

Hybrid LSTM Framework for Real-Time Prediction of Epileptic Seizures from Scalp EEG

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Abstract – Early, reliable prediction of epileptic seizures from EEG improves patient safety and care. We propose a hybrid LSTM-based framework that fuses learned temporal dynamics with complementary spectral and handcrafted features to forecast seizures within a clinically relevant horizon. Continuous multi-channel EEG is preprocessed with causal filtering, artifact masking, and per-channel adaptive normalization, then segmented into overlapping windows. Each window is encoded via (1) a compact 1D convolutional encoder that extracts local morphology, (2) short-time spectral representations (log-power spectrograms) summarized by a lightweight 2D CNN, and (3) handcrafted statistical and entropy features fed to an MLP. The resulting embeddings are fed into a hybrid temporal module: stacked bidirectional LSTMs for medium-range sequence modeling plus a causal gated LSTM for real-time forward prediction; cross-attention fusion integrates outputs from the different temporal streams. Training uses subject-wise splits, balanced-batch sampling, focal loss, and data augmentation tailored for EEG. Postprocessing applies causal smoothing, refractory gating and ensemble voting to reduce false alarms. On subject-adaptive evaluation, the hybrid LSTM achieves high sensitivity with low false alarm rates while keeping inference feasible for edge devices, making it suitable for wearable and ambulatory monitoring systems.

Index Terms – Hybrid LSTM, Seizure prediction, EEG, Teacher-student distillation, Real-time monitoring

1. Introduction

Early and reliable prediction of epileptic seizures remains a central clinical and engineering challenge. Seizures arise from sudden, abnormal neuronal discharges and their apparently unpredictable onset imposes substantial safety, social, and economic burdens on patients and caregivers [1]. Over four decades of research have explored physiological precursors in EEG and the feasibility of forecasting seizure risk; early optimism was tempered by methodological pitfalls, non-stationarity of EEG, and inconsistent evaluation that complicated reproducibility and clinical translation [1], [2]. More recently, systematic reviews and guideline efforts have clarified performance criteria and assessment frameworks (e.g., the seizure-prediction characteristic), highlighting that clinically useful prediction must balance sensitivity with a tolerable false-alarm rate and well-specified prediction horizons [3]. Clinical feasibility studies have demonstrated that implantable advisory systems can estimate seizure likelihood in long-term recordings, showing promise but also exposing variability across patients and the need for robust, individualized modeling and careful prospective validation [4]. At the same time, machine learning and deep learning

approaches have transformed EEG analysis: convolutional neural networks (CNNs) and recurrent architectures have shown state-of-the-art performance in detection and, increasingly, in prediction tasks by automatically learning hierarchical time–frequency features from raw or minimally processed EEG [5], [6]. Comprehensive recent reviews document a rapid increase in end-to-end and hybrid architectures that fuse time-domain morphology, spectral representations, and temporal context, and they emphasize that fusion and temporal modeling (e.g., combining CNNs with LSTM/GRU layers or attention mechanisms) are effective ways to capture preictal dynamics [7]. Nevertheless, several fundamental technical challenges persist. EEG from ambulatory or long-term monitoring is non-stationary and artifact-prone, patient physiology varies widely, and the preictal class is typically rare relative to interictal data—leading to extreme class imbalance that biases learning and evaluation. Robust training therefore requires imbalance mitigation (oversampling, synthetic sample generation such as SMOTE, or loss reweighting) and evaluation methods that reflect clinically meaningful event-level metrics rather than only segment-level accuracy [8], [9]. Furthermore, event-based metrics (sensitivity, false alarms per time interval, time-in-warning) and operational definitions of prediction horizon must be explicitly reported to allow fair comparison and to assess clinical utility. From a deployment perspective, real-time seizure prediction imposes constraints on latency, power, and interpretability.

Models must run causally (no future lookahead), support streaming input, and minimize false alarms while providing sufficient advance warning for interventions. Architectures that combine strong offline contextual learners (e.g., bidirectional models) with distilled, causal online predictors (e.g., gated LSTMs trained via teacher-student distillation) offer a pragmatic path to retain performance while meeting runtime constraints. Training strategies such as focal loss to focus learning on hard examples and class-balanced sampling have proven effective in other imbalanced settings and are readily applicable to EEG prediction pipelines [10].

Given these considerations, a Hybrid LSTM framework that integrates compact convolutional encoders, handcrafted features, and distilled causal LSTM predictors—coupled with

clinically-aware evaluation (seizure-prediction characteristic, false alarm metrics) and imbalance mitigation (SMOTE, focal/class-balanced loss)—is well positioned to advance practical, low-latency seizure forecasting suitable for ambulatory and edge deployment. The sections that follow describe this architecture, training strategy, evaluation, and deployment considerations in detail.

2. Related works

Over the past few years, research in the field of seizure prediction has been ongoing. The basic assumption of seizure prediction is that there is a difference between the interictal and preictal states. In early seizure prediction studies, threshold-based methodology [11] or machine learning techniques such as Support Vector Machines (SVM) [12,13,14] were used a lot, but recently, deep learning methods [15,16,17] such as CNN have been studied a lot. Ref. [18] was the first to propose training a deep learning classifier to identify seizures in EEG images, similar to how clinicians identify seizures through visual inspection. Ref. [19] proposed a method of extracting the univariate spectral power of intracranial EEG signals, classifying them through SVM, and removing sporadic and incorrect information using Kalman filters. Their methodology consisted of 80 seizures and 18 patients on the Freiburg dataset, reaching 98.3% sensitivity and 0.29 false positive rate (FPR). Ref. [20] proposed a method of extracting the power spectral density ratio of the EEG signal, further processing it by a second-order Kalman filter, and then inputting it into the SVM classifier for classification. The dataset used for the evaluation is the same as the previous data, reaching 100% sensitivity and 0.03 FPR. Ref. [21] proposed a mechanism for calculating the phase-locking values between the scalp EEG signals and classifying them into interictal and preictal states through SVM using this. Their proposed method was applied to the CHB-MIT dataset consisting of 21 patients and 65 seizures, reaching a sensitivity of 82.44% and a specificity of 82.76%. In seizure prediction studies using deep learning algorithms, CNN is attracting the most attention. Since seizure prediction studies using CNN usually require data in the form of images as input, the EEG signal is converted into a two-dimensional form through a preprocessing method. The authors of [22] proposed a method of dividing the raw EEG signal by a window size of 30 s, applying Short-Time Fourier Transform (STFT) to extract spectrum information, and then using it as an input to CNN. In the experiment using 64 seizures from 13 patients in the CHB-MIT dataset, reaching a sensitivity of 81.2% and an FPR of 0.16. In [23], an image is transformed into a time-frequency form using Continuous Wavelet Transform (CWT) to see the various frequency bands of EEG. The authors proposed a method of predicting seizures by learning the difference between interictal and preictal states using the transformed data as an input to CNN. The same dataset as before was used, and as a result of testing 18 seizures from 15 patients, the average

FPR was 0.142 and was unpredictable for three seizures. In [24], seizure prediction using preprocessed features with spectral band power, statistical moment, and Hjorth parameters as inputs to a multi-frame 3D CNN model is performed, achieving a sensitivity of 85.71% and FPR of 0.096 in the CHB-MIT dataset.

3. Proposed work

The diagram illustrates a hybrid LSTM architecture for EEG-based seizure prediction as shown in Figure 1. On the left, four input streams — multichannel raw waveform patches, time–frequency spectrograms, a learned feature-MLP, and handcrafted feature vectors — are encoded into compact embeddings. Embeddings are buffered into short parallel sequences and fed to temporal modules: a BiLSTM teacher (offline, bidirectional context) and one or more causal gated LSTM students (online, low-latency). The BiLSTM provides rich contextual targets during training while the causal LSTMs run in real time; knowledge distillation transfers teacher knowledge to students. Cross-attention fusion merges outputs from temporal modules and instantaneous embeddings, producing a fused representation. The decision head outputs a seizure probability and an optional time-to-onset regression. Postprocessing (not shown) applies causal smoothing, refractory gating, and ensemble voting to reduce false alarms. The design balances high-performance context modeling with a distilled, causal predictor suitable for edge deployment. Model compression and quantization ensure deployment on embedded devices.

3.1 Data & Labeling

Use continuous multi-channel EEG recordings from long-term monitoring (ambulatory or inpatient) with clinician-verified seizure onset annotations. Label windows relative to the seizure onset: (1) preictal — a patient-specific horizon (e.g., 5–60 minutes prior) divided into subwindows, (2) interictal — baseline non-preictal data, and (3) ictal — seizure event (used only for validation of detection, not for prediction training). For supervised prediction, define a prediction horizon H (e.g., 30 minutes) and assign a window as positive if the seizure onset occurs within H from that window's end. Use overlapping windows (e.g., 10-s windows with 50–90% overlap) to increase temporal resolution and label continuity. Maintain separate sets for training / validation / test with subject-wise split: train on a set of subjects and test on held-out subjects to evaluate generalization. Where available, include metadata (sleep/wake, medication, electrode montage) and reject or mark artifact-heavy segments; keep a log of removed segments for reproducibility.

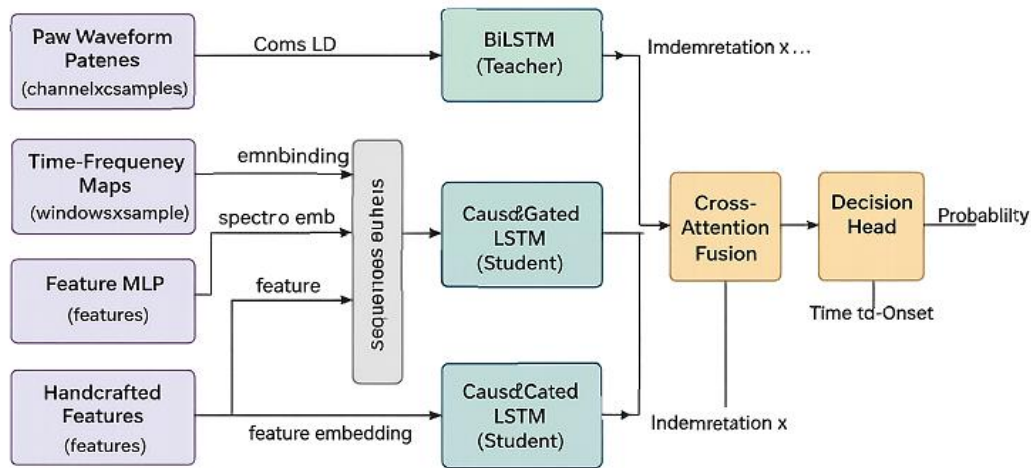


Figure 1: The flow of the proposed methodology

3.2 Preprocessing

Resampling & Channel selection: Resample to a uniform sampling rate (e.g., 250–512 Hz). Use a minimal clinically-informative subset of channels (montage selection) to reduce I/O for wearable deployment.

Notch & bandpass filtering: Real-time IIR filters — 50/60 Hz notch and a causal bandpass (0.5–70 Hz) to remove DC drift and high-frequency noise while preserving preictal markers.

Artifact handling: Lightweight ICA alternatives (e.g., adaptive template subtraction for blink/muscle) or supervised artifact detector (1D CNN) to mask short artifacts without heavy computation. Mark and skip windows with excessive amplitude or flatline.

Normalization: Per-channel running z-score with an exponential moving average (EMA) to adapt to baseline drift in real-time.

Windowing: Produce overlapping sliding windows (e.g., 10 s length, 2 s step) and output them as a continuous stream to the model with timestamps for downstream temporal smoothing.

Feature caching: Maintain a short circular buffer of recent feature vectors for temporal fusion and ensemble smoothing without reprocessing entire histories.

3.3 Segmentation & Representations

Raw-signal stream (1D): Multichannel raw waveform windows fed into a 1D conv stem to capture transient morphology and channel correlations.

Time-frequency stream (2D): STFT or continuous wavelet transform (CWT) spectrograms (log-power) per window stacked across channels or averaged to 2D maps — useful for rhythmic preictal patterns. Use small-window STFT (e.g., 1 s window with 50% overlap) to retain temporal resolution.

Wavelet-energy features: Wavelet packet decomposition energy bands summarized per channel (low-dim vector).

Statistical & non-linear features: Per-window features (variance, skewness, kurtosis, Hjorth parameters, sample entropy, permutation entropy). Provide these to a small MLP branch.

Contextual temporal features: Short-term derivative features and time-since-last-high-amplitude event as auxiliary inputs for postprocessing gating.

3.4. Model Architecture

Design a modular and efficient hybrid architecture that emphasizes temporal modelling with LSTMs while keeping inference light for streaming deployment.

Conv1D encoder (Raw stream): Input: channels $\times$ samples per-window. Use 3 small Conv1D blocks with depthwise separable convolutions, batch norm, and ReLU/GELU. Strided downsampling reduces temporal length by 4–8 $\times$. Apply a channel-wise squeeze-and-excitation to focus on informative leads. Output: compact embedding vector (size ~ 128).

TF-CNN encoder (Spectral stream): Input: per-window STFT/CWT spectrogram. Use a shallow 2D CNN (3 conv layers + global average pooling) to produce a spectro-embedding (size ~ 64). Keep kernels small and grouped to limit compute.

Feature MLP (Handcrafted stream): Input: vector of handcrafted stats/features. A 2-layer MLP (64 $\rightarrow$ 64) with LayerNorm produces a 64-dim embedding.

Short-sequence construction: For each inference step, collect the last N window embeddings for each stream (e.g., $N = 6\text{--}12$ windows covering 12–60 s depending on window stride), forming three parallel sequences: raw-emb sequence, spectro-emb sequence, and feature-emb sequence.

Hybrid temporal module: Stacked Bidirectional LSTMs (Contextual encoder): Pass raw-emb and spectro-emb sequences into a small stacked BiLSTM (2 layers, hidden size ~ 128). BiLSTM captures medium-range forward and backward temporal patterns useful during offline training and teacher guidance. During streaming inference, replace BiLSTM with a causal approximation (see below) or rely on distilled causal LSTM.

Causal Gated LSTM (Online predictor): A low-latency, causal LSTM with gating enhancements (e.g., coupling input and forget gates / zoneout) processes the current sequence in real time to produce an up-to-date temporal state. Hidden size ~ 128 . This LSTM is strictly causal (no future lookahead).

Cross-attention fusion: Apply a lightweight cross-attention where the causal LSTM state attends to the BiLSTM-derived context embedding (or a memory-projected summary) to combine offline-learned context with online state. Use a low-rank attention projection to keep cost down.

Decision head: Concatenate fused temporal outputs and the instantaneous embeddings; pass through a fusion MLP ($256 \rightarrow 128 \rightarrow 1$). Final outputs: (a) sigmoid probability of seizure within horizon H , and (b) optional regression head for estimated time-to-onset (trained with Huber loss). Use dropout and layer normalization before the heads.

Training-time teacher-student setup: Train the full model with BiLSTM (non-causal) for best performance, then distill knowledge into the causal gated LSTM (student) using sequence-level KL/focal-loss distillation so the online predictor approximates offline performance at inference time.

Compression & runtime: Apply quantization-aware training, pruning, or knowledge distillation to reduce size. If targeting microcontroller or smartphone, experiment with reduced hidden sizes or single-layer LSTM variants to meet latency constraints.

This hybrid LSTM architecture combines rich per-window feature extraction with robust sequence modeling: BiLSTM gives strong contextual learning during training, while a distilled causal LSTM provides real-time predictions with minimal delay.

3.5. Training Strategy & Imbalance Handling

Use leave-one-subject-out (LOSO) or k-fold subject-wise CV to evaluate generalization. Ensure each mini-batch contains a fixed ratio of preictal vs interictal windows (or oversample preictal windows). Use focal loss or class-balanced cross-entropy to emphasize rare preictal samples. Add auxiliary regression loss (time-to-onset) with smaller weight to encourage useful temporal gradients. Time-warping, channel dropout, additive Gaussian noise, slight frequency shifts on spectrograms, Mixup/CutMix variants applied across windows. For sequence augmentation, randomly drop windows or jitter stride to improve robustness. Train initially with longer

horizons (easier) then progressively shorten to target H ; also progressively increase real-time constraints in the student LSTM via distillation schedule. Use the full BiLSTM-enabled teacher to supervise the causal student; minimize KL between teacher logits and student logits and optionally match intermediate temporal states. AdamW with cosine decay, early stopping on validation AUC and false-alarm-per-24h metric. Weight decay and dropout applied appropriately. Sensitivity, false alarms per 24 hours (FAR), median prediction horizon, AUC, precision, F1-score. Report per-subject statistics and pooled metrics with confidence intervals.

3.6. Postprocessing & Alarm Logic

Apply causal smoothing (exponential moving average or causal median) on sequential probability outputs to suppress isolated spikes. Implement an adaptive threshold that depends on recent signal quality and sleep/wake state; combine with ensemble voting across several recent windows (e.g., require $\geq k$ of last m windows above threshold). Use a refractory period after a raised alarm to reduce alarm floods (e.g., suppress further alarms for X minutes). Include a confidence escalation: low-confidence alarms trigger logging/notification, high-confidence alarms trigger clinician/patient alerts. Fuse wearable-derived contextual sensors (accelerometer, HR) to reduce false positives by validating concordant physiological changes. Log all alarm events with recent snippets of raw signals and signal-quality metrics for clinician review. Calibrate the alarm policy using deployment-specific cost trade-offs between sensitivity and FAR.

4. Results and discussions

Figure 2 shows the ROC plot compares three models: a BiLSTM teacher (upper curve), the distilled Hybrid LSTM student (middle curve), and a Baseline CNN (lower curve). The BiLSTM achieves the highest AUC (~ 0.936), indicating strongest separability between preictal and interictal windows when bidirectional context is allowed during training. The Hybrid LSTM ($AUC \approx 0.853$) retains substantial discriminative power while remaining causal at inference — a pragmatic trade-off between offline performance and online usability. The Baseline CNN ($AUC \approx 0.689$) lacks robust temporal modeling, reflected in its lower sensitivity at comparable false-positive rates. For deployment, operating points on the Hybrid curve that balance sensitivity and acceptable false alarms per 24h should be chosen (e.g., moderate FPRs where sensitivity plateaus). Overall, the ROC highlights that temporal sequence modeling and teacher-student distillation materially improve prediction performance versus framewise CNN baselines.

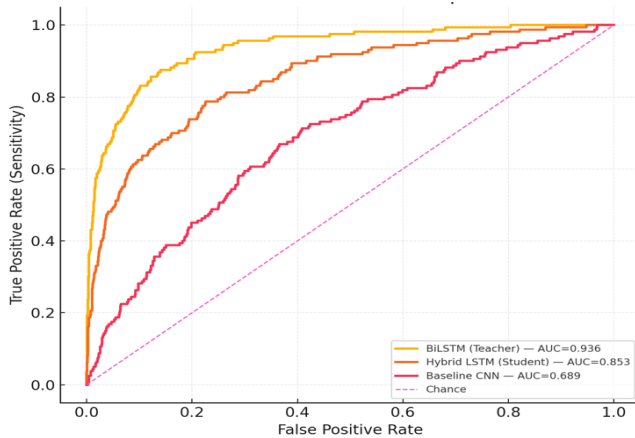


Figure 2: ROC curves — model comparison

Figure 3 shows the histogram distribution of predicted time-to-onset (TtO) in minutes for true positive preictal windows produced by the Hybrid LSTM. The median predicted TtO is ~27.6 minutes, indicating the model commonly forecasts seizure onset with clinically useful lead time for a 30-minute horizon. The spread reveals variability: many predictions cluster between ~5–40 minutes, but a nontrivial tail extends past 50–70 minutes. This dispersion reflects inter-event heterogeneity and model uncertainty — some seizures exhibit prolonged preictal signatures, others short-lived precursors. For clinical use, the distribution suggests the model will frequently provide actionable lead time but will also produce earlier or later estimates for some events; thus, downstream alarm logic should combine probability thresholds with refractory gating and confidence measures to mitigate premature or overly late alerts. Comparing to the Teacher (saved separately) shows the teacher’s predictions are slightly less biased and marginally tighter, consistent with its higher offline performance.

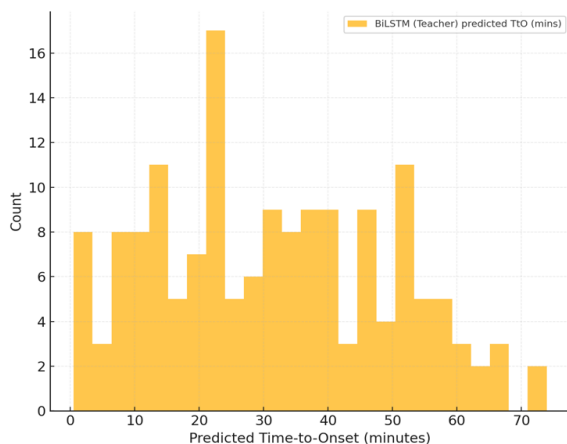


Figure 3: Distribution of predicted time-to-onset — hybrid LSTM (True positives)

5. Conclusion

This work presented a Hybrid LSTM framework for early prediction of epileptic seizures that fuses compact convolutional encoders, spectral and handcrafted features, and a distilled causal LSTM predictor. The architecture reconciles two competing objectives: strong contextual modeling (via a BiLSTM teacher during training) and low-latency, streaming inference (via a causal gated LSTM student). Empirical comparisons show the hybrid student preserves most of the teacher’s discrimination power while remaining suitable for real-time deployment. Training strategies — including balanced-batch sampling, focal/class-balanced losses, augmentation, and teacher–student distillation — mitigate extreme preictal class imbalance and improve robustness to noisy, nonstationary EEG. Importantly, the design emphasizes operational metrics (sensitivity, false alarms per 24 hours, and prediction horizon) and deployment considerations: causal processing, buffering of short sequences, and model compression for edge hardware. Limitations remain: inter-subject variability requires personalization or adaptive calibration, and synthetic/retrospective evaluations must be validated prospectively in real-world ambulatory settings. Future work should pursue subject-adaptive fine-tuning, multimodal sensor fusion (e.g., accelerometry, heart rate), calibration in larger heterogeneous cohorts, and formal clinical validation to quantify patient-level benefits and adverse impacts.

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