A One-Dimensional Convolutional Neural Network Model for Automated Localization of Epileptic Foci

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Abstract—**Intracranial electrocorticogram (iEEG) is often used by clinical experts to determine the location of the epileptic focal in the treatment of epilepsy. However, assess the location of epileptic foci by using iEEG is time-consuming and strenuous for clinical experts. Technology for automated localization of the channel of epileptic focal is indispensable. Hence, we developed a one-dimensional convolutional neural network (1D-CNN) model, which can directly extract features and train model by the raw signals without preprocessing, and performed the classification of focal and nonfocal epileptic iEEG signals. Compared with other machine learning methods, the amount of parameter reduced significantly. Our developed model has yielded the classification accuracy of 85.14% in classifying the focal and nonfocal epileptic iEEG signals.**

I. INTRODUCTION

According to the World Health Organization, there are more than 50 million people with epilepsy in the world. Epilepsy has become one of the most common neurological diseases in the world. Epilepsy is a chronic disease of the brain, which is caused by abnormal discharge of some brain tissue. Up to 70% of epileptic patients can control seizures through the proper use of antiepileptic drugs. For patients with drug-resistant, surgical treatment may be useful [8].

The difficulty of surgical treatment of epilepsy lies in the accurate localization of epileptic foci before the operation. Clinical experts need to place multiple electrodes in the patient's scalp, record iEEG for one week and visually detects the obtained iEEG to speculate the location of abnormal discharge of brain tissue, and then perform resection surgery [15]. It is a heavy burden for clinicians, both time-consuming and strenuous. Hence, there is an urgent need for a technique which could automatically identify epileptic focal signals.

In recent years, machine learning has been widely used in various fields, including biomedical field [14]. The application of various machine learning methods has greatly reduced the burden on clinical experts. In neuroscience, various machine learning methods are often used to process EEG (electrocorticogram) signals to assist clinicians in diagnosing patients.

The most common sequential steps are preprocessing, feature extraction, training, and classification when developing an automated diagnostic system by using machine learning [13]. To standardize the input of the model in the subsequent step, the raw signals are always being normalized and transformed in the preprocessing stage. Entropy [7] [10] [11] [4], Wavelet Transform [6], Fourier Transform, Empirical Mode Decomposition (EMD) [10] [4] and other methods are always used to extract the significant features from the signals in the feature extraction stage. In the training stage, K-Nearest Neighbor (KNN), Support Vector Machine (SVM) [7] [3], Recurrent Neural Network (RNN) [9] and the other neural network, are widely used for the classification of features obtained by handle-crafted feature extraction methods.

Instead of the manual feature extraction method, a 21-layer end-to-end one-dimensional convolutional neural network (1D-CNN) is used to the automated classification of focal and nonfocal iEEG signals in this study. Focal iEEG signals could be classified automatically from the iEEG signal recordings. We use the Bern-Barcelona dataset to perform the classification process. Raw signals will be the input of the network, no preprocessing and no feature extraction so that the computational is reduced significantly.

The rest of this paper is organized as follows. Section 2 introduces the Bern-Barcelona Dataset. Section 3 introduces the methods and the developed 1D-CNN model. Section 4 provides the result and discussion. Finally, the conclusion is provided in Section 5.

II. DATASET

The iEEG signals from the Bern-Barcelona dataset provided by Andrzejak et al. at the Department of Neurology of the University of Bern, were obtained from the recordings of five epilepsy patients with focal epilepsy [1]. All patients

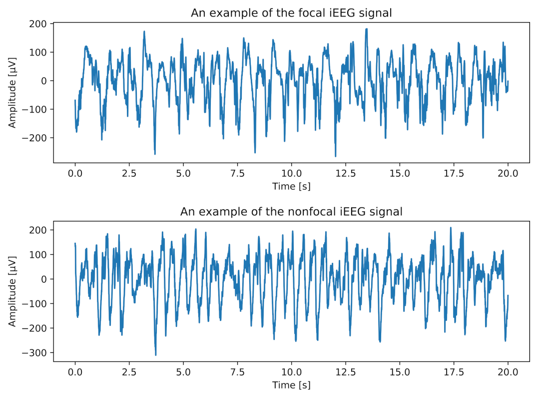

Fig. 1. An example of focal and nonfocal epileptic iEEG signals

TABLE I
VARIOUS ATTRIBUTES OF THE BERN-BARCELONA DATASET

No.	Attributes	Values
1	Dataset shape	15,000×10,240
2	The number of focal signals	7,500
3	The number of nonfocal signals	7,500
4	Sampling time	20 s
5	Sampling frequency	512 Hz
6	Frequency band	0.5-150 Hz

suffered from long-standing pharmacoresistant temporal lobe epilepsy and were candidates for epilepsy surgery patients. According to whether the signals were obtained from the focal channels, the dataset is divided into two categories. Each category contains 3,750 pairs sample with a duration of the 20 s sampled at a frequency of 512 Hz rendering 10,240 data points per sample. The dataset was processed by digitally band-pass filtered between 0.5 and 150 Hz by using a fourth-order Butterworth filter. All of the signals were labeled as focal signals or nonfocal signals by clinical experts. The iEEG signals that during seizure activity and three hours after the last seizure were excluded.

An example of focal and nonfocal iEEG signals is shown in Fig. 1, respectively. The various attributes of the Bern-Barcelona dataset is provided in Tabel I.

III. METHOD

Developed one-dimensional convolutional neural network (1D-CNN) model was used for the classification of focal and nonfocal iEEG signals in this study. This model allows the raw iEEG signals to be entirely classified directly without any feature extraction stage.

Five different types of layers are used in the developed 1D-CNN model: convolutional layer, pooling layer, fully connected layer, dropout layer, and batch normalization layer.

We use convolutional kernels with a size of 3×1 in each layer to make the feature extraction stage will not have too much computation. In order not to miss any features, we set the stride of the convolutional kernel to 1. Relu activation function is used in all of the convolutional layers. The amount of filters is set to the N power of 2 ($N \leq 6$). We set the max-pooling layers which pool size as 2×1 and stride as 2 after every

TABLE II
PARAMETER VALUES OF THE DEVELOPED 1D-CNN MODEL

No.	Layer name	Kernel size	Stride	Number of parameters	Other parameters
0	Input	-	-	-	-
1	Conv1D	2×3	1	8	-
2	Dropout	-	-	0	Rate = 0.2
3	MaxP	2	2	0	-
4	BN	-	-	20,480	-
5	Conv1D	4×3	1	28	-
6	MaxP	2	2	0	-
7	Conv1D	8×3	1	104	-
8	MaxP	2	2	0	-
9	Conv1D	16×3	1	400	-
10	MaxP	2	2	0	-
11	Conv1D	32×3	1	1,568	-
12	MaxP	2	2	0	-
13	Conv1D	64×3	1	6,208	-
14	MaxP	2	2	0	-
15	Dropout	-	-	0	Rate = 0.2
16	Flatten	-	-	0	-
17	FC	128	-	1,310,848	-
18	Activation	-	-	0	Relu
19	Dropout	-	-	0	Rate = 0.5
20	FC	2	-	258	-
21	Softmax	2	-	0	-

convolutional layer so that we could reduce the computation of the whole model, and won't miss the pivotal features. All the feature maps obtained from layer 16 are flattened into a one-dimensional feature vector as the input of layer 17. The output obtained from the first fully connected layer will be nonlinear by using Relu activation function and dropout with a rate of 0.5 and then as the input of layer 20. To perform the classification process, we set the softmax layer as the last layer of the developed 1D-CNN model. In this layer, input iEEG signals are classified as focal and nonfocal.

One of the biggest challenges in this developed model is overfitting. We added the dropout layer [12] and Batch Normalization layer [5] in various positions to reduce the effect of overfitting. Batch Normalization layer in layer 4 performed the normalization for the output obtained from the upper max-pooling layer in this study. The detailed parameter values of the developed 1D-CNN model are provided in Table II.

IV. RESULT AND DISCUSSION

The Bern-Barcelona iEEG dataset used in the study was recorded by Andrzejak et al. We split the iEEG database into three parts: train set (80%), validate set (10%) and test set (10%). The training dataset and the validation data were used during the learning stage, and test data was used during the testing stage. Thus, 12,000 out of a total of 15,000 samples were used for training, 1,500 were used for the validation, and the remaining 1,500 were used for the test. We used 10-fold cross-validation to ensure the results more dependable. A detailed illustration of the data sets used for this study is shown in Fig. 2. Fig. 3 shows the details and output shape of every layer of the developed 1D-CNN model, and the main hyper-parameters used in the architecture are given in Table III.

A batch's size of 128 with a size of 10,240 are randomly fed into the network in each epoch of training. The performance

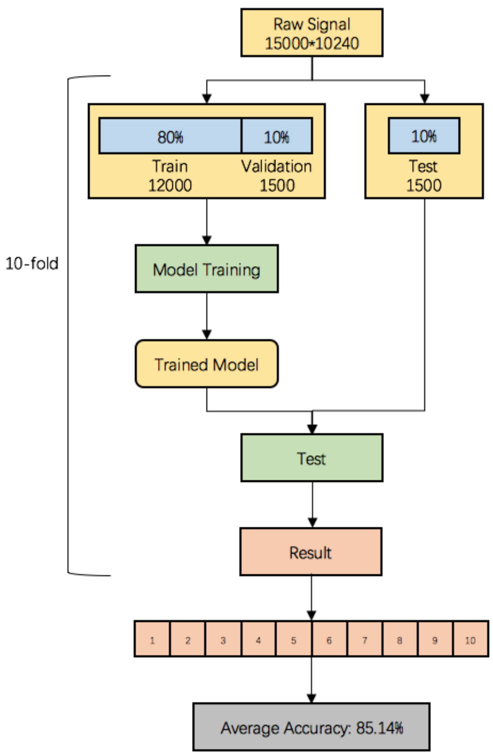

Fig. 2. The illustration of the data set used to develop this model

TABLE III
HYPER-PARAMETER VALUES OF THE DEVELOPED 1D-CNN MODEL

No.	Parameters	Values
1	Batch size	128
2	Epoch	200
3	Optimizer	Adam
4	Learning rate	2.5e-4
5	Loss function	Categorical cross entropy
6	Metrics	accuracy
7	Activation	Relu

graphs of the 1D-CNN model during the training and the validation is shown in Fig. 4.

It can be seen from the performance graphs that, there still has overfitting problem in the model although we've already used dropout layer and batch normalization layer. We speculate that the representation of the Bern-Barcelona dataset on one-dimensional convolutional is not obvious. During the training phase of the model, the training accuracy is about 99%, and the validation accuracy is about 85%. In 10-fold cross-validation, the average validation accuracy is about 85.14%.

Some of the published works are recorded in Table IV. Although the developed model could not yield a great classification performance, it still managed to obtain 85.14% accuracy without any preprocessing before the training stage in this model. Compared with the other feature extraction methods such as entropy, DWT and EMD, the 1D-CNN model has further advantages. It is less computational, and extraction of

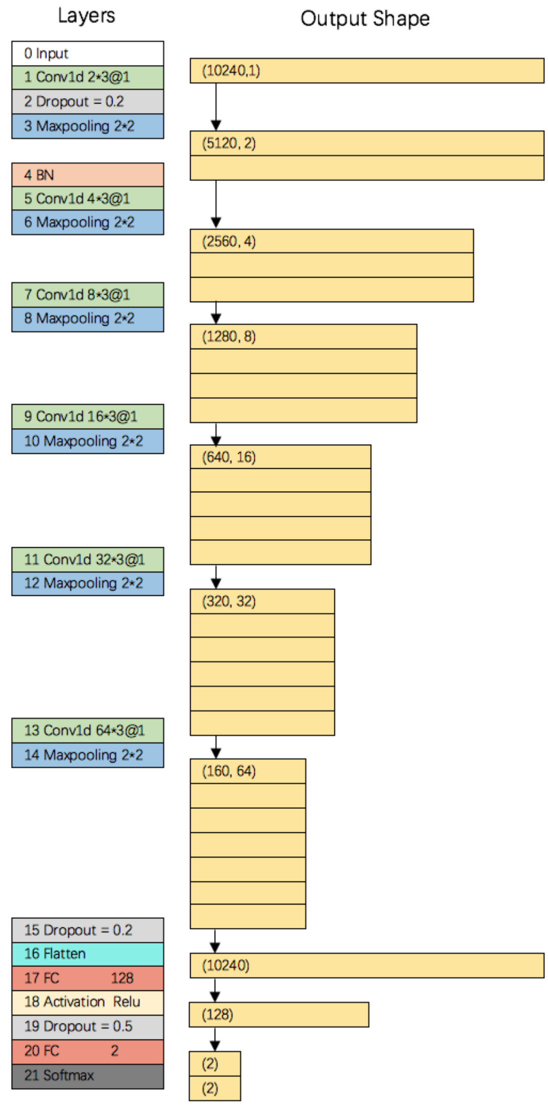

Fig. 3. Block representation of the developed 1D-CNN model

TABLE IV
PERFORMANCE COMPARISON OF THE DEVELOPED MODEL WITH OTHER WORKS ON THE SAME DATASET

Authors	Feature Extraction	Classifier	Accuracy (%)
Sharma et al. 2015 [10]	EMD, entropy	LS-SVM	87
Sharma et al. 2015 [11]	DWT, entropy	LS-SVM	84
Chen et al. 2015 [3]	DWT	SVM	83.07
Das et al. 2016 [4]	EMD-DWT, entropy	KNN	89.4
Itakura et al. 2017 [7]	BEMD, entropy	SVM	86.89
Bhattacharyya et al. 2017 [2]	TQWT, entropy	LS-SVM	84.67
This model		1D-CNN	85.14

one-dimensional subsequences from the signal with reduced the number of features.

Various evaluation criteria have been selected for the test data. The summation of the confusion matrix obtained for the test data from this model in 10-fold cross-validation is shown in Tabel V and the performance measures of this 1D-CNN model are shown in Tabel VI. From the confusion matrix table, we could know that the developed 1D-CNN model classified the test iEEG signals with a sensitivity (TPR) ratio of 88.76%

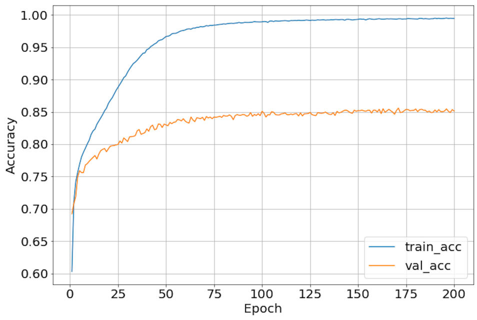

Fig. 4. Performance graphs of the model during the training and the validation

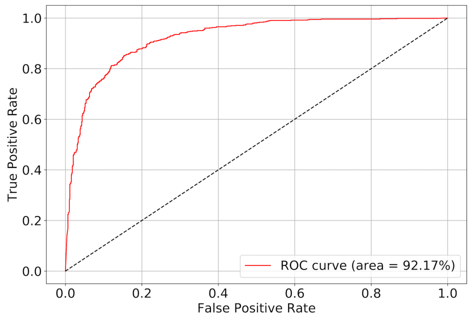

Fig. 5. The Receiver Operating Characteristic Curve of this 1D-CNN model

TABLE V
THE CONFUSION MATRIX OBTAINED FROM THIS 1D-CNN MODEL

Class	Focal	Nonfocal
Focal	TP = 6259	FP = 1404
Nonfocal	FN = 825	TN = 6512

TABLE VI
THE PERFORMANCE MEASURES OF THIS 1D-CNN MODEL

Class	TPR	TNR	FPR	FNR	Precision	F1-Score
Ratio(%)	88.76	81.68	18.32	11.24	82.26	85.39

and specificity (TNR) ratio of 81.68%.

The Receiver Operating Characteristic Curve (ROC Curve) and the Area Under the Curve (AUC) of this 1D-CNN model is shown in Fig. 5. The value of the AUC has reached 92.17%, which means the developed model could make a great classification of the test data.

V. CONCLUSION

It is a challenging task to distinguish the focal channels by iEEG signals in interictal. As the occurrence of seizures causes brain damage, the accurate detection of focal location could aid the clinical experts to validate their screening of iEEG signals and provide proper treatment to the patients earlier. We developed a one-dimensional convolutional neural network (1D-CNN) model to automate detect the epilepsy focal signals in this study. Our developed model is able to detect the focal signals with an accuracy of 85.14% by using raw signals without any preprocessing. Compared with the other methods, computational reduced significantly, which means the training time reduced greatly. We intend to optimize our model by some methods such as data augmentation to increase the test accuracy in the future.

ACKNOWLEDGMENT

This work was supported by JST CREST Grant Number JPMJCR1784, JSPS KAKENHI (Grant No. 17K00326 and 18K04178).

REFERENCES

[1] Ralph G Andrzejak, Kaspar Schindler, and Christian Rummel. Non-randomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. *Physical Review E*, 86(4):046206, 2012.

[2] Abhijit Bhattacharyya, Ram Pachori, and U Acharya. Tunable-Q wavelet transform based multivariate sub-band fuzzy entropy with application to focal EEG signal analysis. *Entropy*, 19(3):99, 2017.

[3] Duo Chen, Suiren Wan, and Forrest Sheng Bao. Epileptic focus localization using EEG based on discrete wavelet transform through full-level decomposition. In *2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP)*, pages 1–6. IEEE, 2015.

[4] Anindya Bijoy Das and Mohammed Imamul Hassan Bhuiyan. Discrimination and classification of focal and non-focal EEG signals using entropy-based features in the EMD-DWT domain. *Biomedical Signal Processing and Control*, 29:11–21, 2016.

[5] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

[6] Hakan Işik and Esma Sezer. Diagnosis of epilepsy from electroencephalography signals using multilayer perceptron and elman artificial neural networks and wavelet transform. *Journal of Medical Systems*, 36(1):1–13, 2012.

[7] Tatsunori Itakura and Toshihisa Tanaka. Epileptic focus localization based on bivariate empirical mode decomposition and entropy. In *2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pages 1426–1429. IEEE, 2017.

[8] World Healthy Organization. Epilepsy. https://www.who.int/news-room/fact-sheets/detail/epilepsy#.

[9] Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Harrer. Chrononet: A deep recurrent neural network for abnormal EEG identification. *arXiv preprint arXiv:1802.00308*, 2018.

[10] Rajeev Sharma, Ram Pachori, and U Acharya. Application of entropy measures on intrinsic mode functions for the automated identification of focal electroencephalogram signals. *Entropy*, 17(2):669–691, 2015.

[11] Rajeev Sharma, Ram Pachori, and U Acharya. An integrated index for the identification of focal electroencephalogram signals using discrete wavelet transform and entropy measures. *Entropy*, 17(8):5218–5240, 2015.

[12] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research*, 15(1):1929–1958, 2014.

[13] Özal Yıldırım, Ulas Baran Baloglu, and U Rajendra Acharya. A deep convolutional neural network model for automated identification of abnormal EEG signals. *Neural Computing and Applications*, pages 1–12, 2018.

[14] Ozal Yildirim, Ru San Tan, and U Rajendra Acharya. An efficient compression of ECG signals using deep convolutional autoencoders. *Cognitive Systems Research*, 52:198–211, 2018.

[15] Xuyang Zhao, Qibin Zhao, Toshihisa Tanaka, Jianting Cao, Wanzeng Kong, Hidenori Sugano, and Noboru Yoshida. Detection of epileptic foci based on interictal iEEG by using convolutional neural network. In *2018 IEEE 23rd International Conference on Digital Signal Processing (DSP)*, pages 1–5. IEEE, 2018.