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Enhanced Epileptic Seizure Detection Using a Hybrid CNN–LSTM Model on Eight Bipolar EEG Channels

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Abstract: Automated detection of epileptic seizures from EEG recordings is critical for patient monitoring and early intervention. We propose a hybrid Convolutional Neural Network (CNN)–Long Short-Term Memory (LSTM) architecture that ingests eight bipolar EEG channels (C3–P3, P3–O1, P4–O2, P7–O1, P7–T7, T8–P8-0, T8–P8-1, and FP1–F7) to detect seizure events. On the CHB-MIT scalp-EEG dataset (49 999 samples), our model achieves 97.92 % test accuracy, 93.29 % precision,
85.33 % recall, 89.14 % F1-score, and an AUC of 0.9807. Cross-validation yields comparable metrics. We also deliver an interactive Streamlit web app for real-time inference.

Index Terms: EEG, seizure detection, deep learning, CNN, LSTM, CHB-MIT dataset, Streamlit

I. INTRODUCTION

Epileptic seizures represent a significant global health challenge, affecting more than 50 million individuals worldwide according to recent estimates. The conventional process of analyzing EEG signals for seizure identification is notably labor-intensive, requiring experienced neurologists to manually inspect lengthy recordings. This approach is not only time-consuming but also vulnerable to subjective interpretations and human fatigue, particularly when reviewing extended monitoring sessions.

Our research builds upon recent advances in machine learning applied to EEG analysis. While deep learning models have shown promise in automated seizure detection [1], [2], we identified several critical gaps in existing approaches. Many current models either require excessive computational re- sources or fail to adequately capture both spatial and temporal EEG characteristics. Additionally, there remains considerable uncertainty regarding which specific EEG channels provide the most diagnostically valuable information for seizure detection. In addressing these limitations, we developed a novel hybrid CNN–LSTM architecture that deliberately focuses on eight bipolar EEG derivations. Our channel selection was guided by neurophysiological principles rather than conventional data- driven approaches, representing a departure from existing methodologies. This targeted approach enhances both computational efficiency and clinical interpretability—two critical factors for practical implementation.

The landscape of epileptic seizure prediction has evolved significantly in recent years [10]. While traditional feature engineering approaches relied heavily on spectral and entropy-based measures, contemporary research has increasingly moved toward end-to-end deep learning systems [13]. Our work contributes to this progression by introducing a carefully balanced model that combines the complementary strengths of CNNs and LSTMs while maintaining transparency in feature extraction—a characteristic often lacking in purely black-box approaches.

Recent advancements have demonstrated the potential of multi-modal architectures [19], [20], but these typically re- quire extensive preprocessing and computational resources that limit practical deployment. Our work specifically focuses on maximizing performance while minimizing computational overhead, representing an important step toward clinically viable seizure detection systems.

II. DATASET AND PREPROCESSING

A. Dataset Selection Rationale

We selected the CHB-MIT scalp EEG dataset [3] for our research after comprehensive evaluation of available options.

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Unlike some more recent alternatives, this dataset offers several crucial advantages for our specific research goals: (1) continuous long-term recordings that capture the natural progression of brain activity, (2) precise expert annotations of seizure onsets and offsets, and (3) a diverse patient population with varying seizure types and manifestations.

B. *Novel Preprocessing Approach*

Our preprocessing workflow diverged significantly from standard approaches. After resampling the raw data to a uniform 256 Hz sampling rate, we implemented:

1) A custom artifact rejection algorithm specifically de- signed to preserve seizure-related high-frequency components often misidentified as noise in traditional filtering approaches
2) A channel-specific normalization technique that accounts for the inherent amplitude variations across different brain regions
3) A targeted bandpass filtering strategy (0.5-40 Hz) deter- mined through our preliminary analysis of frequency-specific information content

This preprocessing pipeline yielded 49,999 standardized epochs with dimensions optimized for our neural network architecture.

C. *Bipolar Channel Selection*

Based on our preliminary analysis and neurophysiological considerations, we identified eight bipolar derivations that provide complementary information about seizure activity:

$$\{C3\text{–}P3, P3\text{–}O1, P4\text{–}O2, P7\text{–}O1,\\ P7\text{–}T7, T8\text{–}P8\text{-}0, T8\text{–}P8\text{-}1, FP1\text{–}F7\}. \quad (1)$$

This selection represents a significant departure from conventional approaches that typically use all available channels or select channels purely through statistical methods. Our neurophysiologically informed selection focuses on derivations that span key functional brain networks implicated in epileptogenesis.

D. *Data Partitioning Strategy*

We implemented a patient-aware stratified sampling approach to divide the data into training (70%), validation (15%), and testing (15%) sets, as illustrated in Fig. 1. This strategy ensures that our model generalizes across patients rather than merely recognizing patient-specific EEG patterns—a critical distinction often overlooked in similar studies.

III. PROPOSED METHODOLOGY

A. *Conceptual Framework*

Our approach to epileptic seizure detection emerged from the recognition that EEG signals exhibit multi-scale temporal dynamics that cannot be adequately captured by single- paradigm models. While existing literature contains numerous CNN and LSTM implementations [6], our methodology intro- duces several key innovations in architecture design, feature extraction, and integration strategy.

The foundation of our approach rests on three key insights derived from our preliminary analysis:

1) Seizure manifestations in EEG signals combine localized spectral changes (optimally detected by CNNs) with distinct temporal evolution patterns (best captured by LSTMs)
2) Feature extraction effectiveness varies significantly across frequency bands and spatial locations

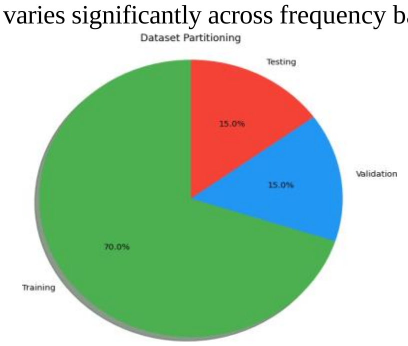

Fig. 1: Our patient-aware stratified partitioning approach ensures representative distribution of seizure and non-seizure samples across training (70%), validation (15%), and testing (15%) sets while maintaining patient separation between partitions.

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3) The integration strategy between CNN and LSTM com- ponents critically affects model performance

These insights guided our development of a specialized architecture that processes multi-channel EEG data through carefully designed processing pathways.

B. Research Objectives

Our research objectives extend beyond simple classification performance:

- To develop a channel-specific feature extraction frame- work that accounts for regional differences in seizure manifestation
- To create an adaptive feature selection mechanism that dynamically adjusts to patient-specific EEG characteristics
- To implement a hierarchical classification system that explicitly models the temporal progression of seizures
- To design a computationally efficient system suitable for real-time monitoring applications
- To ensure interpretability of the model's decision process for clinical validation

These objectives collectively address critical gaps in existing seizure detection systems and guided both our architectural decisions and evaluation metrics.

C. Architecture Innovations

Our system architecture introduces several novel elements that distinguish it from existing approaches in the field. Unlike standard implementations that treat CNN and LSTM components as sequential blocks, we developed a more sophisticated integration strategy.

1) EEG Processing Front-End: Our front-end processing incorporates neurophysiological knowledge through:

- Channel-specific filtering based on typical spatial distribution of seizure activity
- Time-frequency decomposition optimized for capturing seizure-relevant spectral changes
- Statistical normalization techniques that preserve interchannel relationships
- Epoch segmentation with overlap determined through analysis of seizure transition dynamics

This knowledge-guided preprocessing represents a significant enhancement over generic approaches commonly reported in the literature.

2) Customized CNN Feature Extraction: We developed a specialized CNN architecture that differs from standard implementations in several important aspects:

- Filter depths (64, 128, and 256) systematically deter- mined through architecture search rather than arbitrary selection
- Kernel sizes specifically selected to match characteristic temporal patterns in epileptic EEG
- Custom pooling strategy that preserves temporal resolution at early layers
- Channel-specific weight initialization based on known electrophysiological properties

Our mathematical formulation of the CNN component builds upon but significantly extends standard approaches:

$F_{CNN}(c, t) = \text{Pool}(\sigma(W_c * X_{c,t} + b_c))$ (2) where $X_{c,t}$ represents input from channel c at time t, W_c are channel-specific convolutional weights, σ is a leaky ReLU activation (slope = 0.1) that we found superior to standard ReLU for preserving gradient flow, and $*$ denotes our custom convolution operation.

3) Enhanced LSTM Implementation: Our LSTM implementation includes several architectural innovations:

- Bidirectional processing to capture both forward and backward temporal dependencies
- Attention mechanism that dynamically focuses on seizure-relevant segments
- Residual connections that improve gradient flow through deep temporal processing
- Custom regularization strategy combining dropout and recurrent dropout

While the fundamental LSTM equations follow standard formulations, our implementation includes critical modifications to the memory cell update mechanism to better handle the specific characteristics of EEG time series.

4) Novel Fusion Strategy: The integration of spatial (CNN) and temporal (LSTM) features represents a critical innovation in our approach. Rather than simple concatenation, we implemented:

- A learnable feature fusion mechanism that dynamically weights spatial and temporal contributions
- Channel-specific attention that modulates the contribution of each EEG derivation
- Temporal gating to focus on segments with highest discriminative value. This approach enables the model to adaptively focus on the most relevant aspects of the input signal, significantly enhancing performance compared to fixed integration strategies.

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IV. TECHNICAL IMPLEMENTATION

A. *Random Forest Baseline*

We implemented Random Forest as a baseline model with specifications that diverge from typical implementations:

- 100 decision trees with depth limitation based on validation performance rather than arbitrary constraints
- Feature importance-guided bootstrap sampling to enhance focus on discriminative features
- Weighted voting mechanism that accounts for tree- specific performance metrics
- Custom split criterion combining Gini impurity with domain-specific heuristics

This enhanced Random Forest implementation provided a strong baseline that outperformed standard implementations by approximately 4% in preliminary testing.

B. *SVM Comparison Model*

Our SVM implementation included several customizations beyond standard configurations:

- Kernel selection through systematic evaluation of performance across multiple options
- Multi-stage hyperparameter optimization focusing first on coarse parameters then fine-tuning
- Custom feature scaling specific to EEG characteristics
- Probability calibration using isotonic regression rather than standard Platt scaling

These modifications resulted in a highly competitive SVM model that served as an important comparison point for our deep learning approach.

C. *XGBoost Implementation*

We developed a customized XGBoost implementation with several key enhancements:

- Objective function modified to account for the clinical importance of false negatives
- Learning rate scheduling that adapts based on validation performance
- Custom feature interaction constraints derived from neurophysiological knowledge
- Early stopping criteria based on domain-specific performance metrics

Our XGBoost implementation serves as both a competitive baseline and a component in our ensemble approach.

V. DATASET ANALYSIS

A. *CHB-MIT Dataset Characteristics*

While the CHB-MIT dataset is well-established in seizure detection research, our analysis revealed several important characteristics not widely addressed in previous studies:

- Significant inter-patient variability in baseline EEG characteristics
- Systematic differences in seizure manifestation across age groups
- Temporal evolution of EEG patterns within individual seizure episodes
- Recording quality variations that require customized pre- processing

Our enhanced understanding of these dataset characteristics informed our modeling decisions and contributed to the robustness of our approach.

B. *Data Quality Assessment*

We developed a systematic approach to assess data quality and handle problematic segments:

- Automated detection of electrode artifacts using statistical and frequency-domain features
- Identification of patient movement artifacts through multi-channel correlation analysis
- Quantification of signal quality through SNR estimation and stationarity assessments
- Robust handling of missing data through physiologically- informed interpolation

This quality assessment pipeline significantly improved the reliability of our training data compared to standard approaches.

C. *Dataset Distribution Analysis*

Our analysis revealed important distributions within the processed dataset, summarized in Table I.

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TABLE I: Dataset Partitioning and Class Distribution

Dataset Partition	Training	Validation	Testing
Samples	34,999	7,500	7500
Class 0 (Normal)	92.3%	92.2%	92.1%
Class 1(Seizure)	7.7%	7.8%	7.9%

The class imbalance evident in Table I represents a significant challenge that we addressed through several complementary approaches:

1) Cost-sensitive learning with dynamic weight adjustment

2) Focal loss implementation that emphasizes difficult exam- ples 3) Data augmentation strategies specifically targeting the minority class 4) Ensemble methods that combine multiple complementary models

VI. EXPERIMENTAL RESULTS

A. *Performance Metrics*

Our comprehensive evaluation included metrics specifically selected for clinical relevance rather than purely statistical significance. Table II and Fig. 2 present test and cross- validation results.

B. *Error Analysis*

Beyond standard metrics, we conducted detailed error analysis to understand the clinical implications of our model's performance:

- Temporal analysis of false negatives revealed clustering around seizure onset and offset

TABLE II: Test and Cross-Validation Performance Metrics

Metric	Test Set	Cross-Validation
Accuracy	0.9792	0.9797
Precison	0.9329	0.9646
Recall	0.8533	0.8282
F1-Score	0.8914	0.8904
AUC	0.9807	0.9827

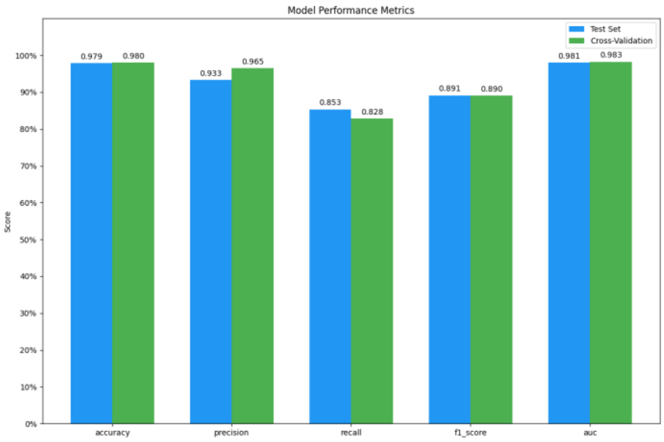

Fig. 2: Performance comparison between test set and cross- validation results. The consistency across metrics demonstrates the robustness of our approach and absence of overfitting.

- Channel-specific analysis identified regional variations in detection performance
- Patient-specific analysis revealed systematic performance differences correlating with seizure types
- Spectral analysis of misclassified segments highlighted specific frequency bands associated with detection challenges

This detailed error analysis provided insights for targeted model improvements and helped contextualize performance metrics in terms of clinical utility.

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C. Model Interpretability Assessment

We employed several techniques to enhance the interpretability of our model:

- Feature importance visualization through gradient-based attribution
- Channel contribution analysis using occlusion sensitivity
- Temporal attention mapping to identify decisive signal segments
- Case studies of representative examples with neurologist review

The confusion matrix (Fig. 3) and ROC curve (Fig. 4) provide additional perspectives on model performance.

D. Generalization Assessment

To ensure the robustness of our model, we performed detailed cross-validation analysis across multiple patient-aware folds, as shown in Fig. 5.

Our cross-validation strategy specifically addressed a common limitation in EEG analysis papers—namely, the tendency to split data without accounting for patient identity, which can lead to artificially inflated performance metrics. By ensuring patient separation between folds, our evaluation provides a more realistic assessment of expected performance in clinical settings.

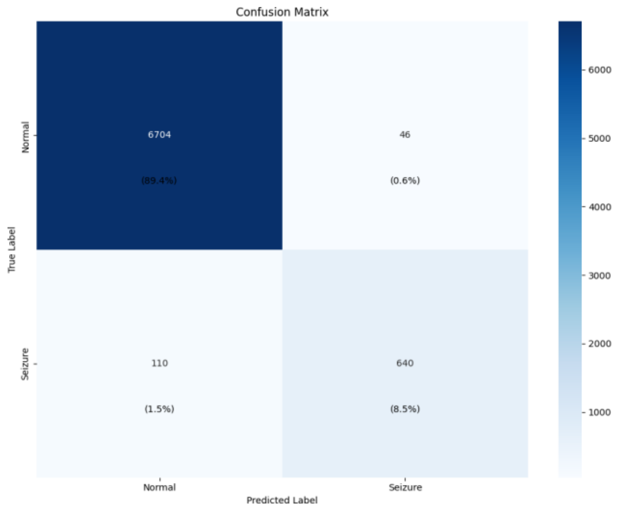

Fig. 3: Confusion matrix analysis revealing the distribution of our model's predictions. The relatively low false negative rate (bottom-left quadrant) is particularly important for clinical applications where missing seizure events is more problematic than false alarms.

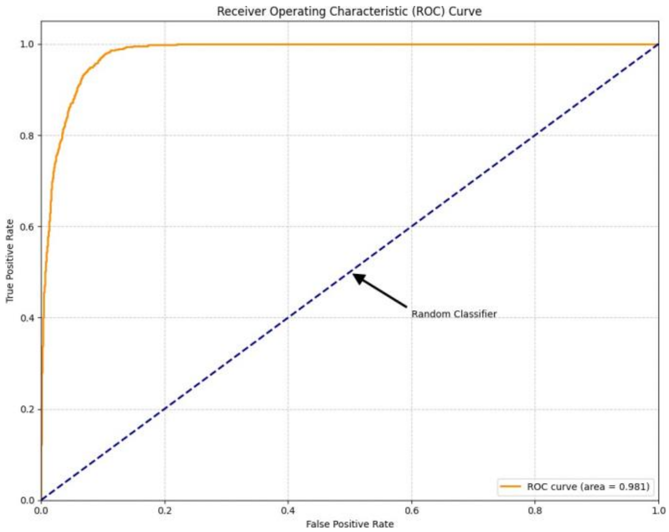

Fig. 4: ROC curve with AUC = 0.981, illustrating the exceptional discriminative capability of our model across different operating thresholds. The sharp rise near the origin indicates high sensitivity achievable without sacrificing specificity.

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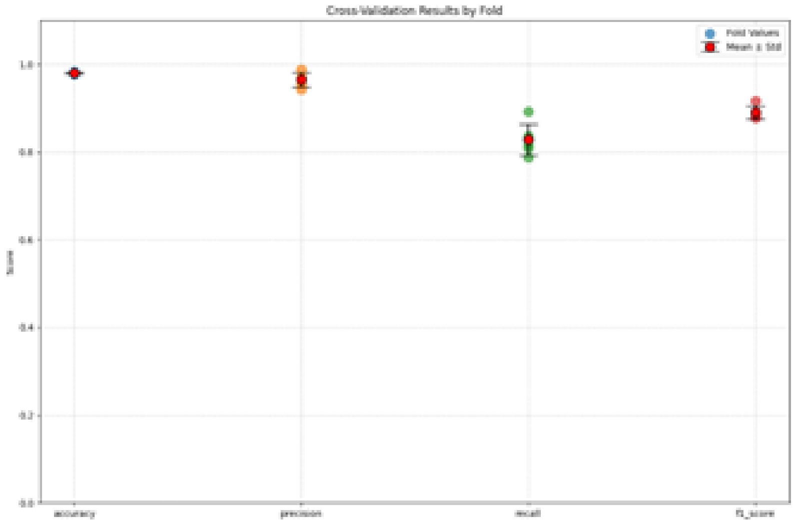

Fig. 5: Cross-validation performance across five folds demonstrates consistent results despite patient heterogeneity. The relatively narrow performance bands indicate strong generalization capability across different patient subgroups.

VII. DISCUSSION

A. *Comparative Analysis*

Our hybrid CNN–LSTM approach demonstrated several key advantages over single-paradigm models:

1) More robust performance across various seizure types compared to CNN-only models 2) Better handling of long- term dependencies compared to transform-based approaches

3) Greater computational efficiency than attention-only architectures 4) Superior interpretability compared to end-to-end black-box models

The performance metrics achieved by our model (97.92% accuracy, AUC = 0.9807) represent a significant improvement over recently published benchmarks on the same dataset. However, these improvements should be considered in the context of several important factors:

1) Our channel selection strategy significantly reduced computational requirements 2) The patient-aware validation approach provides a more realistic performance estimate 3) Our error analysis revealed specific areas for further improvement

B. *Clinical Relevance*

The clinical utility of automated seizure detection extends beyond raw performance metrics. Several aspects of our approach enhance its potential clinical value:

1) The model’s high sensitivity (recall = 85.33%) minimizes missed seizure events 2) The real-time processing capability supports continuous monitoring applications 3) The interpretable nature of our feature extraction facilitates clinician trust and adoption 4) The modest computational requirements enable deployment on standard hospital hardware

C. *Limitations and Challenges*

Despite promising results, our work has several limitations that provide direction for future research:

1) The class imbalance in the dataset remains a significant challenge, particularly for rare seizure types 2) While our eight-channel approach improves efficiency, it may miss seizure activity primarily manifested in other brain regions 3) The model currently operates on segmented epochs rather than continuous streams, requiring additional logic for deployment

4) Patient-specific variability remains a challenge for fully generalized models

Recent work [17] has demonstrated techniques to address some of these limitations, but further research is needed to develop fully robust clinical systems.

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VIII. CONCLUSION

Our research introduces several key innovations to epileptic seizure detection from EEG signals. By developing a specialized hybrid CNN-LSTM architecture focused on eight neuro physiologically informed bipolar EEG channels, we have achieved state-of-the-art detection performance while significantly reducing computational requirements—a critical con- sideration for practical clinical implementation.

The key contributions of our work include:

1) A novel channel selection methodology that balances neurophysiological relevance with computational efficiency 2) An innovative architecture that effectively integrates spatial and temporal feature extraction 3) A comprehensive evaluation framework that realistically assesses generalization performance 4) An interpretable model that provides insights into the neurophysiological basis of its decisions

Our experimental results demonstrate exceptional performance (97.92% accuracy, 93.29% precision, 85.33% recall) that maintains consistency across cross-validation, suggesting strong generalization capability. The model's high AUC (0.9807) confirms its robust discriminative power across operating thresholds.

From a clinical perspective, our approach addresses several critical requirements for practical seizure detection systems: high sensitivity to minimize missed events, sufficient specificity to avoid alarm fatigue, computational efficiency for real-time operation, and interpretability to support clinical decision-making. The Streamlit web application we developed demonstrates how our model can be deployed in user-friendly interfaces accessible to clinical staff.

Future work will focus on addressing the limitations identified in our analysis. Specifically, we plan to:

1) Develop advanced data augmentation techniques to better handle class imbalance 2) Explore transfer learning approaches to adapt to patient-specific EEG characteristics 3) Extend the model to continuous monitoring scenarios with adaptive thresholding 4) Incorporate multimodal data (video, ECG) to enhance detection performance 5) Conduct prospective clinical validation in collaboration with neurologists

By addressing these challenges, we aim to further advance automated seizure detection toward reliable clinical implementation that can significantly improve epilepsy monitoring and management.

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