Epilepsy Detection Using Artificial Neural Networks

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Abstract

Epilepsy is a neurological disorder, where there is a cluster of brain cells that behave in a hyperexcitable manner, the individual can promote injuries, trauma or, in more severe cases, sudden death. Electroencephalogram (EEG) is the most used way to detect epileptic seizures. Therefore, more simplified methods of analysis of the EEG can help in the diagnosis and treatment of these individuals more quickly. In this study, we extracted pertinent EEG characteristics to assess the epileptic seizure period. We use Perceptron Multilayer artificial neural networks to classify the period of the crisis, obtaining a more efficient diagnosis. The multilayer neural network obtained an accuracy of 98%. Thus, the strategy of extracting characteristics and the architecture of the assigned network were sufficient for a rapid and accurate diagnosis of epilepsy.

Keywords: Epilepsy. Electroencephalogram. Artificial neural networks. Multilayer Perceptron. Seizure detection.

1. Introduction

The figures presented by the World Health Organization (WHO) indicate that epilepsy is one of the most common neurological diseases [1]. The disease is characterized as a chronic neurological disorder, presenting convulsive manifestations, where the individual manifests brief episodes of involuntary movements in a certain region of the body or even throughout its length, usually epileptic episodes cause loss of consciousness or uncontrolled bladder and bowel. Thus, epileptic seizures are temporary dysfunctions of a set of neurons, thus reflecting the excessive and hyper-synchronous activity of neurons in the brain [2].

For a few seconds or minutes, a group of brain cells are attacked by excessive electrical discharges, causing problems that extend from muscle spasms and brief lapses of attention to more serious and longer occurrences, thus depending on the region of the brain affected in the first moment and how fast it spreads. In case the problems are restricted, the crisis will be called partial; if they involve both brain hemispheres, widespread. Approximately 30% of patients with epilepsy continue to present crises without remission, despite the existence of adequate treatments with anticonvulsant medications [3].

Electroencephalogram (EEG) is the method used to measure and record electrical pulses in the brain. For this, electrodes are used, capable of capturing and amplifying these pulses, converting them into analog signals with which the analysis of patients' brain activity is performed. Usually, the doctor uses this method manually, making a visual scan of EEG recordings, however, the analysis becomes impressive and time-consuming. To solve this problem, studies have proposed several robust and promising methods to detect epileptic activity in EEG signals [4] - [8].

Some works address different methods and mathematical models to automate and improve the detection of epilepsy in EEG. Thus, methods such as the wavelet transform served to observe the dynamics of EEG epileptic signals [9]. Extraction of time and frequency resources has also been used to classify EEG epileptic signals [10], [11].

In addition, other methods, such as multiple wave transformation and approximate entropy, were used as input to artificial neural networks for classification purposes.

Other works have also applied medium grouping networks and artificial neural networks to classify EEG epileptic signals [6], [11] - [14].

Although there are several studies using artificial neural networks, it is still necessary to use more efficient methods of extracting characteristics for better detection. Thus, the aim of this study is to propose a more efficient classification of epileptic seizures using artificial neural networks.

2. Materials and Methods

2.1 Data base

The EEG samples were extracted from the database of Children's Hospital Boston (www.childrenshospital.org) from pediatric patients with attacks of intractable epilepsy, developed from the monitoring of these individuals without the use of anticonvulsants in order to present in epileptic crises, with each sample referring to a session lasting approximately 1 hour. Brain signals from three patients were used, with only one EEG session from each patient being used.

2.2 Processing of data

The EEG data was extracted in a compressed form in '.edf' files, which consists of a 23x921600 matrix, that is, 23 EEG channels x 921600 signal points. The selected '.edf' files were converted to ASCII format so that it was then possible to save them in the '.csv' extension, thus seeking greater ease of manipulation, since the '.edf' files are more complex to work with. Subsequently, a selection and conversion of the files was established, requiring treatment for each file. The duration of each EEG session was 1 hour, so they were converted to 3600 seconds. The signal characteristics were extracted by the second order statistic, the Variance (σ^2). The variance of a random variable X is defined as the second-order central moment, such as:

$$\mathrm{Var}(X) = \sigma^2 = E[(X - \mu)^2] \quad (1)$$

In this way, a new database with the Variances of the signal was assembled with a total of 3600 points, equivalent to a total of 256 points that corresponded to an interval of 1 second. The data of the three patients were recorded and the periods of the epileptic seizure were classified, according to the indication available at the Children's Hospital Boston. Later, a last line responsible for representing the expected outputs was added to the matrix. Figure 1 shows the flowchart of EEG processing to detect epileptic seizures.

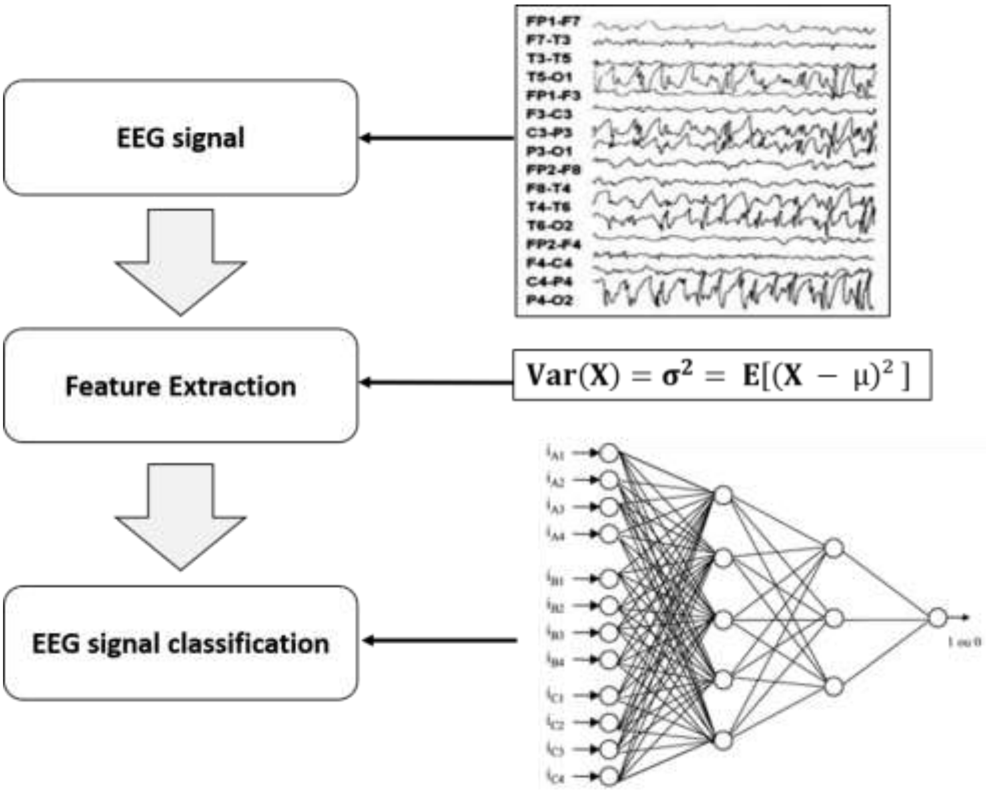

Figure 1 - Flowchart of the EEG classification process.

2.3 Multilayer Neral Network

Artificial Neural Networks were inspired by the functioning of biological neurons in the nervous system of animals. The artificial neuron reproduces the functions, shape and performance of a biological neuron. Thus, the components are changed as follows: dendrites through the inputs, the connections with the cell body are made through weights (similar to the synapses), the stimuli identified by the dendrites (inputs), are processed by the sum function and the axon is replaced by the activation function. In addition, the computational model of a neuron can be combined with more neurons and multiple layers, thus managing to solve complex, non-linearly separable tasks. Figure 2 shows the representation of an artificial neuron [15].

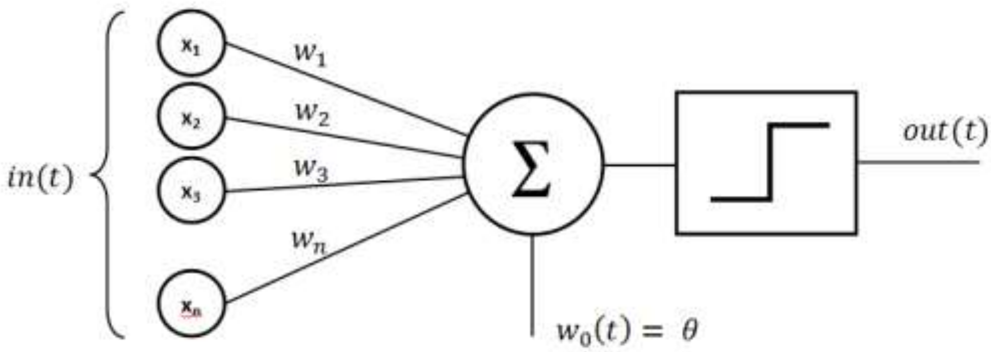

Figure 2 - Artificial neuron [15]

The neural network topology used is the standard feedforward network, known as Multilayer

Perceptron, containing an input layer with 23 neurons, 4 hidden or intermediate layers with 100 neurons each and an output layer with 1 neuron. It is important that the neural network has intermediate layers, as a network with few hidden nodes would be unable to differentiate between complex patterns. In addition, the network uses the sigmoid activation function to filter the output between the intermediate layers and the output layer, as shown in figure 3, in addition, 500 times were established to obtain the network learning.

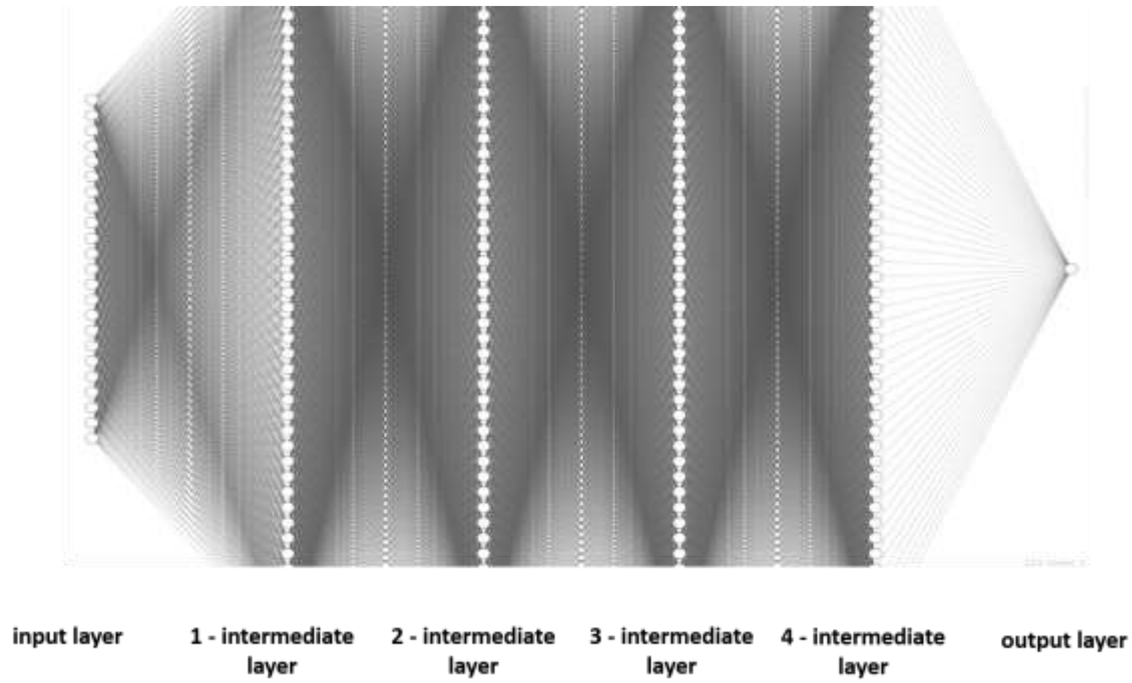

Figure 3 - Neural Network Model Developed.

The network was developed using the Keras library (https://keras.io/), for Python, and the Pandas library (https://pandas.pydata.org/) for manipulating the database in '.csv'. The input data in the artificial neural network were normalized, thus, it was reduced to the limits [0.1] or [-1.1]. The database was divided into 80% for training and 20% for testing. The "rmsprop" function was used as an optimizer and the "binary_crossentropy" function as a loss function. Both aim to minimize network errors, improving their accuracy, and the first (optimizer) performs the downward gradient for this.

3. Results and Discussion.

In this study, the input parameter of the neural network for training was the EEG signal variance. After training the neural network using 80% of the database for 500 periods, the network showed an accuracy of about 99% and in specific cases reaching 100%. During the tests, certain characteristics were noted in the database that allowed the network to achieve such high accuracy. The database has 10,800 samples, each of which represents 1 second, totaling 3 hours of examination, however in the epileptic seizures noted in the EEG signal available in the database used, it presented only a few minutes. At random, the selection of 80% of the database for training was made, and in some moments of execution the network reached an accuracy of 100%, since the data are always chosen at random so that the network is not with data addicted to your training.

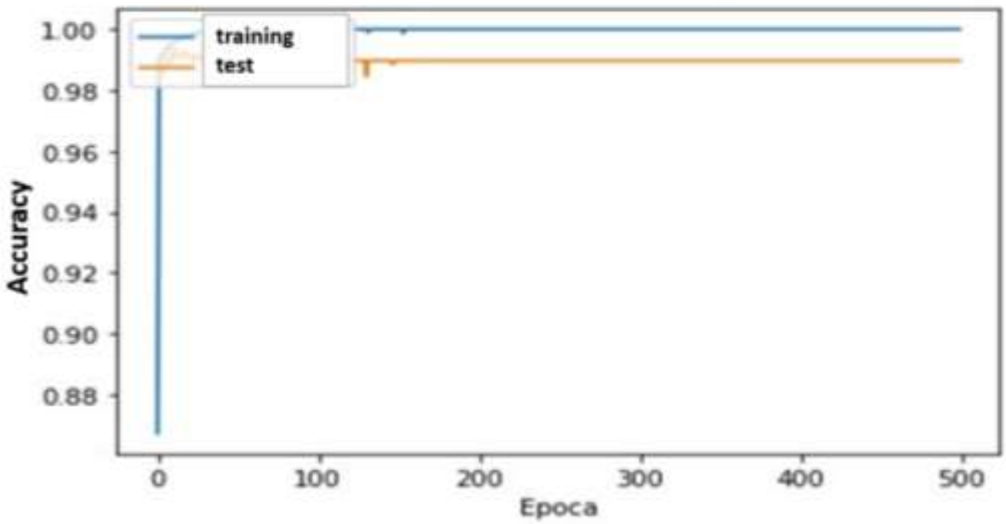

Figure 3 - Model accuracy.

The results for the best performance of the backpropagation neural network baseline were for accuracy and sensitivity. Thus, we achieved an accuracy rate of 98% classification using the proposed architecture, accuracy refers to the proportion of the total cases that were correctly predicted, whether negative or positive. Sensitivity is the percentage of correct predictions for patients who have not had epileptic seizures, with 99%; and specificity is the percentage of correct predictions for patients who had epileptic seizures during the EEG was 77%.

As it could be noted, such metrics resulted in quite satisfactory values, it was possible to reach a number equivalent to 1068 of true positive in an example of execution of the artificial neural network in question, that is, during the execution of the test performed by the neural network, the which corresponds to the execution of 10% of the base, where the whole includes training, testing and validation, 1068 of the positive cases were correctly predicted, while only 2 of them were classified incorrectly. Regarding the classification of negatives, we have a total of 7 cases classified correctly and 3 classified incorrectly.

In a recent study, Variance, Asymmetry and Kurtosis were used together to extract characteristics of EEG signals with epilepsy, machine learning classifiers were used, such as the Steam Support Machine, K-Neighbors and Discriminating Linear Analysis, obtaining an accuracy of 97%, slightly lower than the results obtained in that article [16].

Thus, our results show that only the use of Variance was able to be a good parameter for extracting characteristics and detecting Epilepsy, thus being a more consistent vector of characteristic.

Finally, it is clear the need for studies in this area, not only using statistics, but using other statistical parameters to measure the efficiency of the neural network, in order to obtain better results and advances in studies of patients with epilepsy.

4. Conclusion.

In this study, a multilayer neural network architecture was used to classify epileptic seizures, using Variance as an input parameter. The results of the simulation showed that the proposed network could present satisfactory results with an accuracy of 98% in the detection of seizures. The proposed model can be an alternative to create software to assist health professionals for a quick and accurate diagnosis in hospitals and medical centers.

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