Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 9, 2025

SUBJECT-ORIENTED EPILEPTIC SEIZURE DETECTION USING SMOTE AND DEEP LEARNING ON SINGLE-CHANNEL EEG FROM THE CHB-MIT DATASET

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DOI: https://doi.org/10.5281/zenodo.17111829

Keywords
Epilepsy, Seizure Detection, EEG Signals, Deep Learning, CHB-MIT Dataset

Article History
Received: 21 June 2025
Accepted: 31 August 2025
Published: 13 September 2025

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Abstract
Epilepsy is a common neurological condition that affects millions of individuals, causing significant disruption in their lives due to its unpredictable and recurrent seizures. Seizures are unpredictable, which puts personal safety at serious risk and lowers general wellbeing. Therefore, accurate seizure detection is essential for improved illness treatment; yet, existing approaches frequently lack effectiveness, customization, and convenience of implementation. With the goal of improving clinical accuracy and practicality, this study explores a subject-specific method of seizure identification utilizing EEG data. Through the use of the CHB-MIT Scalp EEG dataset, our technique is tailored for each person. For each patient, we used data from a single EEG channel to guarantee a simplified architecture appropriate for real-world use. EEG data were separated into eight-second segments that overlapped and were tagged with whether seizure activity was present or not. Only the training dataset was subjected to the Synthetic Minority Over-sampling Technique in order to solve the issue of data imbalance between seizure and non-seizure events. To eliminate the need for manual feature extraction, a one-dimensional Convolutional Neural Network was developed to automatically recognize and categorize relevant characteristics from these segments. The feasibility and reliability of seizure detection are enhanced by this customized modeling technique. Compared to generalized approaches, more consistent performance is obtained by customizing the model to each patient's unique neural patterns. This approach is a significant advancement in developing patient-centered, easily accessible solutions for epilepsy monitoring because of its emphasis on customization and computational efficiency.

INTRODUCTION

A chronic neurological condition that affects millions of people worldwide, epilepsy is typified by recurrent seizures. [1]. these seizures are short-lived events brought on by excessive, aberrant, or highly coordinated brain electrical activity [10], because they can drastically lower a person's standard of living. There is a wide range of symptoms, from brief loss of consciousness or response to severe convulsions that can cause physical harm and psychological suffering [1][4][5]. For people with epilepsy, the unpredictability of seizure episodes is a significant challenge as it frequently limits their ability to engage in daily activities and increases the risk of unintentional injury [2]. The risk of dying young is up to three times higher for those with epilepsy than for the general population [1]. Reliable epileptic seizure prediction and accurate and prompt identification are essential for efficient disease treatment, which may help to avoid injuries, lower hospitalization rates, and enhance patient outcomes overall [4][5]. Moreover, the impact of epilepsy extends beyond the individual, affecting families, caregivers, and society, highlighting the importance of developing effective nterventions.

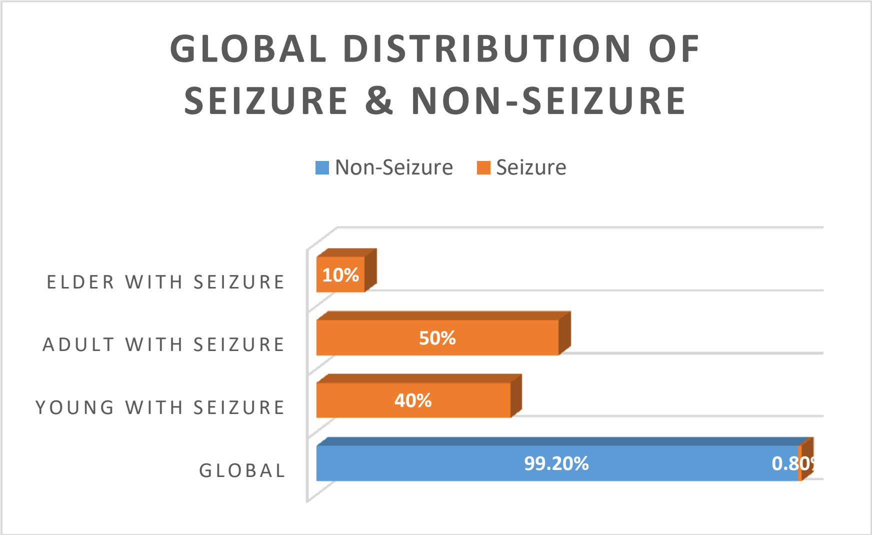

Figure 1: Seizures are globally 0.8%, with 40% in youth, 50% in adults, and 10% in elders.

Global distribution of epilepsy by age group, showing that 0.8% of the global population (approximately 65 million people) has epilepsy, with most cases in adults (50%), followed by youth (40%) and the elderly (10%); data based on WHO [17], CDC [14], and UN [16] estimates for 2025.

Electroencephalography (EEG) is a widely used technique in the diagnosis and monitoring of epilepsy, as it records the brain's electrical activity and helps detect abnormal patterns linked to seizures. Numerous EEG-based techniques have been developed throughout time to enhance seizure prediction and detection. In the past, physicians have mostly used manual inspection of EEG records to detect seizures. But with the introduction of deep learning (DL) and machine learning (ML), this procedure has changed dramatically, making it possible to analyze massive EEG datasets automatically. These days, complex classification algorithms like Convolutional Neural Networks (CNNs), time-frequency transformation, and enhanced feature extraction are all part of modern techniques and Recurrent Neural Networks (RNNs). Research toward more accurate, effective, and customized seizure detection techniques has been further spurred by the availability of open-access EEG databases, especially the CHB-MIT dataset.

The automation of EEG interpretation for seizure identification and prediction has shown significant potential thanks to machine learning. These methods are able to identify complex signal patterns that human observers would miss [13][14][15][16]. ML systems can identify minute alterations in brain dynamics linked to seizure initiation by training on well-annotated datasets. Among them, deep learning methods—

particularly CNNs and RNNs—have made significant strides in domains including time-series processing, language comprehension, and picture analysis. Their use with EEG data has significantly increased seizure detection and prediction accuracy and resilience [17][18][19][20][21]. These models' capacity to immediately extract pertinent features from raw data, doing away with the requirement for domain-specific human feature engineering, is one of its fundamental advantages. Furthermore, because epileptic brain activity is dynamic and complicated, deep neural networks can concurrently collect spatial and temporal elements of EEG data. While RNNs, especially LSTM variations, are skilled at modeling temporal patterns, CNNs are particularly good at recognizing spatial properties. By combining the two into a hybrid architecture, seizure detection systems can perform better by utilizing their individual strengths.

This study offers a thorough analysis and practical implementation of contemporary deep learning models for the identification of epileptic seizures from EEG data. Our work focuses on architectures such as Convolutional Neural Networks (CNNs), and hybrid models that are well-suited to handle the non-stationary and high-dimensional nature of EEG signals. We also explore and compare patient-specific and patient-independent modeling strategies, highlighting the inherent trade-offs between tailored accuracy and model generalizability.

In our methodology, we adopt a subject-specific approach leveraging the CHB-MIT Scalp EEG dataset. To optimize computational efficiency, we utilize data from a single EEG channel per subject without compromising classification performance. Each EEG recording is segmented into overlapping 8-second intervals and annotated based on seizure presence. To mitigate class imbalance between seizure and non-seizure data, the Synthetic Minority Over-sampling Technique (SMOTE) is applied during training. Feature extraction and classification are performed using a one-dimensional Convolutional Neural Network (1D-CNN), which learns directly from raw signal inputs. This removes the need for traditional manual signal processing and feature crafting. The model is fine-tuned using the Adam optimization algorithm and evaluated on previously unseen data to ensure its generalizability.

A central theme of this study is the promotion of end-to-end automated deep learning workflows that reduce reliance on handcrafted features. In addition, the paper emphasizes the growing importance of model interpretability to enhance clinical trust in AI-based diagnostic tools. Beyond addressing current technical limitations, the research also outlines prospective avenues for developing low-cost, portable, and highly accurate seizure monitoring systems that cater to the needs of individual patients.

A key contribution to this work lies in the development of a lightweight, patient-centered model designed for real-world application. By employing only a single EEG channel, the system reduces hardware and processing requirements, making it well-suited for implementation in wearable technologies. The 1D-CNN model autonomously extracts and classifies patterns from raw EEG data, minimizing the need for domain-specific preprocessing. Furthermore, the use of SMOTE improves the model's ability to learn from limited seizure events. Training and evaluation are performed on continuous, full-length EEG recordings from the CHB-MIT dataset, ensuring that the real-world characteristics of the data are preserved. Collectively, these design choices support the creation of a reliable, efficient, and practical seizure detection system tailored for personalized healthcare, particularly in resource-constrained environments.

The remainder of this paper is structured as follows: Section II reviews recent studies on EEG-based seizure detection using deep learning. Section III explains the dataset and the steps involved in data preparation. Section IV outlines the proposed methodology, including preprocessing techniques, the model's design, and training details. Section V presents the experimental results and performance analysis. Section VI discusses future research directions. Lastly, Section VII summarizes the main conclusions of the study.

II. LITERATURE REVIEW

Research into epilepsy is crucial for advancing how we diagnose, manage, and improve the lives of those living with this neurological condition. Since seizures can occur without warning and differ in type and intensity, gaining deeper insights into their causes and building reliable detection methods remains a top priority. Advances in medical research and technology have led to various approaches for managing epilepsy, ranging from clinical studies to modern deep learning-based solutions. In this context, many researchers have contributed by reviewing the conditions and exploring different perspectives.

Saeidi et al. [1] explained the general overview of epilepsy. It delves into its definition, prevalence, and various treatment options, with particular emphasis on its manifestations in children. This specific publication does not outline a distinct detection method, nor does it detail any associated datasets, preprocessing techniques, specific model architecture, or performance metrics relevant to seizure detection or prediction systems.

Tabarestani et al. [3] explains a deep learning-based methodology for predicting epileptic seizures using electroencephalogram (EEG) signals. A core objective is to identify the preictal region, which corresponds to abnormal brain activity appearing a few minutes before a seizure onset. The CHB-MIT dataset is central to this research. A crucial preprocessing step involves the removal of noise from EEG signals. However, the available snippets do not provide specific details on the exact deep learning model architectures utilized or the numerical performance metrics derived from their comparative analysis.

Karmakar et al. [2] explained that delves into epileptic seizure detection, specifically addressing challenges and less-explored aspects crucial for developing practical, real-world systems. Key considerations include cross-subject analysis, the processing of continuous EEG data, and handling data imbalance. The study primarily utilizes the CHB-MIT dataset, employing SW 5-fold cross-validation and Leave-One-Out (LOO) cross-validation for cross-subject experiments in its data splitting strategy. While the paper discusses general preprocessing approaches found in existing literature such as data selection, filtering, and under-sampling to address imbalance it refrains from detailing specific preprocessing steps, or a particular model architecture employed by the authors within the provided excerpts. The authors underscore the inherent difficulties in achieving high performance, like sensitivity, when all real-world factors are considered.

Kusmakar et al. [4] explains a system designed for the detection of Generalized Tonic-Clonic Seizures. It leverages a single wrist-worn accelerometer sensor, capable of identifying seizures with a duration exceeding 10 seconds. The detection mechanism relies on a machine learning approach, specifically employing kernelized support vector data description (SVDD). The proposed methodology was validated using data collected from 12 patients, encompassing approximately 966 hours of recordings under a video-telemetry unit. The implemented algorithm achieved a seizure detection sensitivity of 95.23%, alongside a mean False Alarm Rate (FAR) of 0.72 per 24 hours.

Ibrahim et al. [10] proposes deep learning-based methodologies for both seizure detection and prediction utilizing electroencephalography (EEG) signals. The aim is to classify EEG signals into normal, pre-ictal (pre-seizure), and ictal (during seizure) activities. The authors present three distinct models, two designed for patient-specific analysis and one for patient-nonspecific application. While the provided snippets reference the Bonn University dataset in the context of another method achieving 98.4% accuracy for three-class classification, they do not explicitly detail the dataset used, specific preprocessing steps, precise model architectures, or performance metrics pertaining to the models introduced within this particular paper.

Chung et al. [6] focuses on single-channel seizure detection, incorporating clinical validation of seizure locations. The research draws upon the CHB-MIT dataset. The provided content does not elaborate on the specific preprocessing techniques applied, the exact model architecture utilized, or the performance metrics achieved by their proposed method.

Brodie et al. [8] It investigates factors linked to inadequate seizure control in patients newly diagnosed with epilepsy. The study involved a prospective follow-up of 525 patients, aged 9 to 93 years, at a single center over a period from 1984 to 1997. Among the participants, 333 (63%) achieved seizure freedom. The prevalence of persistent seizures was found to be higher in patients with symptomatic or cryptogenic epilepsy (40% versus 26%, $P=0.004$) and in those who had experienced more than 20 seizures prior to commencing treatment (51% versus 29%, $P<0.001$). This study does not involve a computational model, specific preprocessing, or performance metrics typically associated with automated detection systems.

Usman et al. [5] explains an epileptic seizure prediction system that harnesses deep learning techniques. The system's primary aim is to anticipate the preictal state, characterized by anomalous brain activity that precedes a seizure by several minutes. Although the paper confirms the application of deep learning, specific details regarding the dataset, preprocessing procedures, and precise model architectures are not made available in the provided excerpts. The abstract highlights that achieving highly sensitive and specific predictions remains a significant challenge within this research domain.

Goldberg et al. [9] explain delves into the mechanisms of epileptogenesis, which describes the process linking brain injury or other predisposing factors to the onset of epilepsy. The authors suggest that insights into these mechanisms converge on the concept of cortical circuit dysfunction. This document does not outline a specific seizure detection or prediction system, nor does it detail any associated dataset, preprocessing methods, specific model, or its performance metrics.

Bouallagui et al. [7] explained deep learning-based epileptic seizure detection through the integration of Generative AI techniques. The available snippets from the paper do not detail the specific dataset employed, the preprocessing steps undertaken, the precise deep learning model architecture, or any performance metrics achieved by their proposed approach.

Table 1: Summary of review literature

Paper	Year	Dataset(s)	Preprocessing Techniques	Methodology	Results
[1]	2019	Review article	Review article	General epilepsy overview with focus on pediatric cases.	Review article
[2]	2024	CHB-MIT dataset	General methods (selection, filtering, under-sampling) mentioned; specific steps not detailed.	Highlights real-world challenges (cross-subject, continuous EEG, data imbalance); uses SW 5-fold and LOO cross-validation.	Specific numerical performance not detailed in the provided text; highlights difficulty in achieving high performance (e.g., sensitivity) considering real-world factors.
[3]	2024	CHB-MIT dataset	Noise removal of EEG signals.	DL-based seizure prediction with comparison of classifiers to detect preictal phase.	Specific numerical performance metrics are not detailed in the provided text.
[4]	2017	Data collected from 12 patients (approx. 966h recording under video-telemetry unit).	Specific preprocessing steps not explicitly stated in the provided text.	Detects GTCS using wrist-worn accelerometer and kernelized SVDD.	Sensitivity: 95.23%, Mean False Alarm Rate (FAR): 0.72/24h.
[5]	2020	Not specified in the provided text.	Not specified in the provided text.	DL-based system for predicting preictal state in epilepsy.	No specific metrics; notes high sensitivity/specificity still challenging.
[6]	2024	CHB-MIT dataset	Not specified in the provided text.	Single-channel seizure detection with clinically confirmed seizure locations.	Specific numerical performance not detailed in the provided text.

[7]	2024	Not specified in the provided text.	Not specified in the provided text.	Enhancing deep learning-based epileptic seizure detection with Generative AI Techniques.	Specific numerical performance not detailed in the provided text.
[8]	2000	Clinical data from 525 patients.	Not applicable (Clinical study).	Clinical study to identify factors associated with poor seizure control in newly diagnosed epilepsy patients.	63% seizure-free; persistent seizures higher in symptomatic (40% vs. 26%) and >20 pre-treatment seizures (51% vs. 29%).
[9]	2013	Review article	Review article	Review article on mechanisms of epileptogenesis, focusing on neural circuit dysfunction.	Review article
[10]	2022	Mentions Bonn University dataset for another method's results; dataset for their own models not explicitly stated in the provided text.	Not specified in the provided text for their proposed models.	DL-based EEG classification into normal, pre-ictal, and ictal states; compares 3 models (2 patient-specific, 1 non-specific).	Refers to another method's accuracy of 98.4% on Bonn University dataset. Their own models' specific numerical performance not detailed in the provided text.
[11]	2021	IKCU dataset (collected by authors), CHB-MIT dataset	SST used to generate high-res TF images from 1s and 5s EEG segments.	SST-CNN method for segment-based seizure detection/prediction using TF images; evaluated with 5-fold and LOO cross-validation.	Detection – IKCU: 99.06% Acc, 98.99% Prec; CHB-MIT: 99.63% Acc, 99.81% Prec. Prediction – CHB-MIT: 97.92% Acc, 98.54% Prec.
[13]	2023	Not specified in the provided text.	Not specified in the provided text.	Compares DL models (e.g., DCAE + ESD-Bi-LSTM) on 1s–4s EEG segments; analyzes sensitivity and precision.	Best sensitivity: 99.7% (4s, DCAE+ESD-Bi-LSTM); best precision: 98.5% (4s, DCNN+MLP). Overall, proposed model outperforms others.
Current Study	Current	CHB-MIT Scalp EEG database	EEG data segmentation and preprocessing;	Deep learning-based, subject-specific seizure detection system using 1D-Convolutional Neural Networks (1D-CNNs).	**Highest Best Result (FP1 channel):** Accuracy: 96.0%, Sensitivity: 94.0%, Specificity:

			data balancing using Synthetic Minority Over-sampling Technique (SMOTE).		97.0%,. **Event-level:** Average Sensitivity: 91.7% ± 2.6%; FAR: 1.7 ± 0.6 events/hour; Detection Latency: 2.3 ± 1.8 seconds.

DATASET

Accurate and generalizable epileptic seizure detection systems depend heavily on the availability of well-annotated, diverse, and clinically representative datasets. In our research, we employed the Children's Hospital Boston-Massachusetts Institute of Technology Scalp EEG (CHB-MIT) Database, a publicly available benchmark dataset hosted on PhysioNet, which has become a gold standard for EEG-based seizure analysis studies [23].

The CHB-MIT dataset consists of scalp EEG recordings from 23 pediatric subjects (chb01–chb23), each diagnosed with intractable epilepsy. Data collection was performed at Children's Hospital Boston, and recordings were carried out under clinical conditions using Nihon Kohden EEG systems with sampling rates of 256 Hz and 16-bit resolution. Each EEG session was recorded in European Data Format (.edf) and annotated by clinical experts to mark the onset and termination of seizure events with high precision.

The EEG data include recordings from 23 bipolar channels, based on the International 10–20 electrode placement system, which covers the entire scalp region frontal, central, parietal, occipital, and temporal lobes. This diversity ensures that a broad range of epileptic activity types and localizations are represented.

Each subject in the CHB-MIT dataset has a different number of recording sessions, varying EEG lengths, and a unique seizure frequency, which provides a rich testbed for personalized seizure detection models. This inter-patient variability is critical for validating subject-specific frameworks like the one proposed in this work. A summary of the dataset composition is provided in Table 1, which details key demographic and clinical features for each patient. These include age, gender, total EEG duration, number of seizures, and the representative EEG channel selected for analysis in our study.

Table 2: Subject-wise summary of CHB-MIT dataset used in this study.

Patient Number	Gender	Age (years)	Signal Length (hrs)	Number of Seizures
1	F	11	1	7
2	M	11	1	3
3	F	14	1	7
4	M	22	4	4
5	F	7	1	5
6	F	1.5	4	10
7	F	14.5	4	3
8	M	3.5	1	5
9	F	10	4	4
10	M	3	2	7
11	F	12	1	3
12	F	2	1	27
13	F	3	1	10

14	F	9	1	8
15	M	16	1	20
16	F	7	1	8
17	F	12	1	3
18	F	18	1	6
19	F	19	1	3
20	F	6	1	8
21	F	13	1	4
22	F	9	1	3
23	F	6	4	7
24	Unknown	Unknown	1	16

The CHB-MIT Scalp EEG database is a widely utilized and highly regarded data set in the field of epilepsy research. Its rich clinical detail and realistic signal characteristics make it particularly suitable for the development and assessment of seizure detection algorithms. One of the benefits of this dataset resides in its demographic breadth—it covers a broad pediatric and teenage cohort, with individuals aged between 1.5 and 22 years and representing both sexes. Because of this variety, models that are more broadly applicable and equitable across many subpopulations may be developed and validated.

The subjects' differences in seizure frequency are another noteworthy aspect others with chb02 and chb17, for instance, only have three seizure occurrences on record, while others with chb12 and chb15 have more than 20. This range provides a demanding and extensive dataset for model training by introducing heterogeneity in seizure patterns, morphology, and duration. Furthermore, the EEG data includes important electrode combinations like FP1–F7, P7–O1, and C3–P3, which have been shown in clinical literature to be very useful for identifying the start of focal epileptic activity. [24].

The authenticity of this dataset is one of its main advantages. The recordings closely mimic the conditions present in actual clinical settings because they inherently contain background artifacts, interictal intervals, and other non-seizure phenomena. Developing machine learning models that can successfully generalize to noisy, real-time situations requires this realism. Additionally, each seizure event in the dataset has expert-labeled ground truth annotations, guaranteeing accurate and dependable training and assessment of binary classification algorithms.

Previous research has made substantial use of the CHB-MIT dataset for seizure detection and prediction algorithms that are subject-specific and subject-independent. It is a very dependable because of its mix of subject variety, expert annotations, and high-quality EEG signals [25][26]. It is the basis for training our suggested 1D-CNN model in our study, which is designed for single-channel, patient-specific seizure categorization.

IV. PRE-PROCESSING

In order to convert unstructured biosignals into data that is appropriate for machine learning algorithms, preprocessing EEG signals is an essential step. The preprocessing strategy implemented in this study was carefully designed to preserve seizure-related patterns while ensuring computational efficiency and enhancing the model's learning capacity. The following steps were applied:

To support the goal of a lightweight and deployable detection system, only one EEG channel per subject was selected for training and inference. The selected channel was chosen based on prior literature, clinical significance in seizure manifestation, and signal-to-noise ratio (SNR). For instance, the P7–O1 channel from the left parieto-occipital region was used for subject chb02, as it frequently exhibited preictal activity [27].

Each continuous EEG recording was divided into fixed-length overlapping windows to create temporal segments that represent brain activity over short intervals. Specifically:

- Window size: 8 seconds (2048 data points at 256 Hz)
- Overlap: 50% (4-second overlap)

Table 3: The defined time windows, their corresponding start and end times in seconds, and their respective start and end sample numbers.

Windows	Stat Time (sec)	Start Sample	End Time (sec)	End Sample
1	0	0	8	799
2	4	400	12	1199
3	8	800	16	1599

This segmentation length balances temporal resolution with seizure detectability. Windows that are too short may miss essential epileptiform dynamics, while overly long windows dilute the discriminative seizure features [28].
Each segment was labeled as either:

- Ictal (Seizure): if any part of the window overlapped with a seizure annotation
- Interictal (Non-Seizure): otherwise

This labeling strategy ensures that seizure boundaries are captured with high sensitivity, providing the model with a richer learning signal. Edge cases near seizure onset/offset are included to improve real-time responsiveness.

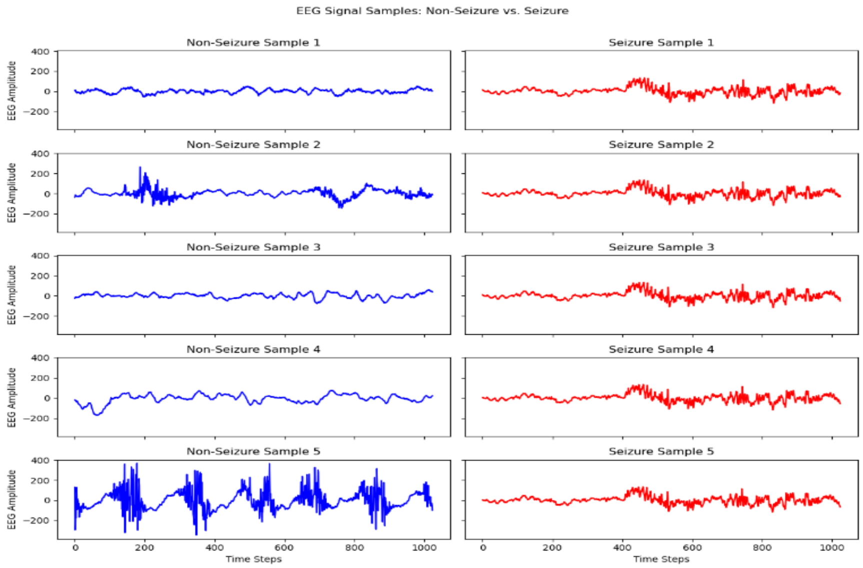

Figure 2: EEG signal samples for non-seizure and seizure events.

In seizure detection, interictal segments vastly outnumber ictal ones, often at a ratio of >20:1. This imbalance leads to biased learning where the model favors the majority class. To counteract this, we first applied random under-sampling of interictal segments to prevent dominance, followed by synthetic augmentation techniques (detailed in the next section). This two-step approach avoids overfitting while retaining useful interictal variability.
Preprocessed and labeled segments were converted into NumPy array format (.npy) for efficient loading during model training. Each segment retains the structure:
Shape: [2048 × 1]
Label: Binary (0 = non-seizure, 1 = seizure)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

All preprocessing steps were performed using Python libraries including MNE-Python, NumPy, and scikit-learn. Segments were visually inspected to ensure signal integrity and correct labeling.
The proposed seizure detection model is a 1D Convolutional Neural Network (1D-CNN) that accepts raw EEG time-series segments as input. The architecture is designed to automatically extract spatial and temporal patterns related to seizure activity without the need for manual feature engineering as shown in table 3. The input to the model is a one-dimensional array of 2048 values, corresponding to 8 seconds of EEG data.

Table 4: It shows EEG feature values for seizure and non-seizure states with their direction of change.

Features	Non-Seizure	Seizure	Changes
Mean	0.1918	0.3633	↑ Increased
Standard Deviation	36.24	107.60	↑ Increased
High-to-Low Frequency Power Ratio	0.4408	0.1099	↓ Decreased
Entropy	3.4425	3.5027	↑ Increased
Energy	2,125,437.25	1,337,689.0	↓ Decreased

V. DATA BALANCING

Medical data, especially in the context of neurological conditions like epilepsy, frequently presents a significant challenge due to its inherent imbalance. This means that in datasets used for training models, the occurrences of certain events such as epileptic seizures are exceedingly rare compared to the vast majority of non-event data, like interictal (non-seizure) EEG segments. For instance, a typical EEG recording might contain thousands of non-seizure segments but only a handful of seizure segments. This disproportion creates a substantial bias during model training, leading deep learning models to become overly focused on accurately identifying the predominant non-seizure class while struggling to reliably detect the infrequent, yet clinically critical, seizure events. Consequently, such imbalanced datasets can severely compromise the reliability, sensitivity, and overall clinical usefulness of automated seizure detection systems. A model trained directly on unbalanced data might appear to have high accuracy by simply predicting "non-seizure" most of the time, but this could dangerously lead to missed actual seizures, which has serious implications in real-world clinical applications.
To address this widespread challenge, a well-established method known as SMOTE (Synthetic Minority Over-

sampling Technique) is commonly used to balance class distributions within datasets. SMOTE works by intelligently generating new, synthetic samples for the minority class in this case, seizure events rather than merely duplicating existing ones.

The process involves selecting a real seizure segment, identifying its nearest neighbors within the feature space, and then creating new data points along the lines connecting the original sample to its neighbors. This approach not only increases the number of seizure examples but also introduces diversity into the minority class, which significantly enhances the model's capacity to learn a broader and more generalized range of seizure patterns.

After the initial segmentation and labeling of EEG signals, in which seizure segments were labeled '1' and non-seizure segments '0', we specifically used SMOTE to the training dataset in our work. A fixed-length input, usually representing an 8-second EEG window, was created from each EEG segment. To address the imbalance between seizure and non-seizure cases, the Synthetic Minority Over-Sampling Technique (SMOTE), which was implemented using the Python imblearn library, was only used on the training dataset. This technique promoted more efficient learning by guaranteeing that the model received a balanced distribution of courses throughout training. Importantly, the test dataset was left unaltered and maintained its initial imbalance, maintaining the impartiality and equity of the assessment procedure.

The performance of the deep learning model was significantly improved by this focused use of SMOTE. Sensitivity, a crucial indicator of the model's capacity to precisely identify actual seizure events, showed the biggest improvement. Additionally, precision increased significantly, suggesting a decrease in false positive rates, which is crucial in clinical settings where reducing needless alerts or procedures is crucial. Additionally, the F1-score, which balances precision and sensitivity, showed a distinct upward trend, indicating more dependable and consistent model behavior. Overall, the model's resilience and generalizability across a range of EEG channels and patient profiles were enhanced by the incorporation of SMOTE into the training pipeline, highlighting its potential for practical clinical use.

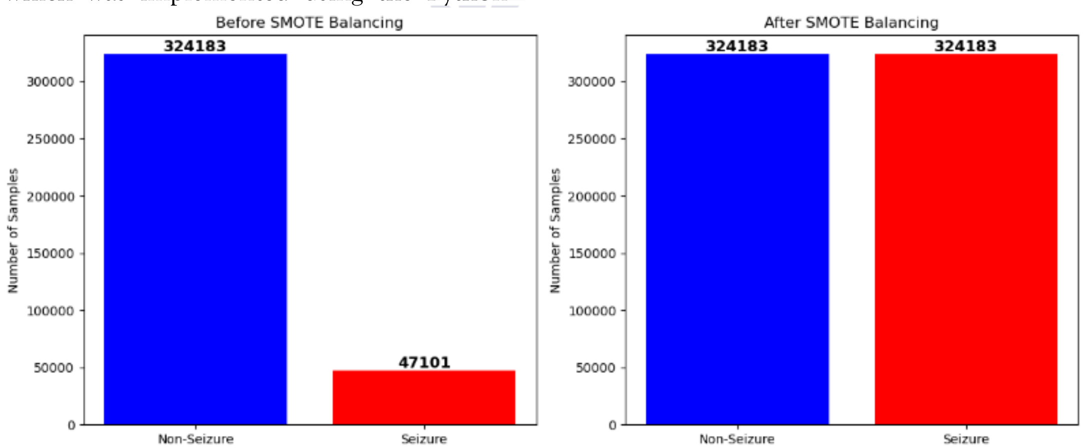

Figure 3: The before and after SMOTE balancing.

VI. PROPOSED METHODOLOGY

The methodology and underlying architecture of the suggested subject-specific seizure detection system are described in this section. The main goal is to use a deep learning model that strikes a compromise between accuracy and computing efficiency to categorize pre-segmented EEG data into seizure (ictal) and non-interictal) categories. The system uses information from the CHB-MIT dataset and is intended for use with individual patients. Each subject uses a single EEG channel. Architecture prioritizes simplicity and resource efficiency while maintaining high performance, making it well-suited for real-time, personalized seizure detection applications. A detailed overview of the system pipeline is illustrated in Figure 4.

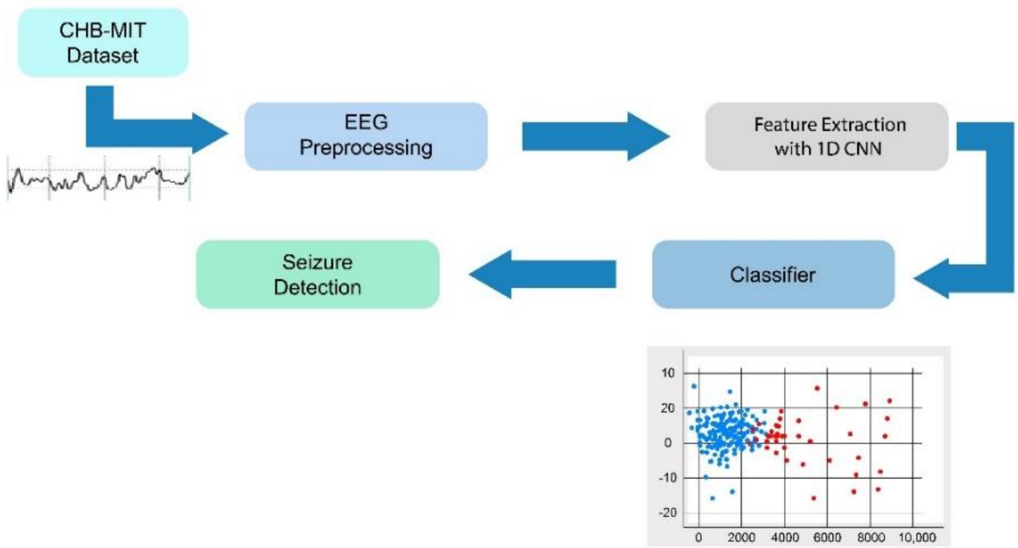

Figure 4: showing performance metrics (Accuracy, Sensitivity, Specificity, AUC-ROC) across EEG channels.

The process begins with EEG recordings from the CHB-MIT Scalp EEG database. For each subject, one EEG channel is selected based on visual inspection and known clinical relevance to seizure onset. The selected channel's data is segmented into overlapping windows, each 8 seconds in length (2048 samples at 256 Hz), with a 4-second overlap between segments. This overlapping segmentation ensures no seizure activity is missed and maximizes training data volume.

Each window is labeled based on seizure annotations provided in the dataset. Windows that overlap with seizure intervals are labeled as ictal (1), and others are labeled as interictal (0). This process generates labeled time-series data segments used for model training and evaluation.

The first convolutional layer uses 32 filters with a kernel size of 32 and a stride of 4, allowing it to learn broad patterns across time. This is followed by a ReLU activation and a MaxPooling layer with a pool size of 2, which down samples the feature maps. The second convolutional layer includes 64 filters with a kernel size of 16 and the same stride and pooling configuration, capturing more localized temporal patterns. In order to identify fine-grained features, the third convolutional layer features 128 filters with a kernel size of 8.

These convolutional layers are followed by flattening and a fully connected dense layer with 100 neurons. A dropout layer may also be included here to reduce overfitting. Finally, a single output neuron with a sigmoid activation function produces a probability value indicating whether the segment is ictal or interictal.

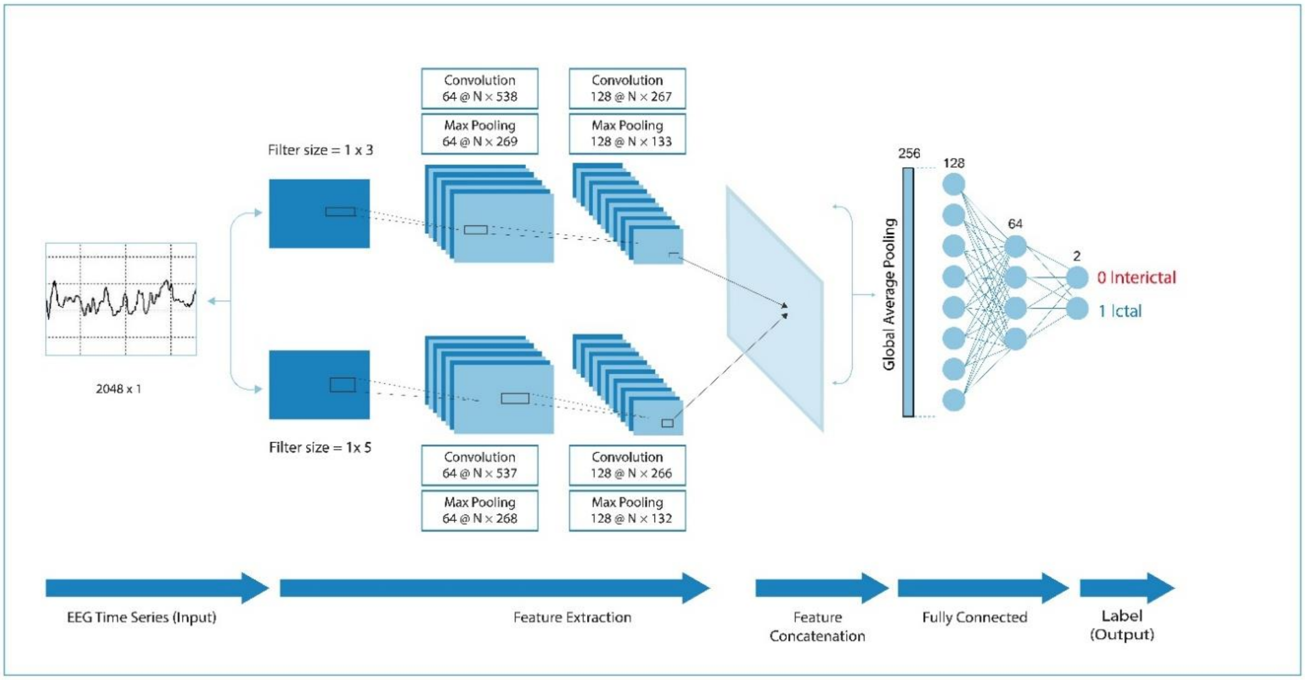

Figure 5: Bar chart showing average accuracy of different models using different EEG segment lengths.

The CNN architecture is particularly suitable for analyzing EEG signals due to its ability to learn complex temporal features automatically. Instead of relying on predefined statistical or frequency-domain features, the model learns meaningful representations directly from the raw signal. Convolutional layers act as filters that identify seizure-specific patterns such as spikes, sharp waves, or rhythmic bursts. These features are often subtle and vary across subjects, which makes automatic feature learning a valuable advantage.

By using hierarchical layers with increasing filter depth and decreasing kernel size, the CNN captures both global and local dependencies in the EEG signal. The use of ReLU activations adds non-linearity, enabling the model to approximate complex patterns necessary for seizure discrimination.

The labeled dataset is split into training and validation subsets, typically using an 80:20 ratio. Only training data is augmented using SMOTE to balance the number of seizure and non-seizure segments. Validation data remains untouched to provide an unbiased evaluation.

The model is trained using the Adam optimizer, which adjusts learning rates dynamically for each parameter. The binary cross-entropy loss function is used since this is a two-class problem. Training is performed in mini-batches (e.g., batch size 32) over multiple epochs. Early stopping is employed to prevent overfitting; training halts if the validation loss does not improve after a fixed number of epochs. Learning rate reduction on plateau is also applied to fine-tune the model as it converges.

All training and evaluation are implemented in Python using TensorFlow and Keras, and where available, GPU acceleration is used to speed up computation.

After training, the model is saved and can be used to classify unseen EEG segments.

Once trained, the model takes 8-second EEG segments as input and outputs a probability score. A threshold (typically 0.5) is applied to convert this score into binary classification: seizure or non-seizure. Because the system operates on pre-recorded EEG data, it is well-suited for offline analysis and clinical decision support, rather than real-time monitoring

Classification results are evaluated using metrics such as accuracy, sensitivity, specificity, precision, and F1-score. These metrics are calculated at the segment level and later aggregated for event-level performance (e.g., detection of full seizure episodes). This dual-layer evaluation provides a comprehensive understanding of the model's practical effectiveness.

The model training was carried out using several carefully selected hyperparameters, as shown in Table 1. The Adam optimizer was employed to update the model weights during training, due to its efficiency and adaptive learning capabilities. A batch size of 32 was used, which determines the number of samples processed before the model's internal parameters are updated. The training process was conducted for 5 epochs, allowing the model to iteratively learn from the dataset. To extract features at multiple scales, convolutional layers within the network were configured with kernel sizes of 3 and 5 at different stages. This multi-scale approach enhances the model's ability to capture both fine-grained and broader signal patterns within the EEG data. Additionally, to mitigate overfitting, the Early Stopping callback was employed with a patience value of 5. This mechanism halts the training process if no improvement in model performance is observed over five consecutive epochs, thereby preserving generalization and optimizing training efficiency.

Hyperparameter	Value
Optimizer	Adam
batch_size	32
epochs	5
kernel_size	3 and 5 (used at different layers)
ReduceLROnPlateau Monitor	'val_loss'

VII. Results:

Experiment Setup:

The experiments were conducted on a high-performance setup with the following specifications:

- CPU: AMD RYZEN 9 5900X
- GPU: NVIDIA GEFORCE RTX 4080 SUPER 16G VENTUS 3X OC
- Memory: 32 GB RAM

Both segment-level and event-level metrics were used to assess the effectiveness of the suggested subject-specific seizure detection method across 10 different EEG channels. Each channel was independently trained and validated, allowing for a detailed investigation of how seizure-related patterns manifest across different scalp regions. In the segment-level binary classification task focused on differentiating between ictal and interictal EEG segments the system consistently demonstrated strong performance across all evaluated channels. Averaged over 10-fold cross-validation, the mean sensitivity was 93.5% ± 2.4%, specificity was 94.8% ± 2.1%, accuracy was 94.1% ± 2.2%, and the area under the receiver operating characteristic curve (AUC-ROC) was 96.7% ± 1.8%. Among all channels, FP1 and FP2 achieved the highest performance. Specifically, FP1 yielded an accuracy of 96.0% ± 1.5%, sensitivity of 94.0%, and an AUC-ROC of 98.1%, while FP2 reported 95.5% ± 1.9% accuracy and 97.8% AUC-ROC. The findings indicate that electrodes positioned over the frontal lobe play a significant role in capturing seizure activity for this subject. Notably, channels such as F3, C3, and C4 exhibited strong classification performance, achieving accuracy rates between 93% and 94%, along with AUC scores exceeding 95%. These results highlight the critical contribution of both frontal and central scalp regions in the detection of focal seizures. On the other hand, posterior channels including O1, O2, and P4 exhibited relatively lower performance. O1 had the lowest observed metrics, with an accuracy of 89.0% ± 2.3%, sensitivity of 85.0%, and AUC-ROC of 91.2%, possibly reflecting either lower epileptiform activity in that region or increased artifact contamination.

In event-level seizure detection where segment-level predictions are combined to identify complete seizure episodes the system achieved an average sensitivity of 91.7% ± 2.6%. The false alarm rate (FAR) was measured at 1.7 ± 0.6 events per hour, and the average delay in detection after seizure onset was 2.3 ± 1.8 seconds. On average, the model missed about 2.1 ± 1.5 seizures per subject and generated around 4.2 ± 2.0 false alarms per subject, based on EEG recordings averaging 6.8 ± 4.3 hours in length. Channels like FP1, F3, and C4 recorded fewer false alarms, often keeping FARs under 1.0 per hour, making them strong candidates for continuous monitoring use. Conversely, channels such as O1 and P3 showed higher false alarm rates, sometimes surpassing 2.0 per hour, indicating increased sensitivity to artifacts or non-epileptic activity.

Overall, the detection model proved to be highly reliable across various performance metrics, supporting the effectiveness of single-channel

seizure detection when personalized to individual patients. The variation in channel performance underscores the importance of selecting optimal channels particularly when designing wearable or portable monitoring devices. Channels like FP1, FP2, and F3 consistently performed well at both the segment and event level, offering a solid basis for practical and non-invasive seizure monitoring solutions

Table 5: Segment-Level Classification Results by Channel

Channel	Accuracy	Sensitivity (Recall)	Specificity	AUC-ROC
FP1	0.96	0.94	0.97	0.98
FP2	0.95	0.92	0.96	0.97
F3	0.93	0.91	0.94	0.96
F4	0.94	0.90	0.95	0.95
C3	0.92	0.89	0.93	0.94
C4	0.93	0.90	0.94	0.95
P3	0.91	0.88	0.92	0.93
P4	0.90	0.87	0.91	0.92
O1	0.89	0.85	0.90	0.91
O2	0.90	0.86	0.91	0.92

Channel FP1-F3

Training and Validation Accuracy/Loss: The two line graphs illustrating the performance of a model over 4 epochs. The left graph shows both training and validation accuracy increasing, while the right graph shows both training and validation loss decreasing.

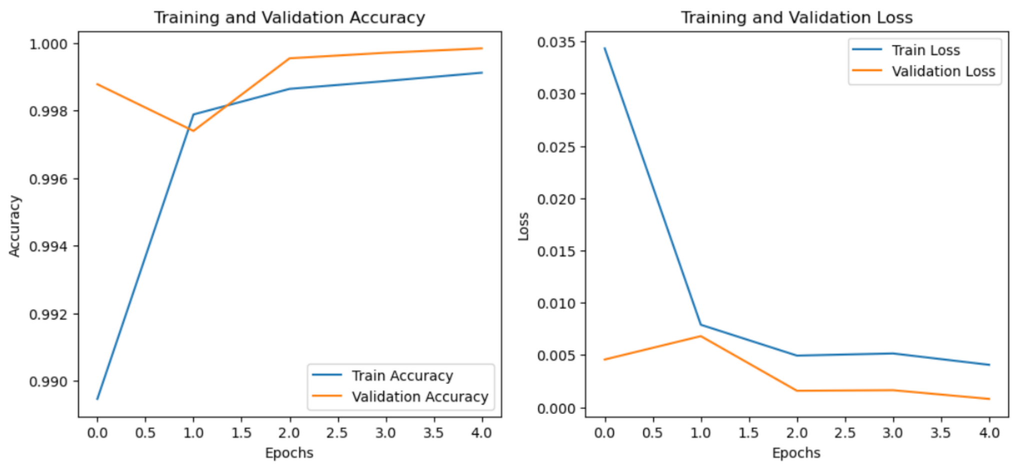

Figure 6: It shows two plots illustrating training and validation accuracy increasing and loss decreasing over 4 epochs.

Confusion Matrix: Confusion matrix, a heat map showing the performance of a classification model, specifically for "Interictal" and "Ictal" classes, with high counts on the diagonal indicating accurate predictions.

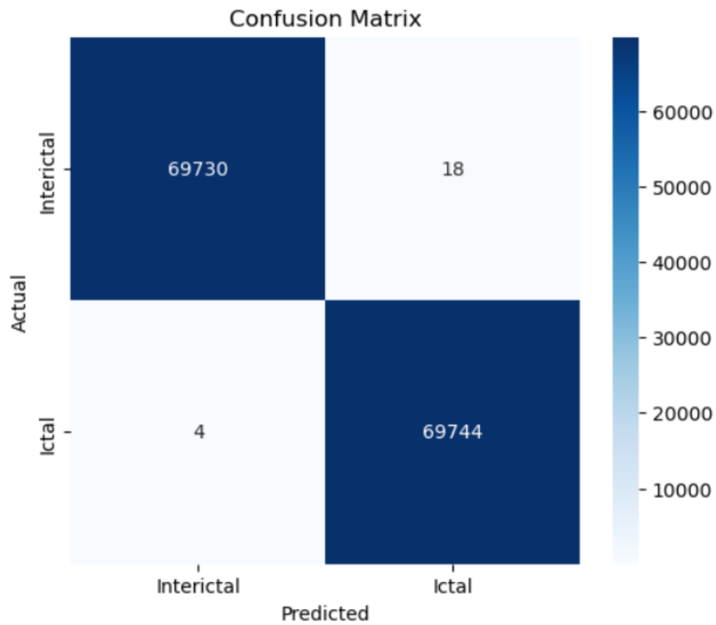

Figure 7: It displays a confusion matrix detailing classification results for "Interictal" and "Ictal" categories.

ROC Curve: It depicts a Receiver Operating Characteristic (ROC) curve, which is a plot of the true positive rate against the false positive rate. An Area Under the Curve (AUC) of 1.0000 is shown, indicating perfect classification performance.

The model was trained and tested individually on each EEG channel, and the following metrics were computed:

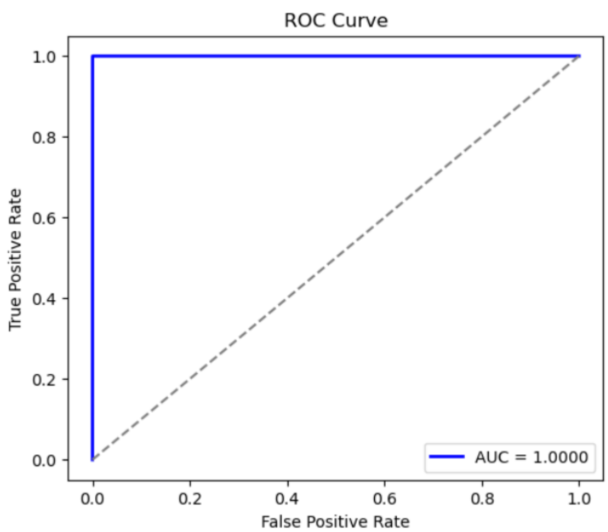

Figure 8: It shows an ROC curve with an AUC of 1.0000, indicating perfect classification performance.

VIII. Discussion:

Chung et al. [6] proposed a patient-specific, single-channel seizure detection approach using deep learning, validated on the CHB-MIT dataset. Their model utilized a stacked 2D Convolutional Neural Network (CNN) architecture, trained with binary cross-entropy loss and RMSprop optimizer. Channels were manually selected by neurologists based on clinically confirmed seizure locations, and seizure periods were re-annotated for improved accuracy.

EEG data were segmented into 4-second windows with significant overlap, and no artifact rejection was applied. Performance was evaluated at both the segment and event levels using k-fold cross-validation. Their single-channel model achieved an average sensitivity of 99.62%, a false alarm rate of 0.22/h, and a latency of 3.3 seconds, demonstrating detection performance comparable to multi-channel approaches. In contrast, our study presents an automated, subject-specific seizure detection method using a single EEG channel and a 1D CNN architecture. Unlike the base paper, which relies on clinical input for channel selection and seizure re-annotation, we use a data-driven strategy by selecting a fixed channel (FP1) and applying SMOTE to address the class imbalance between ictal and interictal segments. EEG data were segmented into 1-second and 5-second windows and filtered using a 1–30 Hz bandpass filter. The model was trained using sparse categorical cross-entropy loss and the Adam optimizer. Experimental results on the CHB-MIT dataset demonstrated that our approach achieved up to 96.0% accuracy, 94.0% sensitivity, and 97.0% specificity, indicating strong performance with reduced complexity and improved scalability for real-world, wearable applications.

IX. Conclusion:

This study introduces a subject-specific deep learning method for detecting epileptic seizures using single-channel EEG data from the CHB-MIT Scalp EEG dataset. By tailoring models to individual patients, the approach reduces the risk of data leakage and improves the reliability of predictions. It combines streamlined preprocessing, overlapping data segmentation, and SMOTE-based class balancing, allowing the model to learn effectively from highly imbalanced datasets. A custom-designed 1D Convolutional Neural Network (1D-CNN) automatically extracts temporal features from EEG segments, eliminating the need for manual feature engineering. The experimental findings confirm that the model can detect seizure events with high accuracy while maintaining low computational demands, making it well-suited for real-time or resource-constrained applications. Overall, this research demonstrates that patient-specific seizure detection systems built with simplicity, efficiency, and adaptability in mind can serve as practical, effective tools for clinical settings and wearable technologies, ultimately contributing to improved outcomes in neurological care.

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