Journal of Advanced College of Engineering and Management

Child Seizure Prediction Using Temporal Features with Temporal Convolutional Neural Network (TCNN)

[1]Sanam Adhikari, [1*]Dibakar Raj Pant, [2]Prijal Bista
[1]Department of Electronics and Computer Engineering, Pulchowk Campus, Tribhuvan University, Nepal*
[2]Department of Computer Engineering, Kantipur Engineering College, Tribhuvan University, Nepal
Email: [2]sanamadhikari98@gmail.com, [2]prijalbistaedu@gmail.com
Corresponding email: [*]pdibakar@gmail.com

DOI: 10.3126/jacem.v12i01.93904

Abstract
Early prediction of epileptic seizures is clinically important because it allows for immediate treatment, reduce injury risk, and improve the quality of life of pediatric patients. This paper presents a subject-specific three-class seizure prediction framework using multichannel electroencephalography (EEG) and a Temporal Convolutional Neural Network (TCNN). The proposed method is evaluated on the publicly available CHB-MIT scalp EEG database. During preprocessing, the raw EEG signals were band-pass filtered between 0.5--40~Hz, notch filtered at 60~Hz, segmented into fixed 5-second windows, and labeled as interictal, pre-ictal, and ictal using seizure annotations, a seizure prediction horizon of 5 minutes, and a seizure occurrence period of 30 minutes. The proposed TCNN learns temporal EEG patterns directly from multichannel inputs, while weighted sampling and focal loss are used to address class imbalance. The main contribution of this study is the development of a lightweight subject-specific three-class framework with class-wise, threshold-independent evaluation. For a representative validation subject, the model achieved 89.03\% accuracy, a macro F1-score of 0.8239, ROC-AUC values of 0.958, 0.965, and 0.997 for interictal, pre-ictal, and ictal classes, respectively, and average precision values of 0.988, 0.874, and 0.952. The results indicate that the proposed TCNN is effective for seizure-state discrimination and near-onset warning, while pre-ictal prediction remains the most challenging task. Overall, this study demonstrates that temporal convolution is a promising approach for pediatric EEG-based seizure prediction, with future work needed to improve pre-ictal specificity.

Keywords*—EEG, Seizure prediction, Pediatric epilepsy, Temporal convolutional neural network, Pre-ictal detection*

1. INTRODUCTION

Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain. In pediatric patients, unpredictable seizures can affect safety, learning, and overall quality of life, making early seizure prediction clinically important. EEG is widely used for epilepsy monitoring, but pediatric EEG signals are highly variable, non-stationary, and often noisy, which makes reliable seizure prediction a challenging task.

Earlier seizure prediction studies mainly relied on handcrafted wavelet, spectral, entropy, and statistical features combined with conventional machine learning classifiers [1, 7, 8]. More recently, deep learning approaches such as CNNs, EEGNet, and LSTM-based models have improved EEG analysis by learning features directly from the signal [2, 3, 4, 9, 10]. However, many existing studies still focus primarily on binary seizure detection rather than explicit three-class seizure prediction, while some approaches remain computationally expensive for long EEG recordings and face challenges in robustness and generalization across subjects and datasets [5, 12, 13].

To address and overcome these challenges, this research is motivated by three core needs:

1. Effective Temporal Modeling: Seizure prediction requires models that can capture temporal EEG patterns efficiently over long recordings.
2. Three-Class State Discrimination: Practical prediction systems should explicitly distinguish interictal, pre-ictal, and ictal states rather than only detecting seizure versus non-seizure.
3. Clinically Meaningful Evaluation: In addition to window-level metrics, seizure prediction models should be evaluated using class-wise, threshold-independent measures.

Based on these needs, this study proposes a subject-specific three-class seizure prediction framework using a Temporal Convolutional Neural Network (TCNN) on the CHB-MIT scalp EEG database [6, 14]. The main research gap is that many previous studies do not provide a clear three-class pediatric seizure prediction framework with transparent labeling and multi-level evaluation. Therefore, the objective of this work is to develop and assess a TCNN-based model for distinguishing interictal, pre-ictal, and ictal EEG states.

The key research questions are whether TCNN can effectively model pediatric EEG for three-class seizure prediction, how well the proposed system performs at both class-wise and event levels, and whether temporal convolution offers a practical alternative to recurrent models.

The main contributions of this study are:

1. Development of a subject-specific TCNN-based three-class framework.
2. Use of annotation-based labeling on the CHB-MIT dataset.
3. Comprehensive evaluation using multiple performance measures.

The findings indicate good interictal and ictal localization, while pre-ictal discrimination remains more challenging. These results suggest that TCNN is a promising approach for pediatric seizure prediction, although further work is needed to improve pre-ictal specificity.

2. LITERATURE REVIEW

Early seizure analysis mainly relied on handcrafted EEG features such as wavelet, spectral, entropy, and statistical descriptors combined with conventional machine learning classifiers [1, 7]. These methods showed that automated seizure analysis was feasible, but their performance depended heavily on manual feature design and expert knowledge.

With the rise of deep learning, CNN-based models became widely used because they can learn hierarchical features directly from raw EEG signals. CNN-based methods have shown strong performance for seizure detection and prediction tasks [2, 3]. Compact architectures such as EEGNet further demonstrated that lightweight convolutional models can still provide effective EEG classification performance [9].

To better capture temporal dependencies, recurrent and LSTM-based methods were introduced for EEG sequence modeling [4, 10]. Although these approaches improved sequential learning, they are often computationally demanding for long EEG recordings. Temporal convolutional networks provide a useful alternative by combining long temporal receptive fields with efficient parallel computation, making them suitable for multichannel EEG analysis [5].

Recent literature has also emphasized the importance of class imbalance handling, event-based evaluation, and appropriate dataset selection. Seizure-related windows are much rarer than interictal windows, which motivates imbalance-aware approaches such as focal loss [11]. In addition, public datasets such as CHB-MIT remain central to pediatric seizure research because they support subject-specific analysis with long-term annotated EEG recordings [6, 14]. However, many existing studies still focus on binary seizure detection rather than explicit three-class modeling of interictal, pre-ictal, and ictal states, which motivates the present work [12, 13].

3. METHODOLOGY

A. Overview of the Proposed Framework

Figure 1 illustrates the overall workflow of the proposed seizure prediction framework. First, multichannel EEG recordings are collected from the publicly available CHB-MIT scalp EEG database. Next, the raw EEG signals are preprocessed using band-pass and notch filtering in order to suppress baseline drift and power-line noise.

The filtered continuous EEG is then segmented into fixed 5-second windows and labeled into interictal, pre-ictal, and ictal classes based on expert seizure annotations. After sample generation, the labeled EEG windows are provided to the Temporal Convolutional Neural Network (TCNN), which learns temporal representations directly from multichannel EEG signals.

Finally, the trained model is evaluated using class-wise metrics, threshold-independent measures, and confusion matrices. Each stage of the framework is described in more detail in the following subsections.

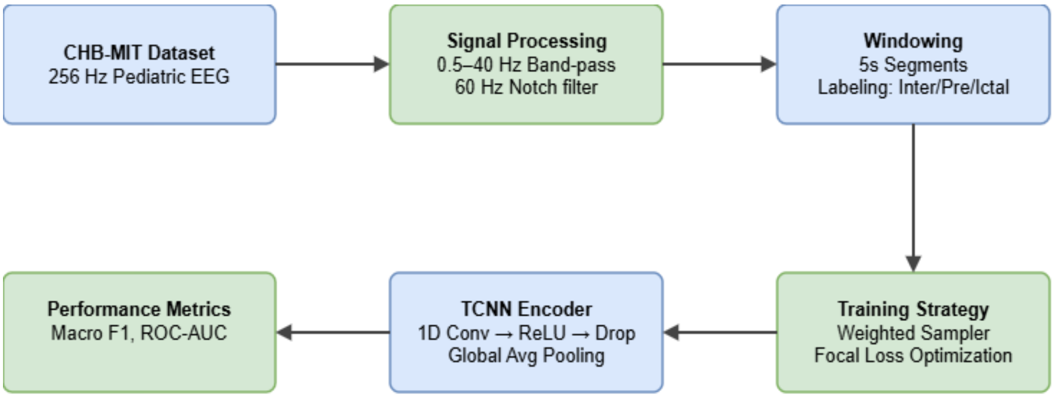

Figure 1: Overview of the proposed seizure prediction framework

B. Dataset

This study uses the CHB-MIT Scalp EEG database, a publicly available pediatric epilepsy dataset containing long-term scalp EEG recordings with expert seizure annotations. The dataset is well suited for seizure prediction research because it provides seizure onset and end times required for supervised temporal labeling.

The EEG signals are sampled at 256 Hz and recorded from multiple scalp channels. In this work, 12 patients are considered, and each patient is modeled separately under a subject-specific setting. This subject-specific design allows the framework to learn patient-dependent seizure patterns more effectively.

C. EEG Preprocessing

The raw EEG recordings are first transformed into a cleaner and more stable form before model training. A band-pass filter of 0.5–40 Hz is applied to retain the main physiological EEG components while suppressing low-frequency drift and high-frequency noise.

In addition, a 60 Hz notch filter is used to reduce power-line interference. These preprocessing steps improve signal quality and help the model focus on meaningful temporal EEG patterns associated with seizure evolution.

D. Segmentation and Sample Formation

After preprocessing, the continuous EEG signals are divided into non-overlapping windows of 5 seconds. Let C denote the number of EEG channels and T denote the number of temporal samples in one window.

Each EEG segment is represented as:

$$X \in \mathbb{R}^{C \times T} \tag{1}$$

where, for the present setting:

$$T = 5 * 256 = 1280 \quad (2)$$

E. Labeling Strategy

The segmented EEG windows are labeled directly from expert seizure annotations. Three classes are defined in this study:

1. **Interictal:** EEG activity outside seizure-related intervals.
2. **Pre-ictal:** The interval from $(s - SPH - SOP)$ to $(s - SPH)$, where s is seizure onset, SPH is the seizure prediction horizon, and SOP is the seizure occurrence period.
3. **Ictal:** The interval from seizure onset to seizure end.

In this work, SPH is set to 5 minutes and SOP is set to 30 minutes. To reduce label contamination, interictal windows located too close to seizure intervals are excluded. This labeling strategy preserves clinically meaningful temporal information while explicitly modeling the transition from normal brain activity to seizure onset.

F. TCNN-Based Seizure Prediction Model

Figure 2 presents the TCNN architecture used for three-class EEG classification. The model receives multichannel EEG windows as input and learns temporal features through stacked one-dimensional convolutional layers.

Compared with recurrent approaches, temporal convolutions provide efficient parallel computation while still capturing temporal dependencies over the input sequence. In the proposed framework, the network extracts discriminative patterns from EEG windows and maps them to interictal, pre-ictal, and ictal classes.

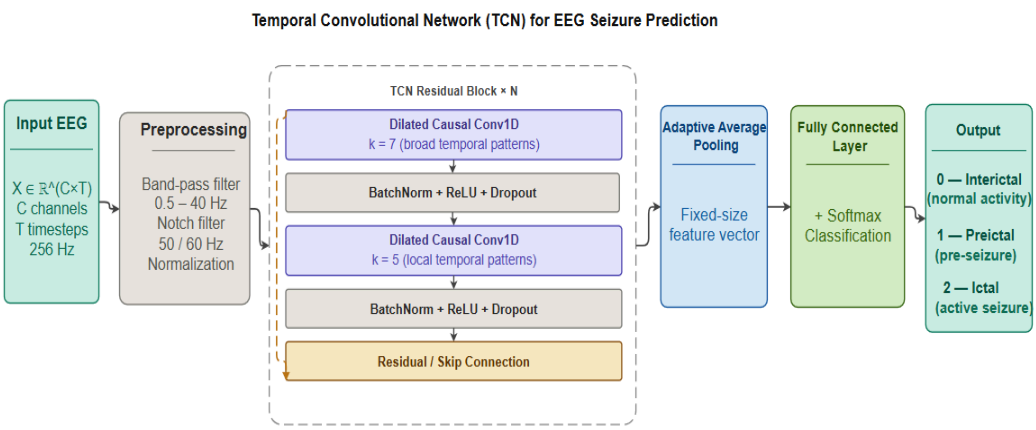

Figure 2: TCNN architecture used for EEG-based seizure prediction.

The input tensor is arranged as *(B, C, T)*, where *B* is the batch size, *C* is the number of channels, and *T* is the temporal dimension. A binary channel mask is applied before convolution as:

$$\tilde{X} = X \odot M \quad (3)$$

where $M \in \{0, 1\}^{C}$ is broadcast over time. This operation ensures that only valid channel information is used during training and inference.

The temporal encoder contains two convolutional blocks. The first block uses a kernel size of 7 and the second uses a kernel size of 5. The feature extraction process is expressed as:

$$h^{(1)} = Dropout(ReLU(Conv1D_{k=7}(\tilde{X}))) \quad (4)$$

$$h^{(2)} = Dropout(ReLU(Conv1D_{k=5}(h^{(1)}))) \quad (5)$$

followed by adaptive average pooling:

$$z = AdaptiveAvgPool1D(h^{(2)}) \quad (6)$$

Finally, a fully connected layer maps the pooled feature vector to the three output classes. In this way, the model jointly learns temporal filters across all EEG channels rather than processing each channel independently.

G. Training Strategy

The generated EEG windows are used to train the proposed TCNN in a subject-specific manner. Because the interictal class dominates the dataset, weighted random sampling and focal loss are employed to address class imbalance.

For a class label y with predicted probability p_t, focal loss is defined as:

$$L_{focal} = -\alpha_t (1 - p_t)^{\gamma} \log log\,(p_t) \quad (7)$$

where α_t is a class-dependent weighting factor and γ is the focusing parameter. In this study, $\gamma = 2.0$.

The model is optimized using Adam with a learning rate of $\mathbf{10^{-3}}$, weight decay of $\mathbf{10^{-4}}$, batch size **64**, dropout **0.2**, and a fixed training schedule of **30 epochs**. The checkpoint with the best validation macro F1-score is retained as the final model. This strategy allows the network to emphasize minority seizure-related classes while maintaining stable convergence during training.

H. Evaluation Strategy

The performance of the proposed framework is assessed using multiple evaluation levels. At the class level, accuracy, precision, recall, F1-score, confusion matrices, ROC-AUC, and average precision are used to measure discrimination ability across interictal, pre-ictal, and ictal states. In addition, probability distribution analysis is used to examine class separability.

4. RESULTS AND DISCUSSION

For the representative validation subject **Patient 8 (Chb08)**, the best epoch was epoch 30, with validation accuracy of 89.03% and macro F1-score of 0.8239. The corresponding test split achieved accuracy of 95.81% and macro F1-score of 0.8256.

A. Confusion Matrix Analysis

Figure 3 shows the confusion matrices of the validation and test sets for the representative patient. In both cases, the diagonal entries are dominant, confirming that the model achieved generally reliable three-class discrimination.

In the validation set, 1419 interictal windows, 184 pre-ictal windows, and 44 ictal windows were correctly classified. Likewise, in the test set, 1546 interictal, 236 pre-ictal, and 23 ictal windows were correctly recognized.

Despite this overall strong diagonal structure, the pre-ictal class remained the most difficult to distinguish, as 172 validation pre-ictal windows and 123 test pre-ictal windows were misclassified as interictal. This pattern indicates that the proposed model is more robust for interictal and ictal recognition than for the transitional pre-ictal state.

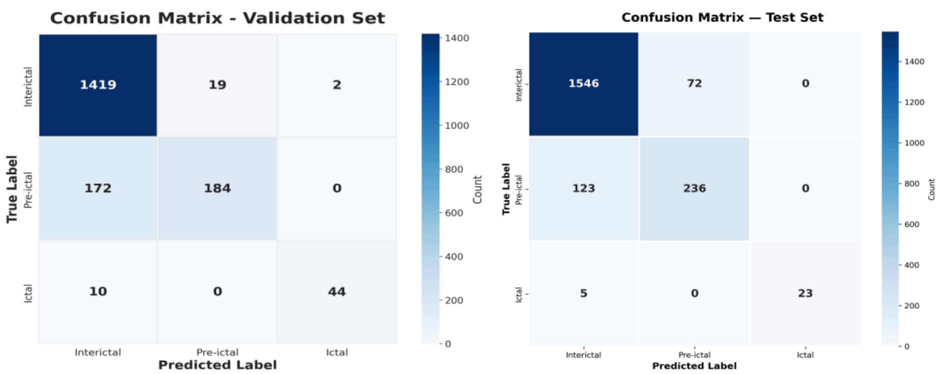

Figure 3: Confusion Matrix for representative patient.

TABLE I: Class-wise validation performance for the representative patient:

Class	Precision	Recall	F1-score
Interictal	0.8863	0.9854	0.9332
Pre-ictal	0.9064	0.5169	0.6583
Ictal	0.9565	0.8148	0.8800
Macro average	0.9164	0.7724	0.8239
Weighted average	0.8922	0.8903	0.8788

Figure 4 presents the one-vs-rest ROC and precision-recall curves. The ROC curves remain close to the upper-left corner, indicating strong separability for all three classes. The ictal class is particularly well separated, with a ROC-AUC of 0.997.

The pre-ictal ROC-AUC of 0.965 is also high, showing that the model ranks pre-ictal windows reasonably well even though the final class decision remains more difficult at a single threshold.

The precision-recall curves provide a more informative view under class imbalance. The interictal and ictal classes preserve high precision over much of the recall range, while the pre-ictal curve declines earlier, reflecting the practical difficulty of distinguishing transitional pre-seizure activity from background EEG.

Even so, the pre-ictal average precision remains 0.874, which supports the claim that the model captures meaningful pre-ictal structure.

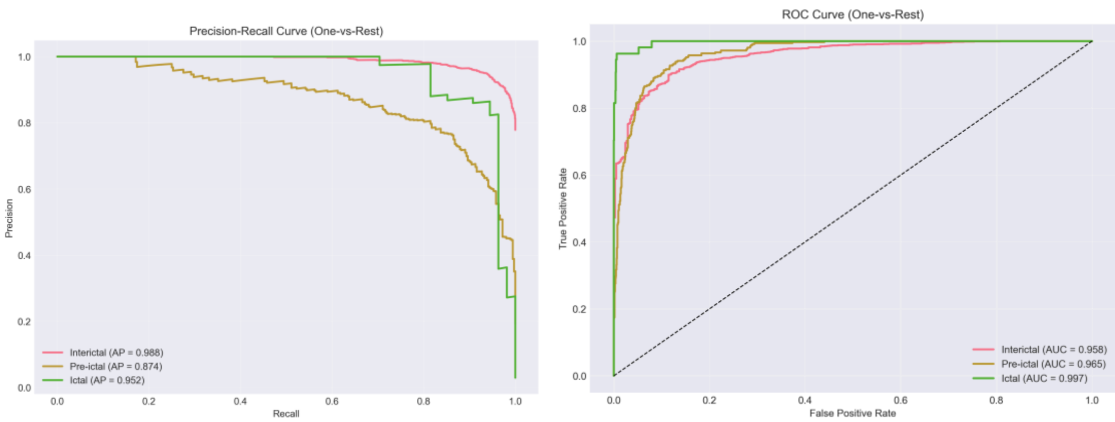

Figure 4: ROC and PR curve of validation set

B. Training Behavior

Figure 5 shows the training history. The training loss falls steadily, while training accuracy and training F1-score increase and stabilize near the end of optimization.

Validation accuracy and validation F1-score fluctuate more strongly, which is expected under subject-specific seizure data with limited minority-class samples. Nevertheless, the final epoch yields the best validation metrics in this run, indicating that the fixed 30-epoch schedule did not yet cause severe overfitting for the retained checkpoint.

At the same time, the widening gap between training and validation curves suggests that future work should evaluate early stopping, learning-rate scheduling, or stronger regularization. Therefore, the present 30-epoch setting is justified as the best observed checkpoint for this experiment, but it should not be interpreted as universally optimal.

Figure 5: Training History Curves

C. Probability Distribution Analysis

Figure 6 shows the class-probability distributions. The interictal panel shows that true interictal samples are concentrated near probability 1.0, indicating strong confidence for the majority class.

In the ictal panel, true ictal segments also cluster at high ictal probability, which is consistent with the high ROC-AUC and average precision for seizure-state discrimination.

The pre-ictal panel is broader and overlaps more with interictal samples, confirming that pre-ictal activity is the least separable state. This probability-level evidence explains why the model performs well overall but remains less reliable for early warning than for seizure-state identification.

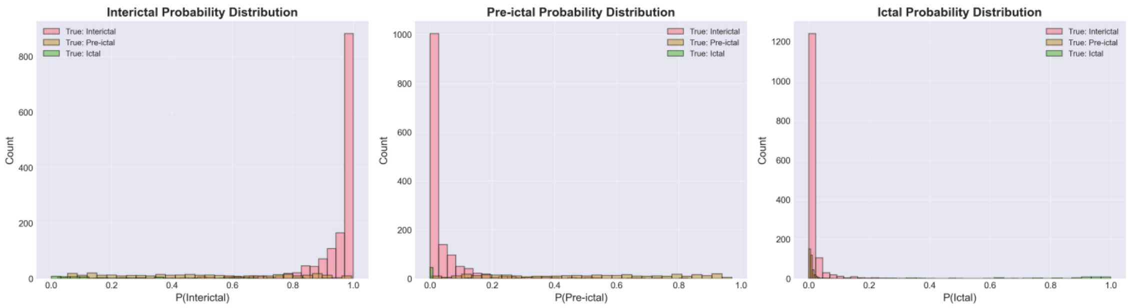

Figure 6: Predicted probability distributions for interictal, pre-ictal, and ictal classes

D. Temporal Prediction Analysis for chb08_21

To further examine the temporal behavior of the proposed model, Figure 7 presents the raw EEG signal, predicted labels, and class-probability evolution for the representative recording *chb08_21*. According to the clinical annotation, the seizure occurred between **2083 s** and **2347 s**.

The model exhibited a clear rise in ictal probability shortly after the annotated seizure onset, with the predicted ictal segment overlapping a substantial portion of the true seizure interval. This indicates that the model successfully captured seizure-related dynamics with good temporal alignment.

In particular, the ictal class became dominant during the main seizure period, showing that the proposed framework is effective in identifying the transition from non-seizure to seizure activity.

In addition, the post-seizure portion of the recording showed a gradual return toward predominantly interictal predictions, suggesting that the model was able to recover baseline-state recognition after the ictal event. This behavior is clinically meaningful, as it demonstrates that the model does not remain permanently locked in the seizure state once the abnormal episode subsides.

However, the pre-ictal and interictal probabilities fluctuated considerably before seizure onset, and no sharply localized pre-ictal buildup was observed over a sustained interval. This suggests that the model is more reliable for seizure localization and ictal-state recognition than for highly specific early seizure prediction.

Therefore, the temporal output of *chb08_21* supports the conclusion that the model performs well as an onset-sensitive seizure detection framework, while further refinement is still needed to improve pre-ictal specificity and early-warning consistency.

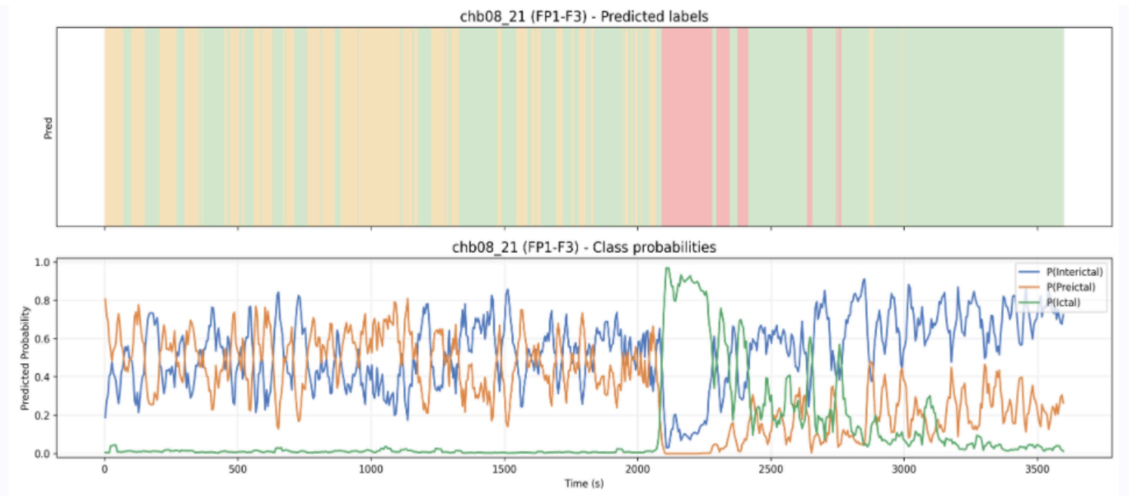

Figure 7: Raw EEG signal, predicted labels, and class-probability evolution for the representative patient.

E. Performance Across All Patients

Table II summarizes the patient-wise training and validation scores reported in the original study. The average training accuracy and validation accuracy are **96.94%** and **89.01%**, respectively, while the average training and validation macro F1-scores are **0.8973** and **0.7172**.

These results confirm that the proposed temporal framework performs strongly overall, but the gap between training and validation metrics also indicates the effect of inter-patient variability and limited seizure-related samples.

TABLE II: Patient-wise training and validation performance

Patient ID	Training Acc. (%)	Validation Acc. (%)	Training F1	Validation F1
patient_01	98.11	99.84	0.9332	0.9954
patient_03	99.71	98.49	0.9908	0.8194
patient_05	99.18	96.48	0.9321	0.8229
patient_07	99.75	96.78	0.9090	0.5668
patient_08	99.37	89.03	0.9747	0.8239
patient_10	96.39	89.66	0.8810	0.7229
patient_11	100.00	88.85	1.0000	0.5993
patient_12	97.09	75.53	0.8718	0.7150
patient_13	99.74	85.97	0.9192	0.6179
patient_14	85.39	88.71	0.6052	0.5590
patient_15	88.89	84.31	0.7864	0.6342
patient_17	99.65	74.44	0.9638	0.7293
Average	**96.94**	**89.01**	**0.8973**	**0.7172**

5. DISCUSSION

The results demonstrate that the proposed TCNN can learn clinically relevant temporal EEG patterns, particularly for interictal and ictal discrimination. However, seizure prediction is a multi-level problem, so no single evaluation metric is sufficient on its own.

For this reason, the present study used accuracy and macro F1-score for global performance assessment, confusion matrices for class-level error analysis, ROC-AUC and precision-recall curves for discrimination under class imbalance, and probability-based analysis for practical clinical interpretation.

From the confusion matrices, it is evident that the strongest performance is obtained for interictal and ictal classes, while the pre-ictal class remains comparatively less separable. A substantial portion of pre-ictal windows are confused with interictal windows, which indicates that transitional EEG activity before seizure onset is harder to model than the seizure state itself.

Therefore, the results support the claim that the model is effective for seizure-state recognition and near-onset warning, but they do not yet indicate equally strong performance for all three classes.

Careful interpretation of the training behavior is also necessary. The growing distance between the training and validation curves indicates that the stopping point might not be globally optimal, even if the model was trained for 30 epochs and the chosen checkpoint matched the best validation macro F1-score in this run.

Therefore, the reported experiment's 30-epoch setup is justified; however, future research should further evaluate early stopping and learning-rate control.

Finally, the probability distributions and temporal prediction plots reveal why pre-ictal prediction remains challenging. Interictal and ictal states show clearer confidence patterns, whereas pre-ictal probabilities overlap more strongly with interictal activity.

Overall, the proposed TCNN provides promising subject-specific performance for pediatric seizure analysis, especially for seizure localization and onset-sensitive warning, while improvement in pre-ictal specificity remains the key direction for future research.

6. CONCLUSION

This study presented a TCNN-based framework for pediatric seizure prediction from multichannel EEG in a subject-specific three-class setting. The proposed method used filtering, fixed-length segmentation, annotation-based labeling, temporal convolutional feature extraction, and imbalance-aware training.

The representative subject achieved strong validation and test performance, including high ROC-AUC values in both validation and test splits. The findings indicate that the temporal model effectively learns discriminative EEG patterns.

However, the lower pre-ictal recall suggests that improving early seizure warning remains an important direction for future work. Future studies should therefore focus on improving pre-ictal sensitivity through richer temporal context, patient-adaptive thresholding, and stronger generalization strategies.

ACKNOWLEDGMENTS

We would like to thank the Department of Electronics and Computer Engineering, Institute of Engineering, Tribhuvan University, for academic support. We also acknowledge the contributors of the publicly available CHB-MIT EEG dataset.

REFERENCES

[1] A. Subasi, “EEG signal classification using wavelet feature extraction and a mixture of expert model,” *Expert Systems with Applications*, vol. 32, no. 4, pp. 1084–1093, 2007.

[2] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, “Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals,” *Computers in Biology and Medicine*, vol. 100, pp. 270–278, 2018.

[3] T. B. Truong, J. Wen, D. K. Nguyen, B. P. Chauvette, and F. R. Mari, “Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram,” *Neural Networks*, vol. 105, pp. 104–111, 2018.

[4] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[5] S. Bai, J. Z. Kolter, and V. Koltun, “An empirical evaluation of generic convolutional and recurrent networks for sequence modeling,” *arXiv preprint arXiv:1803.01271*, 2018.

[6] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, “PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[7] M. G. Frei and I. Osorio, “Intrinsic time-scale decomposition: time–frequency–energy analysis and real-time filtering of non-stationary signals,” *Proceedings of the Royal Society A*, vol. 463, no. 2078, pp. 321–342, 2007.

[8] A. H. Shoeb and J. V. Guttag, “Application of machine learning to epileptic seizure detection,” in *Proceedings of the 27th International Conference on Machine Learning (ICML)*, pp. 975–982, 2010.

[9] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, “EEGNet: A compact convolutional neural network for EEG-based brain-computer interfaces,” *Journal of Neural Engineering*, vol. 15, no. 5, 056013, 2018.

[10] A. Tsiouris, M. Pezoulas, D. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. Fotiadis, “A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals,” *Computers in Biology and Medicine*, vol. 99, pp. 24–37, 2018.

[11] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, “Focal loss for dense object detection,” in *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pp. 2980–2988, 2017.

[12] X. Zhang, Z. Li, Y. Chen, and H. Wang, “A review of epilepsy detection and prediction methods based on electroencephalogram signals,” *Frontiers in Neuroscience*, vol. 18, 1468967, 2024.

[13] K. Slama, A. Benabid, and M. Bessaid, “Comprehensive review of machine learning and deep learning methods for epileptic seizure detection and prediction,” *Bulletin of Electrical Engineering and Informatics*, 2025.