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Supplementary methods

1. Preprocessing

All the encephalography (EEG) recordings were downsampled to 200 Hz if their sampling frequencies were larger than 200 Hz. The signals were band-pass filtered with a passband of 1–30 Hz which has been known as a common frequency band containing most seizure characteristics on scalp EEG recordings.[1,2] Then, we prepared 2 datasets from the ictal EEG segments and interictal EEG recordings for seizure detection model construction as follows:

All the ictal EEG segments were divided into 2-second windows with a 1.5-second overlap (one channel ×400 data points), referred to as processed ictal windows. No additional preprocessing methods was performed to prevent signal distortion. All the processed ictal windows were quadrupled by flipping techniques (left-right, up-down, and left-right followed by up-down). All the interictal EEG recordings were divided into 2-second windows with no overlap (one channel ×400 data points), referred to as processed interictal windows, after defining the interictal intervals for the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) and Seoul National University Bundang Hospital (SNUBH) datasets individually.

For the CHB-MIT dataset, we selected EEG recording files with no seizure and defined all the intervals of the files as interictal intervals for each patient. Then, we randomly selected 10 files among them. We selected all the files if a patient had the number of files less than 10. From the selected files, we segmented corresponding EEG recordings and randomly selected 100 processed interictal windows from each channel. For the SNUBH dataset, we defined interictal intervals as the intervals apart from at least 1 hour before and after ictal intervals for all the patients. Then, we randomly selected 200 processed interictal windows from each channel. For both CHB-MIT and SNUBH datasets, we excluded the processed interictal windows that were suspected to have artifacts based on the 2 conditions: if they had peak-to-peak voltages larger than 1,000 μV or disconnected periods larger than 1 second.

All the processed ictal and interictal windows from the 2 datasets were shuffled with respect to the individual datasets, separately. Then, we made the number of processed ictal and interictal windows being 1:1 by a random selection of the processed interictal windows, yielding 91,552:91,552 and 20,440:20,440 processed ictal and interictal windows for the CHB-MIT and SNUBH datasets, respectively. We merged all the windows from the 2 datasets and shuffled them again, yielding 111,992 processed ictal and 111,992 interictal windows.

2. Postprocessing and evaluation metrics

During the process of the cross-validation, each model was applied to the whole EEG recordings of individual channels in parallel by a sliding window technique using a 2-second window with a 1.5-second overlap. To determine model-generated ictal intervals for each channel, we utilized postprocessing procedures as follows: (1) we smoothed consecutive model outputs by Savitzky-Golay filtering with a window size of 30 and polynomial order of 3 for transient noise reduction; (2) we selected the model outputs equal or higher than a designated threshold; (3) we merged the above-threshold model outputs if they were separated each other less than 30 seconds; and (4) we selected and binarized the model outputs in the previous step if they were equal or longer than a predefined detection length of L. Therefore, we obtained 18 sets of model-generated ictal intervals corresponding to individual channels. As we intended to decide the seizure occurrence if at least one channel had seizures in a certain period, we computed the union of the 18 sets yielding one final set of model-generated ictal intervals for each patient. Seizure detection was finally decided based on the final set from union outcomes. The L was set to 5 seconds. Any postprocessed model-generated ictal intervals longer than 5 minutes were split into 2 intervals. Supplementary Fig. 1 shows our postprocessing procedures to generate model-generated ictal intervals in event-level evaluation.

We used sensitivity, false alarm rate (FAR), and latency for our evaluation metrics. The sensitivity (%) was defined as the ratio between the number of true positives (TPs) and true seizures. The TP was defined as the model-generated ictal interval overlapped with the epileptologist-annotated one. The FAR (/hr) was defined as the ratio between the number of false alarms (FAs) and the total EEG recording time. The FA was defined as the model-generated ictal interval not overlapped with the epileptologist-annotated one. The threshold in the postprocessing steps was adjusted for each patient to have a high sensitivity balanced with a low FAR as much as possible. The latency was defined as the time difference between the starting time point of the model-generated ictal interval and that of the epileptologist-annotated one. A positive latency was considered to be a lag of seizure detection. We calculated 95% confidence intervals of the sensitivity, FAR, and latency based on the Wilson, Poisson, and bootstrap (10,000 repetitions) intervals, respectively.

3. Feature visualization

To visualize feature vectors from the last convolutional layer, we used uniform manifold approximation and projection (UMAP) to reduce the high dimensional vector space to a 2-dimensional plane. We acquired ictal and interictal windows from individual channels for a representative patient. Due to the long duration of interictal intervals, we randomly selected 500 interictal windows in each interval and each channel. To quantify the distance between ictal and interictal distributions, we applied Gaussian kernel density estimation to the UMAP results. We used the center-to-center Euclidean distance and Kullback-Leibler divergence between 2 distributions as distance measures. The center was defined as the point with the highest density.

4. Model architecture

We utilized a stacked 1-dimensional (1D) convolutional neural network (CNN) architecture with a 2-second EEG time series as an input signal, adopted from previous studies on patient-specific seizure detection.[3,4] For the input signal with a size of 1×400 (channel×data point), we constructed 2 1D CNN modules in parallel that each one had a filter size of 1×3 and 1×5, respectively. Each module consisted of 3 consecutive blocks with convolution, batch normalization, and max pooling layers with the number of filters of 32, 64, and 128, respectively. The last block was converted to a 128-length feature vector by global average pooling for each filter size, and the two 128-length feature vectors were concatenated into a 256-length feature vector. The last feature vector was fed into the fully-connected layer with a 128-length hidden layer and sigmoid activation function. The output of the activation function was considered as an ictal probability from 0 to 1. Any outputs were classified into the ictal EEG segments if their probabilities were larger or equal to 0.5 and interictal ones if less than 0.5.

We set the ratio of the number of training, validation, and testing datasets as 8:1:1, the number of epochs as 30, and the batch size as 64 during model training. We used an Adam optimizer with a learning rate of 3×10^{-4} and binary cross-entropy loss function with callbacks of an early stopping method with a patience of 10 to avoid overfitting and ReduceLROnPlateau with a factor of 0.1 and patience of 5 by monitoring validation loss. We used Python 3.8, TensorFlow 2.10, compute unified device architecture 11.8, and an NVIDIA GeForce RTX 4070 Ti Super graphic card. Supplementary Fig. 2 shows detailed information on the architecture of our seizure detection model.

Supplementary references

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