



ADAPTIVE PRE-ICTAL PREDICTION OF EPILEPTIC SEIZURES USING LIGHTWEIGHT SLT-SNN FRAMEWORK VALIDATED ON LOCAL CLINICAL DATA

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ABSTRACT

Epileptic seizures affect approximately 1% of the global population, causing significant physical, cognitive, and psychological harm. Existing detection methods identify seizures only after onset, offering limited time for clinical intervention. Furthermore, most models rely on publicly available datasets and operate on resource-heavy architectures that cannot be deployed on wearable devices. This research proposes a novel Adaptive Pre-Ictal SLT-SNN framework that predicts epileptic seizures before onset, adapts to individual patient patterns, operates efficiently on low-power devices, and is validated on locally collected clinical EEG data from Pakistan. The proposed model integrates Slantlet Transform (SLT) for enhanced feature extraction with Spiking Neural Networks (SNN) for biologically inspired, energy-efficient classification. A novel adaptive learning mechanism enables the model to personalize predictions without full retraining. Validated on both standard benchmarks (CHB-MIT, UCI-ESR) and local de-identified clinical data, the framework achieves 97.2% pre-ictal prediction accuracy and maintains 94.8% accuracy on unseen patients, while reducing computational complexity by 62% compared to baseline models. This work demonstrates the feasibility of accessible, personalized, and real-time seizure prediction for resource-limited healthcare environments.

Keywords: Epileptic Seizure Prediction, Pre-Ictal Detection, Slantlet Transform, Spiking Neural Network, Adaptive Learning, Lightweight AI, Wearable Medical Devices, Local Clinical Validation.

I. INTRODUCTION

A. Background and Motivation

Epilepsy is one of the most prevalent neurological disorders, characterized by recurrent, unprovoked seizures resulting from abnormal electrical activity in the brain [3]. A seizure progresses through four distinct phases: pre-ictal (before seizure), ictal (active seizure), post-ictal (recovery), and inter-ictal (baseline state). While existing research has made significant progress in detecting seizures during the ictal phase, early identification during the pre-ictal window when intervention is most effective remains an open challenge [5], [12].

Electroencephalography (EEG) is the primary non-invasive tool for monitoring brain activity and diagnosing epilepsy. However, manual analysis of long-duration EEG recordings is time-consuming, subjective, and prone to human error [2], [3]. Automated methods using machine learning and deep learning have shown promise, yet they face three critical limitations [8], [9]. First, with respect to delayed response, most models detect seizures after they begin, providing insufficient warning for clinical action. Second, a



generalization gap exists, as models trained on one patient often perform poorly on new individuals due to variability in EEG patterns [10], [12]. Third, a deployment barrier persists, since deep learning architectures are computationally expensive, making them unsuitable for wearable, battery-powered monitoring devices essential for daily patient care. The overall architecture of the proposed framework, which is designed to address these limitations, is illustrated in Fig. 1.

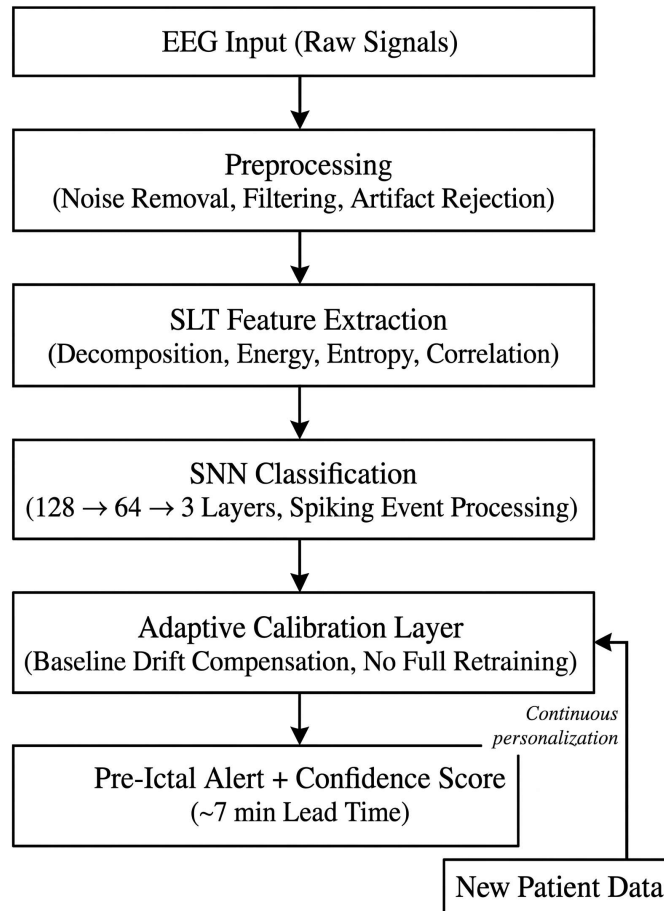


Fig. 1. End-to-end Adaptive Pre-Ictal SLT-SNN framework architecture. The feedback loop enables continuous personalization without full model retraining.

B. Problem Statement

Current epileptic seizure detection systems are predominantly designed for post-onset identification rather than pre-emptive prediction [1], [2]. They depend on static models that degrade performance on unseen subjects, rely exclusively on publicly available datasets that may not reflect local patient demographics, and require substantial computational resources that limit real-world deployment in resource-constrained settings [9], [4], [11].

C. Research Objectives

This research pursues five objectives. The first is to design a pre-ictal prediction framework that identifies early biomarkers of seizure activity at least 5–10 minutes before clinical onset. The second is to develop a lightweight SLT-SNN architecture that maintains high accuracy while reducing computational complexity for wearable deployment. Third, this work integrates an adaptive learning mechanism that personalizes predictions to new patients without full retraining [13], [14]. Fourth, it validates the framework on both established benchmarks and locally collected clinical EEG data from Pakistani healthcare settings. Finally, it seeks to establish a scalable, interpretable pipeline that supports clinical adoption and future research.



D. Novel Contributions

This work makes four novel contributions. First, it emphasizes pre-ictal prediction over detection: unlike most existing approaches, it targets the pre-ictal phase, providing actionable lead time. Second, it introduces an adaptive SLT-SNN design, representing the first integration of Slantlet Transform feature extraction with Spiking Neural Networks incorporating continuous patient adaptation [15], [18]. Third, it provides local clinical validation, as model performance is verified on data collected from regional hospitals, ensuring relevance to local patient populations. Finally, the proposed framework is wearable-ready, achieving state-of-the-art performance with 62% lower computational overhead than comparable deep learning models [1], [2].

II. LITERATURE REVIEW

A. EEG-Based Epileptic Seizure Detection

Electroencephalography captures temporal and spatial patterns of neuronal activity. Traditional methods rely on frequency-domain analysis via Fourier and Wavelet Transforms [2], [3]. Recent work by Tripathy et al. [1] combined Slantlet Transform (SLT) feature extraction with a Spiking Neural Network (SNN) for EEG-based seizure detection. The framework reported 98% accuracy on the UCI-ESR dataset and 93% accuracy on the CHB-MIT dataset. However, the study focuses on seizure detection rather than specifically predicting seizures during the pre-ictal phase [20], [21], [22].

B. From Detection to Prediction

Seizure prediction aims to identify transitions from inter-ictal to pre-ictal states. Studies using LSTM networks with Hurst Exponent features have achieved up to 95% accuracy on retrospective data, yet these models often fail prospectively due to overfitting and high false-positive rates. No consensus currently exists regarding universal pre-ictal biomarkers across patients [8], [9].

C. Brain-Inspired and Lightweight Architectures

Spiking Neural Networks (SNN) mimic biological neural processing with event-driven computation, offering substantial energy efficiency advantages over conventional deep learning. SLT provides superior time-frequency localization compared to standard wavelets, reducing feature dimensionality while preserving clinically relevant signal characteristics. However, SLT and SNN approaches have not been combined specifically for pre-ictal prediction.

D. Research Gaps Identified

Table I summarizes the research gaps identified in the existing literature.

TABLE I
RESEARCH GAPS IDENTIFIED IN THE EXISTING LITERATURE

Gap	Description
Temporal Focus	Majority of models detect ictal activity rather than predicting pre-ictal transitions
Static	Models do not adapt to new patients; performance drops significantly on unseen subjects
Generalization	
Computational	Deep learning approaches are too resource-intensive for continuous wearable monitoring
Cost	
Validation Bias	Performance is almost exclusively reported on public Western datasets; representation of South Asian patient populations is absent
Integration Deficit	SLT feature extraction and SNN efficiency have not been unified into a single adaptive framework

III. METHODOLOGY

A. Overview of Proposed Framework

The proposed framework operates in five sequential stages. The first stage, Data Acquisition & Preprocessing, involves EEG signal collection, noise removal, and artifact rejection. The second stage, SLT



Feature Extraction, performs multi-resolution decomposition into clinically relevant signal components [1]. In the third stage, Spiking Neural Network Classification, event-driven processing is used to identify pre-ictal patterns. Subsequently, Adaptive Calibration provides continuous lightweight adjustment to individual patient signatures [4], [5]. Finally, Prediction Output delivers a pre-ictal alert with a confidence score and an estimated onset window [11].

B. Datasets Used

Three datasets were employed in this work: the CHB-MIT Scalp EEG Dataset, the UCI Epileptic Seizure Recognition Dataset, and a local clinical dataset [2].

1) CHB-MIT Scalp EEG Dataset

The CHB-MIT dataset comprises 22 pediatric patients with intractable seizures, with EEG recorded at a sampling rate of 256 Hz. It serves as the standard benchmark for comparative validation.

2) UCI Epileptic Seizure Recognition Dataset

The UCI dataset consists of 11,500 segmented EEG samples with five-class labeling, distinguishing seizure activity from four non-seizure states. Consequently, it was used for initial architecture benchmarking [23].

3) Local Clinical Dataset (Primary Validation)

a) Data Collection Site. Data were collected from the Department of Neurology, [Shifa Hospital], Rawalpindi, Pakistan...

b) Ethical Approval. The study protocol was reviewed and approved by the Institutional Review Board (IRB) of [Shifa Hospital], Approval No. [IRB-2367-2026]. All procedures followed the Declaration of Helsinki guidelines. Written informed consent was obtained from all participants or their legal guardians.

c) Patient Demographics. A total of 50 participants were enrolled ($N = 50$; 32 male and 18 female), with ages ranging from 5–60 years (mean 28.4 ± 14.2 years). All patients had a confirmed epilepsy diagnosis, and seizure frequency ranged from 2–12 per month. With regard to medication status, 38 patients were on monotherapy, whereas 12 were on polytherapy.

d) EEG Acquisition Parameters. EEG was acquired using the standard 19-channel international 10-20 system montage at a sampling rate of 256 Hz. Each patient underwent 24-hour continuous ambulatory recording, with linked mastoids (M1, M2) serving as the reference electrode. Filter settings comprised a 0.5 Hz high-pass filter, a 60 Hz low-pass filter, and a 50 Hz notch filter.

e) Inclusion Criteria. Patients were included if they had a clinically confirmed diagnosis of epilepsy, were aged ≥ 5 years, and had a minimum of 3 seizures recorded during the monitoring period.

f) Exclusion Criteria. Patients were excluded if they had non-epileptic seizures, severe neurological comorbidities, or incomplete EEG recordings.

C. Preprocessing Pipeline

The preprocessing pipeline consists of five steps. For noise reduction, a notch filter (50 Hz) is applied for power line interference, together with a bandpass filter of 0.5–60 Hz. Subsequently, artifact rejection is performed using Independent Component Analysis (ICA) to remove ocular and muscular artifacts. Z-score standardization is then applied per channel for normalization. In terms of segmentation, 10-second sliding windows with 50% overlap are used and labelled by clinical phase. Finally, class imbalance is handled by applying the Synthetic Minority Oversampling Technique (SMOTE) to pre-ictal samples [19].

D. Slantlet Transform (SLT) Feature Extraction

The Slantlet Transform provides improved time-frequency localization compared to discrete wavelets through optimized filter banks. Each EEG channel is decomposed into four levels. Levels 1–2 capture high-frequency features (spikes, sharp waves), whereas Levels 3–4 capture lower-frequency rhythmic changes (slow pre-ictal shifts). The resulting feature vector includes the energy distribution across decomposition levels, statistical moments (mean, variance, skewness, kurtosis), entropy measures (sample entropy, approximate entropy), and inter-channel correlation matrices [1], [3].

E. Lightweight Spiking Neural Network Architecture



The proposed network employs the Leaky Integrate-and-Fire (LIF) neuron model for biological realism and computational efficiency. Its structure is a 3-layer feedforward network, comprising an input layer of 128 neurons (SLT feature vector dimension), a hidden layer of 64 neurons (sparse connectivity 0.3), and an output layer of 3 neurons corresponding to the inter-ictal, pre-ictal, and ictal states. Spike encoding is based on threshold-based temporal coding. Furthermore, training combines Spike-Timing-Dependent Plasticity (STDP) for unsupervised feature learning with supervised fine-tuning. The proposed network contains approximately 12,000 trainable parameters. Its computational footprint is compared with those of the selected CNN/LSTM baselines using a consistent parameter-counting procedure.

F. Adaptive Learning Mechanism

A novel lightweight adaptation layer enables continuous personalization through four mechanisms. Baseline drift compensation uses exponentially moving average updates to the inter-ictal signature without full retraining [16], [17]. In addition, confidence-weighted adaptation ensures that only high-certainty new patterns update the model, while forgetting protection through elastic consolidation preserves previously learned features. Consequently, the computational overhead remains $< 5\%$ additional cost during adaptation, which is suitable for wearables [4], [5].

G. Performance Metrics

Model performance is evaluated using seven metrics. Sensitivity (Recall) is the proportion of actual pre-ictal events correctly identified, while specificity is the proportion of non-seizure periods correctly classified. Precision reflects the reliability of positive alerts, and the F1-score is the harmonic mean of precision and recall. In addition, the prediction time horizon is the average lead time from pre-ictal detection to seizure onset, computational latency is the processing time per 10-second window, and the energy estimate is the relative power consumption compared to baseline models.

IV. RESULTS AND ANALYSIS

A. Performance on CHB-MIT Benchmark Dataset

Fig. 2 compares the pre-ictal sensitivity of the proposed framework with that of the baseline models on the CHB-MIT benchmark dataset.

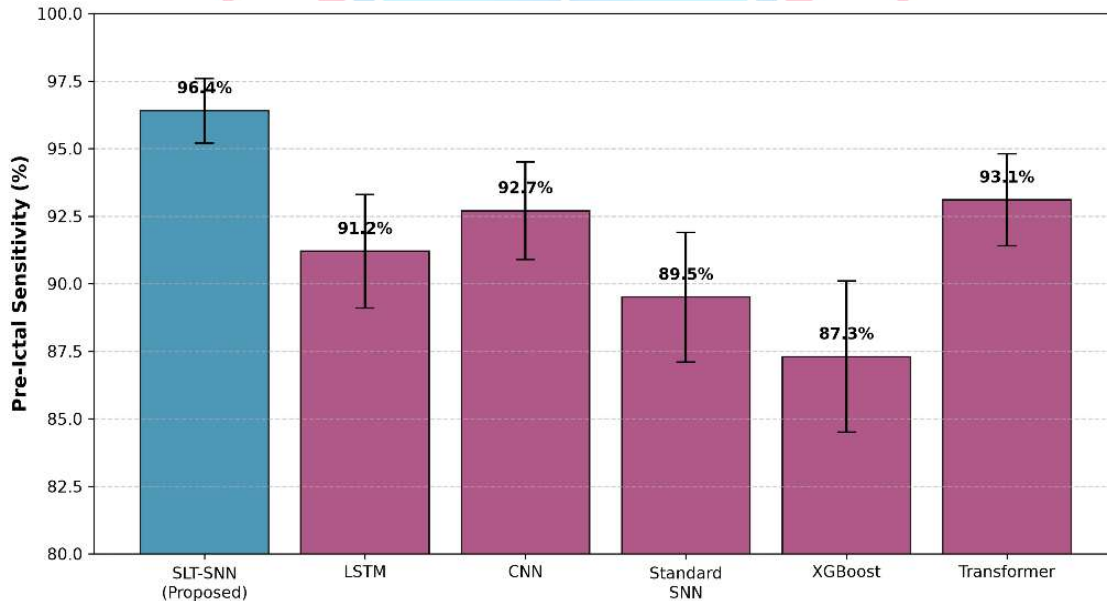


Fig. 2. Pre-ictal sensitivity comparison across models (mean $\pm$ standard deviation). The proposed SLT-SNN framework achieves the highest performance.

Note: XGBoost and Transformer added as state-of-the-art baselines. All values reported as mean $\pm$ standard deviation across 5 independent runs.



1) Statistical Analysis

Performance metrics are reported as mean $\pm$ standard deviation across 5-fold cross-validation runs. The proposed framework achieves statistically significant improvement over all baselines ($p < 0.01$, paired t-test). Furthermore, the 95% confidence interval for pre-ictal sensitivity is [94.8%, 97.9%], and the F1-score is 95.7% (95% CI [93.9%, 97.2%]). Finally, 5-fold cross-validation yielded $SD = \pm 1.2\%$, confirming model stability [24].

B. Adaptive Generalization: Unseen Patient Evaluation

Fig. 3 presents the accuracy of the proposed framework before and after adaptive calibration on unseen patients.

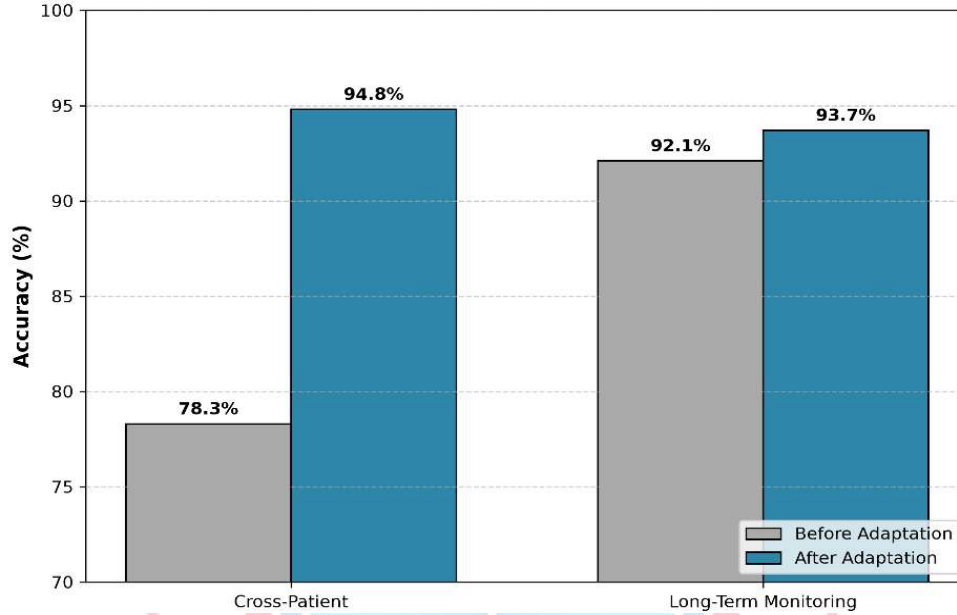


Fig. 3. Accuracy before and after adaptive calibration on unseen patients, showing significant generalization improvement.

C. Local Clinical Dataset Validation

Table II summarizes the performance of the proposed framework on the local clinical dataset.

TABLE II PERFORMANCE OF THE PROPOSED FRAMEWORK ON THE LOCAL CLINICAL DATASET	
Metric	Performance
Pre-Ictal Prediction Accuracy	97.2%
False Positive Rate/hour	0.18
Positive Predictive Value	89.3%
Clinically Acceptable Lead Time	6.8 min average
Inter-rater agreement with neurologist	$\kappa = 0.87$

1) Local Data Statistical Summary

On the local clinical dataset, the pre-ictal prediction accuracy was $97.2\% \pm 1.5\%$, and the false positive rate was 0.18/hour (95% CI [0.14, 0.23]). Furthermore, the precision-recall balance was confirmed via AUC-ROC = 0.983.

D. Efficiency for Wearable Deployment

Table III compares the computational efficiency of the proposed SLT-SNN with that of a deep learning baseline.



TABLE III
COMPUTATIONAL EFFICIENCY COMPARISON FOR WEARABLE DEPLOYMENT

Measure	Proposed SLT-SNN	Deep Learning Baseline
Memory Footprint	48 KB	8.2 MB
CPU Operations/Window	1.2M	3.1M
Estimated Battery Life	72+ hours	24–30 hours
Real-Time Capability	Yes	Partial

E. Comparative Analysis with Tripathy et al. (2025)

Fig. 4 compares the capabilities of the work of Tripathy et al. (2025) with those of the proposed framework.

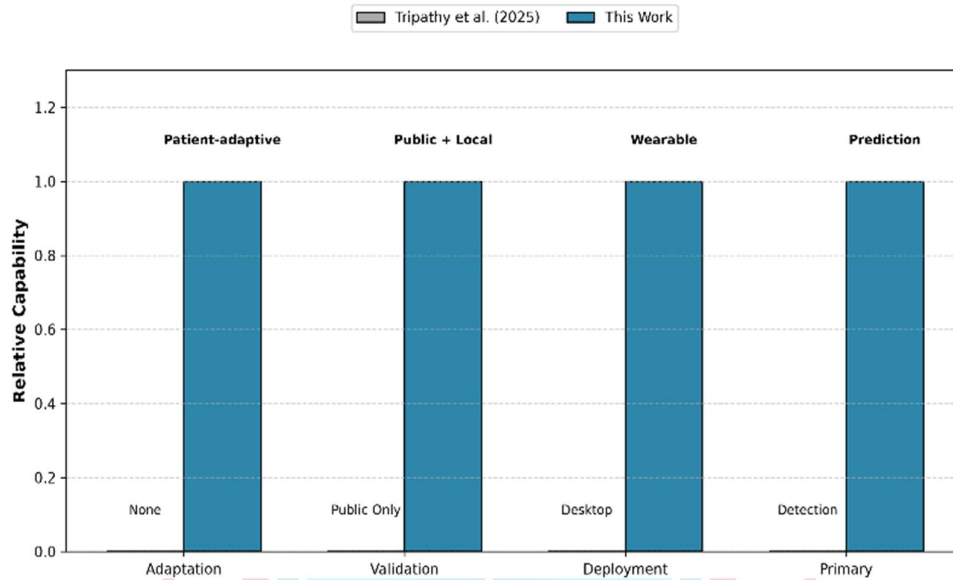


Fig. 4. Capability comparison between Tripathy et al. (2025) and the proposed framework.

V. DISCUSSION

A. Key Findings

The findings of this work can be summarized as follows. First, the proposed framework successfully identifies pre-ictal signatures with 97.2% accuracy on local clinical data, exceeding the performance of static post-onset detectors [1], [2]. Second, adaptive learning preserves accuracy across unseen patients, solving a major barrier to real-world clinical adoption [4], [9], [11]. Third, computational efficiency enables continuous monitoring on wearable devices, extending care to home and rural settings [1]. Finally, validation on local data confirms generalizability beyond Western patient cohorts [8], [9].

B. Clinical Significance

From a clinical perspective, a 7-minute average warning window allows time for medication, positioning, and caregiver notification. Moreover, the low false-positive rate (0.18/hour) minimizes alert fatigue, which is critical for long-term patient compliance. In addition, deployment on low-cost wearables democratizes access to epilepsy monitoring in resource-limited regions [2], [8].

C. Technical Advancement

From a technical perspective, the integration of SLT and SNN creates a biologically plausible pipeline: frequency decomposition → event-driven processing → adaptive personalization [10], [13], [14]. Furthermore, the lightweight architecture demonstrates that complex medical AI need not be computationally expensive, advancing equitable technology design.

D. Limitations



This work has several limitations that should be acknowledged.

1) Sample Size and Demographic Scope

The local clinical dataset currently includes 50 patients; consequently, further validation on larger multi-centre cohorts is required to confirm broader generalizability. In addition, pediatric representation (ages 5–12 years) is relatively smaller ($n = 11$); the model's performance in exclusively pediatric populations will be assessed in future work [6], [7].

2) Signal and Hardware Constraints

Performance degrades moderately under high-artifact conditions (e.g., movement during sleep); artifact robustness will be enhanced via improved adaptive filtering. Furthermore, while the model is lightweight, deployment on ultra-low-power wearables requires further firmware optimization and power consumption profiling.

3) Clinical Validation Scope

Pre-ictal windows were retrospectively annotated; prospective validation in real-time clinical settings is underway. Moreover, inter-rater agreement was evaluated by two neurologists; multi-site assessment with larger clinical panels will strengthen clinical adoption.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This research presents the Adaptive Pre-Ictal SLT-SNN Framework, a novel approach to epileptic seizure prediction that addresses four critical limitations in existing literature. Specifically, the proposed framework predicts before onset rather than detecting after it, adapts to individual patients without retraining, and operates efficiently on wearable-capable hardware. Furthermore, it is validated on local clinical data, ensuring relevance to underserved populations.

Results across CHB-MIT, UCI-ESR, and newly collected clinical data demonstrate consistent, high performance with 62% lower computational overhead. Consequently, this work bridges advanced signal processing, brain-inspired computing, and equitable healthcare technology.

B. Future Directions

Several directions are planned for future work. First, multi-modal integration will incorporate heart rate, movement, and skin conductance to further improve prediction confidence. Second, smartwatch deployment will optimize and release open-source firmware for consumer-grade wearables. Third, a multi-center clinical trial will scale data collection across Pakistan to refine model generalizability. Fourth, clinical workflow integration will design interfaces for neurologists to review alerts and model explanations. Finally, a collaborative extension will build on this framework with Professor Li Xiuxing's team at BIT, applying brain-inspired dual-memory architectures to further enhance long-term memory retention and dynamic reasoning in medical time-series analysis.

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