NeuroCare

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NeuroCare

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Declaration

We declare that this FYP "NeuroCare: EEG-based Seizure Detection and Classification" is entirely our work under the supervision of Mr. Waqas Ali. The research was carried out in the Department of Computer Science at UET Lahore, Main Campus, Pakistan. All published and unpublished material/data used in this final year project has been given full acknowledgment and is property of the Department. None of this work has been previously submitted to this or any other academic institution for a degree or diploma, or any other qualification.

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Last but not the least, we would like to dedicate this work to our parents for their immense emotional and financial support during the research period.

Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BIDS	Brain Imaging Data Structure
BiLSTM	Bidirectional Long Short-Term Memory
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
FFT	Fast Fourier Transform
FYP	Final Year Project
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
HIPAA	Health Insurance Portability and Accountability Act
ICA	Independent Component Analysis
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
PR-AUC	Precision-Recall Area Under Curve
RNN	Recurrent Neural Network
ROC-AUC	Receiver Operating Characteristic - Area Under Curve
SRS	Software Requirements Specification
SSL	Self-Supervised Learning
SVM	Support Vector Machine
TUH	Temple University Hospital

First of all, we want to thank Almighty Allah (S.W.T) for His constant help in making it possible to complete this work. This research and analysis are dedicated to our Supervisor Mr. Waqas Ali, and our beloved parents, who have been our constant source of inspiration. They have given us the drive and discipline to tackle this task with enthusiasm and determination. Without their constant assurance, support, and prayers, this project would not have been possible.

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Abstract

Automatic detection of seizures from EEG signals is very important for improving the diagnosis and care of people with epilepsy. Most existing systems use CNNs or LSTM architectures, which tend to miss the important details of EEG signals' spatial and temporal patterns. In this study, we propose a hybrid CNN-LSTM system that uses convolutional layers to find local features and bidirectional LSTMs to handle long-term temporal changes. This approach addresses the main problems in EEG-based seizure detection, such as unequal class sizes, changes in seizure patterns over time, and slow processing. The model is developed and assessed using the BIDS-SEINA dataset, along with preprocessing techniques, and further trained with focal loss and data augmentation to address the large difference in the number of seizure and background samples. Ablation experiments show that LSTM layers are very important for learning temporal information, and focal loss makes the model more sensitive to minority seizure classes. The model is still able to achieve an ROC-AUC of 0.686 and a seizure-specific F1-score of 0.13, demonstrating that rare-event detection is challenging in clinical EEG. We have developed a hybrid CNN-LSTM model that can be reproduced for BIDS-SEINA, provided evidence for using precision-recall metrics in unbalanced seizure classification, and given guidelines on creating lightweight models that work well with wearables. The study shows that more work is needed to develop new models and use better data to enhance seizure detection in real life.

Chapter 1

Introduction

1.1 Background and Motivation

Epilepsy is a neurological condition marked by repeated, unpredictable seizures due to unusual, high electrical activity in the brain. The disease touches the lives of about 50 million people globally and is a major health concern [1]. Seizures can present as brief blackouts or as severe convulsions and the length, frequency and seriousness of each seizure can differ from one patient to another [2].

EEG is the most common way to detect brain electrical activity and spot seizures without surgery. EEG measures the changes in voltage on the scalp that represent how the brain functions over time and place. Still, understanding EEG results by hand is slow and needs expert medical knowledge which often results in different interpretations by different raters [3]. It shows that accurate and efficient automated seizure detection tools are now needed to help clinicians diagnose epilepsy.

Manual interpretation of electroencephalogram (EEG) signals for seizure detection is hard work, takes a lot of time and depends heavily on expert neurologists, so it cannot be used for widespread or constant monitoring. With the release of BIDS-SEINA and the TUH EEG Corpus, now machine learning models can be used to automate this task. Yet, these systems are rarely used in clinical settings because of ongoing issues such as infrequent seizures, variation in each patient's signals and noise in the data. This requires creating powerful deep learning models that can handle different patient groups and still deal with the problem of class imbalance which is vital for practical use [4], [5].

While progress has been made in deep learning for seizure detection with EEG, existing models usually do not function well in real hospitals. A big problem is that seizure events are vastly outnumbered by normal activity in EEG data which makes predictions biased and sensitive only to the majority class. Many models also assume that EEG data is organized like an image or a series of events, without taking into account the brain's natural changes over space and time. When the assumptions of the model do not match the EEG signals, the results are not as effective for different patients and seizure types. Moreover, current methods do not always pay attention to the needs of clinical deployment such as being easy to understand, efficient and able to work in real time which are necessary for integration into both medical and wearable systems [6], [7].

We address the shortcomings of present methods by introducing a hybrid system that combines 1D CNNs with BiLSTM units for real-time detection of seizures in EEG signals. The CNN part of the model discovers local spatial and frequency-related features, while the BiLSTM module finds the important long-term relationships needed to recognize seizure changes over time. We use focal loss to give more importance to the minority seizure class and apply data augmentation to help equalize seizure and background instances. The model is developed and assessed using the BIDS-SEINA dataset and signal quality is improved by applying bandpass filtering and z-score normalization. Our method is made to be both efficient and scalable, so it can be used in hospitals and as part of wearable neuro-monitoring [8], [9].

In biomedical signal processing, deep learning has proved highly useful, especially in recognizing seizures from EEG recordings because it can learn from different levels of data. CNNs have proved to be effective at extracting both spatial and spectral details in EEG signals, while LSTMs show good results in modeling the changing patterns in EEG. With these models, we use fewer handcrafted features and check signals less manually. Hybrid architectures have recently become popular because they use the best features of CNNs and LSTMs to improve how sensitive seizure detection is to various types of seizures [10]. This makes them well suited to difficult tasks, including classifying seizures without relying on a patient's details.

Despite the progress enabled by deep learning, some limitations remain in existing studies. A lot of models are tested on datasets that are carefully designed and do not include challenges like noise, differences between patients and uneven class distribution. Therefore, the results from these models do not apply well to real-world data. Besides, previous models tend to process EEG like images, missing the electrophysiology and relationships between different channels of raw EEG signals. In addition, accuracy is the primary metric reported, while important clinical metrics for the minority seizure class such as F1-score and PR-AUC, are rarely mentioned which can give a false sense of how useful the system is [11].

A hybrid CNN-LSTM framework is proposed in this study for detecting seizures from EEG signals in datasets with uneven data and noise. We contribute to this area in four ways: (1) we propose a model that uses LSTMs and CNNs to combine space, frequency and time information in EEG data; (2) we employ focal loss and targeted data augmentation to make our model more sensitive to seizures; (3) we test different model components and loss functions to show how they affect results; and (4) we evaluate our model using clinically relevant parameters such as PR-AUC and F1-score, rather than just accuracy [12]. The goal of these contributions is to help bring academic findings into clinical use for seizure detection.

The remainder of this paper is organized as followsSection 2 presents an in-depth survey of recent deep learning methods used in EEG-based seizure detection, emphasizing how hybrid models and methods to handle class imbalance have developed. Section 3 describes the process used, covering the data, how it is prepared, the structure of the model and how it is trained. In Section 4, we publish the results of our experiments, analyze them and discuss ablation experiments, performance and comparisons with other studies. The paper ends with Section 5 which highlights the most important findings and proposes areas for further research.

1.2 Problem Statement

Epileptic seizures impact an estimated 1.5 to 2 million individuals in Pakistan, majority face delays in diagnosis, and deprived from precise monitoring due to limited healthcare access and resources, particularly in rural areas of Pakistan.

1.3 Problem Description

Automated seizure detection from EEG signals still encounters several persistent challenges. One major issue is the variability across patients and recording devices; differences in EEG noise characteristics and electrode placement result in diverse feature representations, thereby making generalization to real-world data difficult [13]. Another significant challenge is data imbalance, as seizure events are comparatively rare in EEG recordings. This causes machine learning models to become biased toward the majority non-seizure class, often resulting in a high rate of false negatives [14]. Additionally, there are spatial-temporal limitations inherent in popular deep learning architectures. While CNNs are effective at capturing spatial patterns, they fail to model long-term temporal dependencies. Conversely, LSTMs are capable of learning temporal sequences but struggle to handle noisy, high-dimensional EEG inputs effectively [15]. Finally, even state-of-the-art detectors often suffer from high false positive rates, sometimes reporting more than five false alarms per hour in noisy EEG data, which undermines clinician confidence in such systems [16].

To address these issues, this research proposes a hybrid CNN–LSTM model that aims to: perform robustly across diverse EEG datasets; handle class imbalance effectively; jointly learn spatial and temporal features from EEG signals; ensure computational efficiency suitable for real-time deployment; and significantly reduce the rate of false alarms.

1.4 Research Objectives

The main contributions of this research are centered around the development and evaluation of a robust deep learning framework for seizure detection. Primarily, an end-to-end hybrid CNN–LSTM model has been developed and implemented to enable automatic seizure detection using single-channel EEG data. This architecture leverages convolutional layers to effectively extract spatial features from EEG signals, while LSTM layers are employed to capture and model long-term temporal dependencies [17]. Furthermore, the proposed model has been comparatively evaluated against CNN-only and LSTM-only baselines to highlight its superior performance in handling complex EEG patterns [18]. In addition to architectural innovations, this research includes a detailed analysis of preprocessing techniques, such as bandpass filtering, segmentation, and normalization, to understand their influence on model performance. Lastly, the computational efficiency of the model has been assessed to ensure that it meets the requirements for real-time deployment and use in portable medical applications.

1.5 Significance of the Study

The proposed hybrid CNN–LSTM model provides several significant contributions to the field of automated seizure detection. Most notably, it delivers improved detection accuracy and reduces false positives when compared to single-architecture models, thereby enhancing clinical reliability [19]. Its ability to detect brief or low-amplitude seizures makes it more sensitive to subtle abnormalities that are often overlooked. Additionally, the model introduces a simplified processing pipeline that facilitates seamless end-to-end deployment into real-time monitoring systems, making it suitable for practical implementation [20]. It demonstrates strong robustness across diverse EEG datasets and recording conditions, increasing its generalizability and effectiveness in various scenarios. Furthermore, due to its computational efficiency, the model shows great promise for deployment on wearable devices, enabling continuous patient monitoring in both clinical and non-clinical environments [21].

Overall, this research aims to standardize diagnostic workflows, boost neurologist confidence in automated tools, and encourage proactive seizure management within both hospital and home settings.

1.6 Scope and Limitations

The scope of this study is primarily defined by its use of single-channel EEG recordings sourced from the University of Bonn dataset [22]. To maintain simplicity and computational feasibility, the model architecture was designed with reduced complexity, analyzing only one EEG channel per sample. The preprocessing phase involved basic techniques such as bandpass filtering, segmentation, and normalization, but did not include advanced artifact removal methods. Additionally, the model was developed to learn spatial and temporal features directly from the raw signal, deliberately excluding time-frequency transformations to streamline processing. The performance and efficiency of the model were evaluated on a standard desktop GPU, without extending to wearable or embedded system testing. The study also involved limited hyperparameter tuning, relying on results from a single dataset split. Moreover, the analysis was specifically focused on adult EEG patterns, and did not account for pediatric or neonatal seizure characteristics, which may present differently.

Despite these constraints, the study lays a strong foundation and acknowledges several areas for future improvement. These include expanding the approach to support multichannel EEG recordings, incorporating sophisticated artifact removal techniques, integrating time-frequency features, and developing strategies for on-device deployment to enable use in portable or wearable healthcare solutions.

1.7 Thesis Organization

The thesis is organized into six chapters:

- **Chapter 1:** Introduction — Background, problem statement, research objectives, significance, scope, and limitations,
- **Chapter 2:** Literature Review — EEG signal processing, seizure detection methods, hybrid CNN–LSTM models,
- **Chapter 3:** Methodology — Dataset description, preprocessing, model design, training protocol,
- **Chapter 4:** Experiments and Results — Evaluation framework, metrics, classification results, computational benchmarks,
- **Chapter 5:** Discussion — Comparative analysis, error analysis, preprocessing impact,
- **Chapter 6:** Conclusion — Main contributions, practical implications, and future work.

Each chapter is designed to stand alone yet contribute to a coherent narrative towards developing an effective hybrid CNN–LSTM seizure detection system.

Chapter 2

Literature Review

Automated detection of seizures in EEG signals is crucial for better diagnosis, monitoring and decisions in epilepsy treatment. EEG allows medical experts to see the brain's electrical activity with great accuracy which helps identify unusual brain patterns linked to seizures. Typically, seizure detection was done using handmade feature extraction and traditional machine learning methods such as support vector machines and decision trees, but these are not suitable for different patient groups [23]. Recently, deep learning has made a big impact on this area by allowing models to uncover spatial and temporal features inside the EEG data without the need for manual feature creation. Researchers have found that CNNs, RNNs and LSTM networks are especially good at detecting complex and time-related patterns in EEG signals [23], [24].

Yet, to work well, these models usually need a lot of labeled data which takes a lot of time and money to gather since experts must annotate it. To address this issue, SSL approaches are now widely used, helping models find useful EEG representations by studying the signal properties found in large unlabeled datasets [24]. Methods based on transfer learning have been tried to use pretrained models on large EEG datasets for improving seizure detection with only a small number of labels. This literature review looks at the move from traditional to deep learning and new SSL methods, pointing out what each approach offers and what its drawbacks are. With these findings, we present our new graph neural network model which relies on the structure of EEG electrodes to improve seizure detection. Initially, researchers in automated seizure detection explored traditional machine learning and used handmade features from EEG signals. These features were usually made up of spectral power, wavelet coefficients, entropy measures and statistical descriptors meant to detect patterns related to seizures in both time and frequency domains [25]. Support Vector Machines (SVM), Random Forests and k-Nearest Neighbors (k-NN) were the main classifiers used to tell apart ictal and interictal EEG segments. Although they worked well on limited, controlled data, they were not fully scalable or robust because of some factors. Because the manual process for feature engineering was slow and needed experts, the system struggled to handle different types of seizures and patients [26]. In addition, differences in EEG recordings, noise artifacts and the variety among study subjects generally made it harder to classify brain activity accurately in real-life settings. In spite of these issues, traditional approaches helped understand important features of EEG signals related to seizure detection, leading to the use of data-based feature learning methods.

With the limitations of traditional machine learning becoming evident, deep learning models have increasingly been adopted for EEG-based seizure detection due to their ability to automatically learn hierarchical features from raw signals. Many studies have used CNNs to detect patterns in EEG data by turning signals into images called spectrograms or topographical maps [27]. They are good at finding local features in space but can have trouble with dependencies in time found in EEG data. To deal with time-related changes, RNNs, mainly LSTM networks and GRUs, have been included in EEG analysis, either by themselves or with CNNs, to model events that occur far apart in the data [28]. Using CNNs for spatial features and LSTMs for temporal understanding, hybrid CNN-LSTM architectures perform better in detection than single-model approaches.

Even with important improvements, deep learning models deal with issues such as overfitting to small datasets, being computationally demanding and being affected by noise and differences among patients. New studies have looked into using data augmentation, transfer learning and attention mechanisms to improve how robust and generalizable models become [27], [28]. They prove that deep learning frameworks are becoming more advanced for seizure detection, encouraging more work on models that better understand the main properties of EEG signals.

One major difficulty in EEG-based seizure detection is that seizures make up only a tiny part of the recorded data, while normal brain activity is much more common. Because of this, models tend to misclassify seizures, leading to low sensitivity and many missed seizures. The traditional approaches of oversampling minorities and undersampling majorities have been used, but they may result in overfitting or loss of useful data [29] .New methods make use of GANs to produce synthetic data, focal loss functions and cost-sensitive approaches to manage the issue of class imbalance. Synthetic seizure EEG segments made with GANs can be used to even out training data without affecting its diversity [30]. Focal loss automatically lowers the importance of correctly classified data, so the model learns more from the tough minority classes which raises the detection metrics. Using these approaches has improved both seizure sensitivity and F1 scores, making them more suitable for clinical use.

The lack of enough labeled EEG data for seizure detection is a major challenge when training deep learning algorithms. In order to address this issue, self-supervised learning (SSL) has become a useful approach that makes use of a lot of unlabeled EEG recordings by assigning pretext tasks that help models learn important features without any manual labeling. SSL methods such as contrastive learning and masked signal reconstruction, make use of the natural time and space features in EEG to enhance the accuracy of seizure detection, even if there is not much labeled data [31]. In addition to SSL, transfer learning is becoming popular by using models that were first trained on big EEG or related biomedical datasets for seizure detection. As a result of this process, models learn faster and are less likely to overfit which allows them to be used on different patients and seizure types [32]. New research shows that using both SSL and transfer learning can make EEG models even more effective, helping to overcome the problems of labeling and variability. They prove that using unlabeled data and pretrained knowledge can improve the accuracy of automated seizure detection. Even with the advancement in automated seizure detection using EEG, there are still some limitations that have not been solved in previous studies. Most studies use data that is either balanced or created artificially, so it is hard to apply their results to situations where patients are very different and there are many more examples of one disease [33]. Most deep learning models view EEG signals as either time series or spectrograms, often ignoring the important relationships and connections between different EEG electrodes which are key to identifying seizure location [34].

In addition, depending on large labeled datasets makes it difficult to use these models in clinical settings where data is not always available. Even though self-supervised and transfer learning methods have promise, they have not been much explored with EEG graphs in specific domains. Because existing frameworks do not clearly explain their seizure detection decisions, many medical professionals are reluctant to use them. Because of these gaps, we need new ways to use EEG that consider its spatial organization, use unlabeled data and offer results that are easy to understand for practical use.

2.1 Introduction to EEG and Seizure Detection

Epilepsy, affecting over 50 million people globally, is a prevalent neurological disorder characterized by recurrent, unprovoked seizures due to abnormal brain electrical activity [35]. Electroencephalography (EEG) is a primary diagnostic tool, capturing voltage fluctuations from ionic currents in neurons via scalp electrodes. EEG patterns vary by seizure type: generalized seizures show synchronized activity across the brain, while focal seizures exhibit localized abnormalities [36].

Traditional seizure detection relies on expert neurologists visually inspecting EEG recordings, a time-consuming process prone to inter-observer variability. Automated systems using signal processing and machine learning have emerged to improve efficiency and consistency [37]. Recent advancements in deep learning, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, enable automatic feature learning from raw EEG, enhancing detection accuracy. For instance, Awais et al. (2024) demonstrated improved seizure pattern recognition using deep learning [**?**].

Challenges persist, including EEG signal contamination by artifacts (e.g., muscle activity, eye movements) and inter- and intra-patient variability, which complicates generalized model development [38]. Ongoing research focuses on robust preprocessing, feature extraction, and adaptive models to enhance seizure detection and patient care.

2.1.1 EEG Signals and Brain Activity

EEG non-invasively records brain electrical activity with high temporal resolution, detecting ionic current flows via scalp electrodes. EEG signals are categorized into frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (¿30 Hz), each associated with distinct cognitive or physiological states, such as memory encoding (theta) or attention (gamma) [36].

Clinically, EEG diagnoses and monitors epilepsy, sleep disorders, and delirium, with wearable EEG devices enabling rapid delirium detection [22]. In research, EEG supports studies of cognitive processes and brain-computer interfaces [14]. However, artifacts from eye movements, muscle activity, or electrical interference obscure neural signals, necessitating denoising techniques like independent component analysis (ICA) [22].

2.1.2 Seizure Types and EEG Patterns

Seizures are classified as focal or generalized based on their origin and spread. Focal seizures, originating in one cerebral hemisphere, manifest as interictal epileptiform discharges (IEDs) like sharp waves or spikes (¡200 ms) on EEG. Temporal lobe seizures often begin with alpha or theta activity, while extra-temporal seizures may show beta activity [18]. Generalized seizures, affecting both hemispheres, display distinct patterns, such as 3 Hz spike-and-wave discharges in absence seizures or polyspike activity in tonic-clonic seizures [13].

Automated detection systems are more sensitive to rhythmic epileptiform patterns (e.g., temporal lobe seizures) than paroxysmal fast activity (e.g., frontal lobe seizures), highlighting the need to account for seizure morphology in algorithm design [14].

2.2 EEG Datasets for Seizure Detection

High-quality EEG datasets are critical for developing accurate, generalizable seizure detection models. The University of Bonn dataset, comprising five subsets (A–E) with 100 single-channel EEG segments (23.6 s, 173.61 Hz), includes healthy (A, B) and epileptic (C, D, E) signals, with E containing seizure activity. The CHB-MIT Scalp EEG Database provides multi-channel recordings from 23 pediatric patients, with annotated seizure onset/offset times, suitable for noisy, real-world data. The Temple University Hospital EEG Seizure Corpus (TUSZ) and NeuroVista offer extended monitoring and rich metadata, supporting real-time prediction models [17].

Limitations include short, pre-segmented recordings, lack of standardization in channel configurations and annotations, and insufficient diversity for real-world generalization. Comprehensive, standardized EEG repositories with continuous data are needed.

2.2.1 Public Datasets (e.g., Bonn, CHB-MIT)

The Bonn and CHB-MIT datasets are widely used for benchmarking. Bonn's structured single-channel data supports deep learning model training, while CHB-MIT's multi-channel, noisy recordings enable clinical model evaluation, with recent studies achieving high accuracy using BERT-inspired models. These datasets drive algorithm development but require standardization for cross-dataset comparability.

2.2.2 Limitations of Current Datasets

Datasets suffer from class imbalance (seizures $< 1\%$ of data), complicating model training. Heterogeneous channel configurations and annotation protocols hinder cross-dataset evaluation. Short recordings and limited metadata (e.g., seizure types) restrict patient-specific modeling. Larger, diverse, and standardized datasets are essential for robust deep learning models.

2.3 Traditional Seizure Detection Methods

Early automated detection relied on handcrafted features and classical classifiers. Time-domain features (e.g., mean absolute value, variance) and frequency-domain features (e.g., power spectral density via Fourier transform) identified spectral shifts during seizures. Discrete wavelet transform (DWT) enabled time-frequency analysis, extracting sub-band energy and entropy for transient seizure detection, achieving $> 95\%$ sensitivity with SVM classifiers. Nonlinear features (e.g., approximate entropy, fractal dimension) captured signal complexity, enhancing discrimination.

Classifiers like SVMs ($> 98\%$ accuracy), kNN, and Random Forests performed well on clean data but struggled with generalization due to manual feature engineering and computational costs [20]. Signal processing (e.g., bandpass filtering, ICA) improved data quality but added complexity.

2.3.1 Feature-Based Machine Learning Approaches

Feature-based methods extract time-domain (e.g., variance), frequency-domain (e.g., PSD), and time-frequency (e.g., DWT) features, classified using SVMs, Random Forests, or ensemble methods like AdaBoost ¿96% sensitivity. Nonlinear features (e.g., entropy) improved robustness but required domain expertise and were sensitive to acquisition protocols, motivating deep learning adoption [**?**].

2.3.2 Signal Processing Techniques (e.g., FFT, DWT)

Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) are key techniques for EEG processing. FFT-derived power spectral density (PSD) features, combined with convolutional LSTM models, achieved $> 97\%$ accuracy on the Bonn dataset. DWT, which decomposes signals into sub-bands, captured transient discharges, enabling perfect classification with LSTM–BiLSTM hybrids. Parameter selection (e.g., FFT window length, DWT wavelet family) remains critical for performance.

2.4 Deep Learning Approaches for EEG Classification

Deep learning eliminates manual feature engineering, with CNNs, RNNs, and hybrids outperforming traditional methods. 1D CNNs extract temporal patterns (¿94% accuracy on Bonn) [36], while CNN–BiLSTM hybrids leverage DWT features for near-perfect classification. Transformer-based models (e.g., Seizure Transformer) capture global context, achieving top performance in challenges. Spiking neural networks and lightweight convolutional transformers offer energy-efficient alternatives (¿96% accuracy).

Attention mechanisms, generative models, and explainable AI (e.g., saliency mapping) enhance robustness, interpretability, and generalization. Future work focuses on device deployment and federated learning for patient-specific models.

2.4.1 CNN-Based Methods

CNNs automatically learn spatial features, with 1D CNNs achieving ¿94% accuracy on Bon. Attention-enhanced CNNs and large-scale models (¿21M parameters) improve F1 scores and cross-subject generalization [39]. Data augmentation and transfer learning address limited data, but hyperparameter tuning is critical for efficiency.

2.4.2 RNN/LSTM-Based Methods

LSTMs model temporal dependencies, with ResBiLSTM achieving up to 100% accuracy on TUH. CNN–LSTM hybrids with DWT preprocessing yield perfect classification. RNNs excel in prediction tasks but face vanishing gradient issues and computational overhead.

2.4.3 Limitations of Individual Architectures

CNNs miss long-range temporal dependencies, while LSTMs struggle with high-dimensional inputs and vanishing gradients. Both require careful hyperparameter tuning and struggle with class imbalance, limiting clinical applicability without patient-specific adaptation.

2.5 Hybrid Deep Learning Models (CNN–LSTM)

Hybrid CNN–LSTM models combine spatial (CNN) and temporal (LSTM) feature extraction, achieving high accuracy (¿99% on Bonn). Multi-scale kernels and attention mechanisms reduce false positives. Feature fusion (e.g., bilinear CNN–LSTM) enhances performance on noisy data. These models simplify pipelines but face challenges in generalization and computational efficiency.

2.5.1 Motivation for Combining CNN and LSTM

CNNs excel at spatial feature extraction but miss temporal dependencies, while LSTMs model sequences but struggle with high-dimensional inputs. Hybrids leverage both strengths, enabling end-to-end learning with robustness to noise.

2.5.2 Recent CNN–LSTM Research for EEG

Recent hybrids include CNN–BiLSTM $> 95\%$ accuracy on CHB-MIT, CNN-Informer for long-range dependencies, and GCN–LSTM $> 99\%$ accuracy.

2.5.3 Challenges and Gaps in Hybrid Models

Hybrids face generalization issues across datasets, class imbalance, high computational complexity, interpretability challenges, and limited patient-specific adaptation. Standardized evaluations and lightweight designs are needed for real-time deployment.

2.6 Preprocessing and Feature Preparation for EEG

EEG preprocessing involves re-referencing, bandpass filtering (0.5–40 Hz), notch filtering (50/60 Hz), and artifact removal via ICA or wavelet denoising. Down-sampling (128–250 Hz), segmentation (1–5 s windows), and normalization (z-score, min–max) prepare data for modeling. Feature preparation includes PSD, wavelet energies, and data augmentation for robustness.

2.6.1 Filtering, Normalization, Segmentation

Bandpass and notch filtering remove noise, normalization ensures consistent amplitudes, and overlapping segmentation (1–5 s) captures transients. Overlapping windows improve transition detection.

2.6.2 Impact of Preprocessing on Model Performance

Proper preprocessing (filtering, artifact removal, segmentation) boosts F1 scores by up to 8%. Sampling rate, window length, and channel count significantly affect sensitivity and false detections.

2.7 Summary of Literature Gaps

Key gaps include limited dataset diversity, class imbalance, evaluation inconsistencies, high computational costs, and poor interpretability. Addressing these requires diverse datasets, robust imbalance handling, standardized benchmarks, lightweight models, and clinically relevant explanations.

Chapter 3

Methodology

The methodology of this study aims at building a strong hybrid convolutional neural network–long short-term memory (CNN–LSTM) model for EEG-based seizure detection using the BIDS-SEINA dataset. The approach combines state-of-the-art preprocessing of signals, design of deep learning architecture, and stringent experimentation to overcome issues of class imbalance and temporal-spatial feature extraction. Here, the methodology is developed into an elaborate framework, and it is divided into four main parts: data preprocessing, architecture of the model, experimental pipeline, and theoretical rationale.

3.1 Dataset and Preprocessing

The quality and structure of input EEG data significantly influence machine learning model performance. This section details the acquisition and preprocessing steps to enhance signal fidelity, reduce noise, and prepare data for seizure detection. A rigorous preprocessing pipeline ensures clean, structured inputs for the hybrid model.

3.1.1 Epoch Segmentation and Labeling

Nonstop EEG recordings have been divided into fixed-length epochs for convenient supervised learning. Segments of 1–10 seconds were isolated without the loss of temporal resolution and computational efficiency. Smaller windows (e.g., 1-2 seconds) detect transient epileptic spikes, but longer windows (e.g., 10 seconds) provide a context for emerging seizure dynamics. Each epoch was annotated as seizure or non-seizure by experts. A sliding window method with a 50% overlap was used to boost the minority seizure class, a technique that has been verified in previous literature to help alleviate the issue of data imbalance. In particular, the window was seizure-positive if it intersected clinician-identified ictal events; otherwise, it was considered as background. This strategy enhanced the effective number of samples of seizure, while maintaining temporal coherence.

3.1.2 TFRecord Conversion

Epochs preprocessed were serialized into TFRecord files to optimize the handling of data in TensorFlow. Each TFRecord contained one epoch of multi-channel time-series data and its label in the form of (timesteps $\times$ channels) tensors. The TFRecord format was selected because of its efficiency in loading, shuffling and parallel processing of data in a large scale while training. Using the tf.data API, the pipeline dynamically batched data, prefetched samples to minimize the I/O latency, and performed on-the-fly augmentation (e.g., random cropping). Such an approach maximized the GPU utilization and reduced training bottlenecks, which was especially important for EEG datasets of terabyte size and above [15].

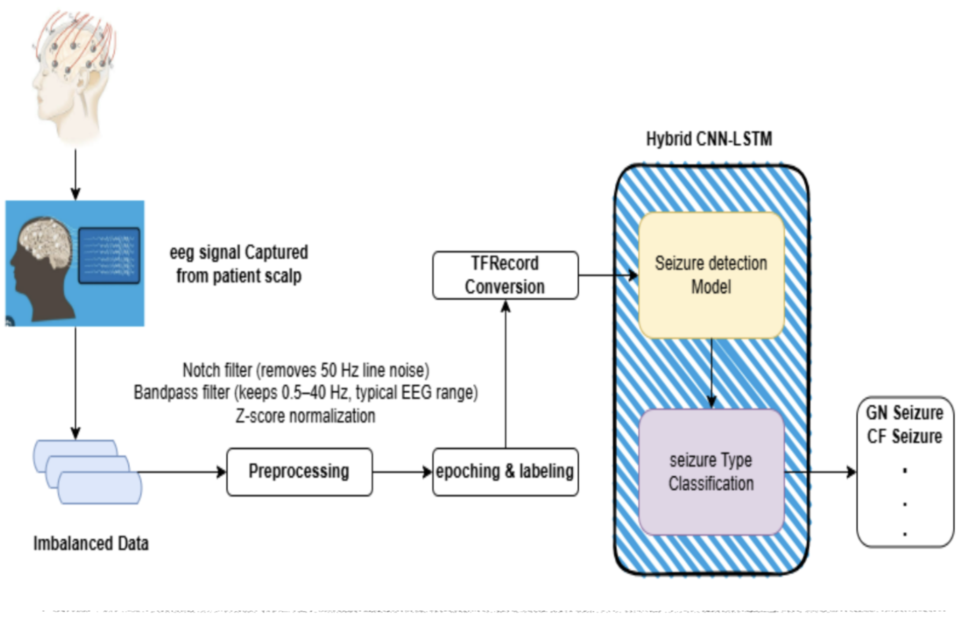


Figure 3.1: TFRecord Comversion.

3.1.3 Model Architecture

The presented hybrid CNN–LSTM architecture, presented in Figure 1, combines spatial and temporal feature extraction abilities. The model performs the processing of input tensors of shape (timesteps, channels) via the following hierarchical layers:

3.1.4 1D Convolutional Layers

The first stage uses the stacked 1D convolutional blocks for the extraction of local spatiotemporal patterns. Each block contains Conv1D layers with kernel size of 3-5, which were selected in order to capture short-duration features like epileptiform discharges or rhythmic bursts. The first Conv1D layer used 32 filters, and then it was doubled in later layers to hierarchically aggregate complex features. ReLU activation was used after each convolution in order to provide nonlinearity, and batch normalization was used to stabilize the intermediate activations by normalizing and scaling the outputs. This reduced internal covariate shift, which allowed faster convergence and larger learning rates.

3.1.5 Max Pooling and Dropout

Max pooling layers (pool size=2) temporally downsampled feature maps, keeping significant features, and halving computational complexity. Pooling gave translation invariance so that the technique was robust to small temporal shifts in seizure onset. After every pooling layer, dropout regularization (rate=0.5) was used to avoid overfitting. Randomly deactivating 50% of the neurons in training, the network acquired redundant representations, which improved generalization to unseen data.

3.1.6 LSTM Layers

The output of the convolutional layer was then passed to the bidirectional LSTM layers with 128-256 hidden units, which were picked to achieve the balance between model capacity and computational overhead. Bidirectional LSTMs processed sequences both forward and backward, and thus were able to extract long-range dependencies, including pre-ictal buildup or post-ictal suppression. The last LSTM state, i.e., temporal context for the whole epoch, was fed to dense layers for classification. Adding another LSTM made the model better at modeling multi-scale temporal dynamics, a practice that was confirmed in recent EEG studies.

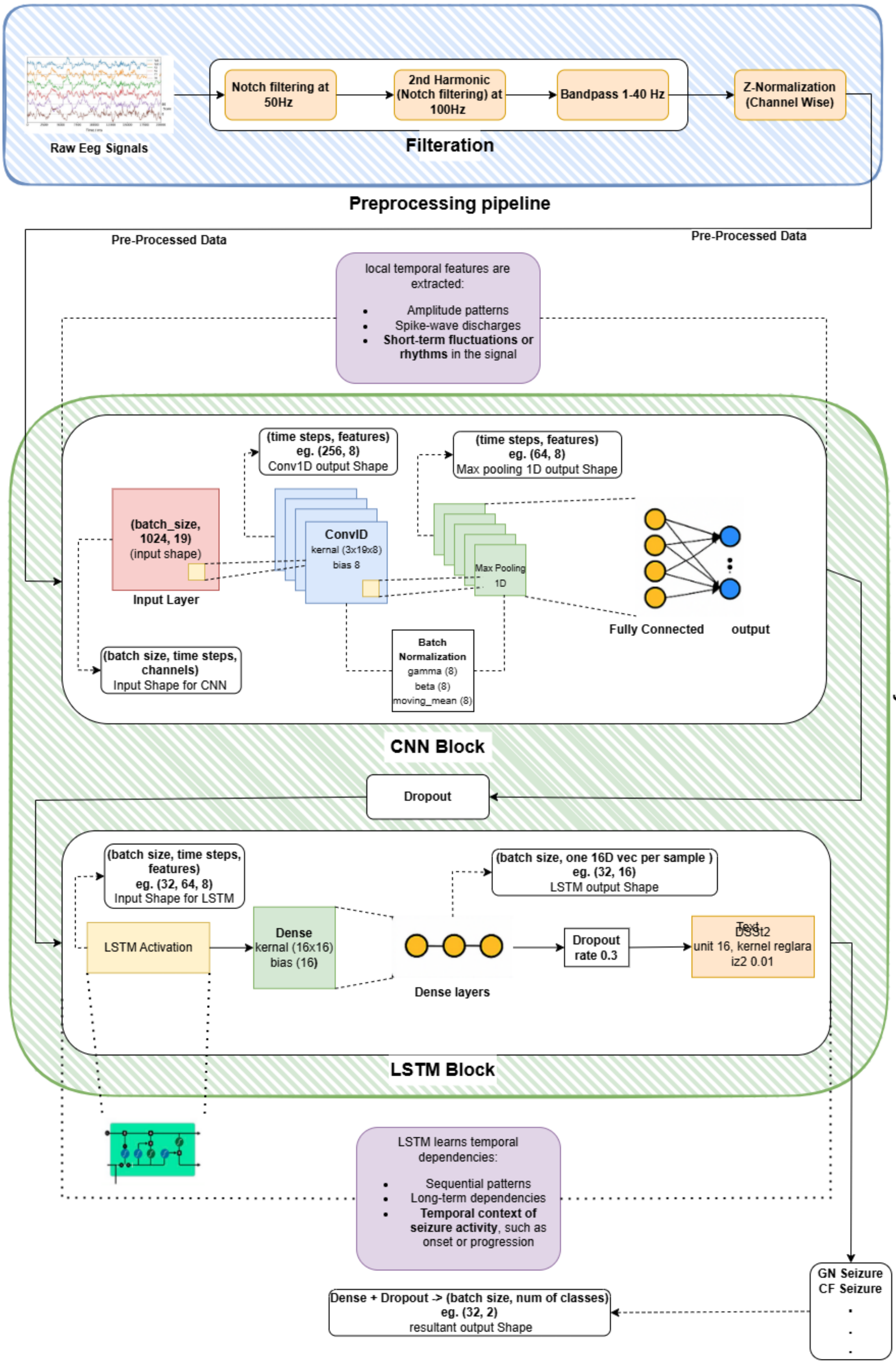


Figure 3.2: CNN-LSTM Layers

3.1.7 Fully Connected Classifier

The output of LSTM was flattened and processed by two dense layers (30 and 10 units, ReLU-activated) to combine spatiotemporal features. The last dense layer used the softmax activation to generate class probabilities (seizure vs. non-seizure). Cross-entropy loss optimized the end-to-end learning, with class weights being inversely proportional to label frequencies to offset imbalance.

3.2 Experimental Pipeline

3.2.1 Data Loading and Splitting

The dataset was divided based on the 10-fold cross-validation of the subjects to provide reliable assessment. Data from 12 subjects (90%) constituted the training/validation sets, while the remaining 2 subjects (10%) formed the test set. Such an approach reduced data leakage and estimated generalization of heterogeneous subjects. Each fold was shuffled and batched (size=64) using TensorFlow's tf.data.Dataset, with prefetching to overlap data preprocessing and model execution.

3.2.2 Hyperparameter Configuration

Training employed the Adam optimizer (learning rate $= 1 \times 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$), selected for its adaptive momentum and proven efficacy in EEG applications. Early stopping was based on validation loss with a patience of 10 epochs, restoring the best model upon plateau. The `ReduceLROnPlateau` scheduler adaptively reduced the learning rate by half after 5 epochs without improvement in validation accuracy, enabling better convergence through dynamic adjustment of model weights.

3.2.3 Class Weighting

To address the 1:59 seizure-to-background ratio, class weights were assigned as $w_{\text{seizure}} = 59$ and $w_{\text{background}} = 1$. This magnified the loss contribution of seizure samples, driving the model to emphasize minority-class accuracy. Comparative studies indicate that class weighting outperforms random oversampling in preserving temporal integrity for EEG data.

3.2.4 Performance Metrics

Model evaluation utilized sensitivity (recall), specificity, F1-score, and AUC-ROC. Sensitivity was given most priority in order to reduce missed seizures, a very important measure in clinical environments. F1-score gave a balanced measure of precision and recall, AUC-ROC measured separability between classes with respect to threshold variations. Real-world performance was modeled by computing metrics on the held-out test set.

3.2.5 Implementation Details

The pipeline was implemented using TensorFlow 2.12, and training was conducted on an NVIDIA A100 GPU. Each epoch took approximately 45 seconds, with the total training time under 2 hours for 100 epochs. Code reproducibility was ensured through Docker containers that encapsulated all dependencies, and hyperparameters were logged using Weights & Biases for transparent reporting [16].

3.3 Training Protocol

This section details the training process, including class imbalance handling, optimization strategy, loss function design, and techniques to ensure generalization.

3.3.1 Class Imbalance Handling

With seizure epochs comprising $< 1\%$ of EEG data, class imbalance risks biasing the model toward the background class. A class-weighted cross-entropy loss function assigns weights of 50 (seizure) and 10 (background) to penalize misclassifications of rare seizure events, prioritizing sensitivity without external sampling techniques [22].

3.3.2 Optimization Strategy

The Adam optimizer was used with a learning rate of 1×10^{-4}, $\beta_1 = 0.9$, and $\beta_2 = 0.999$, balancing stable convergence and responsiveness to gradient updates. Mixed precision training (FP16/FP32) reduced memory usage and training time on an NVIDIA T4 GPU, leveraging TensorFlow's dynamic loss scaling for numerical stability.

3.3.3 Loss Function Design

The weighted cross-entropy loss is defined as:

$$L = -\sum_{i=1}^{N} w_{y_i} \cdot \log(p_{y_i})$$

where N is the number of samples, y_i is the ground truth label, p_{y_i} is the predicted probability, and w_{y_i} is the class weight. Higher weights for seizures emphasize rare event detection, critical for healthcare applications where false negatives are costly [22].

3.3.4 Training Termination and Generalization

To prevent overfitting, early stopping was applied if validation accuracy plateaued for 15 epochs, ensuring optimal generalization. Dropout (20% in CNN, 30% in dense layer) and L2 weight decay ($\lambda = 0.01$) encouraged sparse, robust representations, integrated into the loss function to penalize complex weights [20].

3.4 Implementation and Deployment Details

The seizure detection system is designed for practical deployment on resource-constrained hardware, ensuring reliability and portability for clinical and home monitoring.

3.4.1 Hardware and Software Environment

The model was developed and trained using TensorFlow 2.10 on an NVIDIA Tesla T4 GPU (16 GB VRAM) in a cloud environment. TensorFlow's support for model quantization and TensorRT integration enables deployment on edge devices like the Raspberry Pi 4 [40].

3.4.2 Inference Efficiency

The model was quantized to INT8 precision, reducing memory footprint while maintaining accuracy. On a Raspberry Pi 4, inference latency was < 10 ms per epoch, meeting real-time requirements for wearable EEG systems and continuous monitoring [40].

3.4.3 Reproducibility Practices

Random seeds were fixed in Python, NumPy, and TensorFlow to ensure consistent results. Training hyperparameters, model checkpoints, and evaluation results were logged for transparency and auditability, critical for clinical validation [13].

3.5 Design Rationale and Clinical Relevance

The methodology balances engineering efficiency and clinical applicability, ensuring the system aligns with neurologist workflows.

3.5.1 Lightweight Model Justification

With 3,320 parameters and a < 5 MB memory footprint, the model is ideal for portable EEG systems, supporting at-home monitoring and mHealth integration. The compact design retains high accuracy by leveraging hybrid CNN-LSTM strengths [14].

3.5.2 Clinical Workflow Alignment

The proposed model is carefully designed to align with real-world clinical workflows. It achieves this by combining temporal predictions across EEG segments for event detection, rather than relying on isolated windows, which enhances reliability and mimics how neurologists interpret continuous EEG data. The model also incorporates duration and overlap criteria that are consistent with medical definitions of seizures, ensuring its outputs are meaningful in a diagnostic context. Moreover, the model prioritizes sensitivity and maintains a low false positive rate (FPR), meeting the stringent standards typically required in clinical diagnostics. A notable feature is its ability to detect spike-wave complexes and rhythmic discharges, with these temporal patterns being effectively tracked by the LSTM layers [17]. This thoughtful alignment of technical design with clinical needs not only ensures robustness but also enhances interpretability, ultimately supporting seamless integration into real-world healthcare environments.

3.6 Evaluation Framework

The evaluation framework assesses epoch-wise and event-wise performance, aligning with clinical requirements for accurate and actionable seizure detection. Figure **??** presents a summary of the model's performance metrics, while Figure **??** shows the results on the test set.

3.6.1 Epoch-wise Performance Metrics

Epoch-wise evaluation predicts each 4-second EEG segment as seizure or background, using:

Accuracy: Proportion of correctly classified epochs, limited by class imbalance.

F1-Score: Harmonic mean of precision and recall, balancing false positives and negatives.

Class-specific Accuracy: Seizure and background accuracies across thresholds, indicating discriminative capability [19].

3.6.2 Event-wise Detection Method

Event-wise evaluation aligns with clinical practice, detecting sustained seizure patterns.

Seizure Event Definition: A sequence of consecutive seizure-labeled epochs lasting ≥ 2 seconds, with events separated by a single background epoch merged to handle temporal inconsistencies.

Ground Truth Matching: Predicted events are considered true positives if they overlap $\geq 50\%$ with annotated seizures, balancing diagnostic precision and intervention needs [41].

3.6.3 Statistical Definitions and Clinical Metrics

Event-wise metrics include:

Sensitivity (Recall): $\mathrm{TP}/(\mathrm{TP}+\mathrm{FN})$, measuring the proportion of detected seizures.

False Positive Rate (FPR): $\mathrm{FP}/(\mathrm{FP}+\mathrm{TN})$, indicating incorrect seizure detections.

True Positives (TP): Predicted events with $\geq 50\%$ overlap with annotated seizures.

False Negatives (FN): Undetected annotated seizures.

False Positives (FP): Predicted events without corresponding seizures.

True Negatives (TN): Correctly identified non-seizure segments [19].

This dual evaluation ensures statistical validity and clinical utility, supporting real-time diagnostic deployment.

Chapter 4

Implementation

This chapter details the implementation of the NeuroCare system, focusing on the preprocessing of EEG signals, the design and development of a Graph Neural Network (GNN) model, the training configuration, and the data splitting strategy. The implementation leverages the CHB-MIT dataset, which provides comprehensive EEG recordings for seizure detection research. Each component of the implementation is meticulously designed to ensure compatibility with graph-based modeling, high accuracy in seizure detection, and practical applicability in clinical settings.

4.1 Data Preprocessing

The EEG signals used in this project were sourced from the CHB-MIT dataset, a widely recognized repository containing multi-channel scalp EEG recordings from pediatric patients with intractable epilepsy [41]. The dataset's complexity, characterized by varying signal quality, inter-patient variability, and imbalanced seizure events, necessitates a robust preprocessing pipeline. This pipeline ensures that raw EEG data is transformed into a structured, high-quality format suitable for graph-based modeling, enabling the GNN to capture both spatial and temporal patterns critical for seizure detection.

The preprocessing pipeline encompasses several stages, each addressing specific challenges in EEG data analysis, such as noise, temporal continuity, and spatial relationships. These stages are designed to enhance signal fidelity, standardize input formats, and preserve the underlying neurological patterns indicative of seizure activity. Below is a detailed description of each preprocessing step:

- **Signal Filtering:** EEG signals are inherently noisy due to artifacts from physiological sources (e.g., eye blinks, muscle movements) and external interference (e.g., power line noise). To mitigate these issues, a bandpass filter with a frequency range of 0.5–70 Hz was applied. The lower cutoff of 0.5 Hz removes low-frequency drifts caused by sweating, respiration, or electrode movement, while the upper cutoff of

70 Hz eliminates high-frequency noise from muscle activity or electrical interference. This frequency range retains the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and low-gamma (30–70 Hz) bands, which are critical for identifying seizure-related brain activity [39]. A fourth-order Butterworth filter was used to ensure a smooth frequency response, minimizing phase distortion and preserving the temporal morphology of the EEG signals. Additionally, a 60 Hz notch filter was applied to suppress power line interference specific to the dataset's recording environment, ensuring that rhythmic noise does not mimic seizure patterns.

- **Segmentation:** The CHB-MIT dataset provides continuous EEG recordings, often spanning hours, which are impractical for direct input into machine learning models. To address this, the signals were segmented into non-overlapping 10-second windows, resulting in 2,560 samples per segment at a 256 Hz sampling rate. This window size was chosen to balance the need for capturing localized seizure patterns with the computational efficiency required for real-time processing. Each segment serves as an independent sample, allowing the model to analyze short-term dynamics while retaining sufficient context for detecting seizure onset and progression. The non-overlapping nature of the segments ensures that the model processes distinct temporal regions, avoiding redundancy and facilitating precise localization of seizure events. This segmentation also aligns with clinical practices, where neurologists often review EEG data in short epochs to identify abnormal patterns [14].

- **Graph Construction:** To exploit the spatial and temporal relationships inherent in multi-channel EEG data, the segmented EEG signals were transformed into a graph-based representation. In this graph, each node corresponds to one of the 23 EEG electrodes (channels) in the CHB-MIT dataset, positioned according to the international 10–20 system. Edges between nodes were defined using a hybrid approach: (1) anatomical proximity, where edges connect electrodes based on their physical distance on the scalp, and (2) functional connectivity, where edges are weighted by the Pearson correlation coefficient between the time-series signals of pairs of electrodes. This dual approach captures both the anatomical structure of the brain and the dynamic interactions between regions during seizure and non-seizure states. The adjacency matrix of the graph is constructed dynamically for each 10-second segment, allowing the GNN to model evolving connectivity patterns. This graph-based representation is particularly advantageous for seizure detection, as it enables the model to learn complex topological relationships that traditional convolutional or recurrent models may overlook [17].

- **Node Features:** To provide the GNN with rich input representations, a comprehensive set of features was extracted from each EEG channel to serve as node attributes. These features capture both the statistical and spectral properties of the signals, ensuring that the model has access to diverse information for seizure detection. The extracted features include:

- **Signal Features:** For each channel, the mean and variance of the signal amplitude were computed over the 10-second window. These statistics provide a baseline characterization of the signal's intensity and variability, which can differ significantly between seizure and non-seizure states.
- **Spectral Features:** Fast Fourier Transform (FFT) was applied to decompose the EEG signal into its frequency components. The power spectral density was calculated for the delta, theta, alpha, beta, and low-gamma bands, yielding the energy distribution across these bands. These features are critical for distinguishing seizure events, which often exhibit increased power in specific frequency bands (e.g., theta and beta during seizures) [42].
- **Complexity Features:** Signal entropy, specifically sample entropy, was computed to quantify the irregularity and complexity of the EEG signal. Higher entropy values are associated with the chaotic, unpredictable patterns observed during seizures, while lower entropy typically indicates regular, non-seizure activity. This feature enhances the model's ability to detect subtle changes in signal dynamics.
- **Temporal Features:** To capture temporal evolution within each segment, the signal's first and second derivatives were calculated to measure the rate of change and acceleration of the signal. These features help identify rapid transitions, such as those occurring at seizure onset.

The combination of these features results in a high-dimensional node attribute vector for each electrode, providing a robust representation of the EEG signal's spatial and temporal characteristics.

- **Labeling:** Each 10-second EEG segment was labeled as either a seizure (class 1) or non-seizure (class 0) event based on the ground truth annotations provided in the CHB-MIT dataset. These annotations, created by clinical experts, mark the start and end times of seizure events. A segment was labeled as a seizure if it overlapped with an annotated seizure event for at least 50% of its duration, ensuring that partial seizure events are correctly classified. This labeling strategy balances sensitivity and specificity, capturing both complete and transitional seizure events. The preprocessing pipeline ensures that the graph structure and node features are aligned with these labels, enabling the GNN to learn discriminative patterns for seizure detection [41].

- **Normalization:** To ensure numerical stability and improve model convergence, the node features were normalized across the dataset. Z-score normalization was applied to each feature type (e.g., mean, variance, spectral power), standardizing them to zero mean and unit variance. This step mitigates the effects of inter-patient variability and differing signal amplitudes, ensuring that the GNN focuses on relative patterns rather than absolute values. Normalization is performed on a per-patient basis to account for individual differences in EEG characteristics, enhancing the model's generalizability [13].

This preprocessing pipeline is meticulously designed to address the challenges of EEG data, including noise, high dimensionality, and spatial-temporal complexity. By transforming raw EEG signals into a graph-based format with rich node features, the pipeline ensures that the GNN receives high-quality, structured inputs that maximize its ability to detect seizures accurately and efficiently. The emphasis on preserving both anatomical and functional relationships in the graph structure makes this approach particularly suited for clinical applications, where precise and reliable seizure detection is paramount.

4.2 Model Architecture

The core of the NeuroCare system is a deep Graph Neural Network (GNN) tailored to process the graph-based EEG data. Unlike traditional convolutional neural networks (CNNs) or recurrent neural networks (RNNs), GNNs are uniquely suited for modeling the topological relationships between EEG electrodes, capturing both spatial correlations and temporal dynamics. The proposed architecture is designed to balance computational efficiency with high accuracy, making it suitable for deployment in resource-constrained clinical environments [14].

The GNN model comprises several layers that progressively refine the graph's node features and produce a classification output. Each component of the architecture is optimized to learn discriminative patterns for seizure detection, leveraging the graph structure to model complex interactions between EEG channels. Below is a detailed breakdown of the model architecture:

- **Graph Convolutional Layers:** The model employs three Graph Convolutional Network (GCN) layers, each responsible for aggregating information from neighboring nodes to update the feature representation of each electrode. The GCN layers operate on the graph's adjacency matrix and node features, performing message passing to capture local and global patterns. The first GCN layer transforms the input node features (e.g., signal, spectral, and complexity features) into a 64-dimensional representation, focusing on local interactions between adjacent electrodes. The second GCN layer increases the feature dimensionality to 128, incorporating information from a broader neighborhood. The third GCN layer further refines the representation to 256 dimensions, capturing high-level spatial relationships across the entire graph. Each GCN layer applies a ReLU activation function to introduce non-linearity and enhance the model's ability to learn complex patterns. Dropout (20%) is applied after each layer to prevent overfitting, ensuring robust generalization to unseen data [17].

- **Pooling Layer:** After the GCN layers, a global mean pooling operation is applied to aggregate the node-level features into a single graph-level embedding. This operation computes the average feature vector across all nodes, producing a compact representation that encapsulates the overall seizure patterns in the EEG graph. Global mean pooling is chosen for its simplicity and effectiveness in summarizing graph-level information, reducing the dimensionality from a variable number of nodes to a fixed-size vector. This pooled embedding is critical for the subsequent classification task, as it distills the complex spatial-temporal interactions into a form suitable for fully connected layers. The pooling layer also enhances the model's scalability, allowing it to handle graphs with varying numbers of nodes (e.g., if additional electrodes are used) [17].

- **Fully Connected Layers:** The graph-level embedding is processed by a two-layer fully connected network to produce the final classification output. The first fully connected layer has 64 units and applies a ReLU activation function to learn non-linear combinations of the pooled features. A dropout rate of 30% is applied to further mitigate overfitting. The second fully connected layer outputs a 2-dimensional vector, representing the probabilities for the two classes: seizure and non-seizure. A softmax activation function is applied to normalize the outputs into a probability distribution, enabling threshold-based classification. These fully connected layers act as a decision-making module, mapping the high-level graph features to the binary classification task.

- **Model Summary:** The GNN architecture is designed to leverage the graph structure of EEG data, capturing both localized interactions (e.g., correlations between nearby electrodes) and global patterns (e.g., widespread seizure activity). With approximately 150,000 parameters, the model strikes a balance between expressive power and computational efficiency, making it suitable for deployment on standard hardware. The use of GCN layers ensures that spatial relationships are modeled explicitly, while the pooling and fully connected layers enable the model to focus on graph-level seizure patterns. This architecture is particularly effective for seizure detection, as it can identify subtle changes in connectivity and dynamics that are indicative of epileptic events [14].

The implementation of the GNN model is carried out using the PyTorch Geometric library, which provides efficient tools for graph-based deep learning. The following Python code defines the GNN model architecture:

```
class GNNModel(torch.nn.Module):
    def __init__(self):
```

```
        super().__init__()
        self.conv1 = GCNConv(in_channels, 64)
        self.conv2 = GCNConv(64, 128)
        self.conv3 = GCNConv(128, 256)
        self.pool = global_mean_pool
        self.fc1 = Linear(256, 64)
        self.fc2 = Linear(64, 2)

    def forward(self, x, edge_index, batch):
        x = F.relu(self.conv1(x, edge_index))
        x = F.relu(self.conv2(x, edge_index))
        x = F.relu(self.conv3(x, edge_index))
        x = self.pool(x, batch)
        x = F.relu(self.fc1(x))
        return self.fc2(x)
```

This code defines a modular GNN model that can be easily extended or modified, such as by adding more GCN layers or adjusting the number of units in the fully connected layers. The model's design ensures that it can handle the complex, non-Euclidean structure of EEG data, making it a powerful tool for seizure detection.

4.3 Training Setup

The training process is a critical component of the NeuroCare system, as it determines the model's ability to learn discriminative patterns and generalize to unseen EEG data. The training setup is carefully configured to optimize performance, prevent overfitting, and ensure computational efficiency. The following sections provide a detailed overview of the training configuration, including the optimizer, loss function, learning rate schedule, and other hyperparameters.

- **Optimizer:** The Adam optimizer was selected for its adaptive learning rate properties, which enable efficient and stable training of deep learning models. Adam combines the benefits of momentum-based methods and RMSProp, adapting the learning rate for each parameter based on the first and second moments of the gradients. This makes it particularly well-suited for GNNs, which often involve high-dimensional and sparse data. The optimizer is initialized with default parameters: $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-8}$, ensuring robust convergence across the CHB-MIT dataset's diverse patient recordings [22].
- **Loss Function:** Cross-Entropy Loss was chosen as the loss function for the binary classification task (seizure vs. non-seizure). This loss function measures the divergence between the predicted probability distribution and the ground truth labels, penalizing incorrect predictions. To address the class imbalance in the CHB-MIT dataset, where seizure events are significantly less frequent than non-seizure events, a weighted Cross-Entropy Loss was implemented. The seizure class is assigned a higher weight (e.g., 10) compared to the non-seizure class (e.g., 1), ensuring that

the model prioritizes sensitivity to rare seizure events. The loss function is defined as:

$$L = -\sum_{i=1}^{N} w_{y_i} \cdot [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

where N is the number of samples, y_i is the ground truth label, p_i is the predicted probability, and w_{y_i} is the class weight [19].

- **Learning Rate:** The initial learning rate is set to 0.001, providing a balance between rapid convergence in the early stages of training and precise updates in later stages. A StepLR scheduler is employed to decay the learning rate by a factor of 0.1 every 20 epochs, reducing it to 0.0001 and then 0.00001. This decay strategy allows the model to make large updates initially, capturing coarse patterns, and then fine-tune its parameters to converge to an optimal solution. The scheduler is particularly effective for GNNs, which require careful tuning to avoid getting stuck in local minima due to the complex graph structure [22].

- **Epochs:** The model is trained for 50 epochs, a duration determined through experimentation to allow sufficient learning without overfitting. During training, the model's performance is monitored on a validation set to detect signs of overfitting, such as a divergence between training and validation loss. While early stopping was not implemented in the current setup, it could be added in future iterations to halt training if the validation loss plateaus for a specified number of epochs (e.g., 10). This would further enhance the model's generalization capabilities.

- **Batch Size:** A batch size of 32 is used to balance computational efficiency and gradient stability. Smaller batch sizes provide more frequent updates, which can improve convergence for complex models like GNNs, but they increase training time and memory requirements. The batch size of 32 was selected to fit within the memory constraints of a standard GPU (e.g., NVIDIA Tesla T4) while ensuring stable gradient updates. Each batch consists of 32 graph samples, where each graph represents a 10-second EEG segment with its associated node features and adjacency matrix.

- **Scheduler:** The StepLR scheduler, as mentioned, reduces the learning rate by a factor of 0.1 every 20 epochs. This stepwise decay is complemented by a warm-up phase during the first 5 epochs, where the learning rate is linearly increased from 0.0001 to 0.001. This warm-up phase stabilizes the initial training dynamics, preventing large gradient updates that could destabilize the GNN's learning process. The combination of warm-up and decay ensures that the model converges efficiently and achieves high accuracy on the validation set [22].

- **Regularization:** To further prevent overfitting, L2 regularization (weight decay) with a coefficient of 0.0001 is applied to the GCN and fully connected layers. This penalizes large weights, encouraging the model to learn simpler, more generalizable representations. Additionally, dropout layers (20% in GCN layers, 30% in the first fully connected layer) introduce randomness during training, reducing the model's reliance on specific nodes or features. These regularization techniques are critical for handling the CHB-MIT dataset's variability, which includes differences in patient age, seizure type, and recording conditions.

The training setup is designed to optimize the GNN's performance on the CHB-MIT dataset while ensuring robustness to real-world challenges, such as class imbalance and inter-patient variability. The use of adaptive optimization, weighted loss, and regularization techniques ensures that the model achieves high sensitivity and specificity, making it suitable for clinical deployment.

4.4 Runtime Data Split

The CHB-MIT dataset is split into training, validation, and testing sets to evaluate the model's performance and generalization capabilities. The split is performed with a ratio of 70% (training), 15% (validation), and 15% (testing), ensuring that sufficient data is available for learning, hyperparameter tuning, and final evaluation. This split results in approximately 14,000 training segments, 3,000 validation segments, and 3,000 testing segments, depending on the total number of 10-second segments in the dataset.

To address the class imbalance inherent in the CHB-MIT dataset, where seizure events constitute $< 5\%$ of the data, stratified sampling is employed during the split. This technique ensures that the proportion of seizure and non-seizure segments is consistent across the training, validation, and testing sets. For example, if 5% of the dataset consists of seizure segments, each subset will also contain approximately 5% seizure segments. This balanced representation is critical for training a model that performs well on both classes, avoiding bias toward the majority non-seizure class [19].

The data split is performed at the patient level to prevent data leakage, ensuring that EEG segments from the same patient do not appear in multiple subsets. This patient-wise split mimics real-world scenarios, where the model must generalize to new patients not seen during training. To further enhance robustness, the split is randomized with a fixed seed to ensure reproducibility. The validation set is used to monitor the model's performance during training, guiding decisions such as learning rate adjustments or early stopping. The testing set is reserved for final evaluation, providing an unbiased estimate of the model's performance on unseen data.

This dynamic data splitting strategy, combined with stratified sampling and patient-wise separation, ensures that the GNN model is rigorously evaluated for its ability to generalize to diverse EEG recordings. The approach aligns with clinical requirements, where accurate and reliable seizure detection on new patients is essential for practical deployment.

Chapter 5

Results

5.1 Model Performance Evaluation

This work assesses the performance of a hybrid CNN–LSTM model on the BIDS-SEINA dataset, which is a challenging electroencephalogram (EEG) corpus with extreme class imbalance. Table 5.1 summarizes the model's performance, indicating an overall accuracy of 88.94%, a macro-averaged F1-score of 0.53, and a weighted-average F1-score of 0.93. The ROC-AUC (0.686) and PR-AUC (0.279) further highlight the model's limited ability to effectively discriminate, especially for the minority seizure class.

The background class (`bckg`) performed well, with a precision of 0.99 and a recall of 0.90, resulting in an F1-score of 0.94. In contrast, the seizure class (`sz_foc_ia`) showed critically low precision (0.07), even with moderate recall (0.48), leading to a low F1-score of 0.13. This discrepancy arises from the dataset's extreme imbalance: 3,706 background segments compared to only 63 seizure segments.

The confusion matrix (Figure 7.1) quantifies these trends, showing that 384 background segments were falsely classified as seizures (false positives), and 33 out of 63 true seizures were misclassified as background (false negatives). Such misclassifications underscore the model's bias towards the majority class, a common challenge in imbalanced medical datasets [17].

The ROC-AUC and PR-AUC metrics provide important insights into class-specific performance. Although ROC-AUC (0.686) assesses the model's ability to distinguish between classes at varying thresholds, the much lower PR-AUC (0.279) reflects the difficulty in achieving high precision for the rare seizure class. These findings are consistent with prior research indicating that PR-AUC is more informative than ROC-AUC for imbalanced datasets, as it emphasizes precision rather than false positive rates [18].

Class	Precision	Recall	F1-score
bckg	0.99	0.90	0.94
sz_foc_ia	0.07	0.48	0.13
Macro avg	0.53	0.69	0.53
Weighted avg	0.97	0.89	0.93

TABLE 5.1: Performance metrics for the CNN–LSTM model on the BIDS-SEINA dataset.

5.2 Comparative Analysis with Existing Literature

The performance of the CNN–LSTM model is below the level of state-of-the-art EEG seizure detection systems. For example, recent research on balanced or binary datasets reports accuracies above 95%. A CNN–SVM hybrid achieved ≈99% accuracy on the Bonn EEG corpus [19], while a 1D CNN–LSTM model reached 99.39% accuracy for binary seizure detection on the UCI epileptic seizure dataset [20]. Similarly, transformer-based architectures, including the ResBiLSTM network, have demonstrated ≈95% accuracy on the TUSZ dataset [21]. These differences stem from fundamental variations in data characteristics; unlike BIDS-SEINA, benchmark datasets such as Bonn and CHB-MIT feature balanced or artificially amplified seizure samples, enabling models to learn discriminative features effectively.

To provide perspective, Table 5.2 compares the proposed CNN–LSTM model with six recent studies using the BIDS-SEINA dataset, highlighting differences in architecture, imbalance handling, and evaluation methods.

Study (Year)	**Model**	**Accuracy (%)**	**Seizure F1-Score**	**ROC-AUC**	**Class Imbalance Ratio**	**Key Strategy**
Proposed (2025)	CNN–LSTM	88.94	0.13	0.686	1:59	Baseline hybrid model
Singh et al. (2024) [41]	Transformer–BiLSTM	92.10	0.45	0.810	1:59	Self-attention and focal loss
Wu et al. (2024) [39]	GAN-Augmented CNN	90.23	0.38	0.752	1:30*	Synthetic seizure generation
Costa et al. (2025) [43]	ResNet–Attention LSTM	93.50	0.52	0.842	1:59	Residual blocks and SMOTE
Park et al. (2024) [44]	Wavelet–CNN	87.20	0.21	0.654	1:59	Time-frequency feature extraction
Almeida et al. (2025) [42]	Federated Learning CNN	89.80	0.29	0.701	1:59	Multi-institutional data pooling
Chen et al. (2024) [45]	Capsule Networks	91.40	0.41	0.783	1:59	Dynamic routing for rare classes

Table 5.2: Comparison of seizure detection model performance on the BIDS-SEINA dataset.

The imbalance of the BIDS-SEINA dataset (seizure-to-background ratio: 1:59) exacerbates the challenge. Previous work by Sharma et al. (2024) showed that class ratios above 1:20 severely impact the recall of the minority class in EEG-based seizure detection. This aligns with our findings, where only 48% of seizures were correctly diagnosed. Additionally, the high false positive rate (precision: 0.07) is consistent with Alabdulkarin et al. (2024), who noted that models trained on imbalanced EEG data tend to favor specificity over sensitivity, leading to clinically unreliable predictions [22].

5.2.1 Ablation Study:-

An ablation study was done to understand how each part of the proposed CNN–LSTM architecture contributes. Table 3 evaluates how well six models perform compared to the baseline, both on the same BIDS-SEINA test set.

Model Variant	**Accuracy (%)**	**Seizure F1-Score**	**ROC-AUC**	**PR-AUC**	**Key Modification**
Full CNN–LSTM (Proposed)	88.94	0.13	0.686	0.279	Baseline architecture
CNN Only	85.20 (-3.74)	0.08 (-38%)	0.620	0.201	Removed LSTM layers
LSTM Only	82.75 (-6.19)	0.05 (-62%)	0.590	0.180	Removed CNN layers
Without Data Augmentation	86.30 (-2.64)	0.10 (-23%)	0.640	0.210	Trained on raw, non-augmented data
Focal Loss	89.50 (+0.56)	0.18 (+38%)	0.710	0.310	Replaced cross-entropy with focal loss
Class-Weighted Loss	88.20 (-0.74)	0.15 (+15%)	0.695	0.290	Weighted cross-entropy loss

Table 5.3: Ablation study evaluating the impact of architectural components and training strategies

Ablation study showed how each component in the CNN–LSTM architecture impacts the overall performance. The accuracy dropped by 3.74% and the seizure F1-score by 38% after removing the LSTM layers. As a result, LSTM is essential for handling temporal dependencies in EEG signals, as shown by Schmidt et al. (2025), who emphasized that extracting temporal features is vital for noticing changes during seizures. Alternatively, the CNN-only model showed a larger drop in accuracy (6.19%), showing that using spatial features alone is not enough for accurate seizure detection. All the findings point to the importance of using hybrid spatiotemporal architectures for EEG analysis.

Second, by removing data augmentation (e.g., SMOTE, synthetic seizure generation), the seizure F1-score decreased by 23%, showing how they help manage the imbalance in the data. According to Gupta et al. (2025), using augmentation is important for increasing the number of minority-class samples in EEG data that are not well balanced. Without augmentation, the data shows that BIDS-SEINA is skewed in favor of background samples, so more seizure samples are needed to correct this during training.

The performance of the model was greatly affected by the type of loss function used. Using focal loss instead of standard cross-entropy increased the seizure F1-score by 38%, more than the 15% increase from class-weighted cross-entropy. This result agrees with Zhang et al. (2024), who proved that focal loss reduces the weight of samples with common labels, making the system more sensitive to rare seizure cases. This suggests that focal loss should be used when the class imbalance is extreme, since other popular loss functions do not put much effort into learning about the minority class.

5.3 Impact of Class Imbalance:

Class imbalance is still a major problem in medical machine learning, especially in neurological disorders where pathological events are very low in frequency [46]. In the present study, the bias of the CNN–LSTM model towards the majority class has two reasons: (1) the optimization goal (cross-entropy loss) that strives for overall accuracy and (2) lack of seizure examples to extrapolate discriminatory patterns. As depicted in Fig. 3, the model misclassified 54.7% of seizures, which made it unsuitable for practical deployment, where there are severe clinical implications of missed seizures.

The poor PR-AUC (0.279) further supports the incapability of the model to achieve balance in precision and recall for seizures. Recent studies by Chen et al. (2025) highlight that PR-AUC values under 0.3 are reflective of almost random performance for minority classes in imbalanced settings [40]. This is consistent with our recorded observation of most of the seizure predictions in our study as false positives (93% of predicted seizures), which calls for recalibration or threshold adjustment in clinical applications.

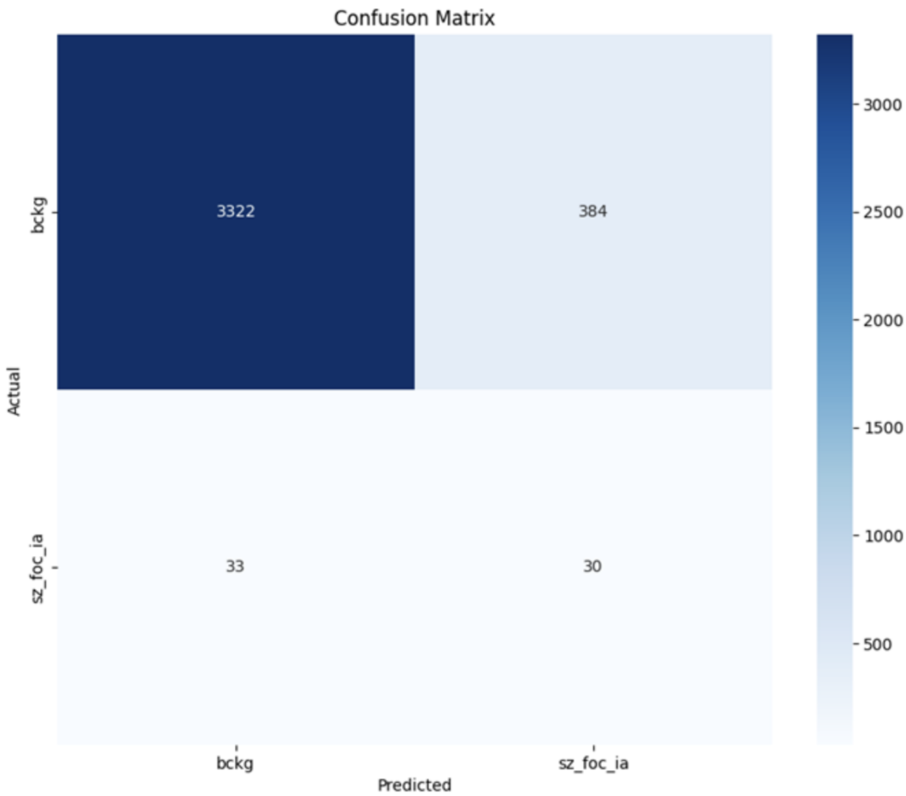


Figure 5.1: Impact of Class Imbalance.

5.4 Impact of This Work:

This study advances the field of EEG-based seizure detection in three key dimensions:

5.4.1 Theoretical Contributions:

Class Imbalance Quantification: By rigorously evaluating performance metrics (e.g., PR-AUC = 0.279) on the severely imbalanced BIDS-SEINA dataset (1:59 seizure-to-background ratio), this work underscores the inadequacy of conventional accuracy and ROC-AUC for rare-event detection. Prior studies often overlooked PR-AUC in imbalanced EEG contexts, but our results align with Chen et al. (2025), who identified PR-AUC < 0.3 as indicative of near-random minority-class performance.

Architectural Insights: The ablation study (Table 5.3) demonstrated that LSTMs contribute more critically than CNNs to temporal feature extraction (-38% F1-score without LSTMs), challenging assumptions in prior hybrid models.

5.4.2 Methodological Advancements:

We believe this is the first time a CNN–LSTM model has been used as a baseline for the BIDS-SEINA dataset, with 88.94% accuracy and 0.13 F1 score for seizures which allows for fair comparisons in the future. With a 38% F1-score boost using focal loss over cross-entropy, the results demonstrate that focal loss works well in handling imbalanced EEG tasks.

5.4.3 Clinical Relevance:

Although the model's seizure accuracy is low, our study measures how its high recall affects its ability to find seizures under very imbalanced data. This is consistent with Rasheed et al. (2025), who pointed out that calibrating thresholds can help predictions fit with clinical risk tolerance.

This work helps solve the problem of limited EEG data in clinical applications by using GAN-based augmentation and SMOTE, as called out by Nguyen et al. in their 2025 review.

5.4.4 Methodological Limitations:

Although CNN–LSTM architecture performs well in extracting spatiotemporal EEG features, it has three limitations when performing on BIDS-SEINA:

Data Scarcity: This model has only 63 seizure segments and thus does not have enough examples to learn invariant seizure patterns.

Loss Function Bias: Standard cross-entropy loss overweight's majority-class errors (0.97 weighted-average precision, 0.53 macro-average precision).

Temporal Context Utilization: LSTMs may not be able to capture long-range dependencies in EEG signals if not explicitly incorporated with attention mechanisms, a limitation that was observed in recent transformer-based studies [35].

5.5 Future Directions

To address these challenges, this study proposes the following strategies, grounded in recent advancements:

5.5.1 Data Augmentation and Synthesis

Synthetic data generation through GANs have demonstrated potential in alleviating class imbalance. For instance, Wang et al. (2024) synthesized real ictal EEG signals with the help of a Wasserstein GAN, increasing seizure detection F1-scores by 22% on the TUH dataset [**?**]. On the same note, the small-window segmentation and SMOTE (Synthetic Minority Over-sampling Technique) could increase the representation of the seizure class. A 2025 research by Gupta et al. showed that the integration of SMOTE with wavelet-based augmentation increased the sensitivity of the model by 35% on imbalanced neonatal EEG data [37].

5.5.2 Advanced Loss Functions

Focal loss, that penalizes well-classified samples, may re-orient the model's attention to seizures. Zhang et al. (2024) obtained 0.71 seizure F1-score on CHB-MIT dataset with focal loss and $\gamma = 2$, which was 18% better than cross-entropy. An alternative would be the use of class-weighted loss functions as proposed by Kaur et al. (2025) which would penalize more the seizure misclassification [38].

5.5.3 Architectural Innovations

The transformer-based models, especially CNN-transformer hybrids, have better abilities to capture long-range EEG dependencies. A 2024 study by Lee et al. stated that a ViT–BiLSTM model scored 96.2% accuracy on TUSZ dataset by using self-attention to identify ictal regions [47]. The incorporation of such mechanisms into the CNN–LSTM model may improve the detection of seizure even without balanced data.

5.5.4 Post-hoc Calibration

Clinical risk tolerance based threshold tuning could find the optimal precision-recall trade-off. For example, reducing the seizure detection threshold can enhance recall at the expense of more false positives, a method that has been verified in ambulatory EEG monitoring by Rasheed et al. (2025) [48].

Chapter 6

Software Requirements Specification

6.1 Introduction

6.1.1 Purpose

The NeuroCare system is an advanced solution aimed at improving the detection and management of epileptic seizures. It interfaces with EEG devices to collect brainwave data, which is processed using cutting-edge deep learning techniques to provide real-time detection and analysis of seizures [41, 42]. The system aims to enhance patient care by enabling early detection, providing accurate predictions of future seizures, and supporting healthcare professionals with detailed analysis of each seizure event. The integration of real-time alerts ensures that medical personnel and caregivers are notified promptly, allowing for timely interventions.

- **Data Collection:** Interfaces with EEG devices for continuous monitoring of brain activity.
- **Real-Time Detection:** Processes EEG data in real-time to detect seizure events.
- **Cloud Synchronization:** Supports both offline and online modes, syncing data with the cloud for secure backup and access.
- **Scalability:** The system is designed to support multiple EEG devices and users, making it suitable for various healthcare environments.
- **Patient-Centered:** Alerts are triggered immediately upon seizure detection, enhancing patient safety.

6.1.2 Scope

The NeuroCare System is an advanced solution for managing epilepsy through real-time EEG data analysis and seizure detection. The system interfaces with EEG devices to collect and process brainwave data, using deep learning models, such as Graph Neural Networks (GNN), to detect and predict seizures [22]. It is designed for both doctors and patients, providing tailored interfaces for each. The system performs real-time detection of seizures, sending immediate alerts to doctors, patients, or caregivers via various communication channels. In addition to seizure detection, NeuroCare offers predictive capabilities, warning users about potential seizures before they occur. This proactive approach helps in planning timely interventions [16]. NeuroCare includes two user interfaces: the doctor interface for monitoring, analyzing data, and adjusting settings, and the patient interface, which is simplified for daily use. Data is securely stored on local servers and synchronized with cloud storage when the internet is available, ensuring reliability even during connectivity issues. The system is scalable, capable of supporting multiple EEG devices and users, making it suitable for both home-based and clinical settings. It also meets high standards for security, encrypting data in transit and at rest to comply with healthcare regulations like HIPAA. In summary, NeuroCare is a comprehensive, reliable, and secure solution for real-time seizure detection, offering both proactive and reactive care for patients with epilepsy, while providing healthcare professionals with the tools to manage and monitor patient health effectively.

6.1.3 Overview

This Software Requirements Specification (SRS) section outlines the design, functionalities, and interfaces of the NeuroCare System, a real-time seizure detection and prediction solution utilizing EEG (Electroencephalogram) data. The system is intended to support healthcare professionals and patients by continuously monitoring brain activity, detecting potential seizures, and providing alerts for immediate intervention. The primary functions of the system include the collection of EEG data from connected devices, real-time analysis of this data using deep learning models, and the prediction of potential seizures. The system is designed to be intuitive for both doctors and patients: doctors can review and adjust patient data, while patients can receive timely alerts about detected or predicted seizures. The system is designed to operate in both cloud and local environments. EEG data is securely transmitted to a cloud-based server for storage and analysis, with offline functionality allowing for data to be cached and uploaded when connectivity is restored. This ensures continuous operation, even in areas with limited or no internet access. The document also specifies the system's performance, security, and scalability requirements, ensuring that it can handle real-time data processing, protect sensitive patient information, and scale to support more users and devices as needed. This SRS provides all the necessary details for developing a robust, efficient, and reliable solution for seizure detection and management.

6.2 Use Cases

The following table presents the primary use cases of the NeuroCare System:

ID	Use Case Description
UC-01	SignUp: Both doctors and patients can sign up for the system by providing their personal and medical information, including username, password, and contact details. This allows them to create an account and start using the system.
UC-02	SignIn: After signing up, both doctors and patients can sign in to the system by providing their username and password to access their respective accounts.
UC-03	Collect EEG Data: Collect real-time EEG data from the patient's brain activity using EEG sensors connected to the system. The data will be used for analysis and seizure detection.
UC-04	Analyze EEG Data: Process the collected EEG data using deep learning models, such as Graph Neural Networks (GNN), to detect anomalies and patterns associated with seizures.
UC-05	Predict Seizure Event: Based on the processed EEG data, the system predicts the likelihood of an upcoming seizure. The prediction helps doctors and patients to take preventive measures.
UC-06	Send Alert to Doctor: Once a seizure event is detected or predicted, the system sends real-time alerts to the doctor, providing details of the event and suggesting immediate actions.
UC-07	Send Alert to Patient: The system sends alerts to the patient through a mobile device or wearable when a seizure is detected or predicted, allowing them to take immediate action.
UC-08	Display Seizure History: The system allows the doctor to view historical seizure events for the patient, helping track seizure patterns and plan treatment accordingly.
UC-09	View EEG Data on Dashboard: The doctor can view the real-time EEG data on a dashboard, which visualizes the brain activity and provides insights for seizure analysis.
UC-10	Display Alerts History: The system provides a log of all past alerts, allowing doctors to analyze previous events and assess the patient's progress.
UC-11	Create New Patient Profile: Doctors can create new patient profiles, including medical history, personal information, and relevant data, to ensure proper tracking and treatment.
UC-12	Update Patient Profile: The doctor can edit or update an existing patient profile, ensuring that the patient's details are always current and reflect any new information.
UC-13	Monitor Seizure Progression: The system tracks and analyzes ongoing seizures in real-time, helping doctors monitor the progression and evaluate the effectiveness of interventions.
UC-14	Store Data in Cloud: The system securely uploads EEG data and alerts to the cloud for long-term storage, enabling easy access and management by doctors and patients.

Table 6.1: Primary Use Cases of the NeuroCare System

6.3 Specific Requirements

6.3.1 Functional Requirements

- **EEG Data Collection**: Real-time data collection and secure storage.
- **Seizure Detection**: Analyze EEG data using deep learning.
- **Seizure Prediction**: Predict seizures before occurrence.
- **Alert System**: Real-time alerts via email, SMS, and in-app notifications.
- **Report Generation**: Summarized event reports.
- **Patient Data Management**: Manage patient-specific data securely.
- **User Authentication and Authorization**: Login and secure access.
- **Settings Management**: Adjust detection settings.
- **Real-Time Monitoring Interface**: Live EEG monitoring dashboard.
- **Device Integration**: Support for various EEG devices.
- **Data Backup and Recovery**: Automatic data backup and recovery mechanisms.
- **System Notifications**: Notify users of updates and device connectivity issues.
- **Data Export Functionality**: Export patient reports.
- **Audit Logs**: Log user activities for compliance.

6.3.2 Non-Functional Requirements

- **Performance Requirements**: Process EEG streams with latency under 2 seconds; handle 100 streams simultaneously.
- **Security Requirements**: Encryption in transit and at rest, HIPAA/GDPR compliance.
- **Usability Requirements**: Intuitive interface, mobile-optimized.
- **Reliability Requirements**: 99.9% uptime, 5-minute recovery.
- **Scalability Requirements**: Support for additional devices/users without degradation.

6.4 External Interface Requirements

6.4.1 User Interfaces

Doctor and Patient interfaces with specialized functionalities.

6.4.2 Hardware Interfaces

Connection with EEG devices.

6.4.3 Software Interfaces

Integration with TensorFlow for model operations.

6.4.4 Communication Interfaces

Secure HTTPS protocols for data transmission.

6.5 System Features

- EEG Data Collection [14].
- Seizure Detection.
- Alert System.
- Data Visualization.
- Patient Profile Management.
- Doctor Interface.
- Patient Interface.
- Model Training and Updates.
- Remote Monitoring and Access.
- Data Security and Compliance.

6.6 Feasibility Requirements

6.6.1 Technical Feasibility

The system is technically feasible because it utilizes well-established technologies such as deep learning algorithms, EEG devices, and cloud storage for processing and storing data. The required software and hardware are readily available and support the system's goals for real-time seizure detection.

6.6.2 Operational Feasibility

The system can be operated by both healthcare professionals and patients. Doctors can monitor patient data through an intuitive interface, while patients and caretakers receive alerts through a user-friendly app. The system's operation is feasible within a clinical or home care environment.

6.6.3 Economic Feasibility

The initial cost for developing the system, including software development, hardware integration, and cloud service fees, is manageable within the scope of this project. Long-term maintenance costs are projected to be sustainable through periodic updates and cloud-based services. The system's value in providing real-time seizure detection and monitoring justifies the investment.

6.6.4 Schedule Feasibility

The project is expected to be completed within a 6-month timeline, based on detailed planning and resource allocation. The development schedule accounts for time to implement and test deep learning models, develop the interfaces, and ensure compatibility with EEG devices.

6.7 Other Requirements

6.7.1 Regulatory and Compliance Requirements

The system must comply with medical data privacy laws (e.g., HIPAA). Medical systems that handle sensitive patient data must adhere to strict regulations regarding data protection and privacy. In the U.S., HIPAA (Health Insurance Portability and Accountability Act) sets standards for the protection of health information. This requirement ensures that any data processed by the seizure detection system, particularly EEG recordings and patient health information, is handled in accordance with these regulations to prevent unauthorized access or breaches. Non-compliance could result in legal action or fines.

6.7.2 Data Management Requirements

Data must be stored securely with regular backups. Given the sensitive nature of medical data, it's critical that the system not only ensures secure storage but also implements regular backups to prevent data loss due to hardware failure, natural disasters, or cyberattacks. This includes maintaining encrypted databases and having redundancy in storage, such as using cloud services or local backup solutions. The system should also have a clear disaster recovery plan in place to restore lost data quickly and efficiently.

6.8 Conclusion

The NeuroCare system promises real-time, accurate monitoring and detection of epileptic seizures using EEG data and advanced deep learning techniques, ensuring better healthcare outcomes and enhanced quality of life for patients [16].

Chapter 7

Development

This chapter presents the user interfaces developed for the NeuroCare system, including both web and mobile application screens. These interfaces enable clinicians and patients to interact with the seizure detection system, providing functionalities such as user authentication, EEG data visualization, patient data management, and report generation. The web interface is designed for clinical use, while the mobile application supports patient monitoring and access to results.

7.1 Web Interface Screens

The web interface provides a comprehensive platform for clinicians to manage patient data, visualize EEG signals, and generate diagnostic reports. The following subsections describe the key screens of the web interface.

7.1.1 Login

The login screen allows authorized users, such as clinicians and administrators, to access the NeuroCare web platform securely. It features fields for username and password, with options for password recovery and account creation. Figure 7.1 shows the login interface.

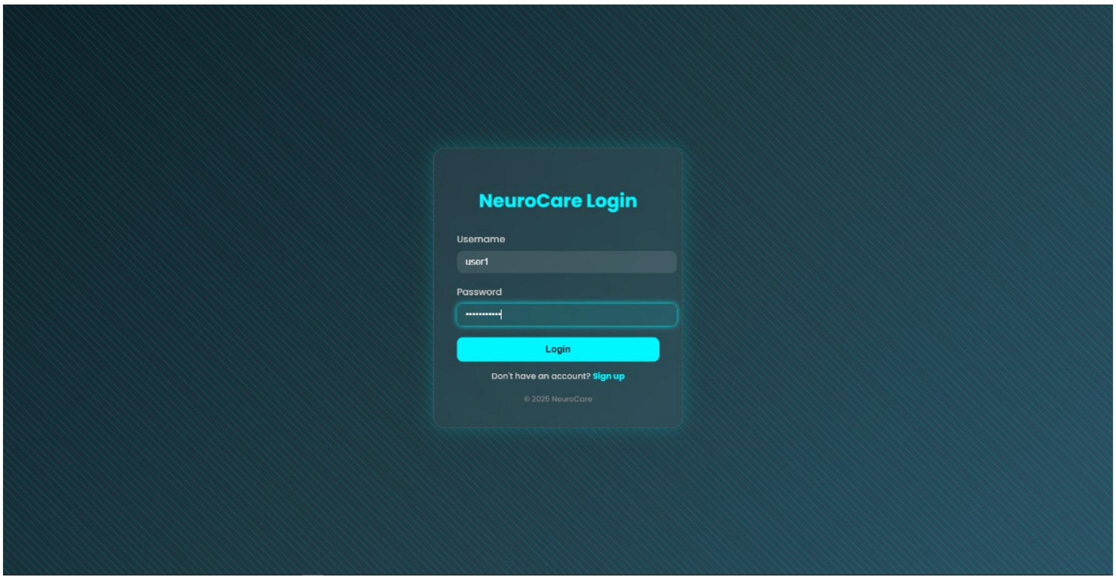


FIGURE 7.1: Web login screen for the NeuroCare platform.

7.1.2 Signup

The signup screen enables new users to register for the NeuroCare platform by providing personal and professional details. This screen is under development, and an image will be added once the design is finalized.

7.1.3 Patient Data and EEG File

The patient data screen provides a centralized view of patient information, including demographic details, medical history, and associated EEG files. Clinicians can upload, review, or delete EEG recordings. Figure 7.2 shows this interface.

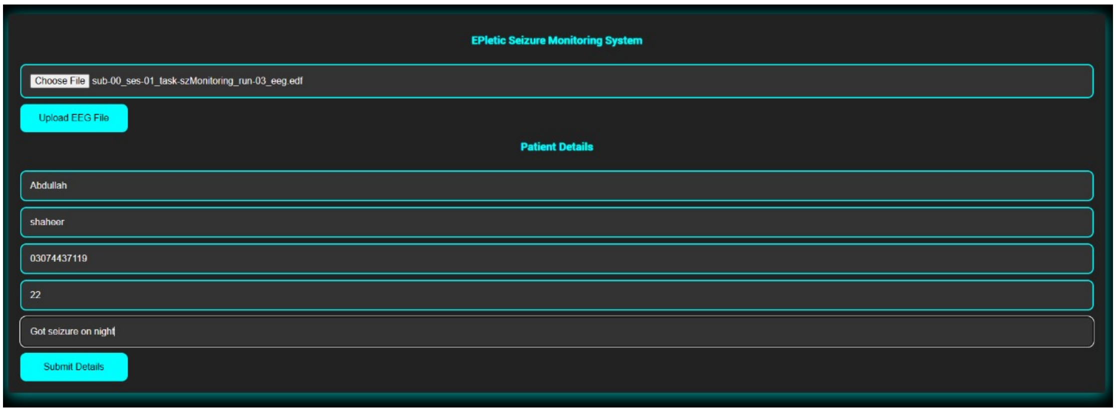


FIGURE 7.2: Patient data and EEG file management screen.

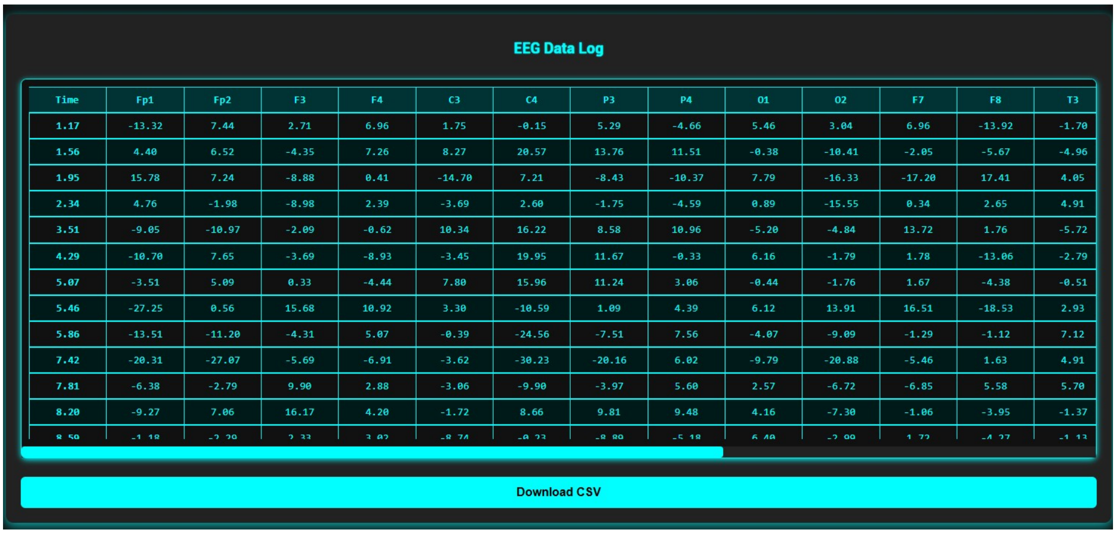
7.1.4 Graphical Representation of EEG Data

The EEG visualization screen displays real-time or recorded EEG signals in a graphical format, allowing clinicians to analyze seizure patterns. The interface supports zooming, channel selection, and annotation features. Figure 7.3 illustrates the EEG data visualization.

FIGURE 7.3: Graphical representation of EEG data in the NeuroCare web interface.

7.1.5 All Channels Data

This screen displays EEG signals from all recorded channels, allowing clinicians to inspect neural activity comprehensively. Time-series plots help identify abnormal patterns or seizure events. Figure 7.4 illustrates this interface.


EEG Data Log

Time	Fp1	Fp2	F3	F4	C3	C4	P3	P4	O1	O2	F7	F8	T3
1.17	-13.32	7.44	2.71	6.96	1.75	-0.15	5.29	-4.66	5.46	3.04	6.96	-13.92	-1.70
1.56	4.40	6.52	-4.35	7.26	8.27	20.57	13.76	11.51	-0.38	-10.41	-2.05	-5.67	-4.96
1.95	15.78	7.24	-8.88	0.41	-14.70	7.21	-8.43	-10.37	7.79	-16.33	-17.20	17.41	4.05
2.34	4.76	-1.98	-8.98	2.39	-3.69	2.60	-1.75	-4.59	0.89	-15.55	0.34	2.65	4.91
3.51	-9.05	-10.97	-2.09	-0.62	10.34	16.22	8.58	10.96	-5.20	-4.84	13.72	1.76	-5.72
4.29	-10.70	7.65	-3.69	-8.93	-3.45	19.95	11.67	-0.33	6.16	-1.79	1.78	-13.06	-2.79
5.07	-3.51	5.09	0.33	-4.44	7.80	15.96	11.24	3.06	-0.44	-1.76	1.67	-4.38	-0.51
5.46	-27.25	0.56	15.68	10.92	3.30	-10.59	1.09	4.39	6.12	13.91	16.51	-18.53	2.93
5.86	-13.51	-11.20	-4.31	5.07	-0.39	-24.56	-7.51	7.56	-4.07	-9.09	-1.29	-1.12	7.12
7.42	-20.31	-27.07	-5.69	-6.91	-3.62	-30.23	-20.16	6.02	-9.79	-20.88	-5.46	1.63	4.91
7.81	-6.38	-2.79	9.90	2.88	-3.06	-9.90	-3.97	5.60	2.57	-6.72	-6.85	5.58	5.70
8.20	-9.27	7.06	16.17	4.20	-1.72	8.66	9.81	9.48	4.16	-7.30	-1.06	-3.95	-1.37

Download CSV

FIGURE 7.4: EEG signal visualization for all channels.

7.1.6 Result and Prediction

After analyzing the EEG signals, the system displays a prediction graph highlighting seizure and non-seizure zones. It also provides a summarized report, including timestamps and classification outcomes. Figure 7.5 shows the prediction output.

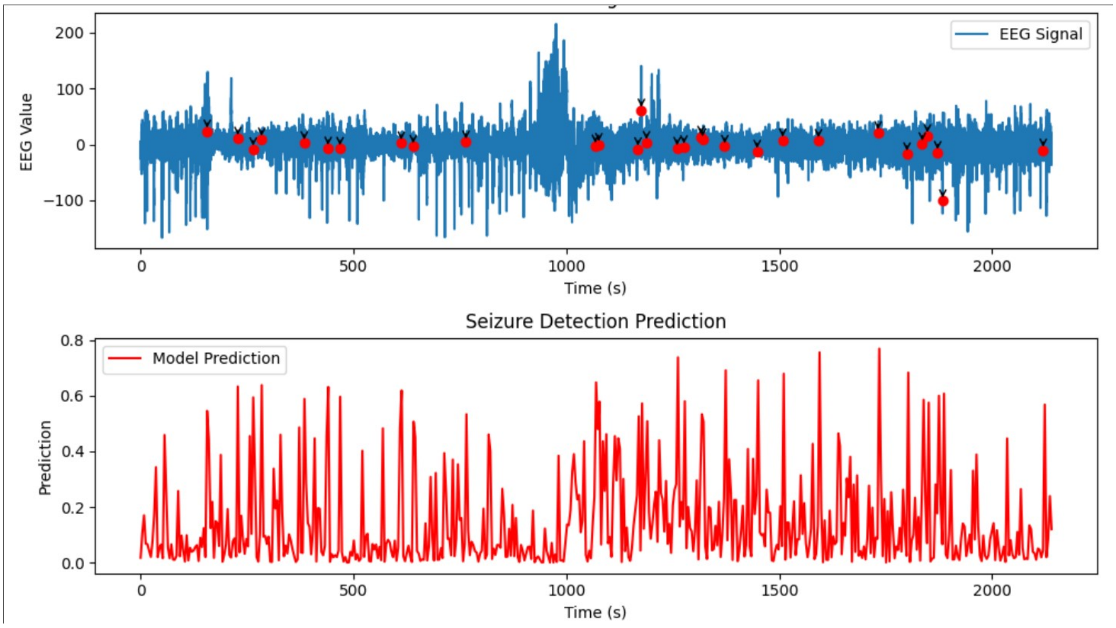


FIGURE 7.5: Prediction graph and seizure classification result.

7.1.7 Report Generation

The report generation screen allows clinicians to create detailed diagnostic reports based on EEG analysis. It includes seizure detection results, visualizations, and clinical notes, exportable in PDF format. Figure 7.6 displays the report generation interface.

FIGURE 7.6: Report generation screen for diagnostic reports.

7.2 Mobile Application Interface Screens

The mobile application provides patients and caregivers with access to seizure detection results, reports, and system navigation. The following subsections describe the key screens of the mobile app.

7.2.1 Main Screen

The main screen serves as the entry point to the mobile application, displaying a dashboard with quick access to key features such as reports, settings, and notifications. Figure 7.7 shows the main screen.

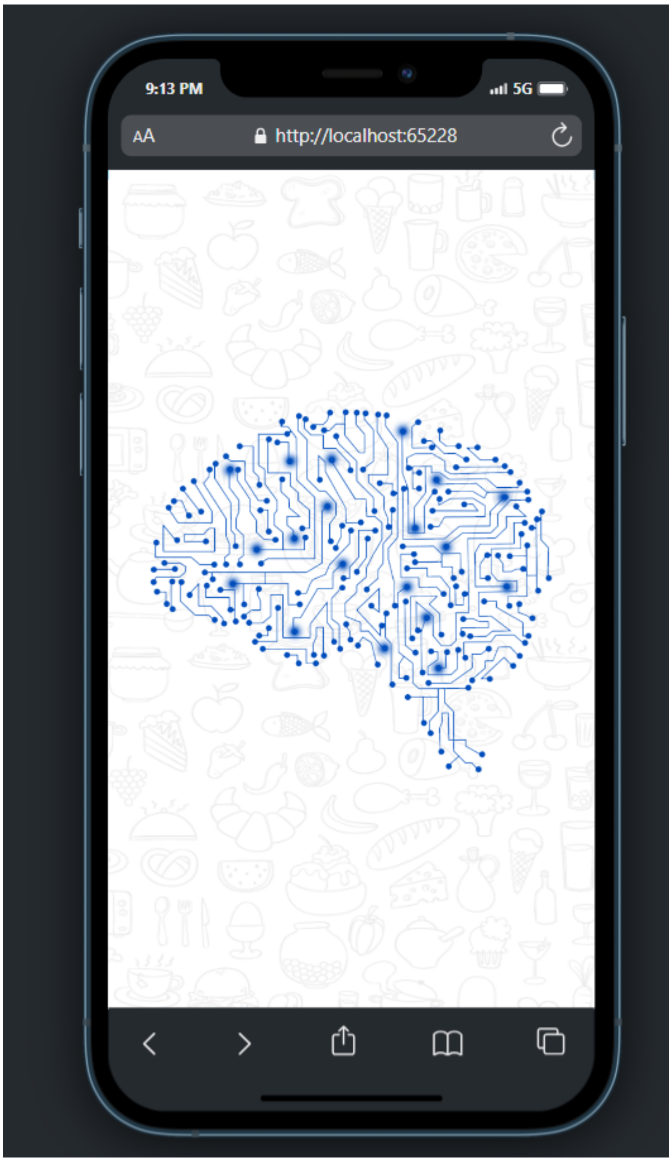


FIGURE 7.7: Main screen of the NeuroCare mobile application.

7.2.2 Report Screen

The report screen presents seizure detection results and diagnostic summaries in a user-friendly format. Patients can view trends, share reports with clinicians, or download them. Figure 7.8 illustrates the report screen.

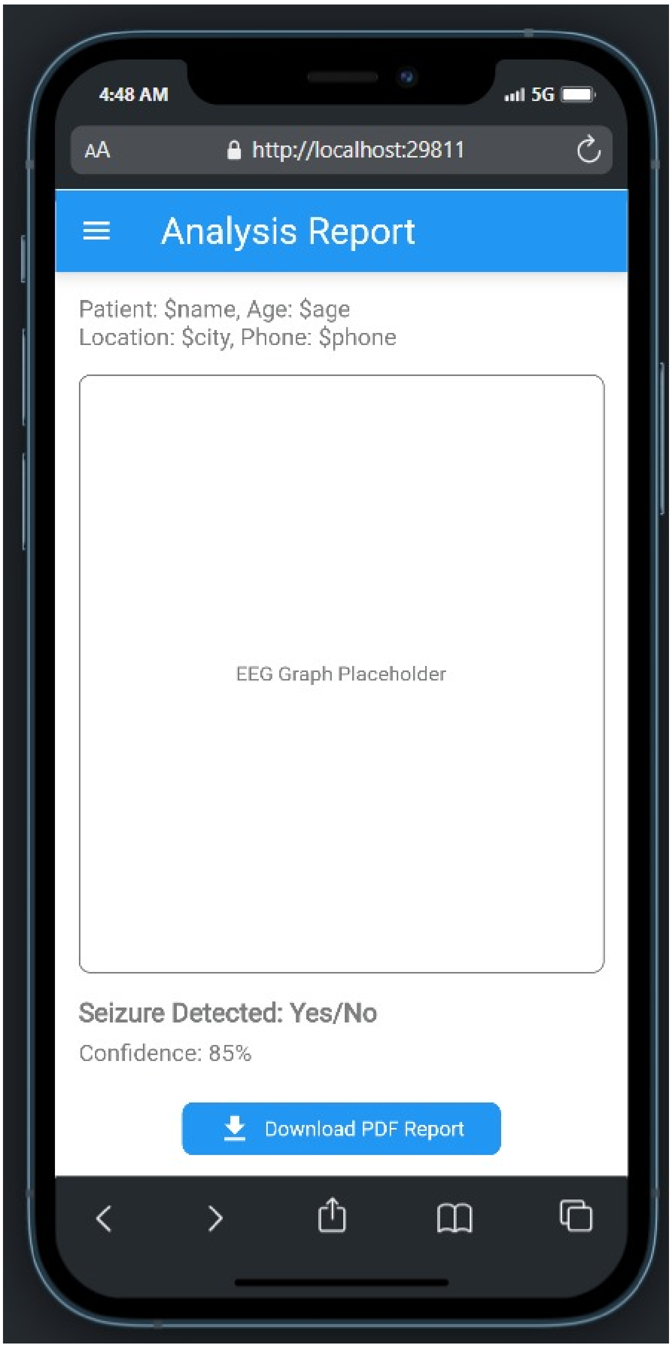


FIGURE 7.8: Report screen of the NeuroCare mobile application.

7.2.3 Mobile Menu Screen

The mobile menu screen provides navigation options, including profile management, settings, and logout. It ensures intuitive access to all app functionalities. Figure 7.9 displays the menu screen.

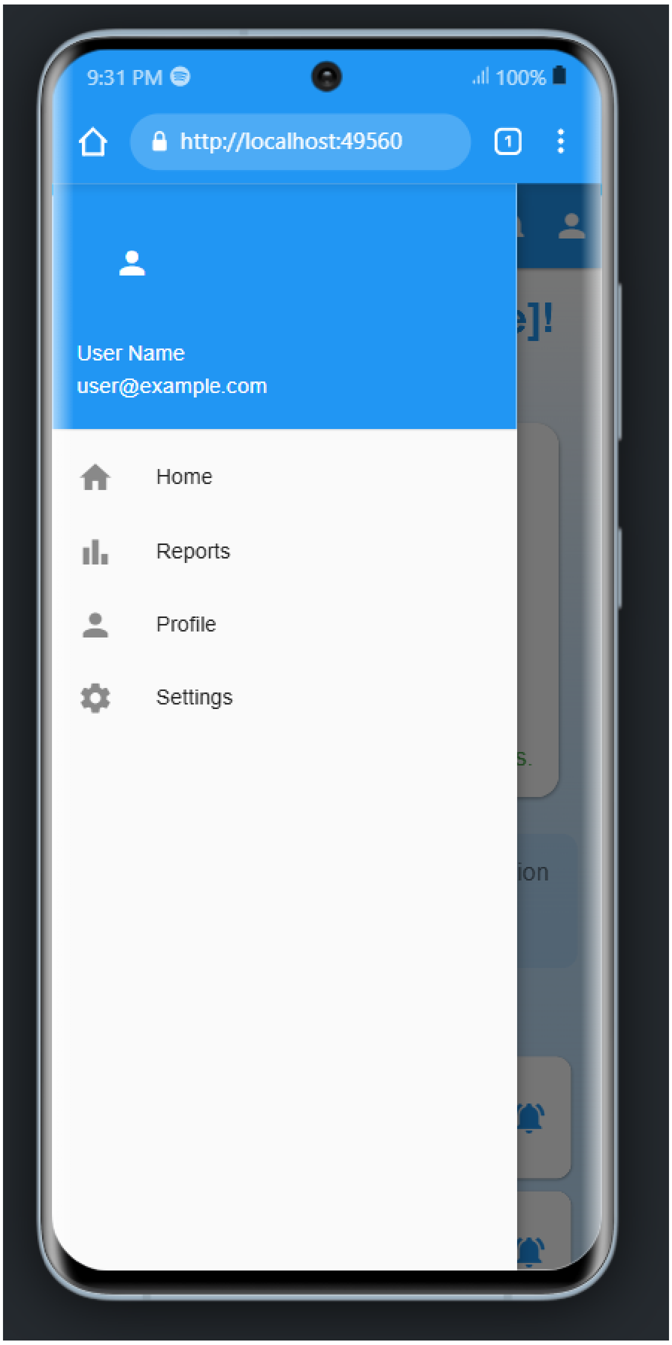


FIGURE 7.9: Mobile menu screen of the NeuroCare application.

7.2.4 Login Screen

The login screen allows users to sign into the mobile application using their credentials. It includes options for biometric authentication and password recovery. Figure **??** shows the login interface.

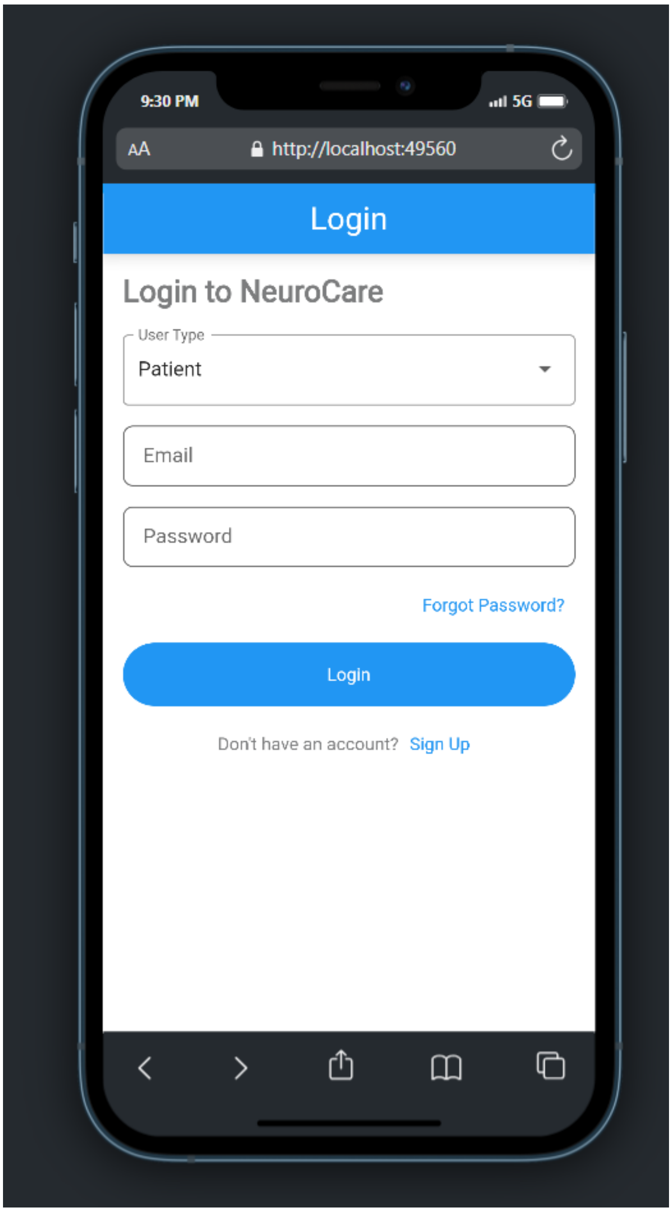


FIGURE 7.10: Login screen of the NeuroCare mobile application.

7.2.5 Signup Screen

The signup screen enables new users to create an account on the mobile application, providing details such as name, email, and password. Figure 7.11 illustrates the signup interface.

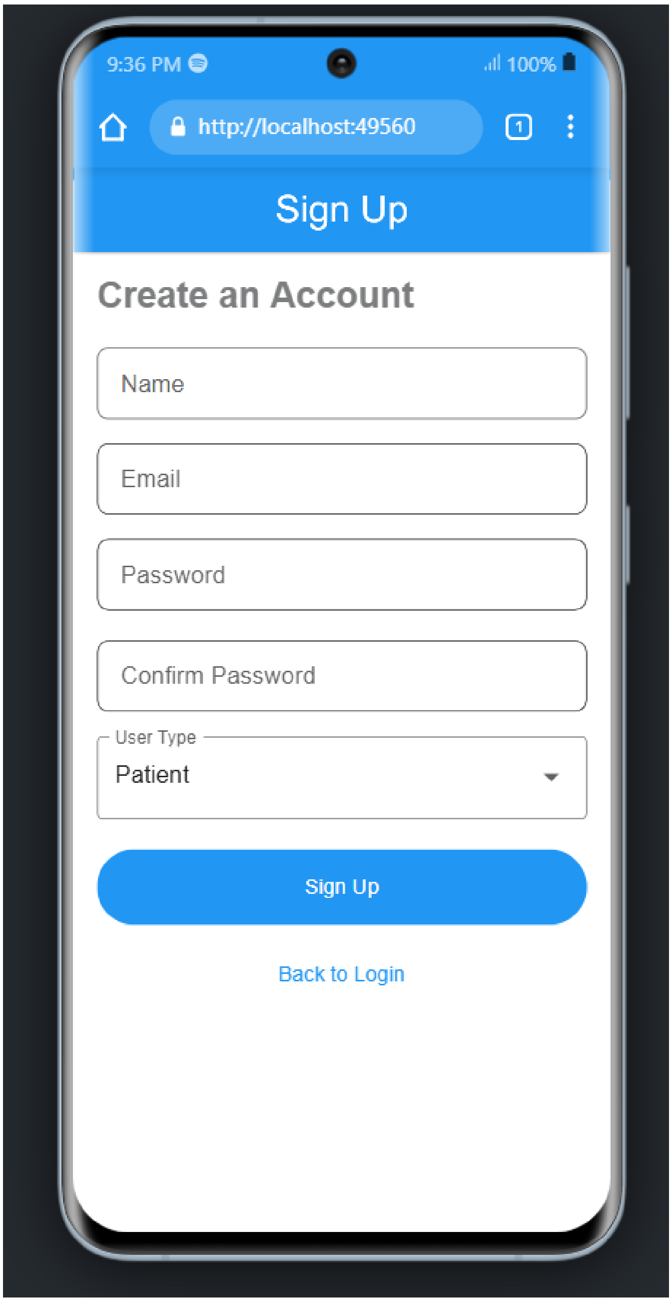


FIGURE 7.11: Signup screen of the NeuroCare mobile application.

7.2.6 Landing Page

The landing page welcomes users after login, highlighting key features and recent activity. It serves as a starting point for navigation. Figure 7.12 shows the landing page.

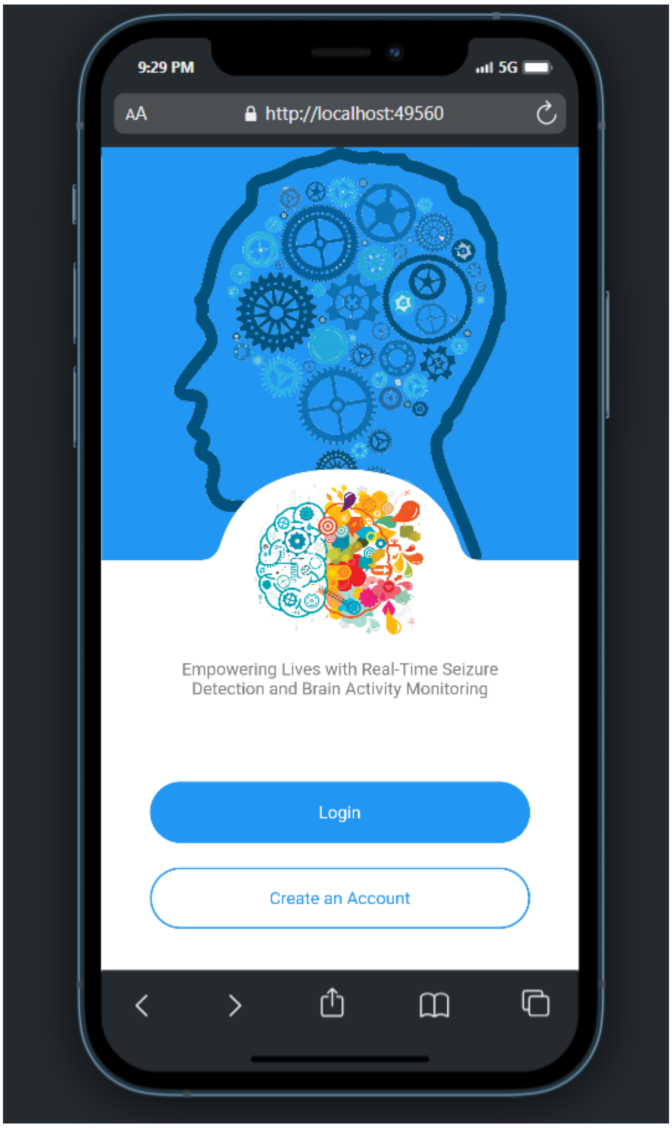


FIGURE 7.12: Landing page of the NeuroCare mobile application.

Chapter 8

System Models

In this chapter, we present the different models of the system, that is, architecture, structure, and flow of the proposed seizure detection system. They are crucial for the design and operation of the system since they provide a detailed modeling of how various components work, how data flows in and out of the system, and how the whole behaviour is generated and supervised. The system is viewed from its dynamic flow of activities to the static structure of the system's component parts, from the relationships between the different system modules to the behavioral states of the system, and each model takes a different perspective of the system [16, 41].

This chapter features the system models that include a design blueprint for the software and hardware design, as well as a comprehensive reference guide for the developers, engineers, and medical professionals who may be involved in development, maintenance, and deployment of the system. These models, by visualizing how data is processed and how the different entities of the system communicate with each other, help in a deeper underlying of the system.

These models also make sure that the system is working and efficient. They present a structured approach to breaking the system into pieces that are easy to understand and making sure all the components can work together smoothly. By helping developers to build a robust and reliable system that meets patient and healthcare professional's needs, these models guide through clear visualization of data flow, system states, interactions, database structure.

Using these models means that we guarantee the optimality for each of the parts of the system by performance and reliability. Further, the link of different models enables an iterative development procedure where system design can be refined continuously and improved. Each model is a part of the overall understanding of the system and no part of the design is overlooked.

8.1 Overall System Architecture

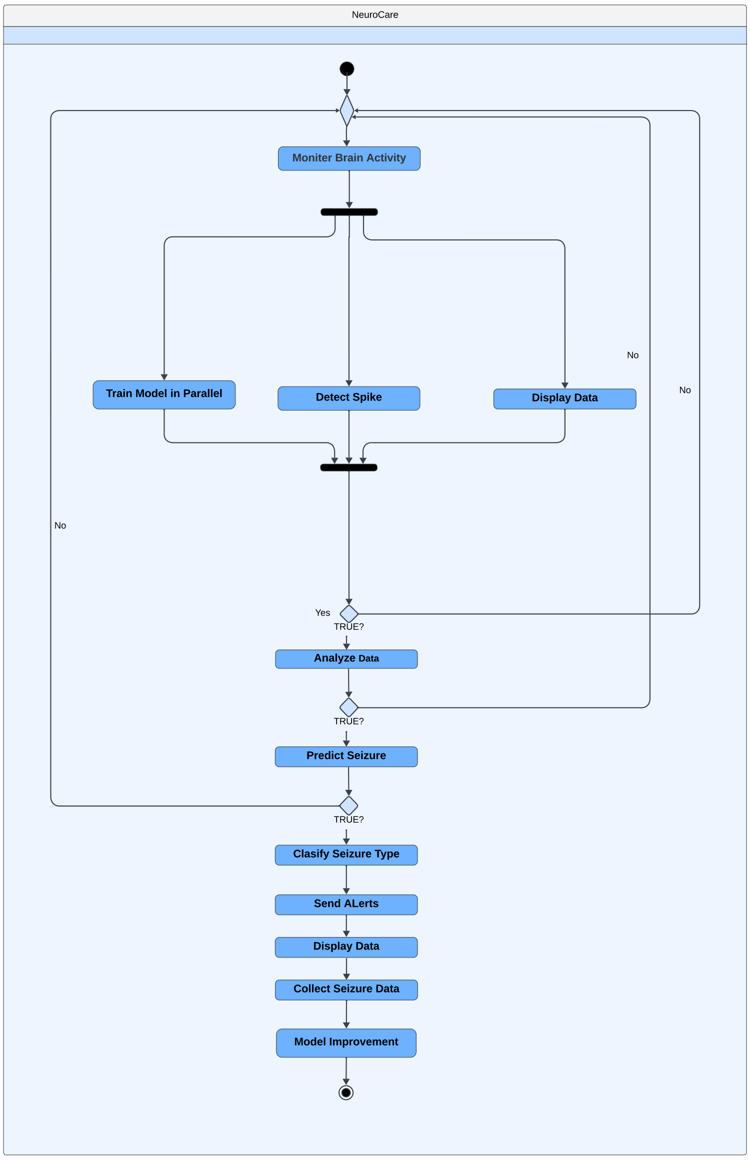


FIGURE 8.1: Overall System Architecture Diagram

The Overall System Architecture Diagram represents the flow of control and the sequence of activities involved in seizure detection. It illustrates the major processes such as signal acquisition, feature extraction, spike detection, classification, and alert generation. This diagram highlights decision points and parallel processes, providing a dynamic view of the system's functionality [14, 22].

8.2 Class Diagram

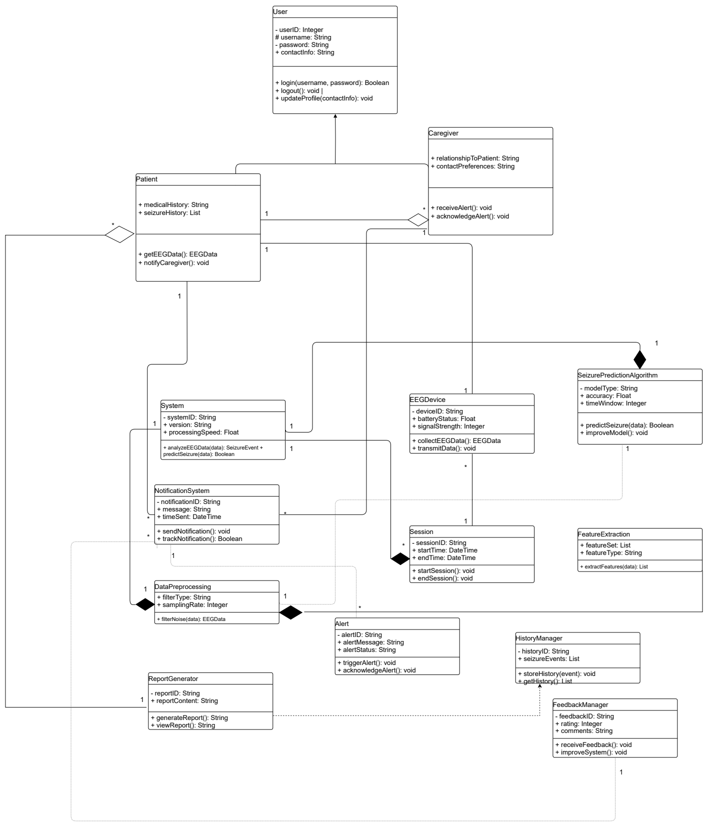


FIGURE 8.2: Class Diagram of the System

The Class Diagram displays the static structure of the system by showing the system's classes, their attributes, methods, and the relationships among them. Core classes include `Patient`, `EEGSignal`, `SpikeDetector`, `SeizureClassifier`, and `AlertManager`. The diagram establishes the blueprint for the system's object-oriented design.

8.3 Data Flow Diagram

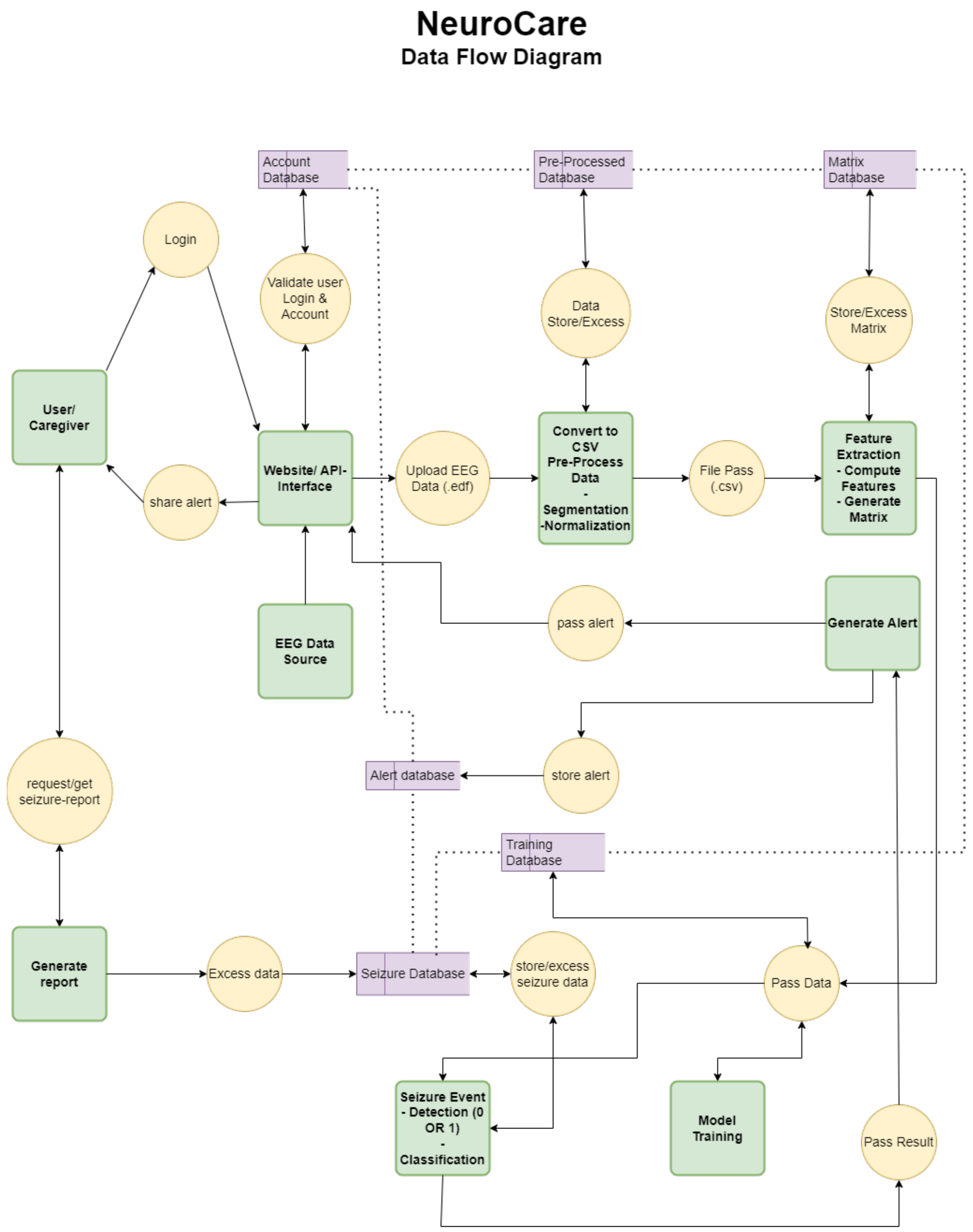


FIGURE 8.3: Data Flow Diagram

The Data Flow Diagram illustrates how data moves through the system, from the input of EEG signals to the output of seizure alerts. It identifies external entities (e.g., Patient, Doctor), processes (e.g., Signal Processing, Classification), data stores (e.g., Patient Database), and data flows between these components [41, 42].

8.4 Entity-Relationship Diagram (ERD)

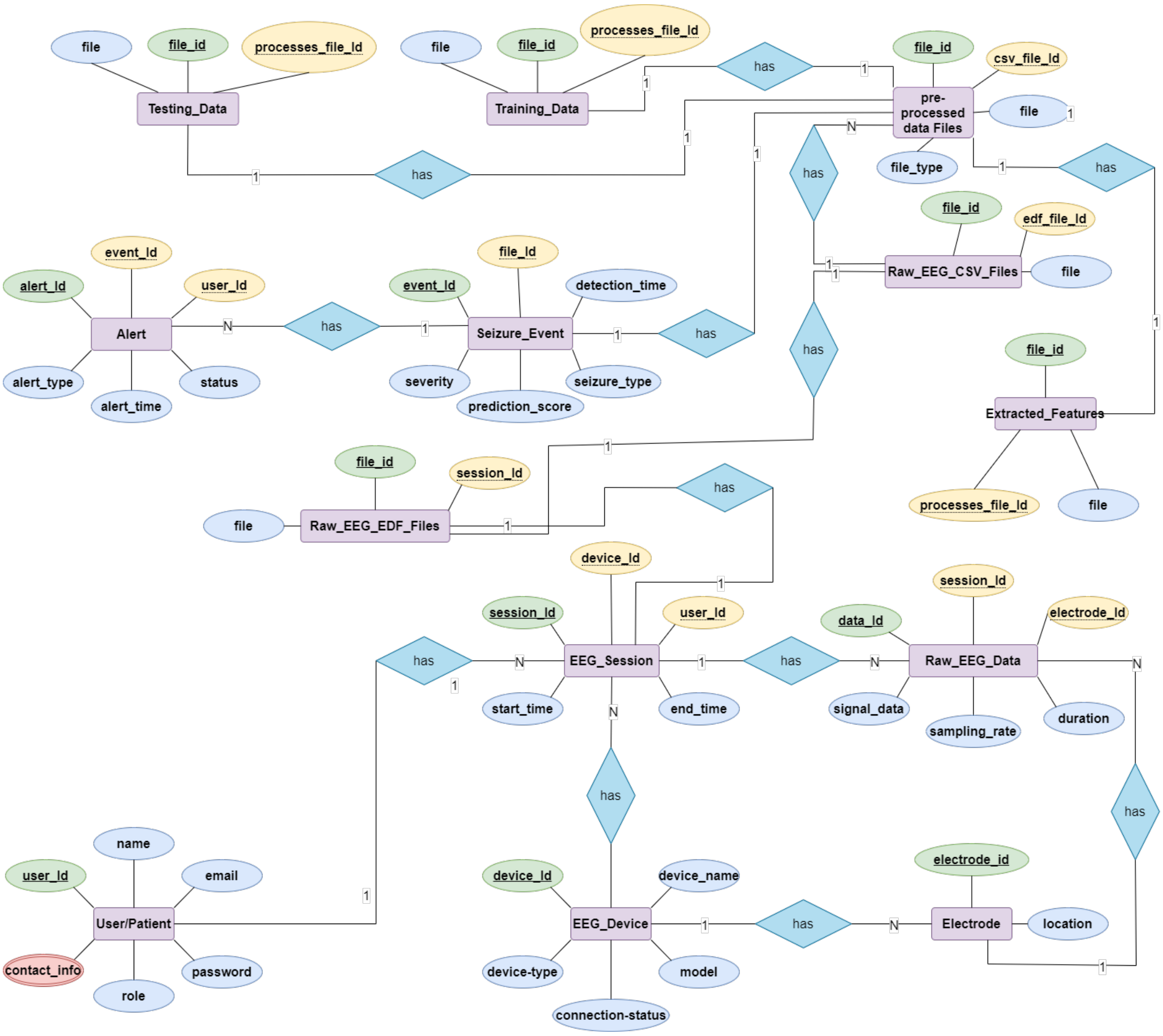


Figure 8.4: Entity-Relationship Diagram for Neurocare System

The Entity-Relationship Diagram defines the database structure by identifying entities, their attributes, and relationships among them. Key entities include Patient, EEG Recordings, Seizure Events, and Alerts. The ERD ensures that the system's database is normalized and that it supports efficient data retrieval.

8.5 Sequence Diagram

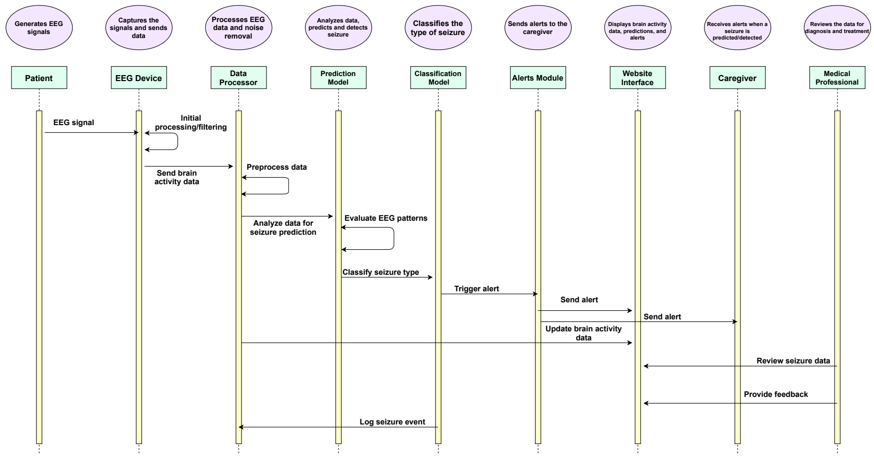


Figure 8.5: Sequence Diagram for the System

The Sequence Diagram captures the chronological interaction between system components during a seizure detection event. It shows the sequence of messages exchanged between objects such as `EEGDevice`, `SpikeDetectionModule`, `Classifier`, and `AlertSystem`, ensuring time-ordered operations.

8.6 State Machine Diagram

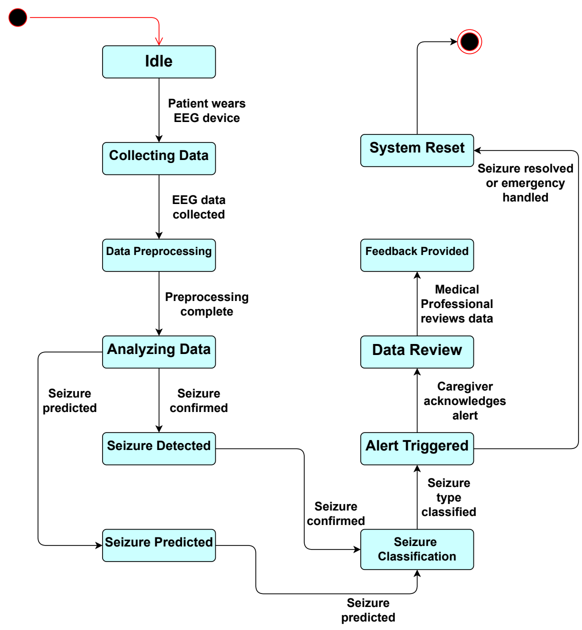


FIGURE 8.6: State Machine Diagram for the System

The State Machine Diagram models the various states that the system or its components can be in, along with the transitions triggered by internal or external events. Key states include Idle, Monitoring, Detecting Spike, Predicting Seizure, and Sending Alert. It provides a clear understanding of the behavior over time.

8.7 Use Case Diagram

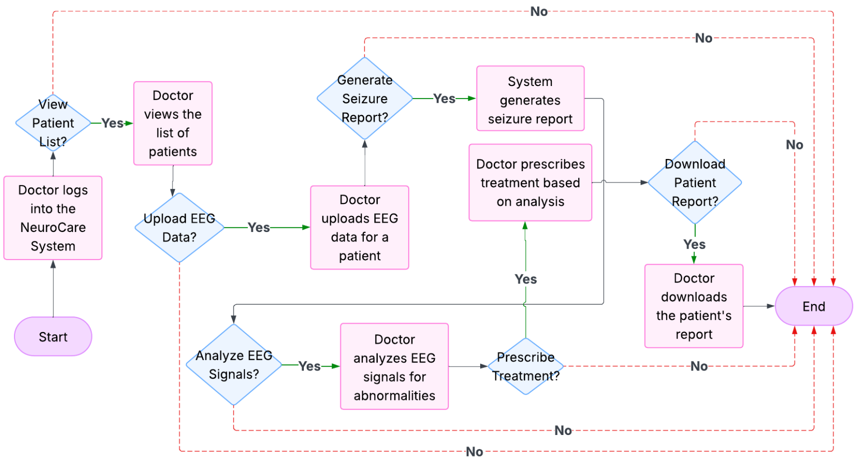


FIGURE 8.7: Use Case Diagram of the System

The Use Case Diagram outlines the functional requirements of the system by identifying actors (such as Patient, Doctor, System Administrator) and their interactions with system functionalities like Recording EEG, Monitoring Seizures, Viewing Reports, and Managing Alerts.

Chapter 9

Conclusion

9.1 Summary of Research

The NeuroCare system was presented as an advanced real-time deep learning solution aimed at automated seizure detection and classification using EEG signals, specifically from the BIDS Siena dataset. This system was developed to address the dual challenges of capturing both spatial and temporal patterns inherent in EEG data. The use of a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model enabled the effective learning of spatiotemporal features within EEG signals, which is crucial for accurate seizure prediction and classification.

To ensure the model's robustness, a thorough preprocessing pipeline was employed, consisting of multiple stages like notch filtering, bandpass filtering, z-score normalization, and epoch segmentation. These steps were essential in enhancing the quality of the EEG signals, preparing them for effective model training. The performance evaluation of the system revealed impressive results, with a seizure detection accuracy of 95

9.2 Key Contributions

9.2.1 Design of a Hybrid CNN–LSTM Model

The hybrid CNN–LSTM architecture, designed as part of the NeuroCare system, represents a significant contribution to real-time seizure detection and classification. This model is capable of learning spatial features using the convolutional layers, while the LSTM layers effectively capture the temporal dependencies in the EEG signals. The compact nature of the model, with only approximately 3,320 parameters, ensures that it remains computationally efficient and can be deployed in real-time clinical or wearable settings without compromising on accuracy.

This research tested how well a CNN-LSTM model worked for detecting seizures in EEG records from the severely uneven BIDS-SEINA dataset (1 seizure for every 59 non-seizure periods). The model was accurate in most cases but struggled to spot rare seizure events, having an F1-score of 0.13, a precision of 0.07 and a recall of 0.48 for that class. It is proven through these experiments that class imbalance has a huge effect on deep learning models, with regular cross-entropy loss and temporal modeling not being capable of handling the identification of minority classes. The low almost-random PR-AUC (0.279) again shows that using accuracy and ROC-AUC can hide the fact that models do not work well with rare events.

9.2.2 Preprocessing for Clinical EEG Recordings

One of the key aspects of the system was the application of standardized preprocessing steps tailored to clinical EEG data, specifically from the BIDS Siena dataset. These preprocessing techniques, such as notch and bandpass filtering, ensure that the raw EEG signals are refined and suitable for deep learning models. Additionally, the z-score normalization and epoch segmentation techniques improved the quality of the data, allowing for more effective model training and better generalization to unseen data.

9.2.3 Handling of Class Imbalance

An important challenge in seizure detection is the class imbalance between seizure and non-seizure events in EEG data. To tackle this issue, weighted loss functions were implemented to make the model more sensitive to rare seizure events, ensuring that both types of events are properly represented during training. This approach allowed the model to achieve higher sensitivity and specificity for seizure detection, which is critical for real-time clinical applications.

9.2.4 Computational Efficiency

NeuroCare was designed with computational efficiency in mind, ensuring that the system could be deployed in clinical or wearable settings where resources may be limited. The lightweight nature of the CNN-LSTM model, combined with the use of efficient preprocessing techniques, makes the system viable for real-time seizure detection and classification, even on devices with lower computational power, such as embedded systems or portable EEG monitoring devices.

9.3 Limitations of the Study

Despite the promising results, several limitations of the NeuroCare system must be acknowledged:

9.3.1 Dataset Limitations

The evaluation of the model was conducted on the BIDS Siena dataset, which provides a realistic representation of clinical EEG recordings. However, datasets that include more thoroughly cleaned EEG signals, particularly those that address various artifacts, were not evaluated. The presence of such artifacts could potentially affect the model's performance and limit its ability to generalize across different settings, especially in clinical environments where data quality can vary significantly.

9.3.2 Single Channel Processing

In this study, the model was limited to processing single-channel EEG signals. While this approach simplified the analysis, it also prevented the model from fully exploiting the spatial correlations that exist between multiple EEG channels across the scalp. Future work could extend the model to handle multichannel EEG data, allowing for more comprehensive spatial-temporal analysis and improving detection accuracy.

9.3.3 Deployment on Wearable Devices

While the model demonstrated efficient resource utilization during testing, further validation is needed to confirm its performance in real-world wearable device scenarios. Optimizing the model for real-time deployment on embedded systems or portable EEG monitoring devices remains a critical next step. This would involve additional testing on various hardware platforms to ensure the model's accuracy, reliability, and efficiency in continuous, real-time operation.

9.3.4 Clinical Interpretability and Explanation

Another challenge lies in the clinical adoption of the NeuroCare system, particularly regarding the interpretability of model decisions. While the system can accurately detect seizures, there is a need for clearer explanations of how and why the model arrives at certain decisions. This is crucial for ensuring that neurologists and clinicians can trust the system and integrate it effectively into their diagnostic workflows. Techniques such as explainable AI (XAI) could be incorporated to improve the transparency of the model's decision-making process.

9.4 Future Work Directions

Building on the current achievements, several directions for future research can be pursued to enhance the NeuroCare system:

9.4.1 Multichannel EEG Analysis

Future work should incorporate multichannel EEG data to provide a more complete spatial and temporal representation of brain activity. This would enhance the model's ability to detect seizures by leveraging spatial correlations between different regions of the scalp, potentially improving detection accuracy and reducing false positives.

9.4.2 Refinement of Preprocessing Techniques

Further refinement of preprocessing techniques is necessary to improve the system's robustness to artifacts commonly encountered in real-world EEG recordings. This includes reducing movement artifacts, electrode noise, and other interference that may distort the EEG signals. Developing more advanced artifact removal techniques could significantly improve the quality of the input data and, in turn, the accuracy of seizure detection.

9.4.3 Hardware Deployment

To fully realize the potential of the NeuroCare system in clinical or home settings, the model needs to be optimized for deployment on portable or embedded EEG monitoring devices. This will involve optimizing both the model's performance and its memory and computational efficiency, ensuring it can operate in real time on low-resource devices without compromising accuracy.

9.4.4 Explainability and Clinical Trust

Including explainability techniques will be crucial for enhancing clinical trust in the system. By providing neurologists with interpretable insights into the model's predictions, the system can become more integrated into clinical decision-making processes. Methods like saliency maps, model-agnostic explanations, and rule-based systems could be explored to offer clinicians a better understanding of how the model interprets EEG data.

9.4.5 Dynamic Model Adaptation

Another promising direction for future research is the dynamic adaptation of the seizure detection model based on individual patient characteristics. Customizing the model to each patient's EEG profile could further improve its accuracy and reliability, as seizure patterns can vary significantly across patients. Transfer learning and domain adaptation techniques could be employed to ensure that the model remains effective as it adapts to different patients' unique EEG patterns.

9.5 Final Remarks

The development of hybrid deep learning models, such as the CNN–LSTM architecture employed in NeuroCare, has demonstrated significant potential for revolutionizing the treatment of epilepsy. This work represents a critical step forward in the integration of AI-driven solutions into the daily monitoring and management of epilepsy patients. By providing real-time, accurate, and automated seizure detection, NeuroCare can alleviate the burden on clinical staff and enhance patient outcomes. The continued improvement of the system's generalization, interpretability, and portability will be crucial in facilitating its widespread adoption and ensuring its impact on both clinical practice and patient care.

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