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Epileptic Seizure Detection using Deep Learning Approach

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ABSTRACT

An epileptic seizure is a sign of abnormal activity in the human brain. Electroencephalogram (EEG) is a standard tool that has been used vastly for detection of seizure activities. Many methods have been developed to help the neurophysiologists to detect the seizure activities with high accuracy. Most of them rely on the features extracted in the time, frequency, or time-frequency domains. The performance of the proposed methods is related to the performance of the features extracted from EEG recordings. Deep neural networks enable learning directly on the data without the domain knowledge needed to construct a feature set. This approach has been hugely successful in almost all machine learning applications. We propose a new framework that also learns directly from the data, without extracting a feature set. We proposed an original deep-learning-based method to classify EEG recordings. The EEG signal is segmented into 4 s segments and used to train the long- and short-term memory network. The trained model is used to discriminate the EEG seizure from the background. The Freiburg EEG dataset is used to assess the performance of the classifier. The 5-fold cross-validation is selected for evaluating the performance of the proposed method. About 97.75% of the accuracy is achieved.

Index Terms: Electroencephalogram, Epilepsy, Epileptic Seizure, Long- and short-term Memory, Seizure Detection

1. INTRODUCTION

Epilepsy is a chronic central nervous system disorder that makes life trouble for more than 50 million people over the world, as reported by the World Health Organization [1]-[5]. It characterizes by a rapid, unpredictable, and temporary change in the electrical activity of the brain able to affect human functionality at all age [6]-[8]. It may be a partial occur in the left or right part of the brain only or could affect both hemispheres of the brain.

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Electroencephalogram (EEG) is one of the most effective techniques to track and record brain wave patterns. Neurologist read and analyzes these EEG records to detect and categorize the type of epilepsy diseases [4]. The EEG examination is a visual process that needs too many hours to examine 1-day of recording. It is time consuming, and tiredness also requires the services of an expert; this is lead to put a heavy load on the neurologist and reduces their efficiency [1], [5].

These encourage the researchers to develop automated seizure detection with machine learning methods, using epileptic multi-channel EEG signals including EEG signal acquisition, preprocessing, features extraction, and classification [2], [5]. Most of the proposed systems rely on feature extraction techniques to discriminate abnormal signals from the background. Selection of discriminative features

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is a matter of the performance of such systems [6]. Deep neural networks enable learning directly on the data without the domain knowledge needed to construct a feature set.

Deep learning is a part of machine learning allows multi-layered computational models to learn data representations with various abstraction levels. Higher representation layers amplify input components for classification procedures that are crucial for discriminating characteristics. Deep learning technique has greatly improved object detection in many fields, such as seizure detection. There are several challenges that face-off deep learning; first, most conventional deep learning models separately feed each channel into seizure classifier and ignore the connection between them, so the general signal types could not be recognized well. Second, most channels in multi-channel EEG signals are unconnected in the brain activity signals, such as seizure starts. These disconnected channels contain noise data that affect performance and decrease the learning method. Third, always good performance is not produced using a simple design of traditional deep learning features with unbalanced datasets or rare events. Finally, seizures type in EEG signals may have different important across patients and even overtime for the same patient, which imply difficulty to develop automatic cross-patient detector [5].

Several studies tried to propose machine learning models for detecting epileptic seizures in EEG signals. They attempt to use a distinct learning method to classify EEG signals into seizure and non-seizure because detecting seizures are a complex classification process that contains many seizure-like activities throughout the entire EEG recordings.

Although there are lots of good practices regarding epileptic seizure detection, the research still ongoing as few of them has been realized. Hence, new methods and efforts attempt to attain more practicable, reliable, accurate, and low complex automatic seizure detection system. The novelty of this research is proposing a long- and short-term memory (LSTM) model to detect an epileptic seizure. The proposed model can be realized on the programmable logic Zynq 7020 FPGA from Xilinx [7]. We offer an automatic seizure detection system to address the challenges mentioned above for classifying EEG signals into normal and abnormal using LSTM algorithm.

2. RELATED WORK

Different domains, such as time, frequency, and time-frequency [8] domains, have been used to analyze EEG signals. Most of them rely on the discriminate features extracted from the signal in the analyzed domain. Previous research showed that the features extracted from a time-frequency domain such as instantaneous frequency [9], [10], spikes characteristic [11], [12], Harlik descriptors [13], and time-frequency flux [14] provide the best performance for classifying EEG signals. Several attempts have been made to develop an automatic epileptic seizure detection method for classifying EEG signals using the deep neural network in which the features are extracted automatically. Ghaderyan, Abbasi and Sedaaghi [15] proposed an optimized novel way using K-nearest neighbor-based on sampling put together with support vector machine (SVM) classifier achieved a sensitivity of 100%. Zheng *et al.* [16] proposed a way for patient-specific seizure detection systems, and greatly help clinical staff to automatically mark seizures in long-term EEG with high performance and an average sensitivity of 92%. Correa *et al.* [17] used spectral power and wavelet analysis to assist detecting seizures in long-term EEG with high performance and sensitivity of 85.39% achieved. Yuan *et al.* [18] developed a novel algorithm to detect seizures within long-term EEG signal recordings and using Log-Euclidean Gaussian kernel-based sparse representation high epoch-based sensitivity of 95.11% achieved. Geng *et al.* [19] proposed a method that depends on improved wavelet neural network is for automatic seizure detection in long-term EEG. The algorithm achieved an average sensitivity of 96.72% and 98.91% of specificity. Parvez and Paul [20] proposed a new method for seizure prediction using phase correlation depending on the spatiotemporal relationship of EEG signals provides a prediction accuracy of 91.95%. Jukic and Subasi [21] used multiscale principal component analysis for removing noises and wavelet packet decomposition (WPD) for feature extraction from the EEG signals. Sharif and Jafari [22] proposed a new approach in automatic seizure prediction using Poincare plane and fuzzy rules for feature extraction depends on the frequency distribution of fuzzy rules. Then, SVM classifier used for separating normal from abnormal EEG signals. The average sensitivity of this method was 91.8–96.6%. Hussein *et al.* [3] used LSTM network for discriminating EEG signal features with using Softmax function for classifying of these features into normal and abnormal. This approach was shown to be robust in noisy real-life conditions compared to other methods that are quite sensitive to noise. The proposed approach achieved high performance with classification accuracies more than 90.00%. Mohammadi *et al.* [14] developed a patient-independent algorithm for automatic seizure detection, and the features extracted from high-resolution time-frequency distributions (TFDs). Then modified highly adaptive TFD used for classification of normal from abnormal EEG signals. They achieved an accuracy of 98.56%. Alfaro-Ponce *et al.* [23] proposed a method to design an automatic classifier for electroencephalographic information used a parallel associative memory classifier depending on recurrent neural networks, although they achieved 97.2% accuracy. Hussein *et al.* [24] used both LSTM network and fully connected (FC) layer to learn the high-level representations for distinct EEG patterns then rely on FC to extract EEG features which are related to epileptic seizures. They achieved classification accuracies 100.00%, 95.20%, and 90.00%, respectively, for two, three, and five classes of classification. Li *et al.* [25] used two entropy methods; fuzzy entropy (FuzzyEn) and distribution entropy (DistEn) to classify interictal and ictal EEG from normal EEG and classify ictal from interictal EEG with using an analytic single window with different window lengths. The accuracy 92.80% with fuzzy entropy and 95.33% with distribution entropy achieved.

The rest of this study organized as follows: The description of the dataset used in this paper is given in section three; the methodology and experimental design is given in section four; the result presented and analyzed in section five. The discussion and conclusion of this study are shown in section six and seven, respectively.

3. DATASET

Our seizure detection system has been trained and tested on the EEG recording and recorded throughout pre-surgical epilepsy observation at the Epilepsy Center of the University Hospital Freiburg, Germany. The data contained or obtained from the invasive recording of 21 patients and their ages different from 12 to 50 years, which they have a hardship from medically intractable focal epilepsy. It has 24 h-long continuous of pre-surgical recording also include eight males patient and remaining are females. The data were consisting of six intracranial EEG channels (three focal and three extra-focal electrodes). The position and kind of seizure very different in patients, however, medically intractable focal epilepsy is shared among all the patients. The EEG data were acquired with 128 channels, 256 Hz sampling rate, and 16 bits analog to digital converter. The data collected and saved into two files; one of them contained ictal, which was seizures data, and the other was inter-ictal, which was normal data with no seizures event. Both ictal and inter-ictal files were saved in ASCI format and contain six channels of EEG time series. The onset and offset times of seizures marked up by EEG experts. The EEG database of 11 patients was used as authors have access to only this portion of the database for this study.

4. METHODOLOGY

The proposed method consists of two significant folds; preprocessing and processing, as illustrated in Fig. 1. The preprocessing includes three stages, which are the normalization of the EEG data, applying appropriate filters to select the interesting parts of the data, and data management (splitting, concatenating, and reshaping). The detail will be discussed in Section A. After preprocessing; the preprocessed data are used to train the LSTM network followed by a Softmax function is used to classify the inputs data into normal and seizure data.

For this study, we used six channels from Freiburg EEG dataset. Figs. 2 and 3 show a part of each file's components.

4.1. Preprocessing

4.1.1. Normalization

The data are normalized as the recordings are related to different patients. To this aim, the mean and standard deviation is computed using the following equations:

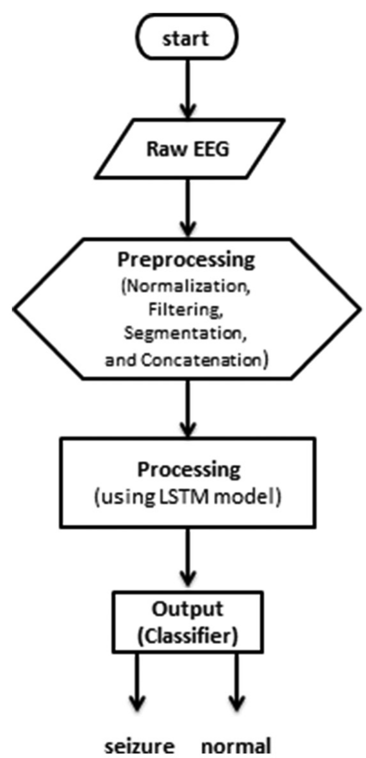

Fig. 1. The flowchart of the proposed system.

$$\overline{X} = \frac{1}{n}\left(\sum_{i=1}^{n} Xi\right) = \frac{X1 + X2 + X3 \ldots\ldots + Xn}{n} \quad (1)\ [26]$$

And

$$\delta = \sqrt{\frac{\sum_{i=1}^{N}\left(Xi - \overline{X}\right)^2}{N-1}} \quad (2)\ [27]$$

Where N is the total number of measurement per raw, and, $\overline{X}$ is the mean. We have standard deviation values for normal and seizure data denoted by δ_n and δ_s, respectively.

After determining both mean and standard deviation value for each signal (normal and seizure) $\overline{X}_n, \overline{X}_s$, and δ_n, δ_s, the normalization operation of electroencephalogram data done using the following equations:

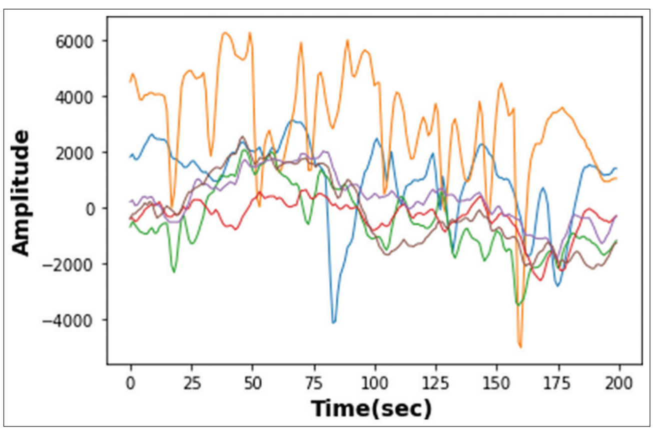

Fig. 2. The plot of six channels electroencephalogram recording brain activity without seizure.

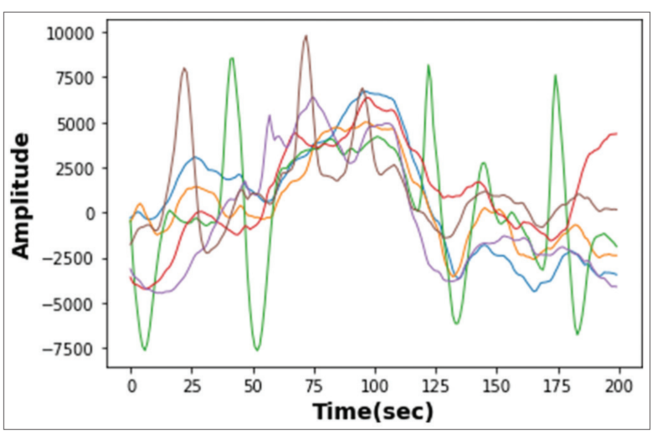

Fig. 3. The plot of six channels electroencephalogram recording of brain activity which has a seizure.

$$Nor_n = \frac{\overline{X}_n}{\delta_n} \quad (3)$$

Where Nor_n is the normalized normal signal, as shown in Fig. 4.

$$Nor_s = \frac{\overline{X}_s}{\delta_s} \quad (4)$$

And Nor_s is normalized seizure EEG, as shown in Fig. 5.

4.1.2. Filtering

There are popular and different types of EEG artifacts by applying various filter operations that can identify and removing them. The following points are the most significant sources of artifacts.

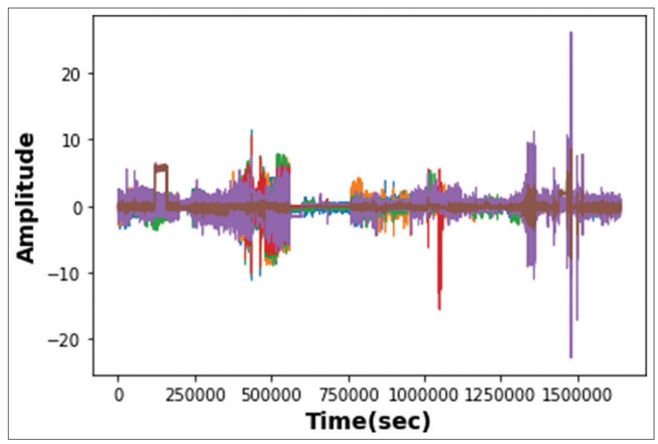

Fig. 4. The plot of a normalized normal data of six-channel electroencephalogram signals.

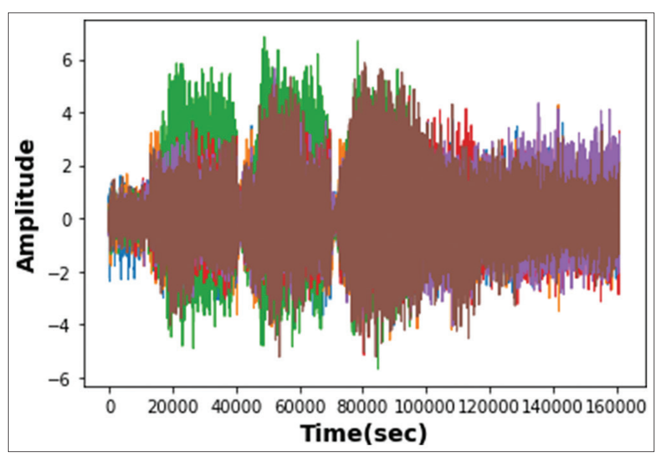

Fig. 5. The plot of a normalized seizure data of six-channel electroencephalogram signals.

Eye movement and blinking are activities that can catch and record during EEG signal recording. Skeletal muscles are producing the signals which are electrical action and interfere with the EEG at the time of recording. There are other noises that involve the EEG signal such as electricity line and environmental noise also dominated as white noise. These artifacts affect the performance for detecting seizure in our model.

The interesting frequency bands of EEG signals are located in the range of 0.01 Hz through 100 Hz. EEG signal recording will be contaminated by those artifacts mentioned above. Removing those undesired artifacts from the EEG is a major preprocessing step after the normalization process for our model. We apply the following filters on the EEG signals:

1. Butterworth low-pass filter used to cutoff and remove high frequencies.
2. Butterworth High-pass filter used to cutoff DC component and remove low frequencies.
3. A notch filter used to remove and cutoff 50 Hz frequency.

The bandpass filters between 0.5 and 100 Hz only allow the frequencies of interest and remove the noise frequencies produced by undesired activities such as head movements identifying by high-frequency activity (>20 Hz) [28]. The notch filter is used to remove exactly 50 Hz power line noise produced by electrical devices. Thus, the objective of the effective removing and attenuation of artifacts are to develop an application specific algorithm with better time and accuracy efficiency.

As mentioned before, we use filtering operations for both normal and seizure data. Figs. 6-8 show EEG signals after applying different filtering operations on the normal signals. Figs. 9-11 show various filtering operations on the seizure signals.

After filtering, we compute the average of the six channels, as shown in Figs. 12 and 13 to produce a single-channel signal for both normal and seizure EEG data.

4.1.3. Data management

The final steps of preprocessing include shuffling, segmenting, and reshaping the data. Each time a series of EEG single channel in seizure and normal file are shuffled and divided into smaller non-overlapping segments. The purpose of this operation is to provide the same probability for each sample to be selected for training or testing.

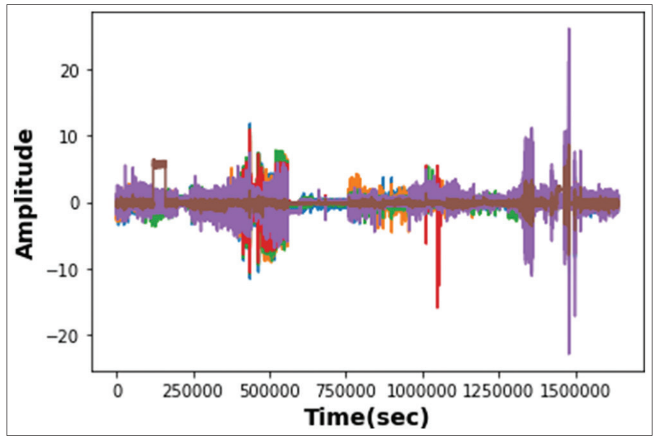

Fig. 6. The plot of a filtered normal electroencephalogram data with Butterworth low-pass filter.

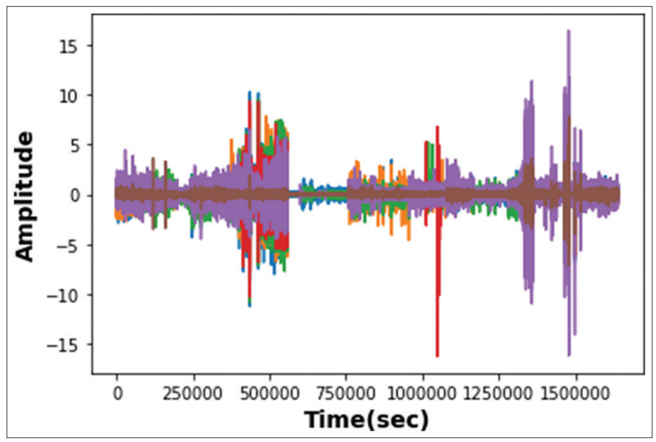

Fig. 7. The plot of a filtered normal electroencephalogram data with Butterworth high-pass filter.

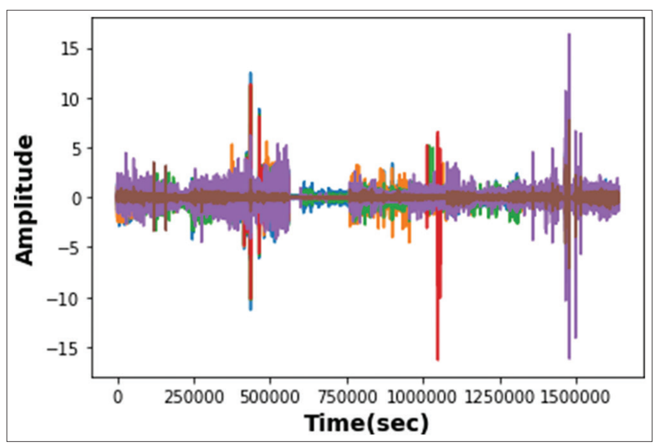

Fig. 8. The plot of a filtered normal electroencephalogram data with a notch filter.

Furthermore, each non-stationary signal is divided into sub stationary signals.

Each EEG raw is reshaped into T x L matrix, where L is the length of each segment, and T is the number of time-steps which is obtained as:

$$T = \frac{D}{L} \tag{5}$$

Thus, the input data of the LSTM model will take shape (D, T, and L).

4.2. Processing

Deep learning is a part of machine learning allows multi-layered computational models (multiple hidden layers) to learn data representations with various abstraction levels. Higher layers of representation amplify elements of the input for classification processes that are essential for discrimination and eliminate irrelevant features. The data representation learning is a collection of techniques allowing a machine to be fed with raw data and to learn the representations automatically which is required for detection [29]. Deep learning method has dramatically improved object detections

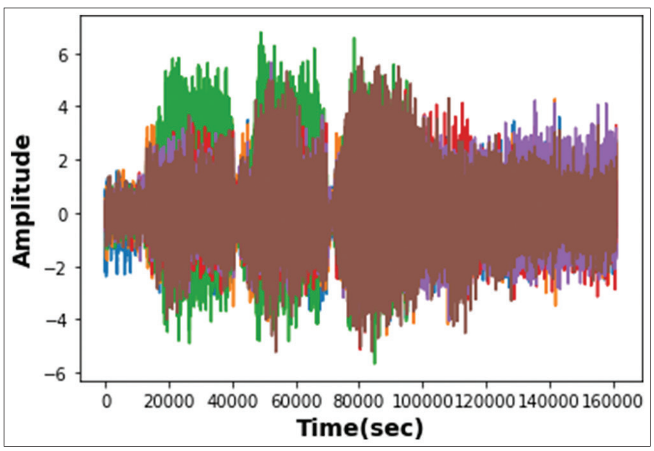

Fig. 9. The plot of a filtered seizure electroencephalogram data with Butterworth low-pass filter.

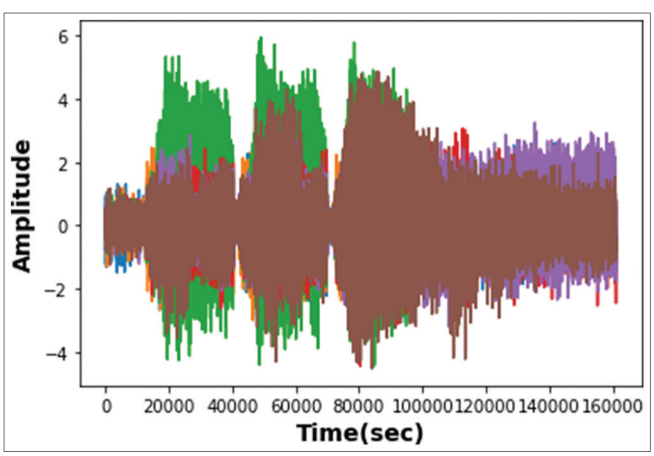

Fig. 10. The plot of a filtered seizure electroencephalogram data with Butterworth high-pass filter.

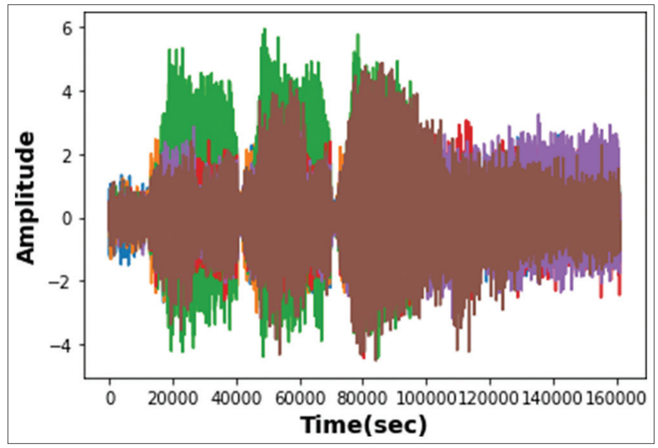

Fig. 11. The plot of a filtered seizure electroencephalogram data with a notch filter.

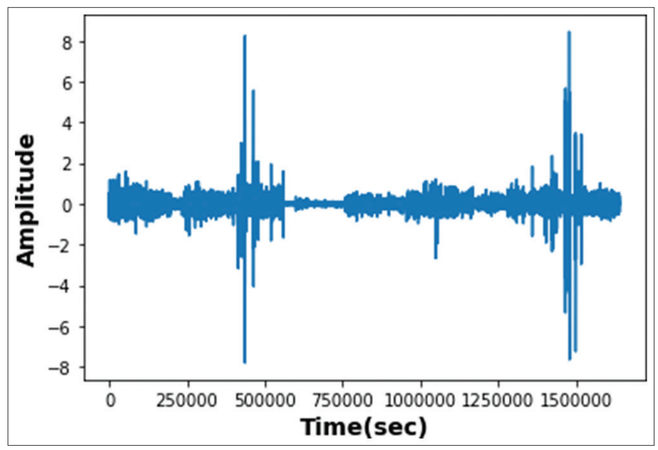

Fig. 12. The plot a single channel of electroencephalogram (EEG) normal signal after computing average of six EEG channels.

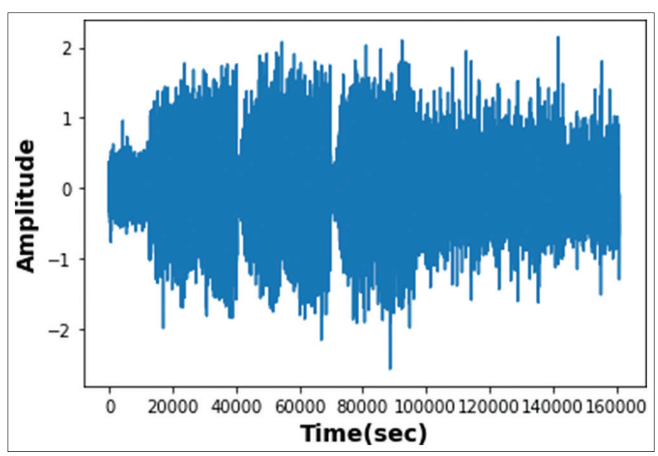

Fig. 13. The plot a single channel of electroencephalogram (EEG) seizure signal after computing average of six EEG channels.

in many domains such as seizure detection which arrange to take out discriminate properties of epileptic seizures in EEG time-series signals.

We use the LSTM network for this work. It works best on time-series with short- and long-term dependencies [24]. Each block of this network has three gates (input, forget, and output); every block output is connected again to the block input [30]. The LSTM cell has the input layer X_t, output layer, the cell input state $\overline{C}_t$, the cell output state C_t, and the previous cell output state C_{t-1}. The LSTM has the gated structure can deal with long-term dependencies to allow useful information to pass through the LSTM network or ability to control a memory cell. The LSTM cell has three gates, including an input gate, a forgotten gate, and an output gate. The output gate is needed to read out the entries from the cell. The input gate is required to decide when to read data into the cell. We need a mechanism to reset the contents of the cell, governed by a forget gate. The motivation for such a design is to be able to decide when to remember and when to ignore inputs into the hidden state through a dedicated mechanism. The gated structure, especially the forget gate, helps the LSTM to be an effective and scalable model for several learning problems related to sequential data. The input gate, the forget gate, and the output gate denoted as I_t, F_t, and O_t, respectively. Fig. 14 shows the architecture of the LSTM block in detail.

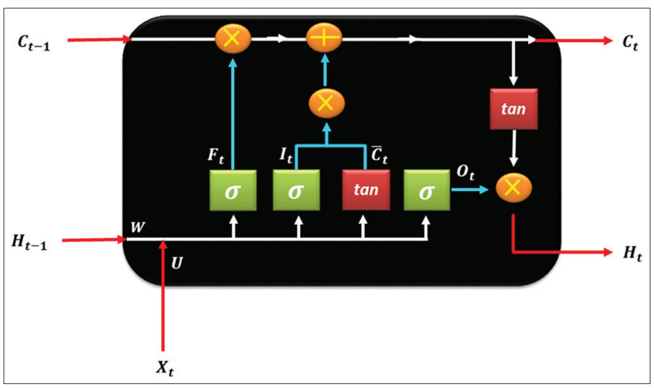

Fig. 14. The detail of schematic architecture of the long- and short-term memory block [35].

Our proposed detection system is described step by step in Fig. 15. After the preprocessing operation, the preprocessed EEG segments are fed into the LSTM cells to learn about deep-level characterizations of the EEG signals at each segment. The outputs of the LSTM cells are used as an input to the time-distributed layer (dense layer).

Our deep neural network design consists of two layers and, with using (Softmax activation function) on the top of the system. In the beginning, the segment of data entered to the LSTM layer, which it passed through 100 cells. In order, the short- and long-term memory learns about the overlapping between each segment in the same EEG signal and dissimilar EEG signal of the same class.

The best characteristic of the LSTM is the retaining information for an extended period and makes the LSTM the strongest nominee for handling long-term EEG signals. Then, the output of the LSTM layer entered as an input into the time distributed layer (dense). Finally, the dense layer output is used as an input to the Softmax layer to classify the incoming data at the output.

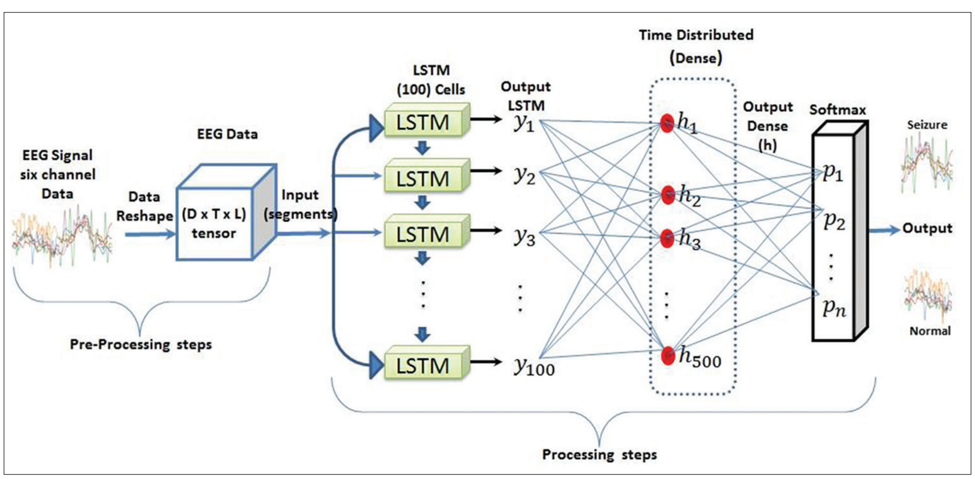

Fig. 15. Overall seizure detection system schematic diagram describes the proposed entire system: (y) is the output of long- and short-term memory layer; (h) stand for units of time distributed layer; (p) represents the probability distribution produced by Softmax.

We use k-Fold cross-validation (CV) to determine the best measure of our model performing over the entire dataset.

5. RESULTS

The data are normalized and preprocessed to select the desired part of the EEG recording. Then, a dataset containing 312 EEG segments with a length of 1024 samples for both normal and seizure with 4s duration for each segment. These segments are fed into the LSTMs model for training. The proposed model has 100 LSTM cells learn about the signal feature spikes at each segment and discriminated from the backgrounds of the signals. The time distributed layer converting this information into meaningful properties. In this study, we use (500) time distributed unit to translate learned information comes from the LSTM turned to meaningful features. Then, the Softmax classify the property of each sample into normal and seizure. All the experiments were executed in the Anaconda Navigator environment on an Intel Core i3 processor with 2.1 GHz.

To evaluate the performance of the proposed method, we use the accuracy measurement calculated and defined as follows:

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ number\ of\ samples} \quad (6)$$

Where *True Positive* is the number of seizure segments that are correctly detected by the algorithm, and *True Negative* is the number of normal (non-seizure) segments that the algorithm correctly recognized.

We used recordings of 11 patients in the freiburg EEG database. To determine the performances of the suggested approach, 5-fold CV method was used, which is a standard mode implemented to compare the various EEG seizure detection approaches. In 5-fold CV, the dataset is divided into five different mutually exclusive folds having the same sizes. Four folds used for training and the remaining one used for testing.

This procedure was repeated 5 times. At the end of each iteration, individual accuracy was computed. The average of five obtained individual accuracies was accuracy. The total classification accuracy of 97.75% was achieved for this method. Table 1 contains the results achieved from the five-fold CV method applied to the database.

Fig. 16 shows the accuracy (accuracy based on testing) and the value of accuracy (accuracy based on testing) results of our proposed model with 5-Fold CV approach.

6. DISCUSSION

The automatic seizure detection is important in epilepsy diagnosis that can also help reduce the medical team's heavy workload. Conventionally, computing valid features that can effectively characterize the behavior of EEG signals and selecting appropriate classifier are critical but difficult and time consuming for a seizure detection system to compute valid features.

This study proposes a method to automatically perform the EEG classification. We represent an approach to detect seizures with LSTM algorithm that has been evaluated on Freiburg EEG dataset. The selecting features from the database are a great importance and appropriate characteristics that can improve the performance of classification as well. The ability of the algorithm to detect these features correctly can be measured based on the accuracy value. Therefore, it is important to detect seizures with high accuracy. In general, the classification of the seizure and non-seizure EEG signals is complex because they are nonlinear and irregular in nature

TABLE 1: Result of our proposed model with the 5-Fold CV that determines the classification accuracy

No. of fold	Folds result (%)
1	100.00
2	98.41
3	93.55
4	96.77
5	100.00
Total accuracy	97.75

CV: Cross-validation

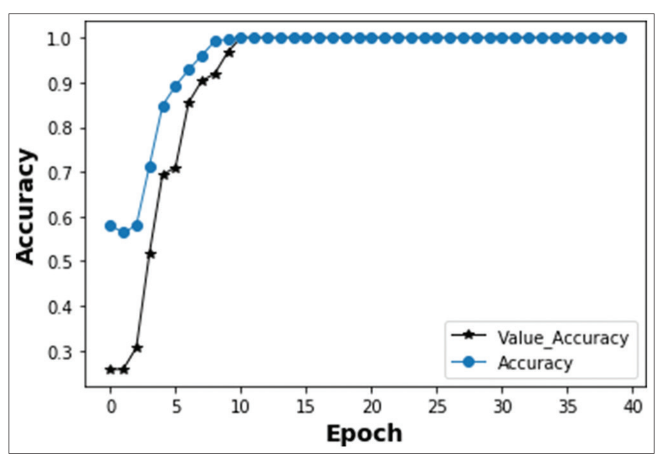

Fig. 16. The plot of showing the result of the proposed system accuracy using 5-fold cross-validation approach.

TABLE 2: The comparison of the state-of-the-art techniques with our proposed method

Method	Year	Database	Classifier	Training and testing	Acc (%)
Xie and Krishnan, 2012 [33]	2012	Freiburg and Bonn database	1-NN	10-fold cross-validation	99 100
Yu *et al*., 2018 [32]	2018	Freiburg and Bonn database	Kernel R-ProCRC	10-fold cross-validation	99.98 99.3
Alickovic *et al*., 2018 [31]	2018	Freiburg database CHB-MIT	Random forest	10-fold cross-validation	100
Tzimourta *et al*., 2019 [34]	2019	Freiburg database Bonn database	Random FOREST	10-fold cross-validation	97.74 95.60
This work	2019	Freiburg database	LSTM	5-fold cross-validation	97.75

LSTM: Long- and short-term memory, R-ProCRC: Robust probabilistic collaborative representation-based classifier

and contain many seizure-like activities throughout the entire recording. To prepare for the consequence of classification, the preprocessing was employed to process the raw EEG signals. The preprocessing on the data is important to raise the performance of the model because it removes noise and undesired parts of the signal, which leads to low complexity and higher performance. The obtained accuracy by the model using the 5-Fold CV for training and testing to determine the best measure of our model performing over the entire dataset is 97.75%.

Table 2 shows the results of seizure detection achieved by the proposed and other state-of-the-art methods based on the accuracy; the best results achieved by Alickovic *et al.* [31]. Many previous papers on seizure detection adopt the used database in this research to evaluate their algorithm. Alickovic, Kevric and Subasi [31] worked on both Freiburg (intracranial EEG) and CHB-MIT (scalp EEG) databases. They used multiscale principal component analysis for de-noising the EEG data and empirical mode decomposition, discrete wavelet transform (DWT) or WPD to decompose EEG signals. 10-fold CV was used to determine performances of the model with 8s length for each segment and 2048 samples. The model achieved an accuracy of 100%. Yu *et al.*, 2018 [32], used kernel version of the robust probabilistic collaborative representation-based classifier for the detection of epilepsy in EEG signals. This method was evaluated based on two EEG datasets (Freiburg and Bonn) with using 10-fold CV achieved 99.98% and 99.3% accuracy. Xie and Krishnan, 2013 [33], developed a wavelet-based sparse functional linear model with a simple classifier (1-NN) to classify EEG signals. They earned result 99% and 100% of accuracy than those obtained using other complicated methods for both Freiburg and Bonn EEG databases. Furthermore, 10-fold CV was used to identify the performance of the model with 16s length for each segment (4096 samples). Tzimourta *et al.*, 2019 [34], they used automated seizure detection based on DWT for feature extraction then fed into random forest classifier to separate between ictal and interictal data. They used 10-fold CV to select performances of the model with 2s length for each epoch (512 samples). They earned above 97.74% of accuracy.

To determine the performance of our method, we used 5-fold CV with 4s length for each segment (1024 samples) and achieved fourth-best performance. Although we achieved a relatively poor performance compared to others, we tackle more challenging problems of discriminating the seizure part from the background, where the pre- and post-seizure parts of the signal are placed in the background.

7. CONCLUSION

We present a method to detect epileptic seizure from EEG recordings. An LSTM block with 100 cells followed by 500-time distributed unit is used to be trained by EEG recordings. The Freiburg EEG dataset is used to train and test the model. The EEG data are bandpass to 0.5 Hz through 100 Hz to remove the noise and capture the interesting data. A notch filter is used to remove the power line noise. The EEG recordings are segmented to 4s and reshaped into images as the inputs to the LSTM. The trained model is used to detect epileptic seizure from the background. 5-fold CV is used to assess the performance of the proposed method. About 97.75% of the accuracy was achieved. For the future study, we test the proposed method using other EEG datasets.

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