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A lightweight solution to epileptic seizure prediction based on EEG synchronization measurement

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Abstract

It is critical to determine whether the brain state of an epilepsy patient is indicative of a possible seizure onset; thus, appropriate therapy or alarm may be delivered in time. Successful seizure prediction relies on the capability of accurately separating the preictal stage from the interictal stage of ictal electroencephalography (EEG). With the booming of brain e-health technologies, there exists a pressing need for an approach that provides accurate seizure prediction while operating efficiently on edge computing platforms with very limited computing resources in Internet of Things environments. This study proposes a lightweight solution to this problem based on synchronization measurement of multivariate EEG captured from multiple brain regions consisting of two phases, i.e., synchronization measurement and classification. For phase one, Pearson correlation coefficient is calculated to obtain the correlation matrices. For phase two, the correlation matrices are classified to distinguish the preictal states from the interictal ones with a simple *CNN* model, and seizure onset can then be predicted. Experiments have been performed to evaluate the performance of the lightweight solution on the CHB-MIT scalp EEG dataset. The experimental results indicate that: (1) the solution outperforms most of the state-of-the-art counterparts with a high accuracy of seizure prediction (89.98% for 15 mins alarm in advance) for all subjects, and (2) the solution incurs a very low computational overhead and holds potentials in brain e-health applications.

Keywords Seizure prediction · Synchronization measurement · Brain e-health · EEG · Epilepsy

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1 Introduction

Epilepsy has been affecting more than 50 million people around the world [39]. Repeatedly emergent seizures accompanied by the disordered neuronal activities can cause server damages to the patients [27]. It is critical to determine whether the brain state of an epilepsy patient is indicative of a possible seizure onset; thus, appropriate therapy or alarm may be delivered in time. This has long been an onerous and challenging task in epilepsy research and practice.

Successful seizure prediction largely relies on the capability of accurately separating the preictal stage (before seizure) from the interictal stage (between seizures) of ictal EEG. This aims to benefit from the high temporal resolution of scalp EEG and its dominance in neuroscience community with significant successes achieved in the study of epileptic seizures from detection [6] to prediction.

Traditional signal processing technologies have been widely applied for this purpose. These started with time-domain and frequency-domain analyses [23], e.g., detection of epileptic spikes in relation to seizures. Subsequently, time-frequency analyses have also been adopted, such as wavelet energy [10]. Successful attempts have also been made by computing the nonlinear dynamics measures of EEG to support seizure prediction. These measures include Lyapunov exponent [12], entropy [21] and dynamic similarity index [8]. These methods generally suffer from the problems of high false positive rate and/or low sensitivity.

Generally speaking, recent methods for seizure prediction are either based on threshold or based on feature combination & classification:

- A threshold-based method normally focuses on checking the increasing or decreasing trend of some chosen *indicator* prior to an onset of seizure, such as spike rate [19], repeating EEG patterns [2] and bivariate mean phase coherence [41]. When the value of the indicator exceeds the activation threshold, an alarm will be raised to declare an incoming seizure. It should be noted that such methods require additional validation such as the seizure time surrogates method [25]. Furthermore, there exists no predictive characteristic or preictal biomarker that is universally effective for epilepsy patients [18].
- Feature-based methods first extract various features from ictal EEG over time and then classify them into a preictal or interictal state using different classifiers [38]. Features could be linear, nonlinear, univariate (single channel) or multivariate (multiple channels) in nature typically including spectral power [40], phase correlation features [29] and interpolated histogram feature [4]. Early work often uses support vector machine (SVM) [29] and multilayer perceptrons (MLP) [4] for classification. Recent years have witnessed the booming of deep learning models such as CNN [35] and LSTM [36]. It is well known that feature-based methods strongly rely on empirical analysis and handcraft features. Complicated algorithms are required, and the methods are constantly compute-intensive.

There are growing evidences that synchronization among neuronal populations changes unusually in interictal state and ictal state and it can be used for seizure prediction [5, 13, 20, 41]. Previous studies have proved that the value of correlation and coherence increases in the preictal state [33] and synchronization measurements can change accordingly with the propagation of a seizure occurrence across a human brain. The classification of patterns of EEG synchronization can be applied for seizure prediction, and synchronization measurements are usually described by bivariate measurements. A typical example is the method using Phase/Amplitude Lock Values (PLV/ALV) to predict an upcoming seizure [26]. The superiority of bivariate measurements for seizure prediction has been confirmed in an extensive comparative study between univariate techniques and bivariate ones [9]. In comparison with alternative measures described previously, a synchronization measure is less sensitive to noises and can be very lightweight in terms of the computational complexity.

Edge computing has been playing a vital role in facilitating e-health services and integrating mobile applications [32, 37]. This certainly includes brain e-health services, in which healthcare of epilepsy patients at home or in hospital persists as an important application. *IoT* applications require a very short response time and involve private data. Brain e-health services should also be pushed from the Cloud to the edge of *IoT* network to enhance runtime efficiency and reliability [34, 16]. To this end, there exists a pressing need for an approach that provides accurate seizure prediction while operating efficiently on edge computing platforms with very limited computing resources.

Inspired by the successes of methods based on synchronization measurement, this study proposes a lightweight solution (Sect. 3.1) to seizure prediction based on EEG synchronization measurement consisting of two phases to address this research challenge:

1.1 Synchronization measurement (Sect. 3.2)

Pearson correlation coefficient (*PCC*) [31] is calculated to reflect the relationship between each pair of EEG channels in different brain states. This aims to benefit from the very low computational complexity of the *PCC* algorithm to support efficient synchronization measurement.

1.2 Classification with Convolutional Neural Network (Sect. 3.3)

A simple *CNN* has been constructed to distinguish the preictal states from the interictal ones by treating the correlation matrices as features obtained from the last step. Then, the seizure onset can then be predicted at the end of the duration of preictal state.

A number of experiments have been carried out to evaluate the performances of the proposed solution (Sect. 4) using the CHB-MIT scalp EEG Dataset [3] to examine: (1) the significance and efficiency of the synchronization measurement and (2) seizure onset prediction against all patients.

The main contributions of this study are as follows:

1. This study develops a lightweight solution to seizure prediction with a high accuracy guaranteed;
2. The synchronization measurement-based method holds potentials in brain e-health services where very limited computing resources are available. Simply computing the linear correlation between EEG channels can provide a meaningful insight of seizure occurrences.

2 Related work

Numerous attempts have been made to improve the performance of seizure prediction, which has long been a research challenge based on scalp EEG data. Studies were undertaken for this purpose focus on (1) finding indicators based on thresholds or (2) state classification based on features. Criteria from synchronization measurement among brain regions have been used to discriminate preictal/interictal states. Researchers have recently started to construct seizure prediction systems using Cloud computing facilities. The most salient work along this direction is introduced as follows:

Nhan et al. [35] proposed a generalized retrospective and patient-specific seizure prediction method. They use short-time Fourier transform (STFT) to extract information in both frequency and time domains, and then, a convolutional neural network model is used for both feature extraction and classification to separate preictal segments from interictal ones. The proposed approach achieves sensitivity of 81.4%, 81.2%, 82.3% and false prediction rate (FPR) of 0.06/h, 0.16/h, 0.22/h on three public datasets, respectively: Freiburg Hospital intracranial EEG (iEEG), Children's Hospital of Boston-MIT scalp EEG (sEEG), and Kaggle American Epilepsy Society Seizure Prediction Challenge's dataset.

Haidar Khan et al. [17] proposed the focal onset seizure prediction by using convolutional networks. Convolutional filters on the wavelet transformation of the EEG signal are used to define and learn quantitative signatures for each period: interictal, preictal, and ictal. The optimal seizure prediction horizon is also learned from the data. The results on the EEG database of 204 recordings are promising, with a sensitivity of 87.8% and a low false prediction rate of 0.142 FP/h.

Kostas M. Tsiouris et al. [36] introduced long short-term memory (LSTM) networks in epileptic seizure prediction using EEG signals. The LSTM model exploits a wide range of features extracted prior to classification between preictal and interictal classes, including time and frequency domain features, between EEG channels cross-correlation and graph theoretic features. The evaluation is performed on the open CHB-MIT Scalp EEG database, suggest that the proposed methodology can provide high rates of seizure prediction sensitivity about 99.28% and low false prediction rates (FPR) of 0.11 false alarms per hour (a preictal window of 15 mins).

As for Cloud-based systems, Sareen et al. [32] enabled automatic seizure prediction using wireless sensor networks (WSNs). The features from the EEG signal collected and analyzed from the Cloud-based services are extracted using the fast Walsh–Hadamard transform (FWHT), and then, they are selected relevant to normal, preictal and ictal states of seizure by the higher-order spectral analysis (HOSA).

Subsequently, the selected features are exploited as input to a k-means classifier to detect epileptic seizure states in a reasonable time. The performance of the proposed model is tested on Amazon EC2 Cloud, and the findings show that with selected HOS-based features, it was able to achieve a classification accuracy of 94.6%.

Hosseini et al. [11] came up with a Cloud-based BCI system for the analysis of this big EEG data to predict seizure to address these challenges that finding a group of manually extracted features is not practical and bigdata produced by using implanted electrodes calls for the need for safe storage and high computational resources. A dimensionality reduction technique is first developed, following a deep learning approach, a stacked autoencoder is trained for unsupervised feature extraction and classification and then a Cloud-computing solution is proposed for real-time analysis of big EEG data. The results on a benchmark clinical dataset illustrate the superiority of the proposed system with an accuracy of 94%.

In contrast to the above, this study is based on synchronization measurement and has the following major concerns: (1) to minimize the computational overhead, and at the same time (2) to ensure the accuracy of seizure prediction for a high quality of brain e-health services.

3 Lightweight solution based on EEG synchronization measurement

This section details the design of the seizure prediction solution based on EEG synchronization measurement upon an edge computing platform. Section 3.1 introduces the architecture and the design of the solution. Section 3.2 describes the method (*PCC*) for synchronization measurement of the ictal EEG, i.e., providing correlation matrices for EEG channel pairs. Section 3.3 presents the *CNN* model for classification of the interictal (far from seizure) stage and the preictal (before the seizure onset) stage.

3.1 Overall system design

In the edge computing paradigm, *things* are not only data consumers but also data producers. Likewise, the patients play as data producers producing scalp EEG signals and data consumers receiving the forecast results. At the edge, the patients can not only request service and content from the Cloud but also perform the computing tasks from the Cloud. Edge can perform computing offloading, data storage, caching and processing, as well as distribute request and delivery service from Cloud to users [34]. In the context of the solution, there exists a pressing need for an approach that provides accurate seizure prediction while operating efficiently on edge computing platforms with very limited computing resources.

Prediction of the epileptic seizure by analyzing EEG recordings is a challenging task due to non-abruptness phenomena of different recordings and inconsistency of the recordings in different brain locations, patient-age, patient-sex and seizure-type [28]. Generally, the stages of epilepsy are defined into four steps following the progress of the event: interictal stage, preictal stage, ictal stage and postictal stage [7].

In order to reduce calculation consumption and ensure the accuracy of prediction, the synchronization features of scalp EEG recordings are calculated first in this system, and then, a classifier is used to classify the state of EEG segment as preictal stage or interictal stage. In this study, we choose CNN as the classifier which is constructed with three convolution blocks and one fully connected layer with a ReLU activation and output sizes of 2. The specific details are described in Sect. 3.3.

The seizure-initiating process might be visualized as a process by which an increasing number of critical interactions between neurons in a focal region and connected units in an abnormal functional network unfold over time [25]. This concept has motivated work on bivariate measures of data recorded at different electrodes, and bivariate measures have been shown to be promising in seizure prediction studies. Bivariate measures exhibited a higher statistical significance with a constant baseline [3].

The correlation measurement between various channels is used to investigate how interaction among several brain regions modulates epileptic seizure activity and has recently been noted as a potentially more efficient standard for seizure prediction. Besides, replacing to find the best features set with synchronization measurement, it is a very simple and effective way to extract features from EEG recordings. Therefore, the synchronization features of the EEG of the pre-seizure period and the inter-seizure period can be used as the input of the classifier.

Traditional methods usually employ certain thresholds to predict seizures after obtaining synchronization measures by calculating bivariate features. When the value of bivariate features exceeds the threshold, the algorithm produces an alarm. However, that kind of method has poor generalization ability for patients. Subsequently, many studies combine bivariate features with traditional machine learning methods to predict epilepsy, such as SVM, but SVM algorithm is difficult to implement for large-scale training samples. Meanwhile, advantages of deep learning techniques are robustness against noise present in the EEG signals and can self-learn from the input training data [1]. Among deep learning techniques, *CNN* is a simple and effective classifier.

The proposed solution for seizure prediction as shown in Fig. 1 could be described as a process with four steps: (1) EEG segmentation and synchronization measurement; (2) online classification (based on CNN model); (3) downloading the trained model; and (4) uploading the EEG synchronization features. The specific implementation details are as follows:

3.1.1 EEG segmentation and synchronization measurement

EEG recordings are first collected through body sensor networks from patients and then transmitted to the edge computing platform. Then, raw EEG recordings are preprocessed by the platform: They are segmented into segments of 8s and the synchronization features are calculated by PCC on all EEG channels. In this step, the fundamental structure provides support for the edge computing service layer. It includes three main modules, namely the operating system, the ongoing EEG synchronization feature database and the network protocol. The calculated EEG synchronization feature will be stored in the database before uploading it to the cloud server.

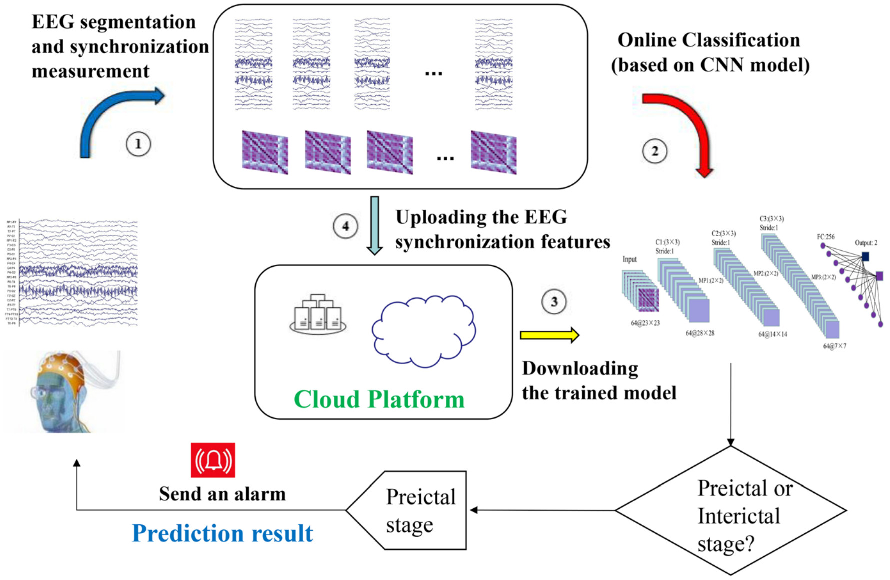

Fig. 1 Overall design of the lightweight solution to epileptic seizure prediction based on EEG synchronization measurement

In addition, any data generated in the gateway will also be stored in the database. Network protocols play an important role in secure transmission between services.

3.1.2 Online classification (based on CNN model)

Afterward, the classier is used online for the classification of the synchronization features in preictal and interictal stages because real-time processing and event response are critical in seizure prediction. After classification, the preictal stage can be used to predict epileptic seizures and the platform sends an alarm to patients, their families and a nearby hospital for emergency assistance.

3.1.3 Downloading the trained model

The classifier used in the previous step of classification needs to be downloaded from the cloud platform in advance. Consequently, the edge computing platform loads the latest trained classier downloaded from the Cloud. It should be noted that the training of the model (deployed on the public Cloud server, Google Colaboratory) is performed offline.

3.1.4 Uploading the EEG synchronization features

The authorized EEG synchronization features are uploaded to the Cloud server after being calibrated, and then, Cloud server trains the model incrementally. The advantage of doing this is that the model trained in this way is more specific to the individual situation, considering that the patient's condition may change over time. In addition, compared to storing EEG recordings, storing synchronization features saves time and memory. After the trained model is evaluated, the corresponding classier model files are saved for platform downloading.

3.2 Synchronization measurement

Synchronization measurement establishes the relationship among EEG recordings recorded from different channels on the brain. The synchronization of brain waves is a hypothetical mechanism of functional connectivity involved in the information processing in the nervous systems, which is altered in many brain disorders, including schizophrenia, Alzheimer's disease, epilepsy, Parkinson's disease and autism [24]. The synchronization measures have been proved effective in epileptic seizure prediction and detection [22]. EEG has been frequently used to study synchronization in the brain. In this study, we only considered synchronization and information coupling between two channels of EEG. Most files contain 23 EEG signals. EEG is streaming data, and all signals of EEG were sampled with sampling frequency 256. The International 10–20 system of EEG electrode positions and nomenclature was used for these recordings. Phase synchronization measures seem to have more predictive power than other nonlinear bivariate features. The concept of phase synchronization requires only a weak interaction and has been observed even for chaotic oscillatory process.

In this study, *PCC* is used for synchronization measurement, which is initially proposed to quantify the linear correlation of two random variables with a value in the range of [−1, 1]. *PCC* between two variables (X, Y) is defined as the quotient of covariance and standard deviation between X and Y:

$$\rho_{X,Y} = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \tag{1}$$

PCC has been widely applied to estimate the functional connectivity (synchronization pattern) with the merit of simplicity in terms of both computation and implementation. The computational complexity of the whole solution can be minimized using *PCC*. For comparison purposes, the maximal information coefficient (*MIC*) [30] is used as the comparison synchronization feature. *MIC* can capture a wide range of correlations of variables, including linear, nonlinear and non-functional correlations (More details see [30]).

PCC and *MIC* measure can only indicate the synchronization strength of bivariate data. Because an EEG data consists of many channels, the correlation among the channels is naturally organized into a correlation matrix (per time window).

3.3 Classification with a simple convolutional neural network

CNN excels in processing non-stationary data and achieves numerous successes in EEG analysis including our previous work [14, 15]. The study [15] presents the design of an online EEG classification system aided by Cloud centering on a

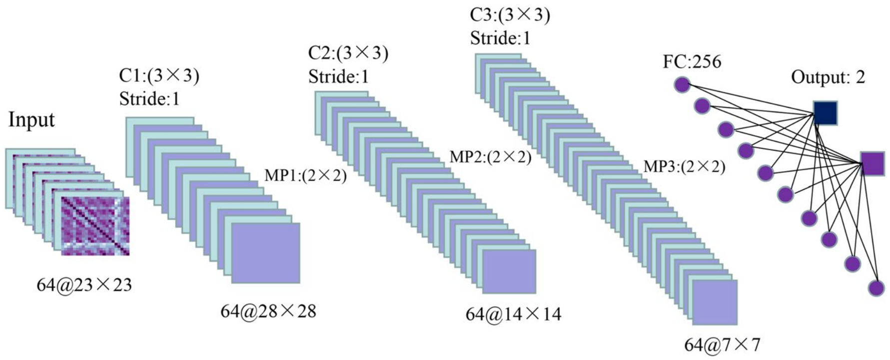

Fig. 2 Structure of the *CNN* which mainly contains three convolution blocks and a fully connected layer

lightweight convolutional neural network (CNN). The system has been evaluated on the diagnosis and treatment results of depression and achieved good classification performance. The study [14] utilizes convolutional neural networks (CNN) for the classification of EEG synchronization patterns. The architecture of the lightweight VGGNet begins with a standalone dropout layer, followed by five convolutional layers with the same configurations and three fully connected (FC) layers. The experimental results proved that seizure states can be identified with high accuracy, sensitivity, and specificity. Compared with the previous works in [38, 39], this research has been further improved. On the one hand, the lightweight CNN used in the study [38] is large that resulting in long training time. In addition, a large amount of data is prone to cloud load overload. On the other hand, the synchronization feature of the EEG used in our study is calculated by the Pearson correlation coefficient, which reduces the amount of calculation compared with the MIC used in the study[39]. Our model is also lighter in the structure of the classifier. This study is intended to keep the overhead of classification low while gaining a high accuracy. The design exploits as few layers as possible for building the convolutional neural network (*CNN*) as illustrated in Fig. 2.

It is constructed with three convolution blocks and one fully connected layer with a ReLU activation and output sizes of 2. Each convolution block consists of a convolution layer with (3×3) kernel size with a ReLU activation function, a max pooling layer with (2×2) size. The convolution layer has (1×1) stride, while the max pooling layer has (2×2) stride. Each of the three convolutional layers has 64 kernels. Following the three convolution blocks, a fully connected layer is placed, which classifies the stage of synchronization features and outputs the final results of identification of the particular correlation matrix. In order to prevent overfitting, a dropout layer with 0.2 dropout rate is positioned behind each convolution layer and each fully connected layer.

After training the *CNN* model, the correlation matrices of the preprocessed EEG recordings could be calculated and then feed to the model for classification. Once the results are classified as the preictal stage, it means the seizure is coming and alarm can be raised.

4 Experiments and results

In order to simulate the actual working scenario of IoT, the CHB-MIT dataset is adopted in this study. Among them, the training set is used to train the model, mainly in the simulation step 4. The test set is used to simulate the patient's EEG data collected in real time in practical applications and then perform data processing on the edge computing platform, classify according to the trained classifier downloaded from the cloud platform and give warnings based on the classification results, Namely the first 3 steps. Experimental studies were performed to evaluate performance of the proposed solution on the publicly available CHB-MIT scalp EEG dataset.[1] The performance was examined against state-of-the-art counterparts in terms of accuracy of seizure prediction. Alternative synchronization measurement methods were also tested.

4.1 Dataset and processing

All EEG recordings in the CHB-MIT dataset were sampled at 256 samples per second with 16-bit resolution. As some recordings contained multiple seizures with short intervals, the experiments in this study only handled the first seizure to confusion. Recordings from 19 patients and 23 channels were selected, and the channels included: FP1-F7, F7-T7, T7-P7, P7-01, FP1-F3, F3-C3, C3-P3, P3-01, FP2-F4, F4-C4, C4-P4, P4-02, FP2-F8, F8-T8, T8-P8, P8-02, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8 and T8-P8. The sampling rate of EEG data in this study is 256 Hz. The volume of EEG data is a total of 5.74GB (respectively, 2.87GB for each period (preictal and interictal). The time overhead of the framework mainly comes from the synchronization measurement and CNN-based prediction model. For each sample, the average time costs of the synchronization measurement and prediction model are, respectively, 0.05 millisecond and 7.33 millisecond. In addition, each EEG sample is a matrix of 23 channels* 2048 time points, and then, the synchronization feature of 23 channels* 23 channels is obtained by synchronization measurement.

In this study, the point of 15 mins ahead of the ictal stage was defined as the preictal stage for the seizure. Thus, enough time was allowed for medication or early warning. Meanwhile, a 15-min duration containing no seizure was selected as the interictal stage.

A slide window applied to the EEG for analysis with a size of 8 seconds and 25% overlap between two consecutive windows set. Synchronization measurement per time window was computed using Pearson correlation coefficient (*PCC*) for each pair of channels. Thus, a correlation matrix for one time window could be constructed during the preictal stage and the interictal stage. For comparison purpose, *MIC* was also measured. Several examples are shown in Fig. 3.

[1] https://physionet.nlm.nih.gov/pn6/chbmit/HEADER.shtml.

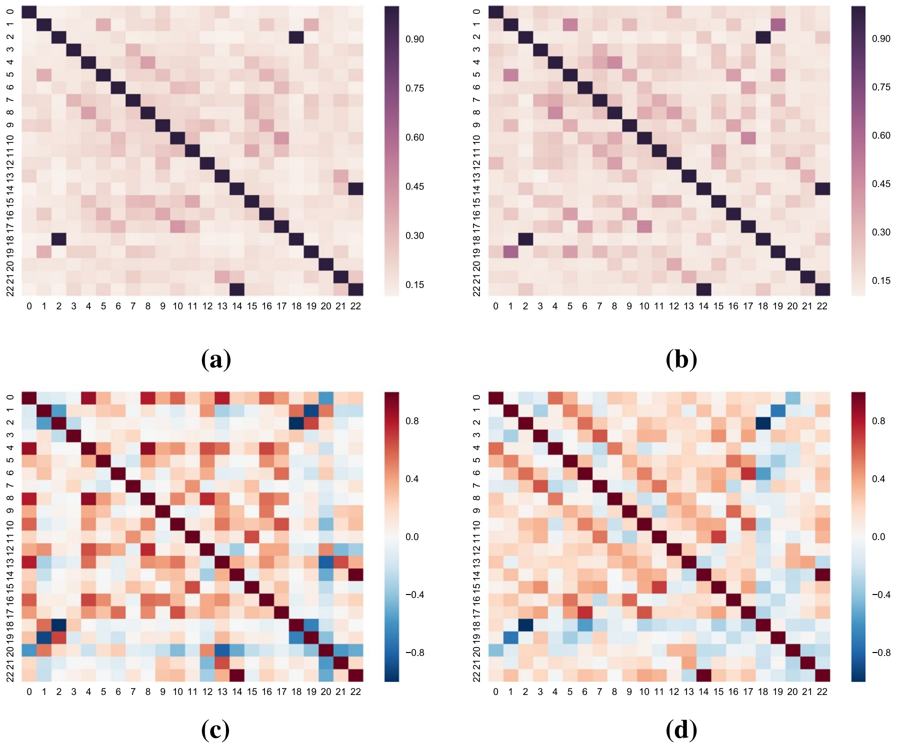

Fig. 3 Examples of correlation matrices at the preictal and interictal stages constructed using *MIC* and *PCC*. **a** *MIC* in preictal stage; **b** *MIC* in interictal stage; **c** *PCC* in preictal stage; **d** *PCC* in interictal stage

The conventional backpropagation (BP) algorithm with a batch size of 128 was employed in training the *CNN*. In this study, the training set consisted of the same number of samples as the test set, 8176 for each set. To prevent overfitting of the model during training, 80% of the total training dataset was used for training and the rest 20% for validation of the model. A total number of 300 epochs were executed for training each referring to one iteration of the full training set.

Sensitivity (Sen), **Specificity** (Spe) and the total **Accuracy** (Acc) are measured as metrics to evaluate the proposed solution: In particular, **Sensitivity** recorded how many of all the preictal segments were correctly predicted; **Specificity** represented many of all the interictal segments were correctly predicted, and **Accuracy** denoted the prediction accuracy of this method. Furthermore, **the parameter amount of the classifier** (ParA) is calculated as an index to evaluate the time cost.

4.2 Performance evaluation

The experiments were performed with the following measures highlighted:

Table 1 Comparison of the results using *PCC* and *MIC*

Measures	Sensitivity (%)	Specificity (%)	Total accuracy (%)
MIC	89.06	84.35	86.71
PCC	92.91	87.04	89.98

4.2.1 Synchronization measurement between the preictal stage and interictal stage

This measure was the Frobenius norm of the correlation matrix. T-test was preformed to compare the synchronization measurement at the preictal stage and the interictal stage. The value of P (0.01, much less than 0.05) showed that there existed obvious differences between the two stages in terms of synchronization.

4.2.2 Comparison between *PCC* and *MIC*

This part compared the results obtained by the two synchronization measurement alternatives. The experimental results are reported in Table 1. It could be concluded that the correlation matrices calculated by *PCC* yielded superior outputs to those by *MIC* in both sensitivity and total accuracy. The values were all above 0.87 and indicated the effectiveness of the proposed method. It should also be noted that *PCC* incurred much less computational overhead than *MIC* did. By default, *PCC* was used for performance evaluation through the rest of this study.

4.2.3 Performance comparisons with the state-of-the-art methods

The part made a comparison between the proposed solution and the state-of-the-art counterparts for seizure prediction as in [7, 17, 35, 36]. Table 2 presents the results together with the duration for prediction. The table also listed the approach for feature extraction and classifier used by each method under examination. Obviously, the proposed solution was superior to the first three counterpart methods in terms of sensitivity.

As for the research [7], the PLVs were used to classify between interictal and preictal stages using a support vector machine. The advantage of their research is to explore the influence of different filtering algorithms on PLV calculation and epilepsy prediction performance and propose that PLVs calculated with the NA-MEMD algorithm could be used as a potential biological marker for seizure prediction. Moreover, the classification rate was the highest for the NA-MEMD with a 0-dB algorithm (83.17%). As a commonly used bivariate measure, PLV can reflect the degree of phase synchronization in a specific frequency band. This means that the synchronization metric of PLV is in the frequency domain, and filtering is first required to decompose the spectral components in the data, which undoubtedly increases the computational burden and is susceptible to noise interference. However, the synchronization feature used in our method is in the time

Table 2 Performance comparison of different methods for seizure prediction

Study	Features	Classifier	Acc (%)	Sen (%)	Spe (%)	Preictal duration (min)	ParA (KB)
Cho [7]	Phase locking value	SVM	83.17	82.44	82.76	5	–
Truong [35]	STFT spectral images	CNN	–	81.20	–	5	162
Khan [17]	Wavelet transform coefficients	CNN	88.60	83.33	–	10	124
KM Tsiouris [36]	Statistical moments, zero crossings, cross-correlation, Wavelet transform coefficients, PSD, graph theory	LSTM	–	99.28	99.28	15	702
This work	Pearson correlation coefficient	CNN	89.98	92.90	87.04	15	146

domain, which can reduce the computational overhead and achieve higher accuracy (89.98%), sensitivity (92.90%) and specificity (87.04%). Additionally, their study decided that the 1s length of time bin might be a suitable choice for their prediction approach. Although this approach has achieved a higher time resolution, in practical applications, this undoubtedly increases the computational cost. In order to achieve a trade-off between higher time resolution and lighter and faster calculations, our choice of the time window is more advantageous, that is, the 8s length of time bin.

This study [35] proposed a novel approach of using a convolutional neural network with minimum feature engineering for all patients. The advantages of their work are that they proposed a proper method to preprocess raw EEG data into a form suitable for convolutional neural networks and propose a guideline to help convolutional neural networks perform well with seizure prediction tasks. However, compared with the short-time Fourier transform features used in their method, the synchronization features we used have a smaller amount of engineering. On the classifier CNN, the CNN we used has fewer network layers. In addition, the sensitivity of our method (92.90%) is obviously higher than the sensitivity of their method (81.20%).

In research [17], convolutional filters on the wavelet transformation of the EEG signal are used to define and learn quantitative signatures for each period: interictal, preictal and ictal. The merit of this study is that the optimal seizure prediction horizon is also learned from the data as opposed to making an a priori assumption. The results demonstrate that the preictal phase transition occurs approximately ten minutes before seizure onset, and the prediction results on the test set are promising, with a sensitivity of 83.33% and an accuracy of 86.60% on the CHB-MIT dataset. However, the spread of prediction time of the preictal transition is large. On the structure of the classifier CNN, the CNN trained had six convolutional layers followed by two dense layers in their method while our method achieves higher sensitivity (92.90%) and accuracy (89.98%) with fewer neural network layers.

As for the fourth method of comparison [36], long short-term memory (LSTM) networks are introduced in epileptic seizure prediction using EEG signals. The proposed methodology is found to be able to achieve high levels of seizure prediction under different conditions, increasing its robustness and capability of handling seizure prediction in the real-life clinical environment. However, a limitation of their study lies within the framework of the evaluation process, since the limited number of preictal EEG segments led us to apply segment shuffling to reduce the impact of overfitting and force the LSTM model to extract more generic preictal information from the entire duration of the preictal state instead. In addition, it needed to compute a number of features including statistical moments, zero crossings, cross-correlation, Wavelet transform coefficients and power spectral density. Excessive overheads were mandatory to obtain these features with a time complexity as high as $\mathcal{O}(n^2)$. In contrast, the time complexity of the *PCC* was $\mathcal{O}(n)$ and easy to implement. With a trade-off between accuracy and overhead, the proposed solution could achieve the best performance and only required very limited computing resources. Furthermore, most features depended on empirical analysis.

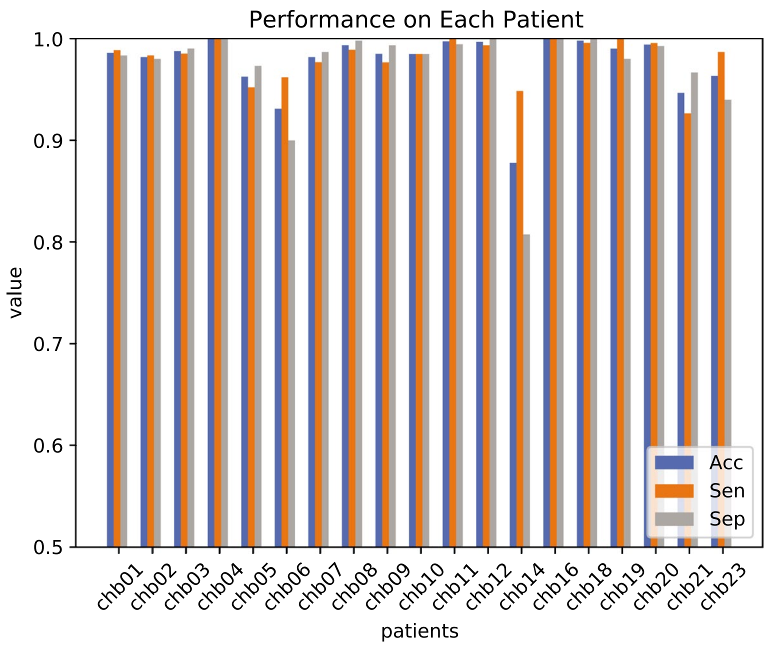

Fig. 4 Performance of this solution on the individual patient

4.2.4 The overhead comparison among the state-of-the-art methods

As we all know, the time complexity of SVM is relatively high. The convolutional neural network architecture is mainly constructed with three convolution blocks and two fully connected layers in the study [35]. As shown in Table 2, our parameter quantity (146KB) is lower than that of the study [35] (162KB). In the study [17], the CNN trained had six convolutional layers followed by two dense layers. According to the results in Table 2, our parameter quantity is slightly higher than that of the study [17] (124KB). However, in general, it is still relatively low. In the study [36], a two-layer LSTM network is selected to evaluate seizure prediction performance. According to the structural information of the LSTM network provided in the study [36], the parameter amount of the classifier is calculated of 702KB. Obviously, the parameter quantity of the study [36] is much higher than our parameter quantity (146KB).

4.2.5 Performance for individual patients

This part examined the performance of the solution for each individual patient. The results for the 19 patients are depicted in Fig. 4. The overall accuracy was always high and varied little with different individuals. It could be observed that the sensitivity and specificity varied approximately from 0.8 to 1.0. The total accuracy of chb14 was a bit lower (0.88), while the sensitivity was very high (0.94). Overall,

all of the three metrics were at high levels and this solution delivered a stable performance on all subjects.

5 Conclusion

It was difficult to provide accurate seizure prediction while operating efficiently on edge computing platforms. Aiming at this challenge, this study developed a lightweight solution based on an efficient synchronization measurement.

The proposed solution took advantages of the efficiency of Pearson correlation coefficient to measure the bivariate synchronization index of the multivariate ictal EEG as the features of ictal states in the form of correlation matrices corresponding to the mutual relations of each pair of EEG channels. The correlation matrices were classified with a simple *CNN* model to distinguish the preictal states from the interictal ones. Epileptic onset could then be predicted based on the identified preictal stages.

Experiments had been performed to evaluate the performance of the lightweight solution on the CHB-MIT scalp EEG Dataset. The results indicated that: (1) the proposed method outperformed most of the state-of-the-art counterparts with high sensitivity (92.90%) in 15 minutes preictal duration and delivered a stable performance on all subjects, and (2) the former was achieved with a very low computational overhead incurred. The results (against *MIC*) also indicated that simply computing the linear correlation between EEG channels could provide a meaningful insight of seizure occurrences. Synchronization measurement-based method could extract meaningful features of ictal states where only very limited computing resources were available.

Overall, the proposed solution proved that it was possible to ensure a high accuracy of seizure prediction with very lightweight algorithms. The solution held potentials in current and future brain e-health applications intensively relying on *IoT* environments.

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