Seizure Prediction using Two-Dimensional Discrete Wavelet Transform and Convolution Neural Networks

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Abstract

Epilepsy is a condition that affects the nervous system. Seizures, strange behavior episodes, and occasional consciousness loss are all symptoms of this condition, which are caused by abnormal brain activity. It is one of the four most common neurological conditions that result in unprovoked and repeated seizures. This study proposes a prediction model that alerts patients early before the onset of epileptic seizures. The proposed model uses two-dimensional discrete wavelet transform (2D-DWT) on 23/30-s EEG time frames to identify essential signs to distinguish between the states of preictal and interictal. While a convolutional neural network (CNN) is used to predict epileptic seizures using discrete wavelet sub-bands, the proposed model predicts epileptic seizures adequately ahead of time and achieves remarkable results. On the CHB-MIT scalp EEG dataset, the proposed method has a sensitivity of 96.54% and a false positive rate (FPR) of 0.015338/h.

Keywords

Epilepsy, seizure prediction, two-dimensional discrete wavelet transform, convolution neural network

1. Introduction

Epilepsy is a chronic condition that causes unprovoked and repeated seizures. A seizure is defined as an unexpected surge of electrical activity that attacks the brain [1]. Epilepsy is identified by seizures, affecting people of all ages [2, 3]. Seizures can be severe when they occur and can lead to injuries, brain damage, life-threatening situations, and even death [4].

A highly reliable diagnostic method for epilepsy detection is through EEG. Measuring and recording the brain's electrical activity is widely used to predict and analyze epileptic seizures [5]. The EEG directly records the cerebral cortex's electrical activities through the electrodes placed on the scalp [1]. Epileptiform in EEG activity is divided into three periods: the ictal period; referring to a seizure event itself, the preictal period; the state occurring immediately prior to the epileptic seizure, and the interictal period; referring to the stable (seizure-free) state between seizures [6].

The main objective of the seizure prediction system is to discriminate between preictal state and other period states. Numerous research methods using machine learning and deep learning techniques are proposed for automatic seizure prediction. In this paper, the main contributions can be summarized as:

1. An improved prediction approach is proposed to predict upcoming seizure events. The proposed approach focuses on the pre-processing and the extraction of features, using the 2D-DWT, from EEG signals to achieve a form suitable for a CNN.

2. Our approach was validated using the public scalp EEG CHB-MIT dataset.

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The paper at hand comprises the following: Section II presents the related work. Section III presents the material and methods of the work. Experiments are illustrated in Section IV. Section V presents the experimented results. Section VI presents the discussion. Finally, section VII concludes the paper.

2. Related Work

A significant amount of research work for epileptic seizure prediction using EEG signals and deep learning techniques has been conducted. Khan et al. [7] use CNN on the continuous wavelet transform of the EEG signals to define and extract the quantitative identifying signs for each of the three periods; interictal, preictal, and ictal. They adopt automatic feature extraction techniques to foresee seizures from EEG made on the scalp so as to warn patients about upcoming seizures. This method achieves a sensitivity of 87.8% and an FPR of 0.142/h. Usman et al. [8] propose a model that provides reliable pre-processing and feature extraction methods. The proposed model predicts epileptic seizures sufficiently earlier prior to the occurrence of a seizure and provides satisfyingly realistic results. Empirical mode decomposition (EMD) for pre-processing is applied, and time and frequency domain features are extracted to train a prediction model. This approach achieves a sensitivity of 92.23% and a specificity of 93.38%. Chen et al. [9] use CNN to automatically extract features and classify them. Their model is specially designed for each patient individually to identify each one's unique features. They tested the model with the CHB-MIT dataset and yielded a sensitivity of 91.4%, an accuracy of 91%, and an FPR of 0.09/h. Kitano et al. [10] propose a method that is patient-specific using a pre-processing wavelet transform combined with self-organizing maps (SOM), a polling-based technique, and an unsupervised machine learning algorithm. This method offers sensitivity up to 98%, accuracy up to 91%, and specificity up to 88%. Jana et al. [11] propose a method that predicts epileptic seizures automatically from raw EEG signals. They use a Dense Convolution Network for interictal and preictal state classification and automatic feature extraction. The specificity of this approach is 95.87%, and the FPR is 0.0413/h. For the time intervals of 0 – 5 minutes, 5 – 10 minutes, and 10 – 15 minutes prior to the seizure episode, they produce average sensitivities of 100%, 97%, and 90%, respectively. Xu et al. [12] propose an end-to-end, patient-specific method by adopting CNN to solve seizure prediction issues. This method is tested on Kaggle intracranial and CHB-MIT scalp EEG datasets. Their approach yields a sensitivity of 93.5%, an FPR of 0.063/h, and a 98.8%, 0.074/h on two datasets in order. Truong et al. [13] propose a technique that is patient-specific for the prediction of an epileptic seizure. Their method is based on convolutional neural networks for autonomous feature extraction and classification. The raw EEG signal is transformed into a corresponding short-time Fourier transform for 30-second EEG recordings to extract information in the frequency and time domains. The American Epilepsy Society Seizure Prediction Challenge dataset, the Freiburg Hospital intracranial EEG dataset, and the Boston Children's Hospital-MIT scalp EEG dataset were all used to test this method. In total, the three datasets had a sensitivity of 81.4%, 81.2%, and 75%, respectively, and a false prediction rate of 0.06/h, 0.16/h, and 0.21/h. Jana et al. [14] demonstrated an effective seizure prediction method based on a Convolutional Neural Network (CNN) with channel minimization. They employed CNN to automatically extract features and classify epilepsy patients' states. Their proposed technique had an average sensitivity and specificity of 97.83% and 92.36%, respectively, with a false positive rate of 0.0764 and an average classification accuracy of 99.47%. Whatever the strategy, all methods mentioned work on epilepsy seizure prediction, some methods achieve low sensitivity or report relatively high FPR while others did not mention the FPR. Some methods select a limited number of patients and use a limited number of data recordings. Most of the models are based on 1D-CNN, while our approach is based on 2D-CNN. This approach matches the visual diagnosis carried out by the clinicians.

3. Materials and Methods

3.1. Wavelet transform

Wavelet transform is an image processing method for object detection and classification which is frequently adopted in computer vision. Wavelets are mathematical functions generated from a mother wavelet by dilations and translations [15, 16].

These wavelet functions are calculated in order to break down a given function or time-series signal into different scale components. One of the techniques used for multi-level decomposition is Two-Dimensional DWT (2D-DWT). This 2D-DWT moves images from the spatial domain to the frequency one. One level of 2D-DWT analyzes the given image by breaking it down into one approximation coefficient with low-pass filtering and three detailed components with high-pass filtering [17].

By applying discrete wavelet transform as an image processing technique, transformation values are yielded, known as wavelet coefficients. The 2D-DWT generates an image as a set of orthonormal shifted and dilated wavelet and scaling functions. The discrete wavelet transform of functions f (x, y) in two dimensions of an image of size MxN is given by:

$$W_{\emptyset}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{X=0}^{M-1} \sum_{Y=0}^{N-1} f(X,Y)\phi_{jo,m,n}(X,Y) \quad (1)$$

$$W_{\varphi}^{i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{X=0}^{M-1} \sum_{Y=0}^{N-1} f(X,Y)\varphi_{j,m,n}^{i}(X,Y) \quad (2)$$

$$i = \{H, V, D\}, \quad (3)$$

where j_0 is an arbitrary starting scale in the one-dimensional case. The $W_{\phi}(j_0, m, n)$ coefficients represent an approximation of f (x, y) of an image at scale j_0. $W_{\psi}^{i}(j, m, n)$ are the horizontal (H), vertical (V), and diagonal (D) details coefficients for scaling $j \geq j_0$, and i is a superscript that carries the values H, V, and D [18]. In our research, we used one level 2D Haar DWT to transform the EEG segments from spatial domain to the frequency domain then we fed the resulting coefficients the horizontal (H), the vertical (v), and the diagonal (D) as an input image to the CNN for the prediction task.

3.2. Convolution neural network

Convolution neural network (CNN) is a class of artificial neural networks that are commonly adopted for the extraction of features and for the classification of time series data and images [19]. CNN's convolution is popularly known to work on spatial or 2D data because under the movement of a fixed time sliding window, the CNN network learns the spatial features between the sequences and extracts them [20]. In this work, the designed architecture of the CNN adopted for predicting patient seizures is illustrated in Figure 2. A CNN with two convolution stages is employed where each convolution stage consists of three operations: a convolution layer with rectified linear unit (ReLU) activation, a batch normalization layer, and a max-pooling layer. By decreasing the pixels' number in the previous convolutional layer's output, the max-pooling layer decreases the dimensionality of the image and allows the model to learn invariant features. The batch normalization is used to normalize the previous layers' output and guarantees that the inputs to the convolution layer have zero mean and unit variance. Fully connected layers gather inputs from all the positions into a 1-D feature vector. Finally, the classification is made using the SoftMax activation function layer.

4. Experiments
4.1. Dataset

In the current study, the proposed model is trained, and its performance is assessed based on the online public CHB-MIT dataset [21]. This dataset is composed of EEG recordings from pediatric patients with intractable seizures. The recordings are sampled from 22 patients with 9-42 successive file recordings per patient. The dataset contains EEG recordings both with and without seizures. Each record has 23 EEG channel signals. The EEG signals are extracted by putting multiple electrodes on the scalp with a conductive gel or paste. The international 10-20 system of EEG electrodes placement is employed for these recordings. All EEG signals are collected at 256 Hz with a 16- bit resolution. Each recording contains interictal, preictal, and ictal durations. In the study at hand, the definition of the interictal periods proposed by Troung et al. [13] is followed. They define the interictal periods as found between a minimum of 4 hours pre-seizure occurrence and 4 hours post one. The main target of the study is predicting the leading seizures. In this dataset, some seizures are found to be less than 30 minutes from the previous one, and in this case, they are considered as only one seizure, and the beginning of the leading seizure is used as the onset of the combined seizure. In addition, patients suffering from fewer than 10 seizures/day are only considered for the prediction task due to the lack of practicality of performing the task for patients who have a seizure on average every 2 hours [13]. Using these definitions and considerations, 11 patients with sufficient data were chosen. The patients chosen have a total of 22 channels, and 57 seizures, and 171.8 interictal hours.

4.2. Preprocessing

EEG data are subject to artifacts that could alter the original signal, distorting the training and testing process. Excluding components in the frequency ranges of 57-63 Hz and 117-123 Hz, canceling the 60 Hz power-line noise for each segment and its main harmonic [13]. The DC component was also removed. The imbalance of the dataset is one of the most common challenges in many classification tasks. To solve this problem, extra preictal segments are generated by applying an overlapped sampling technique during the training phase. particularly, more preictal samples are created, specifically, for the training phase by sliding a 30/23-s; where 23 is the number of EEG channels, and 30 is the time window in seconds, every step S across preictal time-series EEG signals along the time axis. S is assigned to each patient in order to ensure that the training set has an equal number of samples/class (preictal or interictal) [13]. Then feature extraction is applied to extract information for the classification stage. Figure 1 shows our proposed flowchart.

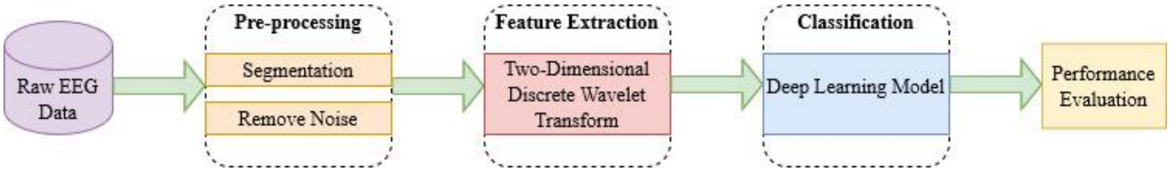

Figure 1: Process of epilepsy prediction using EEG data

The use of time-frequency domain methods, such as the wavelet transform, is the most appropriate method for extracting characteristics from EEG raw data [22] because the EEG signal is non-stationary [23]. One level of 2D Haar DWT is used to convert image segments from the spatial to the time-frequency domain. Before feeding the data to the CNN, horizontal, vertical, and diagonal coefficients are normalized to have a unit norm, and then the DWT coefficients are fed, as an input image, to the CNN prediction model. Before training the CNN, the samples are split randomly into 75-25 % for training and validation.

4.3. Evaluation metrics

In seizure prediction, Maiwald et al. [24] discuss the seizure occurrence period (SOP) and seizure prediction horizon (SPH). As indicated in Figure 3, SOP is the period when a seizure is likely to occur, whereas SPH is the time between the alarm and the beginning of the SOP. An SOP of 30 minutes and an SPH of 5 minutes were used in this investigation. The seizure alarm must come at any time throughout the SOP and after the SPH in order to successfully forecast a seizure. For each subject, a leave-one-out cross-validation attempt is used for a more robust evaluation. If a person suffers N seizures, $N - 1$ seizures are chosen for the training task and the remaining seizures are used for validation. This round is repeated N times, ensuring that each seizure is validated just once. Interictal segments are split into N portions at random. The first N-1 portions are used for training, while the remaining segments are chosen for validation. To avoid over-fitting, the N-1 sections are further separated into monitoring and training sets [13].

The performance of the proposed model is tested by measuring the four different metrics widely employed for the system's performance evaluation: accuracy, sensitivity, specificity, and FPR. The number of correct predictions divided by the total number of cases is known as accuracy. The percentage of seizures correctly predicted divided by the total number of seizures is referred to as sensitivity. Specificity is the proportion of actual negatives which got predicted correctly as negative. False-positive rate (FPR) is the number of false alarms divided by the total number of interictal samples.

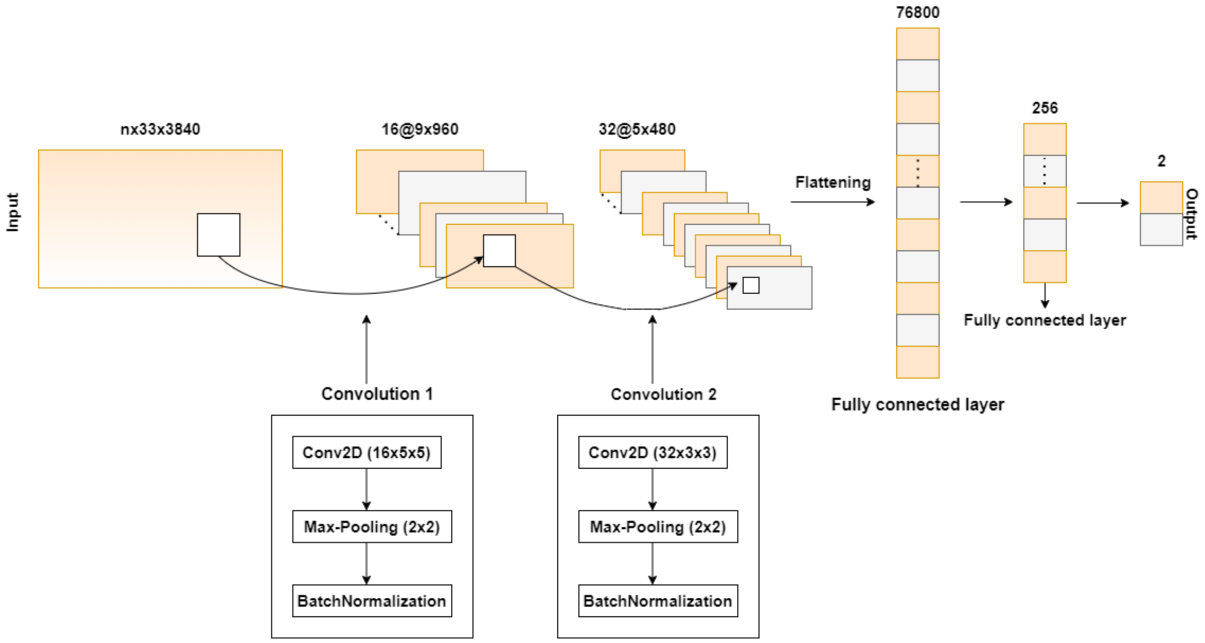

Figure 2: Convolutional neural network architecture

4.4. Implementation and parameter settings

In literature, different models have been proposed for epilepsy seizure prediction. Each model aims to predict seizures before they occur. Our proposed model is shown in Figure 2. The first convolution stage has 16x5x5 kernels with a stride of 2x2. The second convolution stage has 32x3x3 kernels with a stride of 1x1, and a max-pooling of over a 2x2 region. Following the two convolution stages, a dense layer with a dropout set to 0.6 is used for the prevention of overfitting. Following that are two fully connected layers with sigmoid activation and output sizes of 256 and 2. There wasn't a vanishing gradient problem due to the shallow number of neural networks used. A sigmoid activation function is used in the first fully connected layer, while a SoftMax activation function is used in the second. The two fully connected layers have a dropout rate of 0.6. Focal loss is used as the loss function and Adam optimizer is used for loss minimization with the learning rate, β_1, and β_2 of 0.0001, 0.9, and 0.999 respectively.

5. Results

In the present study, the proposed model is tested on the scalp EEG of 11 patients. The data consists of 57 seizures and 171.8 without seizures, from the CHB-MIT dataset. The EEG image samples are divided into two groups: training and validation.

Table 1
SEIZURE PREDICTION RESULTS

Patients	No. of seizures	FPR (/h)	Specificity	Accuracy
CHB01	7	0	100%	100%
CHB02	3	0.001387	99.70%	99.72%
CHB03	6	0.010244	92.65%	93.21%
CHB05	5	0.012169	100%	95.18%
CHB10	6	0.012123	96.49%	96.85%
CHB13	5	0.007259	93.33%	94.06%
CHB14	5	0.102610	87.94%	91.28%
CHB18	6	0.007197	88.18%	88.80%
CHB20	5	0.008150	94.49%	95.06%
CHB21	4	0.007163	96.99%	97.19%
CHB23	5	0.000413	100%	100%
Total	57	0.015338	95.43%	95.58%

The performance of the proposed model is tested by measuring the four parameters: sensitivity, FPR, accuracy, and specificity. Table 1 presents each patient's seizure prediction results. The FPR is calculated for pooled 30-seconds EEG signals. The FPR ranges from 0 to 0.102610/h with an average of 0.015338, where 0 FPR resulted when no true negatives were found. The specificity average is 95.43%, reaching 100% for patients CHB01, CHB05, and CHB23 as no false positives are found. The average accuracy achieved by the model is 95.58% with some patients having neither false negatives nor false positives detected such as patients CHB01 and CHB23. The body of work is compared with the most recently benchmarked seizure prediction approaches, as shown in Table 2.

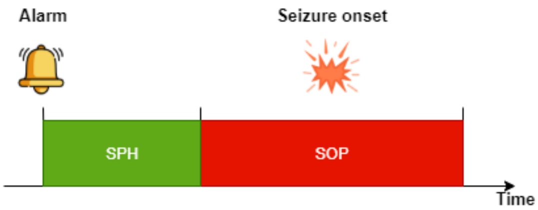

Figure 3: Definition of the seizure occurrence period (SOP) and the seizure prediction horizon (SPH)

6. Discussion

Various methods are commonly adopted to extract features from EEG signals to predict seizures. Without using handmade feature engineering, we employed 2D-DWT to extract features from EEG signals. The 2D-DWT of an EEG segment window has two dimensions, namely: frequency and time. For this reason, we used CNNs with convolution operations that can handle spatial information available in images and make a prediction at each datapoint. We used CNN rather than recurrent neural network (RNN) because CNN outperforms RNN when dealing with spatially related data [20, 25]. To gather changes in both the frequency and the time of the EEG signals, a two-dimensional convolution filter is slid throughout the 2D-DWT. During the training stage, the filter weights are automatically updated, and the CNN functions as a feature extraction method. Following Truong et al. [13], an oversampling technique is adopted here to overcome the imbalance problem of the dataset. In addition, a focal loss is used, and the cost function is changed in such a way that the cost of preictal sample misclassification is multiplied by the ratio of interictal samples to preictal samples per patient, resulting in cost-sensitive learning. For cost-sensitive learning, 2D-DWT is used as a preprocessing step. Based on the proposed method, the specificity is 95.43% and the FPR is 0.015338/h. The model achieves an average sensitivity of 96.54%, and for some individual patients 100% when no false negatives are detected. Some test results, such as CHB01's sensitivity of 100% and FPR of 0, are perfect.

Table 2

COMPARISON STUDY OF PROPOSED METHOD WITH PREVIOUS METHODS

Authors	Feature	Learning technique	Sensitivity (%)	FPR(/h)	Accuracy (%)
Haidar. [7]	CWT	CNN	87.80%	0.142	
Chen Wei Li. [9]	STFT	CNN	91.4%	0.09	91%
Truong Duy. [13]	STFT	CNN	81.2%	0.6	
Syed Muhammad. [8]	Empirical Mode decomposition	Machine learning methods	92.23%		
Kitano. [10]	DWT	Self-organizing maps (SOM)	Up to 98%		Up to 91%
Jana Ranjan. [11]	No Features Extraction.	DenseNet	90%-100%	0.0413	Up to 94%
Xu Yankun. [12]	End to end	CNN	98%	0.063	
Jana et al. [14]	CNN	CNN	97.83%	0.0764	99.47%
Proposed method	2D-DWT	CNN	96.54%	0.015338	95.58%

As indicated in Table 2, the current study's results are compared to those of earlier studies on epilepsy prediction. The results show the highest accuracy of 95.58% and the lowest FPR of 0.015338/h among all compared approaches and the comparable sensitivity is inconsistent with the top result. It is further noticed that the proposed method for epileptic seizures prediction performs better than other methods in terms of accuracy and FPR. Therefore, the proposed model produces effective seizures prediction for the chosen 11 epileptic patients under study.

7. Conclusions

An epileptic seizures prediction method is proposed using deep learning with high accuracy seizure prediction. For feature learning and classification between interictal and preictal states, the proposed model employs CNN. Features are extracted using one level 2D-DWT for features learning and improvement of the classification task. In the current experiment, a public CHB-MIT dataset is used to evaluate the proposed method, and results have proven that the model performs better in terms of both accuracy and FPR in comparison to other models. After applying the proposed model to the dataset, epileptic seizures are predicted 30 minutes before the beginning of a seizure. It is then concluded that, with the aid of the proposed model, epileptic patients can have more time for taking conventional medications in order to prevent the seizure before it occurs.

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