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Four-class EEG Classification for Seizure Prediction and Detection Using a Lightweight CNN-LSTM

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***Abstract*—Epilepsy, a neurological disorder, necessitates prediction and detection of seizures to safeguard patient health. Previous studies have employed 2-class or 3-class classification neural network models for seizure monitoring. However, these models overlooked electroencephalogram (EEG) characteristics in postictal stage, leading to reduced specificity in real-world scenarios. In this work, we introduce a lightweight four-class classification method that combines seizure prediction and detection. By applying the short-time Fourier transform (STFT), raw EEG signals are transformed into time-frequency spectra. The employment of the one-dimensional convolutional neural network (1D-CNN) paired with long short-term memory (LSTM) ensures meticulous extraction and classification of complex EEG patterns. Experimental results demonstrate that the average accuracy of the proposed four-class classification method is 98.44%. In addition, when postictal samples are included in the test set, the specificity of seizure prediction and detection is 99.28% and 100%, respectively. The proposed method effectively addresses the reduction in specificity caused by neglecting postictal stages. The parameters of the proposed method are only 3.7K, whereas other models' parameters range from 1.7 to 60.7 times more, making it particularly suitable for wearable devices in resource-constrained edge computing scenarios. The project code is openly available at https://github.com/0HENGMENG0/network-for-seizures.**

***Index Terms*—Epilepsy monitoring, four-class classification, CNN-LSTM, spectral reconstruction, STFT, lightweight model.**

I. Introduction

Epilepsy is a chronic disorder characterized by transient dysfunction of the brain [1]. During seizures, patients may experience a loss of consciousness. Seizures often occur without apparent precursors, posing unpredictable safety hazards such as suffocation, accidental drowning, and falls. Currently, the method of using electroencephalogram (EEG) from scalp electrodes for diagnosing epilepsy and predicting epileptic seizures has been widely adopted [2].

Portable seizure monitoring devices can effectively assist patients in avoiding potential safety risks. Seizure prediction alarms can notify patients of impending seizures, allowing them to move to a safe location. Seizure detection alarms inform family members or healthcare providers about the patient's condition, facilitating timely and appropriate responses in emergencies. The brain's electrical activity of patients can be categorized into distinct stages based on characteristic variations: preictal, ictal (seizure onset), postictal, and interictal stages [2]. Seizure prediction involves identifying preictal characteristics in a patient's EEG signals, whereas seizure detection focuses on capturing features specific to the ictal stage.

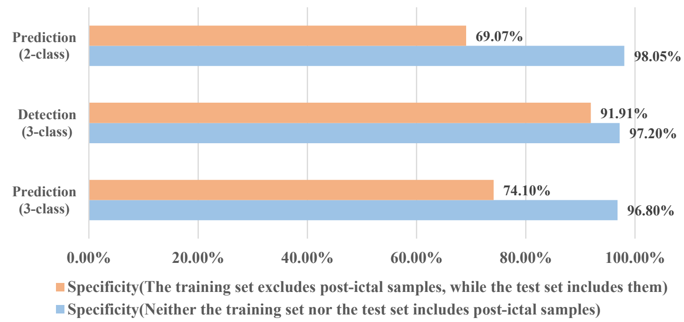

Fig. 1. Comparison of specificity with and without consideration of postictal samples in neural networks [3], [4].

Researchers have proposed many methods for seizure prediction and detection. For example, Wang et al. [5] utilized a stacked one-dimensional convolutional neural network (1D-CNN) model incorporating a random selection and data augmentation strategy, achieving commendable performance in seizure detection. Singh et al. [6] utilized a bidirectional long short-term memory (BiLSTM) based on spectral features for the automated prediction of epileptic seizures. Many researchers have also employed Fast Fourier Transform (FFT) to extract frequency-domain information from patients' EEG signals [7], [8]. However, considering that EEG signals are non-stationary, FFT has limitations in handling such signals. For this reason, researchers have proposed the use of discrete wavelet transform [9] and the short-time Fourier transform (STFT) [10]–[15] to transform patients' EEG signals from the time domain to the time-frequency domain.

However, these studies [2], [6], [9]–[12] have predominantly focused on either forecasting or identifying epileptic episodes in isolation, which inadequately meets the practical demands of patients. A few investigators have accomplished ternary classification (preictal, ictal, and interictal stages) of EEG signals in epileptic cases, facilitating simultaneous seizure prediction and detection [4]. Nevertheless, current 2-class and 3-class classification neural network models often overlook the significant differences in EEG patterns unique to the postictal stage compared to other stages. In previous studies, researchers tended to discard postictal data during the data processing

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stage [2]–[4], [16]–[21], resulting in neural network models failing to learn the features of postictal data. The exclusion of postictal samples from the training dataset will lead to a problem in real-world scenarios: the model may mistakenly classify postictal data as either ictal or preictal, leading to a conspicuous decline in specificity, thereby undermining the reliability of the monitoring system. Fig. 1 illustrates the experimental results comparing traditional 2-class and 3-class classification network models under ideal and real-world scenarios. It can be observed from the figure that when the network models did not consider postictal data during the training phase, the specificity of the model under real-world scenarios (where the test set includes postictal data) significantly decreases compared to the ideal scenario (where the test set excludes postictal data) [3], [4].

This paper introduces a lightweight four-class classification method tailored for epilepsy EEG signal processing. The main contributions are presented as follows:

(1) The model proposed in this paper specifically considers the characteristics of postictal samples, addressing the problem of reduced model specificity under real-world conditions, which researchers have long ignored.

(2) The neural network devised in this paper achieves the integration of seizure detection and prediction.

(3) By incorporating STFT, spectrum reconstruction and 1D-CNN, the model maintains high accuracy even with a small number of parameters, making it suitable for wearable devices in resource-constrained scenarios.

II. Methods

A. EEG Dataset

This work used EEG signals from the Boston Children's Hospital, as recorded in the MIT EEGLAB database, known as the CHB-MIT dataset. The EEG signals in this dataset are sampled at a rate of 256 Hz with a 16-bit resolution. Due to the variability in channel montages within the CHB-MIT dataset, we opted for manual channel selection, retaining 18 channels with consistent montages across all epochs [19]. This strategy of using a subset of electrodes also significantly reduces computational load and parameters.

In the CHB-MIT dataset, experts have annotated the start and end times of each seizure episode, with the active seizure stage marked as the ictal stage. We further define the 25 minutes preceding seizure onset as the preictal stage and the 25 minutes following seizure cessation as the postictal stage. To ensure that our model can discern the unique features of the interictal stage, we exclude the hour before the preictal stage and the hour after the postictal stage, defining the remaining period as interictal. To minimize artifacts in the EEG due to patient activity, we used only interictal period data from the morning and evening, when patient activity levels were lower, as training samples.

Subsequently, EEG signals from each stage were segmented to obtain a sample of 10-second time windows. In the CHB-MIT dataset, the duration of the ictal stage is significantly shorter than the other three stages, posing a challenge to model training effectiveness. To address this, we employed oversampling techniques by reducing the time interval steps for data segmentation during seizures, thereby acquiring more samples. Nonetheless, even after implementing these measures, the quantity of samples for some patients remained insufficient to meet our requirements for data diversity and adequacy. As a result, we ultimately selected data from ten patients: Chb01, Chb02, Chb03, Chb04, Chb05, Chb07, Chb08, Chb09, Chb10, and Chb22.

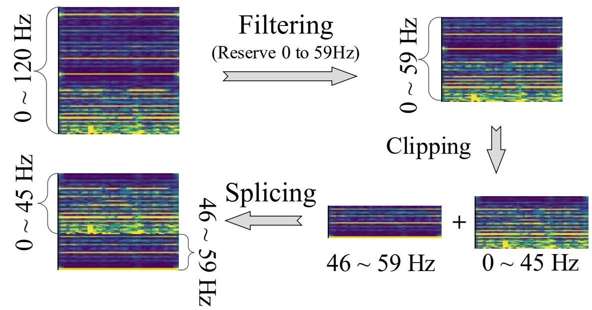

Fig. 2. Flowchart of the spectrum reconstruction proposed in this paper.

B. Pre-Processing

STFT is a widely used technique in the analysis of non-stationary signals. It involves dividing the signal into several brief segments, with an FFT performed independently on each segment to reveal the time-frequency properties of EEG. To mitigate the spectral leakage effect caused by signal truncation, we employ the Hamming window as the window function.

Electrical activity generated by the human brain is composed of five primary frequency bands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–60 Hz) [22]. Therefore, we removed spectral lines above 60 Hz. Given that the CHB-MIT dataset is contaminated by power line harmonics at 60 Hz [23], we further eliminated this specific frequency band to ensure the purity of the signals.

As seen in Fig. 2, it is evident that the key features of the EEG signals are primarily concentrated below 35 Hz. Accordingly, we adopted the following strategy: First, we divided the spectrogram at 45 Hz, yielding a high-frequency portion from 46 to 59 Hz and a low-frequency section from 0 to 45 Hz. Next, by swapping the positions of these two sub-spectra and reassembling them, we achieved a rearrangement of the original spectral layout. Through this spectral reconstruction method, we realigned the information-rich low-frequency spectral lines into the core region of the spectrogram image, while relocating the relatively information-sparse high-frequency part to the image periphery. This method ensures high classification accuracy without requiring additional padding operations in subsequent network layers.

C. Neural Network Architecture

As shown in Fig.3, our study integrates 1D-CNN, LSTM, and fully connected layers into the model architecture. Given that 1D-CNN reduces computational load and parameter count compared to their 2D counterparts, we employed a stack of

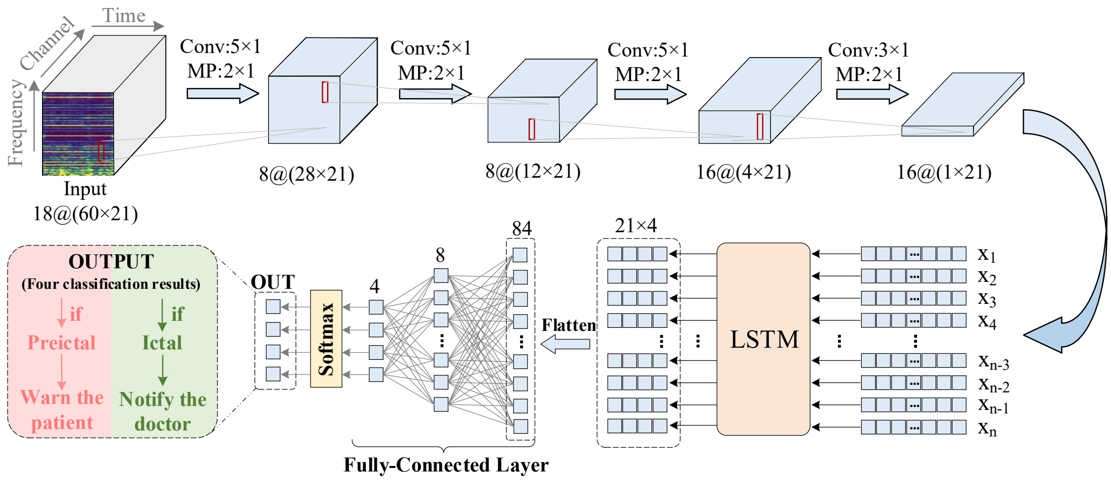

Fig. 3. The proposed four-class classification network architecture consists of a 1D CNN module, an LSTM module, and an FC module.

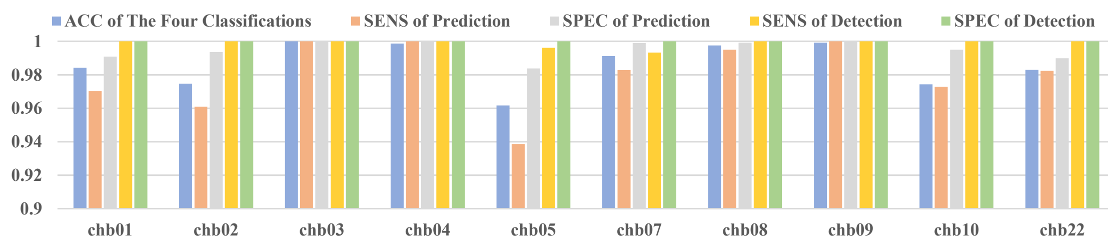

Fig. 4. Seizure detection and prediction results of the proposed method on CHB-MIT 10-patient EEG dataset (10-second window).

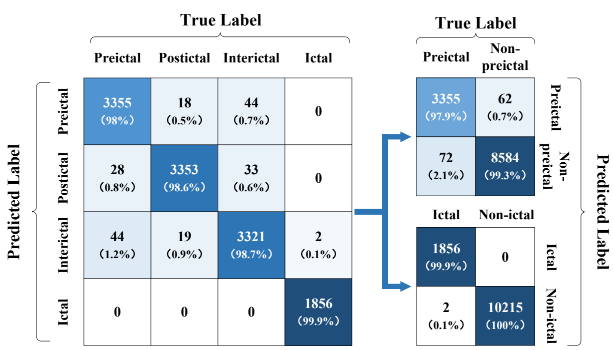

Fig. 5. Confusion matrix for 4-class classification of epileptic EEG signals.

four 1D convolutional layers in our convolutional blocks to extract features along the frequency dimension. The first three convolutional layers utilize filters of size 1×5 accompanied by max pooling kernels of size 1×2, while the fourth layer features filters of size 1×3 and max pooling of size 1×2.

Following this, the output from the convolutional layers is forwarded into LSTM layers to capture temporal features. To enhance the model's generalization capabilities, a dropout layer with a rate of 0.5 is introduced after the LSTM, mitigating the risk of overfitting. Subsequently, two fully connected layers are integrated. The model's output layer utilizes a softmax activation function to produce probability distributions across classes, thereby facilitating the final four-class classification task.

III. Experimental Setup & Results

To assess the model generalizability, we employed a 5-fold cross-validation technique, where the dataset was randomly divided into five equal parts. In each iteration, one subset was used as the test set, while the remaining four subsets served as the training set. Each experimental run comprised 300 epochs of training. To evaluate the classification performance of the model, we consider the total accuracy, specificity, and sensitivity. Sensitivity measures the accuracy of the evaluation method in identifying positive samples to ensure no cases are missed. Specificity measures the method's ability to correctly identify negative samples to avoid misdiagnosis.

We employed a four-class classification network model capable of handling both seizure detection and prediction tasks concurrently. To assess the model's predictive performance, the ictal, interictal, and postictal stages were designated as negative instances, with the preictal stage distinguished as positive, thereby facilitating a meticulous evaluation of the model's specificity and sensitivity in predicting seizures. When evaluating the model's performance in seizure detection, the preictal, interictal, and postictal stages served as negative examples, while the ictal stage was set as positive.

Fig.4 shows the sensitivity of prediction (SENS-P), sensitivity of detection (SENS-D), specificity of prediction(SPEC-P), specificity of detection (SPEC-D), and overall model accuracy for the four-class classification across 10 selected cases from the CHB-MIT dataset. Our model achieved excellent classification results in most patients, with over 99% accuracy in cases such as Chb03, Chb04, Chb07, Chb08, and Chb09. Fig.5

TABLE I
PERFORMANCE COMPARISON OF THE PROPOSED MODEL WITH OTHER WORKS USING THE CHB-MIT DATASET IN IDEAL CONDITIONS

Ref	Cases	Classification Type	Model	Parameter	Feature Extraction	Sensitivity	Specificity	Model ACC [1]
Zhang et al. 2020 [21]	15	2-class(P)[2]	CNN	194.6K	CSP[3]	92.20%(P)	92.00%(P)	90.00%
Wang et al. 2021 [5]	24	2-class(D)[4]	1D-CNN	228.5K	Raw Data	88.14%(D)	99.62%(D)	99.54%
Liu et al. 2021 [18]	12	3-class(P&D)[5]	LSTM	>10K	Raw Data	90.72%(P) 97.61%(D)	- -	-
Zhao et al. 2022 [24]	19	2-class(P)	AdderNet-SCL	120K	Raw Data	94.9%(P)	-	-
Chen et al. 2024 [2]	24	2-class(P/D)[6]	Spiking Transformer	40.3K(P) 9.9K(D)	Raw Data	96.8%(P) 94.9%(D)	89.5%(P) 99.3%(D)	93.1%(P) 97.1%(D)
Our Work	10	4-class(P&D)	CNN-LSTM	3.7K	STFT	97.90%(P) 99.89%(D)	99.28%(P) 100%(D)	98.44%

1 Model ACC denotes the total accuracy of neural network.
2 P indicates a seizure prediction task. 3 CSP denotes common spatial pattern. 4 D indicates a seizure detection task.
5 P&D denotes that the research work enables simultaneous seizure detection and seizure prediction tasks through a single neural network model.
6 P/D denotes that the research work is capable of executing either seizure prediction or seizure detection tasks individually, but not both at the same time.

TABLE II
SPECIFICITY EVALUATION OF THE PROPOSED MODEL COMPARED TO PRIOR WORKS USING THE CHB-MIT DATASET IN REAL-WORLD SCENARIOS

Ref	Method	Model ACC (Ex. post)[1]	Specificity (Ex. post)	Specificity (In. post)[2]
Zhou et al. 2018 [4]	FFT+CNN	96.10%	96.80%(P) 97.20%(D)	74.10%(P) 91.91%(D)
Xu et al. 2020 [3]	CNN	98.00%	98.05%(P)	69.07%(P)
Our work	STFT+CNN-LSTM	98.44%	-	99.28%(P) 100%(D)

1 Ex. post denotes that the training set excludes postictal samples, while the test set includes them.
2 In. post denotes that neither the training set nor the test set includes postictal samples.

illustrates the confusion matrix for the four-class classification of epileptic EEG signals. The average values for SENS-P, SENS-D, SPEC-P, SPEC-D and model accuracy are 97.90%, 99.89%, 99.28%, 100%, and 98.44%, respectively.

Table I compares our study with other research utilizing the CHB-MIT dataset. The results indicate that the proposed model not only accomplishes seizure prediction and detection tasks simultaneously but also achieves highly competitive classification accuracy with fewer parameters. The proposed model, utilizing merely 3.7K parameters, achieves a significant parameter reduction compared to other models, ranging from 1.7-fold to a substantial 60.7-fold decrease.

Notably, the experiments detailed in Table I from prior studies were conducted under ideal conditions that excluded postictal data. To evaluate real-world implications, especially concerning postictal data, we conducted two sets of experiments: one under ideal conditions excluding postictal samples from the test set, and another simulating realistic scenarios by including these samples. As shown in Table II, the specificity of both 2-class and 3-class seizure prediction models decreased by over 23.45% after incorporating postictal samples, while the decrease in specificity for seizure detection models was relatively smaller at 5.44%. The substantial decline in seizure prediction specificity is primarily due to the higher similarity between postictal and preictal features, causing the model to more easily misclassify postictal samples as preictal.

In contrast, the model proposed in this study demonstrates outstanding performance in real-world scenarios involving postictal samples, maintaining a seizure prediction specificity of 99.28% and a detection specificity of 100%. This finding highlights the substantial benefit of the four-class classification model in enhancing the specificity of seizure prediction and detection tasks under real-world conditions, emphasizing its effectiveness compared to conventional approaches.

IV. Conclusion

This study introduces a lightweight four-class classification neural network model designed for both predicting and detecting seizures. The model takes into account the feature differences between the postictal stage and the other stages, allowing it to maintain excellent specificity in real-world scenarios. To better reflect real-world conditions, we included postictal samples in the test set. Experimental results show that traditional 2-class and 3-class classification models experienced significant drops in seizure prediction specificity compared to ideal conditions. However, our proposed model maintains a seizure prediction specificity of 99.28% and a seizure detection specificity of 100%. The parameters of the proposed model are only 3.7K, whereas other models range from 1.7 to 60.7 times this amount. This lightweight design makes the model adaptable for use in resource-limited wearable device scenarios.

V. Acknowledgements

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