A CNN-Attention Model for Epileptic Seizure Detection

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***Abstract*—In this paper, A CNN-Attention model for epileptic seizure detection is proposed. The proposed model composed of a convolutional and attention layers classifies preprocessed EEG data as epileptic seizures or non-epileptic seizures. The proposed method converts the EEG data into the time-frequency domain through Short-Time Fourier Transform (STFT) and samples it every 30 seconds for use in the input of the model. We also oversample epileptic seizures by overlapping them in units of 1 second. To evaluate the performance of the proposed method, experiments are conducted with Cross Validation (CV) and Cross Patient Specific Method (CPSM) using CHB-MIT scalp EEG database. As a result, we obtained a accuracy of 88.73%, a sensitivity of 85.73%, a specificity of 92.14%, and a FPR of 0.077.**

Keywords—Epilepsy, electroencephalography, seizure detection, convolutional neural networks, attention

I. Introduction

Epilepsy is a neurological disease affecting 1% of the world's population[1]. Because epileptic seizures appear without any specific precursors, social life is impossible, and the patient's anxiety about seizures can lead to atrophy in social life. Thus, it is important to analyze the EEG signal accurately for a reliable diagnosis of seizure detection. Most EEG signal analysis is done by visual inspection by a medical professional. However, since it is a time-consuming task for medical professionals to visually examine long-term recordings of electroencephalographic signals, the need for automated seizure detection methods has emerged. Furthermore, when seizures are detected automatically, it is expected that problems can be prevented in advance by the rapid response of the epilepsy patient’s guardian and medical professionals. Therefore, studies related to automatic detection and prediction of epileptic seizures [2] are being actively conducted.

EEG is a recording of brain electrical activity, and can be classified into two types, scalp EEG and intracranial EEG, depending on the measurement location. Scalp EEG can be recorded by attaching electrodes directly to the scalp, and intracranial EEG can be recorded by implanting electrodes into the brain. Scalp EEG has many factors that interfere with seizure detection, such as noise of the skull and scalp. However, since scalp EEG is easier to record than intracranial EEG, scalp EEG is a more preferred signal for diagnosis and analysis of epileptic seizures than intracranial EEG. Therefore, scalp EEG was used in the experiment. It is important to analyze the EEG signal accurately for a reliable diagnosis of seizure detection. Most EEG signal analysis is done by visual inspection by a medical professional. However, since it is a time-consuming task for medical professionals to visually examine long-term recordings of electroencephalographic signals, the need for automated seizure detection methods has emerged.

In this paper, we proposed a CNN-Attention model for epileptic seizure detection. Convolutional layer is very beneficial to extract features of data. Spatial pooling is an essential part of the Convolutional Neural Networks (CNN) abstraction process, and the spatial resolution of the feature map becomes smaller. Therefore, before the features are pooled, an attention layer is added to increase important features and refine less important features to decrease. The proposed method converts the EEG data into the time-frequency domain through Short-Time Fourier Transform (STFT) and samples it every 30 seconds for use in the input of the model. We also oversample epileptic seizures by overlapping them in units of 1 second. Experiments are conducted with Cross Validation (CV) and Cross Patient Specific Method (CPSM) using CHB-MIT scalp EEG database.

II. Related Work

In early seizure detection an studies, various methods such as Fourier transform [3], wavelet transform [4] have been presented and remarkable results were obtained. Threshold-based methodology [5] or machine learning techniques such as Support Vector Machines (SVM) [6] were used a lot. Neural network [7, 8, 9] is also used for EEG discrimination. Recently, deep learning methods [10] such as CNN, RNN and LSTM have been studied a lot.

III. CNN-Attention Model

A. *Dataset*

In this paper, CHB-MIT Scalp EEG Database was used to train the model. The data set consists of EEG data of a total of 24 patients, and is sampled at 256 Hz using 22 electrode channels. EEG was measured by attaching electrodes to the scalp. Epileptic seizures in patients are labeled with start time and end time as judged by the expert. Considering that the electrode channels used for each patient are different, 18 common electrode channels ('FP1-F7', 'F7-T7', 'T7-P7', 'P7-O1', 'FP1-F3', 'F3'-C3', 'C3-P3', 'P3-O1', 'FP2-F4', 'F4-C4', 'C4-P4', 'P4-O2', 'FP2-F8', 'F8-T8' ', 'T8-P8', 'P8-O2', 'FZ-CZ', 'CZ-PZ') were used. Also, patients with epileptic seizure time of less than 30 seconds (chb06, chb16) were excluded.

TABLE I. CHB-MIT Scalp Dataset

Dataset	CHB-MIT (Boston Children's Hospital)
EEG type	Scalp
# of patients	24
# of electrodes	22
# of seizures	245
Sampling rate (Hz)	256
EEG measurement	Bipolar

B. *Preprocessing*

The EEG signal with continuous characteristics changes frequency and amplitude from time to time. Raw EEG signals include many artifacts(noise) that do not occur in the brain, such as eye blinking, muscle movement, and electrocardiography. Because EEG signals can be expressed in a variety of distinctive forms, a pre-processing process is essential for accurate detection of epileptic seizures. The STFT algorithm is used to observe the power value of the filtered signal for a specific frequency band at a specific time. It converts the time domain EEG signal of the waveform into the power spectrum of the frequency domain. We used this method to classify the characteristics of epileptic seizures and non-epileptic seizures in the frequency domain. We extracted seizure characteristics from the 30 seconds signals with cut-off frequency 60 Hz [11].

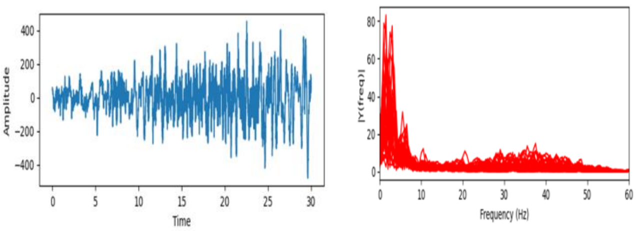

Fig. 1. (a) Time domain EEG signal (b) Frequency domain EEG signal

The CHB-MIT Scalp EEG has a significantly smaller seizure period compared to the non-seizure period, causing data imbalance. Data imbalance can increase the accuracy of the model, but it also increases the False Positive Rate (FPR). Therefore, it is difficult to expect reliable classification of the model. In order to solve this problem, the seizure period was over-sampled by overlapping in units of 1 second.

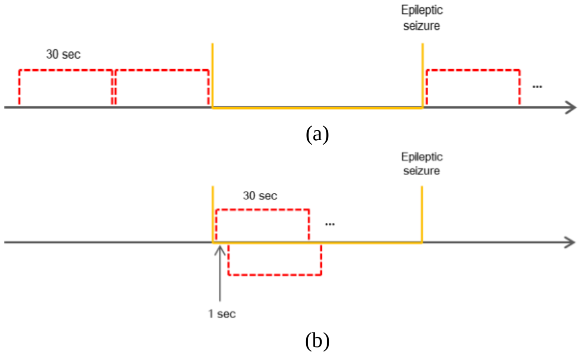

Fig. 2. (a) Sampling non-epileptic seizures and (b) sampling epileptic seizures.

C. *A CNN-Attention Model*

1) *System model*

As shown in Figure 4, we proposed a CNN-Attention model. The proposed model first creates a feature map using a convolutional layer. Afterwards, an attention layer is inserted before the pooling layer, which reduces the spatial resolution of the feature map, to grow important features, and to reduce less important features so that important features are not lost. Attention layer is performed element-wise product on the convolutional features with the attention map normalized to sigmoid function of the convolutional features.

The input data consists of window size of 30 and cut-off frequency of 60, and the number of filters in the convolutional layer of the first CNN is set to 60, and the second is set to 120. Attention layer multiplies the output of the convolutional layer and its value by normalizing it through a sigmoid function. For spatial pooling, Max-pooling was used. The dropout was set to 0.5 and the activation function of the last output was used as a sigmoid.

2) *Cross Validation*

K-fold Cross Validation divides the data set into k folds, uses k-1 folds as training data, and the remaining folds as validation data, and repeats k times. At this time, the weight of the model showing the best verification performance is stored. This Cross Validation helps to improve generalization performance because all data can be used for training and validation [12].

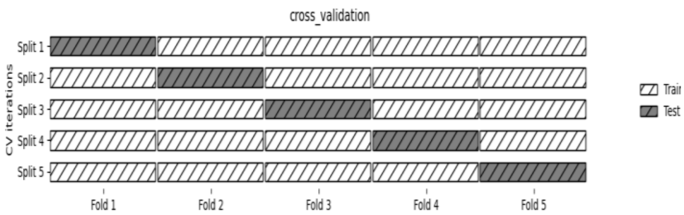

Fig. 3. K-fold Cross Validation

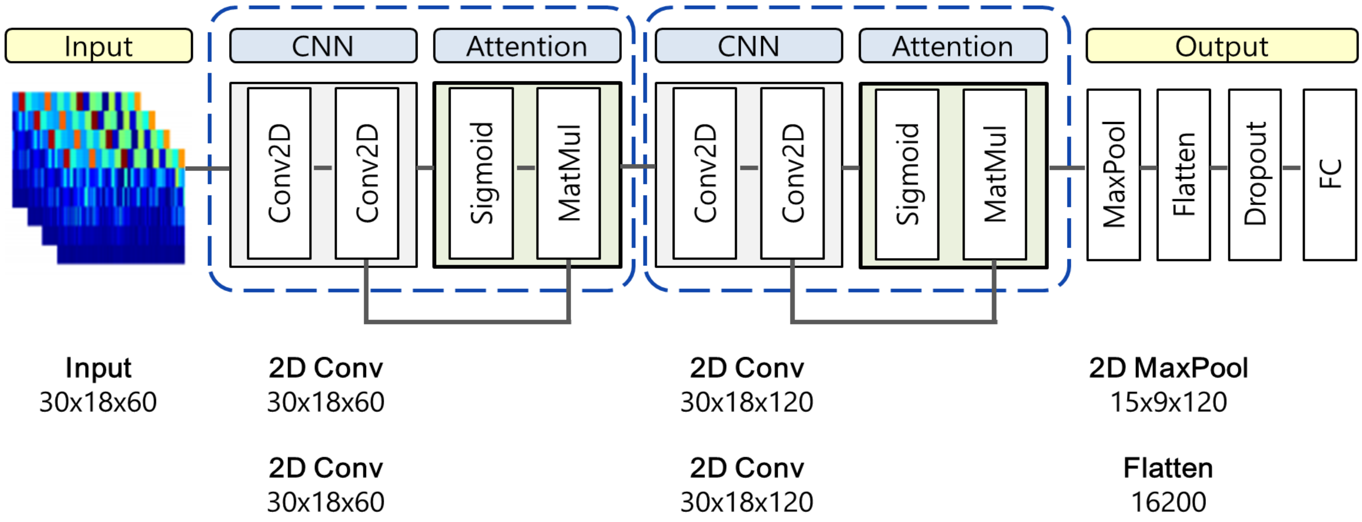

Fig. 4. Proposed CNN-Attention Model

D. *Experiments*

1) Methods

Model Cross Validation and combination were performed through voting using CHB-MIT Scalp EEG Database. The performance of the model was compared and measured by Cross Patient Specific Method (CPSM). CPSM is a method of using data except for one patient from all patients during training and testing the excluded patients. Therefore, CPSM is efficient in measuring the generalization performance of a model.

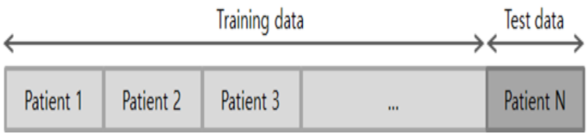

Fig. 5. Cross Patient Specific Method

2) Evaluation

We evaluated the model in terms of accuracy, sensitivity, specificity, and FPR based on the Confusion Matrix. Accuracy is the percentage of patients classified correctly among all patients. Sensitivity is the percentage of correctly identified patients with seizures. Specificity is the percentage of normal among the number of patients classified as normal. FPR is the false positive rate.

TABLE II. CONFUSION MATRIX

Actual / ***Predicted***	**Positive**	**Negative**
Positive	TP (True Positive)	FP (False Positive)
Negative	FN (False Negative)	TN (True Negative)

TABLE III. PERFORMANCE EVALUATION INDICATORS

Performance Indicator	**Formula**
Accuracy	TP / (TP + FP)
Sensitivity	TP / (TP + FN)
Specificity	TN / (TN + FP)
FPR	FP / (FP + TN)

3) Results

We preprocessed the input data with a window size of 30 and a cut-off frequency of 60. The results of Cross Validation and model performance evaluation are shown in the TABLE (IV). The proposed model obtained a accuracy of 88.73%, a sensitivity of 85.73%, a specificity of 92.14%, and a FPR 0.077 from the CHB-MIT Database.

E. *Conclusion*

In this paper, we proposed A CNN-Attention model for epileptic seizure detection. The proposed model composed of a convolutional and attention layers classifies preprocessed EEG data as epileptic seizures or non-epileptic seizures. The proposed method, the EEG data preprocessing was converted to the time-frequency domain through STFT, and the window size was set to 30 and sampled. Patients with epileptic seizure duration of less than 30 seconds (chb06, chb16) were excluded from the experiment. In addition, to solve the data imbalance problem of the CHB-MIT Scalp Database, the seizure data was overlapped in units of 1 second and the number of data was increased. To evaluate the performance of the proposed model, we cross validated the models, combined them using the voting method, and compared them using the CPSM.

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TABLE IV. PERFORMANCE OF PROPOSED MODEL

Patients	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**FPR**
chb01	99	100	98	0.017
chb02	100	100	100	0
chb03	90	82	98	0.01
chb04	92	88	97	0.023
chb05	89	100	78	0.215
chb07	97	96	99	0.008
chb08	89	81	98	0.02
chb09	78	100	57	0.429
chb10	97	100	95	0.041
chb11	98	100	97	0.029
chb12	72	53	90	0.09
chb13	78	89	66	0.332
chb14	53	23	85	0.149
chb15	93	92	93	0.061
chb17	96	93	100	0.05
chb18	88	86	91	0.084
chb19	98	100	97	0.027
chb20	80	61	100	0
chb21	88	76	100	0
chb22	97	94	100	0
chb23	91	90	92	0.071
chb24	89	82	96	0.039
Average	**88.73**	**85.73**	**92.14**	**0.077**