EEG Signal Processing: Applying Deep Learning Methods to Identify and Classify Epilepsy Episodes

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Abstract. Epilepsy is a chronic disease characterized by a deviation from the normal electrical activity of the brain leading to seizures caused by nerve impulses discharge. It is currently considered the fourth global neurological problem, being overcome only by diseases such as strokes. Moreover, according to the World Health Organization, nearly 50 million people suffer from epilepsy, with approximately 2.4 million patients annually diagnosed. It is worth mentioning that the elderly and children are the most exposed categories, but if the situation is considered, one of 26 people is likely to develop this condition at a point in life.

Through three gates, the network can also be used for larger data sequences. Moreover, given that the EEG signals are significantly more dynamic and not linear, an LSTM-based approach has, by definition, an advantage given by the ability to isolate different characteristics of brain activity. In the United States, for example, this condition can be found at 48 people out of 100,000.

Keywords: Epilepsy · EEG · Strokes

1 Introduction

Over the past few years, researchers have discovered that an epilepsy crisis does not occur suddenly but is manifested in a certain way a few minutes before the onset of clinical symptoms. The question was whether this state can be distinguished from the interictal one.

Crises can be controlled with medicines. However, for 25% of patients, crises cannot be controlled by available therapy. A method able to predict the next crisis would greatly improve their quality of life, paving the way for new therapeutic methods such as deep brain stimulation [1].

Electroencephalogram (EEG) is a test commonly used to diagnose epilepsy because the EEG signal contains important information about the electrical activity of the brain. Neuroscientists usually follow the visual signal and identify possible abnormalities. However, such an approach consumes time and is limited by potential impediments

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such as involuntary movements of the body that may occur. Therefore, it is important to develop a system designed to identify and classify epilepsy episodes.

Over time, techniques applied to the pure EEG signal have been used to fragment it into shorter sequences.

The basic principle consists in taking the initial signal and dividing it into non-overlapping segments. Each segment is categorized according to the stage of the patient: before the crisis (precious), during the crisis (ictal) and after the crisis (postictal) [2].

Subsequently, each segment is passed through a module that extracts features of the EEG signal and eventually arrives in an LSTM network that classifies, based on the extracted features, the state of the patient.

The paper is organized as follows: Sect. 2 analyses related work, Sect. 3 describes the database used, while Sect. 4 presents the development of the system and Sect. 5 draws the conclusions and envisions future work.

2 Related Work

The presented paper aims to bring into attention the possibility of resolving a critical healthcare problem. eHealth and eCare solutions are two important subjects that will be probably given during the conference. Therefore, there the concept of an advanced algorithm that will predict and classify the epileptic seizures will be described.

Until now, several encephalogram-based algorithms have used linear and non-linear methods, yielding promising results. Linear predictions are based on frequency analysis. The emergence of the theory of linear dynamics has led to the development of different predictive methods such as dynamic training, the creation of models that simulate neural cells, Kolmogorov entropy [3].

In [4], 10 subjects were tested in the European database, aged between 15 and 57 years. The signals used were taken in two epilepsy centers in Portugal and France. For each patient, 22 invariant features were derived from six channels. Subsequently, these data were processed by a Butterworth filter at 50 Hz to eliminate distortions caused by AC power. The bandwidth is segmented, resulting in the following cases: delta (≤ 3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz) and gamma (>30 Hz).

Analyzing the variations within these frequencies has proven to be a good way of identifying neurological problems [5, 6].

The Fourier transform is applied so to a segmented signal, and then a sum of the resulting coefficients is achieved. For each patient, the dataset provided was divided into two parts: one that corresponds to the training of the SVM (Support Vector Machine) and another to perform the tests. SVM is currently one of the most important tools in the processing of signals based on deep learning. The SVM classifier can be described by the following formula:

$$\mathrm{K}(\mathrm{x}, \mathrm{y}) = e^{-\frac{|x-y|^2}{2 * \sigma^2}} \tag{1}$$

$$\sigma = \text{scale parameter}$$
$$\mathrm{x},\ \mathrm{y} = \text{vectors}$$

Another approach considered was that based on spikes of EEG signals in patients with epilepsy. Spikes are sudden variations of easily distinguishable waves that last between 20 and 70 ms. In the study [7], they used data coming from the Center for the Study of Epilepsy at the University Hospital in Freiburg, Germany. The database contains information from 21 patients. The records can be divided into four stages: preictal, ictal, postictal, and interictal. They were sampled at the frequency of 256 Hz, and the A /D conversion was performed at a 16-bit resolution. Also, for EEG data processing, a low-pass filter between 0.5 and 120 Hz, as well as a notch filter with a frequency of 50 Hz were used. Let be a signal of the form x(k) = y(k) + z(k), where y(k) is an EEG signal with slow variations, and z(k) a signal with fast variations. After x(k) was filtered by means of OC (opening-closing) and CO (closing-opening), the resulting signal is y(k) represented by the following expression:

$$\mathrm{Y(k)} = \frac{1}{2}[\mathrm{OC(x(k))} + \mathrm{CO(x(k))}] \tag{2}$$

The steps for detecting spikes using a combination of OC and CO are as follows:

(1) Removing the transient signal from an EEG segment using OC and CO;
(2) Using the Eq. (2) to eliminate inappropriate amplitudes, resulting in a background signal y(k);
(3) Deduce the signal y(k) from the signal x(k).

The resulting effects indicate a gradual increase in the proximity of the next epilepsy crisis. Almost all existing methods for detecting epilepsy are based on feature extraction techniques.

In the paper [8], features such as Shannon's entropy, standard deviation, and energy were extracted, using the database available from the University of Bonn. An accuracy of 100% and 99.18% for A-E and AB-E cases was thus obtained. However, for the other sets, B-E, C-E, D-E, CD-E and ABCD-E, the percentage was 98.4%. In this study, the signals were analyzed using Dual-tree complex wavelet transform, the resulting coefficients being used to evaluate six characteristic parameters. Particular attention was paid to the phenomenon of over-engaging data that may occur. Also, the complexity of the proposed method was also considered, the largest being equivalent to O (N ^ 2logN) [9].

Another important area in the EEG analysis is given by the graphical representation of some purely theoretical traces. Therefore, graph theory introduced a new approach in studying the anatomical and functional features of the brain.

In paper [10], a non-linear system using an LSTM network was modeled. It was used the input u(k) to simulate and to analyze the behavior. After the network was trained, they concluded that the testing results are good enough. Therefore, by using a recurrent neural network, the study found that LSTM will significantly reduce the computational effort.

Furthermore, Internet of Things (IoT) wearable solutions can be used for monitoring in real-time the EEG and transmit the data to cloud computing platforms [11].

3 Database

The records, grouped in 23 cases, were taken from 22 subjects: 5 males, ages 3 to 22, and 17 females aged 1.5 to 19 years. It is worth mentioning that one of the cases contains records from the same person, but at 1.5 years difference. Each case contains between 9 and 42 files in.edf format. Hardware limitations have caused delays of about 10 s or fewer between certain files, during which no signals have been recorded. To protect the identity of the subjects, all their health information has been replaced, keeping only the temporal relation between the individual files belonging to the same case. In most cases, the.edf file contains a digitally captured signal for one hour, although signals lasting between two and four hours may also appear.

All signals were taken at a rate of 256 samples/second at a resolution of 16 bits.

The data comes from the CHB-MIT database, which is available free of charge on the PhysioNet.org website [12].

The recording was made according to the international standard, which involves the installation of 21 sensors on the surface of the scalp. There is thus a precise positioning of reference points located one at the eye level (nasion) and the other at the base of the skull (inion). Starting from these points, the skull was divided into median and transverse planes, the location of the electrodes being determined by segments at intervals of 10 or 20%. Three electrodes are placed on one side and the other equidistantly to the adjacent ones [13].

In addition to the isolation of the 18 bipolar channels available, no other method has been applied to mitigate any errors that may arise, for example, due to involuntary muscular movements.

The LSTM model allows the evaluation of each characteristic before the classification, especially since there is no other module before it, which should separately analyze each characteristic. Space is internally assessed for each patient by the model that suits the most relevant information to provide a prediction as accurate as possible. Therefore, instead of classifying each individual segment, the network receives more input data representing segments and fits into a class the entire sequence.

4 Development of the System

4.1 The Architecture of a LSTM System

The basic principle consists in taking the initial signal, dividing it into non-overlapping segments and having a duration of 5 s. Each segment is categorized according to the stage of the patient: pre-crisis, during the ictal and after postictal.

EEG segments are passed through a module that extracts the features, producing a 643×1 vector. This module includes units for analyzing signals in time and frequency. Finally, the signal reaches an LSTM network that classifies, based on the extracted features, the state of the patient. The LSTM model thus designed allows the evaluation of each characteristic before the classification, especially since there is no other module before it, which should separately analyze each characteristic separately.

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The structure of the system can be seen in Fig. 1. Write gate takes the input. The output is calculated using the read gate. In the end, only the relevant information is kept by using the forget gate.

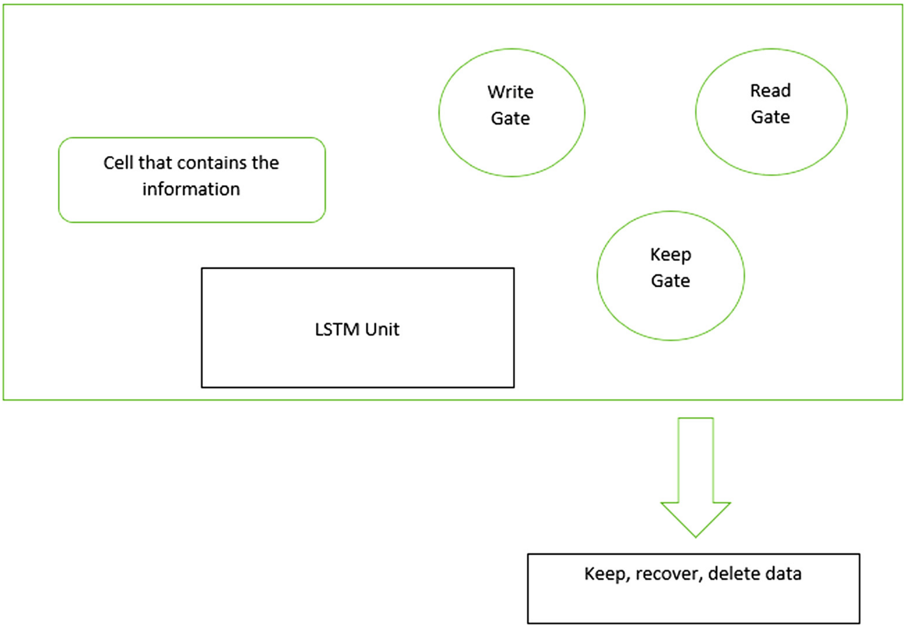

Fig. 1. The structure of a LSTM system

The basic principles of the entire architecture can be seen in Fig. 2.

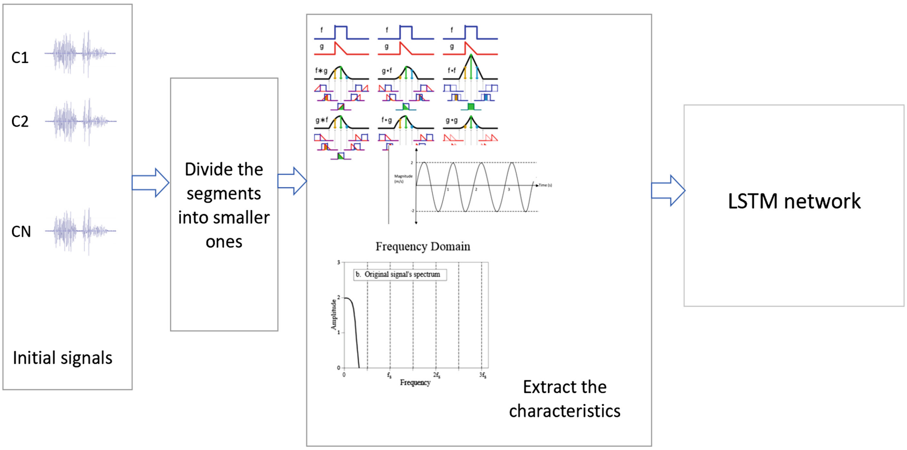

Fig. 2. The basic principle of the whole algorithm

4.2 Experimental Results

As we have previously stated, the initial signal was split into non-overlapping segments and categorized according to the state of the patient. An example of segmentation can be seen in Fig. 3.

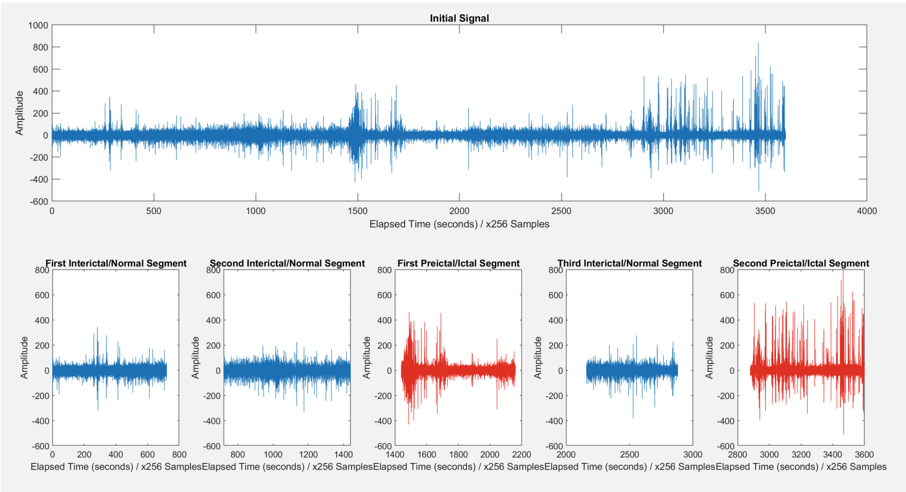

Fig. 3. An example of a divided signal

A single feature was used which shows how the signal behaves in time. Therefore, on the first layer, there will be a single neuron. The response of the system, Y, will have only two values that correspond to possible states of the signal: preictal and interictal.

Since the process of training such a big network that contains this high amount of long signals required computational power, there were chosen several signals to perform the training. The progress that was encountered in terms of accuracy and loss can be seen in Fig. 4.

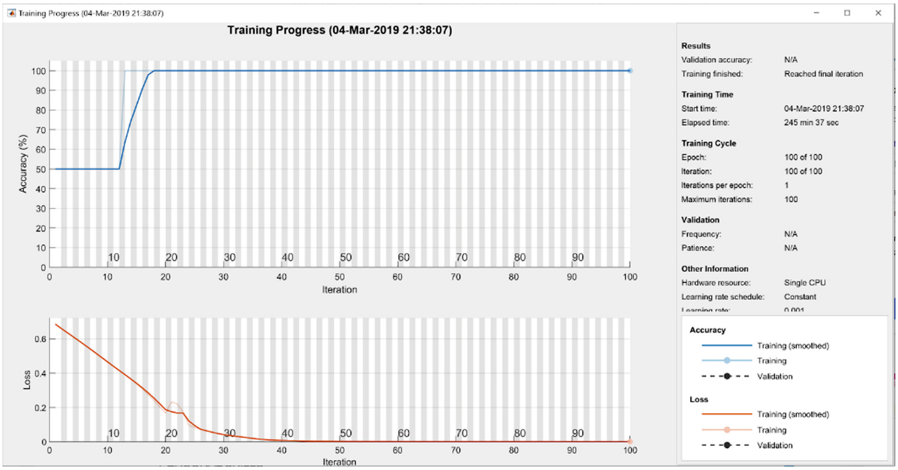

Fig. 4. Training progress of the network

5 Conclusion

The method using LSTM networks has not been used to date to predict epileptic seizures. However, they have found applicability in studies focusing on other areas of analysis of EEG signals. This paper attempts to demonstrate the potential for successful use of LSTM networks in predicting epilepsy seizures, proves that this method provides remarkable performance in terms of the classification of the various stages that occur in the disease, unlike other techniques based on deep learning algorithms used up to now.

Since EEG signals are complex and bring a large amount of color, it has been necessary to look for alternative solutions, and the LSTM-based network has proven to be effective.

In the future, this method can be tested in different clinics, using multiple sets of data this time from adults.

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