A Generalised Seizure Prediction with Convolutional Neural Networks for Intracranial and Scalp Electroencephalogram Data Analysis

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Abstract—Seizure prediction has attracted a growing attention as one of the most challenging predictive data analysis efforts in order to improve the life of patients living with drug-resistant epilepsy and tonic seizures. Many outstanding works have been reporting great results in providing a sensible indirect (warning systems) or direct (interactive neural-stimulation) control over refractory seizures, some of which achieved high performance. However, many works put heavily handcraft feature extraction and/or carefully tailored feature engineering to each patient to achieve very high sensitivity and low false prediction rate for a particular dataset. This limits the benefit of their approaches if a different dataset is used. In this paper we apply Convolutional Neural Networks (CNNs) on different intracranial and scalp electroencephalogram (EEG) datasets and proposed a generalized retrospective and patient-specific seizure prediction method. We use Short-Time Fourier Transform (STFT) on 30-second EEG windows with 50% overlapping to extract information in both frequency and time domains. A standardization step is then applied on STFT components across the whole frequency range to prevent high frequencies features being influenced by those at lower frequencies. 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 89.8% and false prediction rate (FPR) of 0.17/h on Freiburg Hospital intracranial EEG (iEEG) dataset, and sensitivity of 89.1% and FPR of 0.09/h on Children’s Hospital of Boston-MIT scalp EEG (sEEG) dataset.

Index Terms—seizure prediction, convolutional neural network, machine learning, deep learning, iEEG, sEEG.

I. INTRODUCTION

ADVANCES in data mining and machine learning in the past few decade has attracted significantly more attention to the application of these techniques in detective and predictive data analytics especially in healthcare, medical practices and biomedical engineering [1–3]. While the body of available proven knowledge lacks a convincing and comprehensive understanding of sources of epileptic seizures, some early works showed the possibility of predicting, seemingly unpredictable, seizures [4, 5]. In ref. [6], dynamical similarity index, effective correlation dimension and increments of accumulated energy were used as feature extraction. Dynamical similarity index yielded highest performance with sensitivity 42% and false prediction rate (FPR) less than 0.15/h. Mean phase coherence and lag synchronization index of 32-s sliding EEG windows were used as features for seizure prediction [7]. Performance of this approach was still modest at sensitivity of 60% and a comparable FPR. This approach was further improved by combining bivariate empirical mode decomposition and Hilbert-based mean phase coherence as feature extraction [8]. As a result, sensitivity was increased to beyond 70% while FPR dropped below 0.15/h. Another method to exploit the synchronization information was proposed by authors in [9]. In that method, phase-match error of two consecutive epochs is calculated first, then applied discrete cosine transform (DCT) on the phase-match error in order to estimate energy concentration ratio. The average of energy concentration ratio across all channels was then used as global features. The authors extracted local features based on modified deviation and fluctuation functions, and LS-SVM was used for classification which resulted in 95.4% sensitivity and 0.36/h FPR.

A machine learning approach using Support Vector Machine (SVM) with features from nine frequency bands of spectral power was introduced in [10]. This method achieved a decent performance on Freiburg Hospital dataset [11] with sensitivity of 98.3% and FPR of 0.29/h. A similar approach with additional features, power spectral density ratios, was proposed by [12] with very high sensitivity exceeding 98% and FPR less than 0.05/h. However, this approach extremely tailored feature selection for each patient, hence, lacked of generalization. Different from the two approaches above, [13] did a Bayesian inversion of power spectral density then applied a rule-based decision to perform the seizure prediction task. This approach was tested with the same Freiburg dataset with sensitivity of 87.07% and FPR of 0.2/h. The authors, in a recent work [14], extracted six univariate and bivariate features including correlation dimension, correlation entropy, noise level, Lempel-Ziv complexity, largest Lyapunov exponent, and nonlinear interdependence and achieved a comparable sensitivity of 86.7% and lower FPR of 0.126/h.

Based on an assumption that the future events depend on a number of previous events, multiresolution N-gram on amplitude patterns was used as feature extraction in [15]. After optimizing feature set per patient, this method yielded a high sensitivity of 90.95% and a low FPR of 0.06/h. Recently, [16] captured dynamics of EEG by using 64 fuzzy rules to estimate trajectory of each sliding EEG window on Poincaré plane. The features went through PCA to reduce interrelated features before classified by a SVM. This work
achieved a decent performance with sensitivity of more than 91% and FPR below 0.08/h.

Other seizure prediction techniques were proposed by [17, 18]. In [17], features estimated by wavelet energy and entropy were optimized for each patient, then a discriminant analysis was used to separate preictal segments from interictal ones. The results were promising with sensitivity of 88.9% and FPR of 0.3/h testing with intracranial EEG data from six patients from Montreal Neurological Institute dataset. [18] introduced a lightweight approach based on spike rate. This approach was able to achieve a sensitivity of 75.8% with a false prediction rate of 0.09/h.

There have been works claimed to have 100% sensitivity and very low false alarm, less than 0.05/h [12], or even zero false alarm [19]. However, these works employed numerous feature engineering techniques and seizure prediction for each patient performs well only with a certain technique. For example, in [19], the authors used 6 different feature extraction methods and three machine learning algorithms. Similarly, in [12], there were 44 features and a set of 91 cost-sensitive linear SVM classifiers being used to search for the optimal single features or feature combinations that performs the best for each patient. These approaches have two main drawbacks: (1) we do not know which combination of features and classifier will work for a new patient, and (2) we cannot guarantee that the optimal combination will work well with future data of the same patient.

We are seeking for an approach that can be applied for all patients with minimum feature engineering. Neural networks are known with capability to extract features from raw input data to perform a classification task. In this work, we will deploy a convolutional neural network for seizure prediction. The main contributions of this work are: (1) propose a proper method to pre-process raw EEG data into a form suitable for convolutional neural network, and (2) propose a guideline to help convolutional neural network perform well with seizure prediction task with minimum feature engineering. To prove the advantage of our approach, we will use the same preprocessing technique and convolutional neural network configuration for all patients from two different datasets: Freiburg Hospital intracranial EEG (iEEG) dataset and Children’s Hospital of Boston-Massachusetts Institute of Technology (CHB-MIT) scalp EEG (sEEG) dataset.

II. PROPOSED METHOD

A. Dataset

There are two datasets being used in this work: Freiburg Hospital dataset [11] and CHB-MIT dataset [20]. The Freiburg dataset consists of intracranial EEG (iEEG) recordings of 21 patients with intractable epilepsy. Due to lack of availability of the dataset, we are only able to use data from 13 patients. A sampling rate of 256 Hz was used to record iEEG signals from these 13 patients. In this dataset, there are 6 recording channels from 6 selected contacts where three of them are from epileptogenic regions and the other three are from the remote regions. For each patient, there are at least 50 min preictal data and 24 h of interictal. More details about Freiburg dataset can be found in [6].

CHB-MIT dataset contains scalp EEG (sEEG) data of 23 pediatric patients with 844 h of continuous sEEG recording and 163 seizures. Most of scalp EEG signals were captured using 22 electrodes at sampling rate of 256 Hz [20]. We define interictal periods that are at least 4 h away before seizure onset and after seizure ending. In this dataset, there are cases that multiple seizures occur close to each other. For the seizure prediction task, we are interested in predicting the leading seizures. Therefore, for seizures that are less than 30 min away from the previous one, we consider them as only one seizure and use the onset of leading seizure as the onset of the combined seizure. Besides, we only consider patients with less than 10 seizures a day for the prediction task because it is not very critical to perform the task for patients having a seizure every 2 h on average. With the above definition and consideration, there are 13 patients with sufficient data (at least 3 leading seizures and 3 interictal hours).

B. Pre-processing

Since 2-dimensional convolutional neural network will be used in our work, it is necessary to convert raw EEG data into matrix, i.e., image-like format. The conversion must be able to keep the most important information of the EEG signals. Wavelet and Fourier transform were commonly used to convert time-series EEG signals into image shape. They were also used as an effective feature extraction method for seizure detection and prediction. In this paper, we use Short-Time Fourier Transform to translate raw EEG signal into two dimensional matrix comprised of frequency and time axes. We use EEG window length of 30 s with 50% overlapped. Most of EEG recordings were contaminated by power line noise at 50 Hz (see Fig. 1a) for Freiburg dataset and 60 Hz for CHB-MIT dataset. In frequency domain, it is convenient to effectively remove the power line noise by excluding components at frequency range of 47–53 Hz and 97–103 Hz if power frequency is 50 Hz and components at frequency range of 57–63 Hz and 117–123 Hz for power line frequency of 60 Hz. The DC component (at 0 Hz) was also removed. Fig. 1 shows the STFT of a 30-s window after removing power line noise.

Though seizure activities commonly occur at frequencies below 30 Hz [18, 21], high frequency components also contain important information for seizure prediction [16, 22]. It is important to note that components at low frequencies have much higher magnitude than ones at high frequencies (see Fig. 1b). This leads to the possibility that neural network approach tends to capture less information from high frequency range. To overcome this, we propose to do a standardization to bring similar average magnitude levels for all frequencies. For each patient, we calculate the average magnitude at each frequency to estimate a single scale vector for that patient. Fig. 1c illustrates the STFT of a 30-second EEG window after standardization.
network. A common practice is to randomly split 20% of the training set to use as a validation set. After each training epoch, a loss and/or accuracy are calculated with respects to the validation to check if the network starts to over-fit the training set. This approach works well with datasets where there is no time information involved, eg. images for classification task. For seizure prediction, it is logical to use samples from a different time period than those during training to monitor if the model starts to over-fit. In this paper, we carefully select 25% later samples from preictal and interictal sets for validation and the rest for training (Fig. 3).

D. Post-processing

It is common to have isolated false positives during interictal periods. [10] used a second-order discrete-time Kalman filter to reduce these isolated false predictions. In this work, we use a much more simpler method that is $k$-of-$n$ analysis to be consistent with the paper theme of simplicity. In other words, for every $n$ predictions, the alarm only rises if there are at least $k$ positive predictions. The CNN produces predictions every 15 s (30 s window with 50% overlapping). We choose $k = 5$ and $n = 10$ in this work.

E. System evaluation

It is non-trivial to remind how a seizure prediction system should be evaluated. Seizure prediction horizon (SPH) and seizure occurrence period (SOP) need to be defined before estimating performance metrics such as sensitivity and false prediction rate. In this paper, we follow the definition of SOP and SPH that was proposed in [6] and is illustrated in Fig. 4. SOP is the interval where the seizure is expected to occur. The time period between the alarm and beginning of SOP is called SPH. For a correct prediction, a seizure onset must be is after the SPH and within the SOP. Likewise, a false alarm rises when the prediction system returns a positive but there is no seizure occurring during SOP. When an alarm occurs, it will last until the end of the SOP. Regarding clinical use, SPH must be long enough to allow sufficient intervention or precautions. SPH is also called intervention time [3]. In contrast, SOP should be not too long to reduce the patient’s anxiety. Some works failed to mention SPH and SOP properly. In [10], the authors reported using SPH of 30 min but based on their explanation, what they were implicitly using is SPH of 0 min and SOP of 30 min, i.e. if a alarm occurs at any point within 30 min before seizure onset, it is considered as a successful prediction. Similarly, authors in [12] provided a different definition of SPH that is the interval between the alarm and seizure onset. Inconsistency in defining SPH and SOP make the benchmark among methods difficult and confusing.

Metrics used to test the proposed approach are sensitivity, false prediction rate under SPH of 5 min and SOP of 30 min. To have a robust evaluation, we follow a leave-one-out cross-validation approach for each subject. If a subject has $N$ seizures, $(N - 1)$ seizures will be used for training and the withheld seizure for validation. This round
**Fig. 2:** Convolutional neural network architecture. Each convolutional layer (C) is followed by a pooling layer (P). All convolutional layers use ReLU activation function and kernel stride of 1.

**Fig. 3:** Validation approach during training to prevent the convolutional neural network from over-fitting. 25% later samples (diagonal lines) from preictal and interictal sets are used for validation and the rest for training.

**Fig. 4:** Definition of seizure occurrence period (SOP) and seizure prediction horizon (SPH). For a correct prediction, a seizure onset must be is after the SPH and within the SOP.

Similarly, the standardization step also helps to result in better sensitivity and FPR at 89.1% and 0.09 respectively when testing with MIT sEEG dataset. It is important to note that our approach works comparably with both intracranial EEG and scalp EEG recordings without any denoising techniques except power line noise removal.

**TABLE I:** Seizure prediction results using Freiburg iEEG dataset. SOP = 30 min, SPH = 5 min.

| Patient | No. of seizures | Interictal hours | Raw STFT | Standardized |
|---------|----------------|------------------|----------|--------------|
|         |                |                  | SEN (%)  | FPR (/h)     | SEN (%)  | FPR (/h) |
| Pat1    | 4              | 23.9             | 100      | 0            | 100      | 0        |
| Pat3    | 5              | 23.9             | 100      | 0.04         | 100      | 0        |
| Pat4    | 5              | 23.9             | 100      | 0.04         | 100      | 0.04     |
| Pat5    | 5              | 23.9             | 60       | 0.59         | 80       | 0.54     |
| Pat6    | 3              | 23.8             | 100      | 0.71         | 100      | 0.29     |
| Pat14   | 4              | 22.6             | 25       | 0.49         | 100      | 0.4      |
| Pat15   | 4              | 23.7             | 100      | 0.08         | 100      | 0        |
| Pat16   | 5              | 23.9             | 80       | 0.75         | 100      | 0.59     |
| Pat17   | 5              | 24.0             | 80       | 0            | 80       | 0.04     |
| Pat18   | 5              | 24.8             | 100      | 0            | 100      | 0        |
| Pat19   | 4              | 24.3             | 25       | 0.25         | 25       | 0        |
| Pat20   | 5              | 24.8             | 60       | 0.16         | 80       | 0.24     |
| Pat21   | 5              | 23.9             | 100      | 0.04         | 100      | 0.04     |
| Total   | 59             | 311.4            | 79.7     | 0.24         | 89.8     | 0.17     |

Table III demonstrates a benchmark of recent seizure prediction approaches and this work. It is complicated to tell which approach is the best because each approach is usually tested with one dataset that is limited in amount of data. In other words, one approach can work well with this dataset but probably perform poorly on another dataset. Therefore, we add an extra indicator on whether same feature engineering or feature set is applied across all patients to evaluate generalization of each method. From clinical perspective, it is desirable to have long enough SPH to allow an effective therapeutic intervention and/or precautions. SOP, in the other hand, should be short to minimize the patient’s anxiety [6]. Some works that implicitly used zero SPH disregarded clinical
TABLE II: Seizure prediction results using CHB-MIT sEEG dataset. SOP = 30 min, SPH = 5 min.

| Patient | No. of seizures | Interictal hours | Raw STFT | Standardized |
|---------|-----------------|------------------|----------|--------------|
|         |                 |                  | SEN (%)  | FPR (/h)     | SEN (%)  | FPR (/h) |
| Pat1    | 7               | 17               | 100      | 0            | 100      | 0        |
| Pat2    | 3               | 22.9             | 33.3     | 0            | 66.7     | 0        |
| Pat3    | 6               | 21.9             | 100      | 0.18         | 100      | 0.09     |
| Pat5    | 5               | 13               | 80       | 0            | 80       | 0.08     |
| Pat9    | 4               | 12.3             | 50       | 0            | 50       | 0.16     |
| Pat10   | 6               | 11.1             | 66.7     | 0.09         | 83.3     | 0.09     |
| Pat13   | 5               | 14               | 80       | 0.14         | 80       | 0.14     |
| Pat14   | 5               | 5                | 60       | 0.8          | 80       | 0.6      |
| Pat18   | 6               | 23               | 100      | 0.09         | 100      | 0.09     |
| Pat19   | 3               | 24.9             | 100      | 0            | 100      | 0        |
| Pat20   | 5               | 20               | 100      | 0            | 100      | 0        |
| Pat21   | 4               | 20.9             | 100      | 0.19         | 100      | 0.29     |
| Pat23   | 5               | 3                | 100      | 1            | 100      | 0        |
| Total   | 64              | 209              | 84.4     | 0.1          | 89.1     | 0.09     |

As seen in Table III, sensitivity and false positive rate (FPR) have improved over time. This paper proposed a novel way to exploit both frequency and time aspects of EEG signals without handcraft feature engineering. Short-Time Fourier Transform of an EEG window has two axes of frequency and time. A 2-dimensional convolution filter was slid throughout the STFT to collect the changes in both frequency and time of EEG signals. This is where the beauty of convolutional neural network comes in. The filter weights are automatically adjusted during the training phase and the CNN acts like a feature extraction method in an automatic fashion.

This work further improves the capability in feature extraction of CNN with regards to seizure prediction by standardizing the amplitudes of STFT components across the whole frequency range. Though seizure activities commonly occur at frequencies below 30 Hz [18, 21], high frequency components also contain important information for seizure prediction [16, 22]. Amplitude standardization prevents high frequency components from being dominated by those in lower frequency ranges. The two datasets tested in this paper have sampling rate of 256 Hz that means highest frequency after STFT is just 128 Hz. We suggest our approach would give better outcomes with higher sampling rate.

As seizure characteristics may change over time, calibration of seizure prediction algorithm is necessary. Minimum feature engineering brings great advantage that it does not require an expert to carefully extract and select optimum features for the prediction task. Hence, it allows faster and more frequent updates so that patients are able to benefit the most from the seizure prediction algorithm. Also, minimum feature engineering also allows the seizure prediction available to more patients. Since feature extraction task is taken by CNN, neurophysiologists and clinical staff can spend more time in monitoring and recording EEG signals for diagnostic purpose and/or training data collection.

V. CONCLUSION

Seizure prediction capability has been studied and improved over the last four decades. A perfect prediction is yet available but with current prediction performance, it is useful to provide the patients with warning message so they can take some precautions for their safety. This paper proposed a novel approach of using convolutional neural network with minimum feature engineering. The proposed approach gives better outcomes with higher sampling rate.

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| Year | Authors          | Dataset | Feature                                              | Classifier                  | Same FE △ | No. of seizures | SEN (%) | FPR (%/h) | SOP     | SPH     |
|------|-----------------|---------|------------------------------------------------------|-----------------------------|-----------|----------------|---------|-----------|---------|---------|
| 2004 | Maiwald et al.  | FB†, 21 pat. | Dynamical similarity index | Threshold crossing | Yes | 88 | 42 | <0.15 | 30 min | 2 min |
| 2006 | Winterhalder et al. | FB†, 21 pat. | Phase coherence, lag synchronization | Threshold crossing | No | 88 | 60 | 0.15 | 30 min | 10 min |
| 2011 | Park et al.     | FB†, 18 pat. | Univariate spectral power | SVM | Yes | 80 | 98.3 | 0.29 | 30 min | 0* |
| 2012 | Gadhoumi et al. | MNI‡, 6 pat. | Wavelet energy, entropy | Discriminant analysis | No | 38 | 88.9 | 0.30 | N/A | 22 min |
| 2013 | Li et al.       | FB†, 21 pat. | Spike rate | Threshold crossing | Yes | 87 | 72.7 | 0.11 | 50 min | 10 s |
| 2014 | Zheng et al.    | FB†, 10 pat. | Mean phase coherence | Threshold crossing | No | 50 | >70 | <0.15 | 30 min | 10 min |
| 2014 | Eftekhar et al. | FB†, 21 pat. | Multiresolution N-gram | Threshold crossing | No | 87 | 90.95 | 0.06 | 20 min | 10 min |
| 2014 | Aarabi et al.   | FB†, 21 pat. | Bayesian inversion of power spectral density | Rule-based decision | Yes | 87 | 87.07 | 0.20 | 30 min | 10 s |
| 2016 | Zhang et al.    | FB†, 18 pat. | Power spectral density ratio | SVM | No | 80 | 100 | 0.03 | 50 min | 0* |
| 2016 | Zhang et al.    | MIT♦, 17 pat. | Power spectral density ratio | SVM | No | 76 | 98.68 | 0.05 | 50 min | 0* |
| 2017 | Parvez et al.   | FB†, 21 pat. | Phase-match error, deviation, fluctuation | LS-SVM | Yes | 87 | 95.4 | 0.36 | 30 min | 0* |
| 2017 | Sharif et al.   | FB†, 19 pat. | Fuzzy rules on Poincare plane | SVM | Yes | 83 | 91.8–96.6 | 0.05–0.08 | 15 min | 2–42 min |
| 2017 | Aarabi et al.   | FB†, 10 pat. | Univariate and bivariate features | Rule-based decision | Yes | 28 | 86.7 | 0.126 | 30 min | 10 s |
| 2017 | This work       | FB†, 13 pat. | Short-Time Fourier Transform | CNN | Yes | 59 | 89.8 | 0.17 | 30 min | 5 min |
| 2017 | This work       | MIT♦, 13 pat. | Short-Time Fourier Transform | CNN | Yes | 64 | 89.1 | 0.09 | 30 min | 5 min |

△ Same feature engineering across all patients. "No" means feature engineering is carefully tailored for each patient.

* The authors implicitly used zero SPH, disregarded clinical considerations, hence, the results could be over-estimated.

† Freiburg Hospital intracranial EEG (iEEG) dataset.

‡ Montreal Neurological Institute intracranial EEG (iEEG) dataset.

♦ Massachusetts Institute of Technology scalp EEG (sEEG) dataset.

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