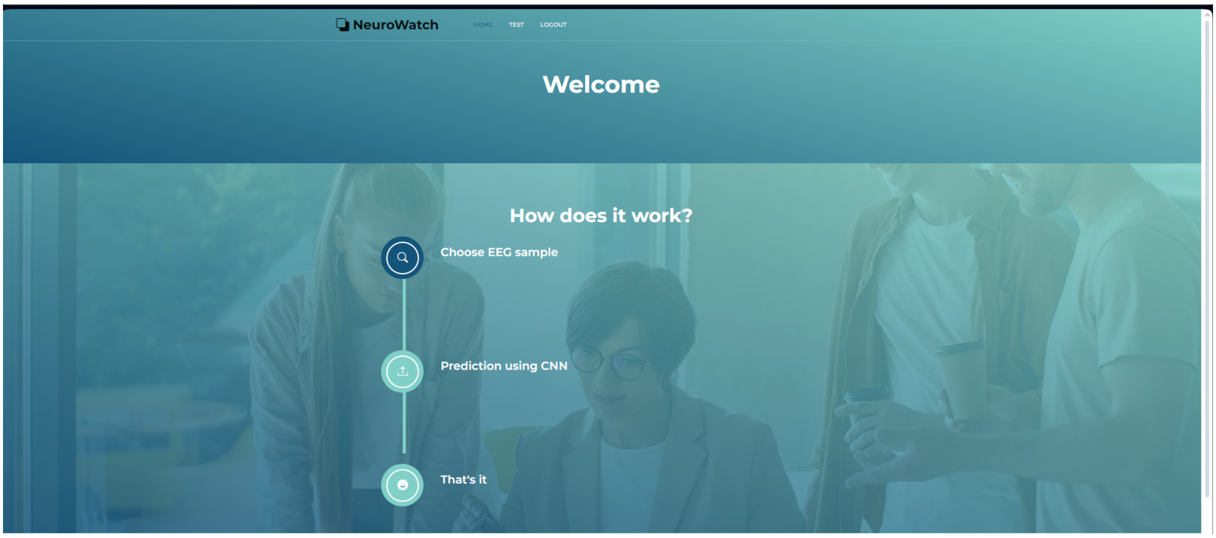

Figure 5.5: Home Page

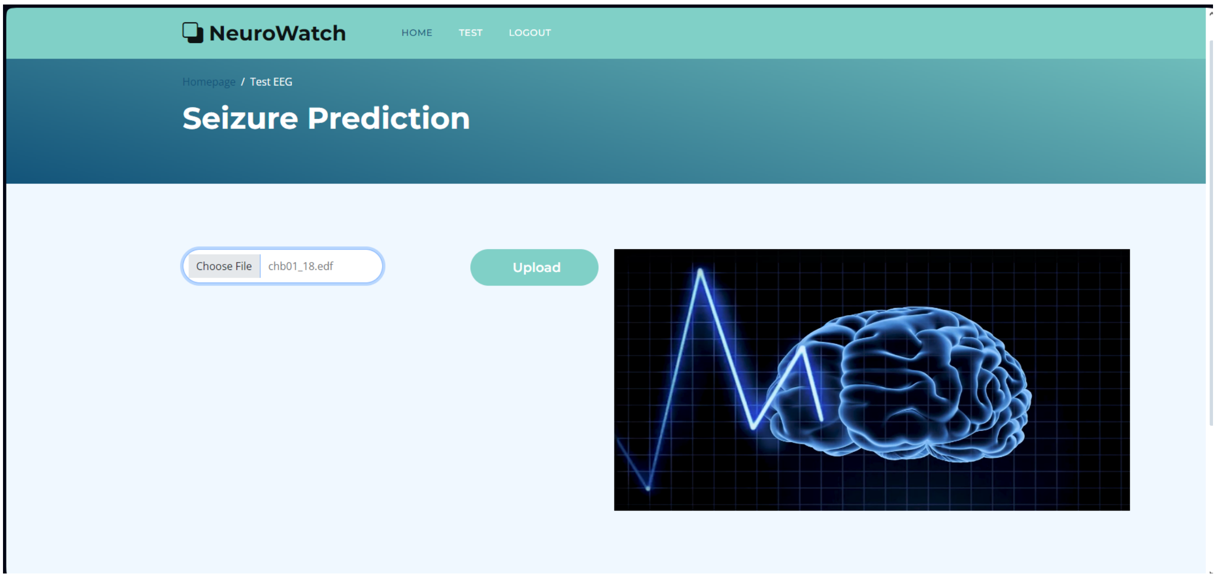

Figure 5.6: Upload Page

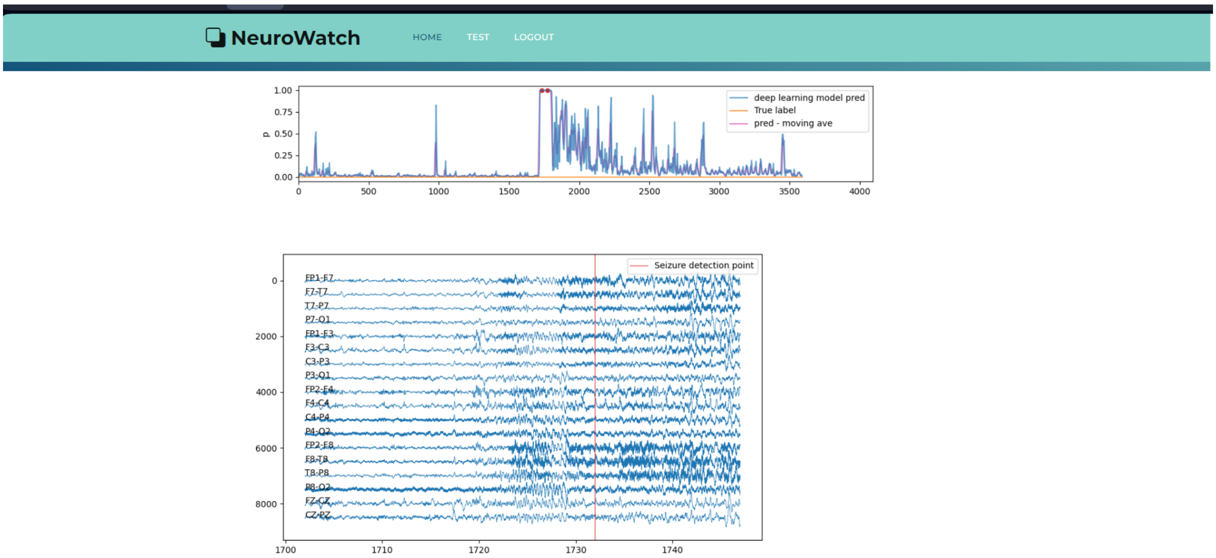

Figure 5.7: Seizure Detected

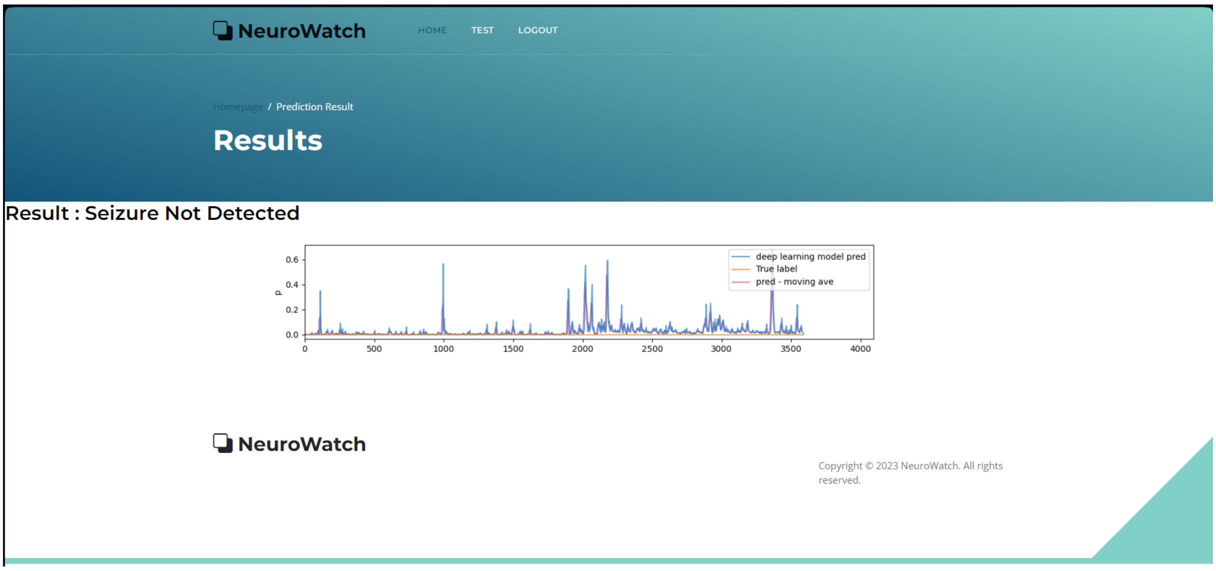

Figure 5.8: No Seizure Detected

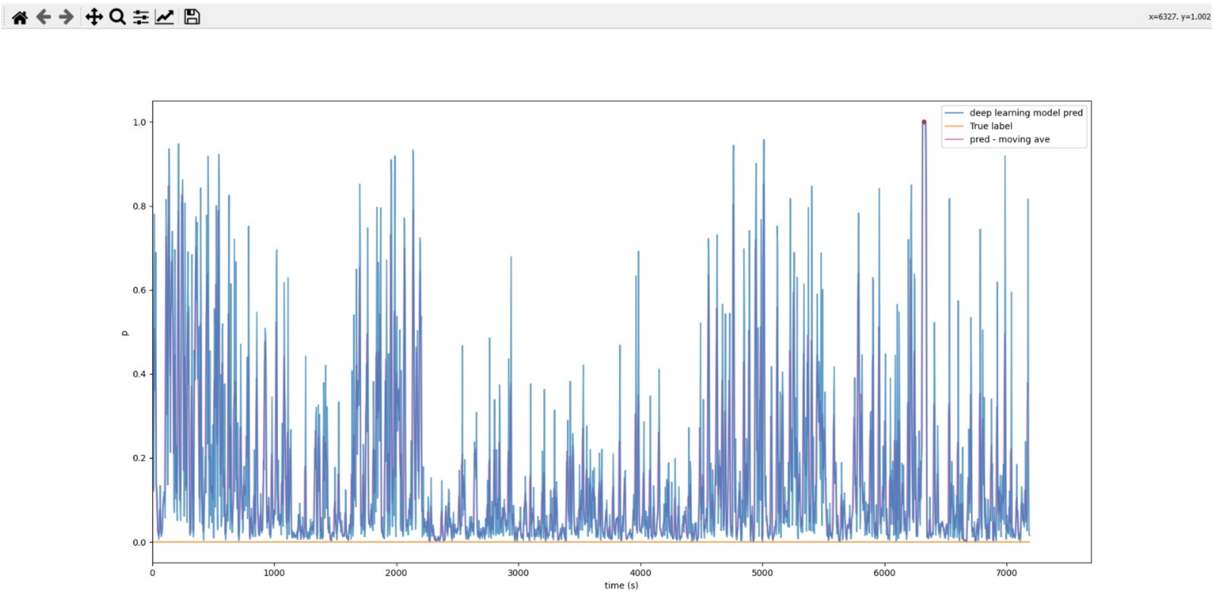

Figure 5.9: No Seizure Detected

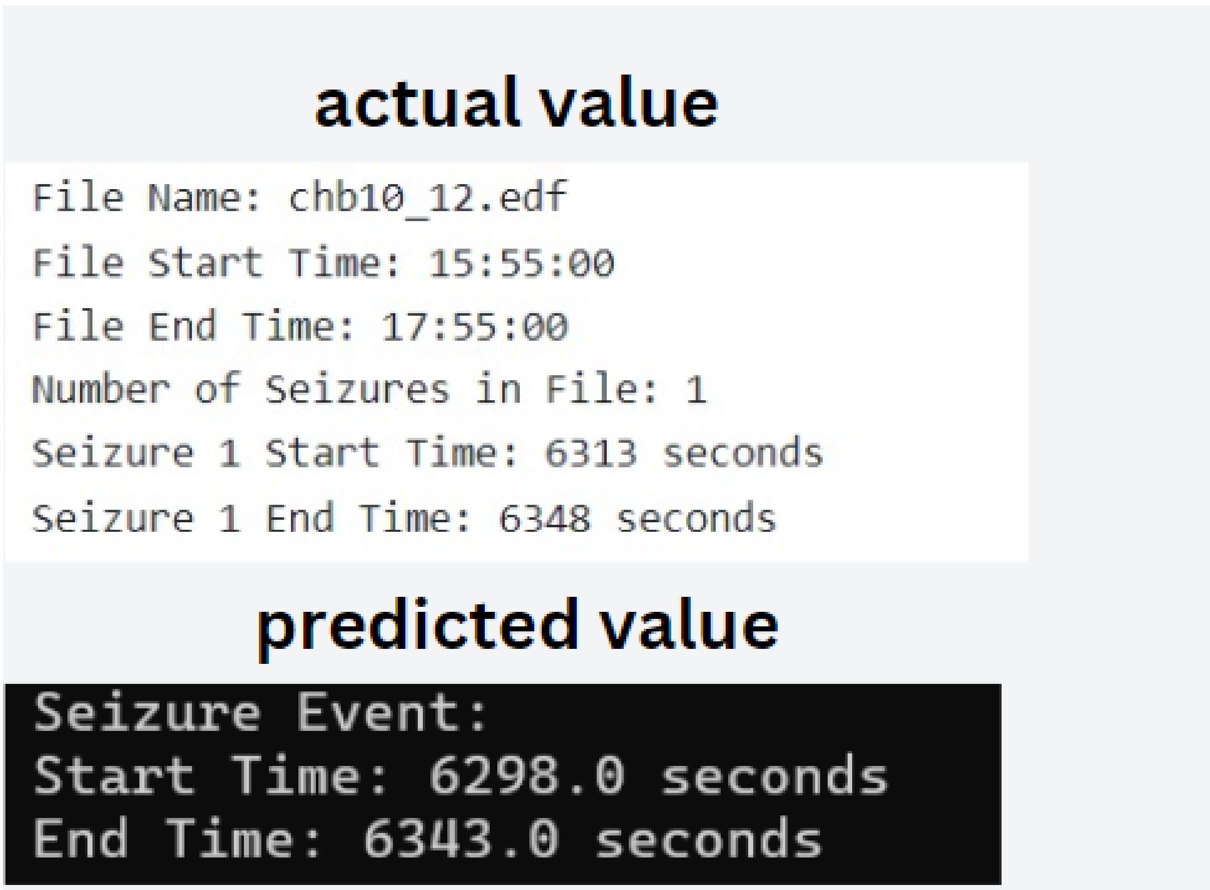

Figure 5.10: No Seizure Detected

Chapter 6

Conclusion

In conclusion, the release of XAI4EEG has marked a significant advancement in the development of deep learning-based seizure identification in EEG time series. By combining deep learning models with domain expertise and providing visual explanations that identify decision-relevant regions in EEG data, XAI4EEG meets the critical need for interpretability and trustworthiness in algorithmic predictions. An analysis of XAI4EEG on a publicly available dataset demonstrates that, while retaining a high degree of accuracy, it performs better than earlier methods in terms of interpretability and reliability. These findings demonstrate the potential of XAI4EEG to enhance clinical decision-making by providing health care providers with trustworthy and easier-to-understand seizure detection data. This will ultimately result in improved patient care and treatment decisions.

When XAI4EEG is included into clinical practice, algorithmic prediction validation in the context of patient care may experience a radical transformation in the future. Because XAI4EEG enables medical experts to more thoroughly understand and validate the predictions generated by deep learning models, it can enhance the overall effectiveness and reliability of algorithmic decision support systems in the medical domain. The success of XAI4EEG also emphasizes how important it is to use explainable AI techniques in medical research, as this will pave the way for more transparent, understandable, and dependable deeper learning applications in healthcare. As the field progresses, the ideas and methods offered by XAI4EEG should encourage further advancements in the development and use of deep learning models for medical decision assistance.

References

1. B. Mandhouj, M. A. Cherni, and M. Sayadi, "An automated classification of EEG signals based on spectrogram and CNN for epilepsy diagnosis."

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5. S. Ramakrishnan, A. S. M. Murugavel, and P. Saravanan, "Epileptic EEG Signal Classification using Multi-class Convolutional Neural Network," in *2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, Vellore, India, 2019, pp. 1–5.

Appendix A: Presentation

EEG SEIZURE DETECTION

ABHINAV R NAIR • ABIN ABRAHAM • ANTONY FRANCIS • ASHOK GOPAL
GUIDE:MS LIYA JOSEPH

CONTENTS

CONTENTS

PROBLEM DEFINITION

- The aim of this project is to develop an automated system for the detection and classification of epileptic seizures in EEG data.

- The system should accurately identify the onset and termination of seizures, differentiate between seizure and non-seizure EEG segments.

- This system aims to improve the management of epilepsy by enabling timely intervention and reducing the risks associated with uncontrolled seizures.

PROJECT OBJECTIVES

- The objective of an EEG seizure detection project is to develop an effective and reliable system for the automated detection and classification of epileptic seizures in EEG data.
- This system aims to improve the management of epilepsy and enhance the well-being of individuals with the condition.
- To find the necessary factors responsible for the occurrence of seizure using XAI.

NOVELTY OF IDEA AND SCOPE OF IMPLEMENTATION

- This project lies in its development of an automated system for detecting and classifying epileptic seizures in EEG data.
- Unlike traditional methods, this system integrates advanced machine learning techniques, particularly Convolutional Neural Networks, to accurately identify seizure onset and termination, distinguish between seizure and non-seizure EEG segments.
- The scope of implementation involves creating a user-friendly web application accessible to medical professionals and caregivers, enabling timely intervention and improving epilepsy management by mitigating risks associated with uncontrolled seizures.

LITERATURE REVIEW

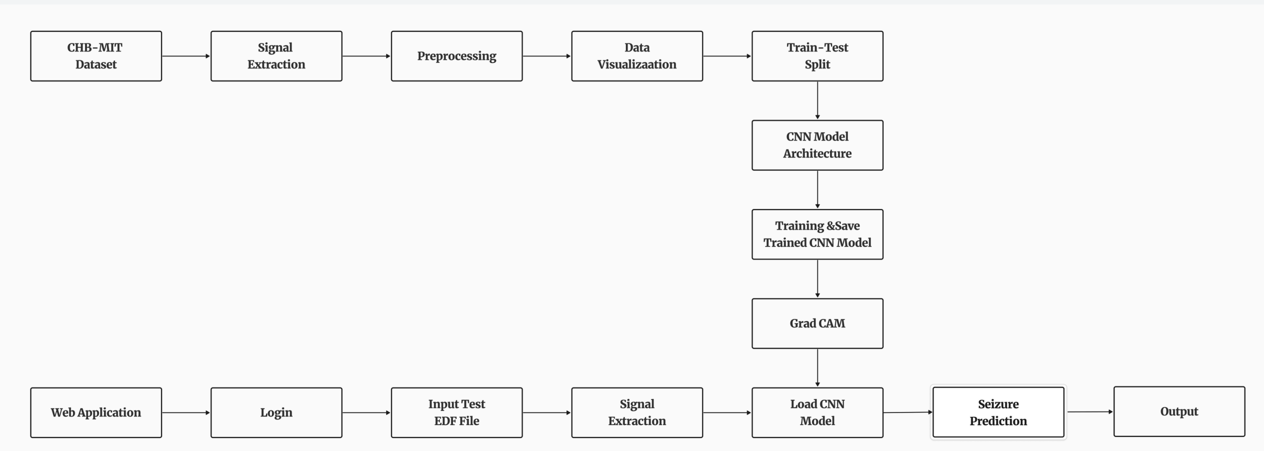
TITLE	AUTHOR	METHOD
XAI4EEG: SPECTRAL AND SPATIO-TEMPORAL EXPLANATION OF DEEP-LEARNING BASED SEIZURE DETECTION IN EEG TIME SERIES	DOMINIK RAAB, ANDREAS THEISSLER, MYRA SPILIOPOULOU	CNN AND EXPLAINABLE AI
DEEP NEURAL NETWORKS MODELING FOR EFFECTIVE EPILEPTIC SEIZURE DETECTION	MOHAMMED SAIDUL ISLAM 1 , IQRAM HUSSAIN, MD MEZBAUR RAHMAN 1	DNN
EXPLAINABLE ARTIFICIAL INTELLIGENCE MODEL FOR STROKE PREDICTION USING EEG SIGNAL	M. S. ISLAM, I. HUSSAIN, M. M. RAHMAN, S. J. PARK, AND M. A. HOSSAIN	MACHINE LEARNING AND EXPLAINABLE AI
EPILEPTIC SEIZURE DETECTION USING DEEP LEARNING BASED LONG SHORT-TERM MEMORY NETWORKS AND TIME FREQUENCY ANALYSIS	BIKESH KUMAR SINGH, KAVITA THAKUR	LSTM
AN AUTOMATED CLASSIFICATION OF EEG SIGNALS BASED ON SPECTROGRAM AND CNN FOR EPILEPSY DIAGNOSIS.	BADREDDINE MANDHOUJ MOHAMED ALI CHERNII MOUNIR SAYADI	2-D CNN

METHODOLOGY

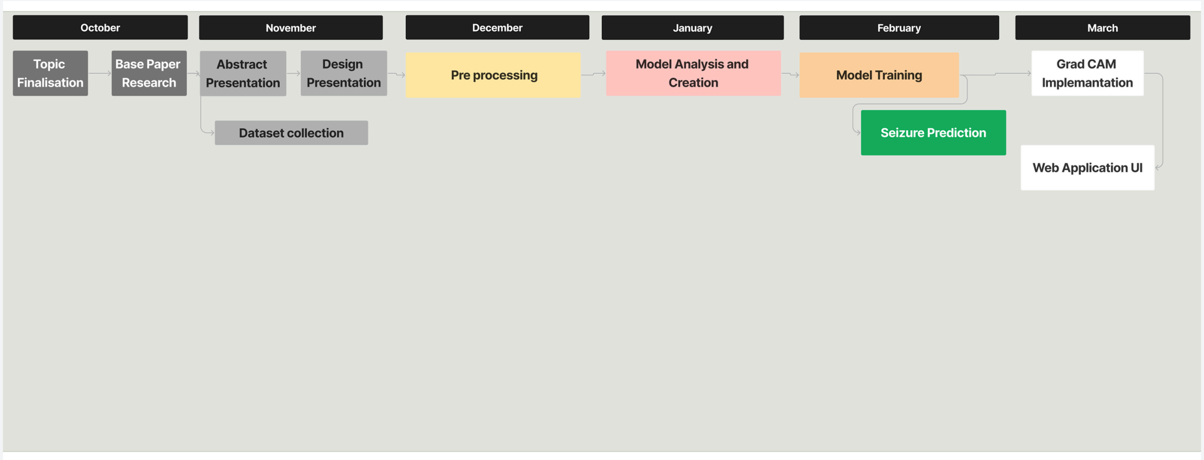
- Data Preprocessing: The CHB-MIT Dataset was used, with EEG signals resampled and segmented into smaller windows to facilitate processing.
- Model Development: CNN architecture was chosen for its effectiveness in capturing spatial features from EEG data, comprising convolutional and pooling layers, with dropout layers to prevent overfitting.
- Training Strategy: Preprocessed data was split into training and validation sets using stratified sampling to ensure a balanced distribution of seizure and non-seizure samples.
- Training Process: The model was trained using a learning rate of 1e-4 and binary cross-entropy loss function, with early stopping and learning rate reduction implemented to prevent overfitting.

- Evaluation Metrics: Performance of the trained CNN model was assessed using various metrics such as accuracy, precision, recall, and F1-score, along with confusion matrices and classification reports.
- Web Application Development: The web application was developed using the Python Django framework, providing users with intuitive access to EEG seizure detection functionalities.
- grad cam: Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to visualize the CNN model's decision-making process, enhancing interpretability and trustworthiness.

ARCHITECTURE DIAGRAM



PROJECT GANTT CHART



WORK DONE DURING 30% EVALUATION

- In 30% output we created two list one with seizure and the other without seizures
- Initially our dataset was 42GB and we reduced the size to 1.3GB by reducing the sampling rate from 256hz-128hz
- Additionally, the signals were segmented into smaller windows of 8 seconds with a 4-second overlap to facilitate feature extraction and model training.

WORK DONE DURING 30% EVALUATION

```
 Information
Number of all the extracted signals: 9505
Number of signals with seizures: 2581
Ratio of signals with seizures: 0.272
(9505, 18, 1024, 1)

Training Set
(7604, 18, 1024, 1)
(7604,)

Testing Set
(1901, 18, 1024, 1)
(1901,)
```

WORK PROGRESS (60% EVALUATION)

- As we got halfway through our project, we split the dataset into two parts: 80% for training set and 20% for testing set.
- Then, we displayed random 5 samples of seizure signals using matplotlib python library.
- Then we build the CNN model with various hidden layers which layers are responsible for learning high-level features and making predictions. for feature extraction and prediction.

WORK DONE DURING 60% EVALUATION

```
Epoch 1/10
238/238 [==============================] - 1725s 7s/step - loss: 0.6726 - accuracy: 0.7071 - val_loss: 0.5799 - val_accuracy: 0.7528
Epoch 2/10
238/238 [==============================] - 1699s 7s/step - loss: 0.5264 - accuracy: 0.7685 - val_loss: 0.4346 - val_accuracy: 0.8022
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Epoch 10/10
238/238 [==============================] - 1699s 7s/step - loss: 0.1437 - accuracy: 0.9540 - val_loss: 0.2137 - val_accuracy: 0.9306
```

RESULTS OF 100% WORK COMPLETION

- Developing a web application for EEG seizure detection involves designing an intuitive interface for uploading data, implementing a Convolutional Neural Network model for predicting and visualizing results.
- Implementation of explainable AI(grad cam)
- Testing, validation of user input where it predicts whether the input signal has seizure or not

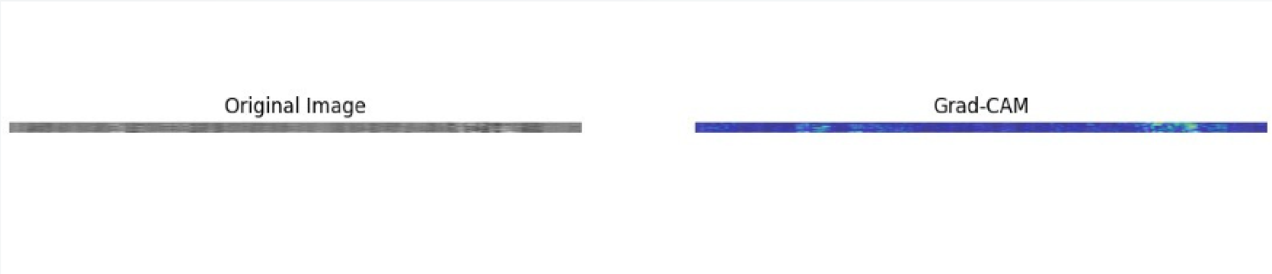
GRAD CAM

- Grad-CAM (Gradient-weighted Class Activation Mapping) is a technique used to visualize and understand which parts of an input image are important for the prediction made by a convolutional neural network (CNN) model.
- It provides a fine-grained visualization of the regions within the input image that contribute most to the model's decision.

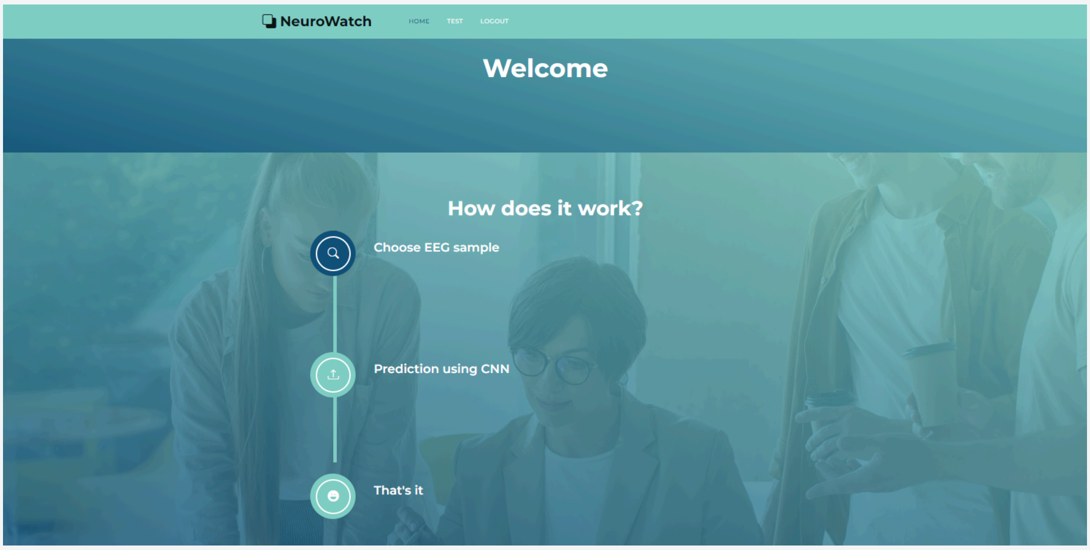
GRAD CAM

- Forward Pass: During the forward pass of the CNN, the input image passes through several convolutional and pooling layers, ultimately producing a final prediction.
- Gradient Calculation: Grad-CAM computes the gradients of the predicted class score with respect to the feature maps of the last convolutional layer in the network. These gradients represent the importance of each feature map in influencing the final prediction.
- Importance Weights: The gradients obtained in the previous step are then used as weights to combine the feature maps of the last convolutional layer, giving higher importance to feature maps that have a larger influence on the prediction.
- Heatmap Generation: Finally, Grad-CAM generates a heatmap by linearly combining the weighted feature maps. This heatmap highlights the regions in the input image that are most relevant to the model's prediction for the target class.

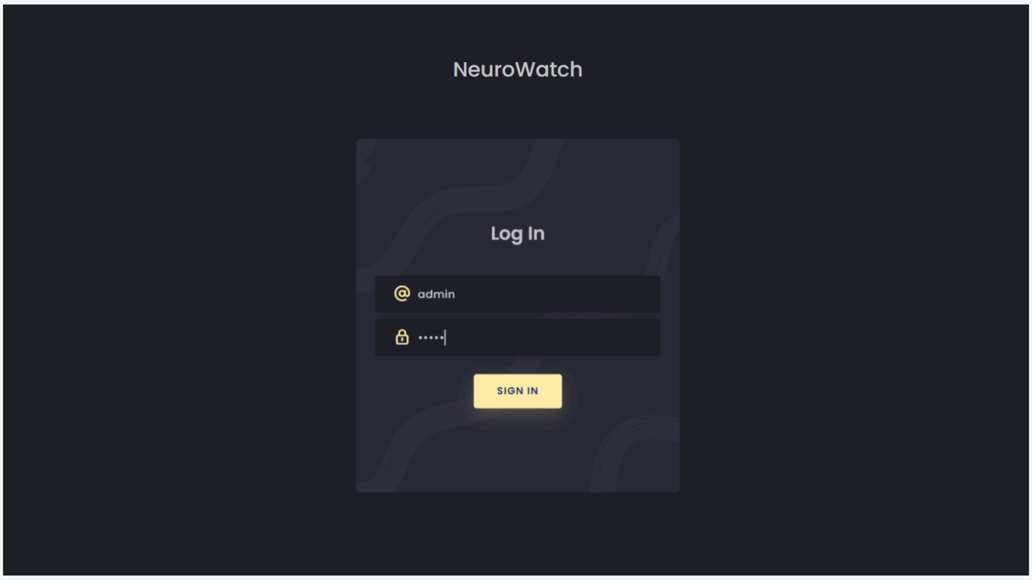
GRAD CAM



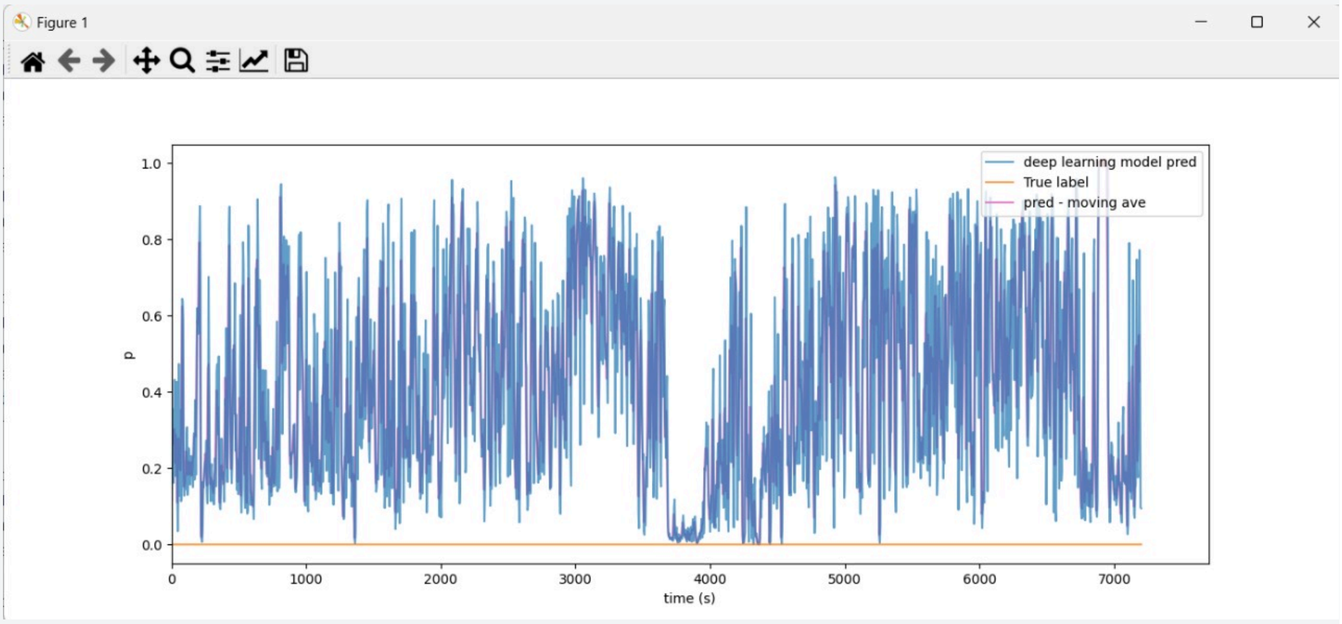
INTERIM RESULTS



INTERIM RESULTS

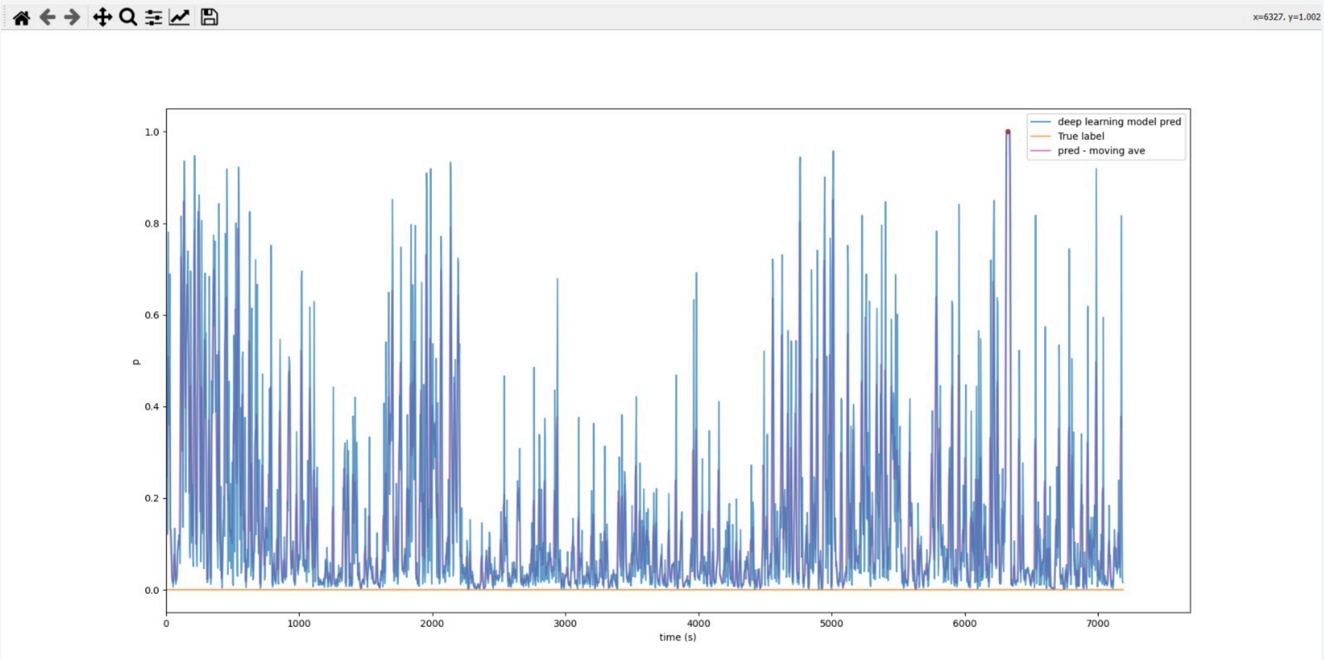


INTERIM RESULTS



INTERIM RESULTS

```
Test/Normal/chb01_17.edf: Reading.
Extracting EDF parameters from C:\Users\ashok\OneDrive\Desktop\EEG_CODE\Test\Normal\chb01_17.edf...
EDF file detected
pre.py:159: RuntimeWarning: Channel names are not unique, found duplicates for: {'T8-P8'}. Applying running numbers for duplicates.
  temp_edf =  mne.io.read_raw_edf(f)
Setting channel info structure...
Creating raw.info structure...
No seizure detected.
```



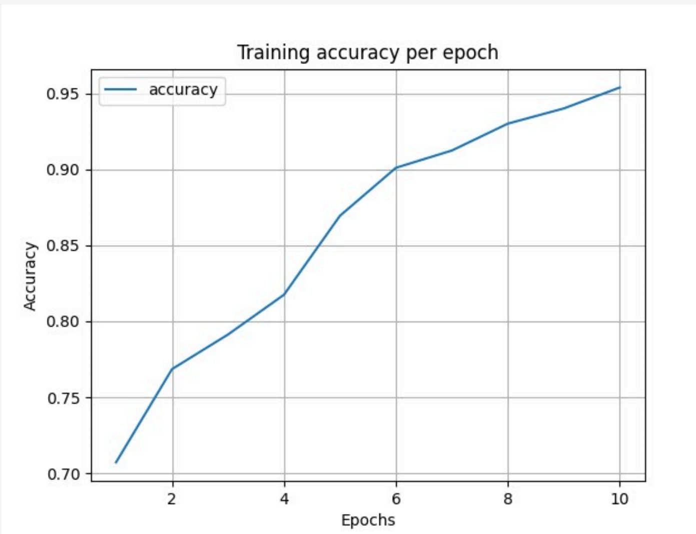
actual value

```
File Name: chb10_12.edf
File Start Time: 15:55:00
File End Time: 17:55:00
Number of Seizures in File: 1
Seizure 1 Start Time: 6313 seconds
Seizure 1 End Time: 6348 seconds
```

predicted value

```
Seizure Event:
Start Time: 6298.0 seconds
End Time: 6343.0 seconds
```

TRAINING ACCURACY



WORK DISTRIBUTION

- Abhinav R Nair : Data Collection , Data Preprocessing and Web Application FrontEnd Development
- Abin Abraham : Web Application BackEnd and Final Integration with Testing
- Antony Francis : Explainable AI , CNN Model Prediction/Testing
- Ashok Gopal K A : CNN Model building , Training and Performance Evaluation

CONCLUSION

In conclusion, leveraging Explainable AI alongside CNN-based EEG seizure detection enhances interpretability, ensuring transparency in decision-making processes.
Despite challenges like dataset diversity, this approach promises improved epilepsy management and patient outcomes, fostering a deeper understanding of seizure mechanisms for enhanced clinical care.

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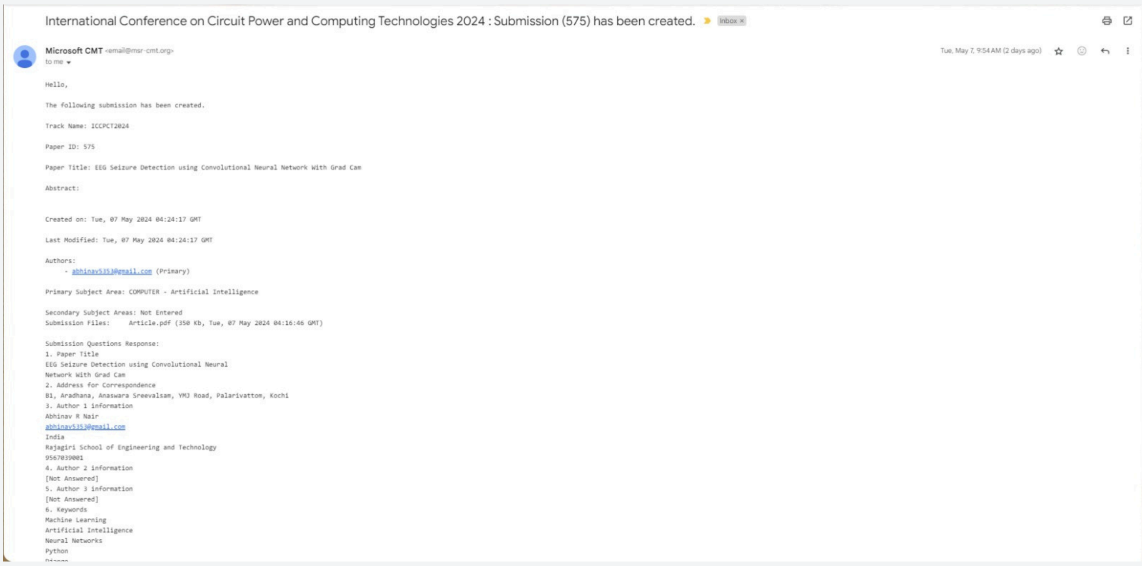
PAPER PUBLICATION

Conference: International Conference on Circuit Power and Computing Technology
Date: 8-9 August 2024
Link: https://www.iccpct.in



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Tue, May 7, 9:54 AM (2 days ago)
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Created on: Tue, 07 May 2024 04:24:17 GMT
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Authors:
- abhinav5353@gmail.com (Primary)
Primary Subject Area: COMPUTER - Artificial Intelligence
Secondary Subject Areas: Not Entered
Submission Files: Article.pdf (350 Kb, Tue, 07 May 2024 04:16:46 GMT)
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Network With Grad Cam
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9567039001
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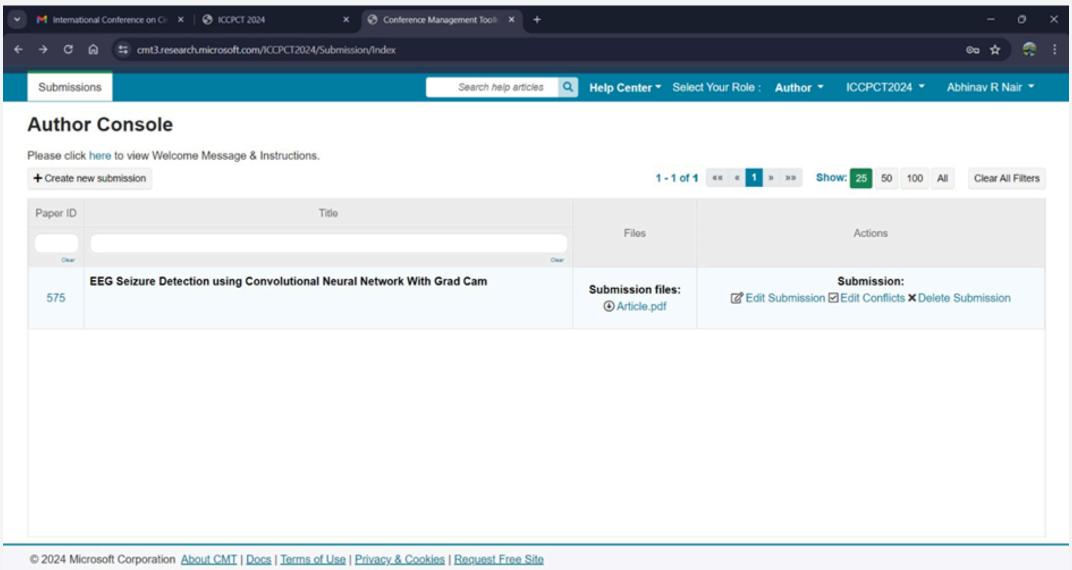
Artificial Intelligence
Neural Networks
Python



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+ Create new submission
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EEG Seizure Detection using Convolutional Neural Network With Grad Cam
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Edit Conflicts
Delete Submission
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YOU

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

100003/ CS722U.1- PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1- PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1- PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1- PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1- PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1- PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1- PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
100003/ CS722U.1- PO10	M	Project brings technological changes in society.

100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like

		network design and administration, database design and knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.