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TriHybrid-SzCORE-PSTC: A Spike-Encoded Low-Latency Pipeline for EEG Seizure Detection

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***Abstract*—EEG seizure detection depends on both model design and how seizure annotations are converted into window-level training targets. This paper presents TriHybrid-SzCORE-PSTC, a practical spike-encoded detection pipeline rather than a new SNN model. The pipeline combines three spike encodings (Delta, Rate, and frequency-selective rate), a 256-hidden-unit HybridSNN classifier, SzCORE sample-based labeling, and an additional patient-specific threshold analysis using Youden's index. On a six-patient CHB-MIT subset with 32 EDF files, 458,424 sliding windows, and a 7,173-window validation set, TriHybrid-SzCORE-PSTC achieved 0.9024 accuracy, 0.8213 seizure precision, 0.7791 seizure recall, 0.7997 seizure F1, and 0.9137 ROC-AUC at the default threshold. Compared with a reproduced Hybrid SNN baseline, it improved seizure recall by 4.63 percentage points and reduced false negatives from 479 to 396. This preliminary evaluation suggests that TriHybrid-SzCORE-PSTC can improve recall-oriented window-level seizure detection under a matched experimental setting, while also increasing false positives and training cost. The method is therefore best interpreted as an evaluation-oriented spike-encoded pipeline rather than a clinically deployable monitoring system.**

***Index Terms*—EEG seizure detection, spiking neural network, SzCORE, Youden index, patient-specific threshold, CHB-MIT**

I. Introduction

Automated seizure detection from scalp EEG is a clinically important but difficult binary time-series problem. Long recordings contain sparse seizure events, patient-specific morphology, and large non-seizure background. Public resources such as CHB-MIT support reproducible development [1], [2], but detectors must still reduce missed seizures while controlling false alarms.

Recent EEG seizure-detection studies have explored machine-learning and deep-learning detectors, cross-patient transformer models, neonatal EEG frameworks, and broader EEG analysis pipelines [3]–[6]. SNNs are relevant for real-time or neuromorphic settings because EEG can be represented as sparse spike events [7], [8]. A close baseline is the Hybrid spike-encoded SNN, which combines sigma-delta and stochastic rate encodings with an SNN classifier [9]. In our reproduction, this baseline was fast and precise but missed more seizure windows.

TriHybrid-SzCORE-PSTC updates the spike representation and classifier capacity. Each EEG window is encoded as Delta, Rate, and frequency-selective rate (FSR) streams, then classified by a 256-hidden-unit HybridSNN. Training windows use the SzCORE sample-based rule, where a window is positive when at least 50% overlaps a seizure annotation [10]. Patient-specific threshold calibration (PSTC) is reported separately by maximizing Youden's index on validation ROC curves [11], [12], consistent with prior patient-specific thresholding work [13].

The contribution is therefore bounded and system-oriented. We do not claim a new spiking neuron model or a universally superior detector. Instead, we integrate three spike encodings and a 256-hidden-unit HybridSNN into a reproducible low-latency pipeline, then evaluate its recall–precision trade-off against a reproduced Hybrid SNN baseline under matched data, hardware, and validation settings. This framing is intended to make the work useful as an evaluation-oriented system study: the paper asks whether a richer spike representation and modest classifier expansion can reduce missed seizure windows without changing the overall HybridSNN family. The pipeline improves window-level recall and F1, while increasing false positives and training cost.

II. Related Work

Machine-learning seizure detection has a long history on scalp EEG. Shoeb and Guttag formulated patient-specific seizure detection on long-term EEG and helped establish CHB-MIT as a benchmark [2]. Recent work has refined EEG seizure detection using end-to-end classifiers, cross-patient transformer-style models, and specialized clinical EEG frameworks [3]–[5]. Reviews emphasize that performance depends on segmentation, subject splits, imbalance handling, and operating-point selection [6].

Related EEG work has also explored task-specific representation learning and adaptive signal fusion, including multimodal EEG and eye-movement analysis [14]. Although the task differs, it supports designing EEG pipelines around representation and evaluation choices rather than the classifier alone. This perspective is important here because the main change is not a new loss function or neuron model, but the way EEG windows are encoded and evaluated.

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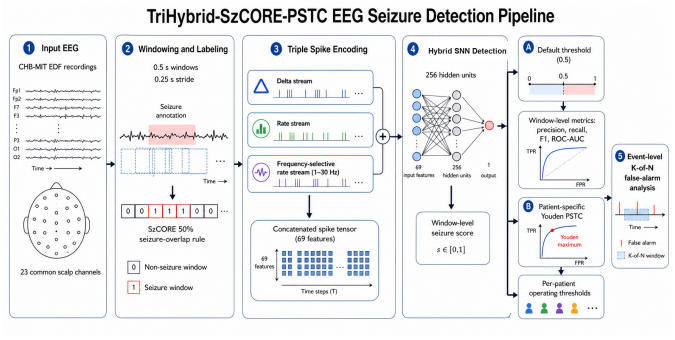


Fig. 1. TriHybrid-SzCORE-PSTC workflow from EEG windowing and SzCORE-style labeling to triple-stream spike encoding, HybridSNN scoring, secondary threshold analysis, and K-of-N false-alarm counting.

SNNs offer a complementary route for EEG analysis. Recent SNN research has benefited from surrogate-gradient learning and deep-learning training practices [7], [8]. Encoding surveys also identify signal-to-spike conversion as a central design choice [15]. The closest Hybrid SNN baseline encodes short EEG windows into spike trains and reports real-time seizure-detection feasibility [9]. TriHybrid-SzCORE-PSTC follows this direction by adding an FSR stream and using a 256-unit hidden layer while retaining the HybridSNN structure.

Evaluation rules and thresholds are also important. SzCORE provides sample-based scoring rules, including the 50% overlap criterion used here [10]. Youden's index and ROC analysis are standard diagnostic tools for threshold selection [11], [12]. Patient-specific EEG thresholds have also improved seizure detection in presurgical evaluation [13]. Here, the default 0.5 threshold is used for the main comparison, while Youden-based PSTC is reported separately.

III. Method

Figure 1 summarizes the workflow: CHB-MIT EDF recordings, overlapping windows, SzCORE-style 50% overlap labels, three spike streams, and HybridSNN scoring. The main comparison uses the default 0.5 threshold, while PSTC and event-level false-alarm counts are secondary analyses.

A. Task and Dataset

The task is binary window-level seizure detection. Experiments used CHB-MIT patients 01, 03, 14, 17, 21, and 24, with 32 EDF files and 23 common scalp EEG channels. Signals were segmented into 128-sample windows at 256 Hz, with 64-sample stride. This produced 458,424 windows, with an original seizure-window ratio of 1.30%.

The balanced training set contained 23,908 samples, including 5,977 seizure windows and 17,931 non-seizure windows. The validation split contained 7,173 windows, including 1,793 seizure windows. All compared models used the same patient subset, files, channels, window length, and validation size. Table I summarizes these data and system settings.

B. SzCORE Window Labeling

For a window beginning at sample t with duration W, let I_t be the time interval covered by the window and let $\mathcal{S}_p$ be the set of annotated seizure intervals for patient p. TriHybrid-SzCORE-PSTC computes the total overlap

$$O_t = \sum_{S \in \mathcal{S}_p} |I_t \cap S|, \tag{1}$$

and assigns the binary label

$$y_t = \begin{cases} 1, & O_t/W \geq 0.50, \\ 0, & O_t/W < 0.50. \end{cases} \tag{2}$$

This follows the SzCORE sample-based seizure-labeling rule [10]. The rule was used only to label training and validation windows; no official SzCORE framework evaluation was performed. In the implemented subset, it produced 5,977 positive windows.

C. Triple-Stream Spike Encoding

TriHybrid-SzCORE-PSTC uses a triple-stream spike representation. Each EEG window has $C = 23$ channels and $T = 128$ samples. The Delta stream captures local temporal changes, the Rate stream encodes amplitude activity, and the FSR stream applies rate coding after 1–30 Hz filtering. Concatenation yields $3C = 69$ input features per time step.

This design preserves the event-based representation of the Hybrid SNN baseline [9], while adding a frequency-selective stream for seizure-relevant rhythmic content. The three streams are intentionally simple and parallel. Delta emphasizes abrupt morphology changes, Rate preserves amplitude-dependent firing, and FSR adds a band-limited view without replacing the original full-band encoding.

D. Hybrid SNN Classifier

The classifier is a HybridSNN with 69 input features, a 256-unit hidden layer, a two-class output layer, and 18,948 trainable parameters. Training used cross-entropy loss, gradient clipping, validation monitoring, and early stopping. The best validation model occurred at epoch 39, and early stopping triggered at epoch 49.

E. Patient-Specific Threshold Analysis

PSTC is reported as a secondary threshold analysis rather than as the operating point used for the main comparison. Let s_i be the seizure score for validation window i and let $p(i)$ denote the corresponding patient. For each patient p, PSTC collects validation pairs (s_i, y_i) and selects the threshold that maximizes Youden's index:

$$J_p(\theta) = \mathrm{Se}_p(\theta) + \mathrm{Sp}_p(\theta) - 1, \tag{3}$$

$$\theta_p^* = \arg\max_{\theta} J_p(\theta). \tag{4}$$

The PSTC-specific label assignment is

$$\hat{y}_i = \mathbf{1}[s_i \geq \theta_{p(i)}^*]. \tag{5}$$

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TABLE I
DATASET AND PROPOSED PIPELINE CONFIGURATION.

Item	Value
Dataset subset	CHB-MIT patients 01, 03, 14, 17, 21, 24
EDF files / channels	32 files / 23 common channels
Window / stride	128 samples / 64 samples
Original windows	458,424, seizure ratio 1.30%
Balanced samples	23,908 (5,977 positive, 17,931 negative)
Validation samples	7,173 (1,793 positive, 5,380 negative)
Training labels	SzCORE-style overlap $\geq 50\%$; no official SzCORE evaluation
Input encoding	Delta + Rate + FSR, $3C = 69$
Classifier	HybridSNN, hidden 256, 18,948 parameters
Secondary threshold analysis	Per-patient Youden PSTC

TABLE II
WINDOW-LEVEL VALIDATION COMPARISON AT DEFAULT THRESHOLD.

Metric	Hybrid SNN	TriHybrid-SzCORE-PSTC
Accuracy	0.9003	**0.9024**
Seizure precision	**0.8477**	0.8213
Seizure recall	0.7328	**0.7791**
Seizure F1	0.7861	**0.7997**
ROC-AUC	0.9118	**0.9137**
PR-AUC	0.8672	**0.8681**
False positives	**236**	304
False negatives	479	**396**

If a patient lacks enough positive or negative validation samples, the implementation falls back to 0.5. No fallback was needed. PSTC is reported separately because it changes the sensitivity-specificity trade-off and was not used for the main default-threshold comparison.

IV. EXPERIMENTS

A. Evaluation Protocol

The reproduced Hybrid SNN baseline and TriHybrid-SzCORE-PSTC were run on the same Intel Core Ultra 5 125H CPU. Window-level metrics include accuracy, seizure precision, recall, F1, ROC-AUC, PR-AUC, false positives, and false negatives. Operational metrics include training time, latency, and K-of-N false-alarm events. The K-of-N analysis used 0.25 s stride and is reported as a stress-test count, not a clinical alarm-rate estimate.

B. Default-Threshold Window Results

At the default 0.5 threshold, TriHybrid-SzCORE-PSTC achieved 0.9024 validation accuracy, 0.8213 seizure precision, 0.7791 seizure recall, and 0.7997 seizure F1. The confusion matrix was TN=5,076, FP=304, FN=396, and TP=1,397. The window-level ROC-AUC was 0.9137 and PR-AUC was 0.8681.

Compared with the reproduced Hybrid SNN baseline, TriHybrid-SzCORE-PSTC improved recall from 0.7328 to 0.7791, F1 from 0.7861 to 0.7997, and false negatives from 479 to 396. Precision decreased and false positives increased from 236 to 304, indicating a shift toward fewer missed seizure windows. Table II reports this comparison, and Fig. 2 shows the corresponding ROC curve.

TABLE III
ENCODING ABLATION UNDER THE MATCHED VALIDATION SETTING.

Encoding	Acc.	Prec.	Rec.	F1	ROC	PR	FP	FN
Delta + Rate	0.8945	0.7806	**0.8037**	0.7920	**0.9151**	**0.8715**	405	**352**
Delta + FSR	0.8942	0.8096	0.7540	0.7808	0.9077	0.8578	318	441
Rate + FSR	0.8565	0.7008	0.7434	0.7215	0.8929	0.8124	569	460
Delta + Rate + FSR	**0.9024**	**0.8213**	0.7791	**0.7997**	0.9137	0.8681	**304**	396

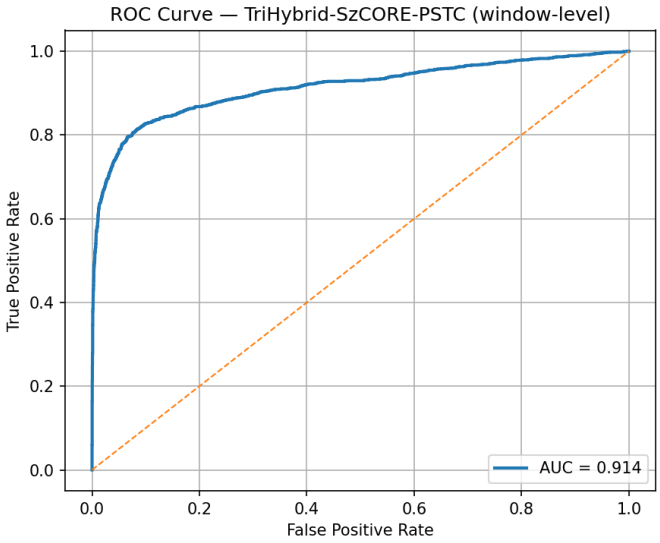


Fig. 2. Window-level ROC curve for TriHybrid-SzCORE-PSTC. The validation ROC-AUC was 0.9137 and PR-AUC was 0.8681.

C. Encoding Ablation

Table III reports three matched dual-stream ablations used to isolate each spike stream: Delta+Rate removed FSR, Delta+FSR removed the full-band Rate stream, and Rate+FSR removed Delta. Each ablation kept the same patient subset, SzCORE labels, balanced validation split, HybridSNN hidden size, and default-threshold evaluation.

The ablation shows different operating trade-offs. Delta+Rate achieved the highest recall, lowest false negatives, ROC-AUC, and PR-AUC, but had more false positives and lower precision than the full pipeline. Adding FSR reduced false positives from 405 to 304 and improved precision from 0.7806 to 0.8213. Rate+FSR performed worst, supporting the value of the combined spike representation rather than any single stream.

D. PSTC Operating Point Analysis

PSTC thresholds varied across patients, from 0.255 for patient14 to 0.577 for patient03. With per-patient Youden thresholds, TriHybrid-SzCORE-PSTC obtained sensitivity of 0.8466, specificity of 0.8907, precision of 0.7208, and F1 of 0.7787. The global Youden threshold was 0.4366, with sensitivity of 0.8137 and specificity of 0.9165. Table IV summarizes the per-patient operating points.

E. Runtime and False Alarms

TriHybrid-SzCORE-PSTC is computationally heavier than the baseline. The full pipeline required about 305 min, includ-

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TABLE IV
PER-PATIENT PSTC THRESHOLDS ON VALIDATION DATA.

Patient	Thr.	Se	Sp	Youden J	Pos.	Neg.
patient01	0.515	0.937	0.921	0.859	175	674
patient03	0.577	0.968	0.970	0.937	248	660
patient14	0.255	0.691	0.774	0.465	220	1226
patient17	0.453	0.948	0.866	0.813	381	507
patient21	0.435	0.910	0.846	0.755	221	648
patient24	0.476	0.730	0.958	0.688	548	1665

TABLE V
OPERATIONAL COMPARISON.

Metric	Hybrid SNN	TriHybrid-SzCORE-PSTC
Pipeline time	**90 min**	305 min
Training time	**86 min**	296 min
Per-sample latency	**1.220 ms**	1.776 ms
FA events	**61**	96
Best epoch	62	**39**
Early stop epoch	72	**49**

ing 296 min for training, compared with 90 min and 86 min for the baseline. Per-sample latency was 1.776 ms, compared with 1.220 ms. This remains shorter than the 0.5 s window length, but the training-time cost is meaningful.

Event-level false alarms are the main weakness. Under K-of-N analysis, TriHybrid-SzCORE-PSTC produced 96 false-alarm events, compared with 61 for the baseline. Because validation duration is short, we report only event counts and do not convert them into a daily alarm-rate estimate. Table V summarizes this operational comparison.

V. DISCUSSION

The results clarify the trade-off introduced by TriHybrid-SzCORE-PSTC. The pipeline improves seizure-window recall, F1, ROC-AUC, and PR-AUC relative to the reproduced Hybrid SNN baseline. It therefore shifts detection toward a recall-oriented operating point under matched conditions, but precision decreases, false positives increase, and event-level false-alarm counts become higher.

Despite these limitations, the pipeline has two practical strengths. First, the triple-stream representation combines change-based, amplitude-based, and frequency-selective information within a low-latency SNN input. This gives the classifier access to complementary views of each window while preserving the spike-encoded structure of the baseline. Second, the 256-unit hidden layer and matched evaluation setting make the comparison controlled. The main value is therefore not a replacement for existing detectors, but a reproducible pipeline for studying how spike encoding and model configuration affect missed-seizure behavior.

This framing also makes the negative results useful. The higher false-positive count shows that improving recall by enriching the spike representation is not automatically sufficient for deployment-style monitoring. However, the ablation indicates that the added FSR stream improves the precision-F1 balance when combined with Delta and Rate, rather than simply pushing the detector toward more positive predictions. This is the main systems-level insight of the study.

At the default threshold, TriHybrid-SzCORE-PSTC detects 83 additional seizure windows and misses 83 fewer seizure windows than the baseline. It also introduces 68 additional false positives. This is the central trade-off: TriHybrid-SzCORE-PSTC favors recall-oriented window detection, whereas the baseline favors false-positive control and runtime.

The ablation further bounds the contribution. Delta+Rate produced the highest recall and AUC values, but increased false positives and reduced precision relative to the full pipeline. Delta+FSR produced lower recall and F1, while Rate+FSR produced the weakest precision, accuracy, and F1. Thus, FSR does not simply increase recall. Within the three-stream configuration, it improves the precision-F1 trade-off and reduces false positives while preserving competitive recall.

PSTC should be interpreted carefully. It raised sensitivity to 0.8466, but precision fell to 0.7208 and F1 to 0.7787 because Youden's index balances sensitivity and specificity, not precision and F1. For monitoring settings where alarm burden dominates, a higher-threshold or event-level objective would be needed.

Several limitations remain. The evaluation uses six CHB-MIT patients rather than the full cohort, and the validation split is class-balanced relative to natural continuous EEG. PSTC is computed on validation data and is reported only as an operating-point analysis. Stronger claims require the full cohort, original imbalanced recordings, independent calibration, and standardized event-level false-alarm analysis.

VI. CONCLUSION

TriHybrid-SzCORE-PSTC is a proof-of-concept spike-encoded pipeline combining three spike encodings, a 256-hidden-unit HybridSNN, SzCORE-style 50% overlap labels, and separately reported Youden-based PSTC. On a matched six-patient CHB-MIT subset, it improved seizure recall, F1, and false negatives relative to the reproduced Hybrid SNN baseline, achieving 0.7997 seizure F1 and 0.9137 ROC-AUC at the default threshold. Ablations showed that Delta+Rate retained the highest recall and AUC values, while the full three-stream configuration achieved the best accuracy, precision, F1, and false-positive control. The method should be understood as an evaluation-oriented system improvement rather than a new seizure-detection model or deployable monitoring system. Future work should evaluate the full cohort, original imbalanced recordings, independent PSTC calibration, and event-level objectives that jointly reduce missed seizures and false alarms.

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