EpilepsySpikeNet: A Neuromorphic Approach to Patient-Specific Epileptic Seizure Prediction

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Abstract

Epileptic seizure prediction for low-power devices remains challenging. We investigate Spiking Neural Networks (SNNs) trained with Surrogate Gradient Descent as an energy-efficient alternative to conventional deep learning. Using the CHB-MIT EEG Database (23 pediatric subjects), we implemented EpilepsySpikeNet, an SNN that classifies preictal versus interictal EEG segments from three patients across multiple recording sessions. Performance varied between subjects: CHB07 achieved perfect classification across all sessions (100% mean accuracy, AUC=1.0), CHB01 achieved mean accuracy of 93.95%, and CHB03 achieved mean accuracy of 86.46%. High AUC values (> 0.879) across all sessions indicate the model effectively captures discriminative EEG features, but patient-specific calibration is critical due to intra-patient variability across recording sessions.

Introduction

Epilepsy affects millions worldwide, with approximately 30% experiencing drug-resistant epilepsy. Implantable EEG devices can predict seizures minutes in advance, but conventional neural networks are energy-intensive.

The Challenge

- **Energy Efficiency:** Low-power devices require energy-efficient algorithms
- **Patient Variability:** Seizure patterns vary significantly between patients
- **Real-time Prediction:** Need for accurate, timely seizure prediction

Our Approach

Spiking Neural Networks (SNNs) offer event-driven, low-power computation as an alternative to conventional deep learning. We train SNNs using Surrogate Gradient Descent to enable end-to-end learning for epileptic seizure prediction.

Key Contributions

This study evaluates:

- **SNN Performance** for patient-specific seizure prediction using raw EEG data
- **Intra-patient Variability** across multiple recording sessions
- **Feasibility** of neuromorphic approaches for low-power medical devices

Dataset

CHB-MIT Scalp EEG Database

Multi-channel EEG recordings from 23 pediatric subjects with intractable epilepsy. For this preliminary study:

- **Selected 3 patients:** CHB01, CHB03, CHB07
- **Multiple sessions** per patient captured
- **Binary classification:** Preictal vs. interictal EEG segments
- **Temporal separation:** Training, validation, and test sets split to prevent data leakage

Methodology

EpilepsySpikeNet Architecture

Implemented in snnTorch with Leaky Integrate-and-Fire neurons ($\beta = 0.95$) over 25 timesteps:

- **Conv Layer 1:** 32 filters, kernel size 1×7
- **Conv Layer 2:** 64 filters, kernel size 1×5
- **FC Layer 1:** 128 units
- **Output Layer:** 2 units (preictal/interictal)

Training Details

- **Method:** Surrogate Gradient Descent
- **Hardware:** NVIDIA RTX 4090 GPU
- **Metrics:** Accuracy, Sensitivity, Specificity, AUC

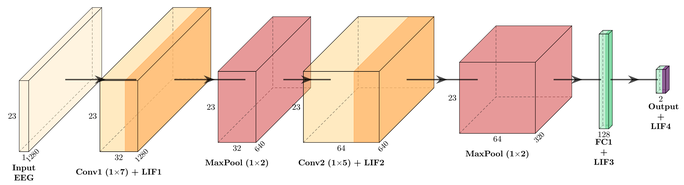
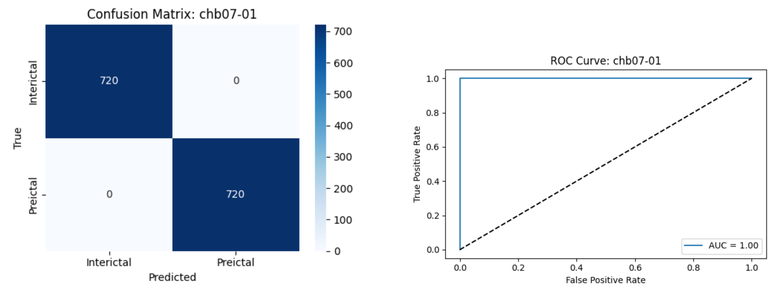


Figure 1. EpilepsySpikeNet Architecture: Two convolutional layers followed by a fully connected layer and output layer for binary classification.

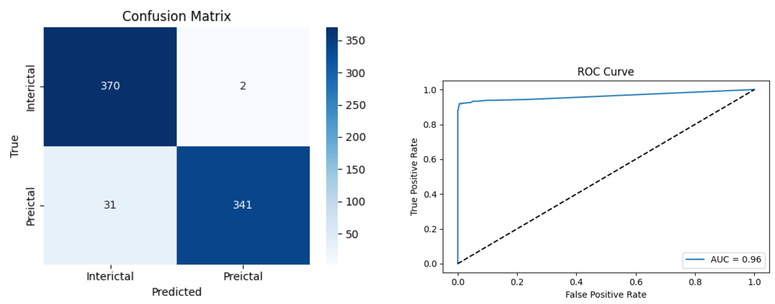
Results: Patient CHB07



(a) Confusion Matrix (b) ROC Curve

Figure 2. CHB07 achieved **perfect classification** across all sessions (100% accuracy, AUC=1.0)

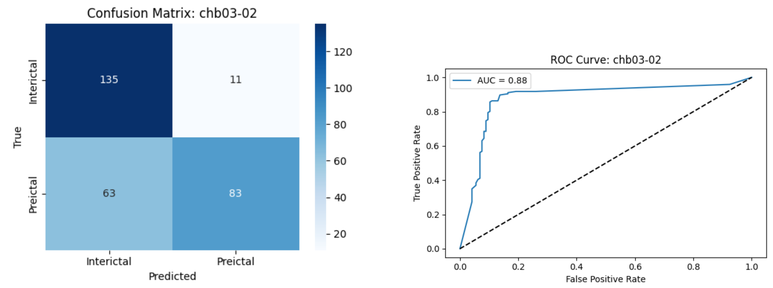
Results: Patient CHB01



(a) Confusion Matrix (b) ROC Curve

Figure 3. CHB01 mean accuracy: **93.95%** across 5 sessions (range: 79.45%–99.67%, AUC=0.96)

Results: Patient CHB03



(a) Confusion Matrix (b) ROC Curve

Figure 4. CHB03 mean accuracy: **86.46%** across 5 sessions (range: 74.66%–96.46%, AUC=0.88)

Performance

Patient	Mean Acc.	Range	AUC
CHB07	100.00%	100%–100%	1.000
CHB01	93.95%	79.45%–99.67%	0.96
CHB03	86.46%	74.66%–96.46%	0.88

Table 1. Performance across multiple recording sessions per patient

High AUC values (> 0.88) across all sessions indicate the model effectively captures discriminative EEG features.

Conclusions

- **Promising Results:** SNNs trained with surrogate gradients show strong potential for epileptic seizure prediction
- **Patient Specificity:** Performance varies significantly between subjects (86.46%–100% mean accuracy)
- **Session Variability:** Intra-patient variability across recording sessions highlights need for patient-specific calibration
- **High Discrimination:** Strong AUC values demonstrate effective feature learning

Future Work

- Expand to larger patient cohort
- Quantify energy efficiency on neuromorphic hardware
- Develop generalized models with patient personalization

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