A GENERALIZABLE MODEL FOR SEIZURE PREDICTION BASED ON DEEP LEARNING USING CNN-LSTM ARCHITECTURE

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ABSTRACT

This work proposes a novel deep learning-based model for prediction of epileptic seizures using multichannel EEG signals. Multichannel images are first constructed by applying short-time Fourier transform (STFT) to Electroencephalography (EEG) signals. After a preprocessing step, a CNN-LSTM neural network is trained on the STFTs in order to capture the spectral, spatial and temporal features within and between the EEG segments and classify them as preictal or interictal stage. The proposed method achieves a sensitivity of 98.21%, a false prediction rate (FPR) of 0.13/h and a mean prediction time of 44.74 minutes on the CHB-MIT dataset. As the main contribution of this work, by using a CNN-LSTM, in addition to capturing the time-frequency features of each segment using the convolutional network, the proposed model is able to capture the temporal patterns and transitions between sequential segments and hence improve the prediction performance in comparison to previous deep learning-based models. The method needs no complex feature extraction or channel and feature selection.

***Index Terms*—** seizure prediction, deep learning, epilepsy, CNN-LSTM, EEG

1. INTRODUCTION

As the fourth most common neurological disorder, epilepsy affects about 65 million people around the world. About one-third of the people with epilepsy live with uncontrollable seizures [1]. However, developing automatic systems for detection and prediction of seizures can help them to avoid the consequences caused by sudden unpredicted seizures. The current work proposes a model for seizure prediction based on deep learning using multichannel EEG signals without a need for hand-crafted feature extraction or channel selection. The proposed method differentiates itself from previous deep models used for seizure prediction not only by modeling the time-frequency features of each segment of the signal but also by considering the temporal dependency of EEG segments for the task of prediction.

As summarized in [2], there are several state-of-the-art research studies on seizure detection with high performances that can be used in the real world to detect the occurrence of seizures. However, for the prediction task, there is still a gap in the literature for a reliable and generalizable method that can be used in practice. This seems to be caused by two main reasons: 1) The scarcity of sufficient labeled data for the prediction task. As it is an accepted fact now, there is often a stage before the seizure onset named the preictal stage, which unlike its onset is not recognizable by eyes from EEG signals and there is still no global consensus about how to define and identify it. Therefore, labeling the preictal stage is much harder than the seizure onsets, making it hard to develop and evaluate a practical and reliable prediction approach. 2) The complexity and variability of the patterns of the preictal stage among different patients and even between different seizures of the same patient. As a result, features which are representative of seizures in some patients may not be applicable to others.

Most of the recent studies on seizure prediction are based on extracting univariate and bivariate features from EEG signals and applying thresholds or classifiers to them in order to discriminate between preictal and interictal segments [3]. In [4], different statistical measures are extracted from EEG signals decompositions as features, and different classifiers are applied to three different subsets of these features. The best combination of classifiers and feature sets achieves an accuracy of 99.77% on the CHB-MIT dataset [5] and the accuracy of 99.66% on the Freiburg dataset [6]. The method proposed in [7] achieves a sensitivity of 86.7% and an FPR of 0.126/h on the Freiburg dataset by extracting six univariate and bivariate features including, correlation dimension, correlation entropy, noise level, Lempfel-Ziv complexity, largest Lyapunov exponent, and nonlinear interdependence. The authors in [8] estimated the trajectory of each EEG sliding window on the Poincare plane using 64 fuzzy rules which yielded a sensitivity of more than 91% and an FPR of less than 0.08/h on the Freiburg dataset. In [9], an approach based on multi-resolution N-gram achieves a sensitivity of 90.95% and an

FPR of 0.06/h on the Freiburg dataset after optimizing the feature set for each patient.

In order to develop a low-complexity method for hardware implementation, [10] uses features based on spectral power. An extra channel and feature selection step are performed for each patient which results in a sensitivity of 98.68% and an FPR of 0.0465 on the CHB-MIT dataset.

There are also studies using a feature named mean phase coherence, which measures the phase synchronization between pairs of EEG channels [11]. Spike rate is another feature used for seizure prediction [12], yielding a sensitivity of 75.8% and an FPR of 0.09/h on the Freiburg dataset.

As we described above, there is a variety of methods for feature extraction and classification of EEG signals for seizure prediction with some of them achieving a high performance. However, in most of them, extracting complex features, heavy feature set optimization, and a channel selection is needed for each patient, making these methods complex, hard to implement, and dataset-specific. Therefore, exploiting neural networks can be an alternative choice, because in existence of sufficient data, they can learn the most useful features from the best channels automatically.

For the first time, a CNN was used for seizure prediction in [13], achieving a sensitivity of 71% and an FPR of 0 on the Freiburg dataset. The network was trained on bivariate features extracted from different EGG channels. Using a CNN trained on short-time Fourier transforms, Truong et al. [14] achieved a sensitivity of 81.2% and an FPR of 0.16/h on the CHB-MIT dataset. Another study trains a CNN on the wavelet coefficients of the EEG signals, achieving a sensitivity of 83.3% and an FPR of 0.147/h on the CHB-MIT dataset [15]. Although these CNN-based methods exploit the advantages of deep learning, their performances need considerable improvement to be comparable to the methods based on hand-crafted feature extraction.

In [16], a 2-layer LSTM network is trained on different hand-crafted features extracted from the sequences of the EEG segments. Although this method achieves a high sensitivity of 99.86 and an FPR of 0.02/h, it still uses a heavy feature extraction step, which makes it complex and not suitable for the real-time application.

In order to address the above-mentioned challenges of the previous deep learning-based methods, we propose using a CNN-LSTM architecture trained on the STFTs extracted from EEG segments. The CNN extracts high-level time-frequency features from the STFTs and the LSTM cell models the temporal trajectory of these features. Our model achieves a sensitivity of 98.21% and an FPR of 0.13/h and a mean prediction time of 44.74 minutes, without any complex and time consuming hand-crafted feature extraction.

The rest of this article is organized as follows: Section 2 describes the material and methods including the dataset, the preprocessing step, the network architecture, and training issues. Experimental results are presented in Section 3, and Section 4 concludes the paper.

2. MATERIAL AND METHODS

2.1. Dataset

The CHB-MIT dataset [5] is the most common publicly available EEG datasets used for seizure detection and prediction. The CHB-MIT dataset contains continuous scalp EEG recordings of 22 pediatric patients, grouped into 23 cases. All signals are sampled at 256 samples per second with 16-bit resolution and most files contain recordings with 23 EEG channels. The dataset is provided with the annotations determining the start and the end of each seizure. For the prediction task, it is common to consider a fixed period before each onset as its preictal stage.

In our work. We only use seizure files with at least 20 minutes of EEG recordings before their seizure onset. Because there is no information about the boundary between interictal and preictal stages, about two hours before and after each seizure file is excluded in order to avoid training the model on mislabeled data. Then, cases with insufficient interictal files, or with frequent changes in their channel setup are excluded. In total, we have selected 14 cases of the dataset based on the data selection criteria mentioned above.

We categorize the signals into four groups: 1) seizure periods categorized as ictal, 2) maximum of 30-minute recordings preceding seizure onsets as preictal, 3) recordings following the seizure onsets until the end of the seizure files as postictal, and 4) other parts as interictal. For multiple seizures in one file, only the first seizure is considered. For the task of prediction, only the interictal and preictal recordings are used for training and testing.

2.2. Preprocessing

We use an overlapping sliding window with a length of 10 seconds to extract EEG segments from continuous signals. A challenging attribute of seizure datasets is the problem of class imbalance because the number of the preictal samples are often much fewer than the interictal ones. As it is shown in [17], deep learning models are not very good at handling imbalanced data. In order to have a more balanced training set, the sliding window's overlap is set to 50% for interictal segments and 75% for preictal segments. We also randomly select N segments from interictal training data (where N is the total number of available preictal segments for each patient) and use it as the final interictal training set.

Since we use a 2D CNN for feature extraction, we need to represent each multichannel segment as a multichannel 2D image. We use short-time Fourier transform (STFT) of each segment as the 2D representation. Although neural networks can be trained on raw signals, a large amount of data and training is needed for a completely end-to-end training. Therefore, we consider STFT a suitable and simple preprocessing step, because it allows the CNN to capture the time-frequency features of EEG segments and in spite of its simplicity, it is a big help to the network to learn more high-level features from the available data. STFTs are extracted from EEG segments using a sliding window with a length of 1 second (256 samples) and 75% overlap.

Since EEG recordings might be contaminated with power line noise at 60 Hz, frequency components in the range of 57-63 Hz and 117-123 Hz are excluded. The DC component is also removed. In order to help the optimization process of the neural network, each frequency in the STFTs is standardized along the time axis to have a mean of zero and a standard deviation of one.

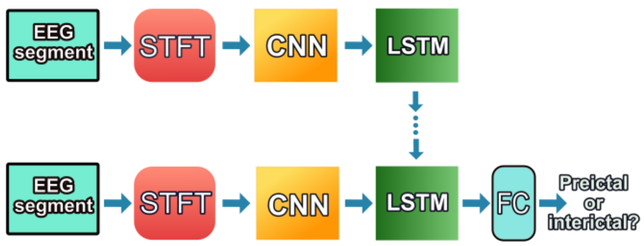

Figure 1. The diagram of the proposed model.

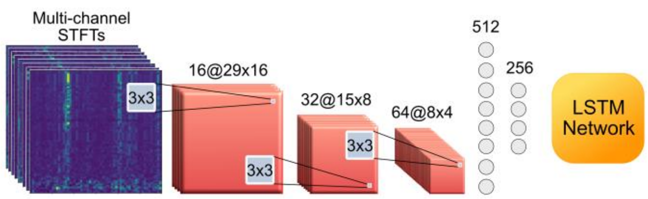

Figure 2. The proposed CNN architecture.

2.3. Network Architecture and Training

To capture the spectral, spatial, and temporal patterns of the preictal stage, a CNN-LSTM architecture is designed. Fig. 1 shows the proposed network architecture. The CNN module shown in Fig. 2 is responsible for extracting time-frequency features from STFT images. A convolutional network is able to select the more representative channels automatically and extract spatial features by learning from patients' data. The CNN used in this model is formed by three convolutional layers and two fully connected hidden layers. Each convolutional layer is followed by a batch normalization, a Dropout, and a max-pooling layer. The layers have sixteen 3x3 filters with a stride of 2, thirty-two 3x3 filters with a stride of 1 and sixty-four 3x3 filters with a stride of 1, respectively. All layers use ReLU as the activation function. The max-pooling layers have a stride of 2 and the Dropout rate is set to 0.25. The hidden fully connected layers have 512 and 256 output neurons, respectively.

As it is shown in [16], not only the time-frequency features of each segment is important for prediction of seizure onsets, but also the temporal trajectory of these features along consecutive segments can be very informative. Long Short-Term Memory units have proven to be very effective for capturing the temporal information of time series [18]. We use an LSTM cell with a hidden layer of size 512. The length of the input sequences fed into the LSTM cell is set to 6 segments. As the classification network, a 2-layer fully-connected network classifies each segment into interictal or preictal classes based on the hidden layer of the LSTM cell as input. The size of the hidden layer of the fully-connected network is 256 and uses ReLU as the activation function. The network uses Adam optimizer [19] for minimizing the cross-entropy loss function. An early stopping technique [20] has been used to stop the training after 8 consecutive epochs of validation accuracy decrease.

To help with the training process, a pre-training is applied to the network. First, the CNN is trained to classify the STFTs of each segment as interictal or preictal. Then the whole network is trained on the sequences of STFTs using the pre-trained CNN parameters as a good parameters initialization.

The proposed model is trained in a patient-specific manner, training a model for each patient only on that patient's data. Pooling data across patients is not recommended because of the diversity of preictal patterns among different patients, which leads to degrading the performance of the model [21].

2.4. Post-processing

After the training, the model is used for seizure prediction based on classifying each sequence into the preictal or interictal class. To reduce the effect of isolated false predictions in the interictal stage, we follow the post-processing proposed in [14]. For each sequence that the model predicts, the last 10 predictions are taken into account. If at least 8 of these 10 sequences are predicted as preictal, the model indicates the prediction of a seizure. After the seizure prediction alarm goes on, no more prediction will happen until 30 minutes later (we expect to have a seizure in 30 minutes based on how we labeled the preictal stage). In this way, false predictions can be reduced dramatically in comparison to the segment-based prediction.

3. RESULTS AND DISCUSSIONS

The proposed method is implemented in python 2.7 using Keras 2.1.2 with Theano 1.0.1 as backend. As the interictal training set, 70% of the interictal files were randomly selected and the rest were used for testing. The preictal training and test sets were selected in a leave-one-out manner. For a patient with N seizures, N-1 seizures were selected for training and one seizure for testing. This was repeated so that all seizures were used for testing. For validation data, 10% of later samples in preictal and interictal training sets were selected. When working with time series, it is important to select the test and validation samples from different time period than samples used for training in order to avoid overfitting, because the patterns of the signals can change through time and the model should be able to have a good performance on the test set without seeing any sample from the test period in the training phase.

The parameters for network architecture and training has been selected practically. As mentioned in Section 2.3, for making each prediction, six segments (equal to 1 minutes) are fed into the LSTM cell. However, if a dataset with more recordings and more seizures is available, the length of the temporal window can be increased, which will help with the training of the LSTM module.

Table I shows the sensitivity (the percentage of the correctly predicted seizures), the FPR (the number of the false predictions per hour) and the mean prediction time achieved using our model for all 14 cases. As can be seen, the proposed model was able to predict almost all of the test seizures, while maintaining a low false prediction rate in the interictal stage. Although the seizure prediction horizon was set to be at most 30 minutes, the model is able to predict the seizure about 45 minutes before the onsets on average.

TABLE I: Results achieved for each case in CHB-MIT dataset using our model.

Case	No. seizures	Performance Metrics		
		Sensitivity (%)	***FPR (/h)***	***Pred. Time (Minutes)***
Case 1	5	100.00	0.08	29.50
Case 2	2	100.00	0.06	50.00
Case 3	4	75.00	0.00	32.00
Case 5	3	100.00	0.00	35.00
Case 7	3	100.00	0.16	49.00
Case 9	3	100.00	0.00	103.00
Case 10	7	100.00	0.50	32.00
Case 17	3	100.00	0.22	43.00
Case 18	4	100.00	0.13	37.00
Case 19	2	100.00	0.00	46.00
Case 20	4	100.00	0.00	26.00
Case 21	4	100.00	0.50	51.92
Case 22	3	100.00	0.18	40.00
Case 23	2	100.00	0.00	52.00
	Average:	**98.21**	**0.13**	**44.74**

Table II provides a comparison between the performance of our model and that of the previous deep learning-based methods proposed for seizure prediction. As can be seen, the CNN-LSTM architecture outperforms the methods based on CNN architecture. Although a high performance is reported for the method based on feature extraction and LSTM in [16], the evaluation set was selected randomly from a set of shuffled data. This means that the evaluation set belongs to the same time period as the training data. As discussed earlier, this is not a suitable method to evaluate a model on time series, specifically in the context of epileptic signals, which are known to have different patterns through time.

TABLE II: Comparison between our model and the recent studies based on deep learning for seizure prediction.

Year	**Authors**	**Dataset**	**Method**	***Sen. (%)***	**FPR (/h)**	**Pred. Time (min)**
2009	Mirowski et al [13]	Freiburg 15 cases	Bivariate features + CNN	71	0	-
2017	Truong et al [14]	CHB-MIT 13 cases	STFT + CNN	81.2	0.16	-
2017	Khan et al [15]	CHB-MIT 13 cases	Wavelet + CNN	83.3	0.14	5.81
2018	Tsiouris et al [16]	CHB-MIT 24 cases	Hand-crafted features + LSTM	99.8	0.02	-
2018	This work	CHB-MIT 14 cases	STFT + CNN-LSTM	98.2	0.13	44.74

For datasets like CHB-MIT, which has no information about the preictal periods, it is required to define fix-length seizure prediction horizon (SPH), which in this work was practically set to 30 minutes. However, the length of the preictal periods may vary across different patients. Therefore, searching for an optimal SPH for each patient can help achieving better results in supervised methods. However, this kind of search needs lots of computation and resources. Another possible solution can be developing an appropriate unsupervised method to determine the preictal stage of the seizures which is the focus of our future work.

4. CONCLUSION

In this paper, a novel approach based on deep learning was presented for seizure prediction from EEG signals. For this purpose, a CNN-LSTM neural network is trained on the STFTs extracted from EEG segments. The time-frequency features of each segment are extracted by the CNN, while the LSTM cell models the trajectory of the extracted features among sequential segments. Yielding a high sensitivity of 98.21% and a low FPR of 0.13/h and a mean prediction time of 44.74 on CHB-MIT dataset, the proposed method outperforms the state-of-the-art algorithms based on deep learning for seizure prediction. While the proposed approach eliminates the need for any complex hand-crafted feature extraction, implementing the model on more extensive datasets would be necessary to achieve higher performances.

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