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SEIZURE PREDICTION USING EEG CHANNEL SELECTION METHOD

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ABSTRACT

Seizure prediction using intracranial electroencephalogram (iEEG) is still challenging because of complicated signals in spatial and time domains. Feature selection in the spatial domain (i.e., channel selection) has been largely ignored in this field. Hence, in this paper, a novel approach of iEEG channel selection strategy combined with one-dimensional convolutional neural networks (1D-CNN) was presented for seizure prediction. First, 15-sec and 30-sec iEEG segments with an increasing number of channels (from one channel to all channels) were sequentially fed into 1D-CNN models for training and testing. Then, the channel case with the best classification rate was selected for each participant. We tested our method on the Freiburg iEEG dataset. A sensitivity of 89.03-90.84%, specificity of 98.99-99.73%, and accuracy of 98.07-98.99% were achieved at the segment-based level. At the event-based level, we attained a sensitivity of 98.48-98.85% and a false prediction rate (FPR) of 0-0.02/h.

***Index Terms*—** Epilepsy, intracranial electroencephalogram (iEEG), seizure prediction, channel selection, one-dimensional convolutional neural networks (1D-CNN),

1. INTRODUCTION

Epilepsy affects nearly 50 million people worldwide. Since the onset of seizures originates from abnormal synchronous discharges of brain cells, electroencephalogram (EEG) is a powerful technique in the diagnosis of epilepsy. However, epileptic seizures have the characteristics of recurrence and uncertainty, which makes epileptic patients miserable. Hence, the prediction of seizures is significant becuase this can allow people to take interventions to suppress the onset of seizures.

In the past two decades, many EEG-based data mining techniques have been used for the analysis of seizure prediction. In conventional machine learning methods, Support Vector Machine (SVM) [1–4], Bayesian [5, 6], Backpropagation Neural Network [7], Multi-layer Perceptron (MLP) [8], etc., were applied in seizure prediction and achieved remarkable results. Recently, deep learning techniques have also been widely used for seizure prediction. Deep learning methods, including One-Demensional Convolutional Neural Networks (1D-CNN) [9], Two-Dimensional Convolutional Neural Networks (2D-CNN) [10–13], Three-Dimensional Convolutional Neural Networks (3D-CNN) [14], Long Short-Term Memory (LSTM) [15–17], Deep Recurrent Neural Network (DRNN) [18] and Generative Adversarial Networks (GAN) [19], were utilized to effectively predict seizures.

In our previous study [9], we mentioned that many seizure prediction studies commonly used EEG signals of all channels, ignoring the consideration of channel selection. Feature selection in the spatial domain (i.e., channel selection) has been largely ignored in this field. Hence, our previous study [9] presented a method of channel selection strategy combined with 1D-CNN to forecast seizures, and the proposed method was tested on the Freiburg intracranial electroencephalogram (iEEG) dataset [20], in which each patient has six channels. There are 63 channel cases ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$) that can be analyzed for each patient. However, we only considered 9 channel cases for the anlysis of seizure prediction for each patient in the study [9]. Consequently, in this study with the same dataset, all channel cases are analyzed and discussed to select the best channel case with the best classification rate for each patient. Then, the best channel case can be applied for the seizure prediction of the patient in the future. Another contribution of this work is that, in preprocessing, iEEG segments are generated using sliding windows of two different lengths (15-sec and 30-sec). Therefore, the results of two different sample sizes are also discussed in this study.

The rest of this paper is given as follows: materials and methods in Section 2, results in Section 3, discussion and conclusion in Section 4.

2. MATERIALS AND METHODS

2.1. Data

The Freiburg iEEG dataset contained 21 patients, 87 seizures, 509 h of interictal and 73 h of preictal or ictal iEEG signals. iEEG signals were recored at a sampling rate of 256 Hz, with the 50 Hz notch filtering and the 0.5-120 Hz bandpass filter-

ing. Each patient had six channels: channels 1-3 (in-focal) and channels 4-6 (out-of-focal) [20].

In EEG-based seizure prediction, two basic concepts, namely seizure prediction horizon (SPH) and seizure occurrence period (SOP), need to be explained. SOP is defined as the period during which a seizure is expected to occur. SPH is the period from an alarm to the beginning of SOP [21]. In this work, we discuss two preictal conditions: (1) SOP = 30 min and SPH = 5 min; (2) SOP = 60 min and SPH = 5 min. For the first preictal condition, seizures with at least 35-min preictal phase are selected. Seizures with at least 65-min preictal phase are selected for the second preictal condition. The details of the selected iEEG signals for two preictal conditions are summarized in Table 1.

Table 1. Details of the selected iEEG signals for each patient in two preictal conditions

Patient	Age	Gender	Interictal (h)	#Seizures[a]	#Seizures[b]
1	15	f	24	4	3
2	38	m	24	3	–
3	14	m	24	5	4
4	26	f	24	5	3
5	16	f	24	5	2
6	31	f	24	3	–
7	42	f	24.6	3	3
8	32	f	24.2	2	2
9	44	m	23.9	5	3
10	47	m	24.5	5	5
11	10	f	24.1	4	3
12	42	f	24	4	3
13	22	f	24	2	2
14	41	f	23.9	4	3
15	31	m	24	4	3
16	50	f	24	5	5
17	28	m	24.1	5	5
18	25	f	24.9	4	5
19	28	f	24.4	4	3
20	33	m	25.6	5	5
21	13	m	23.9	5	4
Total	–	–	508.1	87	66

[a] Preictal condition of SOP = 30 min and SPH = 5 min.
[b] Preictal condition of SOP = 60 min and SPH = 5 min.

2.2. Methodology

2.2.1. Preprocessing

In preprocessing, we used 15-sec and 30-sec sliding windows to segment iEEG signals, respectively. Then, the iEEG segments were used as the inputs of 1D-CNN model. Since the number of 15-sec iEEG segments is twice that of 30-sec iEEG segments. Hence, our work also discusses the comparison of results under two different sample sizes.

The problem of sample imbalance is a key issue that needs to be solved during model training in this work. As shown in Table 1, the number of seizures ranges from 2 to 5, and so the duration of preictal iEEG signals is about 2 to 5 hours. However, the duration of interictal iEEG signals is about 24 hours for each patient. To generate more preictal iEEG segments and solve the problem of sample imbalance during model training, sliding windows with the corresponding overlap ratio are only used to segment the preictal iEEG signals which are selected as the training set. The preictal iEEG signals which are selected as the testing set and the interictal iEEG signals are segmented by sliding windows without the overlap ratio. Fig. 1 shows the details of this preprocessing.

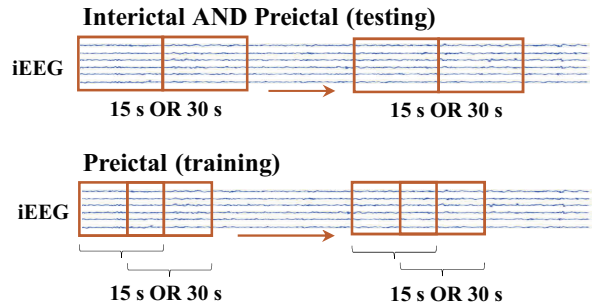

Fig. 1. Preictal iEEG signals which are selected as the testing set and interictal iEEG signals are segmented by sliding windows without the overlap ratio. Preictal iEEG signals which are selected as the training set are segmented by sliding windows with the corresponding overlap ratio.

2.2.2. CNN

As shown in Fig. 2, the model architecture of 1D-CNN consists of two parallel blocks (Block-1 and Block-2) and two fully connected (FC) layers. Each block has the same structure and includes four convolutional parts. Moreover, each convolutional part contains a convolutional layer with rectified linear activation unit (ReLU), a batch-normalization (BN) layer and a max-pooling (MP) layer.

The parameters of the 1D-CNN model are given as follows. In Block-1, the four convolutional layers contain 32 kernels (size = n×3, where n ranges from 1 to 6, and stride = 2), 32 kernels (size = 3 and stride = 2), 64 kernels (size = 3 and stride = 2) and 128 kernels (size = 3 and stride = 1), respectively. The four MP layers have the same pooling size of 3 and the same stride of 2. Compared to Block-1, the differences in Block-2 are the kernel sizes of the four convolutional layers. In Block-2, the kernels sizes are n×5, 5, 5 and 5, respectively (as shown in Fig. 2). Two blocks used in this work are to learn more different features for classification. Then, the outputs of these two blocks are concatenated and globally averaged as the inputs of two FC layers. The first FC layer has 128 neurons (ReLU). The second has 2 neurons using Softmax activation function for classification. During model training, the dropout rate in second FC layer is 0.25.

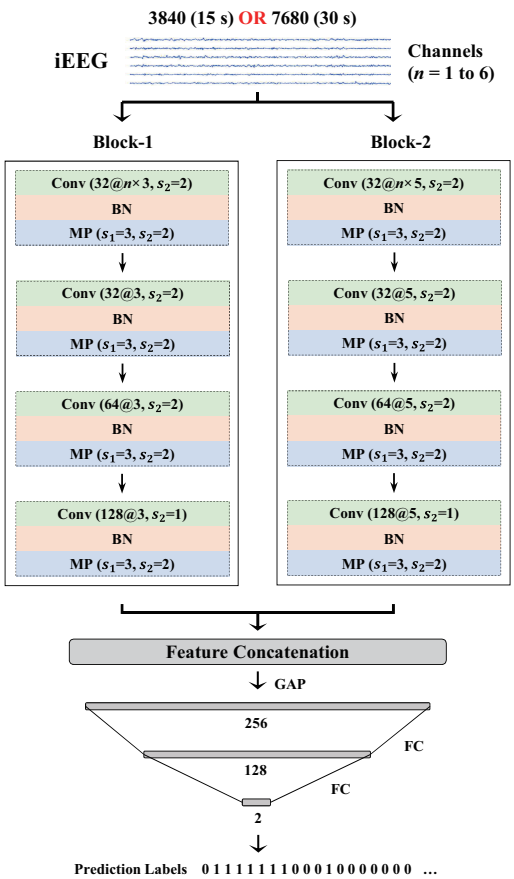

Fig. 2. Architecture of the 1D-CNN model. $M_1@n{\times}k_1$ or $M_2@k_2$: M_1 and M_2 are the number of kernels, k_1 and k_2 are the sizes of kernels. s_1 means pooling size and s_2 means stride. For the inputs, iEEG segments of 63 channel cases ($|C_6^1|+|C_6^2|+|C_6^3|+|C_6^4|+|C_6^5|+|C_6^6|=63$) are fed into the 1D-CNN model in turn.

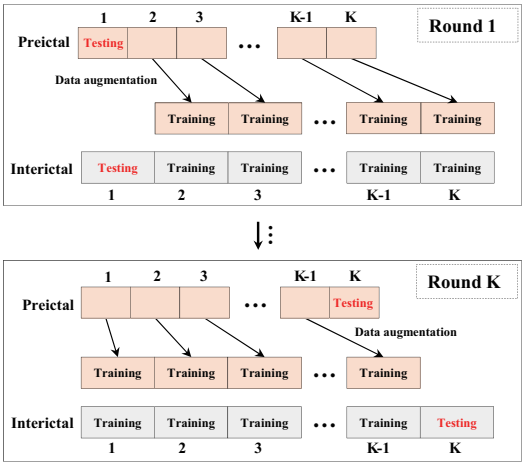

Fig. 3. The K-CV approach combined with the data augmentation technique is applied during model training.

2.2.3. *Model training*

In this work, patient-specific model is trained for each patient. K-fold cross validation (K-CV) is done during model training (as shown in Fig. 3). In K-CV approach, model training is performed K rounds, where K is the number of seizures per patient. In each round, (K-1) preictal and (K-1) interictal parts are used for training, and the remaining segments (one preictal and one interictal part) are used for testing. As shown in Fig. 3, during model training in each round, the size of preictal iEEG segments is augmented to balance samples using sliding windows with overlap mentioned in preprocessing.

2.2.4. *System evaluation*

1) Segment-based level Sensitivity (Sen_1), specificity (Spe) and accuracy (Acc) are used to evaluate the classification results. The three metrics are given as follows, $Sen_1 = \frac{TP}{TP+FN}$, $Spe = \frac{TN}{TN+FP}$, $Acc = \frac{TP+TN}{TP+FP+TN+FN}$, where TP, FP, TN and FN indicate ture positive, false positive, true negative and false negative, respectively.

2) Event-based level Event-based sensitivity (Sen_2) and false prediction rate (FPR) are calculated. The two metrics are given as follows, $Sen_2 = \frac{Number\ of\ True\ Predictions}{Number\ of\ Seizures}$, $FPR = \frac{Number\ of\ False\ Predictions}{Hours\ of\ Interictal\ iEEG}$. At the event-based level, the condition to sound an alarm is that prediction labels within 90 seconds are all positive. It means that six consecutive labels (for 15-sec iEEG segments) or three consecutive labels (for 30-sec segments) are all positive to satisfy the requirement of sounding an alarm. We also compare our method to the random predictor. The probability of random predicting at least k out of K seizures can be expressed as follows, $p_v = \sum_{i\geq k}^{K} p^i(1-p)^{K-i}$, where $p \approx 1 - e^{-FPR\cdot SOP}$ (the probability of a random alarm) [22], k and K are the number of true predictions and all seizures, respectively. In this work, the significance level is set at 0.05, and our method is better than the random predictor if the p_v is less than 0.05.

3. RESULTS

The whole algorithm runs twice, and the averaged results under 63 channel cases ($|C_6^1|+|C_6^2|+|C_6^3|+|C_6^4|+|C_6^5|+|C_6^6|=63$) are computed. At the segment-based level, an averaged Sen_1, Spe, and Acc are obtained. An averaged Sen_2, and FPR are given at the event-based level.

3.1. SOP = 30 min and SPH = 5 min

The results of two different preprocessing conditions (15-sec and 30-sec sliding windows) are discussed in the situation of SOP = 30 min and SPH = 5 min. For example, as shown in Fig. 4, the averaged results of 63 channel cases for patient 1 are given at both levels (segment- and even-based levels) under two different preprocessing conditions. The case of channel 3 is finally selected for two preprocessing conditions

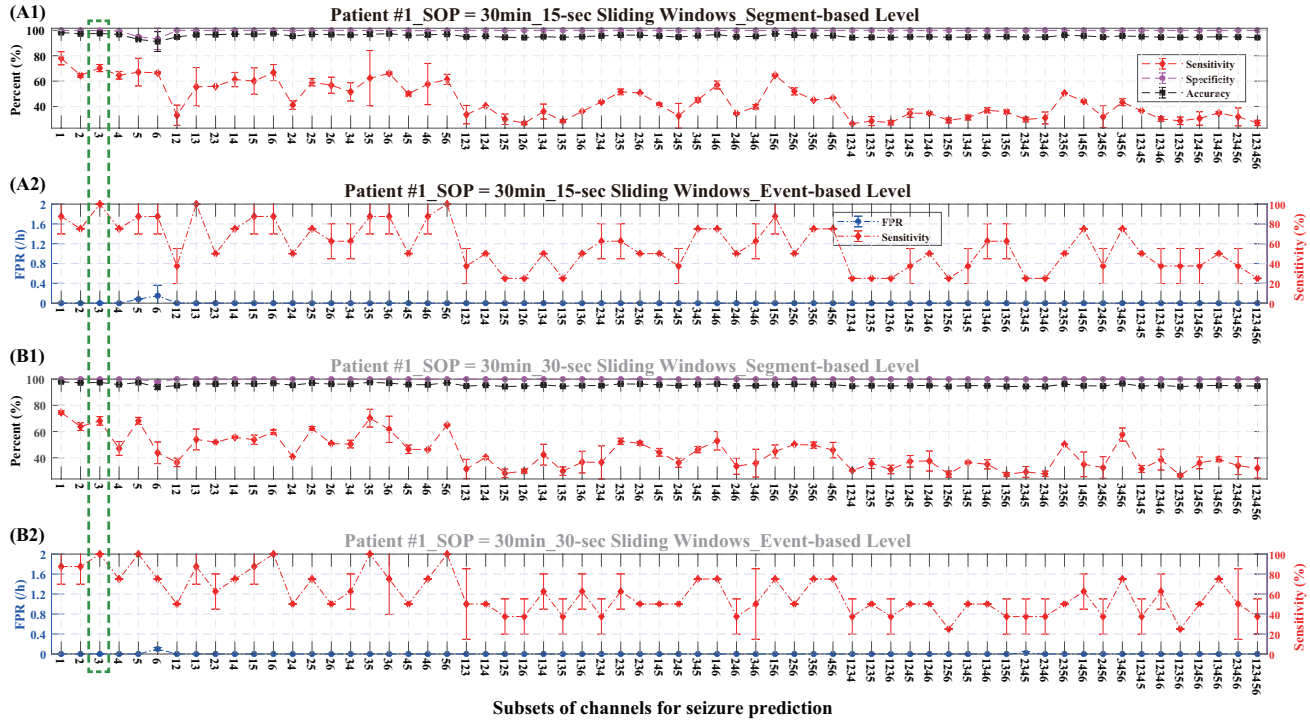

Fig. 4. In preictal condition of SOP = 30 min, the averaged results for patient 1 are showed after the whole algorithm runs twice. In preprocessing of 15-sec sliding widows, classification results of 63 channel cases are given at the segment-based level (A1) and the event-based level (A2). In preprocessing of 30-sec sliding widows, classification results of 63 channel cases are given at the segment-based level (B1) and the event-based level (B2). The case of channel 3 is finally selected and the corresponding results are summarized in Table 2.

Table 2. In the condition of SOP = 30 min, the selected channel cases and corresponding results for each patient.

			15-sec sliding windows, SOP = 30 min							30-sec sliding windows, SOP = 30 min						
				Segment-based level			Event-based level				Segment-based level			Event-based level		
Patient	Interictal (h)	#Seizures	Cs	Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v	Cs	Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v
1	24	4	3	70.31	99.79	97.25	100	0.00	0.000	3	68.13	99.91	97.47	100	0.00	0.000
2	24	3	46	97.67	99.91	99.72	100	0.00	0.000	46	93.33	99.95	99.56	100	0.00	0.000
3	24	5	1	84.75	99.89	98.46	100	0.00	0.000	2	79.00	96.02	94.42	100	0.17	0.000
4	24	5	1	91.92	100	99.24	100	0.00	0.000	1	91.83	100	99.23	100	0.00	0.000
5	24	5	16	91.42	98.22	97.58	100	0.00	0.000	14	84.83	99.25	97.89	100	0.00	0.000
6	24	3	12	85.83	99.97	99.13	100	0.00	0.000	12	94.44	99.93	99.61	100	0.00	0.000
7	24.6	3	16	93.19	99.90	99.51	100	0.00	0.000	16	83.33	99.92	98.96	100	0.00	0.000
8	24.2	2	1235	95.00	100	99.80	100	0.00	0.000	1235	99.17	100	99.97	100	0.00	0.000
9	23.9	5	1 or 5	100	100	100	100	0.00	0.000	1 or 5	100	100	100	100	0.00	0.000
10	24.5	5	3	96.92	99.77	99.51	100	0.00	0.000	3	99.17	99.86	99.80	100	0.00	0.000
11	24.1	4	2	98.54	99.93	99.82	100	0.00	0.000	2	99.17	99.98	99.92	100	0.00	0.000
12	24	4	3	98.65	99.93	99.83	100	0.00	0.000	3	98.13	99.90	99.76	100	0.00	0.000
13	24	2	5	50.00	99.95	97.95	50	0.00	0.000	5	50.00	100	98.00	50	0.00	0.000
14	23.9	4	3	97.71	99.99	99.81	100	0.00	0.000	3	99.38	100	99.95	100	0.00	0.000
15	24	4	2	97.29	99.27	99.54	100	0.00	0.000	2	99.17	99.77	99.73	100	0.00	0.000
16	24	5	45	96.83	99.84	99.55	100	0.00	0.000	45	96.50	99.86	99.54	100	0.00	0.000
17	24.1	5	45	95.33	100	99.56	100	0.00	0.000	45	97.67	99.95	99.73	100	0.00	0.000
18	24.9	5	345	81.83	99.98	98.33	100	0.00	0.000	245	78.50	100	98.04	100	0.00	0.000
19	24.4	4	2	76.46	99.13	97.41	100	0.00	0.000	2	77.92	99.61	97.96	100	0.00	0.000
20	25.6	5	35	87.17	99.88	98.75	100	0.00	0.000	35	94.00	99.79	99.27	100	0.00	0.000
21	23.9	5	3	87.67	99.01	97.94	100	0.04	0.000	3	86.00	99.63	98.34	100	0.00	0.000
Total	508.1	87	–	89.21	99.73	98.99	98.85	0.00	–	–	89.03	99.68	98.91	98.85	0.01	–

Abbr: Cs, the selected channels (red numbers for the in-focus channels; blue numbers for the out-of-focus channels); Sen_1, segment-based sensitivity; Spe, specificity; Acc, accuracy; Sen_2, event-based sensitivity; FPR, false prediction rate.

Table 3. In the condition of SOP = 60 min, the selected channel cases and corresponding results for each patient.

			15-sec sliding windows, SOP = 60 min							30-sec sliding windows, SOP = 60 min						
				Segment-based level			Event-based level				Segment-based level			Event-based level		
Patient	Interictal (h)	#Seizures	Cs	Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v	Cs	Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v
1	24	3	3	75.69	99.38	96.75	100	0.00	0.000	3	78.19	99.93	97.52	100	0.00	0.000
3	24	4	2	90.73	86.61	87.20	100	0.27	0.000	2	88.02	87.73	87.77	100	0.38	0.000
4	24	3	1	93.47	100	99.27	100	0.00	0.000	1	93.00	100	99.26	100	0.00	0.000
5	24	2	156	88.65	99.05	98.25	100	0.00	0.000	156	93.75	98.94	98.54	100	0.04	0.000
7	24.6	3	16	86.39	99.90	98.43	100	0.00	0.000	16	83.19	99.95	98.13	100	0.00	0.000
8	24.2	2	1235	100	100	100	100	0.00	0.000	1235	100	100	100	100	0.00	0.000
9	23.9	3	5	96.11	99.98	99.55	100	0.00	0.000	5	95.97	100	99.55	100	0.00	0.000
10	24.5	3	3	98.50	99.79	99.57	100	0.00	0.000	3	98.17	99.66	99.41	100	0.00	0.000
11	24.1	3	2	97.64	99.67	99.45	100	0.00	0.000	2	99.58	99.25	99.29	100	0.00	0.000
12	24	3	4	96.94	99.77	99.45	100	0.00	0.000	4	94.72	99.79	99.23	100	0.00	0.000
13	24	2	5	49.79	99.99	96.13	50	0.00	0.000	5	50.00	100	96.15	50	0.00	0.000
14	23.9	3	6	95.76	99.88	99.42	100	0.00	0.000	6	99.31	100	99.92	100	0.00	0.000
15	24	3	4	82.99	99.05	97.26	100	0.00	0.000	46	82.50	99.69	97.78	100	0.00	0.000
16	24	5	12	98.46	99.83	99.59	100	0.00	0.000	12	99.92	99.91	99.91	100	0.00	0.000
17	24.1	5	45	90.42	99.58	98.01	100	0.00	0.000	45	93.58	99.62	98.58	100	0.00	0.000
18	24.9	5	1345	91.71	99.97	98.59	100	0.00	0.000	1345	86.42	99.98	97.71	100	0.00	0.000
19	24.4	3	2	98.13	99.44	99.30	100	0.00	0.000	2	98.06	99.64	99.47	100	0.00	0.000
20	25.6	5	235	93.29	99.67	98.63	100	0.00	0.000	235	95.50	99.74	99.05	100	0.00	0.000
21	23.9	4	2	93.75	99.33	98.53	100	0.00	0.000	2	95.73	99.44	98.91	100	0.00	0.000
Total	460.1	66	–	90.44	98.99	98.07	98.48	0.02	–	–	90.84	99.12	98.22	98.48	0.02	–

simultaneously according to the results of both levels. Then, the results of channel 3 for patient 1 are summarized in Table 2. Hence, after channel selection, Table 2 finally summarizes the results of the best channel cases for each patient.

As shown in Table 2, after selecting the best channel cases per patient, the results of two different preprocessing conditions for each patient are given. (1) With the preprocessing of 15-sec sliding windows, an overall 89.21% sensitivity, 99.73% specificity, and 98.99% accuracy are achieved at the segment-based level. At the event-based level, 86 out of 87 seizures are finally predicted (except one seizure in patient 13). An event-based sensitivity of 98.85% and a FPR of 0/h are obtained. (2) With the preprocessing of 30-sec sliding windows, we achieve an overall 89.03% sensitivity, 99.68% specificity, and 98.91% accuracy at the segment-based level. We attain a same event-based sensitivity of 98.85% with a FPR of 0.01/h at the event-based level. About the channel case selected for each patient, most of patients (except patients 3, 5 and 18) have the same channel cases for both preprocessing conditions. Moreover, the performance of our method is better than that of the random predicting for each patient according to the p_v values in Table 2.

3.2. SOP = 60 min and SPH = 5 min

In the situation of SOP = 60 min and SPH = 5 min, patients 2 and 6 are removed because the duration of preictal phase is less than 65 min. The results of two different preprocessing conditions are also discussed. As shown in Table 3, we summarize the results of two different preprocessing conditions for each patient after the best channel cases selected. (1) Under the preprocessing of 15-sec sliding windows, at the segment-based level, an overall sensitivity, specificity, and accuracy are 90.44%, 98.99% and 98.07%, respectively. At the event-based level, 65 out of 66 seizures are correctly predicted (except one seizure in patient 13). An overall event-based sensitivity and a FPR are 98.48% and 0.02/h, respectively. (2) Under the preprocessing of 30-sec sliding windows, an overall 90.84% sensitivity, 99.12% specificity, and 98.22% accuracy are attained at the segment-based level. A same 98.48% sensitivity with 0.02/h FPR is achieved at the event-based level. For the selected channel case per patient, each patient has the same channel case for both two preprocessing conditions. According to the p_v values in Table 3, our method also shows a better performance than the random predicting for each patient.

4. DISCUSSION AND CONCLUSION

With the same iEEG dataset, the results of our work and previous studies using deep learning techniques are given and compared in Table 4. As shown in Table 4, the studies [10] and [11] used 2D-CNNs for the analysis of seizure prediction and attained a sensitivity of 81.4-90.8% with a FPR of 0.03-0.08/h. Our previous work [9] used 1D-CNN for the prediction of seizures and achieved a sensitivity of 98.48-98.85% with 0.01/h FPR. In this work, 1D-CNN was also used for the analysis of the same iEEG dataset. In the situation of SOP = 30 min and SPH = 5 min, an event-based sensitivity of 98.85% and a FPR of 0-0.01/h were obtained. In the situation of SOP = 60 min and SPH = 5 min, an event-based sensitivity of 98.48% and a FPR of 0.02/h were attained. Compared to the results of previous studies in Table 4, we could see that our method shows remarkable performances.

In this paper, the method of channel selection combined with 1D-CNN was further analyzed for seizure preidction. Based on the Freiburg iEEG dataset (21 patients, 87 seizures), our method finally predicted 86 seizures (except one seizure in patient 13) and achieved a high event-based sensitivity of 98.48-98.85% with a low FPR of 0-0.02/h. A segment-based

Table 4. List of previous studies using deep learning methods for seizure prediction based on the Freiburg iEEG dataset.

Authors	Features	Classifier	#Patients	#Seizures	SOP	SPH	Sen_2 (%)	FPR (/h)
Truong et al. (2018) [10]	STFT time-frequency maps	2D-CNN	13	59	30 min	5 min	81.4	0.03
Truong et al. (2019) [19]	STFT time-frequency maps	GAN	13	59	30 min	5 min	–	–
Wang et al (2020) [11]	DTF channel-frequency maps	2D-CNN	19	82	30 min	5 min	90.8	0.08
Wang et al (2021) [9]	30-sec time-channel iEEG maps	1D-CNN	21	87	30 min	5 min	98.85	0.01
			19	66	60 min	5 min	98.48	0.01
This work	15-sec or 30-sec time-channel iEEG maps	Channel-based 1D-CNNs	21	87	30 min	5 min	98.85	0.00-0.01
			19	66	60 min	5 min	98.48	0.02

sensitivity of 89.03-90.84%, specificity of 98.99-99.73%, and accuracy of 98.07-98.99% were attained at the segment-based level. The proposed method also showed a better performance better than the random predictor for all patients. From these results, we could see that our method had a remarkable performance in seizure prediction, and the channel selection for each patient was meaningful.

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