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Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals

Ramy Hussein [a,b,*], Hamid Palangi [c], Rabab K. Ward [a], Z. Jane Wang [a]

[a] *Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, BC V6T 1Z4, Canada*
[b] *Digital Aviation Lab, Boeing, Vancouver, BC V6B 2X6, Canada*
[c] *Microsoft Research AI, Redmond, WA 98052, United States*

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- Body artifacts may negatively affect the epileptic seizure detection based on Electroencephalogram.
- We introduce a deep neural network architecture to learn the robust features pertinent to seizures.
- Our method achieves robust seizure detection performance under ideal and real-life conditions.

A B S T R A C T

Objective: Automatic detection of epileptic seizures based on deep learning methods received much attention last year. However, the potential of deep neural networks in seizure detection has not been fully exploited in terms of the optimal design of the model architecture and the detection power of the time-series brain data. In this work, a deep neural network architecture is introduced to learn the temporal dependencies in Electroencephalogram (EEG) data for robust detection of epileptic seizures.
Methods: A deep Long Short-Term Memory (LSTM) network is first used to learn the high-level representations of different EEG patterns. Then, a Fully Connected (FC) layer is adopted to extract the most robust EEG features relevant to epileptic seizures. Finally, these features are supplied to a softmax layer to output predicted labels.
Results: The results on a benchmark clinical dataset reveal the prevalence of the proposed approach over the baseline techniques; achieving 100% classification accuracy, 100% sensitivity, and 100% specificity. Our approach is additionally shown to be robust in noisy and real-life conditions. It maintains high detection performance in the existence of common EEG artifacts (muscle activities and eye movement) as well as background noise.
Conclusions: We demonstrate the clinical feasibility of our seizure detection approach achieving superior performance over the cutting-edge techniques in terms of seizure detection performance and robustness.
Significance: Our seizure detection approach can contribute to accurate and robust detection of epileptic seizures in ideal and real-life situations.

1. Introduction

Epilepsy is a chronic neurological disorder of the brain that affects people of all ages. Approximately seventy million people worldwide possess epilepsy, making it typically the second most common neurological disease after a migraine (Rogers, 2010). The characterizing feature of epilepsy is repetitive seizures that strike abruptly. Symptoms may run from short suspension of awareness to violent convulsions and once in a while loss of consciousness (Acharya et al., 2013). Electroencephalogram (EEG) is the prime signal that has been widely used for the diagnosis of epilepsy. As the visual inspection of EEG is labor- and time-consuming, research in the EEG-based automatic detection of epileptic seizures has been very active.

Several feature extraction techniques have been developed for automatic seizure detection systems. Most of them use hand-wrought features extracted in the time-domain (Meier et al., 2008; Minasyan et al., 2010), frequency-domain (Correa et al.,

* Corresponding author at: Electrical and Computer Engineering Department, University of British Columbia, Vancouver, BC V6T 1Z4, Canada

E-mail addresses: ramy@ece.ubc.ca (R. Hussein), hpalangi@microsoft.com (H. Palangi), rababw@ece.ubc.ca (R.K. Ward), zjanew@ece.ubc.ca (Z.J. Wang).

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2007; Chan et al., 2008; Aarabi et al., 2009), time-frequency domain (Niederhauser et al., 2003; Güler and Übeyli, 2005; Tzallas et al., 2007; Abibullaev et al., 2010), and sometimes in a combination of two domains (Mitra et al., 2009). However, these domain-based methods encounter three main challenges. First, they are sensitive (not robust enough) to acute variations in seizure patterns. This is because the EEG data is non-stationary and its statistical features change across different subjects and over time for the same subject. Secondly, EEG data acquisition systems are very susceptible to a diverse range of artifacts such as muscle activities, eye-blinks, and white environmental noise. All these sources of noise can alter the genuine EEG features and hence seriously affect the performance of seizure detection systems (Abualsaud et al., 2015). Finally, most existing seizure detection systems have been trained on small-scale EEG datasets collected from a few specific patients, making them less practical in clinical applications.

To address these limitations, Thodoroff et al. took the lead in deploying deep neural networks for automatic detection of epileptic seizures (Thodoroff et al., 2016). They used a combination of convolutional and recurrent neural networks to extract the spatial and temporal EEG representations of seizures. This model achieved an average sensitivity of 85.00% and a false positive rate of 0.8/hour. Moreover, Lin et al. proposed a deep learning framework based on stacked sparse autoencoder (SSAE) to extract and the high-level representations of EEG signals. This framework achieved an average classification accuracy of 96.00% (Lin et al., 2016). More recently, Acharya et al. used the convolutional neural network (CNN) for analyzing EEG signals and detecting epileptic seizures (Acharya et al., 2017). They implemented a 13-layers deep CNN model that attained an average accuracy, sensitivity, and specificity of 88.67%, 90.00%, and 95.00%, respectively. In Yuan et al. (2017), Yuan and his team proposed to feed the time-frequency representations of EEG signals as an input to the SSAE. This strategy helped extract both of the spectral and temporal information pertinent to epileptic seizures, and thus achieve an average classification accuracy of 93.82%.

Despite the encouraging seizure detection results obtained using such deep learning models, there still exist several improvements that can be achieved. First, most of these models are built based on CNNs, which are looking for the same pattern over the EEG signals collected from different patients. The signature of the epileptic seizure, however, varies across different patients and over time for the same patient. The second issue is the assumption that very deep and complex neural network structures would be powerful enough in capturing all the useful information necessary for detecting epileptic seizures. However, increasing the size of the network (especially with a limited amount of data) introduces more parameters that need to learn, and hence increases the chances of overfitting. Third and most important, none of the existing deep learning methods addresses the detection of epileptic seizures in real-life situations. This is when the EEG measurements are contaminated by artifacts (e.g., muscle activities and eye-movement) and in addition white noise. That may alter the genuine EEG features and negatively affect the performance of seizure detection systems.

To address the challenges mentioned above, we propose a robust deep neural network architecture that uses a recurrent neural network (RNN) with long short-term memory (LSTM) cells to effectively exploit the temporal dependencies in time-series EEG signals. A fully connected (FC) layer is used on top of the LSTM layer to learn the most robust and discriminative EEG attributes associated with epileptic seizures. The learned features are then sent into a softmax layer for EEG training and classification. Results on a well-known benchmark EEG dataset demonstrate the *superiority* and *robustness* of the proposed deep neural network architecture for seizure detection. Comparisons with methods based on classical machine learning and deep learning indicate that the proposed method achieves the most remarkable seizure recognition performance under the perfect circumstances (i.e., the EEG measurements are entirely free of noise). The proposed strategy is likewise demonstrated to maintain a robust performance in the existence of common EEG artifacts and environmental noise, making it more suitable for clinical diagnosis.

2. Dataset

2.1. Description of EEG dataset

Our seizure recognition experiments are conducted using the widely used and publicly available EEG database produced by Bonn University (Andrzejak et al., 2001). This database is divided into five diverse sets named A, B, C, D, and E. Each of these sets has 100 time-series EEG signals, each of which is 23.6 seconds time span. Sets A and B include surface EEG signals collected from five healthy participants using the standardized 10–20 system for scalp EEG electrodes placement (Homan et al., 1987). Set A is recorded from the five participants when they were awake and rested with their eyes open, while set B is recorded when their eyes were closed. Sets C, D, and E, on the other hand, include electrocorticography (ECoG) signals collected from the cerebral cortex of five epileptic patients. The main difference between set E and sets C and D is that set E was taken from those patients while experiencing active seizures and sets C and D were recorded throughout the seizure-free interims. The electrodes of set D and set C were implanted within the brain epileptogenic zone and the hippocampal formation of the obverse cerebral hemisphere, respectively. Since set E only included seizure activities, ECoG segments were taken from all recording positions exhibiting ictal activities.

The acquired EEG signals are first amplified using a 128-channel amplifier system and then digitized via a 12-bit analog-to-digital converter at a sampling rate of 173.61 Hz. The digital EEG signals are then stored electronically and filtered using a band-pass filter (BPF) with typical settings of 0.53-40.00 Hz cut-off frequencies. Exemplary EEG signals are shown in Fig. 1.

2.2. Common EEG artifacts

EEG recordings are usually corrupted by several types of artifacts. These artifacts affect the actual manifestation of seizure patterns and negatively influence the performance of seizure detection systems. In Delorme et al. (2007), the common types of EEG artifacts were investigated, and the mathematical models that emulate similar behaviors were developed. In this paper, we used these models to study the three most vital and inevitable sources of artifacts:

1. Electromyography (EMG): EMG signals represent the electrical activities produced by skeletal muscles. They interfere with the brain data during data acquisition causing muscular contamination to the EEG signals (Muthukumaraswamy, 2013). The authors of Delorme et al. (2007) developed a model that emulates muscle artifacts by generating random noise, and then filtering it using 20–60 Hz BPF. The generated noise is then multiplied by a typical muscle scalp map to adjust its magnitude.
2. Eye Movement: EEG also catches other electrical activities such as eye movement and blinking. These artifacts yield a significant distortion to the EEG and thus make the detection of epileptic seizures more troublesome. Besides, the low signal-to-noise-ratio (SNR) of the EEG signal makes the recognition of seizure patterns more challenging (Hallez et al., 2006). In Delorme et al. (2007), the eye movement artifacts were modeled as random noise passed through 1–3 Hz BPF.

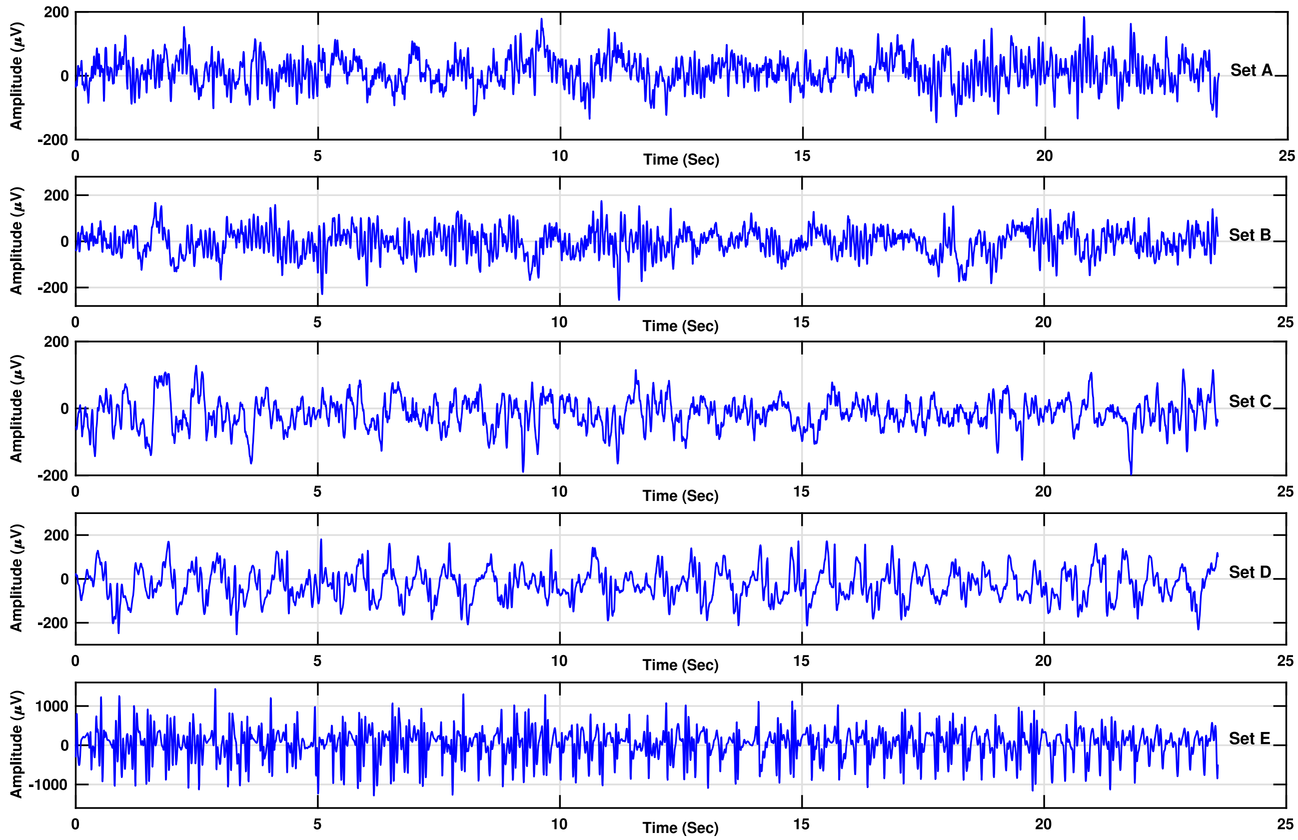

Fig. 1. Samples of EEG signals from each of the five sets of the Bonn University EEG database.

3. White Noise: The other sources of noise such as power line interference and environmental noise can be represented as additive white noise with a Gaussian distribution (Delorme et al., 2007).

Fig. 2(a) depicts an arbitrary clean EEG signal from set A, while Fig. 2(b)–(d) demonstrate the corrupted variants of the same signal after adding synthetic muscle activities, eye movement, and white noise, respectively. Fig. 2(e)–(h) show their corresponding frequency spectra. The amplitudes of the muscle activities and eye movement artifacts, as well as the white noise, is adjustable to generate noise-corrupted EEG signals with different SNRs.

The noisy EEG signals depicted in Fig. 2(b)–(d) are of 0 dB SNR; this is where the noise signal has the same power as the EEG signal. The Matlab™ platform was adopted to generate the synthetic muscle and eye movement artifacts as well as the white noise, and then add them to the noise-free EEG recordings.

3. Related work

The published work related to EEG-based epileptic seizure detection can be sorted into three main classification problems summarized below. It is worth highlighting that none of the studies below takes into consideration the existence of artifacts and their negative influence on the seizure detection accuracy.

3.1. Two-class EEG classification

Most of the two-class seizure recognition problems focus on the classification between normal EEG signals taken from healthy subjects (set A) and seizure EEG patterns taken from epileptic patients while experiencing active seizures (set E) (Aarabi et al., 2006; Subasi, 2007; Polat and Güneş, 2007; Chandaka et al., 2009; Yuan et al., 2011; Khan et al., 2012; Nicolaou and Georgiou, 2012; Kumar and Kolekar, 2014; Song et al., 2016). In Aarabi et al. (2006) developed an automated seizure detection system using a combination of characteristic EEG features extracted from the time, frequency, and time-frequency domains. All these features together with the EEG cepstral features were fed into a back-propagation neural network (BNN) classifier with two hidden layers and resulted in a seizure recognition accuracy of 93.00%. In Subasi (2007) used wavelet transform to derive the EEG frequency bands and then fed all the spectral components into the mixture of experts (ME) classifier; an average classification accuracy of 94.50% was achieved. In Polat and Güneş (2007) achieved a higher classification accuracy of 98.68% using a decision tree (DT) classifier.

Furthermore, Chandaka et al. used the EEG cross-correlation coefficients to compute three statistical features, and hence present them as a feature vector to the support vector machine (SVM) for EEG classification (Chandaka et al., 2009). This model yielded a modest seizure detection accuracy of 95.96%. Yuan et al. obtained comparable detection accuracies using the extreme learning machine (ELM) classifier and a set of non-linear features such as approximate entropy and Hurst exponent (Yuan et al., 2011). Wavelet transform was also used in Khan et al. (2012) to decompose the EEG segments into five approximation and detail sub-bands. Then, the wavelet coefficients located in the low-frequency range of 0-32Hz were used to compute the EEG features of energy and normalized coefficients. The linear discriminant analysis (LDA) classifier was used to prove the potential of the extracted features in detecting seizure onsets with a classification accuracy of 91.80%. Besides, the authors of Nicolaou and Georgiou (2012) leveraged the permutation entropy as a delegate EEG

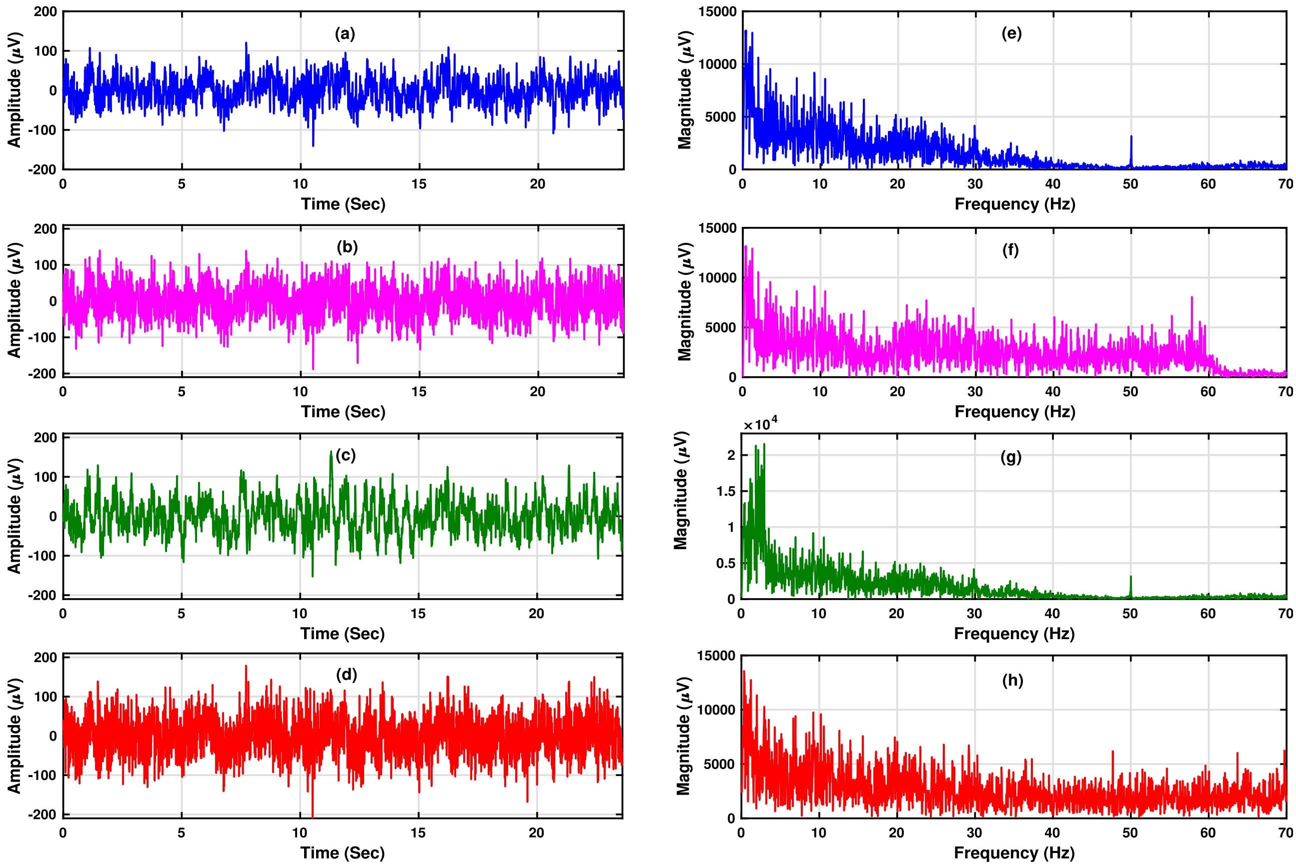

Fig. 2. Clean and noisy EEG signals and their corresponding spectra: (a) clean EEG example from set A; (b–d) noisy EEG examples contaminated by muscle activities, eye movement, and white noise, respectively; (e–h) corresponding frequency spectra of (a–d), respectively.

attribute for automatic recognition of epileptic seizures. An SVM was utilized to distinguish between healthy and ictal EEG epochs; a 93.80% classification accuracy was achieved.

Given the advantages of the wavelet transform outlined in the previous paragraph, it was also used in Kumar and Kolekar (2014) to disband the EEG signals into five distinct frequency rhythms namely delta, theta, alpha, beta, and gamma. A group of statistical and non-linear features was subsequently extracted from these rhythms and fed into an SVM classifier to achieve a superb classification accuracy of 97.50%. The authors in Song et al. (2016) also used the SVM together with the permutation entropy features to obtain a classification accuracy of 97.25%.

An exceptional case of the two-class problems is to differentiate between the seizure activities (set E) and any of the non-seizure activities (sets A, B, C or D). The primary goal of this kind of problems is to accurately identify whether or not the patient experiences an active seizure. This can help patients, caregivers, and healthcare providers to administer the appropriate medication on time. In recent years, many researchers have shed light on this particular problem using a variety of techniques (Guo et al., 2010; Fu et al., 2015; Peker et al., 2016; Jaiswal and Banka, 2017; Wang et al., 2017). In Guo et al. (2010), Guo et al. used the Wavelet-based approximate entropy features together with an artificial neural network (ANN) model to recognize the seizure episodes with 98.27% classification accuracy. In 2015, the authors of Fu et al. (2015) used the empirical mode decomposition approach to extract more robust features such as the spectral entropies and energies of EEG frequency bands. They also used the SVM classifier to improve the seizure detection accuracy to 98.80%. In Peker et al. (2016), the wavelet transform was also leveraged to analyze the EEG data into different rhythms, and then five statistical features were computed from each individual rhythm. These features are concatenated together and supplied to the complex-valued ANN (CVANN) classifier for seizure diagnosis. Accordingly, an average classification accuracy of 99.33% was achieved.

Further, in Jaiswal and Banka (2017), a novel computationally-simple feature extraction technique named local neighbor descriptive pattern (LNDP) was tested with different classification models including SVM, ANN, and DT. Experimental results demonstrate that the best detection performance can be fulfilled using LNDP jointly with the ANN classifier, where the highest classification accuracy of 98.72% is obtained. To further enhance the seizure detection rate, a set of time domain, frequency domain, and time-frequency domain features were used together with the SVM classifier to achieve the best classification rate of 99.25% (Wang et al., 2017).

3.2. Three-class EEG classification

This category of seizure detection problems addresses the classification of three different EEG classes: *Normal* EEG taken from healthy subjects, *Inter-ictal* EEG taken from epileptic patients throughout seizure-free intervals and *Ictal* EEG recorded from epileptic patients while experiencing active seizures. Numerous relevant methods have been presented in the literature (Güler et al., 2005; Tzallas et al., 2007; Ghosh-Dastidar et al., 2008; Übeyli, 2009a; Song and Liò, 2010; Acharya et al., 2012a,b; Niknazar et al., 2013; Gajic et al., 2015; Samiee et al., 2015; Hosseini et al., 2016; Behara et al., 2016). For example, the authors of Güler et al. (2005) investigated the use of the RNN as a classification model for the epilepsy diagnosis. Satisfactory performance of 96.79% classification accuracy was achieved. In Tzallas et al.

(2007) reached a superior detection accuracy of 97.94% by using the ANN classifier together with the energy features of EEG frequency bands. Moreover, the work in Ghosh-Dastidar et al. (2008) introduced a novel classifier named radial basis function neural network (RBFNN), which was integrated with the wavelet features to achieve a seizure diagnostic accuracy of 96.60%.

Furthermore, Übeyli et al. adopted wavelet transform to analyze the EEG signals into their main spectral rhythms (Übeyli, 2009a). At that point, the statistical features representing the characteristics of the different EEG activities were extracted and examined using a multilayer perceptron neural network (MLPNN) classifier. The results achieved were 96.00%, 94.00%, and 94.83% for the sensitivity, specificity, and classification accuracy, respectively. In Song and Liò (2010), a sample entropy-based feature extraction method was utilized together with an ELM classifier and achieved 97.26% sensitivity, 98.77% specificity, and 95.67% classification accuracy.

In an effort to alleviate the computational complexity burden of real-time seizure detection methods, Acharya et al. relaxed the need for EEG pre-processing and worked straightway on the raw data as is (Acharya et al., 2012a,b). In Acharya et al. (2012a), a set of robust EEG features including sample entropy, approximate entropy, and phase entropy was computed from the recorded EEG signals and then fed into fuzzy Sugeno classifier (FSC) for EEG classification. This approach boosted the seizure detection accuracy to 98.10%. The authors in Acharya et al. (2012b) used the wavelet packet transform (WPT) to decompose the EEG segments into eight approximation and detail wavelet sub-bands. The wavelet coefficients of these bands were then used to infer the distinctive eigenvalues and use them as an input to the Gaussian mixture model (GMM) classifier, which in turn achieved an outstanding 99.00% classification accuracy. Similar classification accuracy of 98.67% was accomplished in Niknazar et al. (2013) by leveraging a feature extraction approach based on recurrence quantification analysis integrated with a two-stage classifier named error-correction output code (ECOC).

Further, the authors of Gajic et al. (2015) built a piecewise quadratic (PQ) classification model for detecting epileptic EEG episodes. They integrated this classifier with a set of temporal, spectral, and non-linear features and reached up to 98.70% classification accuracy. In Samiee et al. (2015), a feature extraction method based on the discrete short-time Fourier transform was adopted together with an MLPNN classifier to differentiate between healthy and seizure EEG epochs. As a result, the highest detection accuracy of 99.10% was achieved. Also, the independent component analysis (ICA) method was employed to determine the discriminatory features pertinent to epileptic seizures (Hosseini et al., 2016). The extracted features together with the SVM classifier were used to achieve 96.00% sensitivity, 94.00% specificity, and 95.00% classification accuracy. In Behara et al. (2016), a seizure detection paradigm based on a statistical feature extraction method and a least-square SVM (LSSVM) classifier achieved a 97.19% classification accuracy in a matter of 0.065 seconds computation time.

3.3. Five-class EEG classification

This section addresses the classification of a data sample when the labels are one of five classes (which are *A, B, C, D, and E*. This kind of classification problems is more complicated and harder to solve than the two-class and three-class problems. The main reason is that it attempts to differentiate between similar pathological EEG patterns corresponding to the same class (e.g., the classification between set C and set D, which are both Inter-ictal EEGs). But since the EEG sets of C and D are recorded from different epileptogenic brain zones (Andrzejak et al., 2001), their correct classification holds great potential in localizing the seizure foci inside the brain; making it quite advantageous for such kinds of vital applications. Here, we highlight the most recent work that handles such kinds of problems.

In Guler and Ubeyli (2007), one of the most efficient multi-class EEG classification methods for epileptic seizure detection was introduced. The best typical characteristics were extracted from the EEG wavelet coefficients and Lyapunov exponents. The probabilistic neural network (PNN) was used afterward for EEG classification, where it achieved a notable seizure detection rate of 98.05%. In addition, Übeyli et al. developed an eigenvector-based method for EEG feature extraction, which in turn achieved a 99.30% classification accuracy using SVM (Übeyli, 2008). In Übeyli (2009b), the same authors used simple statistical features instead, and close classification accuracy of 99.20% was obtained. In Shen et al. (2013), SVM was also used in cooperation with the adaptive feature extraction method of wavelet approximate entropy, and outstanding classification accuracy of 99.97% was achieved.

4. Methodology

Deep learning has been successfully applied to several research problems such as face recognition (Taigman et al., 2014), image classification (Krizhevsky et al., 2012), compressive sensing (Palangi et al., 2016b), information retrieval (Palangi et al., 2016a) and speech recognition (Graves et al., 2013). In this study, we propose the use of deep recurrent neural networks, particularly the long short-term memory (LSTM) model (Hochreiter and Schmidhuber, 1997), for automatic detection of epileptic seizures.

4.1. High level picture

Fig. 3 depicts the whole process of the proposed seizure detection system. Each time-series EEG signal is first divided into smaller non-overlapping segments. These segments are then fed into the LSTM layer, which is used for learning the high-level representations of the EEG signals. Next, the output of LSTM layer y is presented as an input to the time-distributed fully connected layer h to find the most robust EEG features pertinent to epileptic seizures. Finally, a softmax layer is used to create the label predictions. The full pipeline of the proposed approach is described in the following subsections.

4.2. Proposed method

4.2.1. EEG segmentation and data reshape

Biomedical data such as EEGs are usually non-stationary signals, *i.e.*, their statistical characteristics change over time (Azami et al., 2011). The purpose of EEG segmentation is to divide a signal into several pseudo-stationary epochs (segments) as these are expected to have similar temporal and spectral features (Hassanpour and Shahiri, 2007). This EEG segmentation is often applied as a pre-processing stage for non-stationary signal analysis.

The other important factor behind EEG segmentation, particularly in this study, is the need for a large number of labeled data samples. In general, it is hard to obtain sufficient well-labeled data for training deep neural networks in real-life applications. The data segmentation, however, can help obtain more training samples, and hence improve the performance of the deep learning architecture under study. Over and above, EEG segmentation helps in finding the dependencies between consecutive EEG data-points in each EEG channel signal.

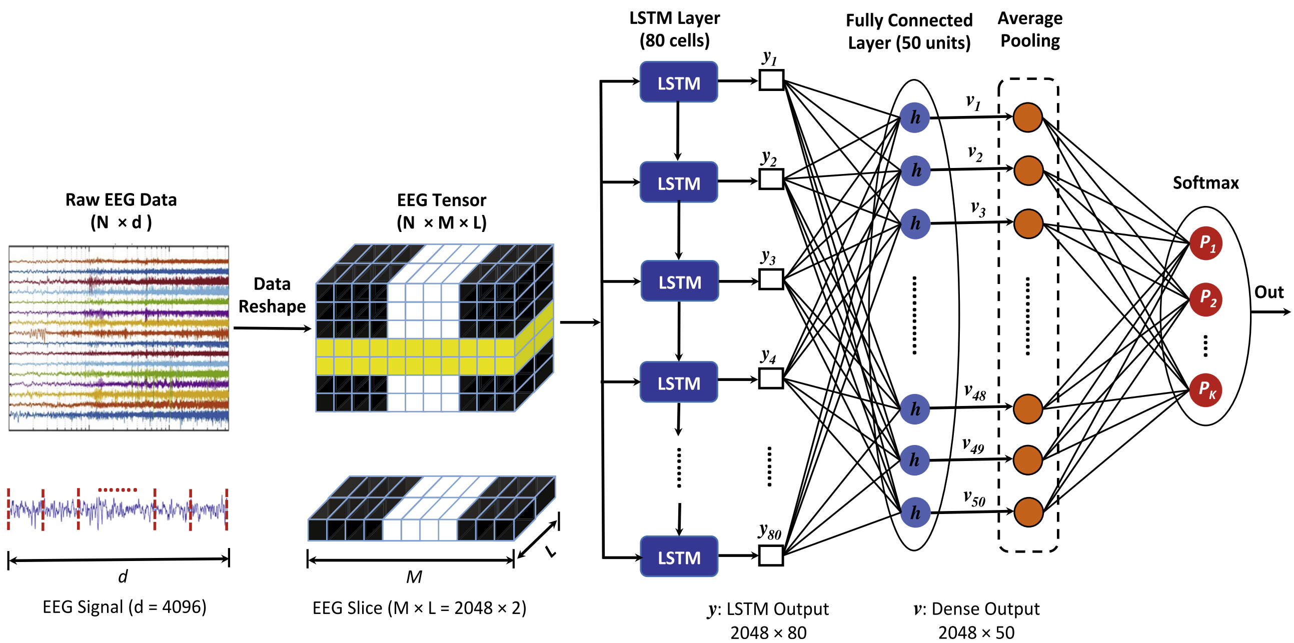

Fig. 3. Schematic diagram of the overall seizure detection approach: Each EEG EEG channel signal of d data-points is segmented into M segments - each segment includes L data-points; LSTM stands for Long-Short-Term Memory; y is the output of LSTM layer; $h_1$represents a fully connected (dense) layer unit; v is the fully connected layer output; $P_1, P_2, P_3, \cdots, P_K$ are the probabilities produced by softmax for the K-classes; **Out** stands for the output of the softmax layer (predicted label).

The EEG dataset under study includes 500 EEG signals; each is of 23.6 seconds duration. So given the sampling frequency of 173.6 Hz, the total number of data points in each EEG signal, d, is equal to 4096. All the EEG signals are divided into non-overlapping segments of a specific length (L). The most natural selection for L is $L = 1$, i.e., having a predictive model with LSTM predicting sample 2 from sample 1, sample 3 from sample 2, and so on. This choice will, however, result in a computationally slow process. To reduce the computational complexity for each L data-point EEG segment, we create vectors of size $L \times 1$ and do all multiplications and additions in parallel for these L data-point vectors. In our experiments, we tested a wide range of the EEG segment lengths, and we inferred that increasing this length can lessen the computational cost of training the proposed neural network architecture but at the cost of decreasing the detection accuracy (Hussein, 2017).

The influence of the EEG segment length on the seizure detection accuracy is presented in details in Appendix A. We found that the EEG segment length L = 2 achieves the optimal trade-off between the computational complexity and seizure detection score. Based on these premises, and as shown in Fig. 3, each one-dimensional EEG signal of size d (here $d = 4096$) is reshaped into a two-dimensional slice of size ($M \times L$), where M is the number of time-steps, and L is the EEG segment length ($L = 2$ in our experiments). Given an N of EEG signals, the input data will take the shape $N \times M \times L$.

4.2.2. EEG deep feature learning

To learn the expressive seizure characteristics from EEG data, deep learning was deployed to extract the discriminative EEG features closely related to epileptic seizures. We design our deep neural network to include three layers, with a softmax layer on top of them. The EEG data samples were first passed through an LSTM layer of 80 cells. The motivation for this was to learn the short- and long-term dependencies between the EEG segments in each signal and between the different EEG signals across the same class. Remembering information for long periods of time is practically the default behavior of LSTMs, making them the best candidate for processing long-term EEG signals. Appendix B provides more details on how the LSTM architecture is different from the architecture of the vanilla RNN, and how this difference helps LSTMs handle the shortcomings of vanilla RNNs.

As illustrated in Fig. 3, the fully connected (dense) layer was adopted as the second layer to translate the information learned by the LSTM layer into meaningful seizure-associated features. Also, since we address a long-term sequence labeling problem, we deployed the time-distributed FC layer (not the ordinary FC layer) so that the cost function is calculated over all EEG time-steps and not on the last time-step only. A time-distributed FC layer of 50 units was used in this model.

The final structural step was to pass the output of the FC layer through a one-dimensional average pooling layer. The motivation for this was that all the EEG segments should contribute equally to the label prediction. The output of the average pooling layer is then presented as an input to the softmax layer for EEG classification. The proposed deep learning model was trained and tested using two common scenarios: (1) The hold-out scenario: the EEG dataset was split into two sets, the first set was used for training, and the second set for classification.[1] Several hold-out percentages were used in this study. (2) The cross-validation scenario: 3-folds, 5-folds, and 10-folds cross-validation were also used to train and test the proposed deep neural network model.

4.2.3. EEG feature classification

As shown in Fig. 3, we add a softmax layer at the top of our model to generate label predictions. Softmax is the most common function used to represent a probability distribution in the machine learning literature (Friedman et al., 2010). From an optimization perspective, it has some subtle properties concerning differentiability. From a machine learning perspective: using a deep neural network with a softmax layer on top can represent any K-class probability function over the feature space.

[1] Our experiments on the EEG feature learning using LSTM were conducted with the open-source software of Keras using TensorFlow backend (Hussein, 2017).

In our EEG classification problem, 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 $\{(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \ldots, (\mathbf{x}^{(N)}, y^{(N)})\}$ of N labeled samples, where $\mathbf{x}^{(i)} \in \Re^{(d)}$. For each test sample $\mathbf{x}$, the softmax hypothesis evaluates the probability that $\mathscr{P}(y = k|\mathbf{x}(t), \mathbf{x}(t-1), \mathbf{x}(t-2), \ldots, \mathbf{x}(t-M))$ for each class label $k = 1, \ldots, K$; where t symbolizes the EEG segment and M is the total number of segments. The summations of these K-probability values should equal to 1 and the highest probability belongs to the predicted class. Thus, the softmax function, denoted by $\mathbf{h}_\theta(\mathbf{x})$, is defined as follows:

$$\mathbf{h}_\theta(\mathbf{x}) = \begin{pmatrix} \mathscr{P}(y = 1|\mathbf{x}; \theta) \\ \mathscr{P}(y = 2|\mathbf{x}; \theta) \\ \vdots \\ \mathscr{P}(y = K|\mathbf{x}; \theta) \end{pmatrix} = \frac{1}{\sum_{j=1}^{K} \exp(\theta_j^T \mathbf{x})} \begin{pmatrix} \exp(\theta_1^T \mathbf{x}) \\ \exp(\theta_2^T \mathbf{x}) \\ \vdots \\ \exp(\theta_K^T \mathbf{x}) \end{pmatrix}$$

where $\theta_1, \theta_2, \ldots, \theta_K$ are the softmax model parameters.

The cost function that has been widely used with softmax is the "cross entropy" $J(\theta)$ (Friedman et al., 2010):

$$J(\theta) = -\left[\sum_{i=1}^{N}\sum_{k=1}^{K} \mathbb{1}\{y^{(i)} = k\} \log \mathscr{P}(y^{(i)} = k|\mathbf{x}^{(i)}; \theta)\right] \quad (1)$$

$$= -\left[\sum_{i=1}^{N}\sum_{k=1}^{K} \mathbb{1}\{y^{(i)} = k\} \log \frac{\exp(\theta_k^T \mathbf{x}^{(i)})}{\sum_{j=1}^{K} \exp(\theta_j^T \mathbf{x}^{(i)})}\right] \quad (2)$$

where $\mathbb{1}\{.\}$ is the "indicator function", which equals to 1 if the statement is true and 0 if the statement is false.

Then, an iterative optimization method such as the stochastic gradient descent (Bottou, 2010), is used to minimize the cost function and maximize the probability of the true class label.

Referring to the LSTM architecture provided in Appendix B, the pseudo-code of the proposed LSTM-based seizure detection method is presented in Algorithm 1.

Algorithm 1. Epileptic Seizure Detection using Long-Short-Term Memory (ESD-LSTM).

Input: d-dimensional EEG/iEEG Signal $\mathbf{x}$; Trained LSTM model
Output: Predicted EEG class label $\tilde{y} \to \{1, \cdots, K\}$
Initialization: $d \leftarrow 4096$; $M \leftarrow 2048$;
Initialization: $K \leftarrow$ number of EEG classes; $K = 2, 3$, and 5 for two-class, three-class, and five-class seizure detection problems.
procedure ESD-LSTM($\mathbf{x}$, K, LSTM)
Pick an EEG segment length $L \in \{2^0, 2^1, 2^2, 2^3, \cdots, d\}$;
Partitioning the EEG/iEEG signal into M segments, each of L length.
while $t \leq M$ **do**
  $t \leftarrow t + 1$
  $\mathbf{z}^t = \mathrm{g}(\mathbf{W}_z\, \mathbf{x}^t + \mathbf{R}_z\, \mathbf{y}^{t-1} + \mathbf{b}_z)$ ▷ LSTM input
  $\mathbf{i}^t = \sigma(\mathbf{W}_i\, \mathbf{x}^t + \mathbf{R}_i\, \mathbf{y}^{t-1} + \mathbf{P}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i)$ ▷ imput gate
  $\mathbf{f}^t = \sigma(\mathbf{W}_f\, \mathbf{x}^t + \mathbf{R}_f\, \mathbf{y}^{t-1} + \mathbf{P}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f)$ ▷ forget gate
  $\mathbf{c}^t = \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t$ ▷ cell
  $\mathbf{o}^t = \sigma(\mathbf{W}_o\, \mathbf{x}^t + \mathbf{R}_o\, \mathbf{y}^{t-1} + \mathbf{P}_o \odot \mathbf{c}^t + \mathbf{b}_o)$ ▷ output gate
  $\mathbf{y}^t = \mathrm{h}(\mathbf{c}^t) \odot \mathbf{o}^t$ ▷ LSTM output
  $\mathbf{v}^t = \mathbf{h}_t\, (\mathbf{y}^t)$ ▷ FC Layer
end
$\mathbf{E} = \mathbf{AP}(\mathbf{v}^t, \mathbf{v}^{t-1}, \mathbf{v}^{t-2}, \cdots, \mathbf{v}^{t-M})$; ▷ Average Pooling
Compute $P_k = \{P_1, \cdots, P_K\} \leftarrow \mathrm{softmax}(\mathbf{E})$
Find Idx $\leftarrow$ Support(max(P_k)) ▷ Index of highest probability
$\tilde{y}$ = Idx; ▷ Predicted class label
end procedure

4.2.4. Network configuration

Our LSTM network was trained by optimizing the "categorical cross-entropy" cost function with "adam" parameter update and a learning factor of 1×10^{-3}. The total numbers of LSTM cells and FC units were set to 80 and 50, respectively. The "return sequence" was set to "True" so that all EEG segments are considered in the feature extraction process. The batch sizes were set to 64, and the network parameters converged after around 2000 iterations with 40 epochs. The data were augmented by adding eye movement and muscle activity artifacts as well as Gaussian white noise, and various noise levels were considered in our experiments. Our implementation was derived in Python using Keras with TensorFlow backend and underwent two hours training on an NVIDIA K40 GPU machine. Although the training of our end-to-end neural network model takes up to two hours, testing the trained model on new data takes less than a second. This fast testing performance makes our model a perfect fit for the real-time processing of EEG signals in real-life and clinical applications.

5. Results and discussion

In this section, we test the performance of our seizure detection approach under ideal and imperfect conditions. The results are also compared to those of the baseline seizure detection methods that use the same clinical dataset. The detection performance was

Table 1
Seizure detection results of the proposed and baseline methods: Two-class problem (A-E).

Method	Year	Classifier	Training/testing	Sens (%)	Spec (%)	Acc (%)
Aarabi et al. (2006)	2006	BNN	Hold-out (50.00–50.00%)	91.00	95.00	93.00
Subasi (2007)	2007	ME	Hold-out (62.50–37.50%)	95.00	94.00	94.50
Chandaka et al. (2009)	2009	SVM	Hold-out (62.50–37.50%)	92.00	100.00	95.96
Yuan et al. (2011)	2011	ELM	Hold-out (50.00–50.00%)	92.50	96.00	96.50
Khan et al. (2012)	2012	LDA	Hold-out (80.00–20.00%)	83.60	100.00	91.80
Nicolaou and Georgiou (2012)	2012	SVM	Hold-out (60.00–40.00%)	94.38	93.23	93.80
Kumar and Kolekar (2014)	2014	SVM	Hold-out (66.67–33.33%)	98.00	96.00	97.50
Song et al. (2016)	2016	SVM	–	94.50	100.00	97.25
Proposed method	2017	ESD-LSTM	Hold-out (66.67–33.33%)	100.00	100.00	100.00
Polat and Güneş (2007)	2007	DT	10-folds cross-validation	98.87	98.50	98.68
Proposed method	2017	ESD-LSTM	10-folds cross-validation	100.00	100.00	100.00

Table 2
Seizure detection results of the proposed and baseline methods: Two-class problem (ABCD-E).

Method	Year	Classifier	Training/testing	Sens (%)	Spec (%)	Acc (%)
Guo et al. (2010)	2010	ANN	Hold-out (50.00–50.00%)	95.50	99.00	98.27
Peker et al. (2016)	2016	CVANN	Hold-out (60.00–40.00%)	100.00	98.01	99.33
Proposed method	2017	ESD-LSTM	Hold-out (80.00–20.00%)	100.00	100.00	100.00
Fu et al. (2015)	2015	SVM	10-folds cross-validation	–	–	98.80
Jaiswal and Banka (2017)	2017	ANN	10-folds cross-validation	98.30	98.82	98.72
Wang et al. (2017)	2017	SVM	10-folds cross-validation	97.98	99.56	99.25
Proposed method	2017	ESD-LSTM	10-folds cross-validation	100.00	100.00	100.00

assessed using the metrics of sensitivity (Sens), specificity (Spec), and classification accuracy (Acc).

5.1. Seizure detection in ideal conditions

We first examine the proposed deep learning approach to clean EEG signals that are free of artifacts and noise. After EEG pre-processing (i.e., data segmentation and reshaping), EEGs are then fed into our deep neural network model with the ultimate objective of effective EEG feature learning and classification.

5.1.1. Two-class classification results

The first category of the two-class seizure detection problems is to distinguish between the normal EEGs collected from healthy volunteers and seizure EEGs recorded from epileptic patients experiencing active seizures. Table 1 reports the results obtained by the proposed and baseline seizure detection strategies. As shown in Table 1, most of the existing seizure detection methods achieve low sensitivity values in the range of 91.00–94.50%. The top sensitivity of 98.87% was accomplished by Polat et al. using a combination of wavelet-based feature extractor and a decision tree classifier (Polat and Güneş, 2007). Our seizure detection approach, however, accomplished the most astounding sensitivity of 100.00%.

Further, our approach achieved an outstanding seizure specificity of 100,00%, which is similar to those of Khan et al. (2012) and Song et al. (2016), and superior to those of the other state-of-the-art methods. Also, our approach can deal with the raw EEG data and does not entail any major pre-processing (e.g., denoising) like those of Khan et al. (2012) and Song et al. (2016). Among all the current seizure detection strategies, our approach yields an unrivaled classification accuracy of 100.00%, which is 1.32% better than the top classification accuracy reported in the literature (Polat and Güneş, 2007).

In the second assessment, we handle the classification problem between any non-seizure activities (sets A, B, C, or D) and seizure activities (set E). Considering the fact that each EEG set comprises 100 signals, this classification problem has an imbalanced class distribution. The reason is that the number of EEG samples belonging to the seizure class is substantially lower than those of the non-seizure class. In this case, the seizure detection systems developed using traditional machine learning algorithms could be inaccurate and prejudiced against the minority class. The proposed approach, instead, can adequately tackle this sort of classification problems and defeat the literature performance. Again, the performance is evaluated in terms of sensitivity, specificity, and classification accuracy values. The seizure detection results achieved by the proposed and baseline methods are reported in Table 2. They verify the superiority of the proposed approach over the state-of-the-art methods, achieving the topmost performance of 100.00% for each of the sensitivity, specificity, and classification accuracy.

5.1.2. Three-class classification results

We also investigate the effectiveness of the proposed method to differentiate between three distinct classes of EEG activities: *normal*, *inter-ictal*, and *ictal*. The EEG classification results achieved by the proposed method are compared to those of the baseline methods presented in Güler et al. (2005) and Behara et al. (2016). For a fair comparison, the performance of all these methods is tested on the same clinical EEG dataset (Andrzejak et al., 2001).

Table 3 includes the performance metrics achieved by the proposed and existing seizure detection strategies. It is clear that our proposed approach yields superior sensitivity, specificity, and classification accuracy. The leading reason was the use of LSTM that investigates the correlation between the EEG signals taken from different subjects and the dependencies among EEG segments of the same subject. The results in Table 3 demonstrate the high potential of deep neural networks in effectively learning the discriminative EEG features that best characterize *normal*, *inter-ictal* and *ictal* EEG activities. It has not escaped our notice that, for the three-class seizure detection problem, our proposed deep learning method achieves 100% sensitivity, which is better than those obtained by all the reference methods. Besides, our approach yields 100% seizure specificity, which is comparable to the specificity values achieved by Acharya et al. (2012a), and superior to those of the baseline methods. All the more strikingly, among all existing sei-

Table 3
Seizure detection results of the proposed and baseline methods: Three-class problem (A-C-E).

Method	Year	Classifier	Training/testing	Sens (%)	Spec (%)	Acc (%)
Güler et al. (2005)	2005	RNN	Hold-out (50.00–50.00%)	95.50	97.38	96.79
Tzallas et al. (2007)	2007	ANN	Hold-out (50.00–50.00%)	95.73	97.86	97.94
Ghosh-Dastidar et al. (2008)	2008	RBFNN	Hold-out (80.00–20.00%)	–	–	96.60
Übeyli (2009a)	2009	MLPNN	Hold-out (50.00–50.00%)	96.00	94.00	94.83
Niknazar et al. (2013)	2013	ECOC	Hold-out (70.00–30.00%)	98.55	99.33	98.67
Samiee et al. (2015)	2015	MLPNN	Hold-out (50.00–50.00%)	99.20	98.90	99.10
Proposed method	2017	ESD-LSTM	Hold-out (50.00–50.00%)	100.00	100.00	100.00
Hosseini et al. (2016)	2016	SVM	Leave-one-out CV	96.00	94.00	95.00
Proposed method	2017	ESD-LSTM	Leave-one-out CV	100.00	100.00	100.00
Acharya et al. (2012a)	2012	FSC	3-folds cross-validation	99.40	100.00	98.10
Proposed method	2017	ESD-LSTM	3-folds cross-validation	100.00	100.00	100.00
Gajic et al. (2015)	2015	PQ	5-folds cross-validation	98.60	99.33	98.70
Proposed method	2017	ESD-LSTM	5-folds cross-validation	100.00	100.00	100.00
Song and Liò (2010)	2010	ELM	10-folds cross-validation	97.26	98.77	95.67
Acharya et al. (2012b)	2012	GMM	10-folds cross-validation	99.00	99.00	99.00
Behara et al. (2016)	2016	LSSVM	10-folds cross-validation	96.96	99.66	97.19
Proposed method	2017	ESD-LSTM	10-folds cross-validation	100.00	100.00	100.00

Table 4
Seizure detection results of the proposed and baseline methods: Five-class problem (A-B-C-D-E).

Method	Year	Classifier	Training/testing	Sens (%)	Spec (%)	Acc (%)
Guler and Ubeyli (2007)	2007	PNN	Hold-out (50.00–50.00%)	98.05	99.50	98.05
Übeyli (2008)	2008	SVM	Hold-out (70.00–30.00%)	99.30	99.82	99.30
Übeyli (2009b)	2009	SVM	Hold-out (50.00–50.00%)	99.20	99.79	99.20
Shen et al. (2013)	2013	SVM	Hold-out (50.00–50.00%)	98.37	100.00	99.97
Proposed method	2017	ESD-LSTM	Hold-out (50.00-50.00%)	100.00	100.00	100.00

zure detection strategies, our approach achieves a notable 100.00% classification accuracy.

5.1.3. Five-class classification results

We also study the potential of the proposed deep learning model to address the five-class EEG classification problem between the EEG sets of A, B, C, D, and E. This is a more challenging problem compared to the two-class and three-class classification problems but has an advantage in numerous clinical applications. It addresses the differentiation between EEG epochs belonging to the same class (e.g., sets C and D, which are both inter-ictal), seeking for providing more useful clinical practices. For example, the discrimination between EEG *set C* and *set D* plays a vital role in seizure localization, as their data were captured from the opposite brain hemispheres. In fact, only a few scholars have focused on the significance of the five-class EEG classification problem (Guler and Ubeyli, 2007; Shen et al., 2013). Nevertheless, they have accomplished adequate EEG classification results, as shown in Table 4.

To assess the efficacy of our proposed method for addressing the five-class EEG classification problem, we compare its performance to the baseline methods of the last decade. Table 4 includes the performance measures attained by our method as well as reference methods. The proposed method is shown to outperform the literature performance achieving superior sensitivity, specificity, and classification accuracy. Comparing our EEG classification results to those of the baseline methods, we find that the multi-class seizure detection method of Shen et al. produces similar results to those achieved by our approach. It achieves 98.37% sensitivity, 100.00% specificity, and 99.97% classification accuracy (Shen et al., 2013). This method, however, necessitates three computationally-intensive pre-processing steps that may hamper its real-time applications. On the contrary, our method does not require any pre-processing stages and deals with the raw data as is; yielding the superior EEG classification performance of 100.00%.

5.2. Seizure detection in real-life conditions

We also study the robustness of the proposed seizure detection approach in the presence of the common artifacts such as muscle activities and eye movement as well as the environmental noise. In Hussein et al. (2016), we have presented a reliable EEG feature learning algorithm that can deal with noise-corrupted EEG signals. This algorithm presumed that only Gaussian noise had been experienced during EEG data acquisition, i.e., EEG artifacts were excluded, which is not the case in practical situations. This study, however, shows that our deep learning model can deal with noisy EEG data contaminated by physical artifacts (muscle activities and eye movement) and in addition Gaussian white noise.

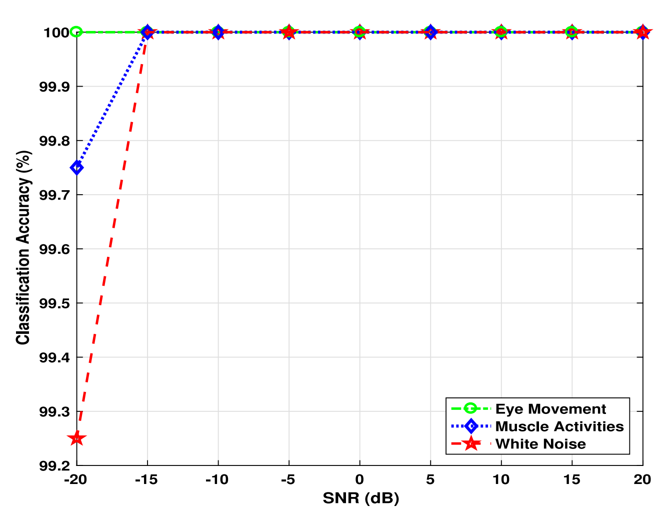

Fig. 4. Classification accuracy vs. SNR plots for the two-class EEG classification problem (A–E).

5.2.1. Two-class classification results

We initially examine the capability of the proposed method to recognize whether the noisy EEGs belong to a healthy subject (set A) or an epileptic patient who experiences active seizures (set E). As depicted in Fig. 4, the performance of the proposed approach is tested at different levels of artifacts and noise. The models depicted in 2.2 have been used to generate the synthetic artifacts of muscle activities and eye movement as well as synthetic white noise. The magnitude of these artifacts and noise is adjusted to produce noise-corrupted EEG signals of different SNRs. Fig. 4 depicts the seizure classification accuracy achieved by our deep learning approach in the presence of muscle activities, eye movement, and white noise at a variety of SNR values between −20dB and 20dB.

Many interesting observations can be made here. First, the proposed approach can efficiently find out the most representative and robust EEG features pertinent to seizures, even when EEG measurements are entirely submerged in noise. For instance, Fig. 4 demonstrates the robustness of the proposed approach in the existence of two common artifacts and noise. Interestingly, for the EEGs corrupted by eye movement artifacts, our method preserves a high classification accuracy of 100.00% at all SNR levels. The same applies to the EEG contaminated by muscle activities and white noise, except when SNR=−20dB. The main reason was that, for SNR=−20dB, the EEG data were completely buried in noise and their original waveform shapes were distorted. The proposed approach, however, maintains an adequate seizure detection performance achieving a classification accuracy of 99.75% and 99.25% for the case of muscle activities and white noise, respectively.

As for the two-class problem of set E versus sets A, B, C, and D (ABCD-E), the proposed method was also tested on noisy EEG segments polluted by muscle artifacts, eye movement, and white noise. Since the class distribution of this binary classification problem is imbalanced, the performance of the proposed method experiences a trivial decay. It is worth highlighting that, for such a hard problem, the proposed approach is shown to preserve an adequate seizure detection accuracy even at excessive noise levels. Fig. 5 displays the seizure detection performance achieved by the proposed method in the presence of the two sorts of artifacts as well as the white noise. It is demonstrated that the minimum classification accuracy of 96.70% was obtained when the EEG signals were wholly buried in white noise (SNR = −20). Concerning the noise-corrupted EEG data of SNR above 0dB, our approach yields a classification accuracy higher than 99.00%.

5.2.2. Three-class classification results

Fig. 6 demonstrates the overall performance of the proposed approach in the presence of muscle activities, eye movement, and white noise at different SNR levels. It is clearly shown that the proposed approach preserves a superb performance when applied to noisy EEG segments of SNR above 0dB. The leading cause is that LSTM networks can effectively extract the most faithful and robust EEG representations pertinent to epileptic seizures - even under noisy conditions. The performance of the proposed method begins to decay when tested on noisy EEG samples of SNRs less than 0dB, especially when these samples are contaminated by Gaussian white noise. Better classification results are accomplished when the EEG data is corrupted by muscle artifacts. The main reason behind this improvement is that muscle activities interfere with EEG data within the tight frequency band of 20–60Hz (Delorme et al., 2007). The superior results are attained when applying our method to EEG data mixed with eye movement artifacts. As shown in Fig. 6, the proposed method is proven to be robust against high and severe levels of eye artifacts achieving classification accuracies above 95.20%. By and large, the proposed method can precisely recognize EEG seizure activities contaminated with artifacts and noise with adequate classification accuracies.

5.2.3. Five-class classification results

We also investigate the performance of our seizure detection method to address the five-class EEG classification problem in real-life situations. i.e., when the EEG data is polluted with muscle activities, eye movement, and white noise of different intensities. Fig. 7 demonstrates the EEG classification results achieved by our deep learning approach at different SNRs. Even though the five-class EEG classification is an intractable problem, particularly in the presence of noise and artifacts, the proposed method is proven to maintain high seizure detection results at low SNR values. For instance, it yields a classification accuracy larger than 94.00% when applied to noisy EEG signals mixed with eye movement artifacts. Inferior recognition accuracy is achieved in the presence of muscle activities artifacts; the diagnostic accuracy is diminished to 70.90% at SNR = −20 dB. The root reason is that muscle artifacts reside in a broad band of EEGs spectra causing a considerable distortion to the

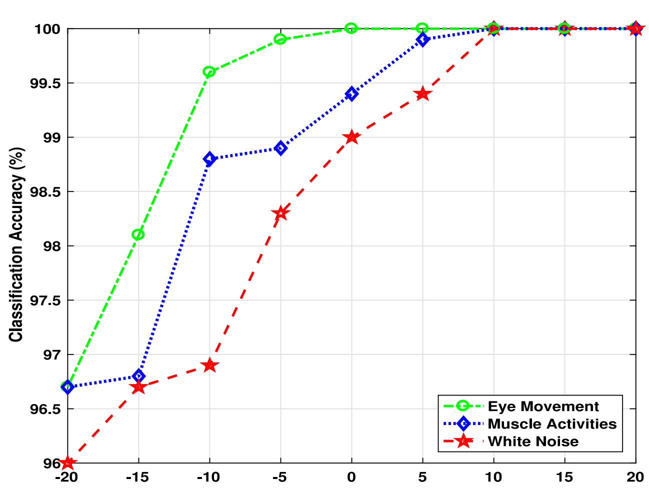

Fig. 5. Classification accuracy vs. SNR plots for the two-class EEG classification problem (ABCD-E).

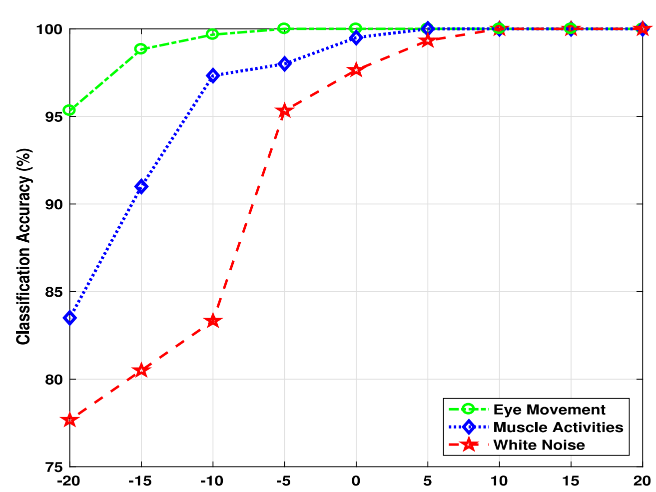

Fig. 6. Classification accuracy vs. SNR plots for the three-class EEG classification problem (A-C-E).

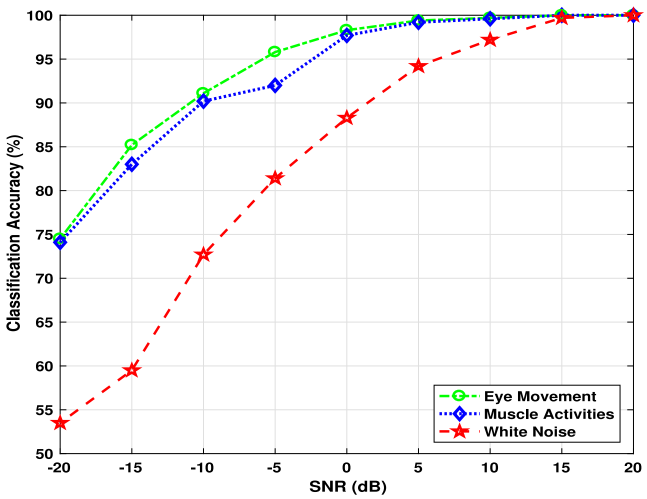

Fig. 7. Classification accuracy vs. SNR plots for the five-class EEG classification problem (A-B-C-D-E).

EEG waveform shapes. A much higher decay in the proposed method's performance is experienced in the presence of high levels of white noise. The classification accuracy goes down to 53.50% for white noise-corrupted EEG data of −20 dB. However, in realistic situations (SNR > 0 dB), our method yields a notable performance with EEG classification accuracies larger than 90.00%.

6. Limitations and recommendations

The EEG dataset used in this study was collected from only five healthy volunteers and five epileptic patients. This makes us more cautious with interpreting the quantitative results reported in this work. To generalize our research results, other experiments on larger datasets are needed.

Our recommendations are:

- Finding a larger EEG dataset that consists of many more patients. This will enable our deep neural network model to learn the various patterns of epileptic seizures across different patients, and hence improving its generalizability. It is well known that the performance of deep neural networks improves as the training data increases.
- Incorporating long-term EEG signals in our seizure detection tests. The ultimate objective, in this case, is to identify the pre-seizure EEG activities and notify the epileptic patients of upcoming seizures.
- Since our method was developed to address the single-channel EEG data, the neural network structure needs some modifications to accommodate the multi-channel EEG systems. One of the suggestions is to add a convolution neural network that can extract the spatial correlations between the EEG epochs collected from different sensor locations on the scalp.

7. Conclusion

This paper introduces a deep learning approach for the automatic detection of epileptic seizures using EEG signals. Compared to the baseline methods, this approach can learn the high-level EEG representations, and can adequately distinguish between normal and seizure EEG activities. Another advantage of this approach lies in its robustness against common EEG artifacts (e.g., muscle activities and eye movement), and also white noise. The proposed approach has been examined on the Bonn EEG dataset and compared to several state-of-the-art methods. The experimental results evidence the effectiveness and superiority of the proposed method for detecting epileptic seizures. It achieves robust seizure detection performance under ideal and imperfect conditions. The proposed method, however, addresses single-channel EEG data only. We plan to modify the deep neural network architecture to accommodate multi-channel EEG systems as well.

Data and codes availability

The pre-processed data in Matlab and comma-separated values (CSV) formats are publicly available on the first author's Github repository (Hussein, 2017). The python codes for the proposed deep neural network structure is also made available on the same repository.

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Conflicts of interest: None of the authors have potential conflicts of interest to be disclosed.

Appendix A. Influence of EEG segmentation on the seizure detection accuracy

In this appendix, we show the impact of the EEG segment length on the detection accuracy of epileptic seizures. Fig. A.1 depicts how the seizure detection accuracy decays with longer segment lengths. It also shows that L = 1 and L = 2 are the only EEG segment lengths that achieve the highest seizure detection accuracy of 100,00%. And since the EEG segment length of 2 yields a lower computational complexity than that of 1; we adopted this length in all our seizure detection experiments. In this regard, each EEG segment is designed to have only two data-points out of 4096, producing 2048 segments for each EEG channel signal.

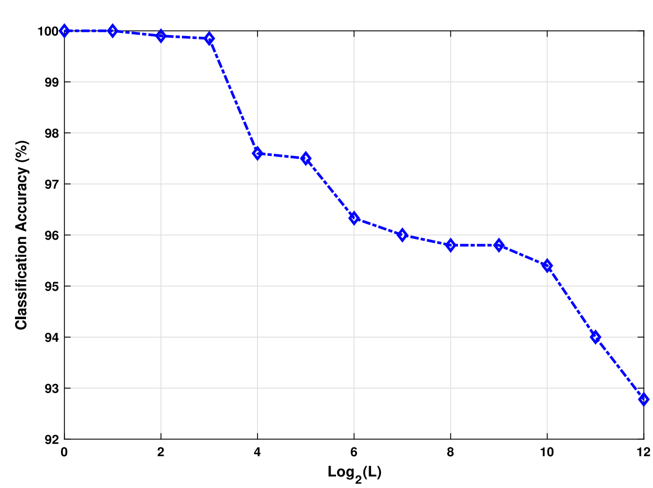

Fig. A.1. Classification accuracy against EEG segments' length.

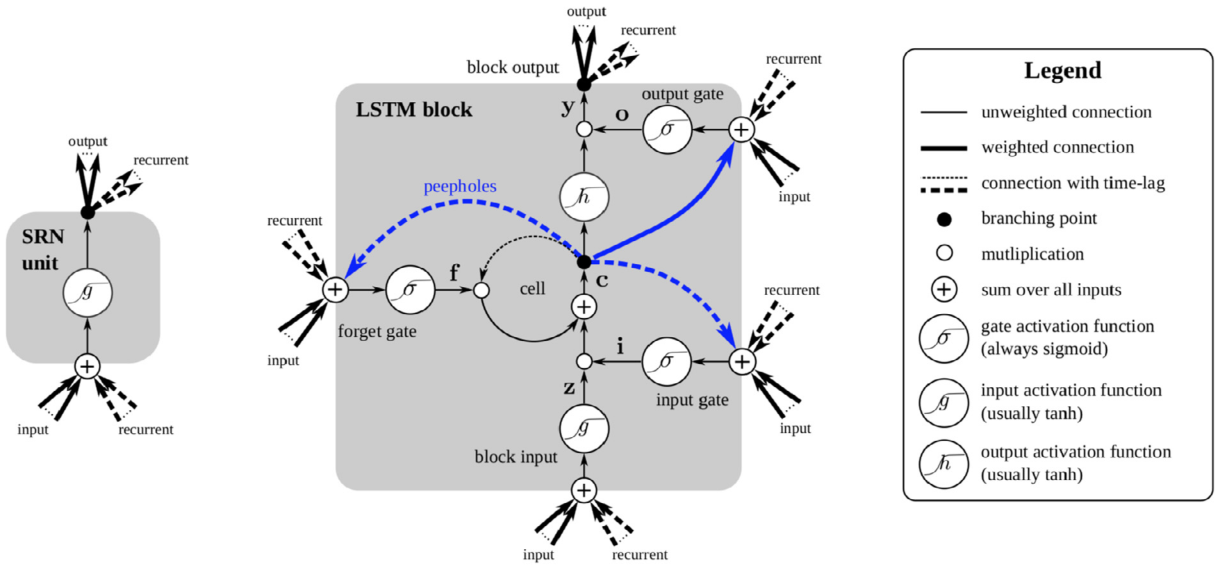

Fig. B.1. Detailed schematic of the Standard Recurrent Network (SRN) unit (left) and a Long-Short-Term Memory (LSTM) block (right) (Greff et al., 2017).

Appendix B. Architecture of vanilla RNN and LSTM

In this appendix, we describe the architecture of the vanilla RNN (the standard recurrent network (SRN)) and the long-short-term memory (LSTM) that have been widely used for solving the sequence labeling problems (Greff et al., 2017). The SRN's architecture, shown in the left part of Fig. B.1, represents the basic structure of RNNs. Although RNNs reveal an outstanding capacity of modeling nonlinear time-series problems, SRNs usually suffer from vanishing or blowing up the gradient during the back-propagation process, and thus, being incapable of learning from long-time sequences (Bengio et al., 1994).

To address this limitation of RNNs, more powerful recurrent architectures, such as LSTM, have been developed. It has been found that LSTM works best on time-series with short- and long-term dependencies. We use the LSTM architecture illustrated in the right part of Fig. B.1 for our seizure detection problem. This Figure has three gates (input, forget, output), a block input, a single cell (the Constant Error Carousel), an output activation function, and peephole connections (Greff et al., 2017). The output of the block is recurrently connected back to the block input and all of the gates.

Let $\mathbf{x}^t$ and $\mathbf{y}^t$ be the LSTM input and output vectors at time t. Then we get the following weights for an LSTM layer:

- Input weights: $\mathbf{W}_z, \mathbf{W}_i, \mathbf{W}_f, \mathbf{W}_O \in \mathbb{R}^{B\times M}$
- Recurrent weights: $\mathbf{R}_z, \mathbf{R}_i, \mathbf{R}_f, \mathbf{R}_O \in \mathbb{R}^{B\times B}$
- Peephole weights: $\mathbf{P}_i, \mathbf{P}_f, \mathbf{P}_O \in \mathbb{R}^{B}$
- Bias weights: $\mathbf{b}_z, \mathbf{b}_i, \mathbf{b}_f, \mathbf{b}_O \in \mathbb{R}^{B}$

Considering Fig. B.1, the definitions of the vector relationships formulas for a basic LSTM layer forward pass can be written as (Greff et al., 2017):

$$\bar{\mathbf{z}}^t = \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} + \mathbf{b}_z \tag{B.1}$$
$$\mathbf{z}^t = g(\bar{\mathbf{z}}^t) \quad \textit{block input} \tag{B.2}$$
$$\bar{\mathbf{i}}^t = \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{P}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \tag{B.3}$$
$$\mathbf{i}^t = \sigma(\bar{\mathbf{i}}^t) \quad \textit{input gate} \tag{B.4}$$
$$\bar{\mathbf{f}}^t = \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{P}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \tag{B.5}$$
$$\mathbf{f}^t = \sigma(\bar{\mathbf{f}}^t) \quad \textit{forget gate} \tag{B.6}$$
$$\mathbf{c}^t = \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t \quad \textit{cell} \tag{B.7}$$
$$\bar{\mathbf{o}}^t = \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{P}_o \odot \mathbf{c}^t + \mathbf{b}_o \tag{B.8}$$
$$\mathbf{o}^t = \sigma(\bar{\mathbf{o}}^t) \quad \textit{output gate} \tag{B.9}$$
$$\mathbf{y}^t = h(\mathbf{c}^t) \odot \mathbf{o}^t \quad \textit{block output} \tag{B.10}$$

where σ, g, and h are point-wise activation functions. The logistic sigmoid $\sigma(.)$ is used as a gate activation function and the hyperbolic tangent $g(\cdot) = h(\cdot) = \tanh(\cdot)$ is used as the input and output activation function of an LSTM unit. $\odot$ denotes the point-wise multiplication of two vectors (Greff et al., 2017).

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