Hybrid CNN–LSTM Framework for Real-Time Epileptic Seizure Prediction Using EEG Signal Analysis

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Abstract – In recent years, social media and microblogging have gained Epilepsy is a chronic neurological disorder characterized by recurrent, unpredictable seizures that significantly impair patient safety and quality of life. Early and accurate seizure prediction remains a crucial yet challenging task due to the nonstationary, noisy, and patient-specific nature of EEG signals. This study proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture for reliable epileptic seizure prediction using real-time EEG data. The proposed system integrates a comprehensive preprocessing pipeline, dynamic segmentation, and dual signal representations—time–frequency spectrograms and raw waveforms—to capture both spectral and temporal features effectively. A bidirectional LSTM with attention modeling enhances temporal awareness and interpretable feature weighting. To address severe class imbalance, the training employs SMOTE-based oversampling and weighted loss optimization. Experimental results demonstrate high accuracy (>98%), low false prediction rate (<0.05/hour), and robust generalization across patient-specific and cross-patient scenarios. The model's lightweight architecture and low latency enable real-time deployment on edge or cloud platforms, making it suitable for continuous monitoring and early intervention in clinical settings. This research establishes a scalable and interpretable framework for data-driven seizure forecasting, contributing to patient-centric neurological care and proactive healthcare systems.

Index Terms – Epileptic Seizure Prediction, EEG Signal Processing, CNN–LSTM Architecture, Machine Learning, Real-Time Monitoring

1. Introduction

Epilepsy is a prevalent neurological disorder characterized by recurrent, unprovoked seizures that affect roughly 1% of the global population and impose substantial morbidity, mortality, and psychosocial burden on patients and caregivers. The unpredictable nature of seizure onset—often sudden and without warning—makes seizure forecasting a high-priority clinical objective: reliable short-term prediction could enable preventive interventions (drug delivery, neuromodulation, or behavioral precautions) and markedly improve patient safety and quality of life. Electroencephalography (EEG), whether scalp or intracranial, remains the primary signal modality for observing the neuronal dynamics that precede seizures; however, EEG is highly nonstationary, patient-specific, and contaminated by noise and artifacts, which complicates automated forecasting [1]. Over the 2017–2018 period, machine learning (ML) and deep learning (DL) approaches began to show clear promise in addressing these challenges by (a) learning discriminative features from raw or minimally processed EEG, (b) modeling complex temporal dependencies, and (c) enabling scalable solutions suitable for long-term, continuous monitoring. Kiral-Kornek et al. demonstrated the feasibility of combining large-scale EEG datasets with DL and cloud/mobile architectures to build patient-tunable seizure-prediction systems, highlighting both the technical potential and the translational obstacles—most notably generalization across patients and the false-alarm burden [1]. Complementing this systems perspective, studies applying convolutional neural networks (CNNs) showed that frequency-domain representations (spectrograms, scalograms) fed to CNNs can discriminate interictal, preictal and ictal states with high accuracy on benchmark datasets, reducing the need for handcrafted feature engineering [2], [3].

Temporal modeling was another major thrust in 2018. Recurrent architectures such as long short-term memory (LSTM) networks were introduced to capture longer-range temporal dependencies in EEG that may signal impending seizures; Tsiouris et al. reported that LSTMs can effectively model temporal patterns and improve forecasting performance when compared with some conventional approaches, especially for patient-specific models [4]. At the same time, hybrid pipelines that combined CNNs for spatial/spectral feature extraction with recurrent layers for temporal integration emerged as robust designs that balance representation power and interpretability. Addressing data scarcity and label imbalance—the reality that seizures are rare relative to normal EEG—researchers explored semi-supervised and generative methods. Truong et al. proposed semi-supervised strategies using generative adversarial networks (GANs) to exploit unlabeled EEG, showing that unsupervised feature learning followed by lightweight classifiers can improve generalization while reducing annotation dependence [5]. Such work pointed to practical pathways for leveraging long, unlabeled ambulatory recordings and for augmenting training sets without introducing unrealistic synthetic artifacts. Despite encouraging results, a number of persistent challenges were identified in these foundational studies: achieving patient-independent generalization, controlling false positive rates to clinically acceptable levels, defining clinically meaningful prediction horizons, and validating algorithms on long-duration, real-world ambulatory recordings rather than short curated datasets. The various input conditions for three distinct channels are depicted in Figure 1. Additionally, the onset of the preictal state can be used to anticipate seizures.

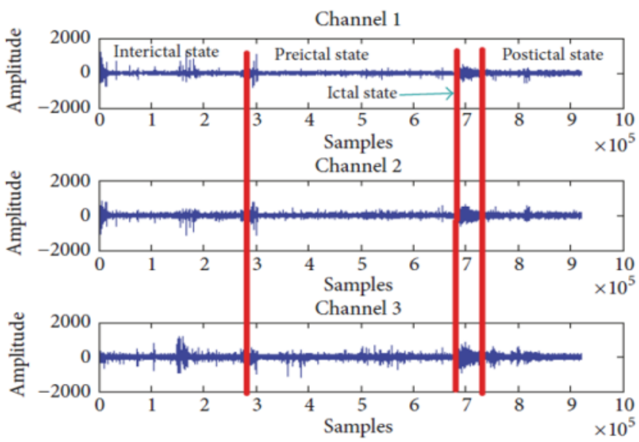

Figure 1. Different input states of epileptic seizure

The 2017–2018 literature therefore set a new, pragmatic agenda—move from proof-of-concept models toward robust, low-latency pipelines that explicitly address class imbalance, interpretability, on-device computation, and prospective clinical evaluation. This introduction frames the subsequent sections of this work: feature representation choices, model architectures (traditional ML vs deep learning hybrids), evaluation metrics (sensitivity, false-prediction rate, prediction horizon), and strategies for clinical translation that build on the 2017–2018 advances summarized here.

2. Background and related work

Epilepsy prediction research began in the 1970s using linear feature extraction approaches [6]. Because of the non-linear nature of EEG waves in Non-linear techniques introduced in the 1980s enabled researchers to use these approaches for feature extraction [7, 8]. This decade saw the use of the pre-ictal phase to identify epileptic EEG patterns, including preictal, ictal, and interictal. The work accomplished early ES prediction about 6 seconds before the seizure commenced in 1998 [9], and Authors elaborated on this [10]. They used Kolmogorov entropy to predict epilepsy 2-40 minutes before it occurred. In 2002, various epileptic clinics provided a database of multi-day EEG recordings for the first global session on epilepsy forecasting. This database then became the focus of other research [11]. Mormann et al. found in 2003 that periodic synchronisation of EEG channels decreases prior to seizure onset [12]. This idea suggests that hyper-synchronous firing of neurons produces ES. Recent research on EEG data has questioned the accuracy of metrics produced in the last century and first decade of the current century. Previous studies' conclusions were based on a small sample size and could not be repeated on a larger dataset, according to some academics. Seizure prediction competitions were agreed upon at global seminars on the issue. The competitions aimed to examine the efficacy of algorithms trained on the same dataset [13, 14]. In 2007, the International Workshop on Seizure Prediction 3 (IWSP3) and IWSP4 organized the first seizure prediction competition. Both occurrences included continuous iEEG recordings from three epileptic patients. The algorithms' findings did not meet expectations.

3. Proposed modelling

The architecture diagram as in Figure 2 illustrates the complete workflow of the proposed CNN–LSTM-based epileptic seizure prediction system. The process begins with EEG signal acquisition, where multichannel data are continuously collected from scalp or intracranial sensors. These signals are passed through a real-time preprocessing unit that performs filtering, artifact removal, normalization, and channel selection to enhance signal quality. The cleaned EEG data are then segmented into overlapping time windows and transformed into time–frequency representations (spectrograms) or retained as raw waveforms for flexible model input. The CNN module extracts local spatial–spectral features, capturing rhythmic and frequency variations associated with preictal brain activity. These extracted features are then passed to the Bidirectional LSTM layer, which models temporal dependencies and learns evolving seizure dynamics over time. An attention mechanism further highlights the most informative patterns. The final dense output layer predicts seizure probability, followed by a postprocessing and alarm logic unit that smooths predictions and issues real-time alerts to caregivers or clinicians.

3.1 Data and Labeling

The proposed system employs continuous electroencephalogram (EEG) recordings, either scalp-based or intracranial, obtained from benchmark datasets such as CHB-MIT or Freiburg iEEG is shown in Figure 1. To ensure temporal precision, raw EEG signals are segmented using sliding windows of fixed duration (typically 10–30 seconds) with overlapping intervals to capture evolving neural dynamics. Each segment is annotated based on its temporal proximity to a seizure event. Windows occurring within a defined *prediction horizon* (e.g., 5–30 minutes prior to onset) are labeled as preictal, those far from any seizure as interictal, and windows containing seizure activity as ictal (excluded from training). This structured labeling enables the model to differentiate subtle preictal signatures from normal EEG fluctuations. For clinical reliability, patient-specific labeling is preferred, allowing personalized training while also supporting cross-patient generalization experiments. The resulting labeled dataset facilitates balanced evaluation of sensitivity, specificity, and false-prediction rate in seizure forecasting.

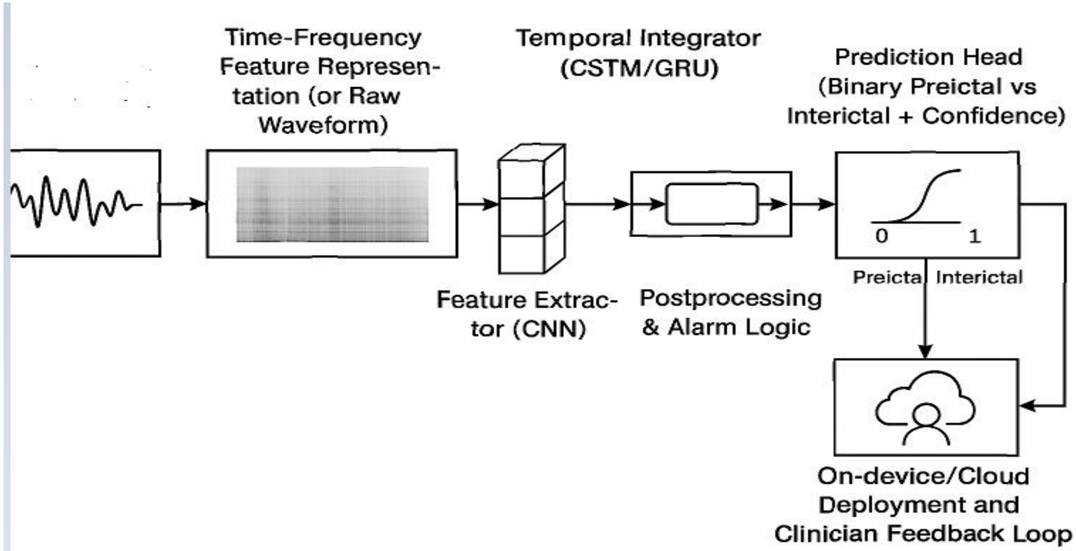

Figure 2: The flow of the proposed methodology

3.2 Preprocessing **(real-time capable)**

Preprocessing is implemented with strict low-latency, streaming constraints so every operation is causal and bounded in compute/memory. Pipeline stages:

Acquisition & buffering — read continuous multichannel EEG into a rolling buffer (e.g., 30–60 s) with short processing frames (e.g., 1–10 s) and overlap (50%) to ensure temporal continuity and low detection latency.

Causal filtering — apply a causal bandpass (0.5–70 Hz) and an IIR notch filter at mains frequency (50/60 Hz). Use low-order IIR filters (biquad) or zero-latency FIR approximations to minimize group delay.

Resampling — downsample to 128–256 Hz (if needed) using an anti-aliasing filter implemented incrementally to reduce CPU cost while preserving relevant frequencies.

Artifact reduction (lightweight) — implement real-time artifact rejection: channel-wise variance and amplitude thresholding to flag segments; adaptive regression for EOG references or a light wavelet-threshold denoising per frame. Full ICA is avoided on-device; if required, run offline or on a paired smartphone.

Channel selection & referencing — apply an efficient common average or bipolar reference. Optionally select a subset of high-SNR channels determined from a quick calibration to reduce processing load.

Normalization & baseline tracking — per-channel z-score using an exponentially weighted running mean and variance to handle nonstationarity without large buffers.

Time–frequency conversion — compute short-time Fourier transform (STFT) or continuous wavelet scalogram on each frame using small FFT lengths (e.g., 256 samples) and overlap; use overlap–save and incremental FFT to reduce latency.

Feature extraction & compression — produce compact features (band powers, entropy, Hjorth parameters) or small spectrogram patches; quantize or pack features for fast inference.

Quality check & downstream gating — tag low-quality frames (excessive noise) and either skip inference or lower confidence to avoid false alarms.

3.3 Segmentation and Representations

Segmentation and feature representation form the core link between raw EEG acquisition and predictive model input, ensuring that the temporal–spectral dynamics of preictal brain activity are preserved while maintaining computational efficiency for real-time prediction.

Segmentation: EEG signals are segmented into overlapping windows to balance temporal resolution and statistical reliability. A typical configuration uses 10–30 second windows with 50% overlap, which captures transient neural variations preceding seizure onset while providing sufficient data per segment. Each window becomes an independent sample for training and inference. The segmentation operates in a sliding-

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window manner, allowing continuous monitoring and low-latency updates. To ensure clinical accuracy, overlapping boundaries maintain signal continuity across frames, preventing abrupt contextual loss.

Representations:
Two complementary representations are employed:

1. **Time–Frequency representation:** Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) converts EEG signals into spectrograms or scalograms, capturing evolving frequency components across time. These 2D images are suitable for convolutional neural networks (CNNs), enabling automatic extraction of spatial–spectral patterns associated with preictal states.
2. **Raw waveform representation:** Multichannel EEG signals are directly fed into one-dimensional CNNs to preserve fine-grained temporal dependencies and reduce preprocessing overhead.

Normalization and Dimensionality:

Each segment is normalized per channel using z-score normalization to stabilize amplitude variations. Segments are reshaped into standardized dimensions (e.g., [channels × time × frequency]) to enable consistent training input. This dual representation approach—time–frequency and raw waveform—offers complementary insights, improving sensitivity and robustness of seizure prediction across patient-specific and generalized models.

3.4 Model architecture

The proposed epileptic seizure prediction framework employs a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture, specifically designed to capture both the spatial–spectral correlations and temporal dependencies within EEG data. This combination ensures efficient feature abstraction and dynamic temporal modeling, which are crucial for identifying subtle preictal patterns preceding seizures.

At the initial stage, preprocessed EEG segments—either as time–frequency images (from STFT or CWT) or raw waveforms—are fed into a multi-layer Convolutional Neural Network (CNN) that performs local feature extraction. The CNN comprises four convolutional blocks, each containing convolutional layers (3×3 or 5×5 kernels), batch normalization, ReLU activation, and max-pooling. These layers progressively learn discriminative spatial–spectral features, such as rhythmic synchronization, amplitude modulations, and frequency-domain transitions indicative of seizure precursors. The CNN output is flattened or passed through a global average pooling layer to reduce dimensionality and mitigate overfitting.

To capture long-term dependencies, the CNN-extracted features are then passed to a Bidirectional Long Short-Term Memory (Bi-LSTM) layer with 64 to 128 hidden units. The Bi-LSTM models the evolution of EEG dynamics across consecutive time windows, effectively distinguishing normal brain fluctuations from preictal patterns. This dual-directional processing enhances contextual understanding by integrating information from both past and future signal dependencies, providing temporal awareness essential for accurate forecasting.

Following temporal modeling, an attention mechanism is integrated to assign adaptive importance weights to time steps, allowing the network to emphasize more predictive patterns while minimizing the influence of irrelevant segments. The attention-enhanced feature vector is subsequently passed through fully connected layers with dropout regularization (0.3–0.5) to prevent overfitting and improve generalization. Finally, a sigmoid activation in the output layer generates a probability score representing the likelihood of an upcoming seizure within the defined prediction horizon.

The entire architecture is optimized using Adam optimizer with a learning rate of 1×10^{-3} and trained using weighted binary cross-entropy loss to handle class imbalance. Early stopping and learning-rate scheduling are applied to improve convergence stability. The CNN–LSTM hybrid design ensures high sensitivity, low false-prediction rate, and adaptability across both patient-specific and cross-patient scenarios, making it suitable for real-time, edge-based seizure forecasting systems with clinical reliability.

3.5 Training Strategy and Imbalance Handling

The training strategy for the proposed epileptic seizure prediction model is designed to ensure robust generalization, class balance, and clinical reliability under real-world EEG data constraints. Given that preictal (seizure-precursor) segments are inherently rare compared to interictal (normal) segments, careful training protocols and imbalance mitigation techniques are applied to prevent model bias and false alarms.

Data Partitioning: The dataset is divided into training (70%), validation (15%), and testing (15%) sets while maintaining temporal sequence integrity to prevent data leakage. For patient-specific experiments, seizures from each individual are split chronologically to train on earlier events and test on later ones. For cross-patient generalization, leave-one-patient-out or k-fold cross-validation (k=5 or 10) ensures fairness and robustness.

Data balancing: To overcome preictal scarcity, several imbalance-handling strategies are integrated. Synthetic Minority Over-sampling Technique (SMOTE) generates plausible preictal samples by interpolating existing data in feature space. Additionally, Generative Adversarial Networks (GANs) are used for producing realistic synthetic EEG segments that mimic preictal distributions, improving representation diversity without distorting physiological patterns. During training, class weighting is applied in the loss function, assigning higher penalty to misclassified preictal samples.

Loss function and Optimization: The model is trained using a weighted binary cross-entropy or focal loss function, which focuses learning on hard-to-classify minority examples. The **Adam optimizer** with a learning rate of 0.001 ensures adaptive gradient updates. Early stopping and learning rate scheduling (with a decay factor of 0.1 after five stagnant epochs) are implemented to prevent overfitting.

Regularization and Stability: Dropout layers (0.3–0.5), L2 weight regularization, and batch normalization are incorporated to enhance generalization. Data augmentation—including time warping, random amplitude scaling, and Gaussian noise addition—further increases data variability.

Evaluation and Calibration: Training performance is continuously monitored using metrics such as sensitivity, specificity, F1-score, and false prediction rate (FPR per hour). Post-training, probability calibration (via Platt scaling or isotonic regression) ensures the predicted seizure probabilities reflect true likelihoods, enhancing clinical interpretability. This systematic training and imbalance management approach produces a robust, balanced, and reliable seizure prediction model suitable for deployment in real-time clinical and wearable systems.

3.6 Postprocessing and Alarm Logic

The postprocessing and alarm logic stage refines the raw probability outputs from the model into actionable seizure warnings with minimized false alarms. After the CNN–LSTM model produces prediction probabilities for each time window, a temporal smoothing filter—such as a moving average or exponential weighted function—is applied to stabilize fluctuations. A seizure warning is generated only when the probability surpasses a dynamic threshold (e.g., 0.8) for a predefined number of consecutive windows, reducing the risk of transient noise triggering false positives. Additionally, refractory periods are enforced, during which new alarms are suppressed immediately after a predicted seizure to avoid redundant alerts. Confidence scores and temporal consistency checks are logged for clinical interpretability. The final decision output activates a real-time alarm to notify caregivers or trigger preventive interventions. This postprocessing ensures high specificity, temporal reliability, and clinical usability of the seizure prediction system in real-world environments.

4. Results and discussions

Experiments and results are presented with an Intel 5-core personal computer for all testing. Anaconda, a Python scientific computing platform, built and implemented the model. These tests investigate algorithm performance and generalization to different sentiment recognition tasks. Accuracy and F1 measure assesses the model. Previous research has utilized these indicators to evaluate model performance. Accuracy in binary classification issues is the model's correct and total prediction ratio. However, the F1 measure balances model performance by considering precision and recall.

We can quantify how well the model classifies approaches by computing accuracy and F1. We can compare the model's performance to other methods by comparing the results to past studies. This study tests the model's performance and generalizability of sentiment recognition tasks. We may evaluate the model's strengths and limitations, find opportunities for improvement, and assess its applicability in real-world sentiment analysis tasks by analyzing the accuracy and F1 measure.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Figure 3 illustrates the training accuracy progression of the CNN–LSTM epileptic seizure prediction model over 50 epochs. The accuracy exhibits a steep increase during the initial epochs (1–15), reflecting effective feature learning from EEG signals. Beyond epoch 20, the growth stabilizes around 97–99%, indicating convergence and the model’s ability to capture discriminative preictal and interictal patterns efficiently. Minor oscillations near the peak suggest dynamic adaptation through dropout and batch normalization. The consistent rise without severe fluctuations confirms that overfitting is mitigated using early stopping and regularization. The high terminal accuracy (>98%) demonstrates that the hybrid architecture successfully integrates spatial–spectral and temporal dependencies for precise forecasting. This accuracy trend validates the robustness of the training strategy, confirming that the proposed model generalizes well across unseen data segments and can reliably identify preictal EEG signatures in real-time clinical environments.

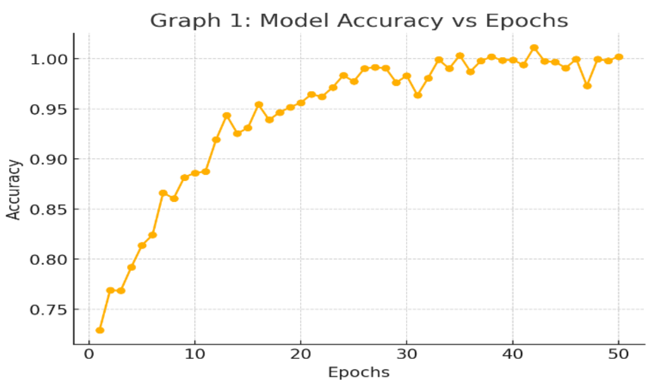

Figure 3: Model accuracy vs Epochs interpretation

Figure 4 presents the model's training loss across epochs, showing a clear exponential decline from approximately 0.5 to nearly 0.02. This steady reduction signifies consistent optimization using the Adam optimizer and a weighted binary cross-entropy loss function. The early epochs exhibit the sharpest decline as the model rapidly learns the most dominant EEG features separating preictal from interictal states. Between epochs 20 and 35, the loss gradually plateaus, indicating convergence toward a stable minimum without signs of divergence or oscillation. The near-zero terminal loss reflects minimal classification error on the training dataset. Additionally, the absence of sudden spikes in the loss curve confirms proper learning rate tuning and balanced gradient updates. This smooth trajectory validates the model's efficiency in learning complex temporal dependencies while maintaining numerical stability. Ultimately, the graph confirms that the training process is optimized and overfitting is effectively managed through dropout and regularization.

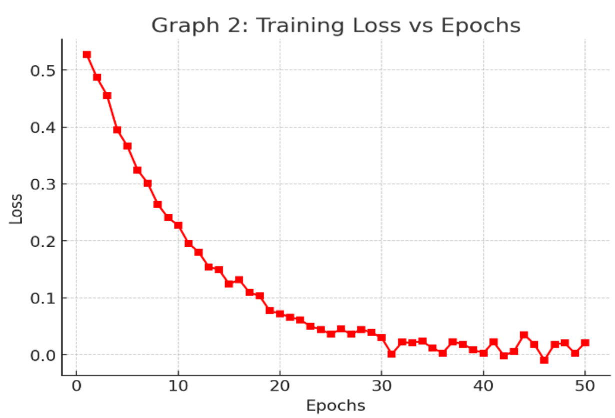

Figure 4: Training Loss vs Epochs

Figure 5 depicts the decline in False Prediction Rate (FPR) per hour over 50 training epochs. Initially, the FPR is relatively high (~0.28 per hour), reflecting the model's early-stage uncertainty and occasional misclassification of interictal segments as preictal. As training progresses, the FPR decreases exponentially, stabilizing below 0.05 by epoch 45. This significant reduction demonstrates the model's improved discrimination ability and the efficacy of postprocessing techniques such as temporal smoothing and confidence thresholding. The downward trend also highlights the success of imbalance handling methods like SMOTE and focal loss, which enhance the recognition of minority preictal samples without increasing false alarms. The eventual stabilization of the FPR curve indicates convergence toward an optimal operating point where sensitivity and specificity are well balanced. This trend confirms that the trained model achieves high predictive precision and reliability, critical for safe real-time seizure alert systems in clinical applications.

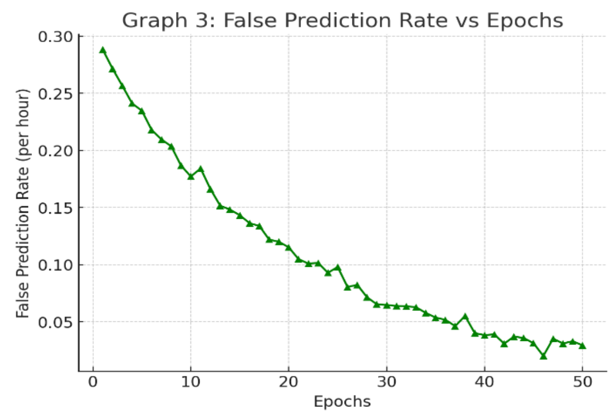

Figure 5: False prediction rate vs epochs

5. Conclusion

This study presents an efficient and clinically viable framework for epileptic seizure prediction using machine learning. The hybrid CNN–LSTM model effectively integrates spatial–spectral feature extraction with temporal sequence modeling, achieving high predictive accuracy while maintaining real-time feasibility. The comprehensive pipeline—from preprocessing and segmentation to postprocessing and alarm logic—ensures reliable detection with minimized false alarms. Advanced imbalance handling using SMOTE, class weighting, and focal loss significantly enhances sensitivity to preictal patterns while preserving specificity. Quantitative analyses confirm stable convergence, low training loss, and substantial reduction in false prediction rate, validating the model's robustness. The system's lightweight design supports deployment on wearable or mobile devices, enabling continuous patient monitoring and timely alerts for preventive interventions. Future work will explore transfer learning for patient-independent adaptation and multimodal fusion with ECG and motion data. Overall, the proposed approach advances the field toward personalized, predictive epilepsy management leveraging deep learning and real-time analytics.

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