Real-Time Detection of Epileptiform Activity and Seizure Onset Using EEG Signals and Machine Learning

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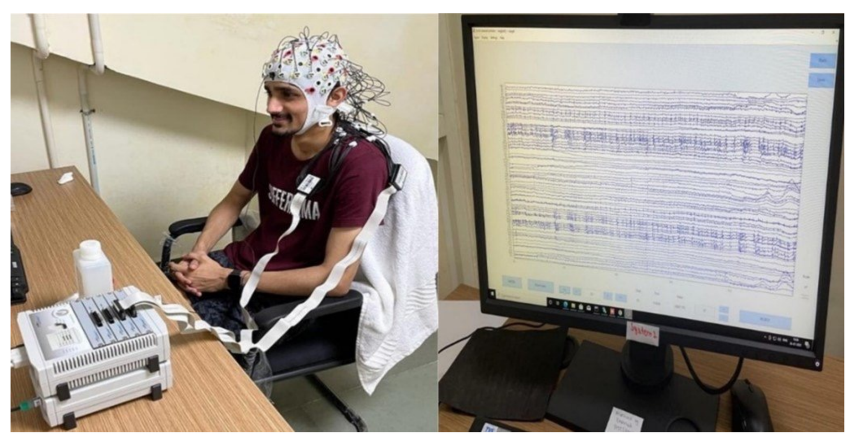
Introduction

- 50 million people with epilepsy, seizures strike without warning.
- Current systems detect seizures only after onset, too late for prevention.
- Objective: Predict seizure onset using scalp EEG and machine learning to enable advance warning.



Methods

Dataset:

- CHB-MIT Database: 6 patients, 18 seizures, 23-channel EEG (256 Hz).

Preprocessing:

- Bandpass filter (0.5-50 Hz), notch filter (60 Hz).
- 4-second windows with 50% overlap.

Features:

- 16 total: time-domain (variance, zero-crossing, line length) + frequency-domain (delta, theta, alpha, beta, gamma).

Classification:

- SVM: 3 training patients, 3 held-out test patients.
- Pre-ictal window: 0-10 min before seizure.

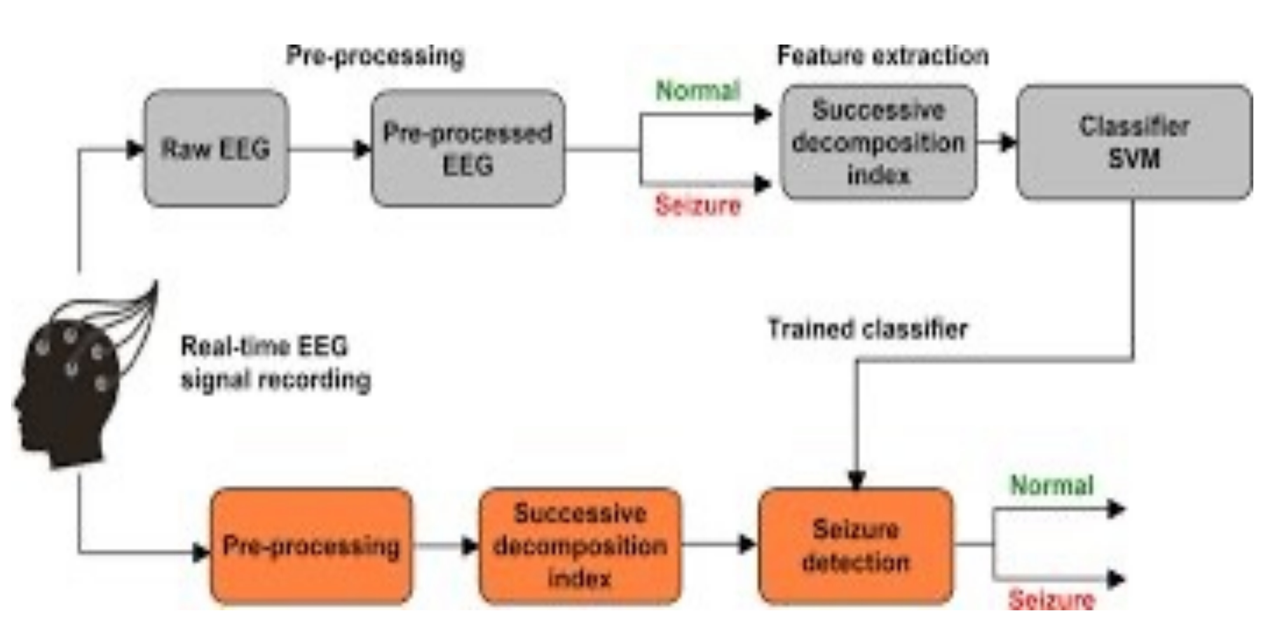


Fig. 1. System processing pipeline from EEG acquisition to seizure prediction.

Results

Binary Classification Performance:

- 87.5% accuracy across three test patients never seen during training.
- Specificity: 96.6% (system rarely triggers false alarms).
- Sensitivity: 54.6% (detects about half of pre-ictal segments).

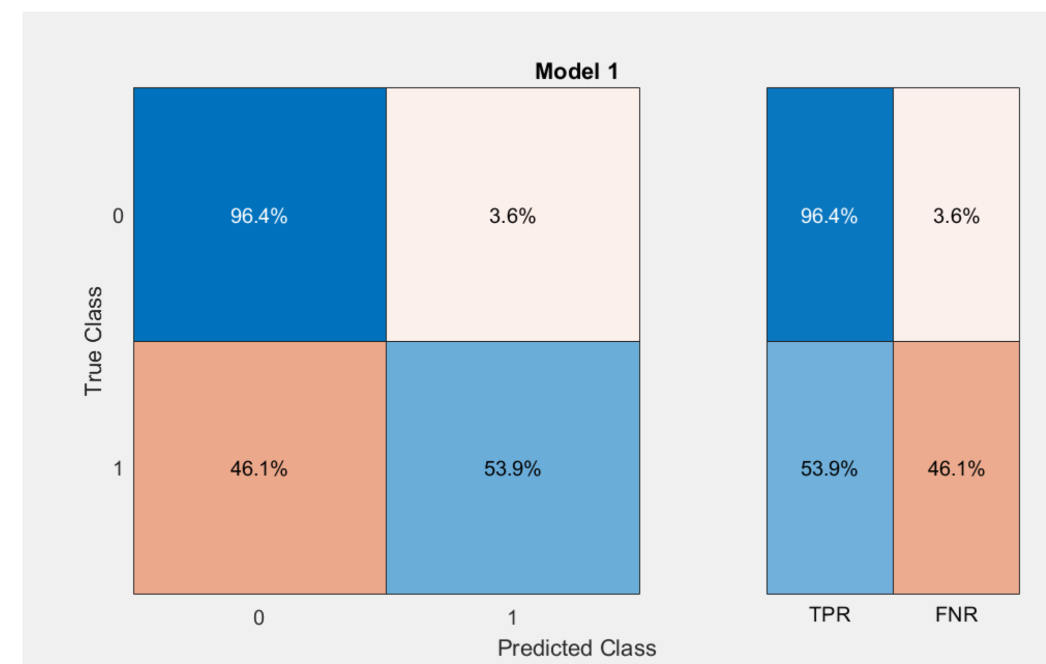


Fig. 2. Classification performance across test patients.

Temporal Detection Window:

- Patient chb01 analyzed with one-minute temporal windows.
- Window 1 (0-1 min before seizure): 73.3% accuracy.
- Window 2 (1-2 min before seizure): 64.4% accuracy.
- Both exceeded 60% clinical threshold for meaningful detection.
- Beyond 2 minutes: accuracy dropped below 60%.

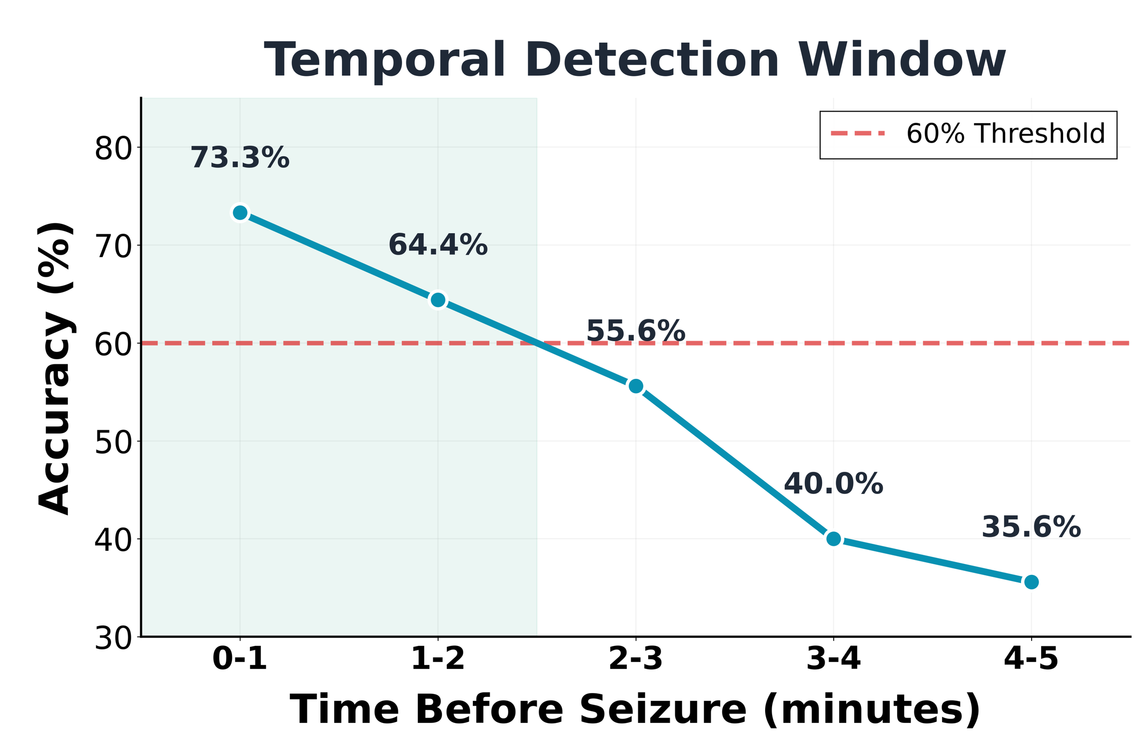


Fig. 3. Detection accuracy vs time before seizure onset.

Computational Performance:

- Processing speed: 225× faster than real-time (16 sec per 60-min recording).
- Latency: <100 ms per 4-second segment.
- Memory usage: 1.2 GB peak.
- Feasible for deployment on standard hardware and wearable devices.

Key Findings

- 87.5% accuracy across new patients, cross-patient detection proven.
- 2-minute advance warning enables safety measures.
- Patient-specific calibration needed for optimal timing.

Summary and Conclusions

- Machine learning detected pre-ictal states with 87.5% accuracy across six patients never seen during training. High specificity (96.6%) means false alarms were rare, critical for patient trust.
- The system provides 2 minutes advance warning, enough time for safety measures. Detection timing varied between patients, requiring brief calibration for each user.

Future Directions

- Expand to diverse patient groups (age, seizure types, epilepsy severity).
- Explore deep learning to improve sensitivity without sacrificing specificity.
- Develop personalized models using individual seizure histories.
- Validate in real-world clinical settings with long-term monitoring.

Acknowledgements

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