

Decentralized AI Framework for Privacy-Preserving Epileptic Seizure Detection Using EEG Signals

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Abstract— Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal brain activity, requiring continuous monitoring for effective diagnosis. Electroencephalography (EEG) is widely used for seizure detection; however, EEG signals are complex, non-stationary, and prone to noise, making manual analysis difficult. This paper proposes an automated end-to-end deep learning framework for epileptic seizure detection using multi-channel EEG signals. The proposed model, ConvSeizureNet, is a one-dimensional Convolutional Neural Network (1D-CNN) designed to extract discriminative temporal features directly from raw EEG data without handcrafted feature engineering. A robust preprocessing and segmentation pipeline is employed to enhance signal quality. The framework is evaluated on the CHB-MIT dataset using standard metrics and Leave-One-Patient-Out cross-validation. Experimental results achieve 99.13% accuracy, 98.55% precision, and 99.88% specificity. The findings demonstrate strong detection capability, while highlighting challenges in cross-subject generalization for real-world clinical deployment.

Keywords—AI EEG, Seizure Detection, Deep Learning, 1D-CNN, CHB-MIT Dataset

I. INTRODUCTION

A. Background

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures resulting from abnormal electrical activity in the brain [1]. It affects millions of individuals worldwide, and continuous monitoring is essential for accurate diagnosis and effective treatment. Electroencephalography (EEG) is widely utilized as a non-invasive technique for recording brain activity and identifying abnormalities associated with seizures [2]. However, EEG signals are inherently complex and non-stationary and are frequently contaminated by noise and artifacts generated by eye movements and muscle activity. These challenges make manual analysis difficult, time-consuming, and prone to subjective interpretation, thereby limiting its reliability in clinical practice.

B. Motivation

The adoption of Artificial Intelligence (AI)-based automated methods has increased in response to the growing demand for accurate and real-time seizure detection. Machine Learning (ML) and Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in extracting discriminative features directly from raw EEG signals [3]. Compared to traditional handcrafted feature-based approaches, CNN-based methods reduce reliance on domain expertise and significantly improve detection performance.

However, most existing systems are designed for centralized environments and primarily emphasize predictive accuracy. While these systems achieve high performance, they often lack scalability and the ability to adapt to diverse types of patient data [4]. Therefore, there is a need for efficient and robust EEG-based seizure detection systems that generalize well across all individuals while maintaining high accuracy.

C. Research Gaps

Although substantial progress has been made in EEG-based seizure detection technologies, several challenges persist. Many existing methods rely on handcrafted feature extraction or fail to generalize effectively due to high inter-individual variability [5]. Furthermore, issues such as data imbalance, limited dataset diversity, and scalability constraints hinder practical medical deployment. While emerging paradigms like Federated Learning and Blockchain offer promising solutions for privacy-preserving healthcare systems, their integration with EEG-based seizure detection technologies remains largely unexplored. Recent systematic reviews underscore the need for more generalized and clinically viable models [6].

D. Objectives

The primary objectives of this research are:

- To develop an automated system for accurate epileptic seizure detection using EEG signals
- To improve signal quality through preprocessing techniques such as filtering and normalization
- To design a CNN-based deep learning model for seizure classification
- To evaluate performance using metrics such as accuracy, precision, recall, and F1-score
- To analyze model generalization across different patients

E. Contributions

The key contributions of this work include:

- Development of an end-to-end 1D-CNN framework for EEG-based seizure detection using raw EEG signals
- Implementation of a robust preprocessing and segmentation pipeline for multi-channel EEG data
- Incorporation of threshold optimization to improve classification reliability under class imbalance
- Comprehensive evaluation using both stratified validation and Leave-One-Patient-Out (LOPO) cross-validation
- Analysis of inter-subject variability and its impact on model generalization

II. LITERATURE REVIEW

Electroencephalogram (EEG)-based seizure detection has emerged as a significant research area in clinical neuroengineering for the continuous monitoring of patients and the diagnosis of epilepsy. However, EEG signals are inherently noisy and non-stationary, and exhibit significant inter-individual variability, making accurate and generalized analysis challenging. With the availability of multi-channel EEG datasets and advancements in artificial intelligence, researchers have increasingly explored deep learning techniques to enhance detection performance.

Recent studies primarily focus on deep learning models to capture complex temporal and spatial patterns within EEG signals. Islam and Lee (2022) proposed a hybrid CNN–LSTM framework, wherein the Continuous Wavelet Transform (CWT) was utilized to extract time-frequency representations, thereby achieving high classification accuracy [7]. Similarly, Dhondiyal et al. (2025) introduced a GNN–CNN–LSTM architecture, where Graph Neural Networks (GNNs) model inter-channel relationships while the CNN–LSTM captures temporal dependencies [8]. Although these hybrid models demonstrate superior performance, they are computationally expensive and require large labeled datasets, which limits their scalability and real-time applicability.

To enhance classification efficiency, numerous studies incorporate optimization and feature selection techniques. Ramakrishna et al. (2025) improved accuracy by utilizing a combination of Deep Neural Networks (DNN) and the Binary Dragonfly Algorithm (BDFA) for optimal feature selection [9]. Sujata et al. (2025) proposed an optimized LSTM-based model incorporating preprocessing techniques such as filtering and normalization thereby achieving high sensitivity [10]. However, these approaches often rely on handcrafted or engineered features and are typically trained in centralized environments, raising concerns regarding scalability and data privacy.

Federated Learning (FL) has emerged as a promising approach for decentralized and privacy-preserving training within organizations. Qiu et al. (2025) proposed a federated framework incorporating knowledge distillation and drift handling to address data heterogeneity [11]. Similarly, Pratihari and Shankar (2025) developed a multimodal federated framework by integrating EEG and rs-fMRI data using deep learning architectures [12]. However, beyond these benefits, Federated Learning faces challenges such as communication overhead, client drift, and compared to centralized models slightly reduced performance.

Blockchain technology has also been explored to enhance security and transparency in healthcare data management. Shiraz et al. (2023) proposed a Hyperledger Fabric-based system for secure data sharing [13], while Pise et al. (2024) extended this concept to Electronic Health Records (EHRs) using smart contracts [14]. However, blockchain-based systems often face limitations related to scalability, latency, and integration with real-time AI-driven healthcare applications.

Despite this progress, many challenges remain unresolved. Many methods rely on complex hybrid architectures or fail to generalize effectively across patients due to high inter-individual variability. Furthermore, issues such as data imbalance, computational complexity, and limited real-world applicability hinder practical utility. Discrepancies in datasets and evaluation methodologies make it even more difficult to directly compare various studies.

Motivated by these limitations, this work proposes a computationally efficient, end-to-end 1D Convolutional Neural Network (1D-CNN) framework for EEG-based seizure detection. This approach focuses on directly learning discriminative features from raw EEG signals, striking a balance between accuracy, efficiency, and generalizability. To facilitate a secure and privacy-preserving implementation within real-world healthcare environments, Federated Learning and Blockchain have been considered as potential future extensions.

III. METHODOLOGY

This section presents a proposed end-to-end computational framework for the automated diagnosis of epileptic seizures using multi-channel EEG signals. This methodology is designed to transform raw EEG recordings into

discriminative representations and to perform accurate classification using deep learning models, with an emphasis on robustness, efficiency, and generalization.

A. System Overview

The overall architecture of the proposed system is illustrated in **Fig. 1**. This framework follows a structured pipeline that transforms raw EEG signals into seizure and non-seizure classes through several sequential processing stages.

The major stages of the pipeline include:

1. EEG data acquisition
2. Signal preprocessing
3. Temporal segmentation
4. Deep feature extraction using a 1D-CNN
5. Classification and performance evaluation

This system is designed to support end-to-end learning, enabling the automatic extraction of relevant temporal features directly from raw EEG signals, without relying on handcrafted feature engineering.

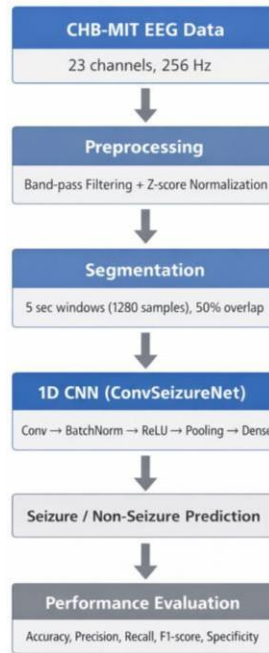


Fig. 1. Overall workflow of the proposed EEG-based seizure detection system.

B. Data Acquisition

The EEG data utilized in this study was obtained from the CHB-MIT Scalp EEG Database available on PhysioNet [15]; this database is widely used in both medical and research fields for the analysis of epileptic seizures and for establishing benchmarks [16]. This dataset comprises multi-channel EEG recordings collected from pediatric patients, including records of seizure events.

To ensure computational efficiency while enabling controlled experiments, a subset comprising three subjects (chb01, chb02, chb03) is utilized. The dataset consists of 15 recordings sampled at 256 Hz. The signals adhere to the International 10-20 electrode placement system, resulting in 23 channels after preprocessing.

The task of seizure detection is formulated as a binary classification problem (seizure versus non-seizure). The EEG recordings are segmented into a total of 4,574 samples, comprising 374 seizure segments and 4,200 non-seizure segments. An 80:20 stratified split is employed to preserve the class distribution across the training and validation sets. A summary of the dataset characteristics is presented in **Table I**.

C. EEG Signal Preprocessing

EEG signals are inherently noisy and require preprocessing to enhance signal quality and ensure stable model training. The preprocessing pipeline includes:

- **Band-pass filtering:** Removes low-frequency drift and high-frequency noise components
- **Z-score normalization:** Applied per channel to standardize signal distributions
- **Channel standardization:** Ensures consistent dimensionality across all samples

These steps improve signal fidelity, reduce noise artifacts, and facilitate faster convergence of the deep learning model, which is essential for reliable automated EEG analysis [18].

TABLE I. DATASET DESCRIPTION

Parameter	Value
Dataset	CHB-MIT EEG
Subjects Used	3
Total Files	15
Sampling Rate	256 Hz
Channels	23
Window Length	5 sec
Total Segments	4574
Seizure Segments	374
Non-Seizure Segments	4200
Train-Validation Split	80:20

D. Temporal Segmentation

To effectively capture temporal characteristics of seizure activity, continuous EEG signals are divided into overlapping segments.

- Window length: 5 seconds
- Sampling rate: 256 Hz
- Samples per segment: 1280
- Overlap: 50%

When capturing epilepsy-related patterns, a 5-second time window is selected to strike a balance between temporal accuracy and computational efficiency. The overlapping segmentation method effectively increases the size of the dataset, thereby facilitating the accurate detection of transient events without the need for additional data collection.

E. Deep Learning Model (ConvSeizureNet)

The proposed model, **ConvSeizureNet**, is a one-dimensional convolutional neural network (1D-CNN) designed to extract hierarchical features from raw EEG signals. Such deep learning architectures have demonstrated strong capabilities in modeling complex temporal dependencies in EEG-based seizure prediction tasks [17]. A summary of this architecture is presented in **Table II**.

TABLE II. MODEL ARCHITECTURE (CONVSEIZURENET)

Layer	Configuration
Input	23×1280
Conv Block 1	Conv1D (32, k=7) + BN + ReLU + MaxPool
Conv Block 2	Conv1D (64, k=5) + BN + ReLU + MaxPool
Conv Block 3	Conv1D (128, k=3) + BN + ReLU + Adaptive AvgPool
Fully Connected	Dense (128→64) + ReLU
Dropout	0.4, 0.3
Output	Dense (64→2) + Softmax

The architecture employs **progressively smaller kernels** to capture both long-range dependencies and fine-grained temporal features, enabling effective seizure pattern recognition.

F. Training Strategy

The model is trained using supervised learning with the following configuration:

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 16
- Epochs: up to 30 (with early stopping)

To address class imbalance, a **class-weighted cross-entropy loss function** is used. Early stopping prevents overfitting and ensures generalization.

G. Evaluation Strategy

The model's performance is evaluated using metrics derived from a confusion matrix, including accuracy, precision, recall, F1-score, and specificity. To enhance the reliability of classification in scenarios involving class imbalance, a threshold optimization strategy is implemented to maximize the F1-score, thereby yielding an optimal decision threshold. These evaluation metrics and threshold-based analyses are widely utilized in classification problems and are supported by ROC-based performance evaluation techniques [19].

To assess generalization across subjects, **Leave-One-Patient-Out (LOPO)** cross-validation is performed. This evaluation highlights the impact of inter-subject variability and provides a realistic assessment of the model's performance in clinical settings.

H. Mathematical Formulation

The convolution operation used in the CNN is defined as:

$$h_i = \sigma(W_i * x + b_i)$$

where W_i denotes the convolutional filter, x represents the input EEG signal, b_i is the bias term, and σ is the activation function.

The output probabilities are computed using the Softmax function:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

where z_i represents the output of the final fully connected layer.

IV. IMPLEMENTATION

In this section, without reiterating the system details, the practical implementation of the proposed seizure detection framework is presented, focusing on system configuration, operational workflow, and reproducibility.

A. Implementation Environment

This framework is implemented in Python, with support for GPUs to facilitate efficient training and inference. PyTorch is utilized as the primary deep learning framework, while supporting libraries provide support for signal processing and numerical computations.

The implementation setup is summarized in **Table III**.

TABLE III. IMPLEMENTATION SETUP

Component	Specification
Programming Language	Python
Deep Learning Framework	PyTorch
Signal Processing	SciPy
Numerical Computation	NumPy
Data Source	PhysioNet (CHB-MIT)
Hardware	GPU-enabled system

B. Data Handling and Execution Pipeline

An automated pipeline has been developed to process EEG data from raw EDF files and transform it into model-ready tensors. This system ensures consistent data formatting and efficient preparation.

Key functionalities include:

- Channel alignment across recordings
- Batch-wise data preparation
- Automated label mapping using annotations

The pipeline minimizes manual intervention, improving consistency and reproducibility.

C. Model Implementation

ConvSeizureNet is implemented using modular PyTorch components, in which the feature extraction and classification stages are decoupled. This architecture supports flexible hyperparameter tuning and efficient multi-channel processing.

Key features include:

- Use of nn.Sequential and custom modules

- Optimized tensor operations
- Full GPU compatibility

This design facilitates scalability and future modifications.

D. Training Workflow

The training process is managed through a structured pipeline that includes mini-batch data loading, gradient-based optimization, and validation monitoring. An early stopping strategy is employed based on validation performance. The best-performing model is stored as:

- best_eeg_model.pt

Training logs are recorded for performance analysis and reproducibility.

E. Evaluation Framework

A dedicated module evaluates the model's performance on unseen data using standard metrics and configurable decision thresholds. Additionally, cross-subject validation is automated; predictions and performance metrics are systematically recorded, and the results are archived for further analysis.

F. Output Management

To ensure reproducibility, all outputs are stored in a structured format.

TABLE IV. OUTPUT FILES

File	Description
best_eeg_model.pt	Trained model
training_history.json	Training metrics
eval_results.json	Evaluation results
lopo_results.json	Cross-validation results
chb01_alarms.json	Detection outputs

G. System Integration

This system is organized as a modular pipeline, wherein preprocessing, training, and evaluation operate independently while maintaining a seamless data flow. This architecture supports scalability and future expansions, such as real-time deployment or the integration of distributed learning.

V. RESULTS AND DISCUSSION

A. Classification Performance

The performance of the proposed ConvSeizureNet model is evaluated on a validation dataset using standard classification metrics. The confusion matrix at an optimal threshold of **0.8589** is presented in **Fig. 2**.

This matrix reveals that the model accurately identifies 839 non-seizure and 68 seizure instances, with only 1 false positive and 7 false negatives. A summary of the corresponding metrics is provided in **Table V**.

These results demonstrate excellent classification performance, particularly in terms of specificity and precision, which are crucial for minimizing false alarms in clinical settings. The slightly lower recall indicates a low number of undetected seizures a common issue in imbalanced EEG datasets.

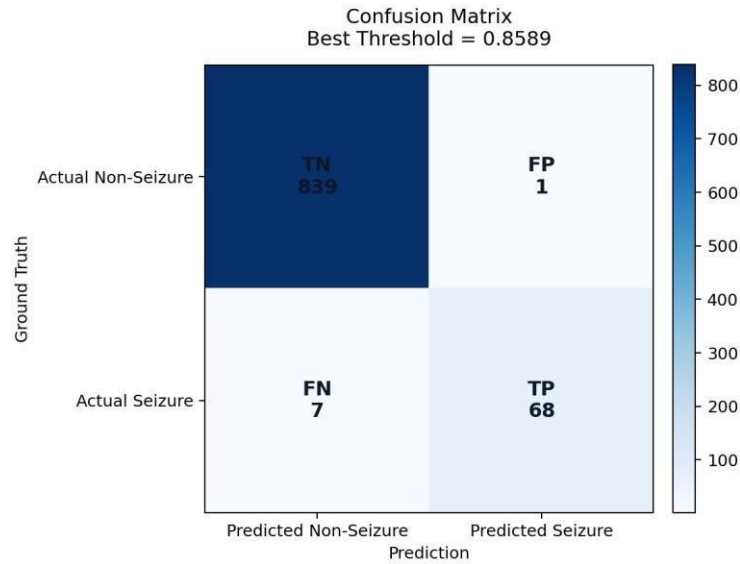


Fig. 2. Confusion Matrix of the proposed model at the optimal threshold (0.8589)

TABLE V. CLASSIFICATION PERFORMANCE METRICS

Metric	Value
Accuracy	99.13%
Precision	98.55%
Recall (Sensitivity)	90.67%
F1-score	94.44%
Specificity	99.88%

B. Training Performance Analysis

The model's training behavior is illustrated in **Fig. 3**, which shows the variation in training and validation loss and accuracy across epochs.

Due to early stopping, the model converges within 17 epochs. In the initial epochs, the training loss decreases rapidly and then stabilizes, while the validation accuracy consistently reaches approximately **99%**. The small gap between the training and validation curves indicates good generalization with minimal overfitting. These results demonstrate the effectiveness of the adopted strategies for achieving stable and efficient convergence, including normalization, dropout, and early stopping.

C. Precision–Recall Analysis

The precision–recall (PR) curve of the model is shown in **Fig. 4**, highlighting performance under class imbalance.

This curve demonstrates that the model maintains high accuracy across a wide range of recall values, indicating a robust distinction between the seizure and non-seizure classes. Threshold optimization further improves the accuracy–recall balance, thereby ensuring reliable detection even in situations involving class imbalance.

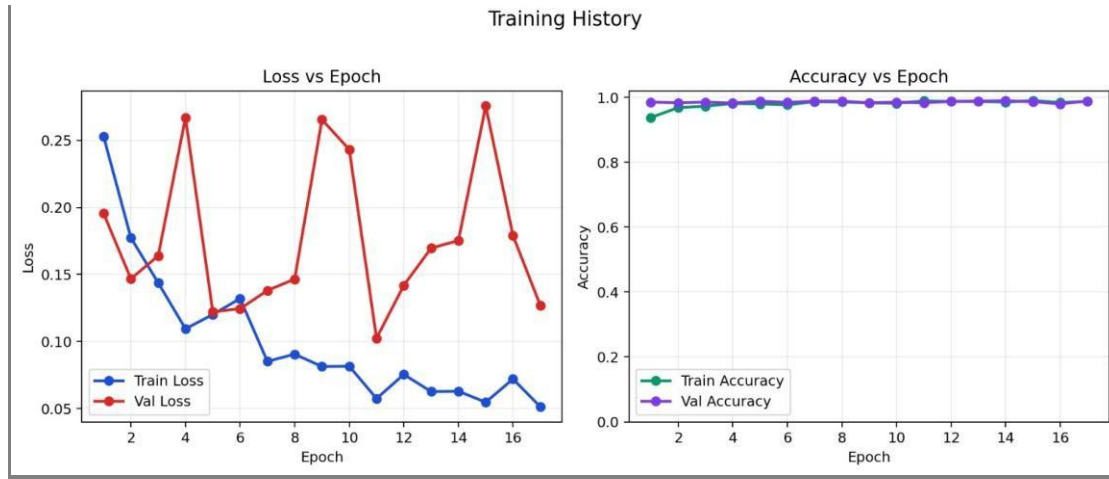


Fig. 3. Training and Validation performance over epochs.

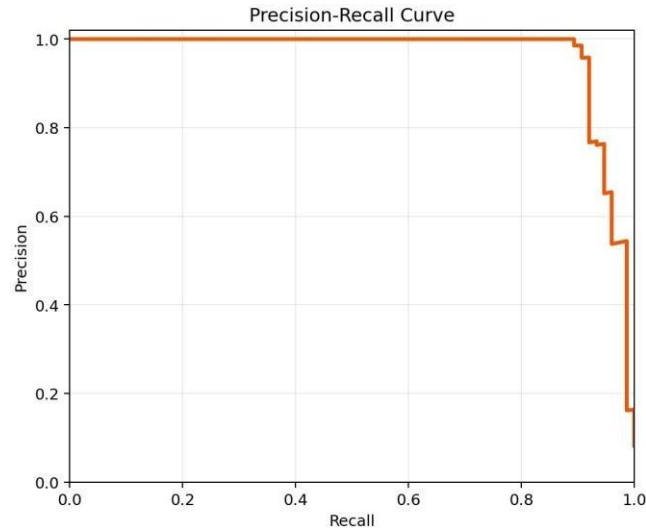


Fig. 4. Precision–Recall curve of the proposed model.

D. Generalization Performance (LOPO Evaluation)

To evaluate generalization across all patients, Leave-One-Patient-Out (LOPO) cross-validation is performed. The performance for each patient is shown in **Table VI**.

Although accuracy remains high, there is a significant decline in recall and F1-scores compared to the validation results, indicating limited generalization to unseen patients.

This is primarily attributed to inter-patient variability in EEG signals, limited training data, and differences in seizure types across individuals.

TABLE VI. LOPO CROSS-VALIDATION PERFORMANCE

Patient	Accuracy	Precision	Recall	F1-score
chb01	93.85	0.9077	0.3041	0.4556
chb02	92.10	0.3968	0.3289	0.3597
chb03	91.85	0.5446	0.5865	0.5648
Average	92.60	0.6164	0.4065	0.4600

E. Signal Quality and Visualization Analysis

The system includes signal visualization and quality assessment modules to evaluate EEG characteristics, as shown in **Fig. 5**.

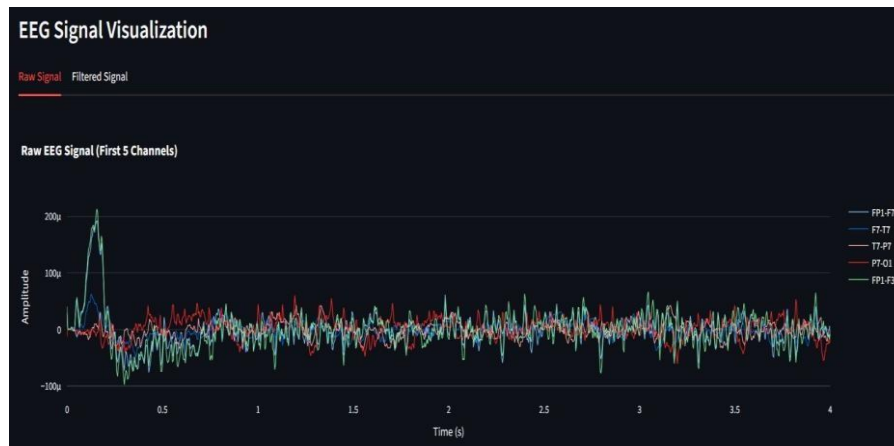


Fig. 5. EEG Signal Visualization (raw and processed signals).

Signal quality parameters, such as the Signal-to-Noise Ratio (SNR) and amplitude characteristics are measured for each channel. The results indicate that signal quality is good across most channels, demonstrating that noise and artifacts were effectively removed during preprocessing. Furthermore, artifact detection identifies high-amplitude disturbances, thereby ensuring reliable downstream classification.

F. System Output and Prediction Analysis

The system provides prediction outputs with confidence scores, as shown in **Fig. 6**.

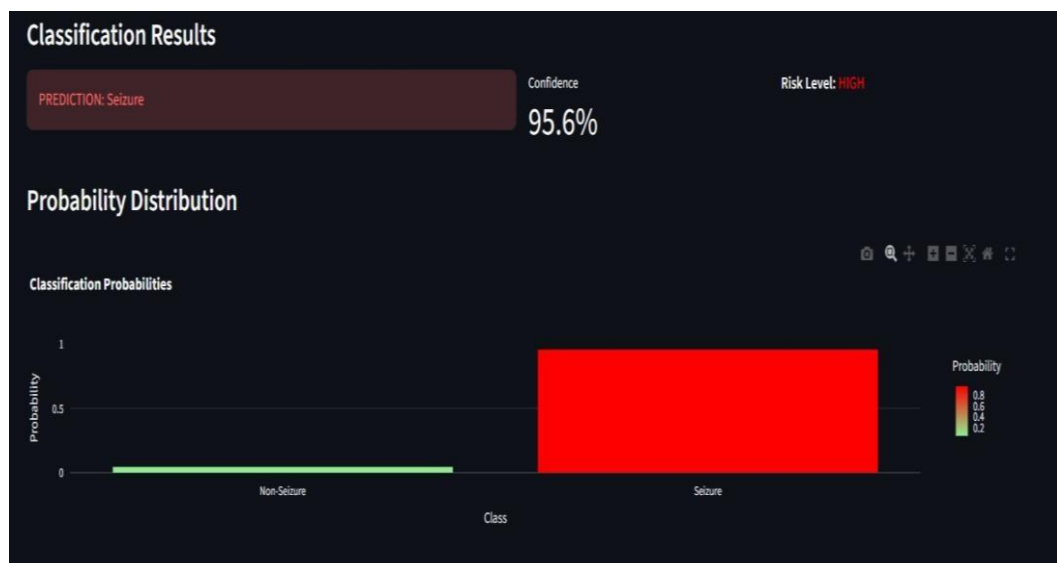


Fig. 6. Example classification output with prediction confidence.

This model predicts tremor events with approximately 95.6% confidence, demonstrating its robust predictive capability. The probability distribution exhibits a clear separation between the classes of tremor and non-tremor events, indicating well-calibrated outputs suitable for decision-support applications.

G. Discussion

Experimental results demonstrate that the proposed CNN-based framework achieves high accuracy and precision in identifying EEG-based seizures. This model effectively captures temporal patterns and provides reliable classification on validation data.

A key strength of this approach is its ability to perform end-to-end learning directly from raw EEG signals, without relying on handcrafted features. High specificity minimizes false alarms, which is essential for clinical applications. The model also exhibits efficient training, characterized by fast convergence and stable performance.

However, certain limitations persist. The reduced performance observed in the LOPO evaluation highlights the challenges of generalizing across patients, primarily due to the inherent variability in EEG data. Furthermore, the relatively small dataset limits the system's robustness in real-world scenarios.

Future work should focus on improving generalizability by utilizing larger and more diverse datasets, domain adaptation techniques, and hybrid models such as CNN-LSTM. Adapting the system for real-time deployment could further enhance its clinical applicability.

VI. CONCLUSION AND FUTURE WORK

Experimental results demonstrate that the proposed CNN-based framework achieves high accuracy and precision in the detection of EEG-based seizures. This model effectively captures temporal EEG patterns and delivers reliable classification on validation data.

A key strengths is the capability to perform end-to-end learning directly from raw EEG signals, without relying on handcrafted features. Its high specificity significantly reduces false alarms a critical requirement for clinical applications. The training process also exhibits efficient convergence and stable performance, underscoring the effectiveness of the architecture and optimization strategies employed.

However, certain limitations persist. The diminished performance observed during 'Leave-One-Patient-Out' (LOPO) evaluation highlights the challenges associated with generalizing across different patients, primarily due to inter-subject variability. Furthermore, the relatively small dataset limits the model's robustness and scalability for real-world applications.

Future Work

Future research could focus on improving the efficiency, generalization, and implementation of the proposed system. The following directions are identified:

- **Dataset Expansion:** Using larger and more diverse EEG datasets to enhance robustness and patient-independent performance
- **Advanced Architectures:** Exploring hybrid models such as CNN-LSTM to capture temporal dependencies more effectively
- **Generalization Techniques:** Applying domain adaptation and transfer learning to handle inter-subject variability
- **Privacy-Preserving Learning:** Integrating federated learning for decentralized training across healthcare institutions

- **Secure Data Management:** Using blockchain frameworks (e.g., Hyperledger Fabric) for secure and tamper-proof data handling
- **Real-Time Deployment:** Developing lightweight models for deployment on edge devices and wearable EEG systems

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REFERENCES

- [1] M. K. Siddiqui, R. Morales-Menendez, X. Huang, and N. Hussain, "A review of epileptic seizure detection using machine learning classifiers," *Brain Informatics*, vol. 7, no. 1, p. 5, May 2020, doi: 10.1186/s40708-020-00105-1.
- [2] M. E. Saab and J. Gotman, "A system to detect the onset of epileptic seizures in scalp EEG," *Clinical Neurophysiology*, vol. 116, no. 2, pp. 427–442, Feb. 2005, doi: 10.1016/j.clinph.2004.08.004.
- [3] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Computers in Biology and Medicine*, vol. 100, pp. 270–278, Sep. 2018, doi: 10.1016/j.combiomed.2017.09.017.
- [4] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: a systematic review," *Journal of Neural Engineering*, vol. 16, no. 5, p. 051001, Aug. 2019, doi: 10.1088/1741-2552/ab260c.
- [5] A. Shoeb and J. Guttag, "Application of machine learning to epileptic seizure detection," in *Proc. 27th Int. Conf. Mach. Learn. (ICML)*, Haifa, Israel, 2010, pp. 975–982, doi: 10.5555/3104322.3104446.
- [6] L. Bai, G. Litscher, and X. Li, "Epileptic seizure detection using machine learning: A systematic review and meta-analysis," *Brain Sciences*, vol. 15, no. 6, p. 634, Jun. 2025, doi: 10.3390/brainsci15060634.
- [7] M. Islam and T. Lee, "Wavelet based Emotion Detection from Multi-channel EEG using a Hybrid CNN-LSTM Model," *TENCON 2022 - 2022 IEEE Region 10 Conference (TENCON)*, Hong Kong, Hong Kong, 2022, pp. 1–6, doi: 10.1109/TENCON55691.2022.9978122.
- [8] S. A. Dhondiyal, D. Singh, S. Saklani, and R. Bisht, "Optimized Hybrid GNN-CNN-LSTM Model for Reliable Epileptic Seizure Detection Using EEG Signals," *2025 10th International Conference on Communication and Electronics Systems (ICCES)*, Coimbatore, India, 2025, pp. 699–703, doi: 10.1109/ICCES67310.2025.11336261.
- [9] J. S. Ramakrishna, K. Srija, M. Srujana, and Y. Srinath, "EEG Based Epileptic Seizure Detection Using Binary Dragonfly Algorithm and Deep Neural Networks," *2025 3rd International Conference on Smart*

- Systems for Applications in Electrical Sciences (ICSSES)*, Tumakuru, India, 2025, pp. 1–6, doi: 10.1109/ICSSES64899.2025.11009854.
- [10] R. Sujatha, S. Mouritha, V. Shridharshini, B. S. Sivadharana, and D. Soundarya, “Deep Learning-Driven Epileptic Seizure Detection using Optimized LSTM Networks,” *2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)*, Bengaluru, India, 2025, pp. 1209–1214, doi: 10.1109/ICICNIS66685.2025.11315795.
- [11] X. Qiu *et al.*, “FedKDC: Consensus-Driven Knowledge Distillation for Personalized Federated Learning in EEG-Based Emotion Recognition,” *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 8, pp. 5527–5540, Aug. 2025, doi: 10.1109/JBHI.2025.3562090.
- [12] R. Pratihara and R. Sankar, “Optimized EEG and fMRI Biomarker Fusion Using Federated Learning for Parkinson’s Disease Diagnosis,” *2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Copenhagen, Denmark, 2025, pp. 1–7, doi: 10.1109/EMBC58623.2025.11254960.
- [13] M. M. Sheeraz, M. A. I. Mozumder, M. O. Khan, M. U. Abid, M. -I. Joo, and H. -C. Kim, “Blockchain System for Trustless Healthcare Data Sharing with Hyperledger Fabric in Action,” *2023 25th International Conference on Advanced Communication Technology (ICACT)*, Pyeongchang, Korea, Republic of, 2023, pp. 437–440, doi: 10.23919/ICACT56868.2023.10079423.
- [14] R. Pise, S. Gavkare, S. Patil, S. Patil, and S. Shinde, “Empowering Healthcare: Hyperledger Blockchain for Unified Electronic Health Records and Organ Donation Integrity,” *2024 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS)*, Pune, India, 2024, pp. 1–6, doi: 10.1109/ICBDS61829.2024.10837436.
- [15] J. Guttag, “CHB-MIT Scalp EEG Database,” *PhysioNet*, ver. 1.0.0, Jun. 2010. [Online]. Available: <https://doi.org/10.13026/C2K01R>.
- [16] B. H. Brinkmann *et al.*, “Crowdsourcing reproducible seizure forecasting in human and canine epilepsy,” *Brain*, vol. 139, no. 6, pp. 1713–1722, Jun. 2016, doi: 10.1093/brain/aww045.
- [17] I. Kiral-Kornek, S. Roy, E. Nurse, B. Mashford, P. Karoly, T. Carroll, D. Payne, S. Saha, S. Baldassano, T. O’Brien, D. Grayden, M. Cook, D. Freestone, and S. Harrer, “Epileptic seizure prediction using big data and deep learning: Toward a mobile system,” *EBioMedicine*, vol. 27, pp. 103–111, 2018, doi: 10.1016/j.ebiom.2017.11.032.
- [18] I. Ullah, M. Hussain, E.-U.-H. Qazi, and H. Aboalsamh, “An automated system for epilepsy detection using EEG brain signals based on deep learning approach,” *arXiv preprint arXiv:1801.05412*, 2018, doi: 10.48550/arXiv.1801.05412.
- [19] T. Fawcett, “An introduction to ROC analysis,” *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, Jun. 2006, doi: 10.1016/j.patrec.2005.10.010.