Author(s): Wang, Xiaoshuang; Zhang, Chi; Kärkkäinen, Tommi; Chang, Zheng; Cong, Fengyu

Title: Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG

Year: 2023

Version: Published version

Please cite the original version:

Wang, X., Zhang, C., Kärkkäinen, T., Chang, Z., & Cong, F. (2023). Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 31, 316-325. https://doi.org/10.1109/TNSRE.2022.3222095

Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG

Xiaoshuang Wang©, Chi Zhang©, Tommi Kärkkäinen©, *Senior Member, IEEE*,
Zheng Chang©, *Senior Member, IEEE*, and Fengyu Cong©, *Senior Member, IEEE*

Abstract—The application of intracranial electroencephalogram (iEEG) to predict seizures remains challenging. Although channel selection has been utilized in seizure prediction and detection studies, most of them focus on the combination with conventional machine learning methods. Thus, channel selection combined with deep learning methods can be further analyzed in the field of seizure prediction. Given this, in this work, a novel iEEG-based deep learning method of One-Dimensional Convolutional Neural Networks (1D-CNN) combined with channel increment strategy was proposed for the effective seizure prediction. First, we used 4-sec sliding windows without overlap to segment iEEG signals. Then, 4-sec iEEG segments with an increasing number of channels (channel increment strategy, from one channel to all channels) were sequentially fed into the constructed 1D-CNN model. Next, the patient-specific model was trained for classification. Finally, according to the classification results in different channel cases, the channel case with the best classification rate was selected for each patient. Our method was tested on the Freiburg iEEG database, and the system performances were evaluated at two levels (segment- and event-based levels). Two model training strategies (Strategy-1 and Strategy-2) based on the K-fold cross validation (K-CV) were discussed in our work. (1) For the Strategy-1, a basic K-CV, a sensitivity of 90.18%, specificity of 94.81%, and accuracy of 94.42% were achieved at the segment-based level. At the event-based level, an event-based sensitivity of 100%, and false prediction rate (FPR) of 0.12/h were attained. (2) For the Strategy-2, the difference from the Strategy-1 is that a trained model selection step is added during model training. We obtained a sensitivity, specificity, and accuracy of 86.23%, 96.00% and 95.13% respectively at the segment-based level. At the event-based level, we achieved an event-based sensitivity of 98.65% with 0.08/h FPR. Our method also showed a better performance in seizure prediction compared to many previous studies and the random predictor using the same database. This may have reference value for the future clinical application of seizure prediction.

Index Terms—Epilepsy, seizure prediction, intracranial electroencephalogram (iEEG), convolutional neural networks (CNN), channel increment strategy.

I. Introduction

EPILEPSY is one of the most common neurological diseases and seriously affects the health of epileptic patients. There are an estimated 70 million people with epilepsy, and approximately 30% of them are intractable to anti-epileptic drugs [1], [2]. For patients with drug-resistant epilepsy, the prediction of seizures may provide them with more treatment options. This is because it can give people a time frame for taking interventions to suppress the onset of seizures.

Electroencephalogram (EEG), as a significant tool, has been widely utilized in the diagnosis of epilepsy [3], [4] and the source localization of epileptic focus [5], [6]. However, EEG-based seizure prediction remains a challenging task. Consequently, EEG-based seizure prediction has attracted an increasing attention in recent years as accurate seizure prediction will greatly reduce the suffering and improve the quality of life for epileptic patients. Seizure prediction using intracranial electroencephalogram (iEEG) and scalp electroencephalogram (sEEG) has been widely studied over the past two decades. The Freiburg iEEG [7] and the CHB-MIT sEEG [8] databases are commonly used in iEEG-based and sEEG-based studies for seizure prediction, respectively. An overview of the related researches is briefly introduced as follows.

First, in studies using the Freiburg iEEG database for seizure prediction, the methods mainly consist of threshold crossing, conventional machine learning, and deep learning. In studies featuring threshold crossing analysis, linear or non-linear features, such as dynamical similarity index [7], phase coherence or synchronization [9], [10], spike rate [11], multiresolution

N-gram [12], correlation dimension [13] and fractal dimensions and intercept values [14], were first extracted from iEEG signals. Then, the appropriate threshold was set according to the trend of these features over time. A sensitivity of 42-92.9%, and false prediction rate (FPR) of 0.04-1/h were achieved among these studies. In studies using conventional machine learning methods, Support Vector Machine (SVM) [15], [16], [17], [18], [19], [20], Least Square-SVM (LS-SVM) [21] and Bayesian [22], [23] were applied in seizure prediction and obtained a sensitivity of 85.11-100% and a FPR of 0.03-0.36/h. In recent studies with deep learning methods for seizure prediction, One-Dimensional Convolutional Neural Networks (1D-CNN) [24], Two-Dimensional Convolutional Neural Networks (2D-CNN) [25], [26], and Generative Adversarial Networks (GAN) [27] were used, and a sensitivity of 81.4-98.85% and a FPR of 0.01-0.08/h were attained.

Second, in studies based on the CHB-MIT sEEG database for the prediction of seizures, the conventional machine learning and deep learning methods were also widely applied. In studies using conventional machine learning methods, SVM [19], [28], [29], [30], Bayesian [31], Backpropagation Neural Network (BPNN) [32] and Multi-layer Perceptron (MLP) [33] were used as classifiers, and these studies achieved a sensitivity of 86.87-98.68% and a accuracy of 83.17-99.70%. In studies with deep learning methods, Long Short-Term Memory (LSTM) [34], [35], [36], 2D-CNN [25], [37], [38], [39], three-dimensional Convolutional Neural Networks (3D-CNN) [40], [41] and Deep Recurrent Neural Network (DRNN) [42] were utilized for classification. Among these studies, a sensitivity of 81.2-100%, accuracy of 92.50-99.72%, and specificity of 93.65-99.60% were attained.

EEG channel selection, as an important feature selection method in the spatial domain, was also effectively applied in seizure detection [43], [44], [45], [46], [47], seizure prediction [48], [49], [50], [51], [52] and other fields [53]. However, most of these studies focused on the combination of channel selection and conventional machine learning methods. There are few studies on the combination of channel selection and deep learning methods to predict seizures. Therefore, channel selection combined with deep learning methods can be further explored and discussed in the field of seizure prediction.

As mentioned above, many conventional machine learning and deep learning methods have been used to achieve remarkable results in seizure prediction. However, there are still several considerations for focus and discussion. The first consideration is that the combination of channel selection and deep learning methods is less studied and should be further analyzed in seizure prediction. Second, it should be noted that, for many previous studies using the Freiburg iEEG database for seizure prediction, performance is commonly evaluated at the event-based level (event-based sensitivity and FPR), while for many previous studies employing the CHB-MIT sEEG database for seizure prediction, performance is commonly evaluated at the segment-based level (sensitivity, specificity and accuracy), thus, both levels can be considered at the same time. Third, consider that LSTM, 2D-CNN have been widely
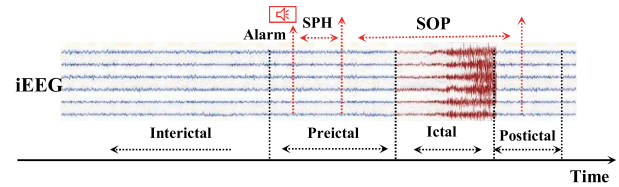

Fig. 1. Example of an accurate seizure prediction. When an alarm rings, a seizure must occur after SPH and within SOP.

used for the prediction of seizures, while the use of 1D-CNN is low. According to these considerations, the main contributions or novelties of this work are summarized as follows:

1) A novel method of channel increment strategy-based 1D-CNN is presented for seizure prediction. In the channel increment strategy, iEEG signals with the varied number of channels (from one channel to all channels) are used in turn as the inputs of 1D-CNN model for classification. Then, the channel case with the best classification rate is selected for each patient.

2) For better evaluating the performances of our method, classification results are simultaneously evaluated at the two levels (segment- and event-based levels). The two levels are also flexibly applied together to select the best channel case. For example, if several channel cases show the same high performance at the event-based level for a patient, the segment-based performance can be used to assist in selecting the best channel case.

3) Two model training strategies (Strategy-1 and Strategy-2) based on the K-fold cross validation (K-CV) are discussed, and they also correspond to two sets of channel selection processes. The Strategy-1 is a basic K-CV, and the best channel case selection is only performed after the K-CV. For the Strategy-2, the difference from the Strategy-1 is that we add a trained model selection step during model training as a preliminary selection of channel cases. Then, the best channel case is selected from these preliminary selected channel cases after the K-CV.

The remaining sections of this paper include the materials in Section II, the methodology in Section III, the results of the proposed method in Section IV, and the discussion in Section V. Section VI presents our conclusion.

II. DATA

The Freiburg iEEG database is utilized and analyzed for the prediction of seizures. The iEEG database is recorded at the sampling rate of 256 Hz, with the notch filtering of 50 Hz and the bandpass filtering of 0.5-120 Hz. It contains 21 patients, 87 epileptic seizures, 509 h of interictal, and 73 h of preictal or ictal iEEG signals [7]. For each patient, there are at least 24 h of interictal and 50 min of preictal iEEG signals. More details of this database can be found in [7].

In the study of seizure prediction, the seizure occurrence period (SOP) is defined as the period during which a seizure is expected to arise. The seizure prediction horizon (SPH) is the period from an alarm to the beginning of SOP [54] (as shown in Fig. 1). SPH is also regarded as the period of interventions to prevent seizure onsets [55]. In this work,
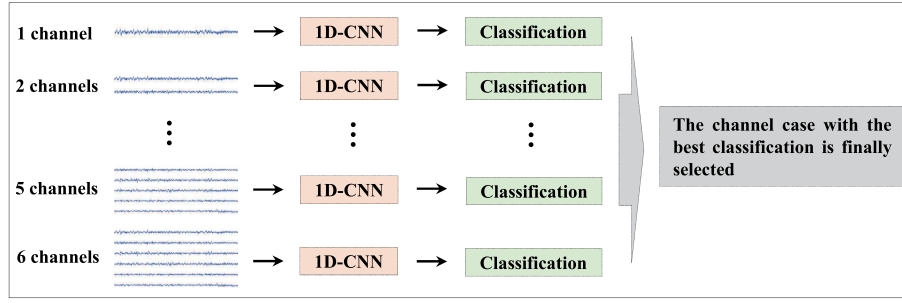
Fig. 2. Overall diagram of the 1D-CNN combined with channel increment strategy for the epileptic seizure prediction.

TABLE I
DETAILS OF THE SELECTED iEEG SIGNALS FOR EACH PATIENT

Patient	Age	Gender	Interictal (h)	#Seizures
1	15	f	24	4
3	14	m	24	5
4	26	f	24	5
5	16	f	24	5
9	44	m	23.9	5
10	47	m	24.5	5
11	10	f	24.1	4
12	42	f	24	4
14	41	f	23.9	4
15	31	m	24	4
16	50	f	24	5
17	28	m	24.1	5
18	25	f	24.9	5
19	28	f	24.4	4
20	33	m	25.6	5
21	13	m	23.9	5
Total	–	–	387.3	74

we discuss the preictal condition of SPH = 5 min and SOP = 30 min (35 min preictal duration before a seizure) based on studies [25] and [26]. Our work only considers patients with at least 4 seizures for ensuring the number of samples during model training. The details of the selected iEEG signals are summarized in Table I.

III. METHODOLOGY

The overall framework of the 1D-CNN combined with channel increment strategy is showed in Fig. 2. For the iEEG database used in this work, each patient has six iEEG channels, including three in-focal channels (marked as channels 1-3) and three out-of-focal channels (marked as channels 4-6). Hence, iEEG signals with an increasing number of channels (from one channel to six channels) are sequentially fed into the 1D-CNN models for classification, and this process is regarded as the *channel increment strategy*. Then, the best channel case is selected according to the classification results (as shown in Fig. 2). The next five parts of this section include preprocessing, channel increment strategy, 1D-CNN model, model training and system evaluation.

A. Preprocessing

In preprocessing, 4-sec sliding windows without overlap are used to segment the raw iEEG signals (as shown in Fig. 3). Since the iEEG signals are recorded at the sampling rate of 256 Hz, each 4-sec iEEG segment is a matrix of $n \times 1024$, where n ($n = 1$ to 6) is the number of channels, and 1024 is the number of points. Then, the 4-sec iEEG segments are used
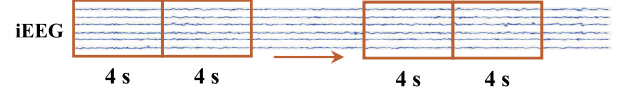

Fig. 3. The raw iEEG signals (interictal and preictal) are segmented by the 4-sec sliding windows without overlap.

TABLE II
NUMBER OF THE 4-SEC SEGMENTS

	Interictal (23.9~25.6 h)	Preictal (30 min)*
Patients with 4 seizures	21510~21960	1800 (450×4)
Patients with 5 seizures	21510~23040	2250 (450×5)

*Due to SOP = 30 min and SPH = 5 min, preictal signals from -35 min to -5 min (total 30 min) before the onset point of a seizure are selected and used for analysis.

TABLE III
ALL CASES ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$)
IN THE CHANNEL INCREMENT STRATEGY

$|C_6^1|$	1	2	3	4	5	6		
$|C_6^2|$	12	13	23	14	15	16	24	25
	26	34	35	36	45	46	56	
$|C_6^3|$	123	124	125	126	134	135	136	234
	235	236	145	245	345	146	246	346
	156	256	356	456				
$|C_6^4|$	1234	1235	1236	1245	1246	1256	1345	1346
	1356	2345	2346	2356	1456	2456	3456	
$|C_6^5|$	12345	12346	12356	12456	13456	23456		
$|C_6^6|$	123456							

Red numbers: in-focus channels; Blue numbers: out-of-focus channels.

as the inputs of the 1D-CNN models. For each patient, the number of the 4-sec iEEG segments is summarized in Table II.

B. Channel Increment Strategy

The iEEG signals of each patient contain six channels: channels 1-3 (in-focal) and channels 4-6 (out-of-focal). In the channel increment strategy, when iEEG segments of one channel are used as the inputs of the 1D-CNN model, there are six channel cases ($|C_6^1| = 6$). By analogy, there are cases of two channels, three channels and all the way to six channels. Consequently, there are 63 channel cases ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$) in total. All channel cases are summarized in Table III.

C. 1D-CNN Model

Since the 4-sec iEEG segments are directly used as the inputs of the classifier, a 1D-CNN model is constructed in this study. As shown in Fig. 4, the framework of the proposed 1D-CNN model includes two parallel blocks (Block 1 and
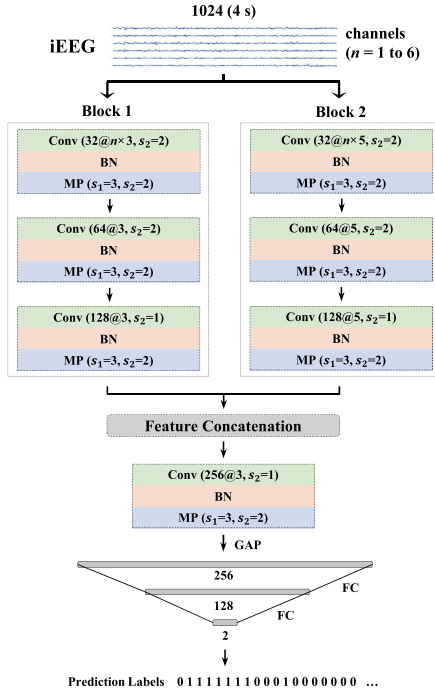
Fig. 4. Framework of the proposed 1D-CNN model. $M_1@n \times k_1$ or $M_2@k_2$: M_1 and M_2 are the number of kernels; k_1 and k_2 are the sizes of kernels. Abbr: Conv, convolution; BN, batch normalization; MP, max-pooling; s_1, pooling size; s_2, stride; GAP, global average pooling; FC, fully connected.

Fig. 5. Example of the Strategy-1 combined with a data down-sampling technique during model training for the patients with 4 seizures.

Block 2), one convolution portion and two fully connected (FC) layers. Each block has the same structure and contains three convolution portions. Moreover, each convolution portion is composed of a convolutional layer with the rectified linear activation unit (ReLU), a batch-normalization (BN) layer, and a max-pool (MP) layer. In this work, the two parallel blocks with different kernel sizes used in the model aim to learn more different representations from the input signals for classification. The function of a convolutional layer is to process the input signals with the convolution calculation and nonlinearization, and the convolution results are commonly fed into a pooling layer for preserving higher-level representations.

The details or parameters of the proposed 1D-CNN model are described as follows. In the Block 1, the three convolutional layers contain 32 kernels (size $= n \times 3$, where n is an integer ranging from 1 to 6, and stride $= 2$), 64 kernels (size $= 3$ and stride $= 2$) and 128 kernels (size $= 3$ and stride $= 1$), respectively. The three MP layers have the same pooling size of 3 and the same stride of 2. Compared to the Block 1, the differences in the Block 2 are the kernel sizes of the three convolutional layers (as shown in Fig. 4). In the Block 2, the kernels sizes of the three convolutional layers are $n \times 5$, 5, and 5, respectively. Then, the diverse representations from the two blocks are concatenated as the inputs of the last convolution portion. It consists of a convolutional layer (256 kernels, size $= 3$ and stride $= 1$), a BN layer, and a MP layer (size $= 3$ and stride $= 2$). Finally, the outputs of the last convolutional portion are globally averaged and fed into the two FC layers. The first FC layer has 128 neurons,
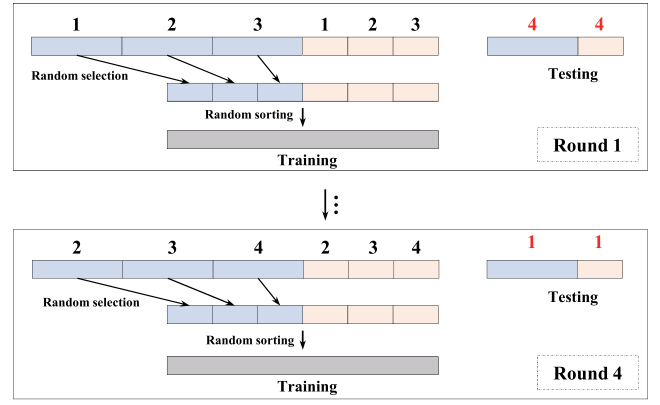
and the second has 2 neurons for the output of classification. The activation functions of these two FC layers are ReLU and Softmax, respectively.

During the model training phase, the dropout rate in second FC layer is set at 0.25. The maximum number of iterations is 60, and the early stopping technique (monitor = "val-loss", patience = 8) is also used to prevent overfitting during model training. The proposed 1D-CNN model is implemented in Python 3.6 based on the Keras-2.3.1 with the Tensorflow-1.15.0 backend, and three parallel Nvidia Tesla P100 GPUs are configured to run the model.

D. Model Training

In this work, the patient-specific model is trained for each patient. Two strategies (Strategy-1 and Strategy-2) based on the K-fold cross validation (K-CV) are performed for model training.

1) Strategy-1: The Strategy-1 is a basic K-CV. For the Strategy-1, the model training is implemented for K rounds, where K is the number of seizures of each patient. In each round, (K-1) parts are used for training, and the remaining one is used for testing. For example, Fig. 5 shows the Strategy-1 for the patients with 4 seizures. First, the interictal segments are sequentially divided into 4 equal parts. Since the number of the interictal segments is much larger than that of the preictal segments, a down-sampling approach is then used before model training. As shown in Fig. 5, the same number of interictal segments are randomly selected from 3 interictal parts in each round. Consequently, the size of the selected interictal segments is equal to that of the preictal segments during model training, while the remaining one (one interictal and one preictal part) is used for testing. Finally, all segments are tested after 4 rounds.

2) Strategy-2: For the Strategy-2, the difference from the Strategy-1 is that a trained model selection step is added in each round (as shown in Fig. 6). The selection criterion of the trained models is based on the F1 score. F1 score can be calculated as follows:

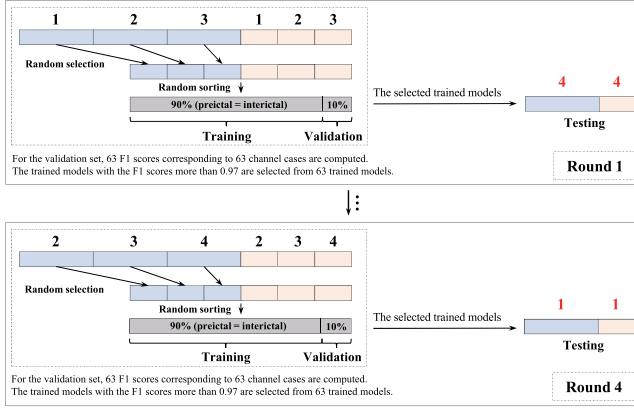$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall},$$

Fig. 6. Example of the Strategy-2 combined with a data down-sampling technique during model training for the patients with 4 seizures.

$$precision = \frac{TP}{TP + FP},$$

$$recall = \frac{TP}{TP + FN},$$

where TP indicates the number of true predicted preictal segments, FP indicates the number of false predicted preictal segments, and FN indicates the number of false predicted interictal segments. In this work, only when F1 scores are more than 0.97, the corresponding trained models are selected from 63 trained models (because of there are 63 channel cases) in each round.

For example, Fig. 6 shows the Strategy-2 for the patients with 4 seizures. First, the sample balance solution is the same as that stated in the Strategy-1. Then, in each round, we leave one part as a testing set, while 90% of the samples from the other three parts are used to train models, and the remaining 10% of the samples are used as the validation set for the selection of trained models (a preliminary selection of channel cases). The trained models with F1 scores more than 0.97 are selected in each round, and the selected models are used again to test the testing set.

E. System Evaluation

In seizure prediction, the system performance is commonly evaluated at the even-based level. However, in this work, the performances of our method are evaluated at the two levels (segment- and event-based levels) simultaneously for two reasons. One reason is that the segment-based performance can be utilized to assist in selecting the best channel case if several channel cases have the same high event-based performance for a patient. Another reason is that the performances at two levels can also make the classification evaluation more comprehensive.

1) Segment-Based Level: At the segment-based level, the sensitivity, specificity, and accuracy are calculated. The formulas of these three metrics are given as follows:

$$Sensitivity = \frac{TP}{P},$$

$$Specificity = \frac{TN}{N},$$

$$Accuracy = \frac{TP + TN}{P + N},$$

where TP indicates the number of true predicted preictal segments, P indicates the number of all preictal segments, TN indicates the number of true predicted interictal segments, and N indicates the number of all interictal segments.

2) Event-Based Level: At the event-based level, the event-based sensitivity and the FPR are computed. The formulas of the two metrics are given as follows:

$$Sensitivity = \frac{number\ of\ true\ predictions}{number\ of\ seizures},$$

$$FPR = \frac{number\ of\ false\ predictions}{hours\ of\ interictal\ iEEG}.$$

To give an accurate alarm in the prediction of seizures, a simple postprocessing for prediction labels is performed. In our work, the condition for an alarm to sound is that prediction labels within 32 seconds are all positive (as shown in Fig. 7). It means that eight consecutive labels must be all positive to meet the requirement of an alarm. Since unnecessary repeated alarms need to be avoided, the time interval between two alarms is the sum of SOP and SPH. Consequently, the second alarm in the duration from the first alarm to the end of SOP is prohibited in the system.

At the event-based level, we also compare the proposed method with the random predictor. The probability of the random predictor predicting at least k out of K seizures is expressed as follows:

$$p_v = \sum_{i \geq k}^{K} p_1^i (1 - p_1)^{K-i},$$

where $p_1 \approx 1 - e^{-FPR \cdot SOP}$ [56], p_1 is the probability of a random alarm, FPR and SOP are the false prediction rate and the seizure occurrence period, respectively. k is the number of true predictions, and K is the number of all seizures. The significance level is set to 0.05 in our work, and it means that the proposed method is better than the random predictor when the p_v is less than 0.05.

IV. RESULTS

A. Results of the Strategy-1

The whole algorithm runs twice. For each channel case (total 63 channel cases, $|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$) at the segment-based level, the averaged sensitivity (Sen1), specificity (Spe), and accuracy (Acc) are achieved. For each channel case at the event-based level, the averaged event-based sensitivity (Sen2), and FPR are attained. Then, from 63 channel cases, based on the results of both levels simultaneously, the best channel case is selected for each patient, and the corresponding classification results are summarized.

For example, as shown in Fig. 8, the averaged results in each channel case for patient 19 are given at the segment-based level (Fig. 8(A)) and the event-based level (Fig. 8(B)). The case of channels 12 is finally selected according to the results of both levels at the same time. And then, the results of channels 12 for patient 19 are summarized in Table IV. Hence, Table IV
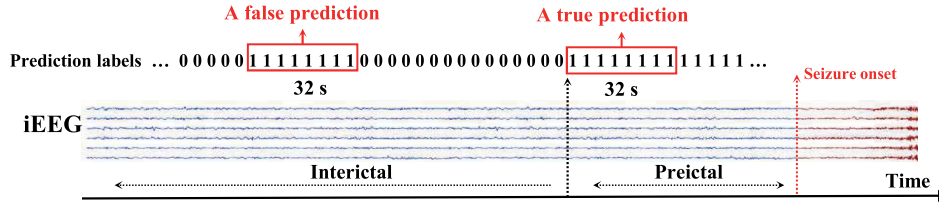
Fig. 7. At the event-based level, a simple postprocessing for prediction labels is performed to accurately sound an alarm. In this work, 32-sec duration is the requirement for sounding an alarm robustly. This means that 8 consecutive labels of 4-sec iEEG segments must be positive.
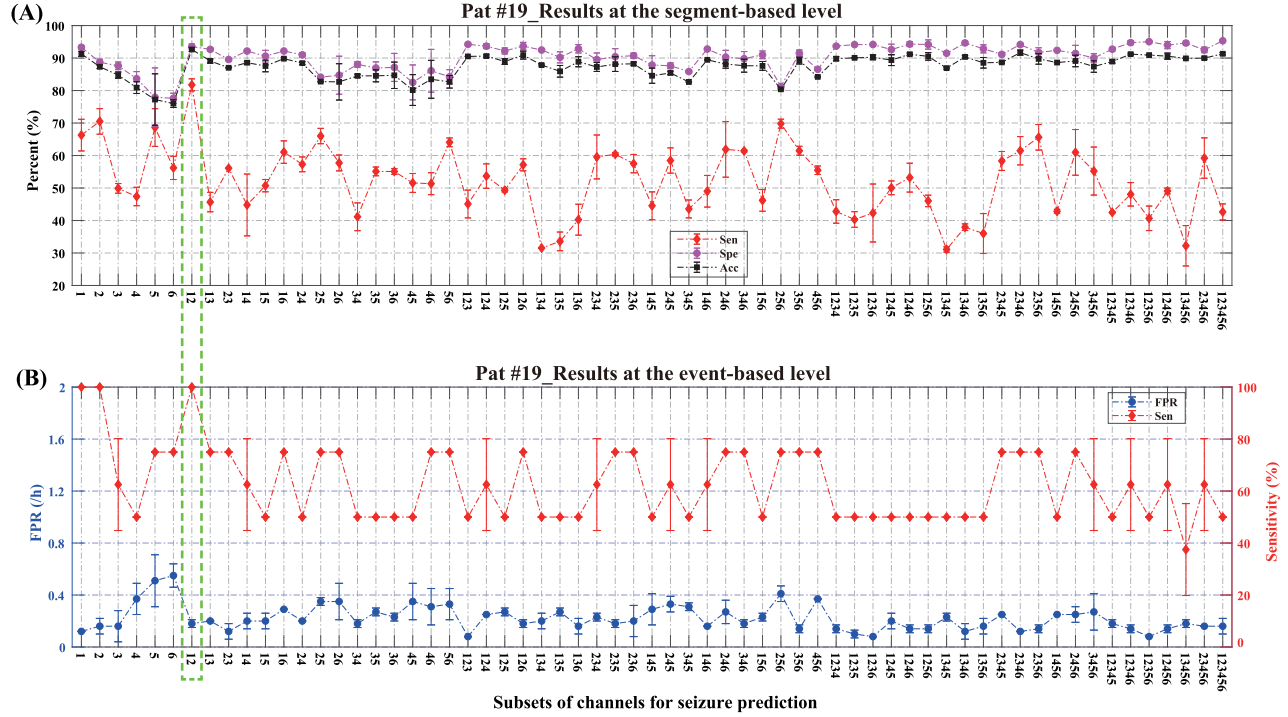

Fig. 8. In the Strategy-1, the averaged results of each channel case for patient 19 are showed after the whole algorithm runs twice. (A) Classification results at the segment-based level. (B) Classification results at the event-based level. The best case of channels 12 is finally selected, and the corresponding results are summarized in Table IV.

TABLE IV
IN THE STRATEGY-1, THE SELECTED CHANNEL CASES AND THE CORRESPONDING RESULTS FOR EACH PATIENT

Patient	#Seizure	Cs	Segment-based level			Event-based level		
			Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v
1	4	2	72.50±5.26	95.87±0.22	94.07±0.20	100±0.00	0.08±0.00	0.000
3	5	1	93.49±1.67	97.24±0.05	96.88±0.20	100±0.00	0.08±0.00	0.000
4	5	2	91.93±0.03	99.81±0.26	99.06±0.23	100±0.00	0.00±0.00	0.000
5	5	16	88.13±0.19	78.18±2.16	79.12±1.98	100±0.00	0.50±0.06	0.001
9	5	4	100±0.00	99.99±0.00	99.99±0.00	100±0.00	0.00±0.00	0.000
10	5	34	92.84±1.63	98.85±0.09	98.29±0.07	100±0.00	0.00±0.00	0.000
11	4	13	97.36±0.75	98.19±1.03	98.13±1.01	100±0.00	0.00±0.00	0.000
12	4	3	98.42±0.43	97.86±1.29	97.91±1.22	100±0.00	0.06±0.03	0.000
14	4	34	95.61±2.12	98.15±0.30	97.95±0.12	100±0.00	0.00±0.00	0.000
15	4	3	93.19±1.53	92.73±1.64	92.77±1.63	100±0.00	0.21±0.06	0.000
16	5	126	90.53±3.96	78.16±0.21	79.32±0.56	100±0.00	0.42±0.00	0.000
17	5	13	85.36±2.61	98.11±1.12	96.91±1.26	100±0.00	0.00±0.00	0.000
18	5	35	93.31±4.31	98.08±0.34	97.64±0.09	100±0.00	0.16±0.00	0.000
19	4	12	81.75±1.85	93.53±0.78	92.64±0.58	100±0.00	0.18±0.03	0.000
20	5	34	84.87±2.23	95.16±1.38	94.25±1.06	100±0.00	0.08±0.06	0.000
21	5	3	83.56±1.70	96.98±0.25	95.71±0.39	100±0.00	0.08±0.00	0.000
All	74	–	90.18±1.89	94.81±0.70	94.42±0.66	100±0.00	0.12±0.02	–

Cs: channel(s) selected; Red numbers: in-focus channels; Blue numbers: out-of-focus channels.

summarizes the best channel cases with the corresponding classification results for all patients.

As shown in Table IV, the results of each patient are provided after selecting the best channel case. The overall 90.18% sensitivity, 94.81% specificity, and 94.42% accuracy are achieved at the segment-based level. At the event-based level, 74 seizures are all predicted, and the event-based sensitivity of 100% with 0.12/h FPR is attained. According to
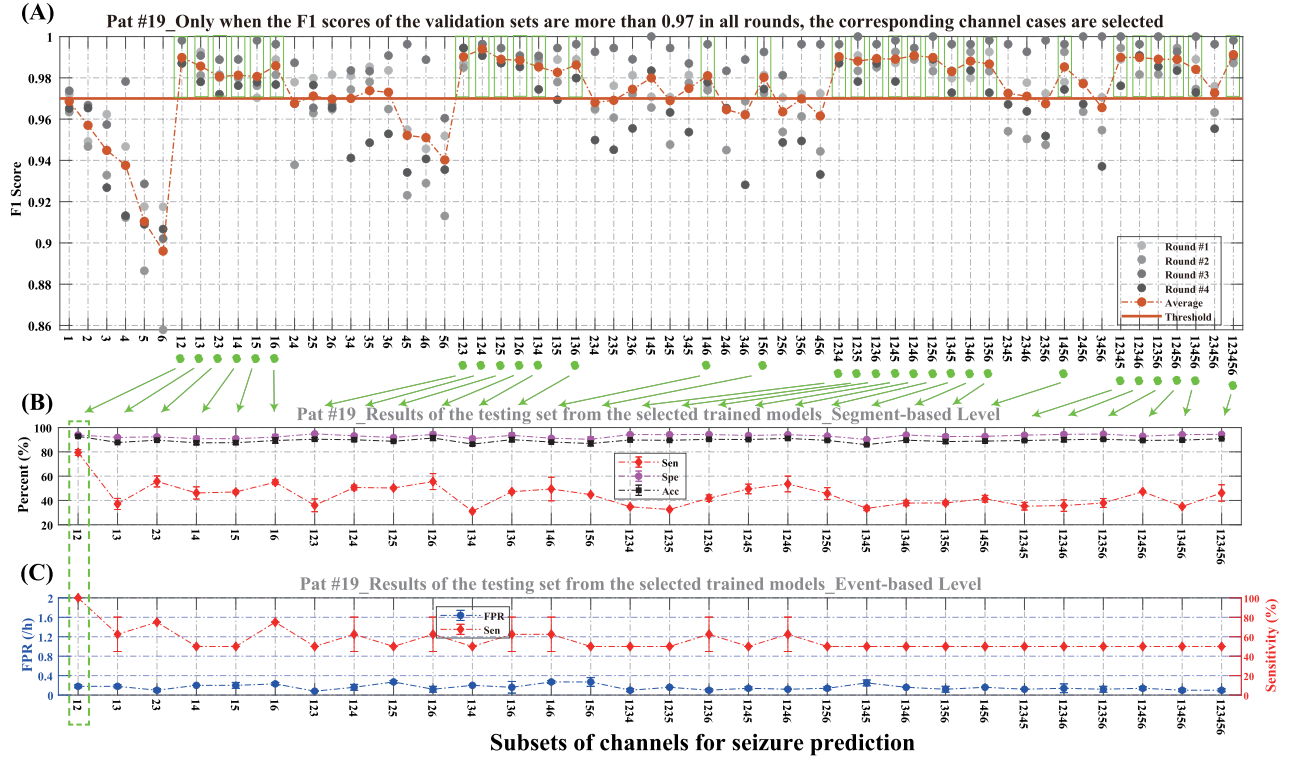
Fig. 9. In the Strategy-2, the averaged results for patient 19 are showed after the whole algorithm runs twice. (A) 30 channel cases (marked with green points) are first selected because of the F1 scores of these 30 channel cases are all more than 0.97 in all rounds (marked with green rectangles). (B) Classification results of the testing set from the 30 selected channel cases at the segment-based level. (C) Classification results of the testing set from the 30 selected channel cases at the event-based level. The best case of channels 12 is finally selected according to (B) and (C), and the corresponding results are summarized in Table V.

the p_v values in Table IV, the performance of our method is better than that of the random predictor for all patients.

B. Results of the Strategy-2

Different from the Strategy-1, we add a model selection step in each round (as shown in Fig. 6). The whole algorithm also runs twice. After running twice, one channel case can attain an averaged F1 score in one round. Thus, for K rounds, one channel case has K averaged F1 scores. In this work, only when K averaged F1 scores of a channel case are all more than 0.97, the corresponding channel case is selected as the pre-selected channel case. After some pre-selected channel cases are obtained, the classification results of the testing sets from these pre-selected channel cases are then calculated for the final best channel case selection. After selecting the best channel case for each patient, the corresponding results are summarized.

For example, as shown in Fig. 9(A), for the patient 19 with 4 seizures, after the whole algorithm runs twice, each channel case has 4 averaged F1 scores. 30 channel cases are first selected because of the F1 scores of these 30 channel cases are all more than 0.97 in all rounds. Then, the classification results of the testing sets from these 30 selected channel cases are showed in Fig. 9(B) and (C). According to the results in Fig. 9(B) and (C), the best case of channels 12 is finally selected from the 30 selected channel cases, and the corresponding results are summarized in Table V.

As shown in Table V, at the segment-based level, the overall sensitivity, specificity, and accuracy are 86.23%, 96.00%, and 95.13%, respectively. At the event-based level, 73 out of 74 seizures are correctly predicted (except one seizure in patient 5). The overall event-based sensitivity, and FPR are 98.65% and 0.08/h, respectively. This method also shows a better performance than the random predictor for all patients according to the p_v values in Table V.

V. DISCUSSION

A. Compared to the Studies Using the Freiburg Database for Seizure Prediction

Based on the same iEEG database, the results of this work and previous studies are also compared. The comparison details, including features, classifiers, number of patients, number of seizures, SOP, SPH, number of the used channels, sensitivity and FPR, are summarized in Table VI.

As shown in Table VI, the methods of previous studies mainly focus on three aspects: threshold analysis, conventional machine learning, and deep learning. (1) For the methods of threshold analysis combined with linear or non-linear features, the studies [7], [9], [10], [11], [12], [13], [14] achieve a sensitivity of 42% to 92.9% and a FPR of 0.04/h to 1/h. In these studies, the study [13] attains a highest sensitivity of 92.9% with a FPR of 0.096/h, but only 10 out of 21 patients are used. (2) For the conventional machine learning methods, the SVM in the studies [15], [16], [17], [18], [19], [20], the

TABLE V
IN THE STRATEGY-2, THE SELECTED CHANNEL CASES AND THE CORRESPONDING RESULTS FOR EACH PATIENT

Patient	#Seizure	F1	Cs	Segment-based level			Event-based level		
				Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FPR (/h)	p_v
1	4	0.982	1	75.11±5.81	96.66±0.33	95.00±0.14	100±0.00	0.10±0.03	0.000
3	5	0.995	1	84.02±3.61	98.00±0.01	96.68±0.33	100±0.00	0.06±0.03	0.000
4	5	0.999	2	91.80±0.03	99.97±0.01	99.20±0.00	100±0.00	0.00±0.00	0.000
5	5	0.970	1235	53.82±2.77	89.86±1.86	86.46±1.42	80±0.00	0.19±0.03	0.000
9	5	0.999	34	99.84±0.03	99.94±0.04	99.93±0.04	100±0.00	0.00±0.00	0.000
10	5	0.989	34	93.67±0.47	98.78±0.34	98.31±0.35	100±0.00	0.00±0.00	0.000
11	4	0.987	16	96.47±0.59	97.60±0.14	97.51±0.18	100±0.00	0.00±0.00	0.000
12	4	0.999	3	98.19±1.53	99.54±0.49	99.44±0.57	100±0.00	0.00±0.00	0.000
14	4	0.991	3	94.92±0.59	98.12±0.33	97.87±0.35	100±0.00	0.02±0.03	0.000
15	4	0.982	23	91.64±0.67	94.03±1.53	93.85±1.36	100±0.00	0.08±0.06	0.000
16	5	0.993	126	96.56±2.11	79.24±1.06	80.87±1.16	100±0.00	0.42±0.00	0.000
17	5	0.991	13	88.96±2.61	98.47±0.06	97.57±0.30	100±0.00	0.02±0.03	0.000
18	5	0.997	56	86.49±3.90	99.17±0.39	98.02±0.71	100±0.00	0.10±0.03	0.000
19	4	0.990	12	79.47±2.40	93.88±0.80	92.79±0.92	100±0.00	0.18±0.03	0.000
20	5	0.981	34	91.56±2.51	95.20±0.49	94.88±0.67	100±0.00	0.06±0.03	0.000
21	5	0.999	1234	57.09±1.23	97.54±0.25	93.72±0.11	100±0.00	0.06±0.03	0.000
All	74	–	–	86.23±1.93	96.00±0.51	95.13±0.54	98.65±0.00	0.08±0.02	–

TABLE VI
LIST OF THE STUDIES USING THE FREIBURG iEEG DATABASE FOR SEIZURE PREDICTION

Authors	Features	Classifier	#Pat	#Sei	SOP	SPH	#Ch[+]	Sen (%)	FPR (/h)
Maiwald et al.(2004) [7]	Dynamical similarity index	Threshold crossing	21	87	30 min	2 min	6	42	0.15
Winterhalder et al.(2006) [9]	Phase synchronization	Threshold crossing	21	87	30 min	10 min	2	60	0.15
Park et al.(2011) [15]	Spectral power from nine frequency bands	SVM	18	80	30 min	0*	6	97.5	0.27
Williamson et al.(2012) [16]	Correlation patterns both within and across channels	SVM	19	83	30 min	0*	6	85.54	0.03
Li et al.(2013) [11]	Spike rate	Threshold crossing	21	66	50 min	10 sec	6	75.8	0.09
Zheng et al.(2014) [10]	Mean phase coherence	Threshold crossing	10	50	30 min	10 min	6	55-90	0.04-1
Ozdemir et al.(2014) [22]	HHT based features	Bayesian	21	87	35 min	5 min	6	96.55	0.21
Wang et al.(2014) [17]	Amplitude and frequency modulation features	SVM	19	83	50 min	0*	6	98.8	0.054
Ghaderyan et al.(2014) [18]	Univariate linear features in eight frequency sub-bands	SVM	18	80	30 min	0*	6	100	0.13
Eftekhar et al.(2014) [12]	Multiresolution N-gram	Threshold crossing	21	87	20 min	10 min	6	90.95	0.06
Bedeeuzzaman et al.(2014) [57]	Mean absolute deviation and inter quartile range	A linear classifier	18	73	51-96 min	0*	6	100	≤0.30
Zhang et al.(2016) [19]	spectral powers and spectral power ratios	SVM	18	80	≤60 min	0*	6	100	0.0324
Parvez et al.(2016) [21]	Phase correlation, fluctuation, and deviation	LS-SVM	21	87	30 min	0*	6	95.4	0.36
Aarabi et al.(2017) [13]	A set of six univariate and bivariate features	Rule-based decision	10	28	50 min	10 sec	6	92.9	0.096
Sharif et al.(2017) [20]	Fuzzy rules on Poincaré plane	SVM	19	83	15 min	2-42 min	6	91.8-96.6	0.05-0.08
Yuan et al.(2018) [23]	Diffusion distance	Bayesian	21	87	30 min	10 sec	6	85.11	0.08
					50 min	10 sec	6	93.62	0.08
Truong et al.(2018) [25]	STFT time-frequency maps	2D-CNN	13	59	30 min	5 min	6	81.4	0.03
Wang et al.(2020) [26]	DTF channel-frequency maps	2D-CNN	19	82	30 min	5 min	6	90.8	0.08
Zhang et al.(2020) [14]	Fractal dimensions and intercept values	Threshold crossing	20	65	30 min	2 min	6	90.42	0.12
					50 min	2 min	6	91.67	0.10
Wang et al.(2021) [24]	30-sec time-channel iEEG maps	1D-CNNs	21	87	30 min	5 min	1,3	98.85	0.01
			19	66	50 min	5 min	1,3	98.48	0.01
This work	4-sec time-channel iEEG maps	1D-CNNs	16	74	30 min	5 min	1-4	98.65-100	0.08-0.12

*SPH = 0 means that the time of interventions to suppress seizure onsets is zero, ignoring practical clinical considerations.
[+]#Ch indicates the number of channels used in seizure prediction.

LS-SVM in the study [21], the Bayesian in the studies [22], [23], and the linear classifier in the study [57] are used for the analysis of seizure prediction, and a sensitivity of 85.11% to 100% and a FPR of 0.03/h to 0.36/h are achieved. A highest sensitivity of 100% and a low FPR of 0.0324/h are obtained by using the SVM in the study [19]. (3) For the deep learning methods, the 1D-CNN [24] and 2D-CNN [25], [26] models are utilized, and these studies attain sensitivities ranging from 81.4% to 98.85% and FPRs ranging from 0.01/h to 0.08/h. The study [24] achives highest sensitivity at 98.85% and lowest FPR at 0.01/h. In our work, the deep learning techniques are also used for the analysis of the same iEEG database, and an event-based sensitivity of 98.65-100% and a FPR of 0.08-0.12/h are obtained. Compared to the results of previous studies in Table VI, the performances of our work are better than that of most of previous studies.

Although the studies [18], [19], [57] achieve a sensitivity of 100%, the time of interventions to suppress seizure onsets is ignored (SPH = 0). Moreover, the highest sensitivity of our work can also reach 100% with a reduced number of channels (as shown in Table IV). Compared to the studies [12], [16], [19], [24], [25], our work attains a little higher FPR of 0.08-0.12/h, but it still meets the requirement that FPR should be less than 0.15/h [54]. For the sensitivity performance, the sensitivity of our work is 98.65-100%, which is higher than that of the studies [12], [16], [25] and is also commendable when compared with that of the studies [19], [24]. In this work, another highlight needs to be emphasized. For the Freiburg iEEG database, most of prior studies only evaluate the performances of seizure prediction at the event-based level (as shown in Table VI), without considering the performances at the segment-based level. Different from these studies, our work evaluates the performances of seizure prediction from both levels (as shown in Tables IV and V), thus, it is more comprehensive.

B. Compared to the Studies Using Channel Selection for Seizure Prediction

Table VII summarizes the studies using channel selection strategy (CSS) for seizure prediction. As shown in Table VII, three CSS, including the pre-specified, the statistical criteria

TABLE VII

LIST OF THE STUDIES USING CHANNEL SELECTION FOR SEIZURE PREDICTION

Authors	Features	Classifier	CSS	Database	#Pat	#Sei	SOP	SPH	#Ch+	Sen (%)	FPR (/h)
Winterhalder et al.(2006) [9]	Phase synchronization	Threshold crossing	Pre-specified	Freiburg	21	87	30 min	10 min	2	60	0.15
Chang et al.(2012) [48]	Synchrony features	SVM	Pre-specified	Freiburg	21	66	–	–	2-6	69.7	–
				CHB-MIT, NTUH	7	36	–	–	3-6	85.0	–
Ibrahim et al.(2019) [49]	Probability density functions	Threshold crossing	Statistical criteria	CHB-MIT	5	31	90 min	0^*	–	93.55	0.054
Coşgun et al.(2021) [50]	Variance difference, WAS	Rusboosted Tree	Statistical criteria	European-Epilepsy	10	69	50-75 min	0^*	1-19	71.8	0.031
Ra et al.(2021) [51]	Permutation entropy	SVM	Statistical criteria	CHB-MIT	22	131	10 min	0^*	3-8	92.42	–
Jana et al.(2021) [52]	Time-channel iEEG maps	2D-CNN	Statistical criteria	CHB-MIT	23	–	10 min	0^*	6	97.83	0.076
Wang et al.(2021) [24]	30-sec time-channel iEEG maps	1D-CNNs	Pre-specified	Freiburg	21	87	30 min	5 min	1,3	98.85	0.01
					19	66	50 min	5 min	1,3	98.48	0.01
This work	4-sec time-channel iEEG maps	1D-CNNs	Sequential search	Freiburg	16	74	30 min	5 min	1-4	98.65-100	0.08-0.12

and the sequential search, are applied in seizure prediction. In studies [9], [24], [48] using the pre-specified strategy, a sensitivity of 60-98.85%, and FPR of 0.01-0.15/h are achieved. For the pre-specified strategy, some channel cases are predefined (the other channel cases are ignored), and the best channel case is only selected from these pre-specified channel cases. Therefore, one drawback of the pre-specified strategy is that the ignored channel cases may contain the real best channel case. In studies [49], [50], [51], [52] using the statistical criteria strategy, the authors finally attain a sensitivity of 70.9-97.83% with a FPR of 0.031-0.076/h. For the statistical criteria strategy, extracted features or classification rates from single or multiple channels are statistically evaluated to select the significant channels. Then, these selected channels are used for seizure prediction. However, feature extraction is a time-consuming task, and complex feature extraction and selection approaches may also result in a low generalization. In our work, we use the sequential search strategy (the number of channels ranges from one to all) for channel selection, and the best channel case is selected from all the channel cases according to the performance of each channel case, without discarding some channel cases in advance. Combined with deep learning method, our method achieves a result of 98.65-100% sensitivity and 0.08-0.12/h FPR, and this also shows a remarkable performance compared to the studies in Table VII.

VI. CONCLUSION

In this paper, a novel method of 1D-CNN combined with channel increment strategy was proposed for the prediction of seizures. In the channel increment strategy, iEEG signals with an increasing number of channels (from one channel to all channels) were sequentially used as the inputs of 1D-CNN model for finding the best classification. The proposed method was tested on the Freiburg iEEG database with six channels per patient. Finally, 74 seizures were all predicted. A high event-based sensitivity of 98.65-100% and a low FPR of 0.08-0.12/h were achieved at the event-based level. At the segment-based level, a segment-based sensitivity of 86.23-90.18%, specificity of 94.81-96.00%, and accuracy of 94.42-95.13% were attained. Compared to the performance of the random predictor, our method was also statistically better than the random predictor for all patients. From these results, we could see that our method had a remarkable performance in seizure prediction with a minimal or reduced number of channels, and the selection of channels for each patient was necessary in this

work. All of these may provide a reference for the clinical application of seizure prediction with a reduced number of channels in the future.

ACKNOWLEDGMENT

REFERENCES

[1] L. Dalic and M. J. Cook, "Managing drug-resistant epilepsy: Challenges and solutions," *Neuropsychiatric Disease Treatment*, vol. 12, p. 2605, Jun. 2016.

[2] L. Kuhlmann, K. Lehnertz, M. P. Richardson, B. Schelter, and H. P. Zaveri, "Seizure prediction—Ready for a new era," *Nature Rev. Neurol.*, vol. 14, no. 10, pp. 618–630, 2018.

[3] J. Pillai and M. R. Sperling, "Interictal EEG and the diagnosis of epilepsy," *Epilepsia*, vol. 47, no. s1, pp. 14–22, Oct. 2006.

[4] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, "Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis," *Seizure-Eur. J. Epilepsy*, vol. 26, pp. 56–64, Mar. 2015.

[5] C. M. Michel, M. M. Murray, G. Lantz, S. Gonzalez, L. Spinelli, and R. G. de Peralta, "EEG source imaging," *Clin. Neurophysiol.*, vol. 115, no. 10, pp. 2195–2222, Oct. 2004.

[6] P. Mégevand and M. Seeck, "Electroencephalography, magnetoencephalography and source localization: Their value in epilepsy," *Current Opinion Neurol.*, vol. 31, no. 2, pp. 176–183, 2018.

[7] T. Maiwald, M. Winterhalder, R. Aschenbrenner-Scheibe, H. U. Voss, A. Schulze-Bonhage, and J. Timmer, "Comparison of three nonlinear seizure prediction methods by means of the seizure prediction characteristic," *Phys. D, Nonlinear Phenomena*, vol. 194, nos. 3–4, pp. 357–368, 2004.

[8] A. Shoeb and J. Guttag, "Application of machine learning to epileptic seizure detection," in *Proc. 27th Int. Conf. Int. Conf. Mach. Learn.*, 2010, pp. 975–982.

[9] M. Winterhalder et al., "Spatio-temporal patient–individual assessment of synchronization changes for epileptic seizure prediction," *Clin. Neurophysiol.*, vol. 117, no. 11, pp. 2399–2413, Nov. 2006.

[10] Y. Zheng, G. Wang, K. Li, G. Bao, and J. Wang, "Epileptic seizure prediction using phase synchronization based on bivariate empirical mode decomposition," *Clin. Neurophysiol.*, vol. 125, no. 6, pp. 1104–1111, Jun. 2014.

[11] S. Li, W. Zhou, Q. Yuan, and Y. Liu, "Seizure prediction using spike rate of intracranial EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 6, pp. 880–886, Nov. 2013.

[12] A. Eftekhar, W. Juffali, J. El-Imad, T. G. Constandinou, and C. Toumazou, "Ngram-derived pattern recognition for the detection and prediction of epileptic seizures," *PLoS ONE*, vol. 9, no. 6, Jun. 2014, Art. no. e96235.

[13] A. Aarabi and B. He, "Seizure prediction in patients with focal hippocampal epilepsy," *Clin. Neurophysiol.*, vol. 128, no. 7, pp. 1299–1307, Jul. 2017.

[14] Y. Zhang, R. Yang, and W. Zhou, "Roughness-length-based characteristic analysis of intracranial EEG and epileptic seizure prediction," *Int. J. Neural Syst.*, vol. 30, no. 12, Dec. 2020, Art. no. 2050072.

[15] Y. Park, L. Luo, K. K. Parhi, and T. Netoff, "Seizure prediction with spectral power of EEG using cost-sensitive support vector machines," *Epilepsia*, vol. 52, no. 10, pp. 1761–1770, 2011.

[16] J. R. Williamson, D. W. Bliss, D. W. Browne, and J. T. Narayanan, "Seizure prediction using EEG spatiotemporal correlation structure," *Epilepsy Behav.*, vol. 25, no. 2, pp. 230–238, 2012.

[17] N. Wang and M. R. Lyu, "Extracting and selecting distinctive EEG features for efficient epileptic seizure prediction," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 5, pp. 1648–1659, Sep. 2015.

[18] P. Ghaderyan, A. Abbasi, and M. H. Sedaaghi, "An efficient seizure prediction method using KNN-based undersampling and linear frequency measures," *J. Neurosci. Methods*, vol. 232, pp. 134–142, Jul. 2014.

[19] Z. Zhang and K. K. Parhi, "Low-complexity seizure prediction from iEEG/sEEG using spectral power and ratios of spectral power," *IEEE Trans. Biomed. Circuits Syst.*, vol. 10, no. 3, pp. 693–706, Jun. 2016.

[20] B. Sharif and A. H. Jafari, "Prediction of epileptic seizures from EEG using analysis of ictal rules on Poincaré plane," *Comput. Methods Programs Biomed.*, vol. 145, pp. 11–22, Jul. 2017.

[21] M. Z. Parvez and M. Paul, "Seizure prediction using undulated global and local features," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 1, pp. 208–217, Jan. 2017.

[22] N. Ozdemir and E. Yildirim, "Patient specific seizure prediction system using Hilbert spectrum and Bayesian networks classifiers," *Comput. Math. Methods Med.*, vol. 2014, Aug. 2014, Art. no. 572082.

[23] S. Yuan, W. Zhou, and L. Chen, "Epileptic seizure prediction using diffusion distance and Bayesian linear discriminate analysis on intracranial EEG," *Int. J. Neural Syst.*, vol. 28, no. 1, Feb. 2018, Art. no. 1750043.

[24] X. Wang, G. Zhang, Y. Wang, L. Yang, Z. Liang, and F. Cong, "One-dimensional convolutional neural networks combined with channel selection strategy for seizure prediction using long-term intracranial EEG," *Int. J. Neural Syst.*, vol. 32, no. 2, Feb. 2022, Art. no. 2150048.

[25] N. D. Truong et al., "Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram," *Neural Netw.*, vol. 105, pp. 104–111, Sep. 2018.

[26] G. Wang et al., "Seizure prediction using directed transfer function and convolution neural network on intracranial EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 12, pp. 2711–2720, Dec. 2020.

[27] N. D. Truong, L. Kuhlmann, M. R. Bonyadi, D. Querlioz, and O. Kavehei, "Epileptic seizure forecasting with generative adversarial networks," *IEEE Access*, vol. 7, pp. 143999–144009, 2019.

[28] S. M. Usman, M. Usman, and S. Fong, "Epileptic seizures prediction using machine learning methods," *Comput. Math. Methods Med.*, vol. 2017, Dec. 2017, Art. no. 9074759.

[29] D. Cho, B. Min, J. Kim, and B. Lee, "EEG-based prediction of epileptic seizures using phase synchronization elicited from noise-assisted multivariate empirical mode decomposition," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 8, pp. 1309–1318, Aug. 2017.

[30] E. Alickovic, J. Kevric, and A. Subasi, "Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction," *Biomed. Signal Process. Control*, vol. 39, pp. 94–102, Jan. 2018.

[31] M. Behnam and H. Pourghassem, "Real-time seizure prediction using RLS filtering and interpolated histogram feature based on hybrid optimization algorithm of Bayesian classifier and Hunting search," *Comput. Methods Programs Biomed.*, vol. 132, pp. 115–136, Aug. 2016.

[32] K. Fei, W. Wang, Q. Yang, and S. Tang, "Chaos feature study in fractional Fourier domain for preictal prediction of epileptic seizure," *Neurocomputing*, vol. 249, pp. 290–298, Aug. 2017.

[33] B. Büyükçakir, F. Elmaz, and A. Y. Mutlu, "Hilbert vibration decomposition-based epileptic seizure prediction with neural network," *Comput. Biol. Med.*, vol. 119, Apr. 2020, Art. no. 103665.

[34] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals," *Comput. Biol. Med.*, vol. 99, pp. 24–37, Aug. 2018.

[35] S. Ryu and I. Joe, "A hybrid DenseNet-LSTM model for epileptic seizure prediction," *Appl. Sci.*, vol. 11, no. 16, p. 7661, Aug. 2021.

[36] X. Liu and A. G. Richardson, "Edge deep learning for neural implants: A case study of seizure detection and prediction," *J. Neural Eng.*, vol. 18, no. 4, Aug. 2021, Art. no. 046034.

[37] J. Cao, J. Zhu, W. Hu, and A. Kummert, "Epileptic signal classification with deep EEG features by stacked CNNs," *IEEE Trans. Cognit. Develop. Syst.*, vol. 12, no. 4, pp. 709–722, Dec. 2020.

[38] Y. Gao, B. Gao, Q. Chen, J. Liu, and Y. Zhang, "Deep convolutional neural network-based epileptic electroencephalogram (EEG) signal classification," *Frontiers Neurol.*, vol. 11, p. 375, May 2020.

[39] R. Hussein, S. Lee, R. Ward, and M. J. McKeown, "Semi-dilated convolutional neural networks for epileptic seizure prediction," *Neural Netw.*, vol. 139, pp. 212–222, Jul. 2021.

[40] A. R. Ozcan and S. Erturk, "Seizure prediction in scalp EEG using 3D convolutional neural networks with an image-based approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 11, pp. 2284–2293, Nov. 2019.

[41] B. Priya Prathaban and R. Balasubramanian, "Dynamic learning framework for epileptic seizure prediction using sparsity based EEG reconstruction with optimized CNN classifier," *Expert Syst. Appl.*, vol. 170, May 2021, Art. no. 114533.

[42] R. R. Borhade and M. S. Nagmode, "Modified atom search optimization-based deep recurrent neural network for epileptic seizure prediction using electroencephalogram signals," *Biocybern. Biomed. Eng.*, vol. 40, no. 4, pp. 1638–1653, Oct. 2020.

[43] L. A. Moctezuma and M. Molinas, "EEG channel-selection method for epileptic-seizure classification based on multi-objective optimization," *Frontiers Neurosci.*, vol. 14, p. 593, Jun. 2020.

[44] A. Temko, G. Lightbody, G. Boylan, and W. Marnane, "Online EEG channel weighting for detection of seizures in the neonate," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2011, pp. 1447–1450.

[45] M. R. Zimbric, C. M. Sharpe, K. C. Albright, and M. P. Nespeca, "Three-channel electroencephalogram montage in neonatal seizure detection and quantification," *Pediatric Neurol.*, vol. 44, no. 1, pp. 31–34, Jan. 2011.

[46] J. Duun-Henriksen, T. W. Kjaer, R. E. Madsen, L. S. Remvig, C. E. Thomsen, and H. B. D. Sorensen, "Channel selection for automatic seizure detection," *Clin. Neurophysiol.*, vol. 123, no. 1, pp. 84–92, Jan. 2012.

[47] S. Faul and W. Marnane, "Dynamic, location-based channel selection for power consumption reduction in EEG analysis," *Comput. Methods Programs Biomed.*, vol. 108, no. 3, pp. 1206–1215, Dec. 2012.

[48] N.-F. Chang, T.-C. Chen, C.-Y. Chiang, and L.-G. Chen, "Channel selection for epilepsy seizure prediction method based on machine learning," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2012, pp. 5162–5165.

[49] F. Ibrahim et al., "A statistical framework for EEG channel selection and seizure prediction on mobile," *Int. J. Speech Technol.*, vol. 22, no. 1, pp. 191–203, 2019.

[50] E. Cosgun, A. Celebi, and M. K. Gullu, "A channel selection method for epilepsy seizure prediction," in *Proc. Int. Conf. Innov. Intell. Syst. Appl. (INISTA)*, Aug. 2021, pp. 1–5.

[51] J. S. Ra, T. Li, and Y. Li, "A novel permutation entropy-based EEG channel selection for improving epileptic seizure prediction," *Sensors*, vol. 21, no. 23, p. 7972, Nov. 2021.

[52] R. Jana and I. Mukherjee, "Deep learning based efficient epileptic seizure prediction with EEG channel optimization," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102767.

[53] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," *EURASIP J. Adv. Signal Process.*, vol. 2015, no. 1, pp. 1–21, Dec. 2015.

[54] M. Winterhalder, T. Maiwald, H. U. Voss, R. Aschenbrenner-Scheibe, J. Timmer, and A. Schulze-Bonhage, "The seizure prediction characteristic: A general framework to assess and compare seizure prediction methods," *Epilepsy Behav.*, vol. 4, no. 3, pp. 318–325, Jun. 2003.

[55] E. Bou Assi, D. K. Nguyen, S. Rihana, and M. Sawan, "Towards accurate prediction of epileptic seizures: A review," *Biomed. Signal Process. Control*, vol. 34, pp. 144–157, Apr. 2017.

[56] B. Schelter et al., "Testing statistical significance of multivariate time series analysis techniques for epileptic seizure prediction," *Chaos: Interdiscipl. J. Nonlinear Sci.*, vol. 16, no. 1, 2006, Art. no. 013108.

[57] M. Bedeeuzzaman, T. Fathima, Y. U. Khan, and O. Farooq, "Seizure prediction using statistical dispersion measures of intracranial EEG," *Biomed. Signal Process. Control*, vol. 10, pp. 338–341, Mar. 2014.