Empowering Cross-Patient Adaptive-Length Epilepsy Diagnosis with ECNorm: A Channel-wise Approach

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Abstract

Automatic seizure detection leveraging artificial intelligence has gained widespread attention. However, existing research has predominantly focused on scenarios with patient-specific and fixed-time lengths, with the practical clinical applications across non-specific patients and variable time lengths remaining underexplored. To address this gap, we introduce a novel method named Electroencephalogram Channel-wise Normalization (ECNorm), designed to thoroughly explore the physical significance and data distribution characteristics of different EEG channels to minimize inter-patient variability. We applied ECNorm to a two-layer LSTM model to facilitate cross-patient adaptive-length epilepsy diagnosis. Ablation studies demonstrate that ECNorm significantly enhances the performance of simple architectures like the two-layer LSTM when compared to batch normalization and layer normalization. Leave-one-out experiments on the public CHB-MIT dataset verify that our approach surpasses existing studies across segments of varying lengths (1 and 100 seconds), establishing a new benchmark for patient-independent automated epilepsy diagnosis.

Keywords: EEG, Epilepsy Detection, Electroencephalogram Channel-wise Normalization (ECNorm), Long Short-Term Memory (LSTM)

Introduction

Epilepsy, a prevalent neurological disorder affecting approximately 50 million people worldwide, is marked by recurrent seizures caused by sudden and abnormal neural activity (Ke, Lin, Lin, Zhou, & Ji, 2022). Among these individuals, around 15 million experience uncontrolled seizures, leading to severe symptoms such as loss of consciousness and convulsions. While 70% of patients can achieve seizure control through medication or surgery, about 30% continue to suffer frequent seizures, increasing their risk of mortality (Yu et al., 2022).

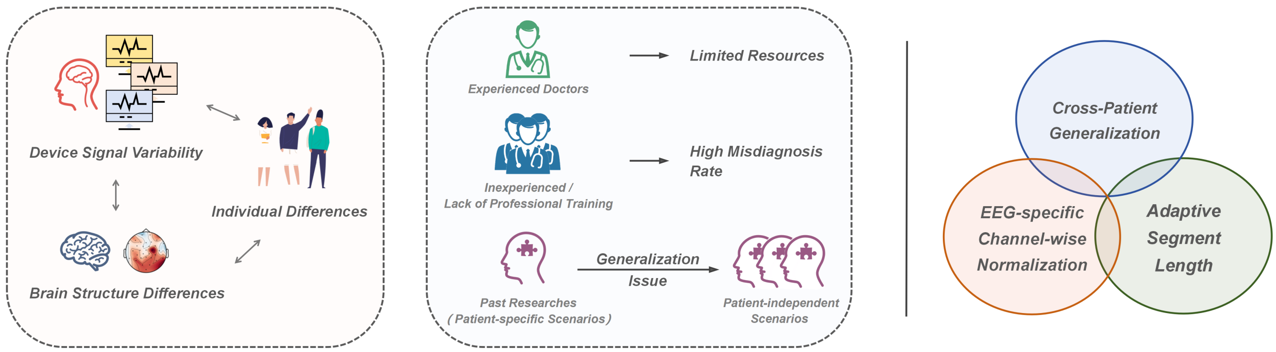
Electroencephalography (EEG) is a fundamental tool for epilepsy diagnosis, evolving from basic paper-based recordings to advanced digital systems with improved spatial resolution and longer recording durations (Liu Xiaoyan, 2017). However, interpreting EEG signals remains challenging, requiring significant expertise to identify epileptic patterns accurately. Misinterpretation is not uncommon, even among specialists, leading to incorrect diagnoses and suboptimal treatment strategies (Benbadis, 2007; Tveit et al., 2023). This challenge has fueled interest in AI-driven automated seizure detection systems, which aim to offer consistent, objective analyses, reducing the burden on clinicians and improving diagnostic accuracy.

Recent advancements in automated seizure detection have predominantly focused on patient-specific models, which are trained and tested on data from the same individual. Although these models demonstrate high efficacy in patient-specific scenarios, their ability to generalize across different patients remains limited (A. Abdelhameed & Bayoumi, 2021; G. Liu, Tian, & Zhou, 2022). Furthermore, the common practice of segmenting EEG signals into short intervals (e.g., 1-30 seconds) oversimplifies real-world clinical conditions, where EEG recordings are typically longer and more complex (Abdallah, Jrad, Abdallah, Humeau-Heurtier, & Van Bogaert, 2023; Ke et al., 2022). These limitations underscore the need for patient-independent models capable of handling diverse and extended EEG recordings. In addition to patient variability, practical challenges include the diversity of EEG acquisition devices, which vary in terms of channels, sampling rates, and hardware configurations. A robust seizure detection system must ensure compatibility across different devices for real-world clinical use.

To overcome these challenges, we propose a novel EEG normalization approach, Electroencephalogram Channel-wise Normalization (ECNorm), incorporated into a two-layer Long Short-Term Memory (LSTM) model. ECNorm targets EEG signal variability across patients by normalizing data channel-by-channel, exploring physical properties and data distributions specific to each channel. This approach not only reduces inter-patient variability but also enhances the generalization capability of our model. The LSTM layers effectively capture temporal dynamics and dependencies across different time steps, allowing the model to adapt to varying segment lengths and perform reliable seizure detection as demonstrated in our experiments (Figure 1).Moreover, our method is designed to be compatible with diverse EEG acquisition devices, ensuring adaptability across different hardware setups. Our contributions include:

- Proposing **ECNorm**, a method that reduces inter-patient variability by capturing the unique characteristics of each EEG channel.
- Developing an end-to-end framework combining **ECNorm** with LSTM, enabling patient-independent epilepsy diagnosis.
- Demonstrating the model's robustness across varying seg-

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*



(a) Signal Variability and Data Processing Challenges

(b) Effective Epilepsy Diagnosis Challenges

(c) Advantages of Our Method

Figure 1: Challenges and Advantages of Our Method. The two subfigures on the left show the two main challenges facing automated epilepsy diagnosis, including both the lack of rational data processing methods in the face of signal variability and the lack of efficient epilepsy diagnosis methods in the diagnostic process. The rightmost subfigure shows the three main advantages that our method demonstrates against these challenges.

ment lengths and ensuring compatibility with diverse EEG acquisition devices, addressing a range of clinical needs.

Related work

Seizure detection has been extensively researched in biomedical signal processing. Early methods relied on conventional signal processing techniques and machine learning algorithms to develop patient-specific detection methods. These involved manual feature extraction from EEG signals, including time-domain, frequency-domain, and time-frequency-domain features. For instance, (Shoeb, 2009) proposed a patient-specific method using Support Vector Machine (SVM), extracting spectral features on each channel, and utilizing fixed-length feature vectors as input to train the SVM model. (Amin & Kamboh, 2016) introduced RUSBoost to address imbalanced seizure/non-seizure data and conducted patient-specific experiments on the CHB-MIT dataset using RUSBoost and a decision tree classifier. (Alkan, Koklukaya, & Subasi, 2005) used frequency domain features such as power spectral density to represent EEG signal energy. Additionally, (W. Zhou, Liu, Yuan, & Li, 2013) proposed a seizure detection algorithm for long-term intracranial EEGs using cleavage degree and Bayesian Linear Discriminant Analysis (BLDA). They conducted patient-specific experiments on intracranial EEG data from the University Hospital Epilepsy Freiburg Center, Freiburg.

With the development of deep learning, deep learning-based epileptic seizure detection has gradually emerged, which is mainly classified into using deep learning models for classification after extracting features manually(Tian et al., 2019; D. Liu, Dong, Bian, & Zhou, 2023; Wang et al., 2023), and using deep learning models for extracting features and classification(M. Zhou et al., 2018; Hu et al., 2020; Abdallah et al., 2023; A. Abdelhameed & Bayoumi, 2021)both methods. Deep learning models, such as convolutional neural networks (CNNs)(Wei, Zou, Zhang, & Xu, 2019; Tanveer, Khan, Sajid, & Naseer, 2021), recurrent neural networks (RNNs)(Vidyaratne, Glandon, Alam, & Iftekharuddin, 2016; Petrosian, Prokhorov, Homan, Dasheiff, & Wunsch II, 2000), their variants(A. M. Abdelhameed, Daoud, & Bayoumi, 2018; Golmohammadi et al., 2017), and more recently transformer-based models(Yang & Modesitt, 2023; Bhattacharya, Baweja, & Karri, 2022; Peh et al., 2023), have been highly effective in capturing complex patterns and dependencies in EEG signals, fueling the development of the field of seizure detection.

While there were fewer cross-patient experiments, we were also pleased to find some experiments that made an attempt at patient-independent scenarios. (T. Liu, Truong, Nikpour, Zhou, & Kavehei, 2020)proposes a hybrid model based on two feature extractors, a convolutional neural network (CNN) and a recurrent neural network (RNN), trained using the short-time Fourier transform (STFT) of one-second SEEG. Other models that perform well in patient-specific scenarios, migrated to patient-independent leave-one-out experiments, achieve only slightly better than randomized prediction dichotomies (Tian et al., 2019). In the study (Zhao et al., 2023) a hybrid attention network (HAN) is proposed for automatic seizure detection. The method utilizes Graph Attention Network (GAT) to extract spatial features at the front end and Transformer to extract temporal features at the back end. The method does not require complex data preprocessing and feature extraction, and overall, the performance of the HAN equals or exceeds that of current state-of-the-art methods, and we have selected this experiment as the benchmark for this paper.

Method

This section describes our data preprocessing approach, the implementation of ECNorm, and its integration into a two-

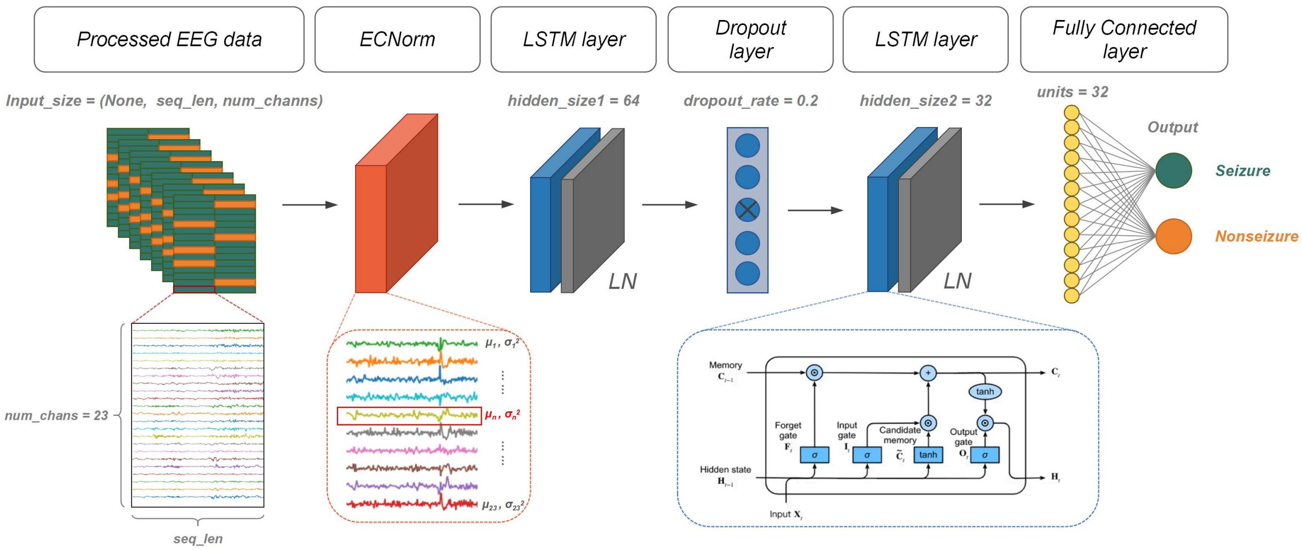


Figure 2: The architecture of the ECNorm-LSTM model, which includes an ECNorm layer, two LSTM layers, and a fully connected layer for final classification.

layer LSTM model for seizure detection.

Data Pre-processing

EEG signals are prone to noise, so we applied a 4th-order Butterworth bandpass filter (1-40 Hz) and segmented the signals into 1-second and 100-second windows with 50% overlap. To avoid precision loss due to the microvolt-level scale, signals were amplified by 1×10^7. The preprocessing pipeline is shown in Figure 3.

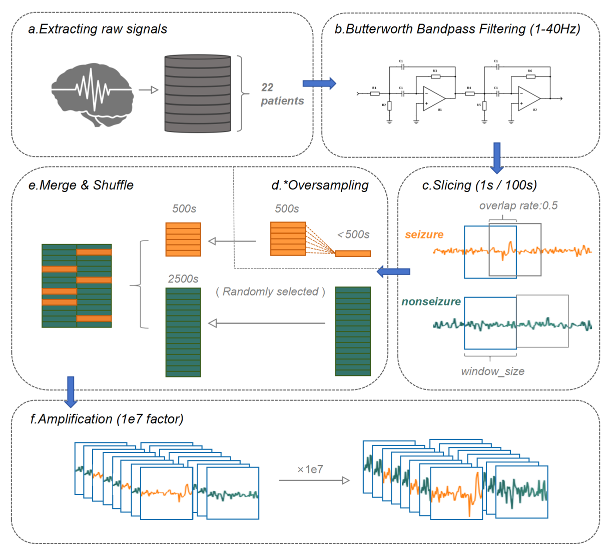


Figure 3: EEG Data Preprocessing Pipeline. This pipeline includes the following steps: (a) Acquisition and conversion of raw signals, (b) Butterworth Bandpass Filtering (1-40Hz), (c) Slicing into 1-second or 100-second segments, (d) *Oversampling, (e) Merging and Shuffling, (f) Amplification with 1e7 factor. *Oversampling is specifically applied to segments of epileptic seizures less than 500s in duration.

Electroencephalogram Channel-wise Normalization (ECNorm)

Electroencephalogram Channel-wise Normalization (ECNorm) is a normalization technique specifically designed for EEG signals. It independently normalizes each EEG channel to address inter-patient variability. Due to factors like electrode placement, individual brain anatomy, and variability in scalp contact, EEG channels often exhibit significant distributional differences. ECNorm takes these factors into account, computing the statistical properties for each channel separately, thereby preserving channel-specific information while reducing cross-patient signal variability and improving model generalization.

ECNorm calculates the mean and variance for each channel independently to normalize the input tensor. Let the input tensor be $X \in \mathbb{R}^{B \times T \times C}$, where B is the batch size, T is the time steps, and C is the number of channels. The ECNorm computation proceeds in the following steps:

1. Channel-wise Mean and Variance Calculation: For each EEG channel c, the mean μ_c and variance σ_c^2 are computed across the time dimension t as follows:

$$\mu_c = \frac{1}{BT} \sum_{b=1}^{B} \sum_{t=1}^{T} X[b,t,c], \quad \sigma_c^2 = \frac{1}{BT} \sum_{b=1}^{B} \sum_{t=1}^{T} (X[b,t,c] - \mu_c)^2$$

2. Normalization: After calculating the mean and variance, each channel is normalized as follows:

$$X_{\text{normalized}}[b,t,c] = \frac{X[b,t,c] - \mu_c}{\sqrt{\sigma_c^2 + \varepsilon}}$$

where ε is a small constant added to avoid division by zero.

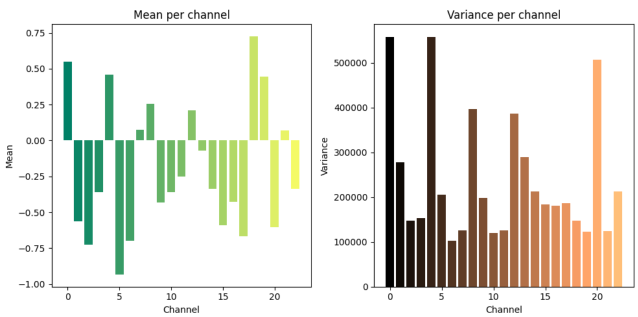


Figure 4: Mean and Variance Per Channel

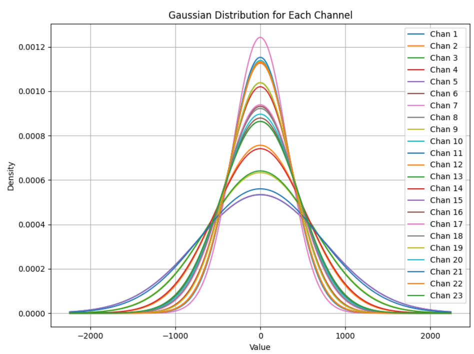


Figure 5: Gaussian Distribution Per Channel

3. Dynamic Adjustment: During training, ECNorm introduces a dynamic adjustment mechanism that allows the mean and variance of each channel to be updated over time.

As shown in Figures 4 and 5, EEG channels exhibit significant differences in their means and variances, which cannot be adequately captured by traditional batch or layer normalization. ECNorm addresses these differences, providing a more granular treatment of the signal distributions, leading to more accurate signal processing and analysis under complex physiological conditions. Additionally, because ECNorm operates independently on each channel, it naturally adapts to various EEG acquisition devices, ensuring robustness across different hardware configurations.

Application to the Two-layer LSTM Model

We integrated ECNorm into a two-layer Long Short-Term Memory (LSTM) model to validate its effectiveness in seizure detection. LSTMs are well-suited for capturing long-term dependencies in sequential EEG data.

As shown in Figure 2, the model first applies ECNorm to normalize the EEG input, reducing inter-patient variability. The normalized data is then processed by two LSTM layers, followed by dropout and layer normalization to enhance stability and prevent overfitting. The LSTM layers capture temporal patterns in the EEG data, crucial for accurate seizure detection. The final hidden state is passed through a fully connected layer for classification, combining ECNorm's normalization with LSTM's ability to model temporal dependencies, improving patient-independent seizure detection across varying EEG segment lengths.

Table 1: CHB-MIT Dataset Overview

Property	Description
Type	Scalp EEG
Subjects	22
Cases	23
Gender	5 males, 17 females
Age Range	1.5–22 years
Sampling Frequency	256 Hz
Resolution	16-bit
EEG Channels	23 (24 or 26 in some cases)
EDF Files per Case	9-42
Recording Duration	1–4 hours per file
Electrode Placement	International 10-20 system
Total Size	42.6 GB

Experimental Setup

CHB-MIT Dataset

The CHB-MIT dataset, comprising long-term EEG recordings from 22 epilepsy patients (organized into 23 cases), is summarized in Table 1; chb12 was excluded due to numerous electrode changes (A. Abdelhameed & Bayoumi, 2021), which could impact the consistency of the data. Data from chb1 and chb24 (same patient) were combined as chb01.

Implementation Details

We used leave-one-out cross-validation with 1-second segments. For each patient, 3000 seconds of data (500 seconds of seizure and 2500 seconds of non-seizure data) were sampled. Seizure data under 500 seconds was oversampled, and random selection was applied for non-seizure data exceeding 2500 seconds. Data from 21 patients (63,000 seconds) were used for training, with the remaining patient for testing.

To handle data imbalance, we applied the Focal Loss function (Lin, Goyal, Girshick, He, & Dollár, 2017):

$$\text{Focal Loss} = -\alpha(1-p_t)^{\gamma}\log(p_t)$$

where $p_t = \exp(-\text{CE\_loss})$, $\gamma = 2$, and $\alpha = 0.75$. The Adam optimizer (learning rate: 0.0001) and a dropout rate of 0.2 were used to prevent overfitting.

The model was trained on 1-second segments and tested on both 1-second and 100-second segments. Experiments were run using PyTorch 2.1.2 with CUDA 12.1 on an NVIDIA Tesla P100 GPU.

Results and Discussion

This section compares the performance of our method with benchmarks and evaluates the impact of different normalization techniques.

Table 2: Leave-One-Out Experiments (1-second vs. 100-second)

Case	**1-second**				**100-second**			
	Sen (%)	**Acc (%)**	**Spe (%)**	**AUC (%)**	**Sen (%)**	**Acc (%)**	**Spe (%)**	**AUC (%)**
1	95.00	94.77	94.72	98.23	100	93.33	92.00	99.20
2	98.00	88.00	86.00	98.69	100	90.00	88.00	98.40
3	97.40	97.47	97.48	98.97	100	100	100	100
4	81.60	92.53	94.72	95.79	100	96.67	96.00	98.40
5	90.00	82.10	80.52	93.46	80.00	86.67	88.00	82.40
6	42.00	50.63	52.36	46.62	100	73.33	68.00	92.00
7	88.40	95.00	96.32	95.29	100	96.67	96.00	100
8	72.20	57.80	54.92	68.59	60.00	66.67	68.00	70.40
9	96.20	97.60	97.88	98.80	100	100	100	100
10	87.00	94.63	96.16	95.47	80.00	96.67	100	98.40
11	96.60	87.77	86.00	98.03	100	100	100	100
13	64.00	52.57	50.28	61.88	80.00	23.33	12.00	49.60
14	38.00	27.40	25.28	22.08	40.00	33.33	32.00	19.20
15	76.40	69.50	68.12	79.57	100	90.00	88.00	97.60
16	35.00	54.97	58.96	49.80	0.00	43.33	52.00	31.20
17	85.40	70.13	67.08	81.57	100	36.67	24.00	78.40
18	97.40	52.17	43.12	91.88	100	23.33	8.00	70.40
19	82.20	95.33	97.96	96.11	100	100	100	100
20	77.40	36.13	27.88	69.34	80.00	30.00	20.00	40.80
21	89.20	87.30	86.92	93.99	100	96.67	96.00	100
22	85.60	95.03	96.92	71.63	80.00	96.67	100	97.60
23	90.80	90.70	90.68	95.58	80.00	96.67	100	97.60
Average	**80.26**	**75.89**	**75.01**	**81.88**	**85.45**	**75.91**	**74.00**	**82.80**

Leave-One-Out Experiments

We evaluated our method on 1-second and 100-second segments using a Leave-One-Out setup, with results shown in Table 2.

1-Second Experiments: Our method achieved an average substantial improvement over existing methods, achieving a sensitivity of 80.26%, an accuracy of 75.89%, and anan AUC of 81.88%. The specificity achieved by our method (75.01%) is comparable to the benchmark (75.7%). Figure 6 visually compares the sensitivity of our method against the benchmark. Notably, our approach significantly enhanced sensitivity in patients 4, 10, 20, and 21. However, the sensitivity was comparatively lower in patients 14 and 16, particularly in patient 16, where notable fluctuations were observed. This could be attributed to significant individual variability in the EEG signals from these patients, which slightly impacted the generalization capability of our model for these specific cases. Despite these few instances of underperformance, our method generally excels at detecting epileptic seizure features across patients, effectively raising the average cross-patient seizure detection rate from 72.75% to 80.26%.

100-Second Experiments: On 100-second segments, the method achieved an average sensitivity of 85.45%, accuracy of 75.91%, and AUC of 82.80%, demonstrating its robustness across different segment lengths and setting a new benchmark for future comparisons.

Comparisons with Other Methods: Table 3 compares the performance of ECNorm-LSTM with various state-of-the-art seizure detection methods under a patient-independent experimental setting. Our method demonstrates clear improvements in both sensitivity and accuracy compared to other approaches.

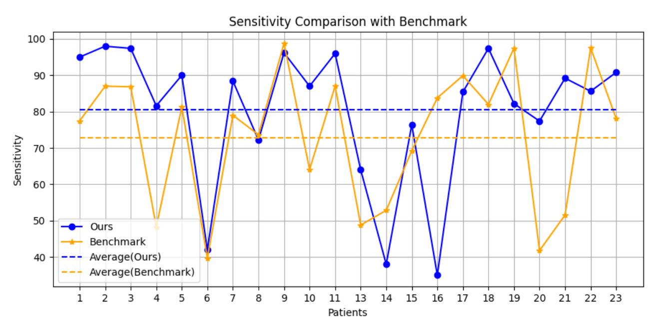


Figure 6: Sensitivity Comparison with Benchmark. Our method was superior to benchmark in most patients, and despite relatively poor results in individual patients, the overall average was significantly better than benchmark.

For example, compared to the SVM-based method by Shoeb et al.(Shoeb, 2009), ECNorm-LSTM achieves higher sensitivity (80.26% vs. 74.6%) and significantly improved accuracy (75.89% vs. 58.32%). Similarly, our method outperforms more complex models like ChronoNet(Thodoroff

Table 3: Comparisons of ECNorm-LSTM and other methods (1-second).

Author	Method	Sen (%)	Acc (%)	Spe (%)
Shoeb(Shoeb, 2009)	SVM	74.6	58.32	42.19
	DT	65.28	57.65	50.11
	NB	59.87	50.1	40.4
Thodoroff(Thodoroff, Pineau, & Lim, 2016)	ChronoNet	74.80	66.32	57.96
Liu(T. Liu et al., 2020)	SHB	75.27	56.02	36.71
Tian(Tian et al., 2019)	MV-TSK-FS	69.6	69.93	70.3
Ullah(Ullah, Hussain, Aboalsamh, et al., 2018)	P-1D-CNN	65.98	62.68	60.0
Zhao(Zhao et al., 2023)	GAT+Transfomer	72.75	73.15	75.7
Ours	**ECNorm-LSTM**	**80.26**	**75.89**	**75.01**

et al., 2016), with better sensitivity (80.26% vs. 74.80%) and accuracy (75.89% vs. 66.32%). Furthermore, ECNorm-LSTM surpasses Zhao et al.'s GAT+Transformer model(Zhao et al., 2023), showing stronger sensitivity (80.26% vs. 72.75%) and accuracy (75.89% vs. 73.15%) when evaluated on 1-second segments.

In addition to outperforming these methods on 1-second segments, ECNorm-LSTM is also compatible with varying segment lengths, including 100-second segments, where it maintains high performance. Consequently, many of the methods in the comparison do not report results for longer segments, further highlighting the adaptability and robustness of our approach across different temporal resolutions.

Overall, ECNorm-LSTM provides a well-balanced performance in terms of sensitivity, accuracy, and specificity, outperforming multiple computationally intensive models while remaining effective for varying segment lengths.

Ablation Experiments

To evaluate the impact of ECNorm on seizure detection, we conducted ablation experiments using data from patient 1, removing ECNorm and inputting raw EEG signals into our two-layer LSTM model. As shown in Table 4, excluding ECNorm resulted in a significant performance drop, with sensitivity plummeting from 96.00% to 12.60%, and accuracy decreasing from 90.97% to 84.47%. This highlights the critical role of ECNorm in improving both sensitivity and accuracy, which are essential for effective seizure detection.

Interestingly, while the model's specificity increased from 89.96% to 98.84% without ECNorm, this improvement was misleading. The higher specificity is likely due to the model's failure to correctly identify seizure events, thus biasing predictions towards non-seizure classifications. Fig 7 further illustrates that ECNorm not only improves convergence speed and stability during training but also reduces loss values, demonstrating its ability to enhance model performance and adaptability.

Table 4: Ablation Experiments - Comparison of Normalization Methods

Method	Sen (%)	Acc (%)	Spe (%)
ECNorm	**96.00**	**90.97**	89.96
Without ECNorm	12.60	84.47	98.84
LayerNorm	38.20	89.00	99.16

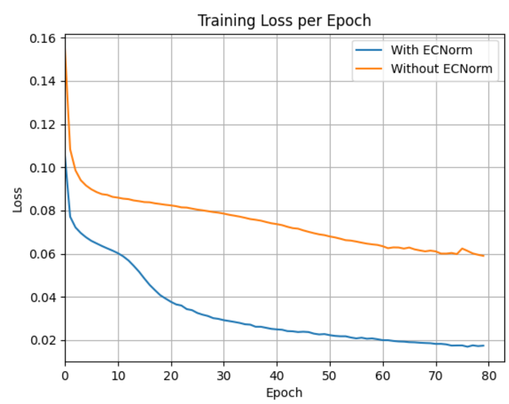


Figure 7: Loss Curves Comparison with and without ECNorm

Conclusion

In this paper, we introduced the Electroencephalogram Channel-wise Normalization (ECNorm) method for EEG data, integrated with a two-layer LSTM network to develop an adaptive, cross-patient epilepsy detection model. Our model outperformed benchmarks on the CHB-MIT dataset, with ablation studies underscoring the importance of ECNorm. Future work will focus on further optimizing the model, incorporating more clinical data, and enhancing its adaptability to improve diagnostic accuracy and clinical applicability.

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