A deep learning approach for epilepsy seizure detection using EEG signals

Un enfoque de aprendizaje profundo para la detección de ataques de epilepsia mediante señales de EEG

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Kaushik, M.; Singh, D., Kishore-Dutta, M.; Travieso, C.M. A deep learning approach for epilepsy seizure detection using EEG signals. *Tecnología en Marcha*. Vol. 35, special issue. November, 2022. International Work Conference on Bioinspired Intelligence. Pág. 110-118.

https://doi.org/10.18845/tm.v35i8.6461

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Keywords

EEG Signal; epilepsy detection; Convolutional Neural network; pattern recognition.

Abstract

Electroencephalogram (EEG) is an effective non-invasive way to detect sudden changes in neural brain activity, which generally occurs due to excessive electric discharge in the brain cells. EEG signals could be helpful in imminent seizure prediction if the machine could detect changes in EEG patterns. In this study, we have proposed a one-dimensional Convolutional Neural network (CNN) for the automatic detection of epilepsy seizures. The automated process might be convenient in the situations where a neurologist is unavailable and also help the neurologists in proper analysis of EEG signals and case diagnosis. We have used two publicly available EEG datasets, which were collected from the two African countries, Guinea-Bissau and Nigeria. The datasets contain EEG signals of 318 subjects. We have trained and verify the performance of our model by testing it on both the datasets and obtained the highest accuracy of 82.818%.

Palabras clave

Señal EEG; detección de epilepsia; red neuronal convolucional; reconocimiento de patrones.

Resumen

El electroencefalograma (EEG) es una forma eficaz y no invasiva de detectar cambios repentinos en la actividad neuronal del cerebro, que generalmente se produce debido a una descarga eléctrica excesiva en las células cerebrales. Las señales de EEG podrían ser útiles en la predicción de convulsiones inminentes si la máquina pudiera detectar cambios en los patrones de EEG. En este estudio, hemos propuesto una red neuronal convolucional (CNN) unidimensional para la detección automática de crisis epilépticas. El proceso automático puede ser conveniente en las situaciones en las que un neurólogo no está disponible y también ayudar a los neurólogos en el análisis adecuado de las señales de EEG y el diagnóstico de casos. Hemos utilizado dos conjuntos de datos de EEG disponibles públicamente, que se recopilaron de los dos países africanos, Guinea-Bissau y Nigeria. Los conjuntos de datos contienen señales de EEG de 318 sujetos. Hemos entrenado y verificado el rendimiento de nuestro modelo probándolo en ambos conjuntos de datos y obtuvimos la precisión más alta del 82,818%.

Introduction

Epilepsy seizure is a neurological disorder. It could affect people in every age group and has been known for a very long time since 4000BC. Around 50 million people suffered from epilepsy in various parts of the world especially in economically backward countries [1]. Symptoms of epileptic seizures varies depending on the part of the brain in which electric discharge affect first. Unconsciousness, disturbance in movement, sensation and other cognitive function are some of the temporary symptoms of the disease.

Seizures with epilepsy can be categorized into two parts, behavioral and electrographic. A behavioral seizure results in physical disturbances in the body of the patient and is monitored by using the observer or video recording while the electrographic seizure is characterized by abnormal paroxysmal EEG patterns. Usually, visual analysis of EEG patterns is the method used for epilepsy detection by the experts but this method has its own limitations including time-intensive tasks and the possibility of human error. For the above reasons, automatic detection of epilepsy has been an area of research and concern since the 1970s [2].

The automatic detection of epilepsy involves stages like recording of EEG signals from the patients, EEG signal preprocessing and analysis using different techniques such as time analysis, frequency analysis, fast Fourier transform (FFT) to extract features and finally use the extracted features to classify the epilepsy cases from the healthy ones. Various techniques have been used for EEG signals analysis such as time series analysis, frequency analysis, wavelet, fast Fourier transform, etc. For classification purposes, various machine learning and deep learning algorithms have been used like SVM, K-means, ANN, and RNN.

The main contribution of this paper is a deep learning based one dimensional convolutional neural network model which could assists a neurologist to decide whether the EEG signal is epileptic signal or control signal. It is a reliable method to identify epilepsy patterns in EEG signals and prevent errors in decision making. The proposed method is frugal, non-invasive, automatic, reliable and fast. The proposed model is trained with epileptic and control (healthy) EEG signals and able to identify epileptic signals in real time.

The rest of the paper is organized as follows: Section II discusses about the related work in the area of epilepsy detection using artificial intelligence techniques, Section III discusses about the dataset and preprocessing of raw EEG signals, Section IV contains discussion about the proposed CCN model, Section V includes discussion about the obtained results which leads to Section VI which is about conclusion and future work.

Related Work

There are various applications of EEG signals [12]. Guerra et al. [3] used wavelet transforms and neural networks to detect epilepsy seizure in EEG signals. They suggested using discrete wavelet transform (DWT) and the maximal overlap discrete wavelet transform (MODWT) to extract features from EEG signals and then use feed forward artificial neural networks (FF-ANN) for classification. They used the dataset provided by the University of Bonn consisting of five parts with each part containing 100 segments of 23.6 seconds of EEG signals. They conducted two different experiments, in the first one they selected only two sets out of five and in the second experiment all five sets was considered from the dataset. Second experiment have shown better results than first experiment [3].

Similarly, Ming yang et al. [4] extended the work further by implementing double-density discrete wavelet transform (DD-DWT) instead of traditional DWT to transform the EEG signals into sub-bands and later using genetic algorithm optimized support vector machines for classification. Input features like Hurst exponent (HE) and fuzzy entropy have been used and found to achieve even better accuracies. The dataset used by Ming yang et al. was same as that used by Guerra [3] which is openly provided by the University of Bonn. For different combinations of sets obtained results were remarkable [4].

Sathak Gupta et al. [5] have presented epilepsy seizure detection using EEG signals. The authors have proposed to use wavelet transform for coefficients extraction and from the extracted coefficients various statistical features like mean, standard deviation, root mean square, skew, kurtosis, maximum fractal length (MFL), coefficient of variation and Shannon entropy were extracted. In the next step various machine learning and deep learning algorithms were experimented on these features. The results indicates that deep learning models have better performance on pre-processed EEG signals than raw EEG signals with extreme gradient boosting [5].

Dataset and Pre-processing

The two EEG Datasets we have used and analyzed for epilepsy signal detection is openly released by Vincent van Hees and Wim Otte [6]. These datasets was created by EEG signal recordings of two African countries named as Guinea-Bissau and Nigeria. EEG signals were recorded with a low-cost, fourteen channels EEG Emotive headset. The datasets contains a total of 318 EEG signals in which 179 are of epilepsy and 139 are of control or normal signals. Country wise, dataset-A (Guinea-Bissau) contains total 97 EEG signals and dataset-B (Nigeria) contains total of 221 EEG signals. The description of datasets are shown in Table 1.

Table 1. Description of Datasets

Datasets	Seizure-Category	Number of Samples
Dataset-A (Guinea-Bissau)	Control	46
	Epilepsy	51
Dataset-B (Nigeria)	Control	93
	Epilepsy	128
Total		318

EEG signals were recorded for the three minutes of closed eyes followed two minutes of opened eyes or three minutes of opened eyes followed two minutes of closed eyes which is random among the participants. EEG signals contains 14 channels which are recorded by 14 electrodes located on the scalp as per the international 10-20 system [7]. The position of electrodes can be viewed in Fig 1. and the names of the electrodes are O1, O2, P7, P8, T7, T8, AF3, AF4, F3, F4, F7, F8, FC5, and FC6.

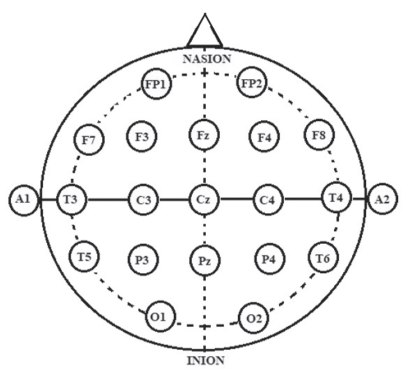

Figure 1. EEG raw data of 14 channel.

Pre-processing is done by removing the outliers from the raw EEG data. The general workflow of methodology is shown in Fig. 2. Initially all 14 channel values are arranged column wise. All the corresponding rows are deleted if any value in a row is smaller than a minimum threshold S_v or larger than a maximum threshold L_v. The values of S_v and L_v are decided based on the statistical method in which mean and standard deviation is calculated for each electrode for each row and then lower and upper bound is decided by subtracting four times the standard deviation from the pre calculated mean. Based on these bounds, we got the values S_v and L_v which is helpful in removing all of the rows for which the value is smaller or larger than these thresholds.

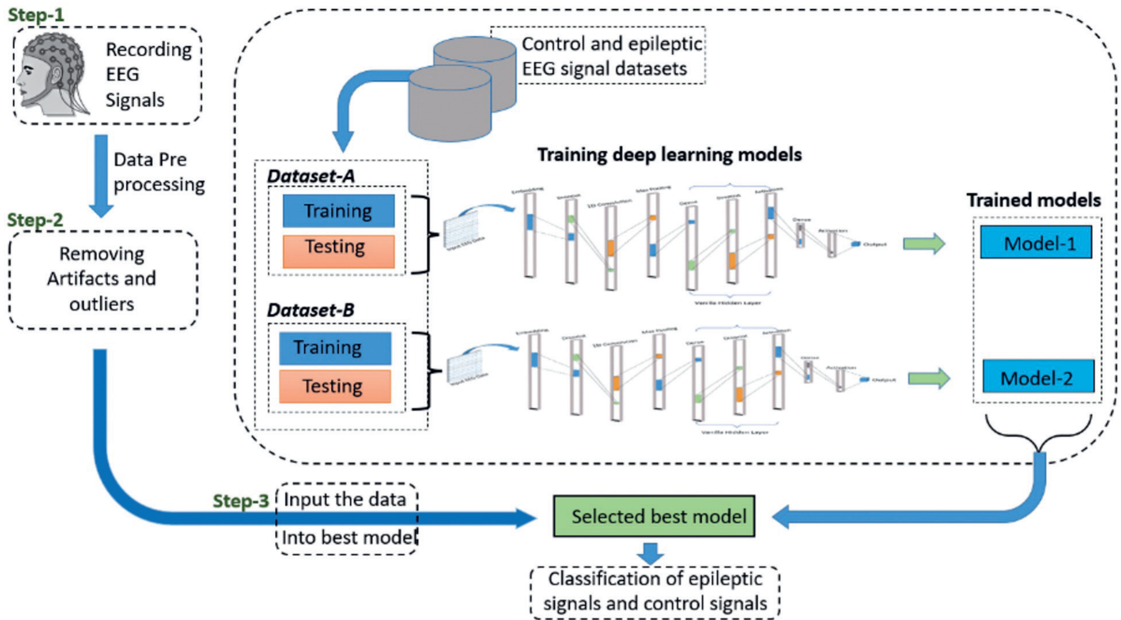

Figure 2. Workflow of the methodology.

After removal of the outliers from the data, transpose of the whole data matrix is performed. All outlier pre-processing is done on both the EEG datasets collected from Guinea-Bissau and Nigeria. Sequence padding is used before splitting the data into training and testing sets. The 14 channel EEG data after outlier removal is shown in Fig.3.

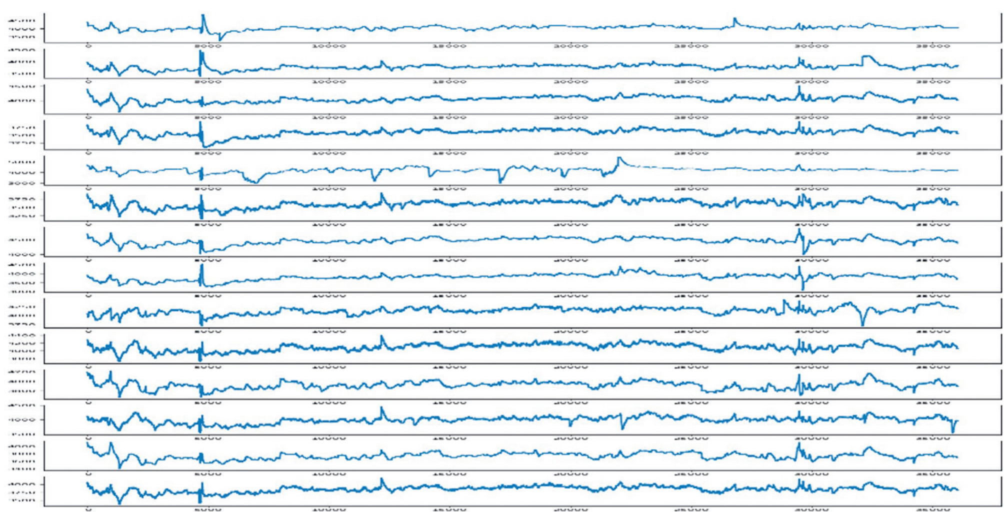

Figure 3. 14 channel EEG data after outlier removal.

Dataset-A contains a total of 97 EEG recordings while dataset-B contains a total of 221 EEG recordings. Training and testing are split by 66% and 34% respectively for both the datasets. The length of the time series EEG signals is unequal, hence equalization of all EEG signal is done by padding and truncating operations. EEG signals which are shorten than fixed length threshold L_v have padded and signals which are larger than threshold L_v have truncated.

CNN Model Architecture

We have used a 1-dimensional convolutional neural network for epilepsy and control EEG signal classification. It contains various hidden layers in the network architecture. The first layer is the embedding layer which is used to convert positive integer values into fixed-sized vectors.

After the embedding layer, the dropout layer is added to prevent the model from over fitting. The dropout layer randomly drop 20% of the neurons. Then, a 1-D convolutional layer is added in the network with 80 output filters. Output filters are used to store the extracted discriminating information by the kernel. Kernel size is set to 3, is a 1D-convolutional window which helps to extract the features.

The hyper parameter, stride value set to be 1 which specifies the step length of the convolutional window. Padding hyper parameter is valid so, no padding is used in the convolution operation. Rectified Linear Unit (ReLU) is used for neuron activation. It calculates the function f(x) =max (0, x) which provides better non linearity and convergence. After the convolutional layer, max pooling-1D layer is added which helps in reducing the number of operations for ensuing layers without losing the salient information. Then, a vanilla hidden layer is added which is a combination of dense layer, dropout layer and activation function. Dense layer preserves the information. ReLU [8] is used as an activation function. Various used hyper-parameters are shown in Table 2.

Table 2. Hyper-parameters used.

Hyper-parameter	Value
Batch Size	32
Loss	‘binary cross-entropy’
Embedding Dimensions	5
Hidden Dimensions	300
Epoch	500
Filters	80
Kernel Size	3
Stride	1
Padding	‘valid’
Optimization Algorithm	‘Adam’

Finally, the vanilla hidden layer output is passed to a single unit output layer which is squashed with sigmoid activation [9]. Binary cross entropy used for loss. Adam optimization function used in the model architecture.

The model architecture with various parameters, layers and corresponding input sizes are shown in Fig. 4. Total number of parameters in the model architecture are 75,881. Two types of activation functions ReLU and Sigmoid have used.

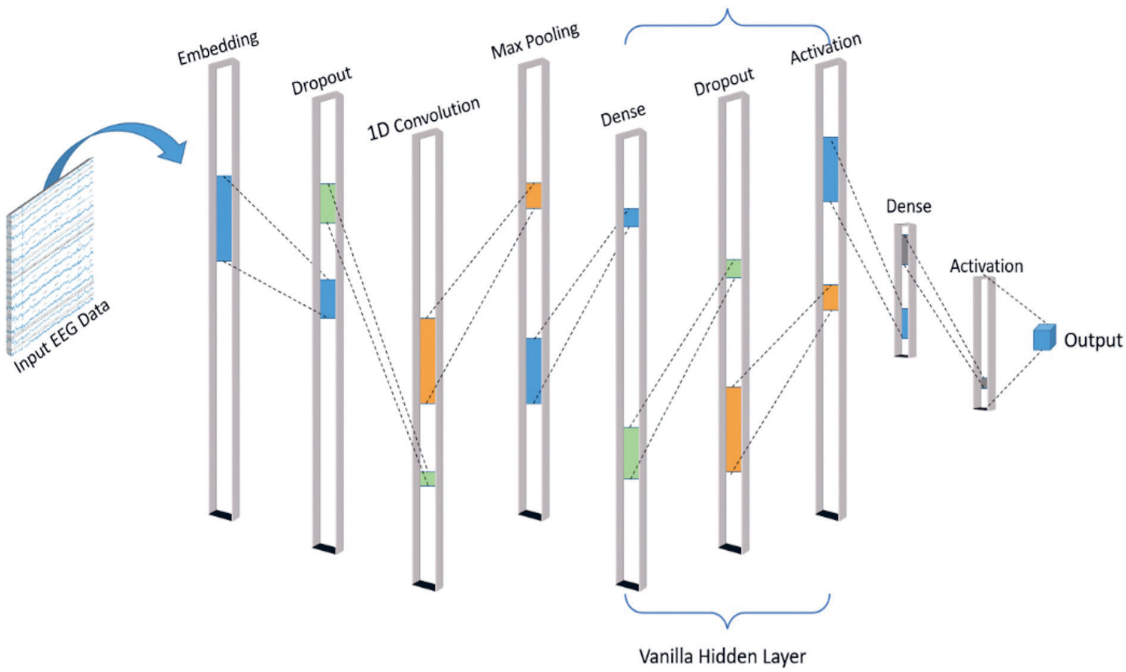

Figure 4. 14 channel EEG data after outlier removal

Results

The datasets contain EEG signals of epilepsy and control from two different countries. When we trained our model for dataset-A (Guinea-Bissau) the accuracy is 82.818% while the accuracy for dataset-B (Nigeria) is 71.493%. Dataset-A contains a total of 97 EEG signals while dataset-B contains a total of 221 EEG signals. We have also analyzed the performance of dataset-A trained model on dataset-B as a testing dataset and vice-versa.

Accuracy comparison of our proposed model and by Vincent et. el. [6] are shown in Table-3.

Table 3. Accuracy comparisons.

Trained Model on	Testing on	Accuracy (proposed model)	Accuracy By Vincent et. el
Dataset-A (Guinea-Bissau)	Test set of dataset-A	82.818%	81%
	Full dataset-B	56.023%	55%
Dataset-B (Nigeria)	Test set of dataset-B	71.493%	70%
	Full dataset-A	59.60%	60%

Accuracies for both the datasets has shown in Fig.5. Out of 33 validation sets for dataset-A 14 correctly classified as Control signals and 13 correctly classified as epilepsy while for dataset-B out of 73 validation sets 9 are correctly classified as control and 41 are correctly classified as epilepsy.

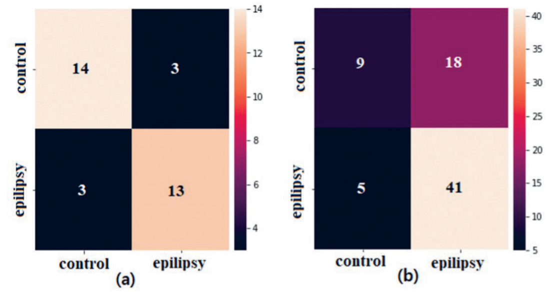

Figure 5. Confusion matrices for (a) Dataset-A (b) Dataset-B.

Conclusions

In this study, we have trained and tested a one-dimensional convolutional neural network for epilepsy and control EEG signals, collected from two African countries Guinea-Bissau and Nigeria. We have tested the trained models extensively and measured the performance on cross datasets testing. This method shows the highest accuracy performance on dataset-A (Guinea-Bissau) with 82.818%. Also features are not extracted separately instead all the features are extracted by CNN filters. Model accuracy is saturated above 500 epochs [10].

In the future different machine learning techniques with more advanced optimization algorithms can be used with separate feature extraction to get better accuracy on this dataset. One dimensional residual network (Res-CNN) can also be applied for time series data analysis [11].

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