ROBUST DETECTION OF EPILEPTIC SEIZURES USING DEEP NEURAL NETWORKS

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ABSTRACT

Robust detection of epileptic seizures in the presence of inevitable artifacts in Electroencephalogram (EEG) signals is addressed. The EEG dataset considered contains 300 signals recorded from 15 volunteers. Current seizure detection systems achieve good performance when the EEG data is entirely free of noise. However, their performance drastically decays with authentic EEG data polluted by real artifacts. We introduce a robust seizure detection method that can address clean and noisy data. The proposed method uses Long Short-Term Memory (LSTM) neural networks to extract the representative EEG features pertinent to seizures. Experimental results show that the proposed method beats existing methods by achieving 100% classification accuracy. Our method is also shown to be robust against the common EEG artifacts (e.g., muscle activities and eye-blinking) and white noise.

***Index Terms*—** Epilepsy, seizure detection, EEG, LSTM

1. INTRODUCTION

Epilepsy is a neurological brain disorder that affects around 70 million people worldwide [1]. The defining characteristic of epilepsy is recurrent seizures that strike without warning. Symptoms may range from brief suspension of awareness to violent convulsions and sometimes loss of consciousness [2]. Routine Electroencephalogram (EEG) has been widely used in clinical settings for the diagnosis of epileptic seizures. However, the visual inspection of EEG is laborious and time-consuming. Even worse, around 75% of people with epilepsy live in low and middle-income countries and may not afford to consult clinicians and neurologists [3]. Automatic seizure detection systems, however, can minutely identify the EEG seizure patterns and help patients watch their own risks and improve their quality of life.

Several methods have been developed for automatic seizure detection using EEG signals. Extracting the best features that describe the characteristics of EEG seizure activities has a significant influence on the performance of seizure detection systems. Numerous feature extraction approaches have been investigated in the literature. The majority of these use EEG features that are manually extracted from the time domain [4], frequency domain [5], time-frequency domain [6] and sometimes from a combination of two domains [7]. In practice, these hand-crafted features experience three main challenges. First, they are very sensitive to variations in seizure activities since EEG is a non-stationary signal and the seizure behavior varies across different patients and over time for the same patient. Secondly, the EEG measurements are highly susceptible to different sources of noise such as muscle activities, eye-blinking/movement, and environmental white noise. These artifacts interfere with the EEG data and seriously impact the detection accuracy of epileptic seizures [8]. Finally, most of the existing seizure detection methods have been built based on limited EEG data taken from few subjects, making them less practical for clinical applications.

To solve these problems, we introduce a robust deep learning approach for robust detection of epileptic seizures. The time-series EEG signals are first divided into small EEG segments, which are then presented as an input to a Long Short-Term Memory (LSTM) network to learn the discriminative characteristics of seizure and non-seizure activities. The softmax model is then used for EEG classification. The overall model is examined, under ideal and real-life conditions, using the popular clinical dataset provided by Bonn University [9]. The results demonstrate that, under ideal conditions, the proposed approach outperforms the baseline methods in terms of the sensitivity, specificity, and classification accuracy. It is also shown that the proposed approach maintains its superior performance in noisy environments.

2. MATERIALS AND PRIOR WORK

2.1. EEG Dataset

In this work, the proposed seizure detection method is examined on the well known EEG dataset provided by Bonn University [9]. In this study, we address the classification problem between the following three different EEG sets: *Normal* EEG taken from five healthy volunteers, *Inter-ictal* EEG recorded from five epileptic patients during seizure-free intervals, and *Ictal* EEG taken from five epileptic patients while having active seizures. Each set contains 100 single-

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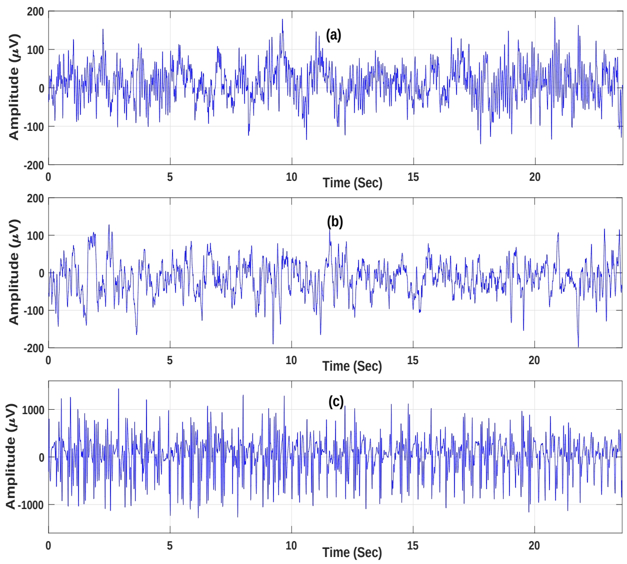

Fig. 1. Time-series EEG plots: (a), (b), and (c) examples of normal, inter-ictal, and ictal EEG activities, respectively.

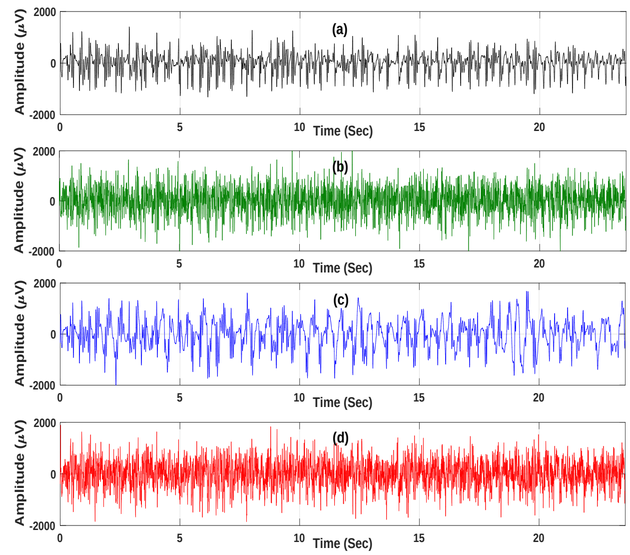

Fig. 2. Time-series EEG plots: (a) clean ictal signal; (b), (c), and (d) ictal signals corrupted with muscle artifacts, eye-blinking, and white noise, respectively.

channel EEG signals, each of 23.6 seconds duration. All the EEG signals had already been denoised, amplified, sampled at 173.6Hz and digitized using a 12-bit analog-to-digital converter. Figures 1(a), (b), and (c) show examples of these time-series EEG signals corresponding to normal, inter-ictal, and ictal activities, respectively.

In practice, several sources of noise affect the EEG signals contaminating the seizure manifestations and negatively affecting the detection accuracy of epileptic seizures. The authors of [10] reviewed the most common EEG artifacts and developed adequate models to mimic their behavior. In this study, we focus on the most three critical and inevitable sources of artifacts, which are:

- Muscle Artifacts: As shown in [10], muscle activities can be modeled by random noise filtered with a band-pass filter (BPF) of 20Hz and 60Hz cut-off frequencies.
- Eyes Movement/Blinking: The eye blinks mixed with EEG data can be modeled as a random noise signal filtered with a BPF of 1Hz and 3Hz cut-off frequencies.
- White Noise: The electrical and environmental noises are characterized as white Gaussian noise [10].

Fig. 2(a) shows an arbitrary noise-free EEG signal corresponding to seizure (ictal) activities, while figures 2(b), (c), and (d) show the noisy versions of the same signal corrupted with muscle artifacts, eye-blinking, and white noise, respectively. The amplitude of each of these artifacts can be adjusted to produce noisy EEG signals with different signal-to-noise-ratios (SNRs). The SNR of the noisy signals shown in Fig. 2 is set to 0dB. This is where the power values of the EEG signal and the noise signal are equal.

2.2. Prior Work

The automatic detection of epileptic seizures using EEG signals has been broadly investigated over the past three decades. In this study, we will cover the prior work that has been recently developed to discriminate between three classes: *Normal*, *Inter-ictal*, and *Ictal* EEG patterns [11]-[22]. In [11], the potential of wavelet transform to obtain and analyze the main spectral rhythms of the EEG signals is investigated. Then, the statistical features that characterize the behavior of the EEGs were extracted and tested using a neural network-based classification model called mixture of experts (ME). The results showed a classification accuracy of 93.17%. This was improved one year later to 94.83% by using the same features to examine the performance of a multilayer perceptron neural network (MLPNN) classifier [12]. In [13], a feature extraction method based on the sample entropy was used together with the extreme learning machine (ELM) classifier, and classification accuracy of 95.67% was reached. Besides, in [14], a set of temporal and spectral EEG features was fed into an MLPNN for EEG classification. This resulted in a classification accuracy of 97.50%.

In an effort to alleviate the computational complexity burden in seizure detection systems, Acharya *et al.* relaxed the need for any pre-processing techniques and worked directly on the raw EEG data [15, 16, 17]. For example, in [15], they extracted a set of 10 robust statistical features from the time-series EEG recordings in the absence of any filtering or denoising approaches. The effectiveness of the selected features was examined along with seven different classifiers. The support vector machine (SVM) achieved better performance than the other classifiers with an average classification accuracy, 94.40%. In [16], Acharya *et al.* significantly improved the performance of their seizure detection model by introducing more representative EEG features. These features were approximate entropy, sample entropy, and phase entropies, and were computed from the recorded EEG signals and then fed into fuzzy Sugeno classifier (FSC) for EEG classification. This approach notably boosted the classification accuracy to 98.10%. Additionally, Acharya *et al.* proposed the use of wavelet packet transform (WPT) to analyze the EEG signals into eight approximation and detail wavelet bands [17]. The wavelet coefficients of these bands were then used to infer the eigenvalues which were used as the input to the Gaussian mixture model (GMM) classifier achieving an outstanding classification accuracy of 99.00%. Comparable classification accuracy of 98.67% was achieved in [18] by using a feature extraction method based on recurrence quantification analysis integrated with a two-stage classifier named error-correction output code (ECOC).

Chiang *et al.* developed an energy-efficient EEG monitoring system for epileptic seizure detection [19]. They introduced a novel EEG feature extraction method. The features were extracted on the sensor side, and the seizure detection was performed on the server side. This resulted in a significant saving in the power consumption, and a detection accuracy of 95.61% was obtained. In [20], a piecewise quadratic (PQ) classifier was built for detecting epileptic EEG episodes, and it was integrated with a combination of temporal, spectral, and non-linear features to reach 98.70% classification accuracy. In [21], a feature extraction method based on the discrete short-time Fourier transform was adopted together with an MLPNN classifier to achieve a high detection accuracy of 99.10%. In [22], a hybrid scheme based on some statistical features and a least-square SVM (LSSVM) classifier showed an average classification accuracy of 97.19%. In [23], the energy features of EEG-based harmonic WPT and fractal dimensions were computed and tested using a relevance vector machine (RVM) to obtain the highest classification accuracy of 99.80%.

3. METHODOLOGY

Deep learning has proven to achieve promising results in different research problems such as information retrieval [24], speech recognition [25], and image classification [26]. In this study, we propose the use of deep recurrent neural networks, particularly the long short-term memory (LSTM) [27], for epileptic seizure diagnosis. Our model follows three main stages. In the first stage, the time-series EEG signals are divided into non-overlapping segments of a specific length. Given the sampling rate of 173.6Hz and signal duration of 23.6 seconds, the total number of data-points in each EEG signal is 4096. In our experiments, we tested a wide range of segments' lengths. We concluded that increasing the segment length can lessen the computational complexity of the LSTM models but at the cost of the detection accuracy [28]. Hence, each EEG segment is designed to have only 2 data-points out of 4096, producing 2048 segments for each EEG signal.

In the second stage, the deep learning model of LSTM was deployed to extract the discriminative EEG features that best describe seizure characteristics. The segmented EEG data samples were initially shuffled randomly to remove any possible drifts. Then, we design our deep neural network to include three layers, with a MaxPooling layer as the top layer. The shuffled EEG data samples were first passed through a fully connected (Dense) layer, which performs a linear operation from the input to the output. The LSTM layer was adopted afterward to learn the most robust EEG features pertinent to seizures. Subsequently, the output of the LSTM layer was fed into the MaxPooling layer to help reduce the overfitting by providing an abstracted form of the EEG representations. MaxPooling layer also reduces the computational cost by reducing the number of parameters to learn and provide basic translation invariance to the internal representation.

In the third stage, the output of the MaxPooling layer is presented as an input to a probabilistic classification model of softmax to create label predictions [29]. The class labels are assumed to be: $y^{(i)} \in 1, \cdots, K$, where K is the total number of classes. Given a training set $\{(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \cdots, (\mathbf{x}^{(N)}, y^{(N)})\}$ of N labeled samples, where $\mathbf{x}^{(i)} \in \Re^{(N)}$. For each test sample $\mathbf{x}$, the softmax hypothesis evaluates the probability that $\mathcal{P}(y = k|\mathbf{x}(t), \mathbf{x}(t-1), \mathbf{x}(t-2), \cdots)$ for each class label $k = 1, \cdots, K$; where t shows the time step of each EEG segment. The summations of these K-probability values should equal to 1 and the highest probability belongs to the predicted class. The cost function of the softmax classifier is the cross entropy, denoted by $\boldsymbol{J}(\theta)$, is defined as follows:

$$\boldsymbol{J}(\theta) = -\left[\sum_{i=1}^{N}\sum_{k=1}^{K} \mathbb{1}\{y^{(i)} = k\} \log \frac{\exp(\theta_k^T \mathbf{x}^{(i)})}{\sum\limits_{j=1}^{K} \exp(\theta_j^T \mathbf{x}^{(i)})}\right] \quad (1)$$

where $\mathbb{1}\{.\}$ is the "indicator function", which equals to 1 if the statement is true and 0 if the statement is false; $\theta = \{\theta_1, \theta_2, \cdots, \theta_K\}$ are the softmax model parameters.

Then, an iterative optimization method such as the stochastic gradient descent [30] is used to minimize the cost function and maximize the probability of the correct class label.

4. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed deep learning-based seizure detection method, we compare its performance to those of the baseline methods that use the same benchmark dataset. The detection performance was assessed using the

Table 1. Seizure detection results of the proposed and state-of-the-art methods.

Methods	Year	Classifier	Sens (%)	Spec (%)	Acc (%)
beyli et al. [11]	2008	ME	92.75	94.00	93.17
beyli et al. [12]	2009	MLPNN	96.00	94.00	94.83
Song et al. [13]	2010	ELM	97.26	98.77	95.67
Naghsh et al. [14]	2010	MLPNN	97.46	98.74	97.50
Acharya et al. [15]	2011	Fuzzy	97.70	94.70	94.40
Acharya et al. [16]	2012	FSC	99.40	100.0	98.10
Acharya et al. [17]	2012	GMM	99.00	99.00	99.00
Niknazar et al. [18]	2013	ECOC	98.55	99.33	98.67
Chiang et al. [19]	2014	SVM	91.82	99.40	95.61
Gajic et al. [20]	2015	PQ	98.60	99.33	98.70
Samiee et al. [21]	2015	MLPNN	99.20	98.90	99.10
Behara et al. [22]	2016	LSSVM	96.96	99.66	97.19
Vidyaratne et al. [23]	2017	RVM	99.00	100.00	99.80
Proposed Method	2017	Softmax	100.0	100.0	100.0

standard metrics of sensitivity (Sens), specificity (Spec), and classification accuracy (Acc).

4.1. Classification of Clean EEG Data

The proposed method is first examined for the ideal conditions, *i.e.*, when the EEG signals are completely free of noise. Our proposed method uses an LSTM network that finds the correlation between the EEG signals taken from different subjects as well as the dependencies between EEG segments of the same subject. Table 1 demonstrates the effectiveness of the LSTM network to learn the representative EEG features that best describe the behavior of normal, inter-ictal and ictal EEG activities.

We compare the performance of the proposed deep learning method to those of the state-of-the-art methods that have been developed in the last 10 years [11]-[22]. The performance metrics are reported in Table 1. It is worth highlighting that the proposed method outperforms all others in terms of the sensitivity, specificity, and classification accuracy. It yields a seizure sensitivity of 100%, which is superior to any of the baseline methods. Further, the proposed method produces an outstanding seizure specificity of 100%, which is similar to the recent results obtained by Vidyaratne *et al.* [23], and is better than those of the reference methods. Also, amongst all existing seizure detection methods, the proposed scheme achieves the highest classification accuracy of 100%.

4.2. Classification of Noisy EEG Data

We further examine the robustness of the proposed deep learning method against two common EEG artifacts as well as white noise. In our previous work, we developed a reliable EEG feature learning method capable of performing on noisy signals and achieving reasonable seizure detection accuracies [31]. This method, however, assumed that the noise introduced during EEG data acquisition had a Gaussian distribution. However, in real life situations, there are

Table 2. Seizure classification accuracies of the proposed method under noisy conditions.

Noise Source	SNR (dB)							
	20	15	10	5	0	-5	-10	-15
Muscle	100.0	100.0	100.0	100.0	99.50	98.00	97.33	91.00
Eye-blinking	100.0	100.0	100.0	100.0	100.0	100.0	99.67	98.83
White noise	100.0	100.0	100.0	99.33	97.65	95.33	83.33	80.50

other non-Gaussian artifacts as well as the Gaussian white noise. In this work, we propose a practical seizure detection system that can address noisy EEG data corrupted with real physical noise (e.g., muscle artifacts, eye-blinking, and white electrical noise).

Table 2 investigates the performance of the proposed method against two common EEG artifacts and white noise at different SNR levels. It can be observed that the proposed method maintains its superior performance when applied to noise-corrupted data of SNRs above 0dB. The main reason is that the LSTM network can effectively learn the most discriminative and robust EEG features associated with seizures, even under the abnormal conditions. The performance of our model starts to decline when applied to noisy EEG data of SNRs below 0dB, particularly when the data is polluted with white noise. Better performance can be achieved for the case of muscle artifacts since the muscle activities interfere with the EEG signals within a limited frequency band of 20-60Hz. The superior performance is achieved for the case of eye-blinking artifacts that interfere with the EEG signals in the low frequency band of 1-3Hz. Table 2 verifies the robustness of the proposed approach against eye-blinking artifacts, even at extremely low SNRs. It can accurately identify the seizure activities immersed in noise with acceptable classification accuracies.

5. CONCLUSION

In this paper, we introduce a deep learning approach for the automatic detection of epileptic seizures using EEG signals. This approach can learn the high-level EEG representations and effectively discriminate between the seizure and non-seizure activities. Another advantage of this approach lies in its robustness against common EEG artifacts (muscle activities and eye-blinking) and white noise. The proposed approach was examined using the Bonn EEG dataset and compared to several baseline methods. The experimental results demonstrate the effectiveness and superiority of the proposed method in detecting epileptic seizures. It is also shown that our method achieves a robust performance with noisy EEG data.

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