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Proficient RO-RNN Learning Model for Seizure Prediction Systems

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Abstract
According to WHO, world widely around 65 million people are affected by epilepsy. Prediction of such a life-threatening neurological disease is of high importance. Predictability of seizures uplifts the patient's life and wellbeing. This paper presents the application of machine learning in the prediction of epileptic seizures. In this work, we used Regularized and Optimized Recurrent Neural Network (RO-RNN). The aim of this work is to investigate the application of bidirectional long short-term memory (LSTM) networks for epileptic seizure prediction. A Weight Dropped (WD) method is used for regularizing the LSTM model and an Averaged Stochastic Gradient Descent (ASGD) is used for optimizing the LSTM model. Regularization and optimization are deployed with the deep neural network architecture to accelerate the convergence rate and to reduce the complexity of the proposed non-linear model. The proposed model is evaluated using two diverse public databases such as traditional CHB-MIT and recent NINC respectively. Also, a private real time SRM database is used for the assessment of the proposed computer-aided seizure prediction approach. Empirical results on 200 recordings outperforms the state-of-art approaches with an accuracy score of 0.91, sensitivity score of 0.89 and false prediction rate of 0.12 FP/h. Experimental results prove that the proposed seizure prediction approach is a promising one for accurate real-time prediction of epilepsy using scalp EEG data.

Keywords: Averaged Stochastic Gradient Descent; bidirectional long short-term memory; computer-aided seizure prediction; deep neural network architecture; Regularized and Optimized Recurrent Neural Network; Weight Dropped.

1. Introduction

Epilepsy is characterized by unexpected occurrences of recurrent seizure episodes [1]. This fear of expectance in the occurrence, leverages stress among the epileptic patients and reduces the quality of their lifetime [2]. Though there are Antiepileptic drugs (AED's) available, AED's are effective only in 70% of the cases. And for these cases too, the intake of AED's may impose several side effects on the epileptic patient's health [3]. According to few clinical studies, around 6.2% epileptic patients reported about several precognitive symptoms. This clearly indicates the possibility of predicting the epileptic seizures. Accurate prediction of seizures well before its onset helps in alarming the patients to take safety measures against injuries. Hence the predictability of seizures uplifts the patient's wellbeing from life threatening activities like driving, swimming, etc.

Neurologists classify the activities of brain into four different states like preictal (before seizures), interictal (between seizures), ictal (seizure) and postictal (after seizures) [4]. Seizures can be predicted by knowing the transition phase between preictal and interictal period of EEG signals of different frequencies [5]. A model categorizing preictal and interictal states is the base for predicting epileptic seizures. Defining an accurate prediction horizon as early as possible considerably increases the quality of patient's life. This prediction horizon period will be suitable for warning these seizures and for administration of drugs.

Recently, deep learning algorithms are extremely implemented in numerous fields due to its astonishing accuracy scores and superior reliability. This stimulated the investigators for implementing these learning algorithms in real-time prediction of epileptic seizures due to its automatic feature extraction technique. LSTM model is used for the extraction of cross-correlation and graph theoretic features from the long-term iEEG recordings. The proposed methodology is able to predict the seizures with a prediction accuracy of about 84%, but no details regarding prediction horizon is briefed in this work [6]. CNN's along with wavelet transform learns and predicts the various periods on iEEG recordings with an accuracy of 82% [7]. A seizure prediction algorithm which uses cooperative multi-scale CNNs for automatic feature learning of iEEG data is proposed and the prediction results show that the proposed algorithm achieved an average sensitivity of 87.85% and accuracy score of 84%, but training such a multiscale network requires longer hours which increase the complexity of the model [8]. A combination of CNN and Gated Recurrent Unit (GRU) networks, called Convolutional Gated Recurrent Neural Network (CGRNN) is used for the prediction of epileptic seizures based on features extracted from EEG data which is represented in time and frequency domains of the signal. CGRNN predicts the epileptic seizures with an average sensitivity of 89%, a mean accuracy of 75.6% and a mean FPR of 1.6 FP/h. The evaluation metrics are highly influenced by the updation parameters of this model [9].

This paper focuses on the prediction of epileptic seizures by classifying the interictal and preictal brain states using the Regularized and Optimized Recurrent Neural Network (RO-RNN). To the best of our knowledge, this is the first work which implements bidirectional WD-ASGD-RNN for predicting the epileptic seizures. Though there are several works on CNN, we incorporated LSTM in our work due to its light weight and best performance for time series input data [6]. The major contributions of this work are as follows:

1. A Weight Dropped (WD) method is implemented for regularizing the LSTM model.
2. An Averaged Stochastic Gradient Descent (ASGD) is used for optimizing the LSTM model
3. A bidirectional long short-term memory (LSTM) networks for epileptic seizure prediction is modelled
4. The proposed model is evaluated on three different datasets like CHB-MIT, NINC and SRM scalp data recordings.

The rest of this paper is organized as follows: materials and methods are discussed in section 2; performance metrics are discussed in the section 3; the results and discussions are provided in section 4 and finally, the conclusion of this work is presented in section 5.

2. Materials and Methods

The materials used as the EEG datasets and its processing are discussed in the following sub-sections.

2.1 EEG Datasets

In this work, we trained and estimated the performance of our proposed model using three EEG databases such as Children's Hospital Boston (CHB-MIT) database, Neonatal EEG recordings with seizure annotations of Neonatal Intensive Care Unit (NICU) acquired from Helsinki university hospital and EEG recordings from SRM medical college and hospital. The CHB-MIT [10] and NICU [11] databases are publicly available, whereas the SRM dataset is a private one collected from the SRM Research Centre of SRM medical college and hospital. The ethical clearance number of this work is 1501/IEC/2018 from SRM Medical College Hospital and Research Centre. Informed consent is obtained from each patient and the ethics committees of the institution approved this study. This database is acquired from 32 channels of RMS EEG 32 Super Spec system equipment.

All of these recordings are long-term, multichannel, noninvasive scalp EEG data and are collected using a bipolar montage of internationally accepted 10-20 standard. Each subject in this work contains more than one seizure. All of these seizures are focal mainly in frontal, central and temporal regions of brain. Totally 200 EEG recordings are used for this work. This model is trained using 90 seizure recordings and 40 seizure-free recordings. Testing of this model is carried out using 50 seizure recordings and 20 seizure-free recordings. So, totally this study is inspected using 140 seizure and 60 seizure-free recordings. The overall EEG recording details of seizure prediction is given in Table 1. An example of multichannel EEG recording used in our study is shown in Fig. 1.

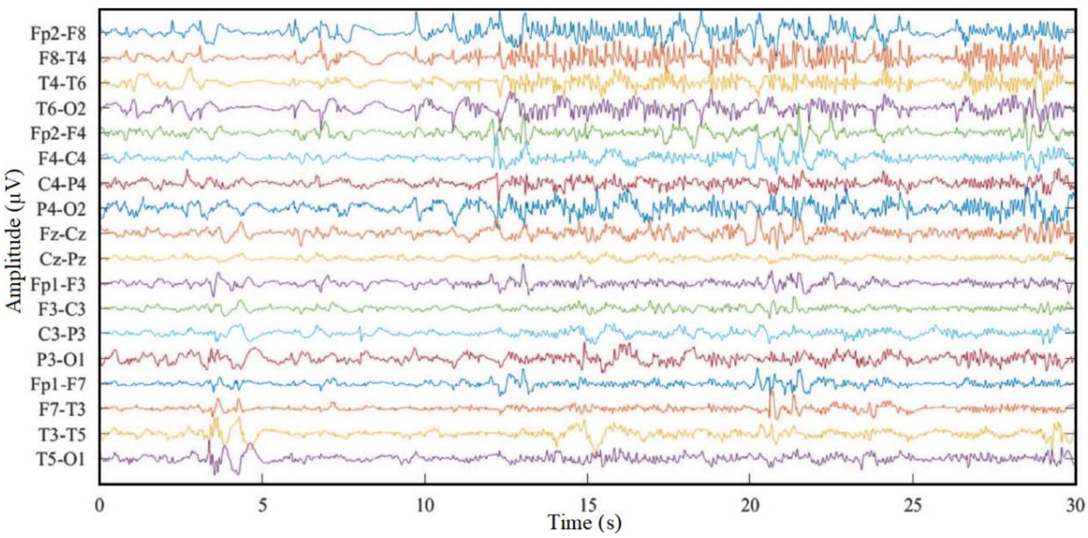

Fig. 1. Multichannel SRM Epileptic EEG recordings

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Table 1: EEG recording details of seizure prediction

CHB-MIT - 24 patients

Training		Testing	
Seizure	Seizure-free	Seizure	Seizure-free
39	19	27	10
Total- 58		Total- 37	
Total recordings – 95			

NINC - 61 patients

Training		Testing	
Seizure	Seizure-free	Seizure	Seizure-free
32	12	12	5
Total- 44		Total- 17	
Total recordings - 61			

SRM - 31 patients
Overall – 116 patients

Training		Testing	
Seizure	Seizure-free	Seizure	Seizure-free
21	10	8	5
Total- 31		Total- 13	
Total recordings – 44			

Training		Testing	
Seizure	Seizure-free	Seizure	Seizure-free
90	50	40	20
Total- 140		Total- 60	
Total recordings - 200			

2.2 Feature Extraction

In order to capture the complex, non-stationary, and nonlinear nature of EEG signals, we extract various the following features from the input EEG signals. The three features extracted are power spectrum, fractal dimension and approximate entropy. These three features seem to be important in defining the different states of epileptic seizures. The power spectrum and approximate entropy of inter-ictal and post-ictal are always lesser than the other two states, also ictal exhibits higher power spectra and is medium for preictal state. The fractal dimension of interictal and postictal are always higher, also ictal exhibits least fractal dimensionality, while medium is for preictal state. The approximate entropy drops sharply in the ictal state, whereas increases gradually in the preictal state and peaks in the interictal and postictal states. All of these features are computed using a non- overlapping sliding window of 10 seconds, containing a feature set of 2560 samples with 7680 features.

For the purpose of feature smoothing, Savitzky - Golay (SG) filtering method is used to adjust the feature space by avoiding the unrelated feature components. Chi-Squared feature selection technique is used for serving the purpose of the dimensionality reduction. This technique estimates the absence of the individuality between the selected features and the target.

2.3 WD-ASGD Bidirectional LSTM learning model

The features extracted are then classified as three states namely interictal, preictal, ictal by using a classifier. By training the features for the preictal EEG seizure segment, seizures (ictal segments) are predicted. The classifier used in our work is the bidirectional LSTM. This bidirectional LSTM is regularized and optimized using Weight Dropped (WD) and Averaged Stochastic Gradient Descent (ASGD) technique. The proposed bidirectional LSTM is regularized using the drop connects to the weights of the hidden layers. The proposed bidirectional LSTM is optimized using a Non-monotonically Triggered Averaged Stochastic Gradient Descent (NT-ASGD) technique, which conventionally triggers the averaging when the validation flops to progress for several cycles.

The proposed classifier consists of 10 forward and 10 backward LSTM cells per layer. This model contains 480 hidden nodes. The final output is gained by linking the output of the last LSTM cell to fully connected layer. The batch size is fixed as 200. The dropout strategy is used in the fully connected layers, which makes few of the hidden layer's nodes to be inactive and avoids over-fitting. Group normalization is used in this model. A softmax classifier for classifying the phases of epileptic seizures. Fig. 2 depicts the proposed WD-ASD-RNN model for seizure prediction and the following are the equations relating to the LSTM classifier model

$$i_t = \delta_g(W^i y_t + U^i h_{t-1} + b^i) \quad (1)$$

$$o_t = \delta_g(W^o y_t + U^o h_{t-1} + b^o) \quad (2)$$

$$f_t = \delta_g(W^f y_t + U^f h_{t-1} + b^f) \quad (3)$$

$$c_t = tanh(W^c y_t + U^c h_{t-1} + b^c) \quad (4)$$

$$c_t = i_t \odot c_t + f_t \odot c_{t-1} \quad (5)$$

$$h_t = o_t \odot \tanh c_t \quad (6)$$

Here, W^i, W^o, W^f, W^c are weight matrices, b^i, b^o, b^f, b^c are the bias vectors, U^i, U^o, U^f, U^c are the weight matrices connecting the previous cell output state and the input cell state. y_t is the input vector to the timestamp t, h_{t-1} is the previous hidden state and c_t is the memory cell state of the model.

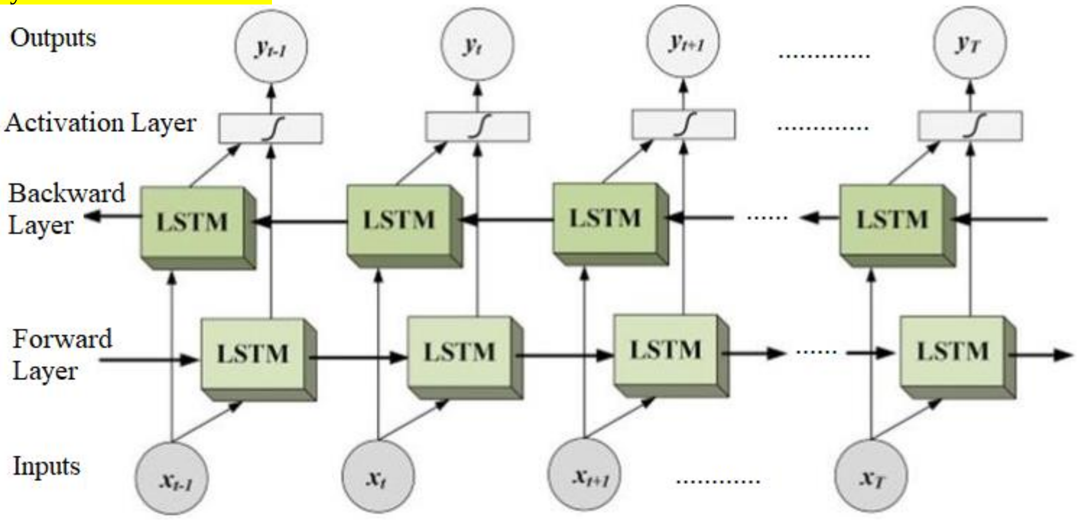

Fig. 2. A WD-ASGD-RNN classifier containing Bidirectional LSTM's

To minimize the loss function, the training parameters of the model are adjusted by using the optimization approaches. In our model, we replaced SGD by NT-ASGD technique. The weights and bias parameter values of each network layers are modified accordingly to reduce the loss function up to the convergence point of the proposed model.

3. Results and Discussions

The proposed seizure prediction approach is validated using the following indexes like true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). TP and TN indicate the total number of appropriately detected seizure free events in EEG and seizure events in EEG respectively. FP and FN indicate the total number of faultily detected seizure free events in EEG and false seizure events in EEG respectively. Using these four terminologies, the performance metrics for a good predictor is formulated. Accuracy is the capability to classify the interictal and ictal segments, which is given in equation (7).

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (7)$$

Specificity is the ability to distinguish the interictal segments, given in equation (8).

$$True\ Positive\ Rate\ or\ Sensitivity = TP / (TP + FN) \quad (8)$$

Sensitivity / True positive rate is the ability to distinguish the ictal segments, which is given in equation (9) and Selectivity is the ability to avoid the inaccurate recognitions of ictal segments, which is given in equation (10).

$$Specificity = TN / (TN + FP) \quad (9)$$

$$Selectivity = TP / (TP + FP) \quad (10)$$

Table 2: EEG recording details of seizure prediction

Model	States	Accuracy (%)	Sensitivity (%)	Specificity (%)	Selectivity (%)
WD-ASGD-LSTM	Interictal	88.53	82.30	84.10	83.00
	Preictal	91.20	89.80	88.69	88.15
	Ictal	92.13	84.10	86.45	85.70
WD- LSTM	Interictal	77.28	76.01	76.14	77.26
	Preictal	79.04	78.39	77.46	78.31

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	Ictal	77.47	77.21	77.11	76.17
LSTM	Interictal	64.39	65.00	68.53	62.30
	Preictal	62.04	68.34	71.28	68.13
	Ictal	62.56	64.21	66.01	64.04

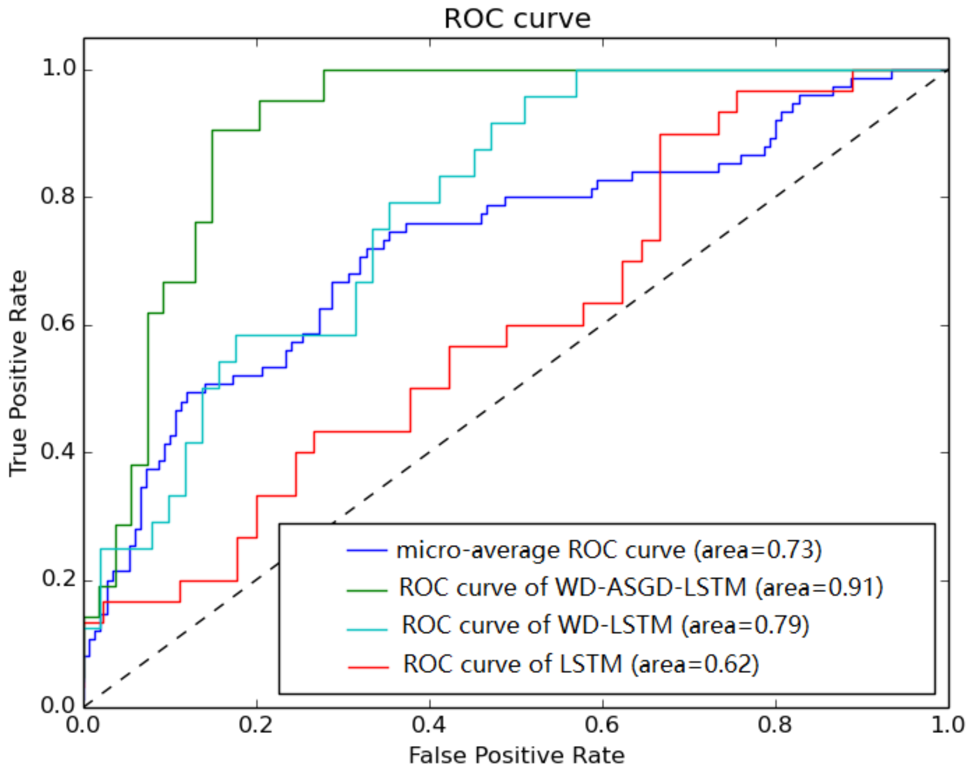

Fig. 3. Receiving Operating Characteristics of test dataset

The performance of the proposed RO-RNN (i.e.) WD-ASGD-LSTM is compared with the other two conventional RNN's such as WD-LSTM and LSTM only. The classification performance of the ictal, preictal and interictal states using these three models are shown in the Table 2. The same is depicted in the Fig. 3 using the Receiver Operating Characteristics (ROC) curve using the indexes like true positive rate and false positive rates.

The overall classification results of the WD-ASGD-LSTM model is better than WD-LSTM and LSTM. From the Table 2, LSTM achieves an accuracy of only about 62%, WD-LSTM achieves 79%, whereas our proposed WD-ASGD-LSTM model achieves an accuracy of about 91%. The reason behind the higher accuracy is that the WD-ASGD-LSTM model reaches the optimal value quickly under few iterative steps itself. Hence, WD-ASGD-LSTM model converges quickly with higher classification accuracy.

Table 3 gives the overall performance comparison of the recent deep learning-based seizure prediction methods available. Our proposed WD-ASGD-LSTM model predicts with an accuracy of about 91%. In the seizure prediction systems, the most challenging constraint is the false alarms, least the number of false alarms, best the accuracy and sensitivity of the system. Our model's FPR is 0.12 with highest sensitivity rate of 89% with a computational time of 6.21 seconds.

Table 3: Performance Comparison of seizure prediction methods

Work	Method	Year	Accuracy (%)	Sensitivity (%)	False Prediction rate (FP/h)
Ali et. al. [6]	Bi-LSTM	2019	84	82	NA
Khan et. al. [7]	CNN	2018	82	87.8	0.142
Hussein et. al. [8]	CNN	2019	84	87.8	0.2
Affes et. al. [9]	CGRNN	2019	75.6	89.0	1.6
Our's	RO-RNN	2020	91	89	0.12

4. Conclusion and Future Scope

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We developed a Regularized and Optimized Recurrent Neural Network (RO-RNN) for investigating the application of bidirectional long short-term memory (LSTM) networks for epileptic seizure prediction. A Weight Dropped (WD) method is used for regularizing the LSTM model and an Averaged Stochastic Gradient Descent (ASGD) is used for optimizing the LSTM model. Regularization and optimization are deployed with the deep neural network architecture to accelerate the convergence rate and to reduce the complexity of the proposed non-linear model. The proposed model is evaluated using CHB-MIT, NINC and real time SRM scalp EEG datasets. The assessment of the proposed computer-aided seizure prediction approach yielded an accuracy score of 0.91, sensitivity score of 0.89 and false prediction rate of 0.12 FP/h. But processing the smaller EEG segments misleads the performance of the proposed system, in future the same model can be implemented using continuous EEG recordings.

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