JYU DISSERTATIONS 584

Xiaoshuang Wang

EEG-Based Detection and Prediction of Epileptic Seizures Using One-Dimensional Convolutional Neural Networks

UNIVERSITY OF JYVÄSKYLÄ
FACULTY OF INFORMATION TECHNOLOGY

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ABSTRACT

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Seizure detection and prediction using electroencephalogram (EEG) signals is still challenging. The accurate detection and prediction of seizures will improve the quality of life and reduce the suffering for people with epilepsy. In this work, deep learning (DL) related techniques are applied. Through the analysis of DL related techniques combined with EEG signals, this dissertation aims to explore the efficient seizure detection and prediction methods or algorithms. Considering the one-dimensional characteristics of EEG signals (time series), our work mainly focuses on the application of one-dimensional convolutional neural networks (1D-CNN) for seizure detection and prediction. Moreover, since the combination of channel selection and 1D-CNN is less studied in seizure prediction, the methods of channel selection strategy combined with 1D-CNN are also proposed for the analysis of seizure prediction.

In the first article, we analyzed a short-term EEG dataset for seizure detection. This work simultaneously used 1D-CNN and two-dimensional convolutional neural networks (2D-CNN) to test the short-term Bonn EEG dataset and achieved remarkable results. In the second article, we further studied the seizure detection by using two long-term EEG datasets, the CHB-MIT sEEG and the SWEC-ETHZ iEEG datasets. In this work, a stacked 1D-CNN model was applied to test these two different datasets. In the third article, our goal was to study the seizure prediction using EEG signals. Therefore, based on the long-term Freiburg iEEG dataset, we proposed a novel method of 1D-CNN combined with channel selection strategy for seizure prediction. Since the third article only considered 9 channel cases (total 63 channel cases) for the best channel case selection, the fourth article further discussed channel selection strategy based on all channel cases for seizure prediction. In the fifth article, a novel method of channel increment strategy-based 1D-CNN was proposed for seizure prediction based on the same iEEG dataset.

In conclusion, our work successfully applied CNNs in the short- and long-term sEEG and iEEG signals for the analysis of seizure detection and prediction, and the methods of channel selection strategy combined with 1D-CNN also showed remarkable performances in seizure prediction.

Keywords: Epilepsy, electroencephalogram (EEG), seizure detection, seizure prediction, one-dimensional convolutional neural networks (1D-CNN).

TIIVISTELMÄ (ABSTRACT IN FINNISH)

Wang, Xiaoshuang
EEG-pohjainen epileptisten kohtausten havaitseminen ja ennustaminen käyttämällä yksiulotteisia konvoluutiohermoverkkoja
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Aivosähkökäyrään (engl. electroencephalography, EEG) perustuva epileptisten kohtausten havaitseminen ja ennustaminen on haastavaa. Täsmällisemmällä kohtausten havainnoinnilla voidaan parantaa epilepsiaa sairastavien elämänlaatua ja vähentää epileptisten kohtausten haittoja. Viime aikoina tekoälyn piirissä on saatu ensiluokkaisia tuloksia eri sovelluksissa, esimerkiksi kuvantunnistus- ja konenäkötehtävissä, käyttämällä niin kutsuttuja syväoppimismenetelmiä. Myös tässä väitöskirjassa sovellettiin ja kehitettiin syväoppimismenetelmiä, joiden avulla EEG-aineistoista pystyttiin luotettavasti havaitsemaan epileptisiä kohtauksia. Koska aivosähkökäyrät itsessään ovat yksiulotteisia aikasarjoja, paneuduttiin tässä työssä erityisesti niin kutsuttujen yksiulotteisten konvoluutioneuroverkkojen käyttöön. Lisäksi huomiota kiinnitettiin menetelmiin, joiden avulla eri mittauskanavilta saatavia aikasarjoja pystyttiin valitsemaan ja hyödyntämään epileptisten kohtausten paremman ennustustarkkuuden saavuttamiseksi.

Konvoluutioneuroverkkoja käytettäessä EEG-aineiston mallinnus aloitetaan valitsemalla verkon rakenne. Tässä työssä rajoituttiin hyödyntämään päälaen ja kallonsisäisäisiä EEG-mittauksia, joiden kestoajat vaihtelivat kymmenistä sekunneista aina satoihin tunteihin. Näiden avulla määriteltyjen konvoluutioverkkojen toimintaa verrattiin aikaisemmassa tutkimuksessa esitettyihin tuloksiin. Johtopäätös oli, että väitöskirjan sisältämissä artikkeleissa esitettyjen menetelmien tarkkuus oli huomattavasti parempi kuin aikaisemmassa tutkimuksessa. Samoin aktiivisten mittauskanavien lukumäärää pystyttiin vähentämään merkittävästi. Kaiken kaikkiaan väitöskirja osoittaa, että konvoluutioneuroverkot soveltuvat sekä lyhyiden että pitkien EEG-aikasarjojen analysointiin ja epileptisten kohtausten havaitsemiseen. Yhdistettynä parhaiden mittauskanavien valintaan saadaan aikaiseksi syväoppimismenetelmiä, joiden ennustustarkkuus ja luotettavuus ovat erinomaisella tasolla.

Avainsanat: Epilepsia, elektroenkefalogrammi (EEG), kohtausten havaitseminen, kohtausten ennustaminen, yksiulotteiset konvoluutiohermoverkot (1D-CNN)

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Xiaoshuang Wang

LIST OF ACRONYMS

EEG	Electroencephalogram
sEEG	Scalp electroencephalogram
iEEG	Intracranial electroencephalogram
SPH	Seizure prediction horizon
SOP	Seizure occurrence period
ML	Machine learning
DL	Deep learning
STFT	Short-time Fourier transform
DWT	Discrete wavelet transform
SVM	Support vector machine
RF	Random forest
KNN	K-nearest neighbor
ANN	Artificial neural networks
DT	Decision tree
CNN	Convolutional neural networks
LSTM	Long-short term memory
RNN	Recurrent neural networks
K-CV	K-fold cross validation
AUC	Area under curve
FDR	False detection rate
ReLU	Rectified linear activation unit
EMD	Empirical model decomposition
FPR	False prediction rate
CWT	Continuous wavelet transform
HHT	Hilbert–Huang transform
GAN	Generative Adversarial Networks

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PII Xiaoshuang Wang, Xiulin Wang, Wenya Liu, Zheng Chang, Tommi Kärkkäinen and Fengyu Cong. One dimensional convolutional neural networks for seizure onset detection using long-term scalp and intracranial EEG. *Neurocomputing, 459, 212-222*, 2021.

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PIV Xiaoshuang Wang, Tommi Kärkkäinen and Fengyu Cong. Seizure Prediction Using EEG Channel Selection Method. *32nd IEEE International Workshop on Machine Learning for Signal Processing (MLSP 2022), IEEE, Xi'an, China*, 2022.

PV Xiaoshuang Wang, Chi Zhang, Tommi Kärkkäinen, Zheng Chang and Fengyu Cong. Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG. *Accepted in IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2022.

1 INTRODUCTION

1.1 Epilepsy and electroencephalogram (EEG)

Epilepsy is one of the most common brain diseases and affects people at any age. Approximately 70 million people worldwide suffer from epilepsy, and nearly 70% of them can be free from seizures if properly diagnosed and treated (Kuhlmann et al., 2018b; Elger and Hoppe, 2018). Epilepsy is characterized by recurrent seizures, which can result in physical convulsions, loss of consciousness, injury, death, etc. (Acharya et al., 2018a; Ridsdale et al., 2011). Therefore, epilepsy seriously reduces the quality of life and affects both physical and mental health for people with epilepsy.

Epileptic seizures originate from abnormal synchronous discharges of brain cells. The excessive electrical discharges can lead to the dysfunction of brain activities and the onset of seizures. For people with epilepsy, electroencephalogram (EEG) is a significant tool in the diagnosis of epilepsy because EEG signals can record and reflect the electrical activities of bran neurons (Pillai and Sperling, 2006; Faust et al., 2015). EEG can be recorded from the scalp and intracranial of the brain, namely, scalp electroencephalogram (sEEG) and intracranial electroencephalogram (iEEG). Normally, iEEG signals have higher signal-to-noise ratio (SNR) (Baldassano et al., 2017). EEG signals generally contain five principal frequency bands: delta (δ, 1-4 Hz), theta (θ, 4-8 Hz), alpha (α, 8-13 Hz), beta (β, 13-30 Hz) and gamma (γ, 30+ Hz) (Ergenoglu et al., 2004; Groppe et al., 2013).

During EEG acquisition from epileptic patients, EEG signals are commonly recorded through multiple channels. Each channel corresponds to a different brain zone and records different electrical activities of the brain. EEG signals of each channel are also changing over time, such as, changes in amplitude and frequency. Consequently, in the diagnosis of epilepsy, EEG has been widely used to find epileptic focuses (Michel et al., 2004; Mégevand and Seeck, 2018), evaluate therapeutic effects after treatment (Noachtar and Rémi, 2009), and detect or predict seizures (Alotaiby et al., 2014; Ramgopal et al., 2014; Siddiqui et al., 2020; Shoeibi et al., 2021).

1.2 EEG-based seizure detection and prediction

The visual assessment of EEG signals is an essential means in clinical epilepsy diagnosis. After collecting a period of epileptic EEG recordings, neurologists commonly try to find some abnormal electrical activities, such as seizures, epileptiform discharges, etc., by studying EEG. However, the manual seizure detection by visual assessment is a time-consuming and labor-intensive task and leads to a reduction in work efficiency. Thus, based on EEG signals, the exploration of automated seizure detection is significant and meaningful. This is because a timely and accurate seizure detection can help neurologists quickly locate the onset of seizures, and this can be regarded as an auxiliary means to support the diagnosis of epilepsy. Since the automated detection of seizures can enable people to take interventions in time, it can also reduce the suffering and improve the quality of life for epileptic patients.

As shown in Fig. 1, epileptic EEG signals can be divided into four phases: interictal (between seizures), preictal (a period of time before a seizure, between interictal and ictal phases), ictal (during a seizure) and postictal (after a seizure) (Fisher et al., 2014; Assi et al., 2017). *EEG-based seizure detection* is to detect the occurrence of seizures during the recording of EEG signals, and distinguish the ictal phase from the other three phases (interictal, preictal and postictal phases can be seen as one phase in seizure detection). During recording EEG signals, a seizure commonly lasts from tens of seconds to several minutes among epileptic patients. Therefore, in long-term (several hours or days) epileptic EEG recordings, the duration of ictal phase is much shorter than that of the other three phases, and this results in a problem of sample imbalance. For solving the problem of sample imbalance in the analysis of seizure detection, appropriate data augmentation or down sampling methods should be considered according to the actual situation of EEG data (Lashgari et al., 2020).

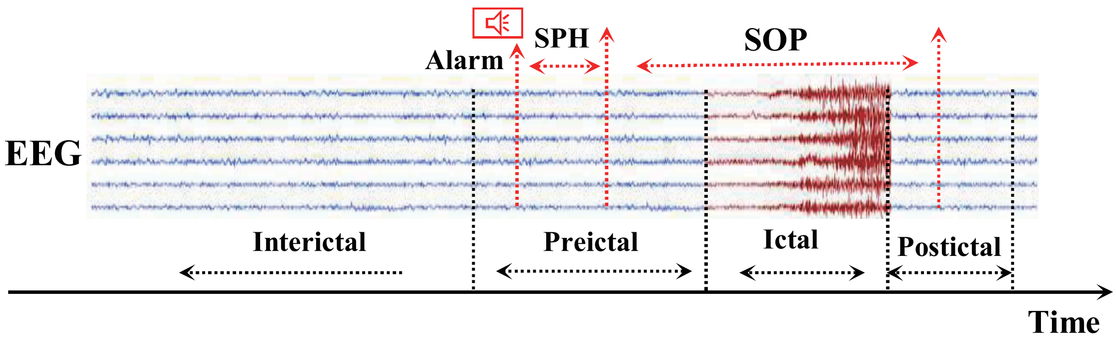

FIGURE 1 Four phases of the epileptic EEG signals: interictal, preictal, ictal and postictal, and definition of an accurate seizure prediction. When an alarm rings, a seizure should occur after SPH and within SOP (Winterhalder et al., 2003).

Compared to seizure detection, a further exploration is focused on seizure prediction. About 30% of epileptic patients are intractable to anti-epileptic drugs (Kwan et al., 2011; Kuhlmann et al., 2018b). For people 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. Consequently, the study of seizure prediction has its unique significance and is also more challenging.

EEG-based seizure prediction is an analysis about the classification of interictal and preictal phases. In seizure prediction, a period of time before the onset of seizures is regarded as the preictal phase (as shown in Fig. 1), and the length of preictal phase needs to be determined. Before determining the length of preictal phase, two basic concepts, namely seizure prediction horizon (SPH) and seizure occurrence period (SOP), need to be explained. As shown in Fig. 1, SOP is defined as the period during which a seizure is expected to occur. SPH is the period from a prediction to the beginning of SOP (Winterhalder et al., 2003). For example, when we make SOP = 30 min and SPH = 5 min, the duration of preictal phase is therefore 35 min. Hence, in the analysis of seizure prediction, the durations of SOP and SPH should be informed, and the determination of SOP and SPH durations can refer to the previous studies. Similar to seizure detection, the problem of sample imbalance also exists and needs to be solved in the analysis of seizure prediction.

1.3 EEG-based methodology for seizure detection and prediction

Fig. 2 shows a diagram of EEG-based methodology for seizure detection and prediction. In conventional machine learning (ML) methods, the analysis process of EEG signals for seizure detection and prediction commonly includes four steps: (1) preprocessing, (2) feature extraction (and selection), (3) model construction and training, and (4) classification for system evaluation (as shown in Fig. 2). The second and third steps are normally regarded as one step in deep learning (DL).

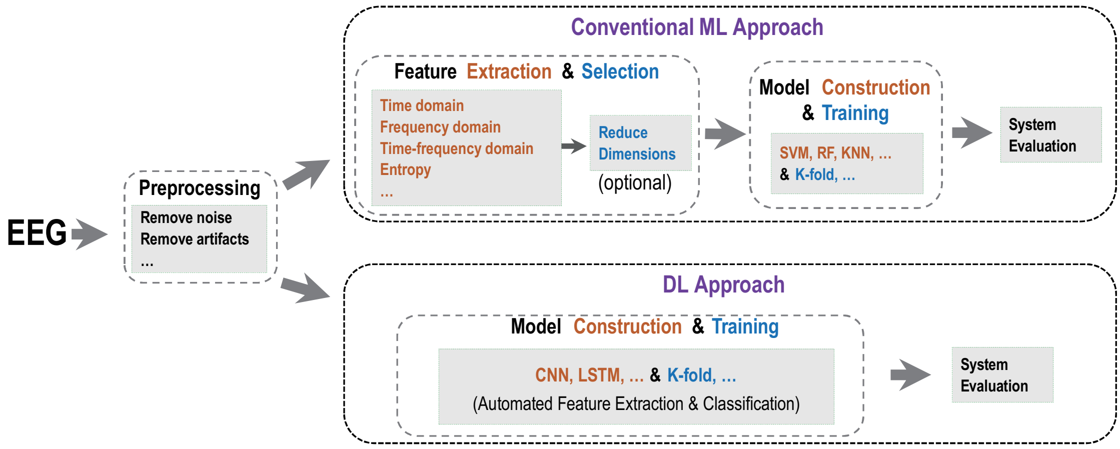

FIGURE 2 Diagram of the EEG-based methodology for seizure detection and prediction.

First, according to the actual situation of EEG data and the actual needs of analysis, we should preprocess EEG signals accordingly. For example, to improve the SNR of EEG signals, the filtering of EEG signals can be performed in a certain frequency range (Cong et al., 2015). To remove eye movement and blink artifacts in EEG signals, the algorithm of independent component analysis (ICA) can be used (Mennes et al., 2010; Cong et al., 2015). To solve the problem of sample imbalance, data augmentation (sliding windows with overlap, etc.) or down sampling (random selection, etc.) approaches can be applied (Wang et al., 2020, 2021). In sum, the aim of preprocessing is to make EEG signals more suitable for subsequent analysis, and a proper preprocessing may also improve the performances of the proposed methods.

After preprocessing, the second step is about the feature extraction and selection of EEG signals. EEG-based features are commonly extracted from the following aspects: time domain, frequency or time-frequency domain, entropy and complexity, etc. In time domain, minimum, maximum, mean, median, standard deviation, skewness, kurtosis and other temporal statistics can be calculated (Boonyakitanont et al., 2020). In frequency or time-frequency domain, short-time Fourier transform (STFT) (Bandarabadi et al., 2015), discrete wavelet transform (DWT) (Alickovic et al., 2018) or other transform methods (Tzallas et al., 2009) can be first used to transform EEG signals into frequency or time-frequency domain representations. Then, about frequency or time-frequency features, such as absolute spectral power of sub-bands (δ, θ, α, β), relative spectral power of sub-bands (δ/all power, θ/all power, etc.), power ratios (δ/θ, δ/α, etc.) and values calculated from sub-bands of DWT, can be obtained. Next, in entropy and complexity, spectral entropy (Das et al., 2018), wavelet entropy (Kumar et al., 2010), sample entropy (Kumar et al., 2010; Song et al., 2012), approximate entropy (Kumar et al., 2014), LZ-complexity (Hu et al., 2006), etc., can be achieved. Through feature extraction, the obtained samples composed of feature vectors are used to train and test models. If necessary, after feature extraction, the analysis of feature selection can be performed for improving classification results. In conventional ML methods, the process of feature extraction is significant because this is directly related to the training and testing of models. In DL methods, the process of feature extraction can be skipped since DL models can automatically extract features by the self-learning.

Next step comes to model construction and training. According to the practical analysis, one or more models can be constructed for classification or the comparison of classification results. In conventional ML methods, Support Vector Machine (SVM) (Alickovic et al., 2018; Cho et al., 2016; Zarei and Asl, 2021), Random Forest (RF) (Wang et al., 2019), K-Nearest Neighbor (KNN) (Xue et al., 2020; Liu et al., 2020), Artificial Neural Networks (ANN) (Qaisar and Hussain, 2021), Decision Tree (DT) (Albaqami et al., 2021), Bayesian (Ozdemir and Yildirim, 2014; Yuan et al., 2018), Extreme Learning Machine (ELM) (Kärkkäinen, 2019; Hämäläin et al., 2020), etc., can be used as classifiers. In DL methods, Convolutional Neural Networks (CNN) (Wang et al., 2021; Acharya et al., 2018b; Truong et al., 2018; Hussein et al., 2021), Long-Short Term Memory (LSTM) (Hussein et al., 2019;

Tsiouris et al., 2018; Liu and Richardson, 2021), Recurrent Neural Networks (RNN) (Borhade and Nagmode, 2020), etc., can be used for classification. Then, model training is performed, and the training strategy of K-fold cross validation (K-CV) is generally carried out. For the methods of threshold analsis, time series analysis-based threshold models can be used (Tong, 2011). In studies using threshold analysis for seizure detection and prediction, linear or non-linear features are first extracted, and then a proper threshold is set according to the trend of these features over time.

The final step is about system evaluation. Classification results need to be evaluated to show the performances of the proposed methods. Two evaluation levels, the segment-based level and the event-based level, can be given. At the segment-based level, it is from the perspective of the correct number of sample classification. The metrics, such as sensitivity, specificity and accuracy, can be calculated. The formulas of these three metrics are given as follows:

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

$$Specificity = \frac{TN}{FP + TN},$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN},$$

where TP, FP, TN and TN indicate true positive, false positive, false negative and true negative, respectively. Other parameters, such as algorithm running time, model complexity, area under curve (AUC), etc., can also be used to evaluate the performances of proposed methods in the analysis of seizure detection and prediction.

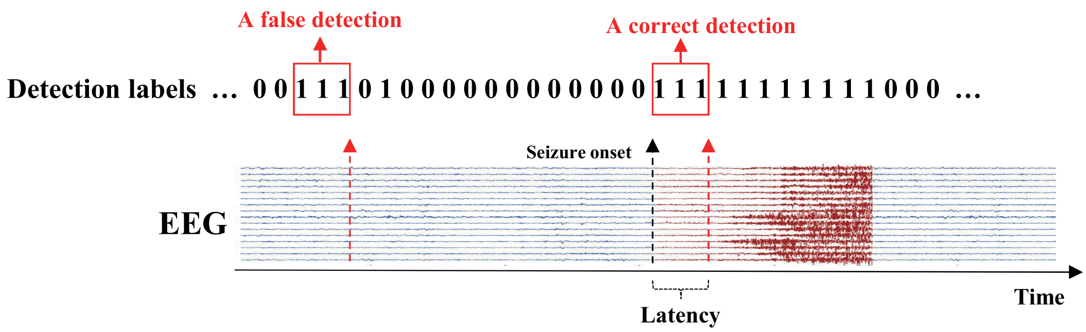

FIGURE 3 Evaluation of seizure detection at the event-based level. Example of a false detection, a true detection and its latency for the evaluation of seizure detection at the event-based level.

As shown in Fig. 3, at the even-based level, it is from the perspective of detecting or predicting an event (or a seizure). The metrics, such as event-based sensitivity, false detection rate (FDR) and latency, can be given. The formulas of even-based sensitivity and FDR are showed as follows:

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

$$FDR = \frac{number\ of\ false\ detections}{hours\ of\ interictal\ EEG}.$$

Latency is the time duration from the onset of a seizure to its detection (as shown in Fig. 3).

1.4 Convolutional neural networks (CNN)

Recently, DL has shown powerful performances in pattern recognition and has been widely applied in many research fields, such as, image recognition (Pak and Kim, 2017; Ohri and Kumar, 2021; Li, 2022), computer vision (Voulodimos et al., 2018; Chai et al., 2021), auxiliary diagnosis of diseases (Bakator and Radosav, 2018; Latif et al., 2019; Aggarwal et al., 2021), etc. CNN and RNN are two main DL techniques. In this work, we focus on the use of CNN for the study of seizure detection and prediction. Thus, this section briefly introduces the basic information of CNN.

A CNN model is illustrated in Fig. 4. A CNN model mainly consists of convolutional layers, pooling layers (or subsampling layers) and fully connected layers. A convolutional layer contains a certain number of convolution kernels and processes the inputs through convolution calculations for learning high-level representations. The nonlinearization of convolution results are generally processed simultaneously by activation functions, and the rectified linear activation unit (ReLU) is commonly used in convolution layers. The outputs of convolutional layers are usually fed into pooling layers for preserving higher-level representations. Pooling processes, including maxi-mum pooling, global average pooling, etc., can be performed if needed. After convolution and pooling processes are implemented several times, the high-level features are subsequently input into fully connected layers for the final classification (LeCun et al., 1998; O'Shea and Nash, 2015).

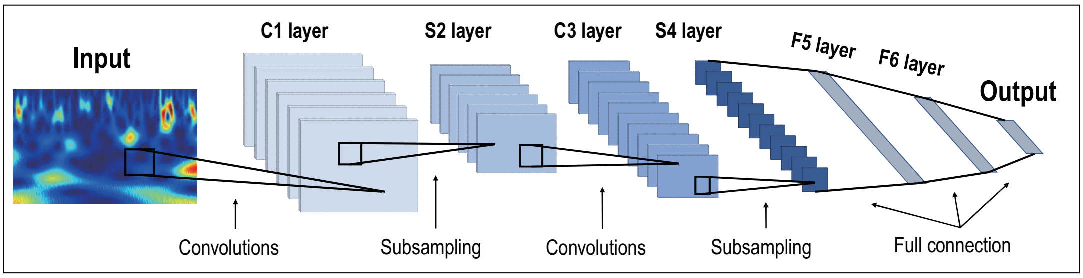

FIGURE 4 Example of a CNN model consisting of convolutional layers, pooling layers and fully connected layers.

CNN includes one-dimensional convolutional neural networks (1D-CNN), two-dimensional convolutional neural networks (2D-CNN) and three-dimensional convolu-tional neural networks (3D-CNN). According to data modalities, the corresponding models are selected for analysis, such as 1D-CNN for sequences, 2D-CNN for images and 3D-CNN for videos (LeCun et al., 2015). EEG signals are

1D arrays, and the time-frequency transform of EEG signals provides 2D representations. Therefore, 1D-CNN and 2D-CNN are used for the analysis of seizure detection and prediction in our work.

1.5 Thesis overview

This study aims to probe effective methods or approaches for seizure detection and prediction through the analysis of DL techniques combined with EEG signals. The dissertation focuses on using CNN related techniques to analyze short- and long-term EEG signals. We first study the problem of seizure detection. 1D-CNN and 2D-CNN are used during the analysis of short- and long-term EEG (including sEEG and iEEG) signals for seizure detection. Then, we further study the problem of seizure prediction, 1D-CNN combined with channel selection strategy is therefore proposed for EEG-based seizure prediction. It is hoped that the new approaches may provide a reference for the clinical application of seizure detection and prediction in the future.

The remaining parts of this dissertation are organized as follows. In Chapter 2, we first review several EEG datasets that have widely used in the analysis of seizure detection and prediction. Then, we summarize the relevant seizure detection and prediction methods based on these datasets. In Chapter 3, we describe the aim of this dissertation and the specific aim of each sub-study. In Chapter 4, each publication, including datasets, methods, results and contributions, is summarized and discussed. In Chapter 5, we conclude the entire work and discuss the limitations and future directions of our work.

2 MATERIALS AND RELATED WORK

This chapter first describes four relevant epileptic EEG datasets. The details of each EEG dataset, including data size, number of patients, number of seizures, number of channels, etc., are given. Then, based on these EEG datasets, the related seizure detection and prediction studies are briefly summarized. Given this, further considerations about EEG-based seizure detection and prediction are discussed to highlight the novelties or contributions of this dissertation.

2.1 Epileptic EEG datasets

2.1.1 Bonn EEG dataset

The short-term Bonn EEG dataset (Andrzejak et al., 2001) consists of 500 single-channel EEG segments (200 sEEG and 300 iEEG segments). Each segment is selected from the continuous EEG recordings after visual inspection, and the duration of each segment is 23.6 seconds. The EEG data are recorded with the sampling rate of 173.61 Hz and the band-pass filtering of 0.53-40 Hz. Two healthy and three epileptic subjects provide the EEG signals, and the relevant EEG details for each subject are summarized in Table 1. The Bonn EEG dataset is commonly used in seizure detection studies.

TABLE 1 Details of the Bonn EEG dataset

Set	Situation of subjects	Data size	EEG	Phase
A	healthy	100 segments	sEEG	eyes open
B	healthy	100 segments	sEEG	eyes closed
C	epileptic	100 segments	iEEG	interictal
D	epileptic	100 segments	iEEG	interictal
E	epileptic	100 segments	iEEG	ictal

Data link: http://epilepsy-database.eu/

2.1.2 CHB-MIT sEEG dataset

The long-term CHB-MIT sEEG dataset (Shoeb and Guttag, 2010) is collected from children with intractable seizures. The pediatric subjects are monitored for several days after stopping anti-seizure medication. The sEEG signals are recorded with a sampling rate of 256 Hz, and these recordings from 23 subjects are grouped into 24 cases. The first 23 cases contain EEG recordings from 22 subjects, including 5 males among 3-22 ages and 17 females among 1.5-19 ages. The 24th case is from the 23rd subject. Most of the sEEG recordings include 23 channels, and few of them include 18 or 24 channels. This dataset totally consists of about 977 hours of sEEG signals and 198 seizures, and details for each subject are given in Table 2. This dataset is usually used in seizure detection and prediction studies.

TABLE 2 Details of the CHB-MIT sEEG dataset.

Case	# Channels	Hours of sEEG	# Seizures
1	23	41	7
2	23	35	3
3	23	38	7
4	23	156	4
5	23	39	5
6	23	67	10
7	23	67	3
8	23	20	5
9	23	68	4
10	23	50	7
11	23	35	3
12	23	21	40
13	18	33	12
14	23	26	8
15	24	39	20
16	18	18	10
17	23	20	3
18	23	35	6
19	23	29	3
20	23	28	8
21	23	33	4
22	23	31	3
23	23	27	7
24	23	21	16
Total	–	977	198

Data link: https://archive.physionet.org/physiobank/database/chbmit/

2.1.3 SWEC-ETHZ iEEG dataset

The long-term SWEC-ETHZ iEEG dataset (Burrello et al., 2019) totally contains 18 subjects, 2656 hours of iEEG and 116 leading seizures. The iEEG signals are collected at a sampling rate of 512 or 1024 Hz. A band-pass filtering of 0.5-120 Hz is performed during recording iEEG signals. The number of iEEG channels ranges between 18 and 128. The iEEG details of each subject are summarized in Table 3. This iEEG dataset, in public from 2019, is mainly used for the analysis of seizure detection.

TABLE 3 Details of the Long-term SWEC-ETHZ iEEG dataset.

Subject	# Channels	Sampling rate (Hz)	Hours of iEEG	# Seizures
1	88	512	294	2
2	66	512	235	2
3	64	512	158	4
4	32	1024	41	14
5	128	512	110	4
6	32	1024	146	8
7	75	512	69	54
8	61	1024	144	4
9	48	1024	41	23
10	32	1024	42	17
11	32	1024	212	2
12	56	1024	191	9
13	64	1024	104	7
14	24	1024	161	2
15	98	512	196	2
16	34	1024	177	5
17	60	1024	130	2
18	42	1024	205	5
Total	–	–	2656	116

Data link: http://ieeg-swez.ethz.ch

2.1.4 Freiburg iEEG dataset

The long-term Freiburg iEEG dataset (Maiwald et al., 2004) can be used to study seizure prediction. This dataset includes 21 subjects, 87 seizures, about 509 h of interictal and 73 h of preictal or ictal iEEG signals. Each subject is monitored using 6 recording electrodes (3 in-focus and 3 out-of-focus electrodes). The sampling rate of the iEEG data is at 256 Hz. The 0.5-120 Hz band-pass filtering and the 50 notch filtering are performed during recording. The details of this iEEG dataset are given in Table 4.

TABLE 4 Details of the Freiburg iEEG dataset

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

Data link: http://epilepsy.uni-freiburg.de/database

2.1.5 Other epileptic EEG datasets

Several other EEG datasets, such as the American Epilepsy Society Seizure Prediction Dataset (Brinkmann et al., 2016), the Melbourne University AES-MathWorks-NIH Seizure Prediction Challenge dataset (Kuhlmann et al., 2018a), the TUH EEG Corpus dataset (Shah et al., 2018), etc., can also be used for the study of seizure detection and prediction or seizure type classification. Since these datasets are not used in our work, more details of these datasets are not described in this dissertation.

2.2 Seizure detection

In this section, the related seizure detection work, based on the Bonn EEG, the CHB-MIT sEEG and the SWEC-ETHZ iEEG datasets, is briefly summarized.

2.2.1 Seizure detection using the Bonn EEG dataset

The short-term Bonn EEG dataset is one of the most commonly used EEG datasets in seizure detection over the past two decades. In related studies, many ML and DL methods have been applied for seizure detection based on this dataset. An overview of these studies is given as follows.

First, conventional ML methods, such as SVM, KNN, RF, ANN, etc., were widely utilized. In studies (Kumar et al., 2014; Fu et al., 2014; Zarei and Asl, 2021; Anuragi et al., 2021), researchers used the SVM to classify EEG samples in the form of different features, such as DWT-based fuzzy approximate entropy (Kumar et al., 2014), statistic values (mean, variance, skewness and kurtosis) computed from Hilbert–Huang transform (HHT)-based time-frequency representations (Fu et al., 2014), fuzzy entropy, approximate entropy, sample entropy, etc., calculated from the DWT and orthogonal matching pursuit coefficients (Zarei and Asl, 2021), and line-length, log-energy-entropy and norm-entropy values based on the Fourier-Bessel series expansion-based empirical wavelet transform method (Anuragi et al., 2021). Then, in studies (Chen, 2014; Liu et al., 2020; Xue et al., 2020), the KNN was used as a classifier. Different EEG features, including dual-tree complex wavelet–Fourier features (Chen, 2014), features calculated from the method of unigram ordinal pattern and bigram ordinal pattern representations (Liu et al., 2020), and features based on suing auto-weighted multi-view discriminative metric learning method (Xue et al., 2020), were extracted for seizure detection among these studies. For the use of RF, wang et al. first extracted features by using STFT combined with principal component analysis (PCA), and then constructed a RF model for classification (Wang et al., 2019). Moreover, ANN was used in studies (Alam and Bhuiyan, 2013; Qaisar and Hussain, 2021) for seizure detection. In these two studies, higher order statistics (variance, skewness and kurtosis) in the empirical mode decomposition (EMD) domain (Alam and Bhuiyan, 2013) and DWT based sub-bands statistics (Qaisar and Hussain, 2021), were computed for feature extraction, respectively. In sum, among the above studies, remarkable results (90%-100% accuracy) were finally achieved, and conventional ML methods showed an excellent performance for seizure detection based on the analysis of the Bonn EEG dataset.

Second, based on the same dataset, DL methods, including CNN, LSTM, etc., were also used. In study (Acharya et al., 2018b), a 13-layer deep 1D-CNN model was constructed to classify normal, interictal and ictal phases, and this method obtained a sensitivity, specificity, and accuracy of 95.00%, 90.00% and 88.67%, respectively. Study (Ullah et al., 2018) proposed a seizure detection system that is an ensemble of pyramidal 1D-CNN models, and this system achieved an accuracy of 99.1±0.9%. Next, study (Zhang et al., 2020a) presented a multi-scale non-local network, mainly consisting of a 1D-CNN with two special layers (signal pooling layer and multi-scale non-local layer), for seizure detection, and an accuracy of 94.01-99.93% was attained. Then, study (Sahani et al., 2021) applied the 1D-CNN and autoencoder techniques for seizure detection, and this method achieved an accuracy of 95.94-100%. Moreover, Study (Pan et al., 2022) used a deep learning network that is a combination of 1D-CNN and 2D-CNN models for classification, and this approach achieved an accuracy of 99.12%. Different from the above studies using CNN methods, study (Hussein et al., 2019) constructed a LSTM model for classification. The proposed method obtained an accuracy of 100% in seizure detection (Hussein et al., 2019). Among the above studies, DL methods also attained remarkable results and showed an outstanding performance for the same EEG dataset.

As mentioned above, many ML and DL methods have been successfully applied in analyzing the short-term Bonn EEG dataset (500 single-channel EEG segments of 23.6-s duration) for seizure detection. However, in the real world, EEG signals recorded from epileptic patients usually last from several hours to several weeks. Therefore, the analysis of long-term and continuous EEG data for seizure detection may have more practical significance. In the next two subsections, we summarize the related work about using long-term EEG signals for the analysis of seizure detection.

2.2.2 Seizure detection using the CHB-MIT sEEG dataset

In the research of seizure detection using long-term EEG signals, the long-term CHB-MIT sEEG dataset was widely used in the past decade. In this subsection, studies using the CHB-MIT sEEG dataset for seizure detection are summarized as follows.

First, based on the CHB-MIT sEEG dataset, the use of conventional ML methods for seizure detection is briefly summarized. SVM as a leading conventional ML method was applied in studies (Zarei and Asl, 2021; Anuragi et al., 2021; Li et al., 2021) for seizure detection. Study (Zarei and Asl, 2021) first extracted some non-linear features (fuzzy entropy, approximate entropy, etc.) and some statistic features (mean, standard deviation, etc.) from sEEG signals, and then SVM model was used for classification. This method achieved an averaged accuracy, sensitivity, and specificity of 97.09%, 96.81% and 97.26%, respectively. In study (Anuragi et al., 2021), line-length, log-energy-entropy and norm-entropy were calculated from sub-band signals (based on the Fourier-Bessel series expansion-based empirical wavelet transform for obtaining sub-band signals) as EEG features. Then, the authors applied the relief-F feature ranking method for feature selection and attained an accuracy of 99.84% using Least Squares Support Vector Machine (LS-SVM) classifier (Anuragi et al., 2021). Different from the above two studies only used one SVM for seizure detection, an SVM group consisting of ten SVMs was utilized in study (Li et al., 2021). The authors used DWT and EMD for preprocessing, common spatial pattern for dimension reduction, and the variance as the only feature. The proposed method finally achieved an accuracy of 97.49% at the segment-based level, and a sensitivity of 98.47% with the false detection rate (FDR) of 0.63/h at the event-based level (Li et al., 2021).

Alickovic et al. (2018) used four classifiers, including SVM, KNN, Multilayer Perceptron (MLP) and RF, for comparison in seizure detection and prediction. In this study, DWT, EMD and wavelet packet decomposition (WPD) were utilized for feature extraction, and an accuracy of 100% was obtained. However, this work specially selected 1000 interictal, 1000 ictal and 1000 preictal 8-s segments from the CHB-MIT sEEG dataset for the analysis of seizure detection and prediction, which greatly damaged the integrity of the data (Alickovic et al., 2018) . Moreover, seven classifiers (SVM, Ensemble, KNN, Linear Discriminant Analysis, Logistic Regression, DT and Naive Bayes) were used simultaneously in study (Ein Shoka et al., 2021) for seizure detection. This study extracted 11 features (standard deviation, mean, variance, median, kurtosis, skewness, entropy, moment, power, maximum and minimum EEG signals) after using the channel selection strategy, and an accuracy of 85% was finally achieved using SVM and KNN.

Second, a brief summary of DL methods for seizure detection is given as follows. Study (Hossain et al., 2019) used a 7-layer 2D-CNN to classify time-channel sEEG maps for seizure detection. With the whole dataset of 23 patients and the cross-patient validation, the proposed method attained an overall sensitivity, specificity, and accuracy of 90.00%, 91.65% and 98.85%, respectively. Next, study (Boonyakitanont et al., 2021) applied a deep 1D-CNN model for detecting seizure onset and offset. With the post-processing strategy and the patient-specific validation, the presented method achieved an averaged accuracy, sensitivity, and specificity of 99.83%, 76.54% and 99.92%, respectively. Then, studies (Hu et al., 2020; Chakrabarti et al., 2021) utilized LSTM techniques for seizure detection. Study (Hu et al., 2020) combined two independent LSTM networks (Bi-LSTM) with the opposite propagation directions for classification. An averaged sensitivity of 93.61% and an averaged specificity of 91.85% were obtained based on the patient-specific strategy. Study (Chakrabarti et al., 2021) proposed a simple LSTM model with one LSTM layer and two fully connected (FC) layers for the analysis of the same dataset, and this method attained a result of 99.9% sensitivity and 0.003/h FDR under the ten-fold cross validation. Different from the above studies only used CNN or LSTM model, a hybrid model of 2D-CNN combined with LSTM was used in study (Liang et al., 2020) for seizure detection. In this 2D-CNN-LSTM model, the 2D-CNN part was responsible for learning the high-level representations of inputs, and the outputs of 2D-CNN were then fed into the LSTM part for classification. An overall sensitivity, specificity, and accuracy of 84.00%, 99.00% and 99.00% were attained under the cross-patient model training strategy (Liang et al., 2020). Moreover, except LSTM, other Recurrent Neural Net-work (RNN) related methods were also applied. Study (Yao et al., 2019) proposed a deep independently recurrent neural network (IndRNN) model, with a dense structure and an attention mechanism, for seizure detection. This model finally attained a result of 88.80% sensitivity, 88.86% specificity and 88.70% accuracy based on the data of 10 patients (totally 24 patients). In study (Zhang et al., 2022), the authors used a bidirectional gated recurrent unit (Bi-GRU) neural network for classification, and this method achieved an averaged sensitivity of 93.89% and an averaged specificity of 98.49%.

Convolutional autoencoder methods were also used for seizure detection. Study (Abdelhameed and Bayoumi, 2021) constructed a model of two-dimensional deep convolution autoencoder (2D-DCAE) combined with Bi-LSTM for classification. With 4-sec sEEG segments as inputs and the ten-fold cross validation scheme, this method achieved a result of 98.79% accuracy, 98.72% sensitivity and 98.86% specificity (Abdelhameed and Bayoumi, 2021). Then, study (Sahani et al., 2021) proposed a novel method of reduced deep convolutional stack autoencoder combined with improved kernel random vector functional link network (RDCSAE-IKRVFLN) for seizure detection., and this method obtained 100% sensitivity, 99.96% specificity, 99.96% accuracy and 0.0391/h FDR under the patient-specific scheme. In addition, Graph Convolution Network (GCN) methods were also utilized. In study (Zhao et al., 2021), the researchers presented a Linear Graph Convolution Network (LGCN) model for the analysis of the sEEG dataset, and the proposed method attained a mean accuracy of 99.30% using the patient-specific model training strategy. Besides the above DL methods, the seizure detection comparison of several DL models was also discussed. In study (Liu and Richardson, 2021), the authors used three DL models (deep neural network (DNN), 1D-CNN and Bi-LSTM) at the same time for comparison in the analysis of seizure detection. Three models achieved the sensitivity and FDR of 87.36%/0.169 h^{-1}, 96.70%/0.102 h^{-1}, and 97.61%/0.071 h^{-1} for DNN, 1D-CNN and Bi-LSTM, respectively.

In short, based on the long-term CHB-MIT sEEG dataset, EEG-based seizure detection using ML and DL methods showed a sustained progress, and these methods will provide a significant reference for the practical application of seizure detection in the future.

2.2.3 Seizure detection using the SWEC-ETHZ iEEG dataset

Since the long-term SWEC-ETHZ dataset was released online in 2019, there are few studies using this dataset for the analysis of seizure detection. A brief overview of the related studies is given as follows.

In study (Burrello et al., 2019), Burrello et al. first used this dataset and proposed an energy-efficient and fast learning algorithm (named as Laelaps) for seizure detection. The Laelaps used end-to-end binary operations by exploiting symbolic dynamics and brain-inspired hyperdimensional computing. The proposed method achieved a mean sensitivity of 85.5% and a mean FDR of 0/h (FDR was computed only on 20 h of iEEG signals that were randomly selected from interictal testing set per patient). This study also compared the LapLaps with other three models, Linear SVM, LSTM and 2D-CNN, and these three models attained 83.3% sensitivity with 0.31/h FDR, 88.4% sensitivity with 0.54/h, and 76.6% sensitivity with 0.36/h FDR, respectively (Burrello et al., 2019). Then, a novel two-step feature ranking algorithm combined with channel selection strategy is presented by Razi et al. for the patient-specific seizure detection. The proposed method achieved a sensitivity, and specificity of 100% and 97.01%, respectively (Razi and Schmid, 2022). However, this study only used 5 patients from the long-term SWEC-ETHZ iEEG dataset (total 18 patients) for the analysis of seizure detection.

Based on the use of DL methods, study (Praveena et al., 2021) presented a Reconstruction Independent Component Analysis-based Long Short-Term Memory (RICA-LSTM) model for the analysis of the same dataset. The presented model obtained an accuracy of 98.92%, sensitivity of 99.01%, specificity of 98.68%. Then, Sun et al. proposed a novel DL network based on the combination of CNN and the transformer network for seizure detection. The proposed method achieved a sensitivity of 92.3%, and specificity of 99.2% at the segment-based level. At the event-based level, 97.5% sensitivity and 0,06/h FDR were achieved (Sun et al., 2022). For this iEEG dataset, our work proposed a novel method of 1D-CNN combined with a random selection and data augmentation strategy for seizure onset detection. More details of this work are given in the study 2 of Chapter 4 in this dissertation.

2.2.4 Summary of seizure detection studies

In sum, we briefly summarized the related seizure detection work according to the three EEG datasets (Bonn, CHB-MIT and SWEC-ETHZ). Although these studies showed remarkable performances in seizure detection, there are still several considerations that need to be focused and discussed. First, sample imbalance is a key problem in seizure detection, especially for the long-term EEG recordings. This is because a seizure usually lasts for ten of seconds to several minutes, while the interictal phase commonly takes up most of the time in long-term EEG recordings. Hence, in seizure detection, proper solutions can be taken to resolve the problem of sample imbalance during the analysis of long-term EEG recordings. Second, classification results can be evaluated at the segment-based level (sensitivity, specificity and accuracy) and the even-based level (event-based sensitivity and FDR) simultaneously, rather than commonly at one level. By this way, the evaluation of the proposed methods can be more comprehensive.

2.3 Seizure prediction

In this section, the related seizure prediction work using the Freiburg iEEG and the CHB-MIT sEEG datasets is briefly summarized.

2.3.1 Seizure prediction using the Freiburg iEEG dataset

Over the past two decades, the long-term Freiburg iEEG dataset was one of the most commonly used EEG datasets in seizure prediction studies. Many iEEG-based seizure prediction methods have been used to analyze this dataset, and these methods mainly includes threshold crossing analysis, conventional ML, and DL. An overview of these methods is given as follows.

First, time series analysis-based threshold methods can be used (Tong, 2011). In studies using the threshold crossing analysis, linear or non-linear iEEG features were first extracted. Then, according to the changing trend of these features over time, a proper threshold was set to give an alarm. Based on the Freiburg iEEG dataset, the extracted linear or non-linear iEEG features, such as dynamical similarity index (Maiwald et al., 2004), phase coherence or synchronization (Winterhalder et al., 2006; Zheng et al., 2014), spike rate (Li et al., 2013), multiresolution N-gram (Eftekhar et al., 2014), correlation dimension (Aarabi and He, 2017) and fractal dimensions and intercept values (Zhang et al., 2020b), were combined with the threshold crossing analysis to predict seizures, and a sensitivity of 42-92.9% and a false prediction rate (FPR) of 0.04-1/h were attained among these studies.

Second, conventional ML methods, such as SVM and Bayes, were used for seizure prediction based on the same iEEG dataset. In studies (Park et al., 2011; Williamson et al., 2012; Ghaderyan et al., 2014; Wang and Lyu, 2014; Zhang and Parhi, 2015; Parvez and Paul, 2016; Sharif and Jafari, 2017), the SVM was used as a classifier. Different iEEG features, such as spectral power from nine frequency bands (Park et al., 2011), correlation patterns both within and across channels (Williamson et al., 2012), univariate linear features in eight frequency sub-bands (Ghaderyan et al., 2014), amplitude and frequency modulation features (Wang and Lyu, 2014), power spectral density and ratio of the spectral power (Zhang and Parhi, 2015), fuzzy rules on Poincaré plane (Parvez and Paul, 2016) and fractal dimensions and intercept values (Sharif and Jafari, 2017), were extracted among these studies. Then, Bayes related methods were used in studies (Ozdemir and Yildirim, 2014; Yuan et al., 2018) for seizure prediction. In these two studies, HHT based iEEG features (Ozdemir and Yildirim, 2014) and iEEG featues from diffusion distance (Yuan et al., 2018) were extracted, respectively. With the above conventional ML methods, these studies achieved a sensitivity of 85.11-100% and a FPR of 0.03-0.36/h.

Third, recently, DL-based methods, including CNN, Generative Adversarial Networks (GAN), were also used for seizure prediction. In study (Truong et al., 2018), a 2D-CNN model with three convolutional layers was first used on the Freiburg iEEG dataset for seizure prediction. In this study, 30-sec iEEG segments were transformed by STFT to attain time-frequency maps, and these maps were fed into the 2D-CNN model for training and testing. With the analysis of 13 patients, the proposed method achieved an overall sensitivity and FPR of 81.4% and 0.06/h, respectively. Then, study (Wang et al., 2020) also used a 2D-CNN model with three convolutional layers for classification. Different from the study (Truong et al., 2018) using STFT to obtain maps, the Directed Transfer Function (DTF) was used on 10-sec segments to generate channel-frequency maps as the inputs of 2D-CNN model. With the analysis of 19 patients, the presented method attained an averaged sensitivity and FPR of 90.8% and 0.08/h, respectively (Wang et al., 2020). Moreover, study (Truong et al., 2019) used a GAN-based DL method for seizure prediction and attained the AUC of 75.35%.

As mentioned above, many iEEG-based data mining techniques have been used on the Freiburg iEEG dataset for the analysis of seizure prediction and achieved remarkable results. However, about using DL methods to analyze the Freiburg iEEG dataset for seizure prediction, only 2D-CNN and GAN methods were utilized. Other DL methods, such as LSTM and 1D-CNN methods, were not applied in this dataset. Therefore, in this thesis, 1D-CNN related methods are used for seizure prediction, and the comparison of the proposed methods and the previous studies are also discussed based on the Freiburg iEEG dataset. More details of the related work are summarized in Chapter 3.

2.3.2 Seizure prediction using the CHB-MIT sEEG dataset

The CHB-MIT sEEG dataset was also widely utilized for seizure prediction in recent years. sEEG-based methods, including conventional ML and DL methods, were used to analyze this sEEG dataset for seizure prediction.

In studies with conventional ML methods, SVM (Zhang and Parhi, 2015; Usman et al., 2017; Cho et al., 2016; Alickovic et al., 2018), Bayes (Behnam and Pourghassem, 2016), Backpropagation Neural Network (BPNN) (Fei et al., 2017) and MLP (Büyükçakır et al., 2020) were applied, and these studies attained an accuracy of 83.17-99.70% in seizure prediction. Then, in studies using DL methods for seizure prediction, 2D-CNN (Truong et al., 2018; Cao et al., 2019; Gao et al., 2020; Hussein et al., 2021), 3D-CNN (Ozcan and Erturk, 2019; Prathaban and Balasubramanian, 2021), LSTM (Tsiouris et al., 2018; Ryu and Joe, 2021), Deep Recurrent Neural Networks (DRNN) (Borhade and Nagmode, 2020) and Deep Convolutional Generative Adversarial Networks (GCGAN) (Rasheed et al., 2021) were used for classification. A sensitivity of 81.2-100%, accuracy of 92.50-99.72%, and specificity of 93.65-99.60% were attained among these studies. Moreover, study (Liu and Richardson, 2021) used three DL models (DNN, 1D-CNN and Bi-LSTM) simultaneously for comparison in the analysis of seizure prediction, while study (Usman et al., 2021) used an ensemble classifier consisting of three models (2D-CNN, LSTM and SVM) for seizure prediction. In short, many sEEG-based ML and DL methods were applied in the CHB-MIT sEEG dataset for seizure prediction and showed remarkable performances. Since the CHB-MIT sEEG dataset is not used for seizure prediction in this dissertation, a more detailed summary is not given here.

2.3.3 Summary of seizure prediction studies

In sum, many ML and DL methods have been used on the above two EEG dataset for seizure prediction and will provide an important reference value for the practical application of seizure prediction in the future work. However, we still need to pay attention to the following considerations. One consideration is that many previous studies commonly used EEG signals of all channels for seizure prediction, and the combination of EEG channel selection and DL methods is less studied. EEG signals are complicated both in spatial and time domains. Feature selection in the spatial domain (i.e., channel selection) can be further researched in this field, especially in the combination with DL methods. Thus, whether EEG channel selection is benefit to seizure prediction have not been well studied yet. Second, sample imbalance is also a key problem in seizure prediction. A proper solution, such as down sampling, data augmentation or recording continuous EEG signals with more seizures, is needed. Third, seizure prediction results can also be evaluated at two levels (segment-based and even-based levels) simultaneously, rather than commonly at one level. Acording to the above considerations, this dissertation combines 1D-CNN methods with channel selection strategy in seizure prediction, and more details of the related work are given in Chapter 4.

3 AIM OF THIS DISSERTATION

This dissertation aims to use CNN related techniques on epileptic EEG signals for seizure detection and prediction. Hence, CNN techniques are applied to analyze several commonly used EEG datasets for exploring effective seizure detection and prediction approaches. In addition, for the problem of sample imbalance and the less study of EEG channel selection combined with CNN, corresponding strategies are also proposed to cooperate with CNN methods during the analysis of EEG signals. The specific aim of each sub-study is given as follows.

1. The use of short-term EEG signals for seizure detection. This study applies 1D-CNN and 2D-CNN simultaneously in the short-term Bonn EEG dataset for seizure detection. (*Article I*)

2. The use of long-term sEEG and iEEG signals for seizure onset detection. This study presents a novel seizure onset detection method of 1D-CNN combined with a random selection and data augmentation (RS-DA) strategy for the analysis of the long-term CHB-MIT sEEG and SWEC-ETHZ iEEG datasets. (*Article II*)

3. The use of long-term iEEG signals for seizure prediction. This study proposes a novel seizure prediction method of 1D-CNN combined with channel selection strategy for the analysis of the long-term Freiburg iEEG dataset. (*Article III*)

4. The further analysis of channel selection strategy in seizure prediction. Since the *Article III* selects the best channel case for each patient only from 9 channel cases (total 63 channel cases), this study further discusses all channel cases for seizure prediction based on the same iEEG dataset. (*Article IV*)

5. The further use of channel selection strategy on long-term iEEG signals for seizure prediction. This study proposes a channel increment strategy-based 1D-CNN method for seizure prediction using the Freiburg iEEG dataset. In addition, two model training strategies are performed for comparison. (*Article V*)

4 SUMMARY OF STUDIES

This chapter gives a brief summary of each study, including objective, method, result and discussion. The author contributions for each study are also presented.

4.1 *Article I*: One and Two Dimensional Convolutional Neural Networks for Seizure Detection Using EEG Signals

Article I: **Xiaoshuang Wang**, Tapani Ristaniemi & Fengyu Cong (2021, January). One and Two Dimensional Convolutional Neural Networks for Seizure Detection Using EEG Signals. In *2020 28th European Signal Processing Conference (EUSIPCO 2020)* (pp. 1387-1391). IEEE.

Objective

CNN, as a leading DL method, has showed remarkable performances in image recognition, etc. The use of EEG-based CNN methods for seizure detection has attracted an increasing attention in recent years. Thus, in this work, 1D-CNN and 2D-CNN were simultaneously used on the short-term EEG signals for the analysis of seizure detection.

Methods

The short-term Bonn EEG dataset (mentioned in subsection 2.1.1) was utilized in this work. First, 1-sec and 2-sec EEG segments were generated by using 1-sec and 2-sec sliding windows to segment raw EEG signals, respectively. Next, continuous wavelet transform (CWT) was used on the EEG segments to obtain time-frequency representations. Then, EEG segments were fed into a 1D-CNN model with three convolutional layers for model training and testing, while the obtained time-frequency maps were fed into a 2D-CNN model with also three convolutional layers 2D-CNN model for model training and testing (as shown in

Fig. 5). We studied the two-classification and the three-classification situations. In the two-classification situation, three conditions, including set A (normal) vs. set E (interictal), set C (interictal) vs. set E (ictal) and set A (normal) vs. set C (interictal), were discussed. In the three-classification situation, two conditions, including set A (normal) vs. set C (interictal) vs. set E (ictal) and sets AB (normal) vs. sets CD (interictal) vs. set E (ictal), were discussed. About model training, the ten-fold cross validation strategy was performed.

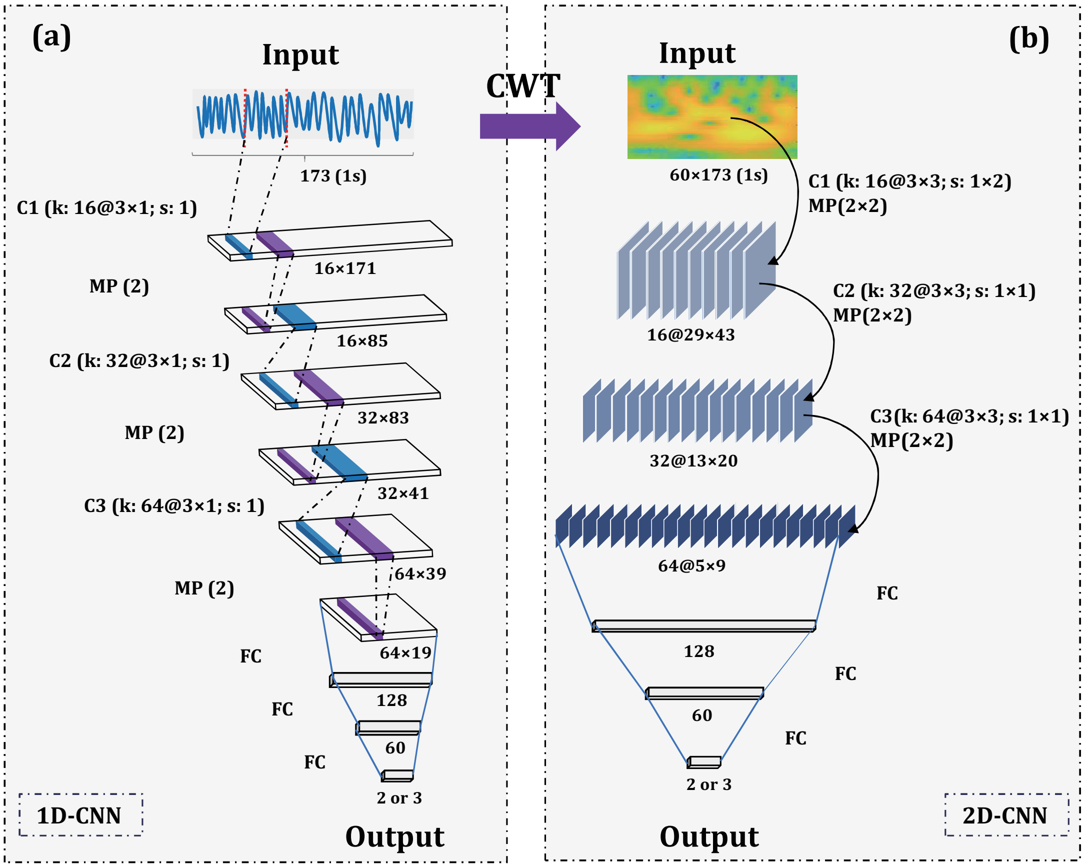

FIGURE 5 Diagram of the used 1D-CNN and 2D-CNN models in seizure detection under the preprocessing condition of 1-sec sliding windows. Abbr: convolutional layers, C1, C2 and C3; Max-pooling layers, MP; Fully connected layers, FC; k, number and size of kernels; s, stride.

Results

In the two-classification situation: (1) Results of set A vs. set E, the 2D-CNN model with the preprocessing of 1-sec sliding windows and the 1D-CNN model with the preprocessing of 2-sec sliding windows achieved a same highest accuracy of 99.92%. (2) Results of set C vs. set E, the 2D-CNN model with the preprocessing of 2-sec sliding windows attained a highest accuracy of 99.28%. (3) Results of set A vs. set C, the 1D-CNN model with the preprocessing of 2-sec sliding windows obtained a highest accuracy of 97.47%.

In the three-classification situation: (1) Results of set A vs. set C vs. set E, the 2D-CNN model with the preprocessing of 2-sec sliding windows achieved an overall highest result of 99.55%% accuracy, 99.16% sensitivity and 99.75% specificity. (3) Results of sets AB vs. sets CD vs. set E, the 1D-CNN model with the preprocessing of 2-sec sliding windows obtained an overall highest result of 99.41% accuracy, 97.80% sensitivity and 99.81% specificity.

Discussion

In this study, we applied 1D-CNN and 2D-CNN models simultaneously for seizure detection, and both models achieved remarkable results based on the short-term Bonn EEG dataset. In the two-classification and the three-classification situations, the highest accuracy can reach at 99.92% and 99.55%, respectively. This showed that our work was effective for the classification of EEG signals in seizure detection.

Author contributions

Xiaoshuang Wang presented the methods, performed the data analysis and wrote the manuscript. **Tapani Ristaniemi** and **Fengyu Cong** supervised the study and revised the manuscript.

4.2 *Article II*: One Dimensional Convolutional Neural Networks for Seizure Onset Detection Using Long-term Scalp and Intracranial EEG

Article II: **Xiaoshuang Wang**, Xiulin Wang, Wenya Liu, Zheng Chang, Tommi Kärkkäinen & Fengyu Cong (2021). One dimensional convolutional neural networks for seizure onset detection using long-term scalp and intracranial EEG. *Neurocomputing*, 459, 212-222.

Objective

The first study only used a short-term EEG dataset for the analysis of seizure detection. However, the use of long-term EEG signals may have more practical significance. This is because EEG recordings of epileptic patients always last from several hours to several days in the real world. Therefore, this study analyzed two long-term EEG datasets (one sEEG and one iEEG) and applied CNN related techniques for seizure detection based on these two datasets.

Methods

Two long-term EEG datasets, the CHB-MIT sEEG and the SWEC-ETHZ iEEG (mentioned in subsections 2.1.2 and 2.1.3), were utilized for seizure onset detection in this work. First, 2-sec sliding windows were used to segment raw EEG

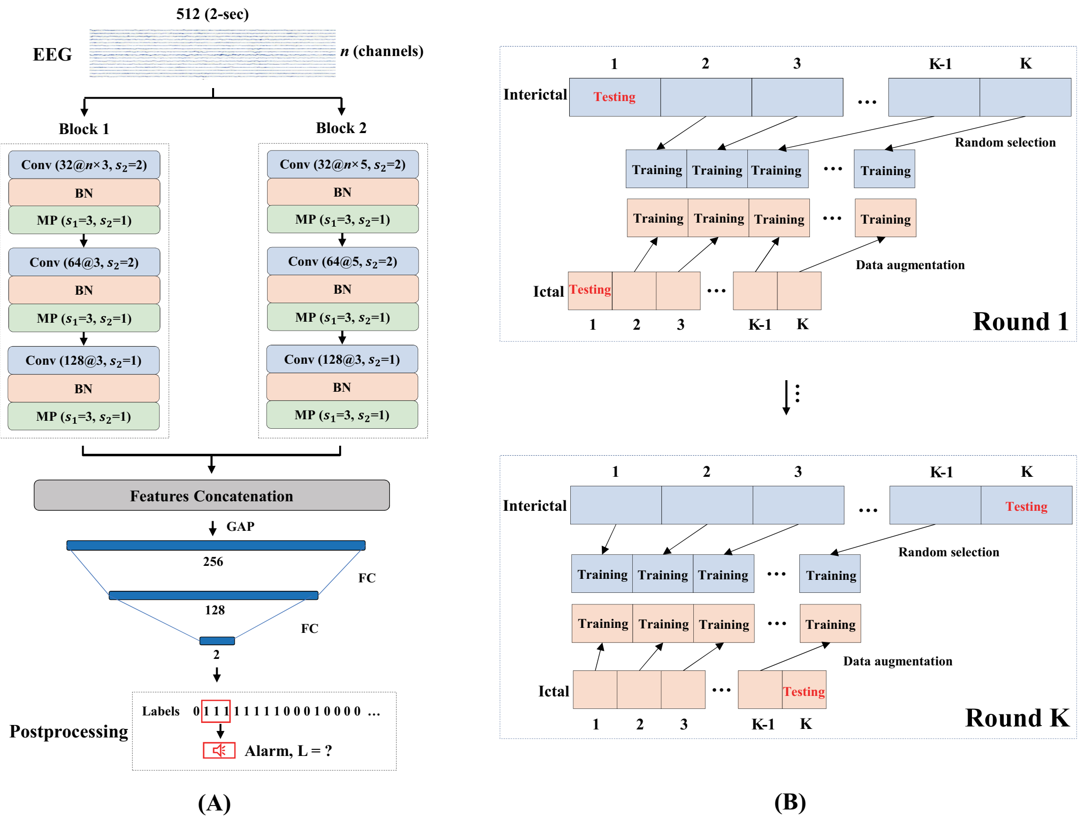

FIGURE 6 Proposed 1D-CNN model and model training strategy for seizure prediction. (A) A stacked 1D-CNN model with two convolutional blocks and two fully connected layers was used for seizure detection. L is the number of consecutive detection labels for an alarm at the event-based level (L=3 was finally set in this work). (B) Event-based K-fold cross validation combined with a RS-DA strategy was performed during model training.

signals. Then, 2-sec EEG segments as the input signals were fed into a stacked 1D-CNN model (as shown in Fig. 6(A)) for model training and testing. In this work, sample imbalance (interictal » ictal) is a key problem and needs to be resolved. Hence, a RS-DA strategy combined with event-based K-fold cross validation (K is the number of seizures per patient) was performed during model training (as shown in Fig. 6(B)). The patient-specific model was trained for each patient. Finally, in system evaluation, we evaluated the classification results at two levels simultaneously, namely the segment-based level and the event-based level. At the segment-based level, the averaged sensitivity, specificity, and accuracy were given. At the event-based level, even-based sensitivity, FDR and latency were computed.

Results

1) Results of the CHB-MIT sEEG dataset As shown in Table 5, the classification results of each patient were calculated and evaluated at the two levels. For the CHB-MIT sEEG dataset, we achieved an overall sensitivity, specificity, and accuracy of 88,14%, 99.62% and 99.54%, respectively. At the event-based level, we attained an overall event-based sensitivity, RDR, and latency of 99.31%, 0.20/h and 8.1 s, respectively.

2) Results of the SWEC-ETHZ iEEG dataset As shown in Table 6, the classification results of each patient were also computed and evaluated at the two levels. For the SWEC-ETHZ iEEG dataset, an overall sensitivity of 90.09%, specificity of 99.81%, and accuracy of 99.73% were obtained at the segment-based level. At the event-based level, an overall even-based sensitivity of 97.52%, FDR of 0.07/h, and latency of 13.2 s were achieved.

TABLE 5 Results for each patient at two levels in the CHB-MIT sEEG dataset.

Patient	#Seizures *K*-Fold	Segment-based level			Event-based level		
		Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FDR (/h)	Lat (s)
1	7	98.00	99.82	99.81	100	0.04	6.3
2	3	91.73	99.90	99.88	100	0	8.7
3	7	99.00	99.84	99.84	100	0.08	6.3
4	4	85.89	99.78	99.73	100	0	8
5	5	97.05	99.91	99.89	100	0	7.2
6	10	86.46	99.73	99.71	100	0.04	8
7	3	92.65	99.93	99.89	100	0.04	7.3
8	5	91.99	98.91	98.77	100	0.6	7.6
9	3	95.10	99.91	99.90	100	0.08	8
10	7	92.45	99.88	99.84	100	0	6.3
11	3	99.02	99.92	99.90	100	0	6
12	10	81.06	98.69	98.17	100	1.42	10
13	8	76.41	99.09	98.92	100	0.79	9.8
14	7	70.16	99.46	99.39	100	0	8.6
15	14	94.98	99.36	99.25	100	0.33	7.7
16	6	69.96	99.56	99.50	83.33	0.08	7.6
17	3	85.02	99.61	99.55	100	0.17	8
18	5	81.15	99.65	99.58	100	0.17	7.6
19	3	92.31	99.91	99.89	100	0	6
20	6	82.58	99.64	99.59	100	0.17	9.7
21	4	97.48	99.66	99.65	100	0.17	6
22	3	89.94	99.95	99.93	100	0.04	14.7
23	5	96.53	99.62	99.59	100	0.61	6
24	14	68.43	99.19	98.82	100	0.08	12.6
Total	145	88.14	99.62	99.54	99.31	0.20	8.1

Abbreviations: Sen_1, segment-based sensitivity; Spe, specificity; Acc, accuracy; Sen_2, event-based sensitivity; FDR, false detection rate; Lat, latency

Discussion

In this work, a novel method of 1D-CNN combined with a DS-DA strategy was proposed for seizure onset detection. The proposed method was tested on two long-term EEG datasets (CHB-MIT sEEG and SWEC-ETHZ iEEG) and achieved remarkable seizure detection performances. This showed that our method was effective for the analysis of two different datasets, sEEG and iEEG. It may provide a reference value for the practical application of seizure detection in the future.

TABLE 6 Results for each patient at two levels in the SWEC-ETHZ iEEG dataset.

Patient	#Seizures K-Fold	Segment-based level			Event-based level		
		Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FDR (/h)	Lat (s)
1	2	93.59	99.94	99.85	100	0	10
2	2	97.67	99.86	99.85	100	0.13	9
3	4	100	99.88	99.88	100	0.17	6
4	14	75.56	99.31	99.19	92.86	0.13	12.8
5	4	100	99.67	99.67	100	0.33	6
6	8	81.61	99.96	99.80	87.50	0	6.6
7	4	70.53	99.89	99.84	75.00	0.04	14
8	7	78.93	99.53	99.04	100	0.04	52.3
9	17	98.64	99.84	99.83	100	0	7.3
10	16	96.44	99.95	99.89	100	0	6.9
11	2	100	99.99	99.99	100	0	6
12	9	97.04	99.80	99.77	100	0	9.6
13	7	86.55	99.85	99.78	100	0	11.4
14	16	94.87	99.61	99.49	100	0	6.8
15	2	94.52	99.98	99.97	100	0	14
16	5	96.44	99.94	99.90	100	0	13.2
17	2	85.57	99.81	99.78	100	0.17	22
18	5	73.70	99.68	99.53	100	0.21	24.4
Total	126	90.09	99.81	99.73	97.52	0.07	13.2

Author contributions

Xiaoshuang Wang presented the methods, performed the data analysis and wrote the manuscript. **Xiulin Wang** and **Wenya Liu** performed the data analysis and revised the manuscript. **Zheng Chang**, **Tommi Kärkkäinen** and **Fengyu Cong** supervised the study and revised the manuscript.

4.3 *Article III*: One-Dimensional Convolutional Neural Networks Combined with Channel Selection Strategy for Seizure Prediction Using Long-Term Intracranial EEG

Article III: **Xiaoshuang Wang**, Guanghui Zhang, Ying Wang, Lin Yang, Zhanhua Liang & Fengyu Cong (2021). One-Dimensional Convolutional Neural Networks Combined with Channel Selection Strategy for Seizure Prediction Using Long-Term Intracranial EEG. *International journal of neural systems*, 32 (02), 2150048.

Objective

After the study of EEG-based seizure detection, a further study comes to the EEG-based seizure prediction. EEG-based seizure prediction is still challenging because of complicated signals in time and spatial domains. Feature selection in the spatial domain (i.e., channel selection) combined with DL methods is less studied in this field. Hence, this study proposed a novel method of 1D-CNN combined with channel selection strategy for seizure prediction.

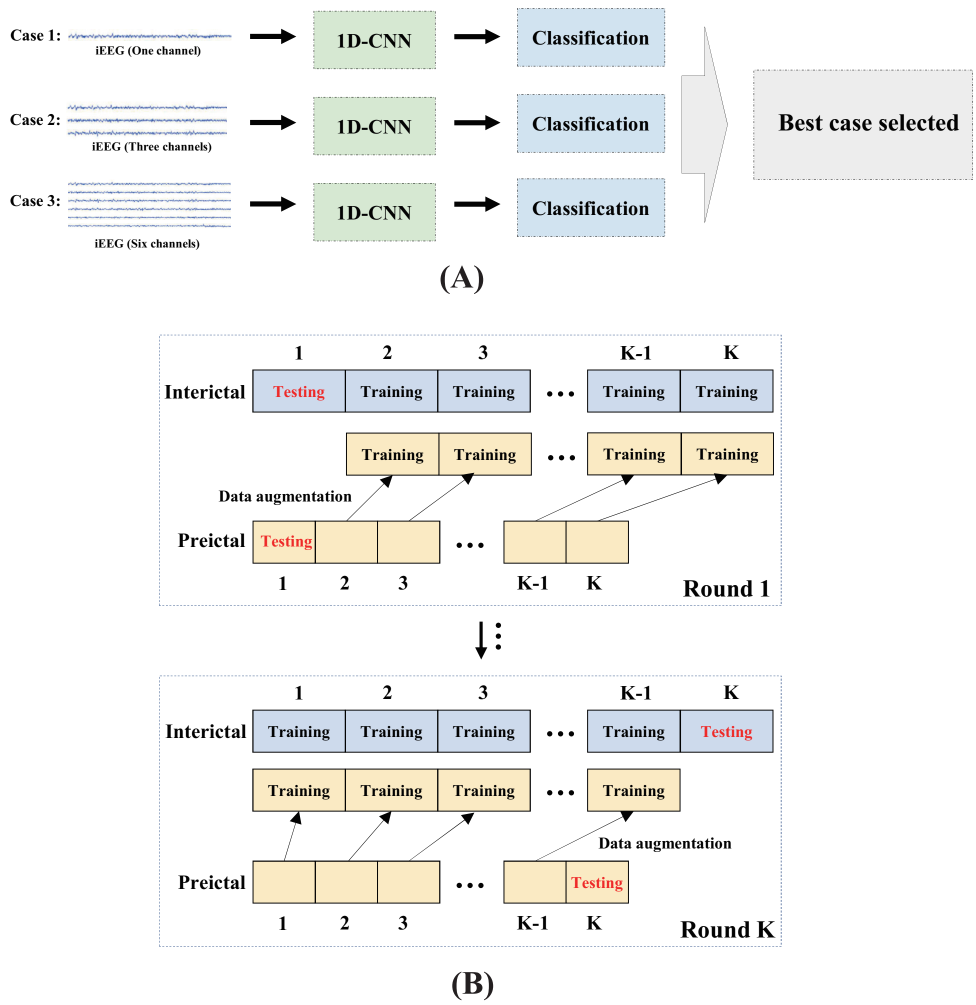

FIGURE 7 Diagram of 1D-CNN combined with channel selection and model training in seizure prediction. (A) Diagram of 1D-CNN combined with channel selection for seizure prediction. (B) K-CV with data augmentation approach during model training.

Methods

The long-term Freiburg iEEG dataset (mentioned in subsection 2.1.4) was utilized for seizure prediction, and each patient had six iEEG channels, three in-focus channels (marked as channels 1-3) and three out-of-focus channels (marked as channels 4-6). First, we used 30-sec sliding windows to segment raw iEEG signals. Then, 30-sec segments with nine channel cases (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6) were sequentially fed into the constructed 1D-CNN model for model training and testing (as shown in Fig. 7(A)). The K-CV (K is the number of seizures per patient) was performed during model training, and in each training round, a data augmentation approach (sliding windows with overlap) was only used on preictal signals which were selected as the training set (as shown in Fig. 7(B)).

Patient-specific model was trained for each patient. Finally, the classification results of nine channel cases were calculated, and the channel case with the highest classification rate was finally selected for each patient. In this work, we discussed two preictal conditions: (1) SOP = 30 min and SPH = 5 min, (2) SOP = 60 min and SPH = 5 min. We also compared our method with the random predictor by computing statistical significance.

Results

1) Results of SOP = 30 min and SPH = 5 min After selecting the best channel case for each patient, we summarized the correspond-ing results of all patients in Table 7. As shown in Table 7, 86 out of 87 seizures (except one seizure in patient 13) were correctly predicted, and our method achieved an overall accuracy, event-based sensitivity, and FPR of 98.60%, 98.85% and 0.01/h, respectively. From the p_{-value} (< 0.05) of each patient, our method was also statistically better than the random predictor for all patients.

TABLE 7 Results of our method with SOP of 30 min and SPH of 5 min.

Patient	Interictal (h)	#seizures	C_s^*	Accuracy (%)	Sensitivity (%)	FPR (/h)	p_{-value}
1	24	4	1^a	99.13±0.77	100±0.00	0.00±0.00	0.000
2	24	3	4^b	99.66±0.02	100±0.00	0.00±0.00	0.000
3	24	5	1^a	98.13±0.02	100±0.00	0.00±0.00	0.000
4	24	5	2^a	99.21±0.00	100±0.00	0.00±0.00	0.000
5	24	5	1^a	95.58±1.93	100±0.00	0.06±0.09	0.000
6	24	3	1^a	99.08±0.05	100±0.00	0.00±0.00	0.000
7	24.6	3	$4\text{-}6^b$	97.65±0.16	100±0.00	0.00±0.00	0.000
8	24.2	2	$1\text{-}3^a$	99.64±0.09	100±0.00	0.00±0.00	0.000
9	23.9	5	5^b	100±0.00	100±0.00	0.00±0.00	0.000
10	24.5	5	3^a	99.41±0.00	100±0.00	0.00±0.00	0.000
11	24.1	4	2^a	99.89±0.07	100±0.00	0.00±0.00	0.000
12	24	4	3^a	99.84±0.18	100±0.00	0.00±0.00	0.000
13	24	2	5^b	97.98±0.02	50±0.00	0.00±0.00	0.000
14	23.9	4	3^a	99.89±0.07	100±0.00	0.00±0.00	0.000
15	24	4	4^b	98.62±0.32	100±0.00	0.00±0.00	0.000
16	24	5	$4\text{-}6^b$	99.32±0.42	100±0.00	0.00±0.00	0.000
17	24.1	5	$4\text{-}6^b$	99.58±0.29	100±0.00	0.00±0.00	0.000
18	24.9	5	4^b	92.80±2.65	100±0.00	0.25±0.06	0.000
19	24.4	4	1^a	98.70±0.49	100±0.00	0.00±0.00	0.000
20	25.6	5	$1\text{-}3^a$	98.20±0.19	100±0.00	0.00±0.00	0.000
21	23.9	5	2^a	98.28±0.16	100±0.00	0.00±0.00	0.000
Total	508.1	87	–	98.60±0.38	98.85±0.00	0.01±0.01	–

The whole algorithm runs twice. The averaged results (accuracy, sensitivity and FPR) and the p_{-value} are summarized for each patient after selecting the best channel case.
[*] *Cs* means channel selected for the best classification; [a] Channels only from seizure onset zones of the brain; [b] Channels only from seizure free zones of the brain.

2) Results of SOP = 60 min and SPH = 5 min Patients 2 and 6 were excluded because of the preictal phase of these two patients was less than 65 min. Therefore, only 19 patients were considered. After selecting the best channel case for each patient, we also summarized the corresponding results of 19 patients in Table 8.

TABLE 8 Results of our method with SOP of 60 min and SPH of 5 min.

Patient	Interictal (h)	#seizures	Cs^*	Accuracy (%)	Sensitivity (%)	FPR (/h)	p_{-value}
1	24	3	1^a	97.27±0.85	100±0.00	0.00±0.00	0.000
3	24	4	1^a	97.69±1.54	100±0.00	0.00±0.00	0.000
4	24	3	2^a	99.26±0.00	100±0.00	0.00±0.00	0.000
5	24	2	5^b	91.19±0.68	100±0.00	0.19±0.03	0.000
7	24.6	3	1^a	98.21±0.44	100±0.00	0.00±0.00	0.000
8	24.2	2	$1\text{-}3^a$	99.92±0.02	100±0.00	0.00±0.00	0.000
9	23.9	3	5^b	99.57±0.00	100±0.00	0.00±0.00	0.000
10	24.5	5	3^a	99.80±0.04	100±0.00	0.00±0.00	0.000
11	24.1	3	2^a	99.64±0.11	100±0.00	0.00±0.00	0.000
12	24	3	4^b	99.31±0.11	100±0.00	0.00±0.00	0.000
13	24	2	5^b	96.12±0.05	50±0.00	0.00±0.00	0.000
14	23.9	3	3^a	99.66±0.18	100±0.00	0.00±0.00	0.000
15	24	3	4^b	97.89±0.55	100±0.00	0.00±0.00	0.000
16	24	5	$4\text{-}6^b$	99.40±0.41	100±0.00	0.00±0.00	0.000
17	24.1	5	$4\text{-}6^b$	97.75±0.14	100±0.00	0.04±0.00	0.000
18	24.9	5	$4\text{-}6^b$	98.06±1.72	100±0.00	0.00±0.00	0.000
19	24.4	3	3^a	99.80±0.06	100±0.00	0.00±0.00	0.000
20	25.6	5	$1\text{-}3^a$	98.47±0.08	100±0.00	0.00±0.00	0.000
21	23.9	4	2^a	99.05±0.25	100±0.00	0.00±0.00	0.000
Total	460.1	66	–	98.32±0.38	98.48±0.00	0.01±0.00	–

As shown in Table 8, 65 out of 66 seizures (except one seizure in patient 13) were accurately predicted. Our method attained an overall accuracy, event-based sensitivity, and FPR of 98.32%, 98.48% and 0.01/h, respectively. The performance of our method was also statistically better than that of the random predictor according to the p_{-value} of each patient in Table 8.

Discussion

In this study, a novel method of 1D-CNN combined with channel selection strategy was proposed for seizure prediction. The proposed method finally achieved an accuracy, sensitivity, and FPR of 98.32-98.60%, 98.48-98.85% and 0.01/h, respectively. Compared to most of the previous studies using the same iEEG dataset, our method showed a better performance in seizure prediction. This showed that our method was effective in seizure prediction, and the channel selection for each patient was necessary.

Author contributions

Xiaoshuang Wang presented the methods, performed the data analysis and wrote the manuscript. **Guanghui Zhang** performed the data analysis and revised the manuscript. **Ying Wang** and **Lin Yang** revised the manuscript. **Zhanhua Liang** and **Fengyu Cong** supervised the study and revised the manuscript.

4.4 *Article IV*: Seizure Prediction Using EEG Channel selection Method

Article IV: **Xiaoshuang Wang**, Tommi Kärkkäinen & Fengyu Cong (2022). Seizure Prediction Using EEG Channel selection Method. *32nd IEEE International Workshop on Machine Learning for Signal Processing (MLSP 2022)*, IEEE.

Objective

In *Article III*, we proposed a 1D-CNN combined with channel selection method for seizure prediction, and the proposed method was tested on the Freiburg iEEG dataset (21 patients, each patient has six iEEG channels). Consequently, there are 63 channel cases ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$) that can be analyzed. However, *Article III* only considered nine channel cases (1, 2, 3, 4, 5, 6, 1-3, 4-6, 1-6) for channel selection. Therefore, in this seizure prediction study, based on the same iEEG dataset, we analyzed all channel cases for channel selection. This work also discussed and compared the classification results under the condition of two different sample sizes.

Methods

The used dataset was the same as that of *Article III*. First, 15-sec and 30-sec were used to segment raw iEEG signals, respectively. Next, 15-sec iEEG segments with an increasing number of channels (from one channel to six channels) were sequentially input into the 1D-CNN model for model training and testing. The processing of 30-sec iEEG segments was the same as that of the 15-sec iEEG segments. Then, K-CV combined with a data augmentation approach (same as the *Study 3*) was performed during model training. We evaluated the classification results at the two levels (segment- and event-based levels) simultaneously for selecting the best channel case for each patient. Patient-specific model was trained per patient. In this work, we also discussed two preictal conditions: (1) SOP = 30 min and SPH = 5 min, (2) SOP = 60 min and SPH = 5 min. In each preictal condition, the classification results of two different sample sizes (15-sec and 30-sec) were also computed and compared.

Results

1) Results of SOP = 30 min and SPH = 5 min After selecting the best channel case for each patient, we summarized the corresponding results in Table 9. For the preprocessing of 15-sec sliding windows, we attained an averaged sensitivity, specificity, and accuracy of 89.21%, 99.73% and 98.99% at the segment-based level. At the event-based level, an event-based sensitivity of 98.85 and an FPR of 0/h were achieved. For the preprocessing of 30-sec sliding windows, we obtained an averaged sensitivity of 89.03%, specificity of 99.68%, and accuracy of 98.85% at the segment-based level. At the event-based level, we achieved a same averaged event-based sensitivity of 98.85% with an FPR of 0.01/h. About the channel case

TABLE 9 Selected channel cases and corresponding results for each patient in the condition of SOP = 30 min.

			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	–

Red numbers: in-focus channels; Blue numbers: out-of-focus channels. 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 10 Selected channel cases and corresponding results for each patient in the condition of SOP = 60 min.

			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	–

selected for each patient, most of patients (except patients 3, 5 and 18) had the same channel cases for both preprocessing conditions. The performance of our method was also statistically better than that of the random predictor for all patients according to the p_v in Table 9.

2) Results of SOP = 60 min and SPH = 5 min Patients 2 and 6 were not considered due to the preictal phase of less than 65 min. Table 10 summarized the classification results of each patient after selecting the best channel case per patient. As shown in Table 10, under the preprocessing of 15-sec sliding windows, an overall 90.44% sensitivity, 98.99% specificity, and 98.07% accuracy were achieved at the segment-based level. An overall 98.48% event-based sensitivity and 0.02/h FPR were obtained at the event-based level. Under the preprocessing of 30-sec sliding windows, we attained an overall 98.84% sensitivity, 99.12% specificity and 98.22% accuracy. At the event-based level, the overall results were the same as those of the preprocessing of 15-sec sliding windows. For the selected channel case per patient, each patient had the same channel case for both two preprocessing conditions. From the p_v in Table 10, our method also showed a better performance than the random predictor.

Discussion

In this study, the method of 1D-CNN combined with the channel selection strategy was further discussed for seizure prediction. Different from the *Article III* only used nine channel cases, this work considered all channel cases for channel selection per patient. Based on the same iEEG dataset, the proposed method finally achieved a high event-based sensitivity of 98.48-98.85% and a low FPR of 0-0.02/h at the event-based level. At the segment-based level, the overall sensitivity of 89.03-90.84%, specificity of 98.99-99.73%, and accuracy of 98.07-98.99% were obtained. From these results, we could see that our method had a remarkable performance in seizure prediction.

Author contributions

Xiaoshuang Wang presented the methods, performed the data analysis and wrote the manuscript. **Tommi Kärkkäinen** and **Fengyu Cong** supervised the study and revised the manuscript.

4.5 *Article V*: Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG

Article V: **Xiaoshuang, Wang**, Chi Zhang, Tommi Kärkkäinen, Zheng Chang, & Fengyu Cong (2022). Channel Increment Strategy-Based 1D Convolutional Neural Networks for Seizure Prediction Using Intracranial EEG. Accepted in *IEEE*

Transactions on Neural Systems and Rehabilitation Engineering.

Objective

In this study, we also used the long-term iEEG dataset for the analysis of seizure prediction. Our work proposed a channel increment strategy-based 1D-CNN method for seizure prediction and discussed two model training strategies for the comparison of classification results.

Methods

16 patients with at least 4 seizures were selected from the Freiburg iEEG dataset (total 21 patients) for seizure prediction. For the selected iEEG signals, 4-sec sliding windows without overlap were first used to segment raw iEEG signals. Next, 4-sec segments with a varied number of channels (from one channel to all channels) were fed into the 1D-CNN model in turn for classification. About model training, two model training strategies (Stratrgy-1 and Strategy-2) were discussed. (1) In the Strategy-1, a basic K-CV (as shown in Fig. 8(A)), the model training was done K rounds, where K is the number of seizures per patient. (2) In the Strategy-2, the difference from the Strategy-1 is that a trained model selection is added during model training. (as shown in Fig. 8(B)). We first leaved one part as a testing set, while the other parts were used as the training set (90%) for model training and the validation set (10%) for selecting excellent trained models from the all trained models (because there are 63 trained models corresponding to 63 channel cases, and the selection criteria of the trained models are based on the F1 score of the validation set). Then, the selected trained models were used to test the testing set. Patient-specific model was trained for each patient. We evaluated the classification results at two levels (segment- and event-based levels), and one preictal condition of SOP = 30 min and SPH = 5 min was considered in this work.

Results

1) Results of the Strategy-1 The whole algorithm runs twice. The averaged sensitivity (Sen_1), specificity (Spe), and accuracy (Acc) are computed at the segment-based level. At the event-based level, the averaged event-based sensitivity (Sen_2), and FPR are calculated. Then, from 63 channel cases ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$), the best channel case is selected for each patient based on the results of both levels simultaneously, and the corresponding classification results are summarized. After selecting the best channel case for each patient, the correspongding results of each patient are given in Table 11. As shown in Table 11, at the segment-based level, an overall 90.18% sensitivity, 94.81% specificity, and 94.42% accuracy were attained. At the event-based level, the event-based sensitivity of 100% (74 seizures are all predicted) with 0.12/h FPR was attained. Based on the p_v values in Table 11, the performance of the proposed method is better than that of the random predictor for all patients.

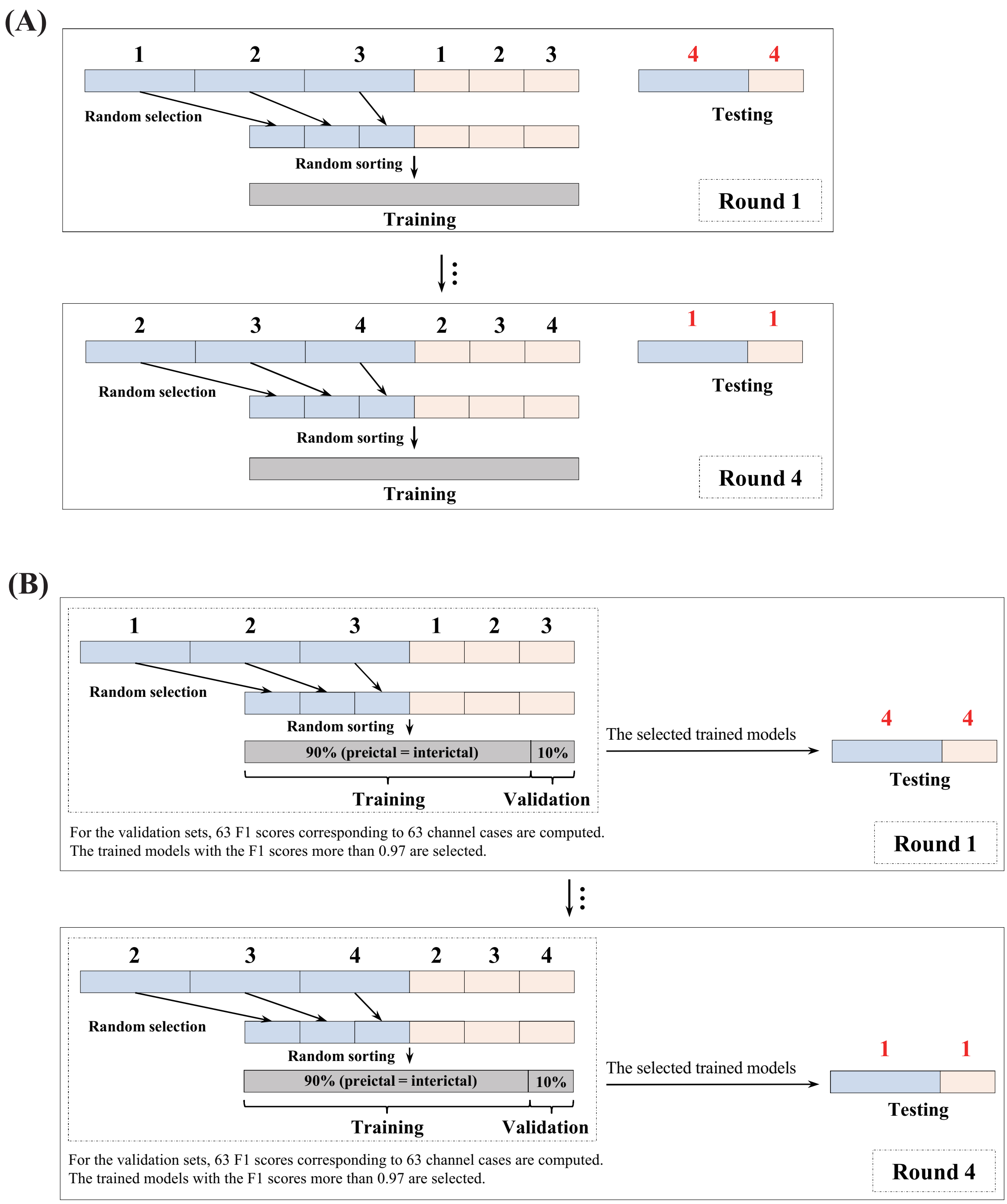

FIGURE 8 Two model training strategies based on the K-CV in seizure prediction. (A) Example of the Strategy-1 combined with the data random selection approach (for solving sample imbalance) during mode training for patients with 4 seizures. (B) Example of the Strategy-2 for patients with 4 seizures.

TABLE 11 Selected channel cases and corresponding results for each patient in the Strategy-1.

			Segment-based level			Event-based level		
Patient	#Seizure	Cs	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.

2) Results of the Strategy-2 Different from the Strategy-1, a trained model selection step is added in each round (as shown in Figure 8(B)). The whole algorithm also runs twice. After running twice, one channel case can achieve an averaged F1 score in one round. Consequently, one channel case has K averaged F1 scores after K rounds. In this work, only when K averaged F1 scores of a channel case are all greater than 0.97, the corresponding channel case is considered and selected for the final best channel case selection. After some satisfactory channel cases are first selected, the classification results of the testing sets from the 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. As shown in Table 12, we attained an overall 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 overall event-based sensitivity, and FPR of 98.65% and 0.08/h, respectively. 73 out of 74 seizures were correctly predicted (except one seizure in patient 5). According to the p_v values in Table 12, the proposed method also showed a better performance than the random predictor for all patients.

Discussion

In this study, a channel increment strategy-based 1D-CNN method was proposed for seizure prediction. In the Strategy-1, the proposed method predicted all seizures, and a high event-based sensitivity of 100% and a low FPR of 0.12/h were achieved at the event-based level. At the segment-based level, a sensitivity of 90.18%, specificity of 94.81%, and accuracy of 94.42% were attained. In the Strategy-2, 73 out of seizures were predicted, and an event-based sensitivity of 98.65 and a low FPR of 0.08/h were attained. A sensitivity of 86.23%, specificity of 96.00%, and accuracy of 95.13% were obtained at the segment-based level. From these

TABLE 12 Selected channel cases and corresponding results for each patient in the Strategy-2.

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	–

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

Author contributions

Xiaoshuang Wang presented the methods, performed the data analysis and wrote the manuscript. **Chi Zhang** revised the manuscript. **Zheng Chang**, **Tommi Kärkkäinen** and **Fengyu Cong** supervised the study and revised the manuscript.

5 DISCUSSION AND CONCLUSION

In this chapter, we first summarize this dissertation according to the mentioned studies. Then, the limitations of this dissertation and the future directions are discussed.

5.1 Summary of the dissertation

In this dissertation, CNNs were effectively applied in both sEEG and iEEG signals for the analysis of seizure detection and prediction. Two articles (*Articles I* and *II*) focused on using CNNs on sEEG and iEEG signals for seizure detection. Three articles (*Articles III*, *IV* and *V*) focused on the combination of channel selection and 1D-CNNs for seizure prediction using long-term iEEG signals.

In seizure detection studies, we explored the performances of CNNs on seizure detection. *Article I* first used 1D-CNN and 2D-CNN simultaneously on the short-term sEEG and iEEG signals for seizure detection. In this study, 12-layer 1D-CNN and 2D-CNN models were constructed and tested on the short-term Bonn EEG database for seizure detection. Both models finally achieved remarkable results in seizure detection. *Article II* focused on the application of 1D-CNN in long-term sEEG and iEEG signals for the analysis of seizure detection. This study constructed a stacked 1D-CNN model and effectively evaluated the proposed 1D-CNN model on two long-term EEG datasets (CHB-MIT sEEG and SWEC-ETHZ iEEG). To solve the problem of sample imbalance, this study also proposed a RS-DA strategy to balance samples during model training. The above two studies successfully applied CNNs in short- and long-term sEEG and iEEG signals for seizure detection, and the achieved results showed that CNNs have remarkable performances in seizure detection.

From the research of seizure detection, seizure prediction using EEG signals was further researched in this dissertation. Considering the combination of EEG channel selection and DL methods is less studied in seizure prediction, the combination of EEG channel selection and DL methods was therefore further explored. *Articles III* and *IV* proposed a novel method of 1D-CNN combined with channel selection in seizure prediction. The proposed method was tested on the Freiburg iEEG dataset and achieved commendable results. With the same iEEG dataset, in *Article V*, an iEEG-based method of channel increment strategy combined with 1D-CNN was presented to predict seizures. In this study, two model training strategies based on the K-CV were also discussed to evaluate the proposed method, and remarkable results were attained. The three mentioned studies showed that the combination of channel selection and CNN is effective in seizure prediction, and channel selection is an significant method when using EEG signals for seizure prediction.

In conclusion, this dissertation systematically used both sEEG and iEEG signals for the study of seizure detection and prediction. With sEEG and iEEG signals, several different CNN models (1D-CNN and 2D-CNN) were constructed and successfully tested, and channel selection also plays a significant role in seizure prediction.

5.2 Limitations and future directions

As we mentioned in the dissertation, CNNs were well used on sEEG and iEEG signals for the analysis of seizure detection and prediction, and the combination of channel selection and CNNs was also effectively applied for seizure prediction. However, there are several limitations or considerations that need to be discussed. One limitation is about the use of EEG data. In this dissertation, the analysis of seizure detection and prediction is based on four public EEG datasets. About these four EEG databsets, two of them are from two decades ago, and one of them is from ten years ago. Therefore, more new sEEG and iEEG signals should be collected from epileptic patients for the research of seizure detection and prediction in the future. Moreover, multi-model data, such EEG, electroencephalogram (ECG), electromyography (EMG), video, etc., can be used together for the robust and reliable seizure detection and prediction. The second limitation is that the proposed methods focus on the analysis of offline classification, ignoring the exploration of online classification. This is because the practical application of seizure detection and seizure prediction is a real-time process in the future. Thus, the further exploration of online classification is significant in the field of seizure detection and prediction. The third limitation is that this dissertation only focuses on the use of 1D-CNN and 2D-CNN for seizure detection and prediction. Hence, other DL methods, such as 3D-CNN, LSTM, the combination of CNN and LSTM, etc., can also be utilized for the analysis of seizure detection and prediction. Moreover, DL-based feature extration combined with conventional ML methods can also be further studied in this field.

According to above limitations or considerations, the future directions in seizure detection and prediction are briefly given as follows.

1. The cooperation with hospitals for the collection of more new EEG signals

is significant, and this can allow us to achieve more practical results in the analysis of seizure detection and prediction. Moreover, the application of multi-model data (EEG, ECG, EMG, etc.) is a trend for the robust and reliable seizure detection and prediction in the future.

2. The practical application of seizure detection and prediction is a significant task, and this can improve the quality of life and reduce the suffering for epileptic patients. Therefore, the exploration of seizure detection and prediction algorithms not only focuses on the research of offline classification, but also pays more attention to the exploration of online classification in the future work.

3. DL methods are important techniques in seizure detection and prediction. Thus, various DL methods, such CNN, LSTM, the combination of CNN and LSTM, etc., should be analyzed and discussed to find the practical and effective DL methods for the real application in the future study.

4. The source localization of epileptic focus is helpful for the diagnosis of epilepsy using EEG signals. Hence, EEG-based seizure onset detection combined with the source localization of epileptic focus is also a research direction in the future.

YHTEENVETO (SUMMARY IN FINNISH)

Tässä väitöskirjassa sovellettiin konvoluutioneuroverkkoja (CNN) sekä sEEG- että iEEG-signaaleissa esiintyvien epileptisten kohtausten luotettavaan havaitsemiseen ja ennustamiseen. Kaksi ensimmäistä artikkelia (artikkelit I ja II) keskittyivät nimenomaan tähän kun taas kolme jälkimmäistä artikkelia (artikkelit III, IV ja V) tarkastelivat kanavan valinnan ja yksiulotteisten konvoluutioverkkojen yhdistämistä pitkäaikaisten iEEG-signaalien analysoimiseksi.

Kohtausten havaitsemistutkimuksissa tarkasteltiin erityisesti konvoluutioverkkojen suorituskykyä ja tarkkuutta. Artikkelissa I käytettiin yksiulotteista konvoluutioverkkoa (1D-CNN) ja kaksiulotteista verkkoa (2D-CNN) samanaikaisesti lyhytaikaisissa sEEG- ja iEEG-signaaleissa esiintyvien epileptisten kohtausten havaitsemiseen. Rakenteeltaan 12-kerroksisia 1D-CNN- ja 2D-CNN-malleja testattiin avoimen Bonnin EEG-tietokannan avulla. Molemmat mallit antoivat tarkkoja tuloksia kohtausten havaitsemisessa. Artikkeli II keskittyi 1D-CNN:n soveltamiseen pitkäaikaisissa sEEG- ja iEEG-signaaleissa esiintyvien kohtausten havaitsemiseen. Ehdotettu 1D-CNN-malli toimi tehokkaasti kahdella pitkän aikavälin EEG-tietojoukolla (CHB-MIT sEEG ja SWEC-ETHZ iEEG). Näytteiden epätasapaino-ongelman ratkaisemiseksi tässä tutkimuksessa ehdotettiin myös RS-DA-strategian käyttämistä mallien koulutuksen aikana. Edellä mainituissa kahdessa tutkimuksessa sovellettiin onnistuneesti CNN:iä lyhyen ja pitkän aikavälin sEEG- ja iEEG-signaaleissa esiintyvien kohtausten havaitsemiseen. Saavutetut tulokset osoittivat, että CNN:illä saavutetaan erinomainen havaitsemistarkkuus.

EEG-kanavan valinnan ja konvoluutioverkkopohjaisen syväoppimisen yhdistelmää on tutkittu vähemmän. Artikkeleissa III ja IV ehdotettiin uutta 1D-CNN-menetelmää yhdistettynä kanavan valintaan. Ehdotettua menetelmää testattiin Freiburg iEEG -tietojoukolla, jolle saavutettiin erinomaiset tulokset. Tutkimuksessa käsiteltiin kahta erityyppistä ristiinvalidointiin perustuvaa oppimisstrategiaa, joille molemmille saavutettiin ensiluokkaisia tuloksia. Kolme jälkimmäistä tutkimusta osoittivat, että kanavan valinnan ja CNN:n yhdistelmä on tehokas tapa nostaa kohtausten ennustamistarkkuutta.

Yhteenvetona voidaan todeta, että tässä väitöskirjassa käytettiin systemaattisesti sekä sEEG- että iEEG-signaaleja kohtausten havaitsemisen ja ennustamisen tutkimuksessa. SEEG- ja iEEG-signaaleille rakennettiin ja testattiin useita erilaisia CNN-malleja (1D-CNN ja 2D-CNN), joiden yhteydessä EEG-kanavan valinnalla todettiin olevan merkittävä rooli epileptisten kohtausten ennustamistarkkuudelle.

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ORIGINAL PAPERS

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ONE AND TWO DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS FOR SEIZURE DETECTION USING EEG SIGNALS

by

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One and Two Dimensional Convolutional Neural Networks for Seizure Detection Using EEG Signals

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***Abstract*—Deep learning for the automated detection of epileptic seizures has received much attention during recent years. In this work, one dimensional convolutional neural network (1D-CNN) and two dimensional convolutional neural network (2D-CNN) are simultaneously used on electroencephalogram (EEG) data for seizure detection. Firstly, using sliding windows without overlap on raw EEG to obtain the definite one-dimension time EEG segments (1D-T), and continuous wavelet transform (CWT) for 1D-T signals to obtain the two-dimension time-frequency representations (2D-TF). Then, 1D-CNN and 2D-CNN model architectures are used on 1D-T and 2D-TF signals for automatic classification, respectively. Finally, the classification results from 1D-CNN and 2D-CNN are showed. In the two-classification and three-classification problems of seizure detection, the highest accuracy can reach 99.92% and 99.55%, respectively. It shows that the proposed method for a benchmark clinical dataset can achieve good performance in terms of seizure detection.**

***Index Terms*—Electroencephalogram (EEG), seizure detection, convolutional neural networks (CNN), deep learning, time-frequency representation**

I. Introduction

Epilepsy is a chronic noncommunicable disease of the brain, which affects more than 50 million people worldwide. Clinically intractable epilepsy is commonly associated with the risk of fainting, injury, and death [1]. Electroencephalogram (EEG) is a significant tool that has been widely used for the diagnosis of epilepsy [2]. However, since the interpretation of EEG signals by visual assessment is labor- and time-consuming, the related research for EEG-based automatic seizure detection is very active. Automated and accurate identification of epileptic seizures based on EEG signals can improve work efficiency and patient quality of life.

The data mining techniques with feature-based engineering have been widely researched for the automated detection of epileptic seizures. Most of them use hand-wrought features extracted mainly from time domain [3], [4], time-frequency domain [5], [6], nonlinear dynamics [7], [8], and sometime in a combination of several domains [9] for seizures classification. However, these feature-based methods have several main challenges. First, EEG is non-stationary signal and can be susceptible to artifacts such as power-line interference, electrooculogram (EOG), electromyography (EMG) and white environment noise. All these noise sources can change the authenticity of features and hence seriously affect the performance of seizure detection systems. Second, feature extraction and selection has always been a time-consuming engineering. This is because the EEG data need to be processed, or further selected, to obtain desired features for classification.

Deep learning has proved its ability in image and audio recognition tasks [10], [11]. For solving the limitations mentioned above, convolutional neural network is used for the automated detection of seizures, and it is a machine learning technology based on representation learning. The system automatically learns and discovers the features needed for classification by processing multi-level input data [11]. In this work, one and two dimensional convolutional neural networks (1D-CNN and 2D-CNN) are used for seizure detection. Firstly, through preprocessing and continuous wavelet transform (CWT), we obtain the definite one-dimension time segments (1D-T) and two-dimension time-frequency representations (2D-TF), respectively. Then, two models are used on 1D-T and 2D-TF signals for classification, respectively. Finally, the classification results from two models are given. Two-classification and three-classification problems are discussed with the proposed method for seizure classification.

II. Data

The opening EEG data (http://epilepsy.uni-freiburg.de/database) collected by Andrzejak et al. [12] are used in this research. After removing EEG contaminated by artifacts (eye movements or muscle activity) through visual inspection, five sets (denoted A-E) of EEG data were selected. Each set contained 100 single-channel EEG segments of 23.6-sec duration. Sets A and B consisted of scalp EEG of five healthy volunteers with eyes open (A) and closed (B), respectively. The EEG signals in sets C and D were recorded from five patients during the seizure free intervals. Set C contained the EEG signals measured in the hippocampus, while the EEG signals of set D were measured in the epileptogenic zone. The EEG signals that are recorded during seizures in the epileptogenic zone were collected in set E. The sampling frequency is 173.61Hz with using 12bit resolution. A bandpass filter between 0.53 and 40Hz was used in the processing of recording. More details can be found in [12]. Fig. 1 shows the exemplary EEG signals of five sets A-E.

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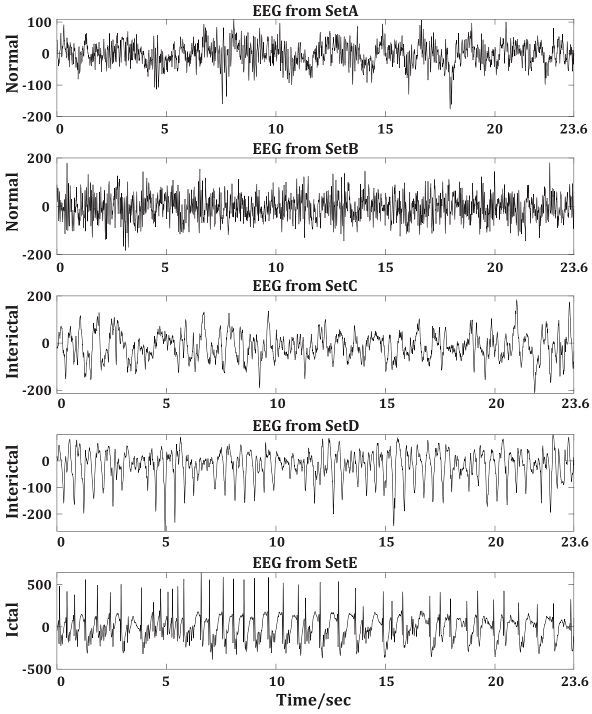

Fig. 1. Examples of EEG signals from each of the five sets of Bonn University EEG database.

III. Methodology

A. Preprocessing

Firstly, the 100 single-channel EEG segments from each set are integrated into one segment with length of 2360-sec duration. For obtaining different sample sizes, we then use two different sliding time windows (1-sec and 2-sec) without overlap to cut out the integrated EEG segments for attaining definite one-dimension time EEG fragments (1D-T) with lengths of 1-sec and 2-sec, respectively. In total, five integrated EEG segments A-E can obtain 11840 (1-sec) and 5920 (2-sec) samples, respectively.

B. Time-frequency representation

The changes of EEG signal are usually reflected in amplitude and frequency. Thus, time-frequency analysis is often used in abnormal EEG signals for seizure detection [5], [6]. Waveform transform is a commonly used time-frequency analysis method. For a EEG fragment $x(t)$, its time-frequency representation can be generated by using continuous wavelet transform (CWT), as follows:

$$\begin{aligned} \mathrm{TFR_x} &= |CWT_x(a,\tau)|^2 \\ &= |\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\,\psi*(\frac{t-\tau}{a})dt|^2 \end{aligned} \tag{1}$$

where ψ and $*$ are the mother wavelet and function of complex conjugate, respectively. Parameters a and τ denote the oscillatory frequency and shifting position of the wavelet, respectively.

After attaining 1D-T signals by preprocessing, we then use CWT on them to generate the scalograms in time-frequency representation. In this paper, Morlet is used as mother wavelet to generate EEG time-frequency representations [6]. The time-frequency examples of EEG fragments from sets A-E are showed in Fig. 2.

C. Convolutional neural networks (CNN)

Fig. 3 shows the whole process of the proposed seizure detection system. Firstly, by preprocessing and time-frequency transform, we obtain the 1D-T and 2D-TF signals, respectively. Then, 1D-CNN is used for classifying 1D-T signals, while 2D-CNN is used for classifying the 2D-TF signals. Finally, the results from two CNNs are showed.

A CNN generally contains three types of layers: convolutional layer, pooling layer and fully connected layer. For a convolutional layer, it has a number of convolution kernels (filters) which perform convolution calculations on the input signals. Filtering results from convolution kernels are then nonlinearized by activation functions, such as rectified linear activation unit (ReLU) or Sigmoid functions. The output of a convolutional layer is usually known as the feature maps. Pooling layer is also called the down-sampling layer. Max-pooling operation is currently often used on the output from convolutional layer, it can preserve the most significant values from feature maps and improve the distortion tolerance of the model. After the operation of convolutional layers and pooling layers, the output is entered into the full connected layer. The results of classification are then achieved.

In this work, we use two different models (1D-CNN and 2D-CNN) and compare the results for exploring higher performance of seizure classification. About 1D-CNN, it contains three convolution blocks. Each convolution block consists of a convolution layer with ReLU as activation function, a batch normalization layer and a max-pooling layer. The three convolution layers have 16, 32 and 64 kernels, respectively, and kernels of the three convolution layers with same size of 3×1 and same stride of 1. Each batch normalization layer follows each convolution layer. Following each batch normalization layer is the max-pooling layer, with pooling size of 2. After the three convolution blocks, there are three fully connected layers. The first and second fully connected layers have 128 and 60 neurons with ReLU activation functions, respectively. The final layer is also known as output layer, and with 2 output neurons (two classification problem) or 3 output neurons (three classification problem). The Softmax activation function is used in the final layer. As showed in Fig. 3(a).

For 2D-CNN, it also contains three convolution blocks. Each convolution block also consists of a convolution layer with ReLU as activation function, a batch normalization layer and a max-pooling layer. The first convolution layer has 16 kernels with size of 3×3 and stride of 1×2. The second and third convolution layers have 32 and 64 kernels, respectively, and kernels of the two convolution layers with same size of 3×3 and same stride of 1×1. Each batch normalization layer follows each convolution layer. Following each batch

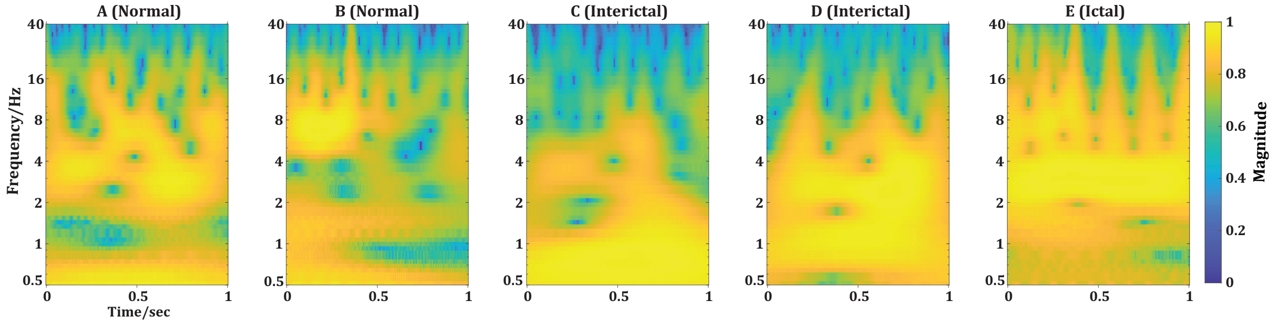

Fig. 2. Time-frequency representations of 1-sec EEG fragments from each of the five sets with using continuous wavelet transform.

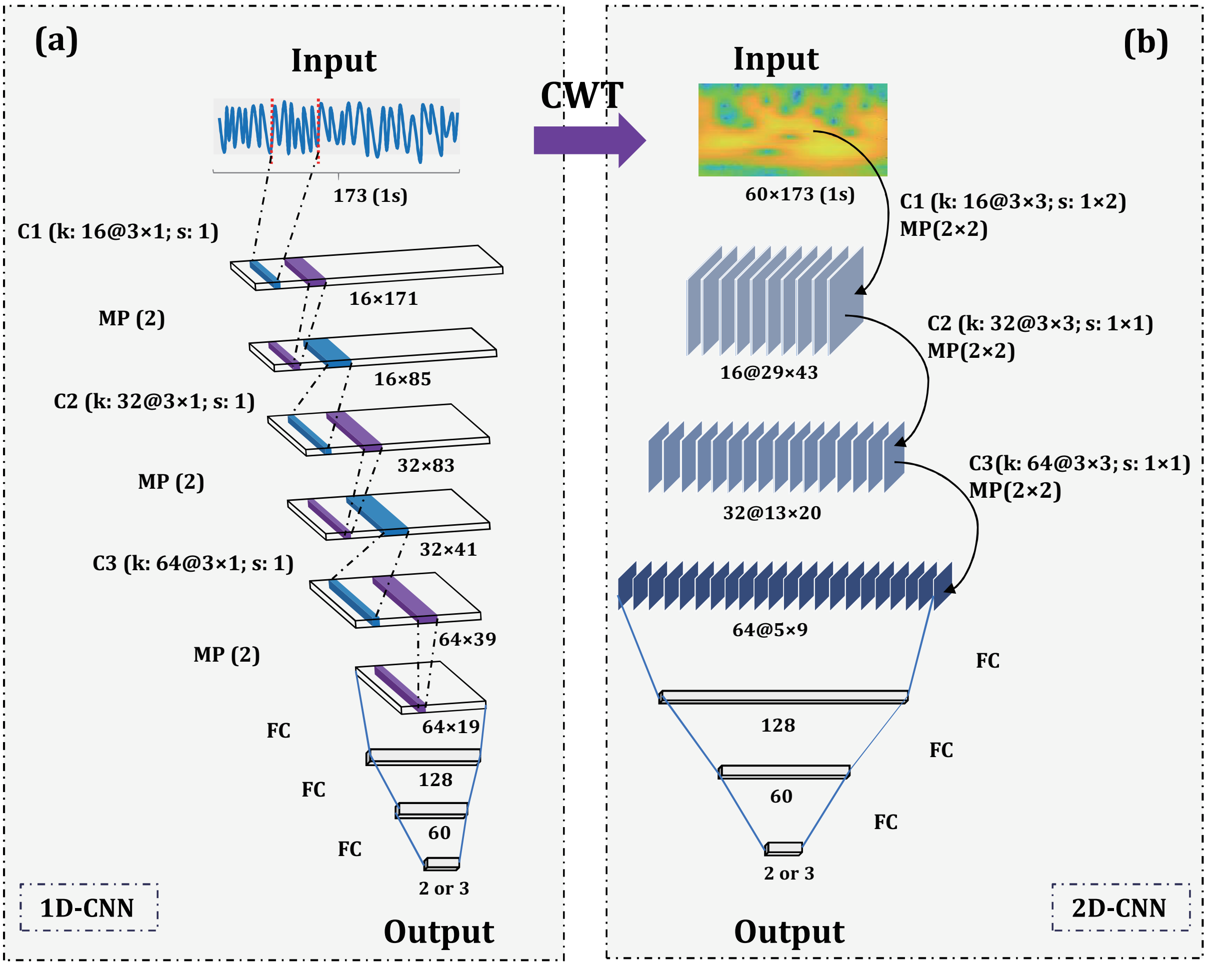

Fig. 3. Schematic diagram of the overall seizure detection approach with the preprocessing of 1-sec sliding time window. For simplicity, the batch normalization layers between the convolutional layers and the max-pooling layers are not shown. There are three convolution layers, named C1, C2, and C3. MP means max-pooling layer, and FC means full connected layer. The convolution kernel and stride are expressed as k and s, respectively.

normalization layer is the max-pooling layer, with pooling size of 2×2. Following the three convolution blocks are also three fully connected layers. The first and second fully connected layers also have 128 and 60 neurons with ReLU activation functions, respectively. The third layer has 2 output neurons or 3 output neurons with the Softmax activation function. As showed in Fig. 3(b).

D. Training and testing of CNN models

The ten-fold cross-validation method is used. All samples are first randomly divided into ten equal parts. Then, nine parts out of ten are used to train the CNN, while the remaining one is used to test the performance of trained CNN. This strategy is repeated ten times by shifting the test and training dataset.

TABLE I
THE CONFUSION MATRIX OF A VS. E ACROSS ALL TEN-FOLDS

	Normal (A)	Ictal (E)				Normal (A)	Ictal (E)			
	Predicted (1D-CNN, 1s)		ACC (%)	SEN (%)	SPE (%)	**Predicted (2D-CNN, 1s)**		ACC (%)	SEN (%)	SPE (%)
Original	2359	9	99.75	99.87	99.62	2368	0	**99.92**	**99.83**	**100**
	3	2365				4	2364			
	Predicted (1D-CNN, 2s)					**Predicted (2D-CNN, 2s)**				
	1184	0	**99.92**	**99.83**	**100**	1183	1	99.87	99.83	99.92
	2	1182				2	1182			

TABLE II
THE CONFUSION MATRIX OF C VS. E ACROSS ALL TEN-FOLDS

	Interictal (C)	Ictal (E)				Interictal (C)	Ictal (E)			
	Predicted (1D-CNN, 1s)		ACC (%)	SEN (%)	SPE (%)	**Predicted (2D-CNN, 1s)**		ACC (%)	SEN (%)	SPE (%)
Original	2343	25	99.01	99.07	98.94	2352	16	99.16	98.99	99.32
	22	2346				24	2344			
	Predicted (1D-CNN, 2s)					**Predicted (2D-CNN, 2s)**				
	1179	5	98.94	98.31	99.58	1177	7	**99.28**	**99.16**	**99.41**
	20	1164				10	1174			

TABLE III
THE CONFUSION MATRIX OF A VS. C ACROSS ALL TEN-FOLDS

	Normal (A)	Interictal (C)				Normal (A)	Interctal (C)			
	Predicted (1D-CNN, 1s)		ACC (%)	SEN (%)	SPE (%)	**Predicted (2D-CNN, 1s)**		ACC (%)	SEN (%)	SPE (%)
Original	2288	80	95.50	94.38	96.62	2243	125	93.69	92.65	94.72
	133	2235				174	2194			
	Predicted (1D-CNN, 2s)					**Predicted (2D-CNN, 2s)**				
	1161	23	**97.47**	**96.88**	**98.06**	1151	33	96.66	96.11	97.21
	37	1147				46	1138			

TABLE IV
THE CONFUSION MATRIX OF A VS. C VS. E ACROSS ALL TEN-FOLDS

	Normal (A)	Interictal (C)	Ictal (E)				Normal (A)	Interictal (C)	Ictal (E)			
	Predicted (1D-CNN, 1s)			ACC (%)	SEN (%)	SPE (%)	**Predicted (1D-CNN, 1s)**			ACC (%)	SEN (%)	SPE (%)
Original	2292	76	0	96.26	96.79	95.99	2209	157	2	95.03	93.29	95.90
	187	2171	10	95.99	91.68	98.14	191	2161	16	94.69	91.26	96.41
	3	12	2353	99.65	99.37	99.79	3	13	2352	99.52	99.32	99.62
	Predicted (1D-CNN, 2s)						**Predicted (2D-CNN, 2s)**					
	1146	36	2	96.96	96.79	97.04	1148	36	0	**96.93**	**96.96**	**96.92**
	70	1106	8	96.51	93.41	98.06	71	1107	6	**96.59**	**93.50**	**98.14**
	0	10	1174	99.44	99.16	99.58	2	8	1174	**99.55**	**99.16**	**99.75**

TABLE V
THE CONFUSION MATRIX OF AB VS. CD VS. E ACROSS ALL TEN-FOLDS

	Normal (AB)	Interictal (CD)	Ictal (E)				Normal (AB)	Interictal (CD)	Ictal (E)			
	Predicted (1D-CNN, 1s)			ACC (%)	SEN (%)	SPE (%)	**Predicted (1D-CNN, 1s)**			ACC (%)	SEN (%)	SPE (%)
Original	4550	183	3	96.12	96.07	96.16	4437	290	9	94.85	93.69	95.62
	261	4446	29	95.18	93.88	96.04	299	4356	81	93.86	91.98	95.12
	12	98	2258	98.80	95.35	99.66	12	57	2299	98.66	97.09	99.05
	Predicted (1D-CNN, 2s)						**Predicted (2D-CNN, 2s)**					
	2309	59	0	**97.33**	**97.51**	**97.21**	2283	83	2	96.96	96.41	97.33
	93	2266	9	**96.94**	**95.69**	**97.78**	90	2260	18	96.28	95.44	96.85
	6	20	1158	**99.41**	**97.80**	**99.81**	5	29	1150	99.09	97.13	99.58

IV. RESULTS

In this section, the results from two CNN models are showed, and two-class classification problem and three-class classification problem are discussed. For two-class classification problem, there are three cases discussed, namely A (normal) vs. E (ictal), C (interictal) vs. E (ictal), A (normal) vs. C (interictal). For three-class classification problem, two cases are discussed, namely A (normal) vs. C (interictal) vs. E (ictal), AB (normal) vs. CD (interictal) vs. E (ictal). The confusion matrix across all ten-folds in this paper is showed, and the accuracy (ACC), sensitivity (SEN), and specificity

(SPE) values are calculated.

A. Two-classification problem

Table I reports the classification of A and E. As showed in Table I, model 2D-CNN with preprocessing of 1-sec sliding time window and model 1D-CNN with 2-sec sliding time window have the same top results that the accuracy, sensitivity and specificity are 99.92%, 99.83% and 100%, respectively. For C and E, Table II shows that model 2D-CNN with preprocessing of 1-sec sliding time window has the best result with the accuracy of 99.28%, sensitivity of 99.16% and specificity of 99.41%. Table III shows the top result from model 1D-CNN with preprocessing of 1-sec sliding time window, it has the accuracy of 97.47%, sensitivity of 96.88% and specificity of 98.06%, respectively. From the results, we can see that the accuracy of A vs. E, C vs. E are all greater than 99%, while A vs. C only has more than 97% accuracy.

B. Three-classification problem

We also study the performance of the proposed method in classifying three distinct classes of EEG activities: normal, interictal, and ictal. Table IV gives the results of A vs. C vs. E. As it shows, the best overall classification result from model 2D-CNN with preprocessing of 2-sec sliding time window. It is observed that a high percentage of 96.96% of normal EEG signals are correctly classified as normal EEG signals with 3.04% of the EEG signals wrongly classified as interictal (3.04%) and ictal (0%) classes. For interictal EEG signals, only 93.50% of them are correctly classified as the interictal EEG signals, and a small percentage of 6.00% and 0.50% of them are wrongly classified as normal and ictal, respectively. Similarly, 99.16% of the ictal EEG signals are correctly classified as ictal class with 0.84% wrongly classified as normal (0.17%) and preictal (0.67%) classes.

The classification results of AB vs. CD vs. E are reported in Table V. Unlike the three classifications mentioned above, the normal (AB) and interictal (CD) groups have twice as many samples as the ictal (E) group. Model 1D-CNN with using 2-sec sliding time window for preprocessing has the best overall performance. For the normal EEG signals, a high percentage of 97.51% of them are accurately classified as the normal class, and a small percentage of 2.49% and 0% of them wrongly classified as the interictal and ictal classes, respectively. It is also observed that 95.69% of the interictal EEG signals are accurately classified as the interictal class with 4.31% of them are wrongly classified as normal (3.93%) and ictal (0.38%). Similarly, 97.80% of the ictal EEG signals are accurately divided into the ictal class with 2.20% wrongly classified as the normal (0.51%) and interictal (1.69%) classes.

V. Discussion and Conclusion

In this study, we discussed two-classification and three-classification problems in seizure detection. For exploring performance of classification, two models (1D-CNN and 2D-CNN) were used as classifiers. About two-classification problem, three cases, namely A (normal) vs. E (ictal), C (interictal) vs. E (ictal), A (normal) vs. C (interictal), were discussed. About three-classification problem, two cases, namely A (normal) vs. C (interictal) vs. E (ictal), AB (normal) vs. CD (interictal) vs. E (ictal), were discussed. For C vs. E and A vs. C vs. E, the performance of 2D-CNN was better than that of 1D-CNN, while for A vs. C and AB vs. CD vs. E, the performance of 1D-CNN was better. For A vs. E, the two models had the same best performance of classification. As shown in the five tables, A vs. E had the highest accuracy of 99.92% in two-classification problem, while A vs. C vs. E had the best overall classification result in three-classification problem.

Through preprocessing with using two different sliding windows (1-sec and 2-sec) for changing sample sizes, the results showed that two models have the good generalization and robustness in working well with the benchmark clinical dataset. The application of CNNs also has minimum feature engineering. All of these give medical staff more opportunities to efficiently and accurately detect the seizures, and help patients to improve the quality of life.

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PII

ONE DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS FOR SEIZURE ONSET DETECTION USING LONG-TERM SCALP AND INTRACRANIAL EEG

by

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One dimensional convolutional neural networks for seizure onset detection using long-term scalp and intracranial EEG

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ABSTRACT

Epileptic seizure detection using scalp electroencephalogram (sEEG) and intracranial electroencephalogram (iEEG) has attracted widespread attention in recent two decades. The accurate and rapid detection of seizures not only reflects the efficiency of the algorithm, but also greatly reduces the burden of manual detection during long-term electroencephalogram (EEG) recording. In this work, a stacked one-dimensional convolutional neural network (1D-CNN) model combined with a random selection and data augmentation (RS-DA) strategy is proposed for seizure onset detection. Firstly, we segmented the long-term EEG signals using 2-s sliding windows. Then, the 2-s interictal and ictal segments were classified by the stacked 1D-CNN model. During model training, a RS-DA strategy was applied to solve the problem of sample imbalance, and the patient-specific model was trained with event-based *K*-fold (*K* is the number of seizures per patient) cross validation for detecting all seizures of each patient. Finally, we evaluated the performances of the proposed approach in the two levels: the segment-based level and the event-based level. The proposed method was tested on two long-term EEG datasets: the CHB-MIT sEEG dataset and the SWEC-ETHZ iEEG dataset. For the CHB-MIT sEEG dataset, we achieved 88.14% sensitivity, 99.62% specificity and 99.54% accuracy in the segment-based level. From the perspective of the event-based level, 99.31% sensitivity, 0.2/h false detection rate (FDR) and mean 8.1-s latency were achieved. For the SWEC-ETHZ iEEG dataset, in the segment-based level, 90.09% sensitivity, 99.81% specificity and 99.73% accuracy were obtained. In the event-based level, 97.52% sensitivity, 0.07/h FDR and mean 13.2-s latency were attained. From these results, we can see that our method can effectively use both sEEG and iEEG data to detect epileptic seizures, and this may provide a reference for the clinical application of seizure onset detection.

1. Introduction

Epilepsy is a chronic neurological disease, which results from sudden abnormal and synchronous electrical activities of brain neurons. It has affected nearly 1% of the world's population, and about 30% of people with epilepsy are resistant to antiepileptic drugs [1]. Electroencephalogram (EEG) has become an effective screening technique in diagnosing epilepsy. Since the manual detection of seizures by reviewing long-term and continuous EEG is a time-consuming and laborious task, the automated and timely detection of seizures can greatly improve diagnostic efficiency and reduce workload.

EEG-based analysis for the automated detection of seizures has been widely explored in the last two decades. In the previous researches about EEG-based seizure detection, the short-term Bonn EEG dataset [2] and the long-term CHB-MIT scalp EEG (sEEG) dataset [3] were the two most commonly used datasets [4]. For the short-term Bonn EEG dataset, many conventional machine learning and deep learning methods, including Support Vector Machine (SVM) [5–7], Random Forest (RF) [8], K-Nearest Neighbor (KNN) [9,10], Artificial Neural Network (ANN) [11], Convolutional Neural

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Networks (CNN) [12–14] and Long-Short Term Memory (LSTM) [15], have been applied to analyze this dataset for seizure detection and obtained the accuracy ranging from 88.87% to 100%. Although these methods achieved high performances on the short-term Bonn EEG dataset, this benchmark clinical dataset was a small and special-selected dataset. As stated in [2], the short-term Bonn EEG dataset consisted of 500 single-channel EEG segments of 23.6-s duration (200 sEEG segments and 300 intracranial EEG (iEEG) segments), and each segment was cut out from continuous EEG recordings after visual inspection. However, in the real world, the EEG recordings of people with epilepsy usually last from several hours to several weeks. Therefore, the analysis of long-term and continuous EEG data for seizure detection may have more practical significance.

For the long-term CHB-MIT sEEG dataset (24 patients, about 916 h and 198 seizures), an overview of works is briefly introduced. In conventional machine learning methods, the studies [7,16] used SVM classifiers for seizure detection and achieved the sensitivity ranging from 96.81% to 97.34% and the specificity ranging from 97.26% to 97.50%. In [17], seven classifiers, including SVM, Ensemble, KNN, Linear Discriminant Analysis (LDA), Logistic Regression (LR), Decision Tree (DT) and Naive Bayes (NBs), combined with the strategy of channel selection were used for calssification, and the KNN finally achieved the highest accuracy of 84.8%. In [18], Alickovic et al. applied four classifiers (SVM, RF, Multilayer perceptron (MLP) and KNN) simultaneously to classify the feature samples that were extracted by Discrete Wavelet Transform (DWT), empirical mode decomposition (EMD) and wavelet packet decomposition (WPD), and an overall accuracy of 100% was finally achieved in ictal vs. interictal sEEG. However, only 1000 interictal, 1000 ictal and 1000 preictal 8-s segments were specially selected from the CHB-MIT sEEG dataset for the analysis of seizure detection, which greatly damaged the integrity of the data. Recently, several leading deep learning techniques, including CNN, LSTM and recurrent neural network (RNN), were also applied to the CHB-MIT sEEG dataset. In [19], 1D-CNN was used to classify the 4-s raw sEEG segments, and it achieved 66.76% sensitivity, 99.63% specificity and 99.07% accuracy. Hossain et al. applied a 7-layer two-dimensional convolutional neural network (2D-CNN) to classify the time-channel sEEG matrixes, and this approach obtained an overall sensitivity, specificity and accuracy of 90.00%, 91.65% and 98.05%, respectively [20]. Different from the 2D-CNN used in [20], Liang et al. achieved an accuracy of 99.00% by using a 2D-CNN-LSTM model for seizure detection. In this model, 2D-CNN was used as the feature extraction model for learning the high-level representations of inputs. The outputs of 2D-CNN were then fed into LSTM for classification [21]. In [22], a bidirectional LSTM (Bi-LSTM) network was utilized for the classification of 4-s sEEG epochs, and the method attained 93.61% sensitivity and 91.85% specificity. The RNN model was applied by Yao et al. for seizure detection, and it achieved the averaged sensitivity, specificity and accuracy of 88.80%, 88.60% and 88.69%, respectively [23].

As mentioned above, many conventional machine learning and deep learning methods have been applied to the CHB-MIT sEEG dataset for seizure detection, but many relevant studies only evaluated the performances in a segment-based level. In the segment-based level, many studies concatenated all seizures of a patient into one seizure, and then the ictal segments cut from the concatenated seizure were used for classification, ignoring the detection of each seizure (the event-based level). From the perspective of the detection of a seizure or in the event-based level, when detecting seizures during long-term EEG recoding, an excellent system should alarm accurately with short latency and low false detection rate (FDR). Therefore, both levels (the segment-based level and the event-based level) should be evaluated simultaneously in the analysis of long-term EEG recordings for seizure detection.

In this paper, the long-term sEEG and iEEG recordings are analyzed for the detection of seizures. In the long-term EEG recordings, most of the EEG recordings are in the interictal stage, while the time duration of a seizure usually ranges from tens of seconds to several minutes. Consequently, the problem of sample imbalance should be considered and properly resolved in the analysis of the long-term EEG recodings. The novelty and main contributions of this paper are summarized as follows:

- Two long-term datasets, the CHB-MIT sEEG dataset and the SWEC-ETHZ iEEG dataset [24], are analyzed in this paper. Therefore, the effectiveness of the proposed method in seizure detection is tested with two different datasets, sEEG and iEEG.
- A stacked 1D-CNN model is proposed in this study. Two different parallel 1D-CNNs with different calculation sizes are used to learn the high-level representations simultaneously. Then, the diverse features of these two 1D-CNNs are concatenated for classification.
- Since sample imbalance is a key problem in the long-term EEG recordings, a random selection and data augmentation (RS-DA) strategy is proposed to balance samples during the model training phase.
- To better evaluate the performances of the proposed method, we evaluate the classification results for each patient in the two levels: the segment-based level and the event-based level. In the segment-based level, sensitivity, specificity and accuracy are calculated. In the event-based level, we calculate the sensitivity, FDR and latency (time duration from the onset of a seizure to its detection).

The remaining of this paper is organized as follows: Section 2 describes the materials and the proposed method. Results are showed in Section 3. Discussion and conclusion are given in Section 4 and Section 5, respectively.

2. Materials and methods

In this section, we first describe two long-term EEG datasets (the sEEG dataset and the iEEG dataset). Then, we present the proposed method including preprocessing, CNN model, model training and system evaluation.

2.1. Data preparation

The CHB-MIT sEEG dataset (https://archive.physionet.org/physiobank/database/chbmit/) [3] and the SWEC-ETHZ iEEG dataset (https://ieeg-swez.ethz.ch) [24] were used for the analysis of seizure detection.

The CHB-MIT sEEG dataset consists of 916 h of sEEG and 198 seizures. The sEEG recordings from 24 patients are recorded at a sampling rate of 256 Hz, and most of recordings contain 23 channels [3]. In this study, 24 h of interictal sEEG data (all if less than 24 h) were selected for each patient. The selection criteria of seizures were as follows: (1) If the time interval between two seizures was short (less than 20 min), the two seizures were concatenated into one seizure, (2) A concatenated seizure or a raw seizure lasting more than 10 s was chosen, and so seizures which lasted less than 10 s were not considered. The details of the selected sEEG signals were summarized in Table 1.

In the SWEC-ETHZ iEEG dataset, it contains 2565 h of iEEG and 116 leading seizures from 18 patients. The sampling rate is 512 or 1024 Hz, and the number of iEEG channels ranges from 24 to 128.

Table 1
Details of the selected sEEG singals from the CHB-MIT sEEG dataset.

Patient	# Channels	Interictal (h)	# Seizures	mean ± std (s)*
1	23	24	7	63 ± 30
2	23	24	3	57 ± 41
3	23	24	7	57 ± 8
4	23	24	4	94 ± 31
5	23	24	5	111 ± 9
6	23	24	10	15 ± 3
7	23	24	3	108 ± 30
8	23	15	5	184 ± 49
9	23	24	3	68 ± 9
10	23	24	7	64 ± 17
11	23	24	3	268 ± 418
12	23	12	10	96 ± 69
13	18	24	8	67 ± 55
14	23	19	7	24 ± 12
15	24	24	14	142 ± 98
16	18	13	6	14 ± 9
17	23	18	3	98 ± 15
18	23	24	5	63 ± 13
19	23	24	3	79 ± 2
20	23	23.3	6	49 ± 22
21	23	24	4	50 ± 28
22	23	24	3	68 ± 9
23	23	23	5	85 ± 60
24	23	12.3	14	36 ± 23
Total		518.6	145	

* Mean and standard deviation of the time duration of seizures per patient.

More details of this dataset can be found in [24]. For this dataset, we also selected 24 h of interictal iEEG for each patient. The selection criteria for seizures were the same as described in the CHB-MIT sEEG dataset. Then, the selected iEEG signals were uniformly down-sampled to 256 Hz (same sampling rate as the CHB-MIT sEEG dataset). We summarized the details of the selected iEEG signals in Table 2.

2.2. Methodology

2.2.1. Preprocessing

Before training and testing the proposed model, we need to generate a certain number of samples. In the preprocessing, 2-s sliding windows were applied to segment the long-term EEG signals (as shown in Fig. 1). Since a seizure lasted from tens of seconds to several minutes (as shown in Tables 1 and 2), the size of 2-s ictal segments was very small. In order to generate more ictal segments, 2-s sliding windows with the corresponding overlap ratio were used to segment the raw ictal EEG signals only during the model training phase. The overlap ratio ranged from 0.75 to 0.9 (depending on the number and the time duration of seizures). For example, the ictal segments from patients 6 and 16 in Table 1 and patient 5 in Table 2 were obtained with the overlap ratio of 0.9, while the ictal segments from patient 15 in Table 1 and patient 1 in Table 2 were attained with the overlap ratio of 0.75. In obtaining 2-s interictal segments, we used 2-s sliding windows without overlap. The preprocessing in obtaining the segments of interictal and ictal signals is illustrated in Fig. 1.

Table 2
Details of the selected iEEG signals from the SWEC-ETHZ iEEG dataset.

Patient	# Channels	Interictal (h)	# Seizures	mean ± std (s)
1	88	24	2	601 ± 17
2	66	24	2	88 ± 2
3	64	24	4	64 ± 4
4	32	24	14	41 ± 14
5	128	24	4	16 ± 1
6	32	24	8	45 ± 33
7	75	24	4	69 ± 38
8	61	24	7	219 ± 176
9	48	24	17	67 ± 47
10	32	24	16	75 ± 21
11	32	24	2	91 ± 11
12	56	24	9	146 ± 33
13	64	24	7	102 ± 61
14	24	24	16	96 ± 39
15	98	24	2	94 ± 35
16	34	24	5	190 ± 51
17	60	24	2	97 ± 1
18	42	24	5	199 ± 100
Total		432	126	

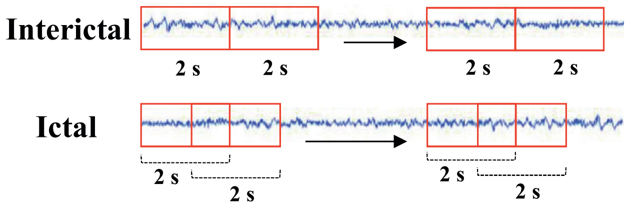

Fig. 1. For interictal EEG signals, we used 2-s sliding windows without overlap. For ictal EEG signals which were selected as the training set, we used 2-s sliding windows with the corresponding overlap ratio (0.75–0.9).

Due to the sampling rate of 256 Hz, one 2-s EEG segment can be regarded as a matrix of $n \times 512$, where n is the number of channels of each patient, and 512 is the number of sampling points. In this study, the 2-s EEG segments were used as the direct inputs of the proposed 1D-CNN model.

2.2.2. Convolutional neural networks (CNN)

CNN is generally composed of convolutional layers, pooling layers and fully connected layers. A convolutional layer contains a certain number of convolution kernels and performs convolution calculations on the input signals. The convolution results are then nonlinearized by activation functions. In our 1D-CNN model, the rectified linear activation unit (ReLU) was used in convolutional layers. The pooling layer is also called the down-sampling layer, which performs pooling operations on the outputs of the convolutional layer to preserve higher-level representations. Pooling processes including maximum pooling and global average pooling were used in our model. After the signals pass through convolutional layers and pooling layers, the high-level features are usually fed into fully connected layers for the final classification.

In this work, a stacked 1D-CNN model was proposed for seizure detection. As shown in Fig. 2, it has two parallel blocks, and the EEG segments are sent to both blocks at the same time. The two blocks are named *Block 1* and *Block 2*, respectively. The *Block 1* contains three convolutional blocks. The first convolutional block consists of a convolutional layer (32 kernels with the size of $n \times 3$ and the stride of 2, where n is the number of channels), a batch normalization (BN) layer and a max-pooling (MP) layer (the pooling size of 3 and the stride of 1). In the second convolutional block, it includes a convolutional layer with 64 kernels (the size of 3 and the stride of 2), a BN layer and a MP layer with the pooling size of 3 and the stride of 1. The third convolutional block also contains a convolutional layer (128 kernels with the size of 3 and stride of 1), a BN layer and a MP layer with the pooling size of 3 and the stride of 1. The structure of the *Block 2* is the same as that of the *Block 1*, and the only difference is the size of convolution kernels in the first and second convolution layers. In the *Block 2*, the kernel sizes of these two layers are $n \times 5$ and 5, respectively. At the end of the *Block 1* and the *Block 2*, the learned high-level representations are concatenated. Then, the concatenated features are globally averaged as the inputs of two fully connected layers. The first fully

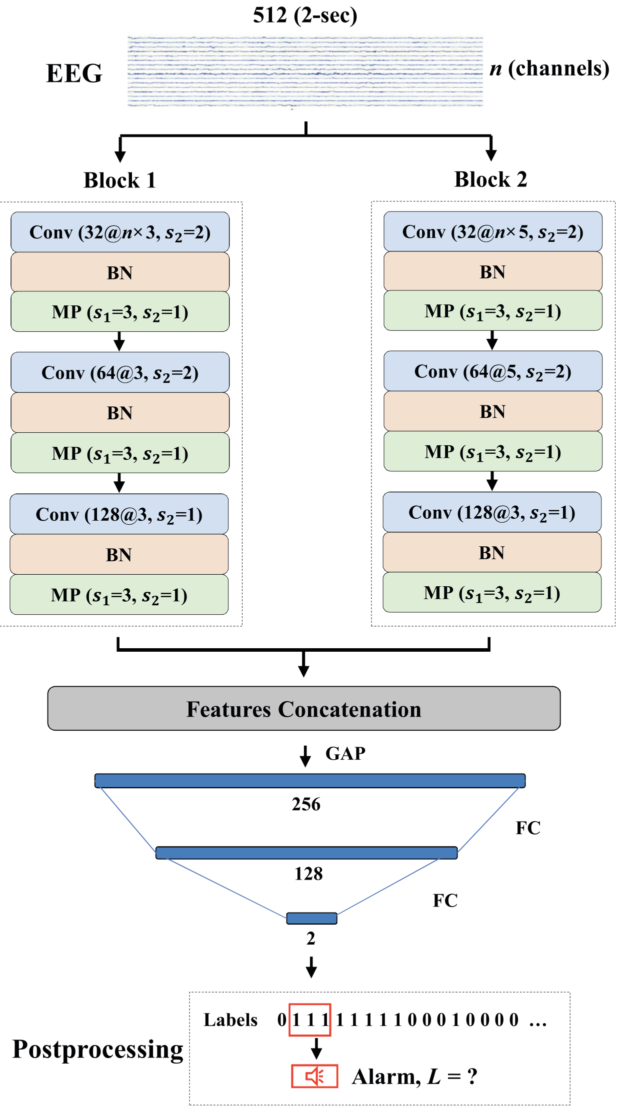

Fig. 2. A stacked 1D-CNN model was proposed for seizure detection. $M@n \times k_1$ or $M@k_2$: M is the number of kernels, $n \times k_1$ and k_2 are the sizes of convolutional kernels. Abbreviations: Conv, convolution; BN, batch normalization; MP, max-pooling; s_1, pooling size; s_2, stride; GAP, global average pooling; FC, fully connected. L is the number of consecutive detection labels for an alarm.

connected layer has 128 neurons with ReLU function. The second fully connected layer is the output layer with 2 neurons with Softmax function. According to the 1D-CNN model, the number of calculation parameters and the output shape in each layer are summarized in Table 3.

For the outputs from the stacked 1D-CNN model, a simple post-processing was performed for accurately detecting a seizure and sounding an alarm (as shown in Fig. 2). In order to sound an alarm accurately and reliably, it must meet a condition that L consecutive detection labels were positive. The value of L ranged from 2 to 5, and the final L value was determined according to the classification results. In theory, when the L value increases, the FDR decreases and the latency of an alarm becomes longer. To avoid unnecessary repeated alarms, we should set the minimum time interval (MTI) between two alarms. In this work, the averaged time duration of seizures of each patient was set as the MTI between two alarms for each patient. Therefore, when the first alarm sounded, in the following MTI, the second alarm was prohibited.

Table 3
In the proposed 1D-CNN model, the number of calculation parameters and the output shape in each layer are summarized as below. $f \times n$ is the size of the input matrix, where f is equal to 512, and n (18 to 128) is the number of EEG channels.

Layer and type	Output shape	# Parameters
Input	$f \times n$	0
2 * Conv[a]	2 * (f/2 × 32)	4672–32832[b]
2 * (BN + MP)[a]	2 * (f/2 × 32)	256
2 * Conv	2 * (f/4 × 64)	16512
2 * (BN + MP)	2 * (f/4 × 64)	512
2 * Conv	2 * (f/4 × 128)	49408
2 * (BN + MP)	2 * (f/4 × 128)	1024
GAP	256	0
Dense	128	32896
Dense	2	258
Total		105538–133698

[a] Two parallel layers.
[b] The number is related to the value of n (18 to 128).

2.2.3. Model training

The patient-specific model was trained for each patient. For detecting all seizures of each patient, the approach of event-based K-fold cross validation was used, where K was the number of seizures per patient. If a subject has K seizures, the model training is performed K rounds. In each round, (K-1) seizures are selected for training, and the remaining one is used for testing (as shown in Fig. 3).

Since the time duration of interictal EEG is about 50 to 1300 times longer than that of ictal EEG among different patients (as shown in Tables 1 and 2), the sample imbalance is a key problem in this work. In order to solve the problem during model training, we proposed a RS-DA strategy. As shown in Fig. 3, we augmented (K-1) ictal seizures by using the oversampling technique mentioned in the preprocessing (Section 2.2.1). However, the size of the augmented ictal segments was still much smaller than that of interictal segments. Therefore, the random selection was performed on interictal segments. We first divided interictal segments into K equal parts. Then, an equal number of interictal segments were randomly selected from (K-1) parts to make the size of the selected interictal segments equal to that of the augmented ictal segments. Finally, the selected interictal segments and the augmented ictal segments were used to train (80%) and monitor (20%) the model during model training. The remaining segments (one interictal part and one seizure) were used to evaluate the trained model. Through this way, all interictal segments and seizures could be tested without repetition after K rounds.

During model training, the Early-Stopping technique was also used to prevent overfitting, and the dropout rate of the second fully connected layer was set to 0.25. Based on Keras 2.3.1 with Tensorflow-1.15.0 backend, our model was implemented in Python 3.6, and one Nvidia Tesla P100 GPU was configured to run the proposed model.

2.2.4. System evaluation

We evaluated the performances of the proposed method in the two levels: the segment-based level and the event-based level.

- Segment-based level

In the segment-based level, sensitivity, specificity and accuracy were calculated to evaluate the classification of EEG segments. The three metrics can be expressed as follows:

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

$$Specificity = \frac{TN}{TN + FP} \quad (2)$$

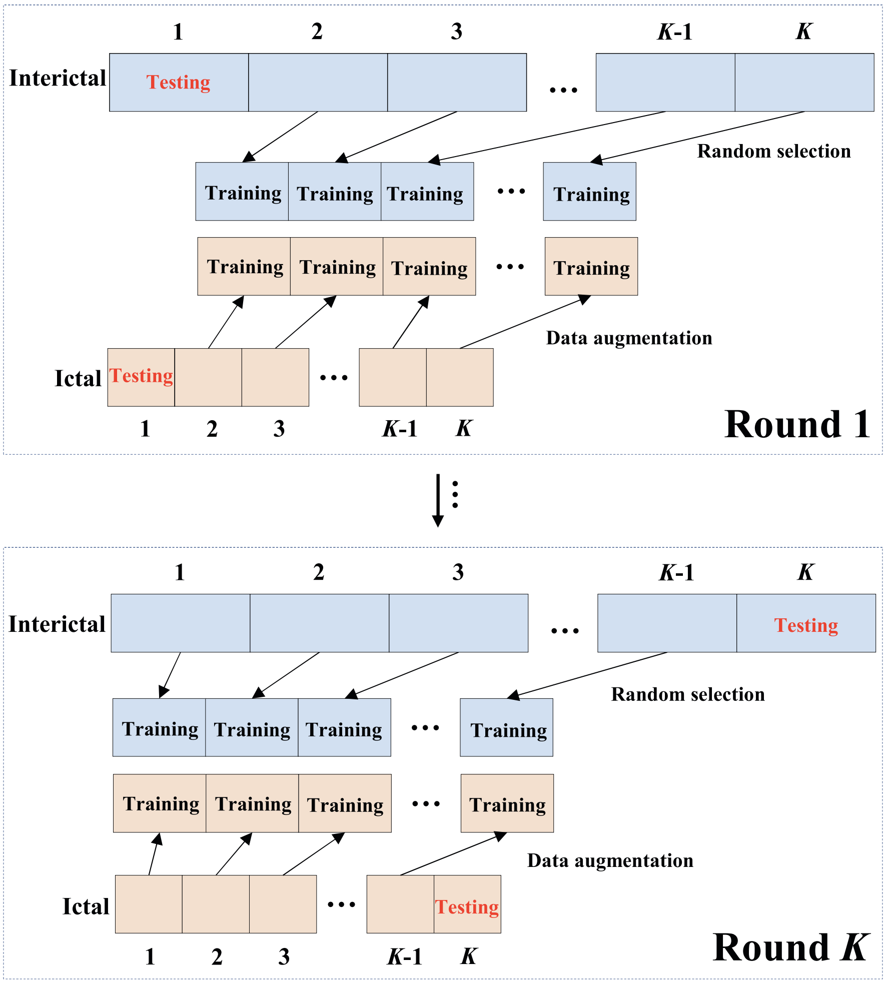

Fig. 3. Event-based *K*-fold cross validation combined with a RS-DA strategy is applied during model training. If a subject has *K* seizures, the model training is performed *K* rounds. In each round, one seizure and one interictal part are used as the testing sets, and the remaining (*K*-1) seizures and (*K*-1) interictal parts are used as the training sets. After *K* rounds, all seizures and interictal EEG can be tested without repetition.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (3)$$

where *TP* is true positive, indicating the number of true detected ictal segments from ictal segments; *FN* is false negative, indicating the number of ictal segments which are wrongly classified as interictal segments; *TN* is true negative, indicating the number of true detected interictal segments from interictal segments; *FP* is false positive, indicating the number of interictal segments which are wrongly classified as ictal segments. Sensitivity is the percentage of true detected ictal segments to total ictal segments, and specificity is the percentage of true detected interictal segments to total interictal segments. An excellent classifier should have high sensitivity and specificity at the same time.

- Event-based level

In the event-based level, we calculated the three metrics: sensitivity, FDR and latency. Sensitivity and FDR can be expressed by the following two formulas:

$$Sensitivity = \frac{number\ of\ correctly\ detected\ seizures}{number\ of\ all\ seizures} \quad (4)$$

$$FDR = \frac{number\ of\ incorrect\ detections}{hours\ of\ interictal\ EEG}. \quad (5)$$

Latency is the time duration between the onset of a seizure and its detection. Fig. 4 shows an example of a false detection, a correct detection and its latency. An outstanding system should have high sensitivity with short latency and low FDR.

3. Results

The results from the CHB-MIT sEEG dataset and the SWEC-ETHZ iEEG dataset are given in this section. The performances of the proposed method are evaluated in the two levels at the same time. In the segment-based level, the averaged results (sensitivity, specificity and accuracy) are calculated for each patient. In the event-based level, the sensitivity, the FDR and the averaged latency of an alarm are calculated.

3.1. Results of CHB-MIT sEEG dataset

Table 4 shows the results of each patient in the two levels after event-based *K*-fold cross validation. As shown in Table 4, in the segment-based level, the overall sensitivity, specificity and accuracy are 88.14%, 99.62% and 99.54%, respectively. The accuracy of most patients (except patients 8, 12, 13 and 24) is higher than 99%, and that of all patients is higher than 98%. In the event-based level, 144 out of 145 seizures (except one seizure of patient 16) are accurately detected, with a sensitivity of 99.31%. The over-

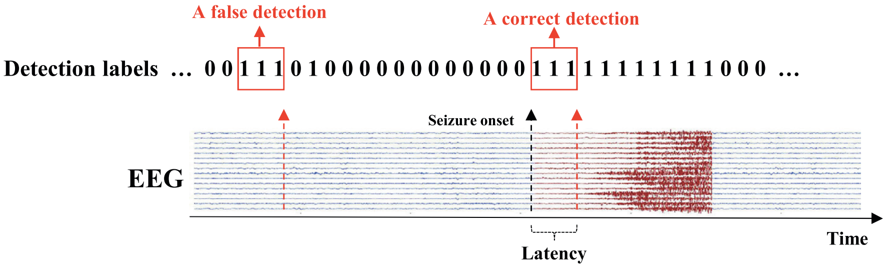

Fig. 4. Event-based level: the example of a false detection, a correct detection and its latency.

all FDR is 0.2/h, and 7 patients (2, 4, 5, 10, 11, 14 and 19) have a FDR of 0/h. The overall latency is 8.1 s, and the patient 22 has the longest averaged latency of 14.7 s.

The value of L is related to sensitivity, FDR and latency in the event-based level. We also calculate these three metrics under different L values. In this work, the value of L ranges from 2 to 5. As shown in Fig. 5(a), we can see that, as the value of L increases, the overall sensitivity and FDR show a decreasing trend, but the overall latency of an alarm shows an increasing trend. When the value of L is 5, the overall sensitivity and FDR are the lowest (93.53% and 0.04/h, respectively), and the overall latency is the longest, at 13 s.

3.2. Results of SWEC-ETHZ iEEG dataset

Based on the analysis of the SWEC-ETHZ iEEG dataset, Table 5 also gives the results of each patient in the two levels after event-based K-fold cross validation. In the segment-based level, the overall sensitivity of 90.09%, specificity of 99.81% and accuracy of 99.73% are achieved. The accuracy of all patients is higher than 99%. In the event-based level, 123 out of 126 seizures (except one seizure in patients 4, 6 and 7) are correctly detected, and its sensitivity is 97.52%. The low overall FDR is 0.07/h, and the FDR of 10 patients (1, 6 and 9 to 16) is 0/h. The overall latency of an alarm is 13.2 s, and the longest averaged latency is 52.3 s for patient 8.

The overall sensitivity, FDR and latency with different L values are also calculated in the event-based level. In Fig. 5 (b), as the L value increases from 2 to 5, the sensitivity and FDR also show a general downward trend, but the overall latency has a upward trend. When the L value is equal to 4 or 5, the overall sensitivity and FDR are the lowest, at 96.41% and 0.02/h, respectively. The longest overall latency is 18.1 s when the L value is 5.

4. Discussion

In this work, we proposed a stacked 1D-CNN model combined with the RS-DA strategy for seizure detection. The details of previous studies and this work, including the number of patients, processing and the corresponding metrics were summarized in Table 6 (the segment-based level) and Table 7 (the event-based level). Since the long-term SWEC-ETHZ iEEG dataset was available from 2019[24], we compared the results only based on the CHB-MIT sEEG dataset.

As shown in Table 6, the conventional machine learning methods, including LDA [25], Extreme Learning Machine (ELM) [26], SVM [7,16,27], RF [28], ANN [29] and KNN [17,30], were appiled for seizure detection. The accuracy obtained by these methods ranged from 84.8% to 99.41 %, and the highest accurcy of 99.41% was achived by the RF in [28]. The deep learning methods, such as CNN [19,20,31–33], autoencoders [34–37], LSTM [21,22] and RNN [23], achieved the accuracy ranging from 84.00 % to 99.33%, and the stacked 2D-CNN used in [33] attained the highest accuracy of 99.33%. In this work, the proposed approach achieved the accuracy of 99.54% and 99.73% for the CHB-MIT sEEG dataset and the SWEC-ETHZ iEEG dataset, respectively. Therefore, from the perspective of the accuracy, the performance of our method was better than that of most previous studies in Table 6, and this proved that the proposed stacked 1D-CNN was effective.

From the perspective of the sensitivity (in the segment-based level), although the studies [7,16] attained higher sensitivities at 96.81% and 97.34%, respectively, the time-consuming and complex feature extraction and selection engineering was applied. The other three studies [28,30,32] achieved the high sensitivity of 97.91%, 96.66% and 98.84%, respectively, but one reason for the high sensitivity was that it used the oversampling technique to generate more ictal samples for classification. Because of the overlapping information between these augmented ictal samples, in some sense, their classification was a repeated classification of similar samples. Therefore, in [28,32,30], the high sensitivity was overestimated. Different from the studies [28,32,30], in our work, the oversampling technique was only used during the model training phase, and the ictal samples that were selected as the testing set were obtained without oversampling. In fact, the number of raw ictal samples is small (it can be seen from Tables 1 and 2 minimal amount of misclassification can greatly reduce the sensitivity. Hence, as shown in Table 6, the 88.14% sensitivity of our work was relatively high.

In the event-based level, the results of this work and previous studies using the CHB-MIT sEEG dataset were summarized in Table 7. The threshold method [38] and the conventional machine learning methods including SVM [3,16,39], Neural Network Classifier based on Improved Particle Swarm Optimization (IPSONN) [40], Relevance Vector Machine (RVM) [41] and Adaptive Distance-based Change-point Detector (ADCD) [42] were applied for the detection of seizures. These methods achieved the sensitivity of 88.5% to 98.47% and the FDR of 0.08/h to 0.63/h, and the highest sensitivity of 98.47% was obtained using an SVM group with ten SVMs in [16]. Deep learning methods, including CNN [31,43], Deep Recurrent Neural Network (DRNN) [44] and AE [45], were used to analyze the same dataset for seizure detection, and the sensitivity ranging from 86.29% to 100% and the FDR ranging from 0.08/h to 0.74/h were achieved. Our method also showed the high performances: (1) the sensitivity of 99.31% and the FDR of 0.2/h for the CHB-MIT sEEG dataset; (2) 97.52% sensitivity and 0.07/h FDR for the SWEC-ETHZ iEEG dataset. Hence, under the event-based level, our method also performed better than most of the methods in Table 7.

In [44], a sensitivity of 100% was attained, but only 5 out of 24 patients were used for the detection of seizures. The detection of seizures with short latency (less than 20 s) can early eliminate symptoms of the seizures [46,47]. Although the averaged latencies (8.1 s and 13.2 s) of the CHB-MIT and the ETHZ-SWEC EEG datasets were slightly longer than those in Table 7, they were still in the acceptable range.

Table 4
In the CHB-MIT sEEG dataset, results of each patient are given in the two levels. L = 3 is finally selected for the event-based level.

Patient	# Seizures *K*-Fold	Segment-based level			Event-based level		
		Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	FDR (/h)	Lat (s)
1	7	98.00	99.82	99.81	100	0.04	6.3
2	3	91.73	99.90	99.88	100	0	8.7
3	7	99.00	99.84	99.84	100	0.08	6.3
4	4	85.89	99.78	99.73	100	0	8
5	5	97.05	99.91	99.89	100	0	7.2
6	10	86.46	99.73	99.71	100	0.04	8
7	3	92.65	99.93	99.89	100	0.04	7.3
8	5	91.99	98.91	98.77	100	0.6	7.6
9	3	95.10	99.91	99.90	100	0.08	8
10	7	92.45	99.88	99.84	100	0	6.3
11	3	99.02	99.92	99.90	100	0	6
12	10	81.06	98.69	98.17	100	1.42	10
13	8	76.41	99.09	98.92	100	0.79	9.8
14	7	70.16	99.46	99.39	100	0	8.6
15	14	94.98	99.36	99.25	100	0.33	7.7
16	6	69.96	99.56	99.50	83.33	0.08	7.6
17	3	85.02	99.61	99.55	100	0.17	8
18	5	81.15	99.65	99.58	100	0.17	7.6
19	3	92.31	99.91	99.89	100	0	6
20	6	82.58	99.64	99.59	100	0.17	9.7
21	4	97.48	99.66	99.65	100	0.17	6
22	3	89.94	99.95	99.93	100	0.04	14.7
23	5	96.53	99.62	99.59	100	0.61	6
24	14	68.43	99.19	98.82	100	0.08	12.6
Total	145	88.14	99.62	99.54	99.31	0.20	8.1

Abbreviations: Sen_1, segment-based sensitivity; Spe, specificity; Acc, accuracy; Sen_2, event-based sensitivity; FDR, false detection rate; Lat, latency.

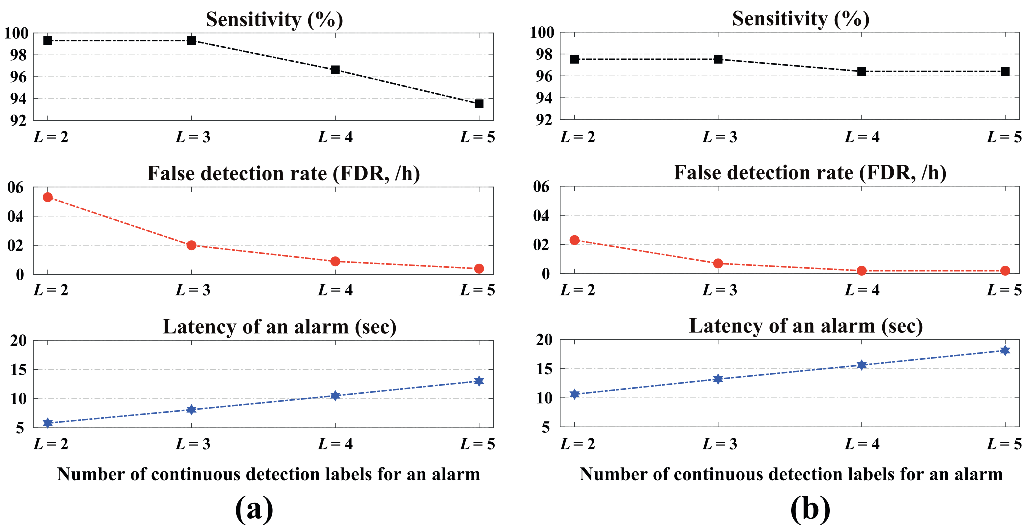

Fig. 5. In the event-based level, the value of L ranges from 2 to 5. **(a)** For the CHB-MIT sEEG dataset, the overall sensitivity, FDR and latency are showed. **(b)** For the SWEC-ETHZ iEEG dataset, the overall sensitivity, FDR and latency are showed. L = 3 is finally selected for the event-based level in this work.

As the results shown in Tables 6 and 7, our method showed high performances in the two levels, and it performed better than most of the methods in Tables 6 and 7. Moreover, the proposed method was effective for both datasets, the sEEG and the iEEG. According to our work, there are several highlights that need to be emphasized. Firstly, a 1D-CNN model is used in this study, which can be directly applied for the classification of raw EEG signals without additional preprocessing of EEG signals, such as frequency domain analysis and time–frequency domain analysis. Secondly, in order to obtain more different high-level representations for a better classification, we proposed a stacked 1D-CNN model consisting of two parallel 1D-CNN blocks. The two parallel 1D-CNN blocks with different calculation sizes can learn different high-level representations at the same time, and the diverse features of these two 1D-CNN blocks are then concatenated for the further analysis. Thirdly, the RS-DA strategy is first utilized to solve the problem of sample imbalance during model training.

Table 5
In the SWEC-ETHZ iEEG dataset, results of each patient are given in the two levels. $L = 3$ is finally selected for the event-based level.

Patient	# Seizures *K*-Fold	Segment-based level			Event-based level		
		Sen_1 (%)	Spe (%)	Acc (%)	Sen_2 (%)	**FDR (/h)**	**Lat (s)**
1	2	93.59	99.94	99.85	100	0	10
2	2	97.67	99.86	99.85	100	0.13	9
3	4	100	99.88	99.88	100	0.17	6
4	14	75.56	99.31	99.19	92.86	0.13	12.8
5	4	100	99.67	99.67	100	0.33	6
6	8	81.61	99.96	99.80	87.50	0	6.6
7	4	70.53	99.89	99.84	75.00	0.04	14
8	7	78.93	99.53	99.04	100	0.04	52.3
9	17	98.64	99.84	99.83	100	0	7.3
10	16	96.44	99.95	99.89	100	0	6.9
11	2	100	99.99	99.99	100	0	6
12	9	97.04	99.80	99.77	100	0	9.6
13	7	86.55	99.85	99.78	100	0	11.4
14	16	94.87	99.61	99.49	100	0	6.8
15	2	94.52	99.98	99.97	100	0	14
16	5	96.44	99.94	99.90	100	0	13.2
17	2	85.57	99.81	99.78	100	0.17	22
18	5	73.70	99.68	99.53	100	0.21	24.4
Total	126	90.09	99.81	99.73	97.52	0.07	13.2

Table 6
Segment-based level: list of previous studies and this work using the CHB-MIT sEEG dataset for seizure detection.

Author	Year	Dataset	Processing	# Patients	Sen (%)	Spe (%)	Acc (%)
Khan et al. [25]	2012	CHB-MIT	Multiple wavelet scales + LDA	5	83.6	100.0	91.8
Ammar et al. [26]	2016	CHB-MIT	DWT + ELM	3	–	–	94.85
Janjarasjitt et al. [27]	2017	CHB-MIT	Wavelet based features + SVM	24	72.99	98.13	96.87
Yuan et al. [34]	2017	CHB-MIT	STFT + SSDA	9	–	–	93.82
Bhattacharyya et al. [28]	2017	CHB-MIT	Channel selection, EWT + RF	23 (177 h)	97.91	99.57	99.41
Yuan et al. [35]	2018	CHB-MIT	STFT, ChannelAtt + SSDA	9	–	–	96.61
Wen et al. [36]	2018	CHB-MIT	Channel selection + CNN-AE	24	–	–	92
Boonyakitanont et al. [19]	2019	CHB-MIT	DWT, feature extraction, normalization + 1D-CNN	24 records[+]	66.76	99.63	99.07
Yuan et al. [37]	2019	CHB-MIT	Data augmentation, STFT + CNN-AE	24	–	–	94.37
Hossain et al. [20]	2019	CHB-MIT	2D array (time * channels) + 2D-CNN	23	90.00	91.65	98.05
Liang et al. [21]	2019	CHB-MIT	2D array (time * channels) + 2D-CNN-LSTM	24	84.00	99.00	99.00
Wei et al. [31]	2019	CHB-MIT	MIDS, WGANs + 1D-CNN	24	72.11	95.89	84.00
Tian et al. [32]	2019	CHB-MIT	Oversampling, FFT, WPD + 2D-CNN, 3D-CNN	24	96.66	99.14	98.33
Yao et al. [23]	2019	CHB-MIT	Windowing + IndRNN	24	88.80	88.60	88.69
Cao et al. [33]	2019	CHB-MIT	STFT, MAS, AWF + S-2D-CNN	24	–	–	99.33
Zabihi et al. [29]	2020	CHB-MIT	Phase space, nullcline + LDA-ANN	23 (171 h)	91.15	95.16	95.11
Li et al. [30]	2020	CHB-MIT	Channel selection, NMD, FCM, + KNN	24	98.40	99.01	98.61
Hu et al. [22]	2020	CHB-MIT	LMD, statistical feature extraction + Bi-LSTM	24	93.61	91.85	–
Zarei et al. [7]	2021	CHB-MIT	OMP, DWT, Non-linear features + SVM	23	96.81	97.26	97.09
Li et al. [16]	2021	CHB-MIT	EMD, CSP + an SVM group consisting of ten SVMs	24	97.34	97.50	97.49
Shoka et al. [17]	2021	CHB-MIT	Variance channel selection + KNN	23	–	–	84.8
This work	2021	CHB-MIT	2D array (time * channels), RS-DA strategy + S-1D-CNN	24	88.14	99.62	99.54
This work	2021	SWEC-ETHZ	2D array (time * channels), RS-DA strategy + S-1D-CNN	18	90.09	99.81	99.73

STFT, short-time Fourier transform; SSDA, stacked sparse denoising autoencoders; EWT, empirical wavelet transform; ChannelAtt, channel-aware attention mechanism; CNN-AE, convolutional autoencoder; MIDS, merger of the increasing and decreasing sequences; WAGNs, wasserstein generative adversarial nets; FFT, fast Fourier transform; 3D-CNN, three-dimensional CNN; IndRNN, independently RNN; MAS, mean amplitude of spectrum map; AWF, adaptive and discriminative feature weighting fusion; S-2D-CNN, stacked 2D-CNN; S-1D-CNN, stacked 1D-CNN; NMD, nonlinear mode decomposition; FCM, fractional central moment; LMD, local mean decomposition; OMP, orthogonal matching pursuit; CSP, common spatial pattern.
[+]The CHB-MIT sEEG dataset contains a total of 686 records, while one record of each patient is selected.

However, one limitation of this study is that only a 1D-CNN model is applied. Other deep learning models, such as 2D-CNN and LSTM, combined with the RS-DA strategy can also be applied to the same datasets for more detailed comparisons. Another limitation is that we ignore the use of epilepsy-related EEG features for seizure detection. The EEG features, including statistical parameters, frequency or time–frequency domain features, entropies, etc., can be extracted and incorporated as the input to the 1D-CNN model. By this method, it may improve the results of seizure detection. In the future work, this highlight can be further analyzed and discussed.

5. Conclusion

In this paper, we presented a stacked 1D-CNN model for the detection of seizure onset. In this model, two parallel 1D-CNN blocks with different calculation sizes were used to learn the high-level representations of the EEG inputs simultaneously. The outputs of these two parallel 1D-CNN blocks were then concatenated for the final classification. Since the sample imbalance was a key issue in the long-term epileptic EEG recordings, a RS-DA strategy combined with the event-based *K*-fold cross validation was proposed for balancing samples during model training. In this

Table 7
Event-based level: list of previous studies and this work using the CHB-MIT sEEG dataset for seizure detection.

Author	Year	Dataset	Processing	# Patients	Sen (%)	FDR (/h)	Lat (s)
Shoeb et al. [3]	2010	CHB-MIT	Spectral and spatial features + SVM	24	96	0.08	3
Nasehi et al. [40]	2013	CHB-MIT	DWT, DFT + IPSONN	23	98	0.125	–
Satirasethawong et al. [38]	2015	CHB-MIT	Amplitude-integrated EEG + Thresholding	24	88.5	0.18	–
Vidyaratne et al. [44]	2016	CHB-MIT	Filtering, Montage Mapping + DRNN	5	100	0.08	≈7.0
Vidyaratne et al. [41]	2017	CHB-MIT	HWPT, FD, spatial and temporal features + RVM	24	96	0.1	1.89
Khanmohammadi et al. [42]	2017	CHB-MIT	PCA-CSP + ADCD	24	96	0.12	4.21
Yuvaraj et al. [43]	2018	CHB-MIT	Filtering + 1D-CNN	24	86.29	0.74	2.1
Wei et al. [31]	2019	CHB-MIT	MIDS, WGANs + 1D-CNN	24	90.57	–	4.68
Raghu et al.[39]	2019	CHB-MIT	Filtering, successive decomposition index + SVM	23	97.28	0.57	1.7
Tang et al. [45]	2020	CHB-MIT	PCA-CSP, MMSE, feature selection + uMMD-AE	20	97.2	0.64	1.1
Li et al. [16]	2021	CHB-MIT	EMD, CSP + an SVM group consisting of ten SVMs	24	98.47	0.63	–
This work	2021	CHB-MIT	2D array (time * channels), RS-DA strategy + S-1D-CNN	24	99.31	0.20	8.1
This work	2021	SWEC-ETHZ	2D array (time * channels), RS-DA strategy + S-1D-CNN	18	97.52	0.07	13.2

DFT, discrete Fourier transform; PCA-CSP, principal component analysis-common spatial patterns; MMSE, multivariate multiscale sample entropy; uMMD-AE, unified maximum mean discrepancy-based autoencoder.

way, we tested all samples of the selected EEG without abandoning the interictal samples. The proposed method was evaluated on two long-term EEG datasets (the CHB-MIT sEEG dataset and the SWEC-ETHZ iEEG dataset) at the same time. To better evaluate the performances of the proposed method, two kinds of evaluation levels (the segment-based level and the event-based level) were calculated. For the CHB-MIT sEEG dataset, in the segment-based level, an accuracy of 99.54% was achieved. In the event-based level, 144 out of 145 seizures were accurately detected with 0.2/h FDR and 8.1-s latency. For the SWEC-ETHZ iEEG dataset, an accuracy of 99.73% was obtained in the segment-based level. In the event-based level, 123 out of 126 seizures were correctly detected with 0.07/h FDR and 13.2-s latency. Moreover, the selection of the L value was significant in the event-based level, and $L = 3$ was finally selected in this work. Based on the results obtained, the proposed method showed that it could perform well in the seizure detection with both sEEG and iEEG data. The theoretical contribution of our work may provide more epilepsy patients with the opportunity to possess a seizure detection device in clinical applications.

CRediT authorship contribution statement

Xiaoshuang Wang: Writing - original draft, Data curation, Writing - review & editing. **Xiulin Wang:** Writing - review & editing, Data curation. **Wenya Liu:** Writing - review & editing, Data curation. **Zheng Chang:** Supervision, Writing - review & editing. **Tommi Kärkkäinen:** Supervision, Writing - review & editing. **Fengyu Cong:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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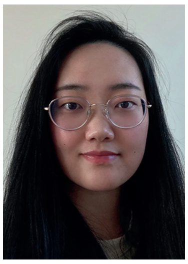

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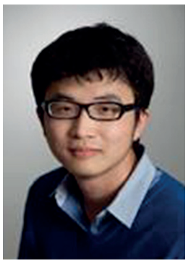

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PIII

ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS COMBINED WITH CHANNEL SELECTION STRATEGY FOR SEIZURE PREDICTION USING LONG-TERM INTRACRANIAL EEG

by

Xiaoshuang Wang, Guanghui Zhang, YingWang, Lin Yang, Zhanhua Liang and Fengyu Cong 2021

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One Dimensional Convolutional Neural Networks Combined with Channel Selection Strategy for Seizure Prediction Using Long-term Intracranial EEG

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Seizure prediction using intracranial electroencephalogram (iEEG) has attracted an increasing attention during recent years. iEEG signals are commonly recorded in the form of multiple channels. Many previous studies generally used the iEEG signals of all channels to predict seizures, ignoring the consideration of channel selection. In this study, a method of one dimensional convolutional neural networks (1D-CNN) combined with channel selection strategy was proposed for seizure prediction. Firstly, we used 30-sec sliding windows to segment the raw iEEG signals. Then, the 30-sec iEEG segments, which were in three channel forms (single channel, channels only from seizure onset or free zone and all channels from seizure onset and free zones), were used as the inputs of 1D-CNN for classification, and the patient-specific model was trained. Finally, the channel form with the best classification was selected for each patient. The proposed method was evaluated on the Freiburg Hospital iEEG dataset. In the situation of seizure occurrence period (SOP) of 30 min and seizure prediction horizon (SPH) of 5 min, 98.60% accuracy, 98.85% sensitivity and 0.01/h false prediction rate (FPR) were achieved. In the situation of SOP of 60 min and SPH of 5 min, 98.32% accuracy, 98.48% sensitivity and 0.01/h FPR were attained. Compared with the many existing methods using the same iEEG dataset, our method showed a better performance.

Keywords: Epilepsy; Seizure prediction; Intracranial electroencephalogram (iEEG); Convolutional neural network (CNN); Channel selection.

1. Introduction

Epilepsy is a chronic neurological disease, which predisposes a person to recurrent seizures. About 50 million people suffer from epilepsy, and 30% of them are resistant to anti-epileptic drugs.[1,2] Clinical refractory epilepsy is commonly associated with the risks

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of fainting, injury and death.[3] Electroencephalogram (EEG) has become a powerful technique in epilepsy diagnosis,[4–6] and many EEG-based methods, including threshold analysis,[7,8] Support Vector Machine (SVM),[9,10] k-Nearest Neighbor (KNN),[11] Random Forest (RF),[12] Linear Classifier[13] and deep learning,[14–16] have been successfully applied for seizure detection. However, seizure prediction using EEG remains one of the main challenges. The accurate prediction of seizures and timely interventions can greatly reduce the suffering of epilepsy patients. The previous EEG-based seizure prediction methods mainly consisted of threshold analysis, conventional machine learning and deep learning.

Firstly, the methods of linear or nonlinear features combined with threshold analysis were applied to the seizure prediction. Maiwald et al. used the dynamical similarity index as the nonlinear feature and evaluated the approach on the Freiburg Hospital intracranial electroencephalogram (iEEG) dataset.[17]A sensitivity of 42% and a false prediction rate (FPR) of less than 0.15/h were achieved.[17] With the same iEEG dataset, Winterhalder et al. combined phase and lag synchronization measure to evaluate the changes of iEEG synchronization and obtained a result of 60% sensitivity and 0.15/h FPR.[18] Based on the combination of bivariate empirical mode decomposition and Hilbert transformation, Zheng et al. calculated the mean phase coherence from multiple iEEG channels. This method achieved a sensitivity of more than 70% and a FPR of less than 0.15/h.[19] Then, Eftekhar et al. combined symbol dynamics methodologies with an N-gram algorithm for seizure prediction and obtained 90.95% sensitivity and 0.06/h FPR.[20] Aarabi et al. extracted correlation dimension, correlation entropy, noise level, Lempel-Ziv complexity, largest Lyapunov exponent and nonlinear interdependence as the features, and the rule-based decision making technique was used for classification. The proposed method obtained a better result of 92.9% sensitivity and 0.096/h FPR in the situation of seizure occurrence periods (SOP) of 50 min and seizure prediction horizon (SPH) of 10 s.[21] Although the performances of the threshold analysis methods have been improved to some extent, there is still room for the further improvement.

Secondly, the conventional machine learning methods were also used for seizure prediction. Park et al. used the SVM to classify the feature samples extracted from nine frequency bands of iEEG signals. The method was evaluated on the Freiburg Hospital iEEG dataset, and a sensitivity of 97.5% and a FPR of 0.27/h were achieved.[22] Williamson et al. calculated the principal components from the eigenspectra of space-delay correlation and covariance matrices for feature extraction. The SVM finally predicted 71 out of 83 seizures (85.54% sensitivity) with a FPR of 0.03/h using the same iEEG dataset.[23] Ozdemir et al. used Hilbert-Huang transform for feature extraction and Bayesian network for classification. A result of 96.55% sensitivity and 0.21/h FPR was obtained.[24] Then, Parvez et al. extracted phase-match error, deviation and fluctuation as the features and used Least Square-Support Vector Machine (LS-SVM) for classification. The method attained a result of 95.4% sensitivity and 0.36/h FPR.[25] Based on the analysis of ictal rules on Poincaré plane for feature extraction, Sharif et al. applied the SVM for classification and achieved a sensitivity of 91.8% to 96.6% and a FPR of 0.05/h to 0.08/h.[26] Although the conventional machine learning methods were used in the seizure prediction, the feature extraction and selection of iEEG signals was a time-cosuming engineering, and it also had the low generalization. Therefore, the feature engineering techniques were commonly complex in the analysis of iEEG signals for seizure prediction.

Recently, deep leaning techniques have shown excellent performances in image recognition,[27,28] image retrieval,[29] multi-object tracking[30,31] and foreground detection,[32,33] and iEEG-based deep learning techniques have also been applied for seizure prediction. Truong et al. used Short-Time Fourier Transform (STFT) to attain the iEEG time-frequency input maps and utilized Two Dimensional Convolutional Neural Networks (2D-CNN) with three convolution blocks for classification. Three datasets, the Freiburg Hospital iEEG dataset,[17] the CHB-MIT scalp electroencephalogram (sEEG) dataset[34] and the American Epilepsy Society Seizure Prediction Challenge iEEG dataset,[35] were evaluated with the proposed method. This method finally achieved 81.4%, 81.2% and 75% sensitivity and 0.06/h, 0.16/h and 0.21/h FPR, respectively.[36] Truong et al. also applied Generative Adversarial Networks (GAN) for the seizure forecasting and attained the operating characteristic curve (AUC) of 75.47 % using the Freiburg Hospital iEEG dataset.[37] Based on the same iEEG dataset, Wang et al. used a 2D-CNN with three convolution

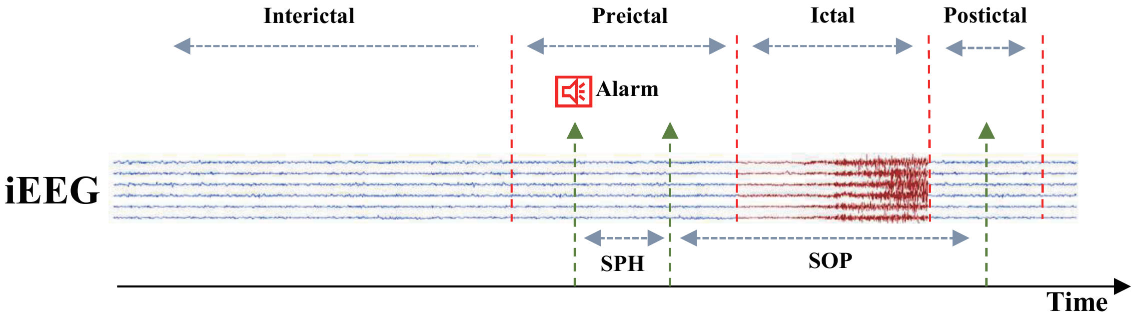

Fig. 1. The four stages of epileptic iEEG: interictal, preictal, ictal and postictal, and the definition of an accurate seizure prediction. When an alarm rings, a seizure must occur after SPH and within SOP.

blocks to classify the channel-frequency input maps that were obtained by using Directed Transfer Function (DTF). The method attained 90.8%sensitivity and 0.08/h FPR.[38] Daoud et al. used four deep learning models, including Multi-Layer Perceptron (MLP), Deep Convolutional Neural Network (DCNN) + MLP, DCNN + Bidirectional Long Short-Term Memory and Deep convolutional Autoencoder (DCAE) + Bi-LSTM, for the analysis of seizure prediction. The DCNN + Bi-LSTM model and the DCAE + Bi-LSTM model finally obtained the highest accuracy of 99.6% and the lowest FPR of 0.004/h, but the sEEG signals of only eight patients from the CHB-MIT sEEG dataset were used.[39]

Although the many previous studies used the iEEG to explore the prediction of seizures, most of them used all channel iEEG signals, ignoring the consideration of iEEG channel selection. Whether iEEG signals of all channels are conducive to the seizure prediction has not been studied well. iEEG signals are commonly recorded in the form of multiple channels (or electrodes), and the electrodes usually record iEEG signals from multiple zones of the brain, including seizure onset zones and seizure free zones. Therefore, the iEEG channel selection is needed and significant for a better prediction of seizures. Based on the above considerations, in this work, we explored the seizure prediction with a iEEG channel selection strategy. Three channel cases (single channel, channels only from seizure onset or free zone and all channels from seizure onset and free zones) combined with the corresponding One Dimensional Convolutional Neural Networks (1D-CNN) were studied and discussed. Then, the channel case with the best classification was finally selected for each patient. In the seizure prediction, the time duration of iEEG signals before seizure onset is needed to be defined as the preictal period. After defining two different preictal periods, the proposed method was evaluated on each preictal period.

2. Materials and Methods

2.1. *Data preparation*

The Freiburg Hospital iEEG dataset (http://epilepsy.uni-freiburg.de/) was used for the analysis of seizure prediction in this work . The iEEG dataset consisted of 21 patients, with a total of 87 seizures, 509 h of interictal and 73 h of preictal or ictal iEEG signals. Each patient contained at least 24 h of interictal and 50 min of preictal iEEG signals. The iEEG signals were recorded with the sampling rate of 256 Hz, and a bandpass filter between 0.5 and 120 Hz and a 50 Hz notch filter were used to eliminate the possible noise.[17] More details about this iEEG dataset were described in [17].

In the seizure prediction, it is to explore the distinction between interictal stage and preictal stage (as shown in Fig. 1). It means that the time durations of SPH and SOP need to be defined. SOP is defined as the period during which a seizure is expected to occur. SPH is the period between the alarm and the beginning of SOP.[40] The SPH is also called the intervention time.[41] In real-world conditions, the time duration of SPH should be long enough for potential interventions to prevent seizure onset. In this work, the time duration of SPH was set to 5 min,[36,38,42,43] while we discussed two different durations of SOP, namely 30 min and 60 min. According to the two different durations of SOP, the final selected iEEG signals and their details were summarized in Table 1.

Table 1. The details of the selected iEEG signals for each patient

Patient	Gender	Age	Interictal (h)	#seizures (SOP = 30 min)	#seizures (SOP = 60 min)+
1	f	15	24	4	3
2	m	38	24	3	–
3	m	14	24	5	4
4	f	26	24	5	3
5	f	16	24	5	2
6	f	31	24	3	–
7	f	42	24.6	3	3
8	f	32	24.2	2	2
9	m	44	23.9	5	3
10	m	47	24.5	5	5
11	f	10	24.1	4	3
12	f	42	24	4	3
13	f	22	24	2	2
14	f	41	23.9	4	3
15	m	31	24	4	3
16	f	50	24	5	5
17	m	28	24.1	5	5
18	f	25	24.9	5	5
19	f	28	24.4	4	3
20	m	33	25.6	5	5
21	m	13	23.9	5	4
Total			508.1	87	66

+ When SOP = 60 min and SPH = 5 min are defined, preictal iEEG signals with the time duration of at least 65 min can be selected.

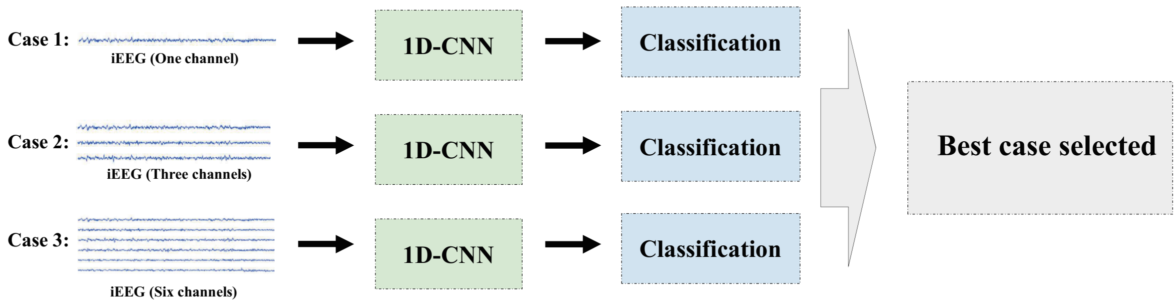

Fig. 2. The architecture of the proposed method for seizure prediction. The iEEG signals of three channel cases (one channel, three channels and six channels) are classified using the 1D-CNN model. Then, the channel case with the best classification is finally selected for each patient.

2.2. *Methodology*

In the Freiburg Hospital iEEG dataset, the iEEG signals of each patient are recorded using six recording channels, three of which are in-focus channels (from seizure onset zones of the brain, denoted channels 1-3), and the other three are out-of-focus channels (from seizure free zones of the brain, denoted channels 4-6). Based on the iEEG dataset, we discuss three cases about the use of different iEEG channels. The proposed method based on the channel-based 1D-CNN for seizure prediction is showed in Fig. 2. Case 1 shows that only one channel (channel 1 to 6, each channel in turn) is used for the prediction of seizures. Case 2 shows that three channels (in-focus channels 1-3 or out-of-focus channels 4-6) are used at the same time. Case 3 shows that all channels (channels 1-6) are used simultaneously. The best channel case is finally selected for each patient according to the classification results.

2.2.1. *Preprocessing*

We used 30-sec sliding widows to segment the long-term raw iEEG signals. For one 30-sec iEEG segment with the sampling rate of 256 Hz, it can be seen as a vector or matrix of $n \times 7680$, where n ($n = 1$, 3 and 6) is the number of the selected channels. The 30-sec iEEG segments are used as the inputs of the proposed 1D-CNN.

As shown in Table 1, the time duration of interictal iEEG signals is about 24 hours, while that of preictal iEEG signals ranges from about 2 to 5 hours (depending on the number of seizures of each patient). It means that the sample imbalance is a key problem in this work. In order to solve the problem during the model training phase, an overlapped sliding window technique was used.[36,38] We used 30-sec sliding windows without overlap to segment interictal iEEG signals. However, for preictal iEEG signals that were selected as the training set, we used 30-sec sliding windows with the corresponding overlap rate to generate more preictal segments. Fig. 3 shows the details of the oversampling technique.

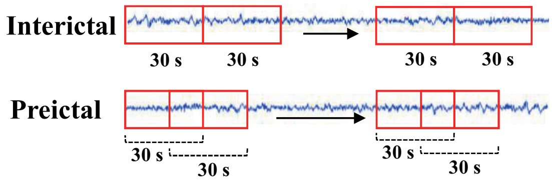

Fig. 3. For interictal iEEG signals, we use 30-sec sliding windows without overlap. For preictal iEEG signals that were selected as the training set, we use 30-sec sliding windows with the corresponding overlap rate.

2.2.2. *Convolutional neural network (CNN)*

CNNs have achieved the remarkable results in the seizure detection,[44–47] the seizure control[48] and the detection of interictal epileptiform discharges.[49] A CNN model generally consists of convolution layers, pooling layers and fully connected layers. A convolution layer performs convolution calculations on input signals, and the convolution results are then nonlinearized by activation functions. In this work, the rectified linear activation unit (ReLU) function was used in the convolution layers. A pooling layer commonly performs pooling operations on the outputs of a convolution layer to preserve higher-level representations. In our 1D-CNN model, pooling processes, including maximum pooling and global average pooling, were used. After passing through convolutional layers and pooling layers, the outputs are usually fed into fully connected layers for the final classification.

In this work, the proposed 1D-CNN model is showed in Fig. 4. Our model has four convolution-block layers and two fully connected layers. The first two convolution-block layers contain four convolution blocks. For the two convolution blocks on the left, the first convolution block contains a convolution layer (32 kernels with the size of $n \times 3$ and the stride of 2), a batch normalization (BN) layer and a max-pooling (MP) layer (the pooling size of 3 and the stride of 2), and the second convolution block also contains a convolution layer with 32 kernels with the size of 3

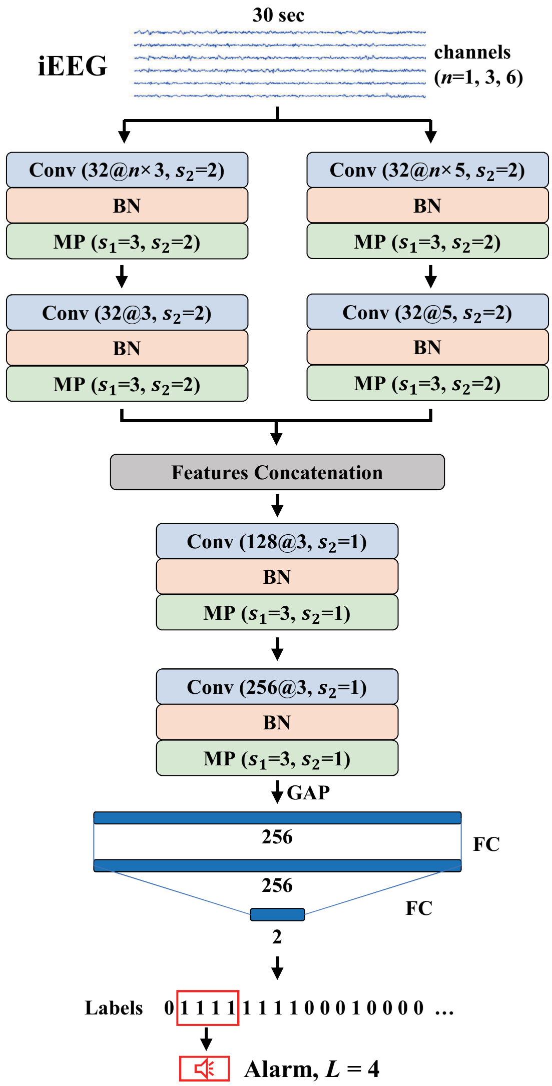

Fig. 4. The proposed 1D-CNN is showed. M@$n \times \mathrm{k}_1$ or M@k_2: M is the number of kernels, $n \times \mathrm{k}_1$ and k_2 are the sizes of kernels. Abbreviations: Conv, convolution; BN, batch normalization; MP, max-pooling; s_1, pooling size; s_2, stride; GAP, global average pooling; FC, fully connected. L is the number of consecutive prediction labels for an alarm.

and the stride of 2, a BN layer and a MP layer with the pooling size of 3 and the stride of 2. The structure of the two convolution blocks on the right is the same as that of the two convolution blocks on the left. The only difference is that the size of convolution kernels in the first and sencond convolution layers. The kernel sizes of these two convolution layers are $n\times5$ and 5, respectively. The first two convolution-block layers can process the input signals in parallel and extract different feature maps with different kernel sizes. The outputs of the first two convolution-block layers are then concatenated. For extracting deeper feature information, the concatenated feature maps are sent into the third and fourth convolution-block layers successively. The third convolution-block layer has one convolution block with a convolutional layer with 128 kernels (the size of 3 and the stride of 1), a BN layer and a MP layer with the pooling size of 3 and the stride of 1. The fourth convolution-block layer also has one convolution block including a convolutional layer (256 kernels with the size of 3 and the stride of 1), a BN layer and a MP layer (the pooling size of 3 and the stride of 1). The outputs of the fourth convolution-block layer are globally averaged as the inputs of the two fully connected layers. The first and the second fully connected layers have 256 neurons with ReLU function and 2 output neurons with Softmax function, respectively.

In order to accurately predict seizures and issue alarms, the postprocessing for the outputs of 1D-CNN was performed (as shown in Fig. 4). The condition for an alarm to sound is that L consecutive predicted labels are positive. In this work, the L value was finally set to 4 after many tests. For avoiding unnecessary repetitive alarms, when the first alarm sounds, the second alarm can only sound after the end of SOP. Hence, the second alarm in the period from the moment the first alarm sounds to the end of SOP is prohibited by the system.

2.2.3. *Model training*

The patient-specific model was trained for each patient. In order to predict all seizures of each patient, the approach of leave-one-out cross validation was applied. It means if a patient has K seizures, the model training is performed K rounds. In each round, (K-1) seizures are used for training, and the remaining one is used for testing. All seizures can be predicted after K rounds. Fig. 5 shows the details of the leave-one-out cross validation. As shown in Fig. 5, in each round, we also increased the preictal training samples by using the oversampling technique mentioned in the preprocessing (Section 2.2.1), and the number of segments reserved for training and testing was summarized in Table 2.

During model training, the Early-Stopping technique was also applied to prevent overfitting, and the dropout rate of second fully connected layer was set to 0.25. Based on Keras 2.3.1 with the Tensorflow 1.15.0 backend, our model was established and implemented in Python 3.6, and two Nvidia Tesla P100 GPUs were configured to run the proposed model.

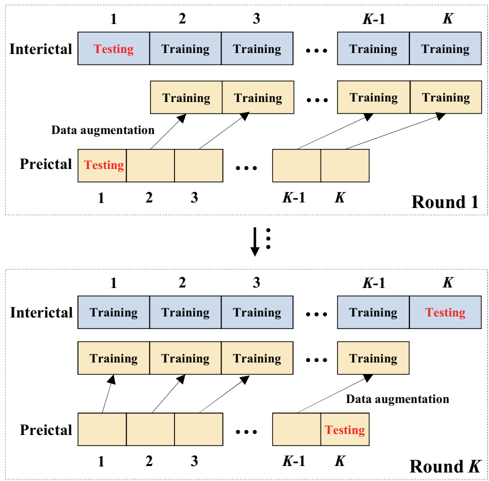

Fig. 5. Leave-one-out cross validation: in each round, (K-1) seizures are used for training, and the remaining one is used for testing. All seizures can be predicted after K rounds. In each round, the oversampling technique is also applied to increase the preictal training samples.

2.2.4. *System evaluation*

We evaluated the performances of the proposed method in the two levels (the segment-based level and the event-based level) at the same time. Combining the results of the two levels, we finally selected the best channel case for each patient.

- Segment-based level

In the segment-based level, the accuracy of sample classification is calculated. The accuracy is expressed as following:

$$Accuracy = \frac{TP + TN}{Total\ number\ of\ segments}, \quad (1)$$

Table 2. During model training with the leave-one-out cross validation, in each round, the number of segments reserved for training and testing is summarized as below.

		SOP = 30 min and SPH = 5min					SOP = 60 min and SPH = 5 min			
		Training		Testing			Training		Testing	
Patient	#Seizures	Interictal	Preictal	Interictal	Preictal	#Seizures	Interictal	Preictal	Interictal	Preictal
1	4	2160	2160	720	60	3	1920	1920	960	120
2	3	1920	1920	960	60	–	–	–	–	–
3	5	2304	2304	576	60	4	2160	2160	720	120
4	5	2304	2304	576	60	3	1920	1920	960	120
5	5	2304	2304	576	60	2	1440	1440	1440	120
6	3	1920	1920	960	60	–	–	–	–	–
7	3	1968	1968	984	60	3	1968	1968	984	120
8	2	1452	1452	1452	60	2	1452	1452	1452	120
9	5	2292	2292	573	60	3	1912	1912	956	120
10	5	2352	2352	588	60	5	2352	2352	588	120
11	4	2169	2169	723	60	3	1928	1928	964	120
12	4	2160	2160	720	60	3	1920	1920	960	120
13	2	1440	1440	1440	60	2	1440	1440	1440	120
14	4	2151	2151	717	60	3	1912	1912	956	120
15	4	2160	2160	720	60	3	1920	1920	960	120
16	5	2304	2304	576	60	5	2304	2304	576	120
17	5	2312	2312	578	60	5	2312	2312	578	120
18	5	2388	2388	597	60	5	2388	2388	597	120
19	4	2196	2196	732	60	3	1952	1952	976	120
20	5	2456	2456	614	60	5	2456	2456	614	120
21	5	2292	2292	573	60	4	2151	2151	717	120

where TP is true positive, indicating the number of true predicted preictal segments from preictal segments, and TN is true negative, indicating the number of true predicted interictal segments from interictal segments.

- Event-based level

In the event-based level, sensitivity and FPR are calculated, and the definitions of them are proposed in [40]. The sensitivity and the FPR are expressed by the following formulas:

$$Sensitivity = \frac{number\ of\ correct\ predictions}{number\ of\ all\ seizures}, \quad (2)$$

$$FPR = \frac{number\ of\ incorrect\ predictions}{hours\ of\ interictal\ iEEG}. \quad (3)$$

An excellent system is supposed to sound alarms with higher sensitivity and lower FPR.

For testing statistical significance of the proposed method, it needs to be compared with the random predictior. The probability of a random alarm can be defined as:[50,51]

$$p_1 \approx 1 - e^{-FPR \cdot SOP}, \quad (4)$$

where FPR and SOP are false prediction rate and seizure occurrence period, respectively. Therefore, the probability of randomly predicting at least k out of K independent seizures can be expressed as following:

$$p_{-value} = \sum_{j \geq k} \binom{K}{j} p_1^j (1 - p_1)^{K-j}, \quad (5)$$

where k is the number of the predicted seizures, and K is the number of all seizures. In this study, the significance level is set to 0.05. It means when the calculated p_{-value} is less than 0.05, our method is better than the random prediction.

3. Results

The proposed method with three channel cases (single channel, three channels and all channels) is evaluated on two different preictal periods: (1) SOP of 30 min and SPH of 5 min; (2) SOP of 60 min and SPH of 5 min. The whole algorithm runs twice, and the averaged results of the two levels are calculated for the further analysis.

According to the results of the segment-based level and the event-based level, the selection criteria for the best channel case are defined as following: (1) We first select the best channel situation according to the sensitivity and FPR (the event-based level); (2) If a patient has the same sensitivity and FPR under several channel situations, we then combine the accuracy (the segment-based level) of these chan-

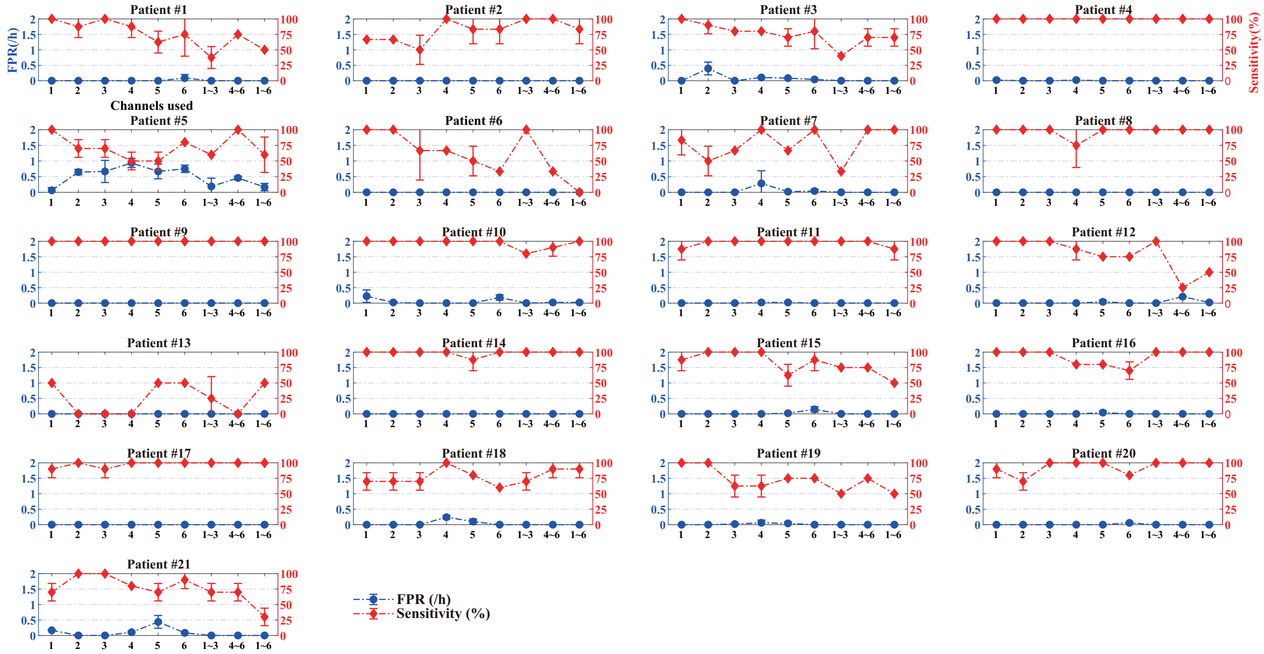

Fig. 6. In the event-based level with SOP of 30 min and SPH of 5 min, each subfigure shows the averaged sensitivity and FPR of each patient under the nine channel situations (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6). The best channel situation is selected for each patient. The left blue Y-axis and the right red Y-axis represent the FPR and the sensitivity, respectively.

Table 3. The results of our method with SOP of 30 min and SPH of 5 min. The whole algorithm runs twice. After selecting the best channel situation, the averaged results (accuracy, sensitivity and FPR) and the p_{-value} are given for each patient.

Patient	Interictal (h)	#seizures	C_s	Accuracy (%)	Sensitivity (%)	FPR (/h)	p_{-value}
1	24	4	1[a]	99.13±0.77	100±0.00	0.00±0.00	0.000
2	24	3	4[b]	99.66±0.02	100±0.00	0.00±0.00	0.000
3	24	5	1[a]	98.13±0.02	100±0.00	0.00±0.00	0.000
4	24	5	2[a]	99.21±0.00	100±0.00	0.00±0.00	0.000
5	24	5	1[a]	95.58±1.93	100±0.00	0.06±0.09	0.000
6	24	3	1[a]	99.08±0.05	100±0.00	0.00±0.00	0.000
7	24.6	3	4-6[b]	97.65±0.16	100±0.00	0.00±0.00	0.000
8	24.2	2	1-3[a]	99.64±0.09	100±0.00	0.00±0.00	0.000
9	23.9	5	5[b]	100±0.00	100±0.00	0.00±0.00	0.000
10	24.5	5	3[a]	99.41±0.00	100±0.00	0.00±0.00	0.000
11	24.1	4	2[a]	99.89±0.07	100±0.00	0.00±0.00	0.000
12	24	4	3[a]	99.84±0.18	100±0.00	0.00±0.00	0.000
13	24	2	5[b]	97.98±0.02	50±0.00	0.00±0.00	0.000
14	23.9	4	3[a]	99.89±0.07	100±0.00	0.00±0.00	0.000
15	24	4	4[b]	98.62±0.32	100±0.00	0.00±0.00	0.000
16	24	5	4-6[b]	99.32±0.42	100±0.00	0.00±0.00	0.000
17	24.1	5	4-6[b]	99.58±0.29	100±0.00	0.00±0.00	0.000
18	24.9	5	4[b]	92.80±2.65	100±0.00	0.25±0.06	0.000
19	24.4	4	1[a]	98.70±0.49	100±0.00	0.00±0.00	0.000
20	25.6	5	1-3[a]	98.20±0.19	100±0.00	0.00±0.00	0.000
21	23.9	5	2[a]	98.28±0.16	100±0.00	0.00±0.00	0.000
Total	508.1	87		98.60±0.38	98.85±0.00	0.01±0.01	

C_s means channel selected for the best classification; [a] Channels only from seizure onset zones of the brain; [b] Channels only from seizure free zones of the brain.

nel situations to finally determine the best channel situation.

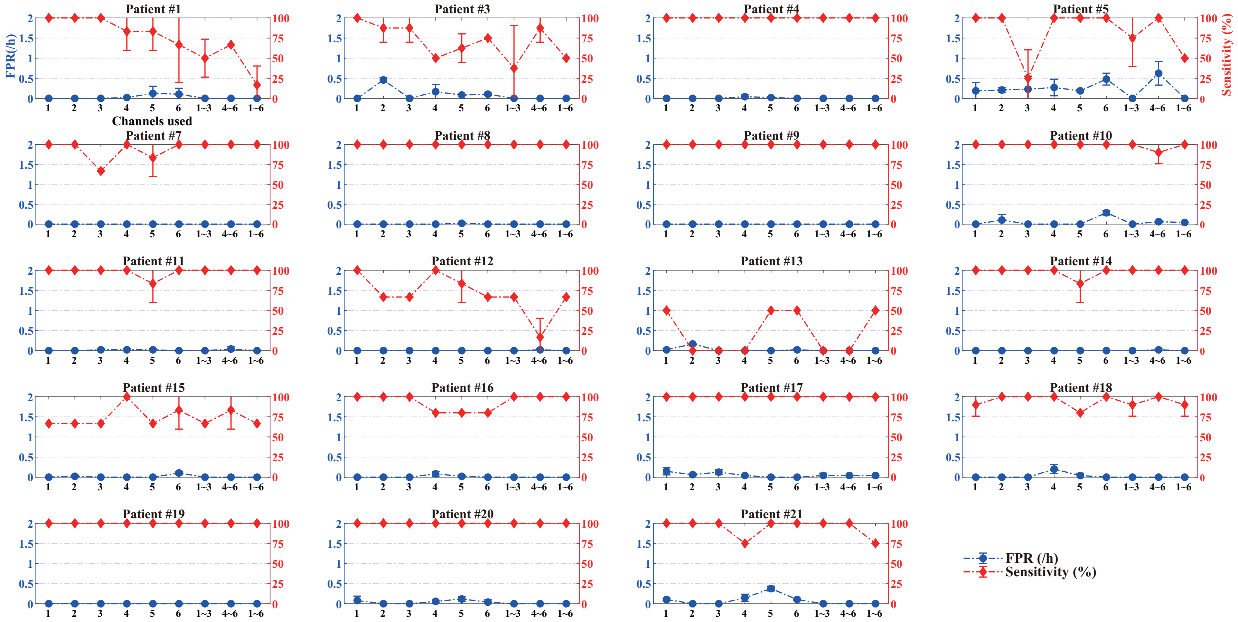

Fig. 7. In the event-based level with SOP of 60 min and SPH of 5 min, each subfigure shows the averaged sensitivity and FPR of each patient under the nine channel situations (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6). The best channel situation is selected for each patient. The left blue Y-axis and the right red Y-axis represent the FPR and the sensitivity, respectively.

Table 4. The results of our method with SOP of 60 min and SPH of 5 min. The whole algorithm runs twice. After selecting the best channel situation, the averaged results (accuracy, sensitivity and FPR) and the p_{-value} are given for each patient.

Patient	Interictal (h)	#seizures	Cs^*	Accuracy (%)	Sensitivity (%)	FPR (/h)	p_{-value}
1	24	3	1^a	97.27±0.85	100±0.00	0.00±0.00	0.000
3	24	4	1^a	97.69±1.54	100±0.00	0.00±0.00	0.000
4	24	3	2^a	99.26±0.00	100±0.00	0.00±0.00	0.000
5	24	2	5^b	91.19±0.68	100±0.00	0.19±0.03	0.000
7	24.6	3	1^a	98.21±0.44	100±0.00	0.00±0.00	0.000
8	24.2	2	1-3^a	99.92±0.02	100±0.00	0.00±0.00	0.000
9	23.9	3	5^b	99.57±0.00	100±0.00	0.00±0.00	0.000
10	24.5	5	3^a	99.80±0.04	100±0.00	0.00±0.00	0.000
11	24.1	3	2^a	99.64±0.11	100±0.00	0.00±0.00	0.000
12	24	3	4^b	99.31±0.11	100±0.00	0.00±0.00	0.000
13	24	2	5^b	96.12±0.05	50±0.00	0.00±0.00	0.000
14	23.9	3	3^a	99.66±0.18	100±0.00	0.00±0.00	0.000
15	24	3	4^b	97.89±0.55	100±0.00	0.00±0.00	0.000
16	24	5	4-6^b	99.40±0.41	100±0.00	0.00±0.00	0.000
17	24.1	5	4-6^b	97.75±0.14	100±0.00	0.04±0.00	0.000
18	24.9	5	4-6^b	98.06±1.72	100±0.00	0.00±0.00	0.000
19	24.4	3	3^a	99.80±0.06	100±0.00	0.00±0.00	0.000
20	25.6	5	1-3^a	98.47±0.08	100±0.00	0.00±0.00	0.000
21	23.9	4	2^a	99.05±0.25	100±0.00	0.00±0.00	0.000
Total	460.1	66		98.32±0.38	98.48±0.00	0.01±0.00	

[*] Cs means channel selected for the best classification; [a] Channels only from seizure onset zones of the brain; [b] Channels only from seizure free zones of the brain.

3.1. *SOP of 30 min and SPH of 5 min*

In the event-based level, the averaged results (sensitivity and FPR) are reported in Fig. 6. Each subfigure in Fig. 6 shows the sensitivity and FPR of each patient under nine channel situations (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6). For example, patient 20 obtains the same sensitivity and FPR from channels 3, 4, 5, 1-3, 4-6 and 1-6 (as shown in Fig. 6). Based on the selection criteria for the best channel case, we then calculate the accuracy of these channel situations, and the best channel situation (channels 1-3) is determined due to the highest accuracy of 98.20±0.19% (as shown in Fig. 8(a)). After selecting the best channel situation for each patient, we summarize the corresponding sensitivity, FPR and accuracy in Table 3.

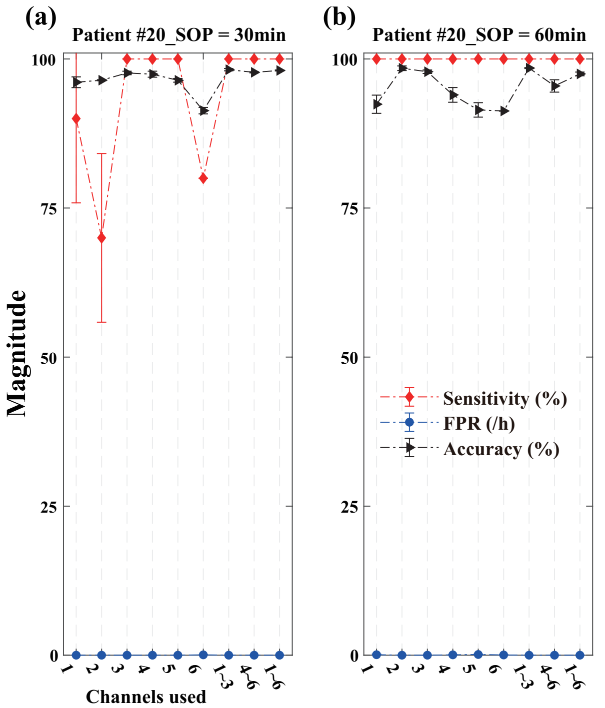

Fig. 8. The example of patient 20 includes both event-based and segment-based results for the selection of the best channel situation. According to the results in the conditions of SOP = 30 min and SOP = 60 min, the best channel situation of channels 1-3 is finally selected.

As shown in Table 3, in the event-based level, 86 out of 87 seizures are accurately predicted, with a sensitivity of 98.85%. The FPR is low at 0.01/h. From the p_{-value} of each patient, we can see that the performance of the proposed method is much better than that of the random prediction. In the segment-based level, the accuracy of 19 patients is higher than 97%. The accuracy rates of the other two patients (patients 5 and 18) are at 95.58% and 92.80%, respectively. The averaged accuracy of 21 patients is 98.60%, which shows that our method can classify interictal and preictal segments well.

3.2. *SOP of 60 min and SPH of 5 min*

In this preictal period, patients 2 and 6 are excluded, and so total 19 patients are analyzed. Fig. 7 shows the averaged sensitivity and FPR of 19 patients. Each subfigure in Fig. 7 also shows the sensitivity and FPR of each patient under nine channel situations. According to the selection criteria for the best channel case, the best channel situation is selected for each patient. For example, patient 20 attains the best result also with the channel situation of 1-3 (as shown in Fig. 8(b)). For each patient, the best channel situation and the corresponding sensitivity, FPR and accuracy are summarized in Table 4.

As shown in Table 4, 65 out of 66 seizures are accurately predicted by the proposed method. The high sensitivity of 98.48% and the low FPR of 0.01/h are obtained (the event-based level). According to the calculated p_{-value} of each patient, our method is much better than the random prediction in the seizure prediction. In the segment-based level, 17 patients have an accuracy of more than 97%, and the accuracy rates of patients 5 and 13 are 91.19% and 96.12%, respectively. The averaged accuracy of 19 patients is 98.32%.

3.3. *Channel selection*

Based on the results in Table 3 and Table 4, there are several points that we need to explain. Firstly, none of the 21 patients achieves the best result using all channel (channels 1-6) iEEG signals. From this point, we can see that the channel selection for each patient is necessary. Secondly, most patients attain the best results when only using single-channel rather than multi-channel iEEG signals. Thirdly, under two preictal periods, namely SOP of 30 min and SOP of 60 min with the same SPH of 5 min, most patients have the same channel selection in obtaining the best results, and so it shows the reliability of the results and the stability of the proposed method.

According to the results in Table 3 (SOP of 30 min and SPH of 5 min) and Table 4 (SOP of 60 min and SPH of 5 min), we also count the number of patients corresponding to two types of channel conditions. As shown in Fig 9, the number of patients with channels selected only from the seizure onset zones is slightly more than that of patients with channels selected only from the seizure free zones. However, the number of patients with channels selected from both zones is zero. Based on the findings, we can have the following two thoughts: (1) The iEEG signals recorded from the seizure free zones are important in the seizure prediction, and their predictive performance is sometimes better than the iEEG signals recorded from the seizure onset zones; (2) In the prediction of seizures, all channel iEEG signals are not necessarily valid and channel selection is necessary.

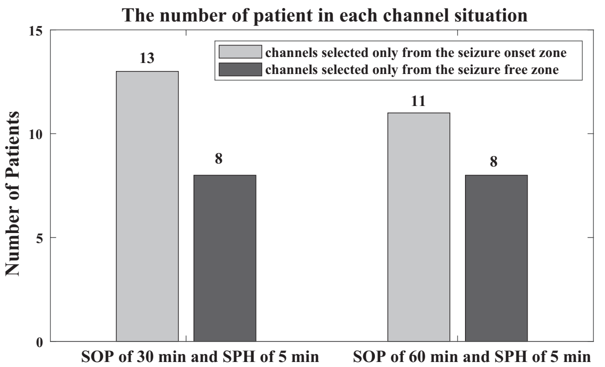

Fig. 9. In two different preictal periods, the number of patients with the different channel conditions.

4. Discussion

CNNs have been used for the prediction of seizures in [36], [38] and [56], while the studies used all channel iEEG signals, ignoring the channel selection. Although the channel selection strategies have been applied in [57–60] for seizure prediction, these studies mainly focused on the conventional machine learning methods.[57–60] Hence, in this work, we proposed a method of 1D-CNN combined with channel selection strategy for seizure prediction. From the perspective of incremental learning, the iEEG signals with a channel increase strategy (from single channel to multiple channels, and then to all channels) were used as the inputs of 1D-CNNs with the same structure. The patient-specific model was then trained, and the best channel case was selected for each patient according to the classification results. From the results in Table 3 and Table 4, we achieved high accuracy (98.60% and 98.32%), high sensitivity (98.85% and 98.48%) and low FPR (0.01/h and 0.01/h). It indicated that our method was effective and had well performance in using the long-term iEEG signals to predict seizures.

We also compared the results of this work and the previous studies using the Freiburg Hospital iEEG dataset. The details of the previous studies and this work, including the total number of seizures, feature extraction methods and classifiers, were given in Table 5. The four significant metrics related to seizure prediction, namely sensitivity, FPR, SOP and SPH, were also given in Table 5. As shown in Table 5, the methods of threshold analysis combined with linear or nonlinear features achieved the sensitivity ranging from 42% to 92.9% and the FPR ranging from 0.06/h to 0.15/h.[17–21,52,55] The highset sensitivity (92.9%) was attained in the study [21], but the study only used 10 patients for the analysis of seizure prediction. The conventional machine learning methods, including SVM,[22,23,26,53,54] LS-SVM[25] and Bayesian[24] , were used for the prediction of seizures. The sensitivity and the FPR obtained by these methods ranged from 85.5% to 100% and 0.03/h to 0.36/h, respectively. The SVM in the study [54] achieved the highest sensitivity of 100% with the FPR of 0.0324/h. The deep learning methods, including 2D-CNN[36,38] and GAN,[37] combined with the preprocessing techniques (STFT and DTF) were used to analyze the same iEEG dataset, and the sensitivity ranging from 81.4% to 90.8% and the FPR ranging from 0.03/h to 0.08/h were attained. The 2D-CNN used in the study [38] achieved the highest sensitiivty of 90.8% with the FPR of 0.08/h.

Compared with the results in Table 5, our method achieved high sensitivity (98.85% and 98.48%) and low FPR (0.01/h and 0.01/h), which showed that the performances of our method were better than that of most previous studies. Although the sensitivity of 100% and the FPR of 0.03 were obtained in the study [54], the authors ignored the actual clinical considerations by setting SPH to zero, and they also used the time-consuming and complex feature selection for each patient.

In this work, the Freiburg Hospital iEEG dataset is recorded with three in-focus channels (channels 1-3) and three out-of-focus channels (channels 4-6). Consequently, the number of the combinations of channels is 63 ($C_6^1 + C_6^2 + C_6^3 + C_6^4 + C_6^5 + C_6^6$). One limitation of this work is that our method discusses nine channel combinations (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6) for seizure prediction. Therefore, more subsets of channels can to be selected and tested. In the future work, all the channel combinations combined with deep learning approaches will be further analyzed and discussed. The second limitation is that our work only uses a 1D-CNN model combined with the channel selection strategy for the classification of

Table 5. The list of previous studies and this work using the Freiburg Hospital iEEG dataset for seizure prediction.

Authors	#Patients	#Seizures	Feature	Classifier	SEN (%)	FPR (/h)	SOP	SPH
Maiwald et al. (2004)[17]	21	88	Dynamical similarity index	Threshold crossing	42	0.15	30 min	2 min
Winterhalder et al. (2006)[18]	21	88	Phase coherence, lag synchronization	Threshold crossing	60	0.15	30 min	10 min
Park et al. (2011)[22]	18	80	Spectral power of nine bands	SVM	97.5	0.27	30 min	0^c
Williamson et al. (2012)[23]	19	83	Correlation patterns	SVM	85.5	0.03	30 min	0^c
Li et al. (2013)[52]	21	87	Spike rate	Threshold crossing	75.8	0.09	50 min	10 sec
Zheng et al. (2014)[19]	10	50	phase synchronization	Threshold crossing	>70	<0.15	30 min	10 min
Eftekhar et al. (2014)[20]	21	87	Multiresolution N-gram	Threshold crossing	90.95	0.06	20 min	10 min
Ozdemir et al. (2014)[24]	21	87	Hilbert-Huang transform	Bayesian	96.55	0.21	35 min	5 min
Wang et al. (2014)[53]	19	83	Amplitude and frequency modulation features	SVM	98.55	0.054	50 min	0^c
Zhang et al. (2016)[54]	18	80	Power spectral density ratio	SVM	100	0.0324	50 min	0^c
Parvez et al. (2017)[25]	21	87	Phase-match error, deviation, fluctuation	LS-SVM	95.4	0.36	30 min	0^c
Sharif et al. (2017)[26]	19	83	Fuzzy rules on Poincaré plane	SVM	91.8-96.6	0.05-0.08	15 min	2-42 min
Aarabi et al. (2017)[21]	10	28	Univariate and bivariate nonlinear features	Rule-based decision making	92.9	0.096	50 min	10 sec
Truong et al. (2018)[36]	13	59	STFT	2D-CNN	81.4	0.03	30 min	5 min
Truong et al. (2019)[37]	13	59	STFT	GAN	–	–	30 min	5 min
Wang et al. (2020)[38]	19	82	DTF	2D-CNN	90.8	0.08	30 min	5 min
Zhang et al. (2020)[55]	20	65	Fractal dimension, intercept	Gradient boosting classifier	90.42	0.12	30 min	2 min
	20	65			91.67	0.10	50 min	2 min
This work	21	87	30-sec iEEG segments	Channel-based 1D-CNN	98.85	0.01	30 min	5 min
	19	66			98.48	0.01	60 min	5 min

Abbreviations: SEN, sensitivity; FPR, false prediction rate; SOP, seizure occurrence period; SPH, seizure prediction horizon; SVM, support vector machine; LS-SVM, least square-SVM; STFT, short-time Fourier transform; DTF, directed transfer function; 2D-CNN, two dimensional convolutional neural network; GAN, generative adversarial networks; 1D-CNN, one dimensional convolutional neural network

^{c} SPH is also called the intervention time. When SPH is set to zero, it means that the time left for clinical intervention is zero, ignoring actual clinical considerations.

the iEEG signals. Other deep learning and machine learning algorithms, such as 2D-CNN and LSTM, Enhanced Probabilistic Neural Network,[61] Neural Dynamic Classification Algorithm,[62] Dynamic Ensemble Learning Algorithm[63] and Finite Element Machine,[64] combined with the channel selection strategy can also be applied to the same iEEG dataset for seizure prediction.

5. Conclusion

In this paper, a novel method of 1D-CNN combined with channel selection strategy was proposed for the prediction of seizures. Different from the many previous studies only using all channel iEEG signals, the iEEG signals of single channel, multiple channels and all channels were classified using a 1D-CNN model with four convolution-block layers. Then, according to the results of classification, the channel case with the best classification result was finally selected for each patient.

The proposed method was evaluated on the Freiburg Hospital iEEG dataset recorded with three in-focus channels (channels 1-3) and three out-of-focus channels (channels 4-6), and the iEEG signals of nine channel situations (1, 2, 3, 4, 5, 6, 1-3, 4-6 and 1-6) were analyzed to select the channel case with the best classification for each patient. Our method successfully predicted 86 out of 87 seizures (except one seizure in patient 13). The overall results, (1) 98.60% accuracy, 98.85% sensitivity and 0.01/h FPR in the SOP of 30 min and SPH of 5 min; (2) 98.32% accuracy, 98.48% sensitivity and 0.01/h FPR in the SOP of 60 min and SPH of 5 min, were achieved. Compared with the many previous studies using the same iEEG dataset, our method showed a better performance in the seizure prediction. Our method was also statistically better than the random prediction for all patients in the Freiburg Hospital iEEG dataset.

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SEIZURE PREDICTION USING EEG CHANNEL SELECTION METHOD

by

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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 filtering. 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.

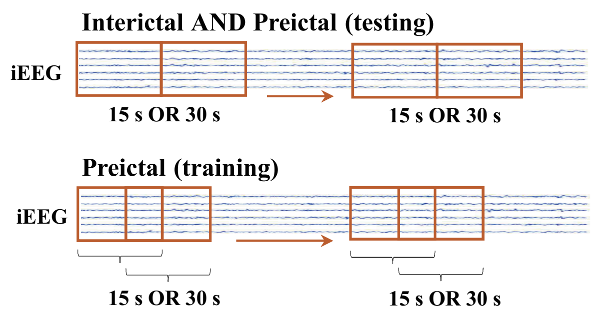

Fig. 1. Preictal iEEG signals which are selected as the testing set and interictal iEEG signals are segmented by sliding windows without the overlap ratio. Preictal iEEG signals which are selected as the training set are segmented by sliding windows with the corresponding overlap ratio.

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.

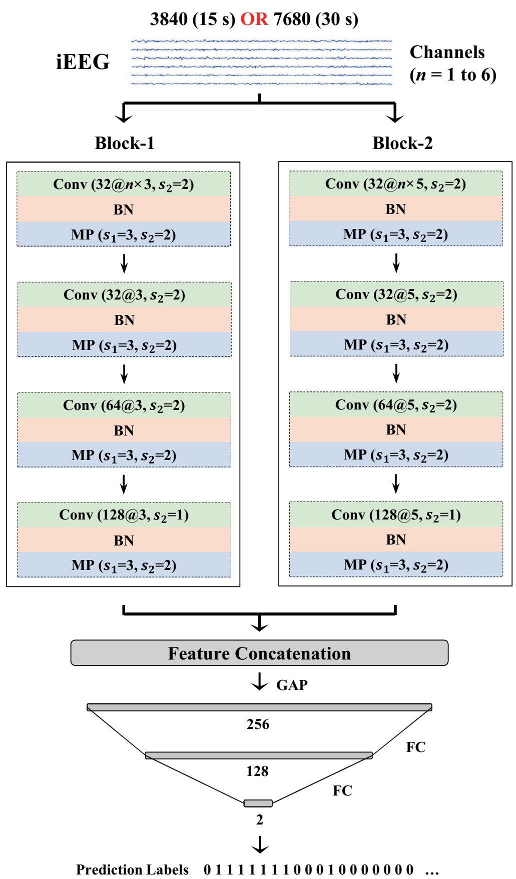

Fig. 2. Architecture of the 1D-CNN model. M_1@n×k_1 or M_2@k_2: M_1 and M_2 are the number of kernels, k_1 and k_2 are the sizes of kernels. s_1 means pooling size and s_2 means stride. For the inputs, iEEG segments of 63 channel cases ($|C_6^1| + |C_6^2| + |C_6^3| + |C_6^4| + |C_6^5| + |C_6^6| = 63$)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

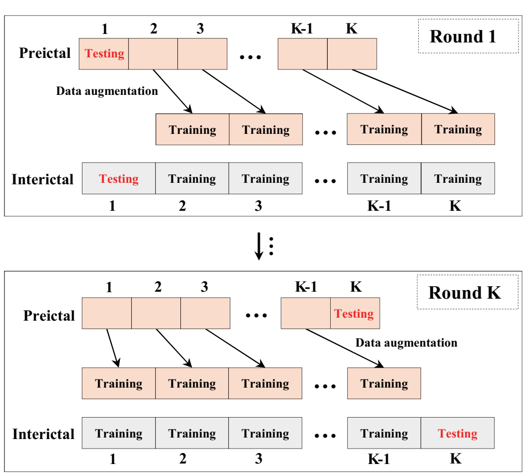

Fig. 3. The K-CV approach combined with the data augmentation technique is applied during model training.

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

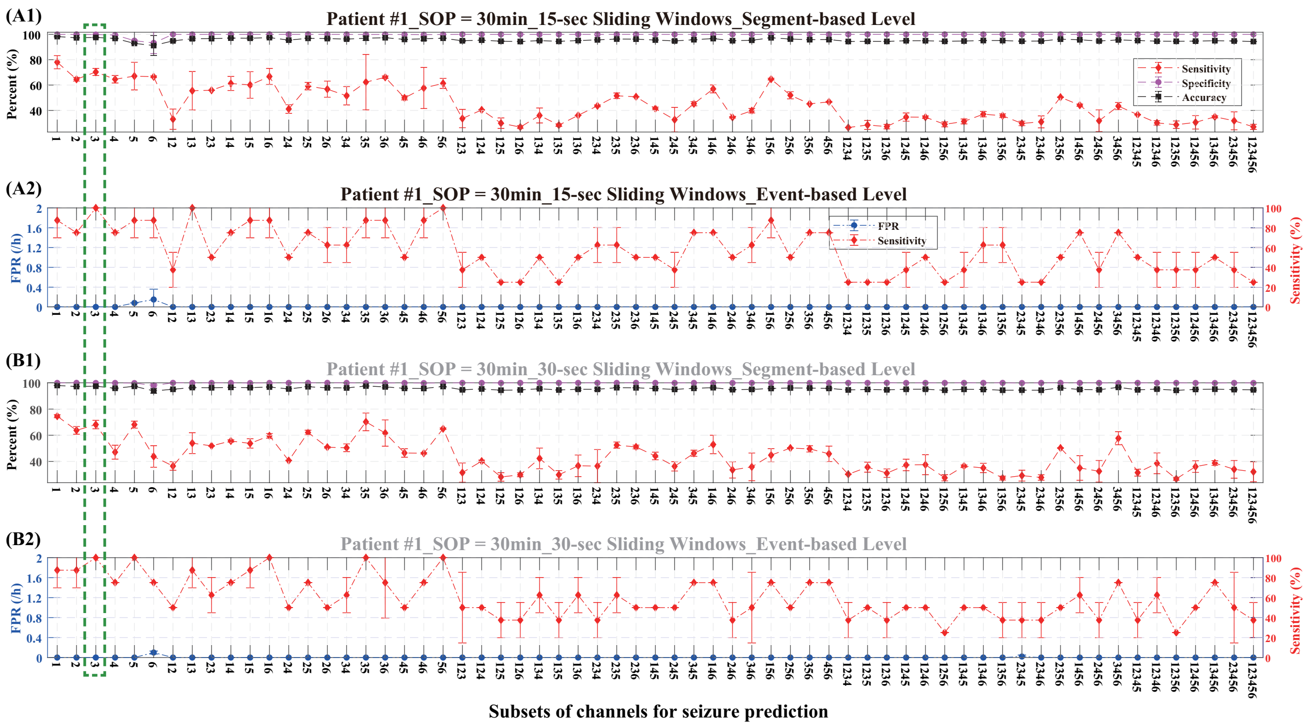

Fig. 4. In preictal condition of SOP = 30 min, the averaged results for patient 1 are showed after the whole algorithm runs twice. In preprocessing of 15-sec sliding widows, classification results of 63 channel cases are given at the segment-based level (A1) and the event-based level (A2). In preprocessing 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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CHANNEL INCREMENT STRATEGY-BASED 1D CONVOLUTIONAL NEURAL NETWORKS FOR SEIZURE PREDICTION USING INTRACRANIAL EEG

by

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

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***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.**

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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

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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]–[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]–[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]–[36], 2D-CNN [25], [37]–[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]–[47], seizure prediction [48]–[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 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].

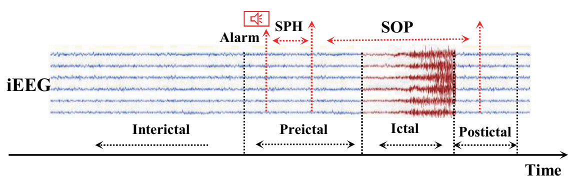

Fig. 1. Example of an accurate seizure prediction. When an alarm rings, a seizure must occur after SPH and within SOP.

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, 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

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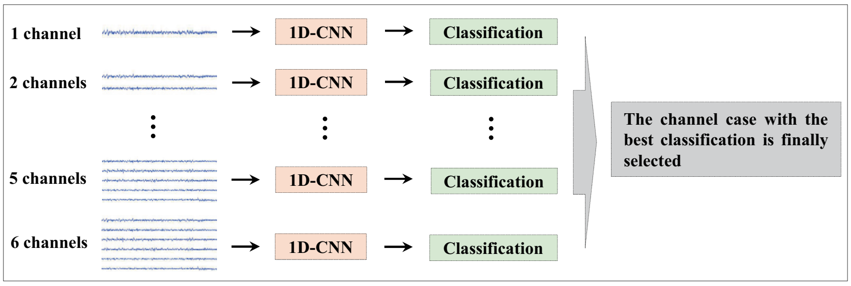

Fig. 2. Overall diagram of the 1D-CNN combined with channel increment strategy for the epileptic seizure prediction.

for ensuring the number of samples during model training. The details of the selected iEEG signals are summarized in Table I.

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

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

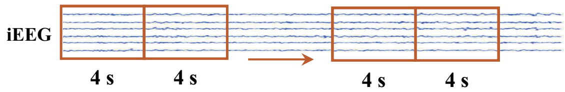

Fig. 3. The raw iEEG signals (interictal and preictal) are segmented by the 4-sec sliding windows without overlap.

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.

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.

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.

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

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

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 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.

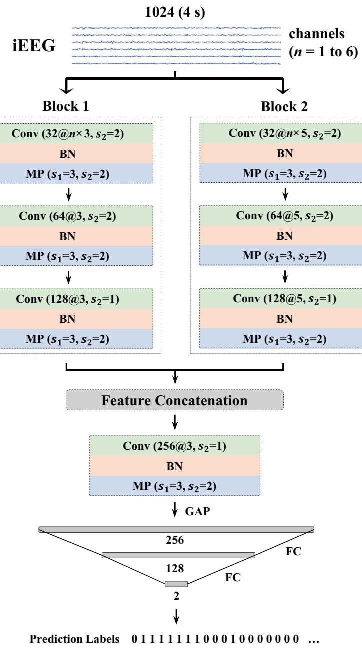

Fig. 4. Framework of the proposed 1D-CNN model. $M_1@n{\times}k_1$ or $M_2@k_2$: M_1 and M_2 are the number of kernels; k_1 and k_2 are the sizes of kernels. Abbr: Conv, convolution; BN, batch normalization; MP, max-pooling; s_1 , pooling size; s_2 , stride; GAP, global average pooling; FC, fully connected.

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×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×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.

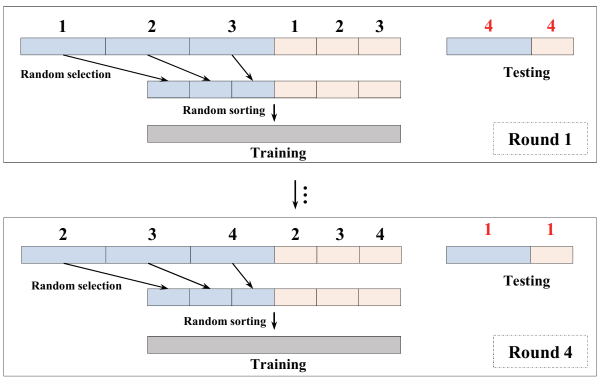

Fig. 5. Example of the Strategy-1 combined with a data down-sampling technique during model training for the patients with 4 seizures.

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:

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

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

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

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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.

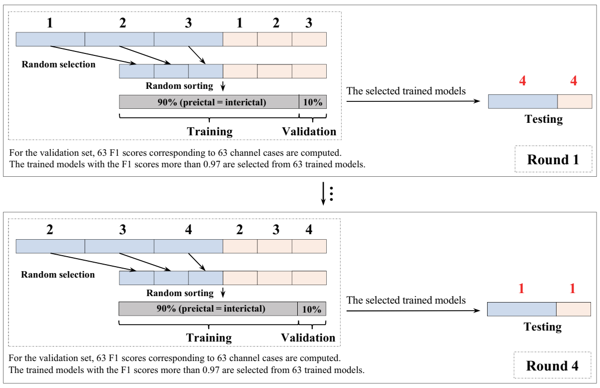

Fig. 6. Example of the Strategy-2 combined with a data down-sampling technique during model training for the patients with 4 seizures.

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 (Sen_1), specificity (Spe), and accuracy (Acc) are achieved. For each channel case at the event-based level, the averaged event-based sensitivity (Sen_2), 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 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

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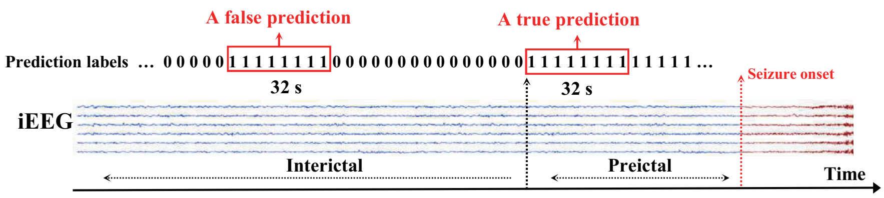

Fig. 7. At the event-based level, a simple postprocessing for prediction labels is performed to accurately sound an alarm. In this work, 32-sec duration is the requirement for sounding an alarm robustly. This means that 8 consecutive labels of 4-sec iEEG segments must be positive.

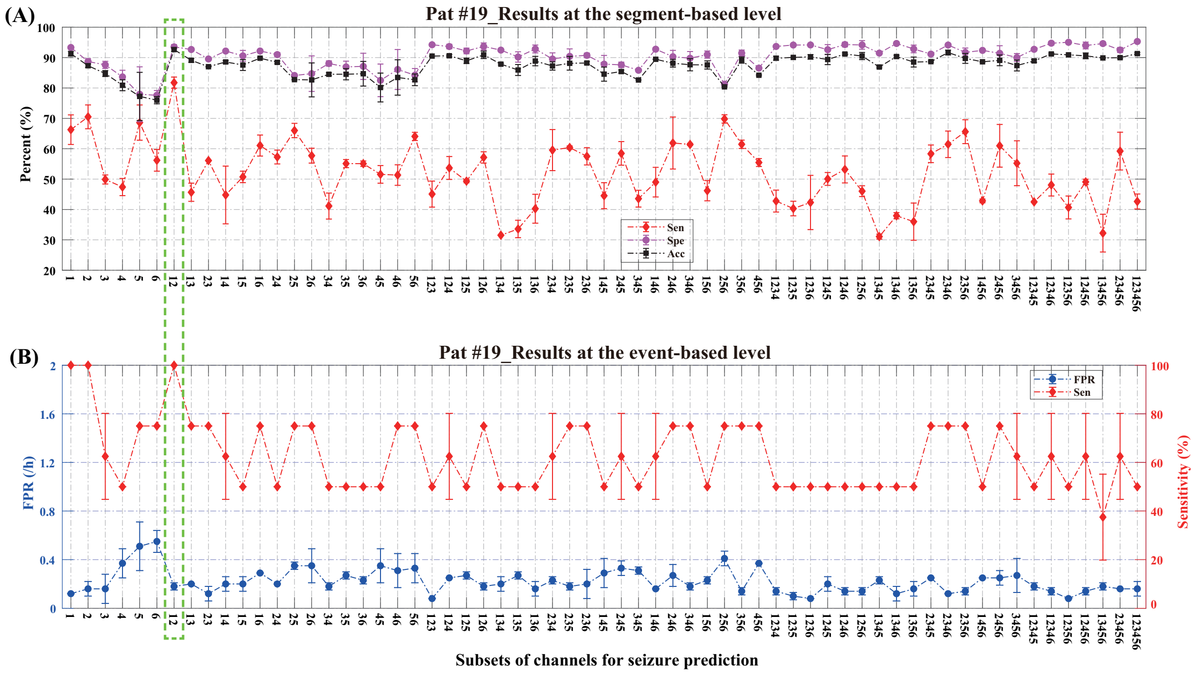

Fig. 8. In the Strategy-1, the averaged results of each channel case for patient 19 are showed after the whole algorithm runs twice. (A) Classification results at the segment-based level. (B) Classification results at the event-based level. The best case of channels 12 is finally selected, and the corresponding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

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

			Segment-based level			Event-based level		
Patient	#Seizure	Cs	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.

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 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

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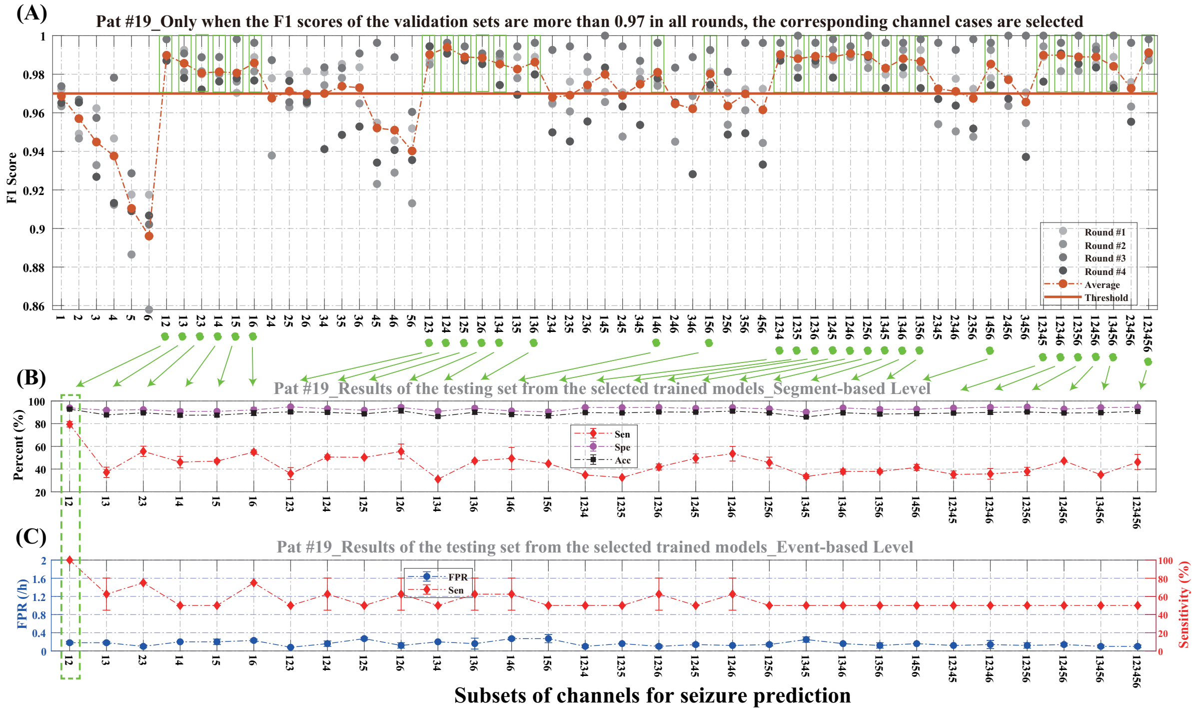

Fig. 9. In the Strategy-2, the averaged results for patient 19 are showed after the whole algorithm runs twice. (A) 30 channel cases (marked with green points) are first selected because of the F1 scores of these 30 channel cases are all more than 0.97 in all rounds (marked with green rectangles). (B) 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.

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

				Segment-based level			Event-based level		
Patient	#Seizure	F1	Cs	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	–

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

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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]–[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]–[20], the 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 and the sequential search, are applied in seizure prediction. In studies [9], [24] and [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]–[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.

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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	$\leq$0.30
Zhang et al.(2016) [19]	spectral powers and spectral power ratios	SVM	18	80	$\leq$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.

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

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