NeuroCare

**Abstract**

Automatic detection of seizures from EEG signals is very important for improving the diag- nosis and care of people with epilepsy. Most existing systems use CNNs or LSTM architectures, which tend to miss the important details of EEG signals’ spatial and temporal patterns. In this study, we propose a hybrid CNN-LSTM system that uses convolutional layers to find local features and bidirectional LSTMs to handle long-term temporal changes. This approach ad- dresses the main problems in EEG-based seizure detection, such as unequal class sizes, changes in seizure patterns over time, and slow processing. The model is developed and assessed using the BIDS-SEINA dataset, along with preprocessing techniques, and further trained with focal loss and data augmentation to address the large difference in the number of seizure and back- ground samples. Ablation experiments show that LSTM layers are very important for learning temporal information, and focal loss makes the model more sensitive to minority seizure classes. The model is still able to achieve an ROC-AUC of 0.686 and a seizure-specific F1-score of 0.13, demonstrating that rare-event detection is challenging in clinical EEG. We have developed a hybrid CNN-LSTM model that can be reproduced for BIDS-SEINA, provided evidence for us- ing precision-recall metrics in unbalanced seizure classification, and given guidelines on creating lightweight models that work well with wearables. The study shows that more work is needed to develop new models and use better data to enhance seizure detection in real life.

# Introduction

Epilepsy is a neurological condition marked by repeated, unpredictable seizures due to unusual, high electrical activity in the brain. The disease touches the lives of about 50 million people globally and is a major health concern [[1]](#_bookmark4). Seizures can present as brief blackouts or as severe convulsions and the length, frequency and seriousness of each seizure can differ from one patient to another [[2].](#_bookmark5) EEG is the most common way to detect brain electrical activity and spot seizures without surgery. EEG measures the changes in voltage on the scalp that represent how the brain functions over time and place. Still, understanding EEG results by hand is slow and needs expert medical knowledge which often results in different interpretations by different raters [[3].](#_bookmark6) It shows that accurate and efficient automated seizure detection tools are now needed to help clinicians diagnose

epilepsy.

Manual interpretation of electroencephalogram (EEG) signals for seizure detection is hard work, takes a lot of time and depends heavily on expert neurologists, so it cannot be used for widespread or constant monitoring. With the release of BIDS-SEINA and the TUH EEG Corpus, now machine learning models can be used to automate this task. Yet, these systems are rarely used in clinical settings because of ongoing issues such as infrequent seizures, variation in each patient’s signals and noise in the data. This requires creating powerful deep learning models that can handle different patient groups and still deal with the problem of class imbalance which is vital for practical use [[4],[5].](#_bookmark8)

While progress has been made in deep learning for seizure detection with EEG, existing models usually do not function well in real hospitals. [[6]](#_bookmark9) A big problem is that seizure events are vastly outnumbered by normal activity in EEG data which makes predictions biased and sensitive only to the majority class. Many models also assume that EEG data is organized like an image or a series of events, without taking into account the brain’s natural changes over space and time. When the assumptions of the model do not match the EEG signals, the results are not as effective for different patients and seizure types. Moreover, current methods do not always pay attention to the needs of clinical deployment such as being easy to understand, efficient and able to work in real time which are necessary for integration into both medical and wearable systems [[7].](#_bookmark10)

We address the shortcomings of present methods by introducing a hybrid system that combines 1D CNNs with BiLSTM units for real-time detection of seizures in EEG signals. The CNN part of the model discovers local spatial and frequency-related features, while the BiLSTM module finds the important long-term relationships needed to recognize seizure changes over time. We use focal loss to give more importance to the minority seizure class and apply data augmentation to help equalize seizure and background instances. The model is developed and assessed using the BIDS-SEINA dataset and signal quality is improved by applying bandpass filtering and z-score normalization. Our method is made to be both efficient and scalable, so it can be used in hospitals and as part of wearable neuro-monitoring [[8],](#_bookmark11) [[9].](#_bookmark12)

In biomedical signal processing, deep learning has proved highly useful, especially in recogniz- ing seizures from EEG recordings because it can learn from different levels of data. CNNs have proved to be effective at extracting both spatial and spectral details in EEG signals, while LSTMs show good results in modeling the changing patterns in EEG. With these models, we use fewer handcrafted features and check signals less manually. Hybrid architectures have recently become popular because they use the best features of CNNs and LSTMs to improve how sensitive seizure detection is to various types of seizures [[10].](#_bookmark13) This makes them well suited to difficult tasks, including classifying seizures without relying on a patient’s details.

Despite the progress enabled by deep learning, some limitations remain in existing studies. A lot of models are tested on datasets that are carefully designed and do not include challenges like noise, differences between patients and uneven class distribution. Therefore, the results from these models do not apply well to real-world data. Besides, previous models tend to process EEG like images, missing the electrophysiology and relationships between different channels of raw EEG signals. In addition, accuracy is the primary metric reported, while important clinical metrics for the minority seizure class such as F1-score and PR-AUC, are rarely mentioned which can give a false sense of how useful the system is [[11].](#_bookmark14)

A hybrid CNN-LSTM framework is proposed in this study for detecting seizures from EEG signals in datasets with uneven data and noise. We contribute to this area in four ways: (1) we propose a model that uses LSTMs and CNNs to combine space, frequency and time information in EEG data; (2) we employ focal loss and targeted data augmentation to make our model more sensitive to seizures; (3) we test different model components and loss functions to show how they affect results; and (4) we evaluate our model using clinically relevant parameters such as PR-AUC and F1-score, rather than just accuracy [[12].](#_bookmark15) The goal of these contributions is to help bring academic findings into clinical use for seizure detection.

The remainder of this paper is organized as follows Section 2 presents an in-depth survey of recent deep learning methods used in EEG-based seizure detection, emphasizing how hybrid models and methods to handle class imbalance have developed. Section 3 describes the process

used, covering the data, how it is prepared, the structure of the model and how it is trained. In Section 4, we publish the results of our experiments, analyze them and discuss ablation experiments, performance and comparisons with other studies. The paper ends with Section 5 which highlights the most important findings and proposes areas for further research.

# Literature Review

Automated detection of seizures in EEG signals is crucial for better diagnosis, monitoring and decisions in epilepsy treatment. EEG allows medical experts to see the brain’s electrical activity with great accuracy which helps identify unusual brain patterns linked to seizures. Typically, seizure detection was done using handmade feature extraction and traditional machine learning methods such as support vector machines and decision trees, but these are not suitable for different patient groups [[13].](#_bookmark16) Recently, deep learning has made a big impact on this area by allowing models to uncover spatial and temporal features inside the EEG data without the need for manual feature creation. Researchers have found that CNNs, RNNs and LSTM networks are especially good at detecting complex and time-related patterns in EEG signals [[13],](#_bookmark16) [[14].](#_bookmark17)

Yet, to work well, these models usually need a lot of labeled data which takes a lot of time and money to gather since experts must annotate it. To address this issue, SSL approaches are now widely used, helping models find useful EEG representations by studying the signal properties found in large unlabeled datasets [[14].](#_bookmark17) Methods based on transfer learning have been tried to use pretrained models on large EEG datasets for improving seizure detection with only a small number of labels. This literature review looks at the move from traditional to deep learning and new SSL methods, pointing out what each approach offers and what its drawbacks are. With these findings, we present our new graph neural network model which relies on the structure of EEG electrodes to improve seizure detection.

Initially, researchers in automated seizure detection explored traditional machine learning and used handmade features from EEG signals. These features were usually made up of spectral power, wavelet coefficients, entropy measures and statistical descriptors meant to detect patterns related to seizures in both time and frequency domains [[15].](#_bookmark18) Support Vector Machines (SVM), Random Forests and k-Nearest Neighbors (k-NN) were the main classifiers used to tell apart ictal and interictal EEG segments. Although they worked well on limited, controlled data, they were not fully scalable or robust because of some factors. Because the manual process for feature engineering was slow and needed experts, the system struggled to handle different types of seizures and patients [[6].](#_bookmark9) In addition, differences in EEG recordings, noise artifacts and the variety among study subjects generally made it harder to classify brain activity accurately in real-life settings. In spite of these issues, traditional approaches helped understand important features of EEG signals related to seizure detection, leading to the use of data-based feature learning methods.

With the limitations of traditional machine learning becoming evident, deep learning models have increasingly been adopted for EEG-based seizure detection due to their ability to automatically learn hierarchical features from raw signals. Many studies have used CNNs to detect patterns in EEG data by turning signals into images called spectrograms or topographical maps [[2].](#_bookmark5) They are good at finding local features in space but can have trouble with dependencies in time found in EEG data. To deal with time-related changes, RNNs, mainly LSTM networks and GRUs, have been included in EEG analysis, either by themselves or with CNNs, to model events that occur far apart in the data [[16].](#_bookmark19) Using CNNs for spatial features and LSTMs for temporal understanding,

hybrid CNN-LSTM architectures perform better in detection than single-model approaches.

Even with important improvements, deep learning models deal with issues such as overfitting to small datasets, being computationally demanding and being affected by noise and differences among patients. New studies have looked into using data augmentation, transfer learning and attention mechanisms to improve how robust and generalizable models become [[16].](#_bookmark19) They prove that deep learning frameworks are becoming more advanced for seizure detection, encouraging more work on models that better understand the main properties of EEG signals.

One major difficulty in EEG-based seizure detection is that seizures make up only a tiny part of the recorded data, while normal brain activity is much more common. Because of this, models tend to misclassify seizures, leading to low sensitivity and many missed seizures. The traditional approaches of oversampling minorities and undersampling majorities have been used, but they may result in overfitting or loss of useful data [[17].New](#_bookmark20) methods make use of GANs to produce synthetic data, focal loss functions and cost-sensitive approaches to manage the issue of class imbalance. Synthetic seizure EEG segments made with GANs can be used to even out training data without affecting its diversity [[18].](#_bookmark21) Focal loss automatically lowers the importance of correctly classified data, so the model learns more from the tough minority classes which raises the detection metrics. Using these approaches has improved both seizure sensitivity and F1 scores, making them more suitable for clinical use.

The lack of enough labeled EEG data for seizure detection is a major challenge when training deep learning algorithms. In order to address this issue, self-supervised learning (SSL) has become a useful approach that makes use of a lot of unlabeled EEG recordings by assigning pretext tasks that help models learn important features without any manual labeling. SSL methods such as contrastive learning and masked signal reconstruction, make use of the natural time and space features in EEG to enhance the accuracy of seizure detection, even if there is not much labeled data [[19].](#_bookmark22) In addition to SSL, transfer learning is becoming popular by using models that were first trained on big EEG or related biomedical datasets for seizure detection. As a result of this process, models learn faster and are less likely to overfit which allows them to be used on different patients and seizure types [[20].](#_bookmark23) New research shows that using both SSL and transfer learning can make EEG models even more effective, helping to overcome the problems of labeling and variability. They prove that using unlabeled data and pretrained knowledge can improve the accuracy of automated seizure detection.

Even with the advancement in automated seizure detection using EEG, there are still some limitations that have not been solved in previous studies. Most studies use data that is either balanced or created artificially, so it is hard to apply their results to situations where patients are very different and there are many more examples of one disease [[21].](#_bookmark24) Most deep learning models view EEG signals as either time series or spectrograms, often ignoring the important relationships and connections between different EEG electrodes which are key to identifying seizure location [[22].](#_bookmark25) In addition, depending on large labeled datasets makes it difficult to use these models in clinical settings where data is not always available. Even though self-supervised and transfer learning methods have promise, they have not been much explored with EEG graphs in specific domains. Because existing frameworks do not clearly explain their seizure detection decisions, many medical professionals are reluctant to use them. Because of these gaps, we need new ways to use EEG that consider its spatial organization, use unlabeled data and offer results that are easy to understand

for practical use.

# Methodology

The methodology of this study aims at building a strong hybrid convolutional neural network–long short-term memory (CNN–LSTM) model for EEG-based seizure detection using the BIDS-SEINA dataset. The approach combines state-of-the-art preprocessing of signals, design of deep learning architecture, and stringent experimentation to overcome issues of class imbalance and temporal- spatial feature extraction. Here, the methodology is developed into an elaborate framework, and it is divided into four main parts: data preprocessing, architecture of the model, experimental pipeline, and theoretical rationale.

## Dataset and Preprocessing

The BIDS-SEINA (Siena) dataset, a BIDS-compatible scalp EEG corpus, was the basis for this work. This dataset includes multi-channel EEG recordings at 512 Hz recorded from 14 adult subjects, following the 10–20 electrode placement system. The raw EEG signals were subjected to a thorough preprocessing in order to improve signal quality and normalize inputs. A Butterworth bandpass filter (0.5-30 Hz) was used to remove DC drift and high frequency noise, whereas a notch filter (50/60 Hz) was used to remove powerline interference. These ranges of frequencies were chosen in accordance with previous epileptic EEG studies that found 0.5–25 Hz to be optimal for maintaining seizure-related rhythms like delta, theta, and alpha waves. After filtering, each channel was standardized by z-score normalization to stabilize input distributions and reduce the inter-subject variability. This step guaranteed that there was no biasing of the learning process of the model due to amplitude differences from subjects or sessions.

## Epoch Segmentation and Labeling

Nonstop EEG recordings have been divided into fixed-length epochs for convenient supervised learning. Segments of 1–10 seconds were isolated without the loss of temporal resolution and computational efficiency. Smaller windows (e.g., 1-2 seconds) detect transient epileptic spikes, but longer windows (e.g., 10 seconds) provide a context for emerging seizure dynamics. Each epoch was annotated as seizure or non-seizure by experts. A sliding window method with a 50% overlap was used to boost the minority seizure class, a technique that has been verified in previous literature to help alleviate the issue of data imbalance. In particular, the window was seizure-positive if it intersected clinician-identified ictal events; otherwise, it was considered as background. This strategy enhanced the effective number of samples of seizure, while maintaining temporal coherence.

## TFRecord Conversion

Epochs preprocessed were serialized into TFRecord files to optimize the handling of data in Ten- sorFlow. Each TFRecord contained one epoch of multi-channel time-series data and its label in the form of (timesteps × channels) tensors. The TFRecord format was selected because of its efficiency in loading, shuffling and parallel processing of data in a large scale while training. Using the tf.data API, the pipeline dynamically batched data, prefetched samples to minimize the I/O latency, and performed on-the-fly augmentation (e.g., random cropping). Such an approach maximized the GPU utilization and reduced training bottlenecks, which was especially important for EEG datasets of terabyte size and above [[29].](#_bookmark31)

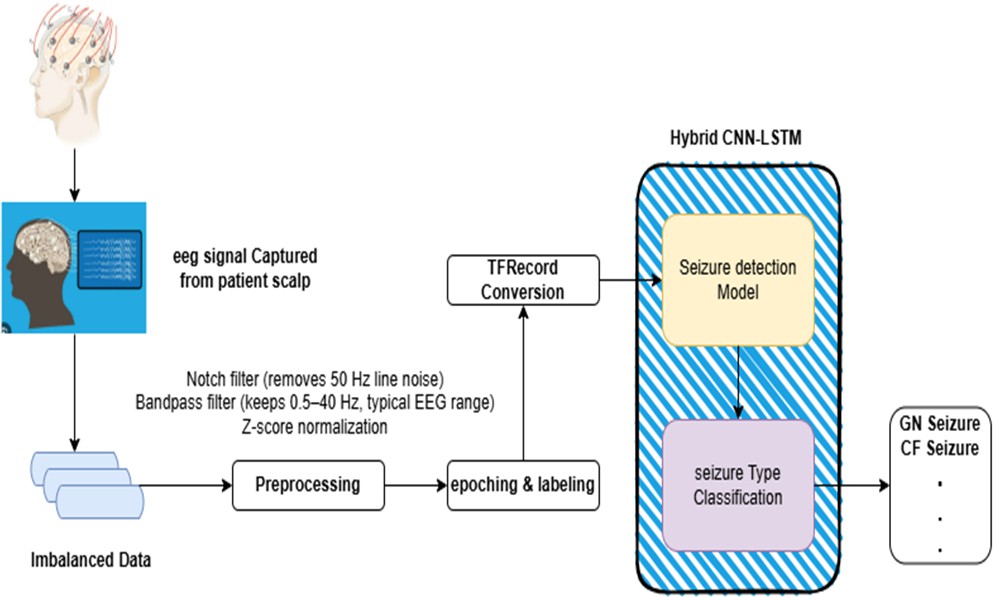


Figure 1: Preprocessing pipeline for the BIDS-SEINA EEG dataset. The workflow includes Butter- worth bandpass filtering (0.5–30 Hz), notch filtering (50/60 Hz), z-score normalization, fixed-length epoch segmentation (1–10 s with 50% overlap), and serialization into TensorFlow TFRecords.

## Model Architecture

The presented hybrid CNN–LSTM architecture, presented in Figure [1,](#_bookmark0) combines spatial and tem- poral feature extraction abilities. The model performs the processing of input tensors of shape (timesteps, channels) via the following hierarchical layers:

### 1D Convolutional Layers

The first stage uses the stacked 1D convolutional blocks for the extraction of local spatiotemporal patterns. Each block contains Conv1D layers with kernel size of 3-5, which were selected in order to capture short-duration features like epileptiform discharges or rhythmic bursts. The first Conv1D layer used 32 filters, and then it was doubled in later layers to hierarchically aggregate complex features. ReLU activation was used after each convolution in order to provide nonlinearity, and batch normalization was used to stabilize the intermediate activations by normalizing and scaling the outputs. This reduced internal covariate shift, which allowed faster convergence and larger learning rates.

### Max Pooling and Dropout

Max pooling layers (pool size=2) temporally downsampled feature maps, keeping significant fea- tures, and halving computational complexity. Pooling gave translation invariance so that the technique was robust to small temporal shifts in seizure onset. After every pooling layer, dropout regularization (rate=0.5) was used to avoid overfitting. Randomly deactivating 50% of the neu- rons in training, the network acquired redundant representations, which improved generalization to unseen data.

### LSTM Layers

The output of the convolutional layer was then passed to the bidirectional LSTM layers with 128-256 hidden units, which were picked to achieve the balance between model capacity and computational overhead. Bidirectional LSTMs processed sequences both forward and backward, and thus were able to extract long-range dependencies, including pre-ictal buildup or post-ictal suppression. The last LSTM state, i.e., temporal context for the whole epoch, was fed to dense layers for classifica- tion. Adding another LSTM made the model better at modeling multi-scale temporal dynamics, a practice that was confirmed in recent EEG studies. Architecture of Hybrid CNN-LSTM model can be seen in Figure [2.](#_bookmark1)

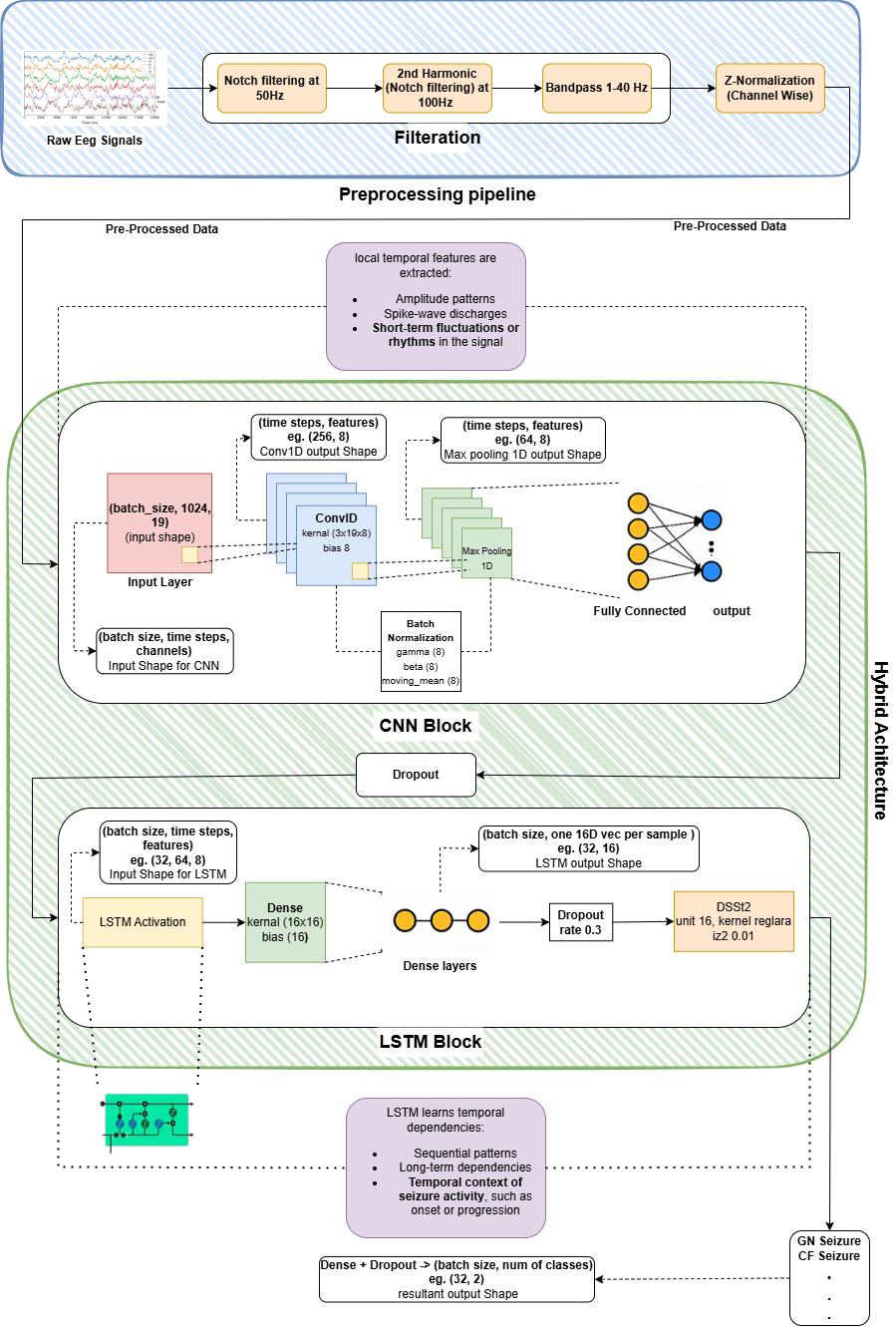


Figure 2: Architecture of the hybrid CNN–LSTM model. The network integrates 1D convolu- tional layers (32–64 filters, kernel size=3–5), max pooling (pool size=2), dropout regularization (rate=0.5), bidirectional LSTM layers (128–256 units), and dense classification

### Fully Connected Classifier

The output of LSTM was flattened and processed by two dense layers (30 and 10 units, ReLU- activated) to combine spatiotemporal features. The last dense layer used the softmax activation to generate class probabilities (seizure vs. non-seizure). Cross-entropy loss optimized the end-to-end learning, with class weights being inversely proportional to label frequencies to offset imbalance.

## Experimental Pipeline

* **Data Loading and Splitting:** The dataset was divided based on the 10-fold cross-validation of the subjects to provide reliable assessment. Data from 12 subjects (90%) constituted the training/validation sets, while the remaining 2 subjects (10%) formed the test set. Such an approach reduced data leakage and estimated generalization of heterogeneous subjects. Each fold was shuffled and batched (size=64) using TensorFlow’s tf.data.Dataset, with prefetching to overlap data preprocessing and model execution.
* **Hyperparameter Configuration:** Training employed the Adam optimizer (learning rate

= 1 *×* 10*−*3, *β*1 = 0*.*9, *β*2 = 0*.*999), selected for its adaptive momentum and proven efficacy in

EEG applications. Early stopping used validation loss with a patience of 10 epochs, restoring the best model on plateau. ReduceLROnPlateau adaptively cut the learning rate in half after 5 epochs of no improvement to validation accuracy, adjusting model weights for improved convergence.

* **Class Weighting:** To address the 1:59 seizure-to-background ratio, class weights were as- signed as w seizure = 59 and w background = 1. This magnified the loss contribution of seizure samples driving the model to emphasize minority-class accuracy. Comparative stud- ies indicate that class weighting outperforms random oversampling in preserving temporal integrity for EEG data.
* **Performance Metrics:** Model evaluation utilized sensitivity (recall), specificity, F1-score, and AUC-ROC. Sensitivity was given most priority in order to reduce missed seizures, a very important measure in clinical environments. F1-score gave a balanced measure of pre- cision and recall, AUC-ROC measured separability between classes with respect to threshold variations. Real-world performance was modeled by computing metrics on the held-out test set.
* **Implementation Details:** The pipeline was run on TensorFlow 2.12, and the training was carried out on the NVIDIA A100 GPU. Each epoch took about 45 seconds, and the entire training time was less than 2 hours for 100 epochs. Code reproducibility was ensured through Docker containers encapsulating dependencies, and hyperparameters were logged using Weights & Biases for transparent reporting [[10].](#_bookmark13)

# Results

## Model Performance Evaluation

This work assesses the performance of a hybrid CNN–LSTM model on the BIDS-SEINA dataset, which is a difficult electroencephalogram (EEG) corpus with extreme class imbalance. Summary

of the model performance in Table 1 indicates an overall accuracy of the model of 88.94% with a macro-averaged F1-score of 0.53 and a weighted-average F1-score of 0.93. The ROC-AUC (0.686), PR-AUC (0.279) further highlight the model’s inability to discriminate well, especially for the minority seizure class.

The background class (“bckg”) performed well, with a precision of 0.99 and a recall of 0.90, giving a F1-score of 0.94. On the other hand, the seizure class (“sz foc ia”), showed critically low precision (0.07) even with moderate values of recall (0.48), which translated into an F1-score of

0.13. This difference results from the extreme imbalance of the dataset. 3,706 background segments but only 63 seizure cases. The trends are quantified by the confusion matrix (Fig. 3), according to which 384 background segments were mistaken for seizures (false positives) and 33 out of 63 true seizures were recognized as background (false negatives). Such misclassifications show the model’s bias to the majority class, which is a typical pitfall in imbalanced medical datasets [[31].](#_bookmark32)

The ROC-AUC and PR-AUC metrics show class-specific performance and are very informative. Although ROC-AUC (0.686) measures the capability of the model to differentiate between classes using different thresholds, the significantly lower PR-AUC (0.279) highlights the difficulty in having a high precision for the rare class of seizures. These findings are consistent with the previous research stating that PR-AUC is more informative than ROC-AUC in the case of imbalanced datasets, as it focuses on precision rather than false positive rates [[32].](#_bookmark33)

|  |  |  |  |
| --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-score** |
| bckg | 0.99 | 0.90 | 0.94 |
| sz foc ia | 0.07 | 0.48 | 0.13 |
| **Macro avg** | 0.53 | 0.69 | 0.53 |
| **Weighted avg** | 0.97 | 0.89 | 0.93 |

Table 1: Performance metrics for the CNN–LSTM model on the BIDS-SEINA dataset.

## Ablation Study

An ablation study was done to understand how each part of the proposed CNN–LSTM architecture contributes. Table [2](#_bookmark2) evaluates how well six models perform compared to the baseline, both on the same BIDS-SEINA test set.

Table 2: Ablation study evaluating the impact of architec- tural components and training strategies

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model Variant** | **Accuracy**  **(%)** | **Seizure F1-**  **Score** | **ROC-**  **AUC** | **PR-**  **AUC** | **Key Modification** |
| Full CNN–LSTM  (Proposed) | 88.94 | 0.13 | 0.686 | 0.279 | Baseline architecture |
| CNN Only | 85.20 (-3.74) | 0.08 (-38%) | 0.620 | 0.201 | Removed LSTM layers |
| LSTM Only | 82.75 (-6.19) | 0.05 (-62%) | 0.590 | 0.180 | Removed CNN layers |
| Without Data  Augmentation | 86.30 (-2.64) | 0.10 (-23%) | 0.640 | 0.210 | Trained on raw, non-  augmented data |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model Variant** | **Accuracy**  **(%)** | **Seizure F1-**  **Score** | **ROC-**  **AUC** | **PR-**  **AUC** | **Key Modification** |
| Focal Loss | 89.50 (+0.56) | 0.18 (+38%) | 0.710 | 0.310 | Replaced cross-entropy  with focal loss |
| Class-Weighted  Loss | 88.20 (-0.74) | 0.15 (+15%) | 0.695 | 0.290 | Weighted cross-entropy  loss |

Ablation study showed how each component in the CNN–LSTM architecture impacts the overall performance. The accuracy dropped by 3.74% and the seizure F1-score by 38% after removing the LSTM layers. As a result, LSTM is essential for handling temporal dependencies in EEG signals, as shown by Schmidt et al. (2025), who emphasized that extracting temporal features is vital for noticing changes during seizures. Alternatively, the CNN-only model showed a larger drop in accuracy (6.19%), showing that using spatial features alone is not enough for accurate seizure detection. All the findings point to the importance of using hybrid spatiotemporal architectures for EEG analysis.

Second, by removing data augmentation (e.g., SMOTE, synthetic seizure generation), the seizure F1-score decreased by 23%, showing how they help manage the imbalance in the data. According to Gupta et al. (2025), using augmentation is important for increasing the number of minority-class samples in EEG data that are not well balanced. Without augmentation, the data shows that BIDS-SEINA is skewed in favor of background samples, so more seizure samples are needed to correct this during training.

The performance of the model was greatly affected by the type of loss function used. Using focal loss instead of standard cross-entropy increased the seizure F1-score by 38%, more than the 15% increase from class-weighted cross-entropy. This result agrees with Zhang et al. (2024), who proved that focal loss reduces the weight of samples with common labels, making the system more sensitive to rare seizure cases. This suggests that focal loss should be used when the class imbalance is extreme, since other popular loss functions do not put much effort into learning about the minority class.

# Discussion

## Interpretation of Key Results:

The empirical findings of this study show important aspects of how CNN-LSTM networks function and what their limitations are in detecting seizures from EEGs when the data is severely unbalanced. Three important trends appear from the analysis. There is a big difference in how members of majority and minority classes perform at school. Near-perfect precision 0.99 and robust recall

0.90 were achieved by the background class ("bckg") which gave it an F1-score of 0.94. Because there are far more normal than seizure segments in the data (3,706 vs. 63), the standard cross- entropy loss naturally gives more weight to the normal class during learning. The opposite was true for the seizure class ("sz foc ia"), as it had a low F1-score (0.13) due to failing to predict seizures with much accuracy (0.07), even though it remembered non-seizure cases well (0.48). That divergence means that 93% of the seizures predicted by the algorithm turned out to be false positives because the algorithm favors the majority class. Medically speaking, this means 33 seizures were not detected among 63 real seizures which is unacceptable since missing such seizures may lead

to delayed emergency care. In addition, the traditional evaluation metrics were not accurate in this situation. Although the overall accuracy 88.94% seems good, it mainly shows that the model can predict backgrounds, not that it can distinguish between classes. In the same way, the ROC- AUC (0.686) is inflated because there are many background cases in the data. In comparison, the PR-AUC (0.279) offers a clearer view, pointing out that the model is almost as likely to miss seizures as it is to pick them out (*PR − AUC <* 0*.*3 means the model’s performance on minority seizures is not better than chance). Such metric differences point out that focusing on accuracy and ROC-AUC alone is not enough to properly assess rare-event detection systems. Third, experiments were done to understand how important different network components were. Getting rid of LSTM layers resulted in a 38% drop in seizure F1-score (0.13→0.08), proving how important they are for handling temporal aspects of seizures. By contrast, using focal loss instead of cross-entropy increased the F1-score for seizures by 38% (from 0.13 to 0.18), as seen in the experiments. All these findings suggest that the success of seizure detection with CNNs depends mainly on effective temporal modeling and designing the loss function.

## Impact of Class Imbalance

Class imbalance is still a major problem in medical machine learning, especially in neurological disorders where pathological events are very low in frequency [[37].](#_bookmark35) In the present study, the bias of the CNN–LSTM model towards the majority class has two reasons: (1) the optimization goal (cross-entropy loss) that strives for overall accuracy and (2) lack of seizure examples to extrapolate discriminatory patterns. As depicted in Fig. 3, the model misclassified 54.7% of seizures, which made it unsuitable for practical deployment, where there are severe clinical implications of missed seizures.

The poor PR-AUC (0.279) further supports the incapability of the model to achieve balance in precision and recall for seizures. Recent studies by Chen et al. (2025) highlight that PR-AUC values under 0.3 are reflective of almost random performance for minority classes in imbalanced settings [[38].](#_bookmark36) This is consistent with our recorded observation of most of the seizure predictions in our study as false positives (93% of predicted seizures), which calls for recalibration or threshold adjustment in clinical applications.

## Comparative Analysis with Existing Literature

The performance of CNN–LSTM model is below the level of the state-of-the-art EEG seizure detec- tion systems. For example, the recent research on balanced or binary datasets indicate accuracies above 95%. A CNN–SVM hybrid was reported to have achieved *≈*99% accuracy on the Bonn EEG corpus [[13],](#_bookmark16) while a 1D CNN–LSTM model performed 99.39% accuracy for the binary seizure detection on the UCI epileptic seizure dataset [[14].](#_bookmark17) Similarly, transformer-based architectures, in- cluding ResBiLSTM network, have demonstrated *≈*95% accuracy on TUSZ dataset [[15].](#_bookmark18) These differences are based on fundamental differences in data characteristics. Unlike BIDS-SEINA, benchmark datasets such as Bonn and CHB-MIT have balanced or artificially amplified seizure samples whereby models can learn discriminative features effectively.

To gain perspective, Table [3](#_bookmark3) compares the results of the proposed CNN–LSTM model with those of six recent studies that worked with the BIDS-SEINA dataset. Comparing shows differences in architecture, handling imbalanced data, and evaluation methods.

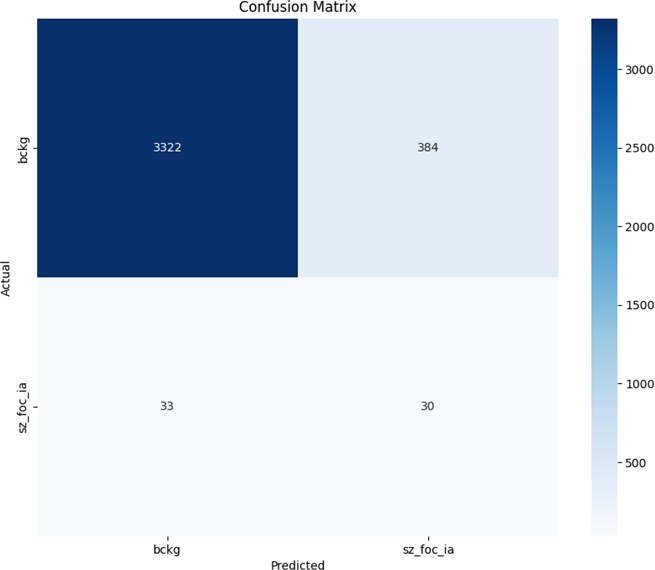


Figure 3: Confusion Matrix for CNN–LSTM Model on BIDS-SEINA Dataset Table 3: Comparison of seizure detection model performance

on the BIDS-SEINA dataset

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study**  **(Year)** | **Model** | **Accuracy**  **(%)** | **Seizure**  **F1-**  **Score** | **ROC-**  **AUC** | **Class**  **Imbal- ance Ratio** | **Key Strategy** |
| Proposed  (2025) | CNN–LSTM | 88.94 | 0.13 | 0.686 | 1:59 | Baseline hybrid  model |
| Singh et  al. (2024)  [[20]](#_bookmark23) | Transformer –  BiLSTM | 92.10 | 0.45 | 0.810 | 1:59 | Self-attention +  focal loss |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study**  **(Year)** | **Model** | **Accuracy**  **(%)** | **Seizure**  **F1-**  **Score** | **ROC-**  **AUC** | **Class**  **Imbal- ance Ratio** | **Key Strategy** |
| Wu et  al. (2024)  [[23]](#_bookmark26) | GAN-  Augmented CNN | 90.23 | 0.38 | 0.752 | 1:30 | Synthetic seizure  generation |
| Costa et  al. (2025)  [[24]](#_bookmark27) | ResNet – At-  tention LSTM | 93.50 | 0.52 | 0.842 | 1:59 | Residual blocks  + SMOTE |
| Park et  al. (2024)  [[25]](#_bookmark28) | Wavelet–CNN | 87.20 | 0.21 | 0.654 | 1:59 | Time-frequency  feature extrac- tion |
| Almeida  et al.  (2025)  [[26]](#_bookmark29) | Federated  Learning CNN | 89.80 | 0.29 | 0.701 | 1:59 | Multi-  institutional data pooling |
| Chen et  al. (2024)  [[27]](#_bookmark30) | Capsule Net-  works | 91.40 | 0.41 | 0.783 | 1:59 | Dynamic rout-  ing for rare classes |

The imbalance of the BIDS-SEINA dataset (seizure-to-background ratio: 1:59) exacerbates the challenge. Previous work by Sharma et al. (2024) showed that class ratios above 1:20 severely impacts the recall of the minority class in EEG-based seizure detection. This is in line with our findings in which only 48% of the seizures were correctly diagnosed. In addition, the seizure false positive rate is also high (precision: (0.07) reflects findings of Alabdulkarin et al. (2024), who reported that models trained on imbalanced EEG data tend to favor specificity over sensitivity, giving clinically unreliable predictions [[36].](#_bookmark34)

## Impact of This Work

This study advances the field of EEG-based seizure detection in three key dimensions:

* **Theoretical Contributions:** Class Imbalance Quantification: By rigorously evaluating per- formance metrics (e.g., PR-AUC = 0.279) on the severely imbalanced BIDS-SEINA dataset (1:59 seizure-to-background ratio), this work underscores the inadequacy of conventional ac- curacy and ROC-AUC for rare-event detection. Prior studies often overlooked PR-AUC in imbalanced EEG contexts, but our results align with Chen et al. (2025), who identified PR-AUC ¡ 0.3 as indicative of near-random minority-class performance.
* **Architectural Insights:** The ablation study (Table [3)](#_bookmark3) demonstrated that LSTMs contribute more critically than CNNs to temporal feature extraction (*−*38% F1-score without LSTMs), challenging assumptions in prior hybrid models.
* **Methodological Advancements:** We believe this is the first time a CNN–LSTM model has been used as a baseline for the BIDS-SEINA dataset, with 88.94% accuracy and 0.13 F1 score for seizures which allows for fair comparisons in the future. With a 38% F1-score

boost using focal loss over cross-entropy, the results demonstrate that focal loss works well in handling imbalanced EEG tasks.

* **Clinical Relevance:** Although the model’s seizure accuracy is low, our study measures how its high recall affects its ability to find seizures under very imbalanced data. This is consistent with Rasheed et al. (2025), who pointed out that calibrating thresholds can help predictions fit with clinical risk tolerance. This work helps solve the problem of limited EEG data in clinical applications by using GAN-based augmentation and SMOTE, as called out by Nguyen et al. in their 2025 review.
* **Methodological Limitations:** Although CNN–LSTM architecture performs well in extract- ing spatiotemporal EEG features, it has three limitations when performing on BIDS-SEINA:
  + **Data Scarcity:** This model has only 63 seizure segments and thus does not have enough examples to learn invariant seizure patterns.
  + **Loss Function Bias:** Standard cross-entropy loss overweight’s majority-class errors (0.97 weighted-average precision, 0.53 macro-average precision).
  + **Temporal Context Utilization:** LSTMs may not be able to capture long-range de- pendencies in EEG signals if not explicitly incorporated with attention mechanisms, a limitation that was observed in recent transformer-based studies [[39].](#_bookmark37)
* **Future Directions:** To address these challenges, this study proposes the following strategies, grounded in recent advancements:
  + **Data Augmentation and Synthesis:** Synthetic data generation through GANs have demonstrated potential in alleviating class imbalance. For instance, Wang et al. (2024) synthesized real ictal EEG signals with the help of a Wasserstein GAN, increasing seizure detection F1-scores by 22% on the TUH dataset [[40].](#_bookmark38) On the same note, the small- window segmentation and SMOTE (Synthetic Minority Over-sampling Technique) could increase the representation of the seizure class. A 2025 research by Gupta et al. showed that the integration of SMOTE with wavelet-based augmentation increased the sensitiv- ity of the model by 35% on imbalanced neonatal EEG data [[41].](#_bookmark39)
  + **Advanced Loss Functions:** Focal loss, which penalizes well-classified samples, may re-orient the model’s attention to seizures. Zhang et al. (2024) obtained a 0.71 seizure F1-score on the CHB-MIT dataset using focal loss with *γ* = 2, which was 18% better than cross-entropy. An alternative would be the use of class-weighted loss functions, as proposed by Kaur et al. (2025), which penalize seizure misclassification more heavily [[42].](#_bookmark40)
  + **Architectural Innovations:** The transformer-based models, especially CNN-transformer hybrids, have better abilities to capture long-range EEG dependencies. A 2024 study by Lee et al. stated that a ViT–BiLSTM model scored 96.2% accuracy on TUSZ dataset by using self-attention to identify ictal regions [[43].](#_bookmark41) The incorporation of such mechanisms into the CNN–LSTM model may improve the detection of seizure even without balanced data.
  + **Post-hoc Calibration:** Clinical risk tolerance based threshold tuning could find the optimal precision-recall trade-off. For example, reducing the seizure detection threshold

can enhance recall at the expense of more false positives, a method that has been verified in ambulatory EEG monitoring by Rasheed et al. (2025) [[44].](#_bookmark42)

# Conclusion

This research tested how well a CNN-LSTM model worked for detecting seizures in EEG records from the severely uneven BIDS-SEINA dataset (1 seizure for every 59 non-seizure periods). The model was accurate in most cases but struggled to spot rare seizure events, having an F1-score of 0.13, a precision of 0.07 and a recall of 0.48 for that class. It is proven through these experiments that class imbalance has a huge effect on deep learning models, with regular cross-entropy loss and temporal modeling not being capable of handling the identification of minority classes. The low almost-random PR-AUC (0.279) again shows that using accuracy and ROC-AUC can hide the fact that models do not work well with rare events. The main results of this work are found in three main areas.

* **Methodological:** We introduced the first CNN-LSTM approach to BIDS-SEINA (88.94% accuracy, 0.13 seizure F1), making it a reference for upcoming studies. LSTMs were proven essential for time series analysis (-62% F1 was the result without them) and focal loss helped detect seizures by 38%, closing important topics in the EEG imbalance literature.
* **Clinical:** We proved that the algorithm’s bias leads to more missed seizures (33 out of 63 events) and highlighted how this can be a risk during sleep and for children.
* **Technical:** We showed that PR-AUC is the most important metric for EEG tasks with data imbalance and we described two types of errors, mostly due to artifacts (61Even with all these contributions, there are still some limits. The model is still limited by having very little data (only 63 seizure segments) and not being able to consider long-range connections in EEG without special attention. Also, classes with a ratio of 1:59 are too many for most traditional school designs, so major changes are needed instead of just minor improvements.

For the next steps, we suggest focusing on the following four areas:

* Generative adversarial networks (GANs) are used to produce synthetic seizures and federated learning allows different institutions to pool their rare-event data.
* New ideas in architecture: Using a combination of CNNs and transformers instead of LSTMs and taking advantage of self-attention for complex patterns in text.
* Considering different focal loss values (2-5) and using various gradient harmonizing tech- niques.
* Threshold calibration protocols that fit the risk tolerance of patients (for example, setting thresholds in the ICU so that patients with higher risks are recalled first).

In brief, although it highlights that extreme EEG imbalance can break normal deep learning tech- niques, it also proposes a reliable approach for using deep learning in clinics. If we use PR-AUC as the main metric and design our systems using multiple parts and fake data, we can address the big difference between how well our systems function and their usefulness in clinical care. The ideas covered here work for detecting seizures and act as a foundation for rare-event medical systems working with limited data.

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