Computers in Biology and Medicine 109 (2019) 148–158

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Classification of epileptic EEG recordings using signal transforms and convolutional neural networks☆,☆☆

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ARTICLE INFO

Keywords:
Electroencephalogram
Epileptic EEG signal classification
Epilepsy
Seizure detection
Convolutional neural networks
Fourier transform
Wavelet transform and Empirical Mode Decomposition (EMD)

ABSTRACT

This paper describes the analysis of a deep neural network for the classification of epileptic EEG signals. The deep learning architecture is made up of two convolutional layers for feature extraction and three fully-connected layers for classification. We evaluated several EEG signal transforms for generating the inputs to the deep neural network: Fourier, wavelet and empirical mode decomposition. This analysis was carried out using two public datasets (Bern-Barcelona EEG and Epileptic Seizure Recognition datasets) obtaining significant improvements in accuracy. For the Bern-Barcelona EEG, we obtained an increase in accuracy from 92.3% to 98.9% when classifying between focal and non-focal signals using the empirical mode decomposition. For the Epileptic Seizure Recognition dataset, we evaluated several scenarios for seizure detection obtaining the best results when using the Fourier transform. The accuracy increased from 99.0% to 99.5% for classifying non-seizure vs. seizure recordings, from 91.7% to 96.5% when differentiating between healthy, non-focal and seizure recordings, and from 89.0% to 95.7% when considering healthy, focal and seizure recordings.

1. Introduction

Epilepsy is a neurological disorder that affects more than 50 million people worldwide, increasing by two million every year [1]. This disorder can appear at any age and can be produced by brain malformations, intracranial hemorrhages or brain tumors [2]. This disorder produces malfunctions in patient perception and/or motion (depending on the neurons affected) [3] and can produce epileptic seizures [4]. An epileptic seizure is defined as a period of time in which the patient experiments a set of symptoms with different levels of severity [5]: uncontrolled shaking movements involving much of the body with loss of consciousness (tonic-clonic seizure), shaking movements of a specific part of the body with variable levels of consciousness (focal seizure) or short moments with loss of awareness (absence seizure). These attacks appear due to abnormally excessive or synchronous neuronal activity in the brain [6] and last less than 2 min, taking some time to return to normal [7]. Although the antiepilectic treatments have alleviated the incidence of seizures [8], these attacks are a significant problem in daily activity as they are very difficult to predict.

The study of epilepsy requires the analysis of a multidimensional time series generated from Electroencephalogram (EEG) recordings [9]. The analysis of EEG signals has traditionally been carried out by experts in visual inspection. This manual process is time consuming [10] and can be affected by the clinician's subjectivity. In order to alleviate these problems, automatic systems are being developed to evaluate and classify epileptic EEG signals [11]. This paper focuses on two main classification problems:

- The first problem consists of differentiating between EEG signals recorded from epileptic and non-epileptic areas of the brain: classifying between focal and non-focal EEG signals. This classification permits possible causes of the epilepsy (malfunctions, hemorrhages and tumors) to be detected and localized. Locating epileptogenic areas allows targeted therapies be defined to limit the symptoms.
- The second problem is the detection of epileptic seizures. Seizure detection is important to improve the treatment of epileptic patients: for example, this detection would allow seizure diaries to be developed to obtain patterns of seizure susceptibility. With these patterns, physicians can design focused therapies adapted to each patient. In this study, we considered several scenarios for seizure detection.

This paper addresses these two classification problems using a deep learning structure and analyzes several signal transforms to generate

☆ This manuscript is the authors' original work and has not been published nor has it been submitted simultaneously elsewhere.
☆☆ All authors have checked the manuscript and have agreed to the submission.

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https://doi.org/10.1016/j.compbiomed.2019.04.031
Received 1 March 2019; Received in revised form 22 April 2019; Accepted 23 April 2019

the inputs to the deep learning structure. The main contributions are:

- The proposal and analysis of a Deep Neural Network (DNN) made up of two convolutional layers for extracting features from EEG signals and three fully connected layers for epileptic EEG signal classification.
- The evaluation of several signal transforms as inputs to the DNN: Fourier, wavelet, Empirical Mode Decomposition (EMD) and raw data directly.
- The signal transforms and the DNN were evaluated in the two aforementioned classification problems. We used two public datasets, the Bern-Barcelona EEG dataset [12] and the Epileptic Seizure Recognition dataset [13], obtaining significant improvements in both classification problems: differentiating epileptic and non-epileptic brain areas, and detecting epileptic seizures.

This paper is organized as follows. Section 2 describes the related work on epileptic EEG signal classification. Section 3 reviews the methodology, materials and methods used in this study, including a description of the methodology, datasets, signal transforms and the DNN. Section 4 describes the experiments and the results obtained, comparing them with previous studies. Finally, section 5 summaries the main conclusions of the paper.

2. Related work on epileptic EEG signal classification

This section reviews related work in automatic systems for epileptic EEG signal classification. These automatic systems are made up of two main modules. Firstly, a feature extractor preprocesses the EEG signals and obtains the main signal characteristics, and secondly, these characteristics are used as the input to a classifier that identifies the recognized category [14]. The related work description is organized in accordance with these two main modules, differentiating the references according to the classification problem addressed: classification of focal and non-focal signals, and detecting epileptic seizures.

As regards feature extraction, previous papers proposed characteristics from the signal domain (time features) and from transformed domains like Fourier, wavelet or EMD for the two classification tasks considered in this paper.

For the classification of focal and non-focal EEG signals, Das and Bhuiyan [15] used entropy features from the combination of EMD and wavelet domains. Gautam et al. [16] compared the corresponding resultant peaks after obtaining the Intrinsic Mode Functions (IMFs) using EMD. The plots relating energy and correlation calculations on the IMFs were used as a feature for the classification. Fasil and Rajesh [17] analyzed different time-domain features including several types of entropy like Shannon, Renyi or Tsalli and energy based features, proposing exponential energy as a new feature. They obtained an accuracy of 89.0% on the Bern-Barcelona EEG dataset. Sriraam and Raghu [18] used 26 different features from time and frequency domains including mean, median frequency, root mean square, entropy, zero crossing, quartiles, skewness, kurtosis, first and second derivatives of mean, variance and standard deviation, and reported an accuracy of 92.15% with the Bern-Barcelona EEG dataset.

For epileptic seizure detection, several works investigated energy features from sub-bands of EEG signals [19–22]. In some of these works, features were extracted from the wavelet decomposition [19,20]. Zhang et al. [23] evaluated 47 features extracted from several domains (time, frequency, time-frequency and spatio-temporal), obtaining the best results from those related to wavelet coefficients, absolute power and synchronization in the frequency domain. Logesparan et al. [24] analyzed the discriminative performance of 65 features, obtaining the best results with the line length and relative power in the 12.5–25 Hz band. Jaiswal and Banka [25] introduced two feature extraction techniques: Local Centroid Pattern (LCP) and one-dimensional local ternary pattern (1D-LTP). Tsiouris et al. [26] included features from the time domain, Fourier transform and graph theory, and Adeli et al. [27] used the nonlinear dynamics of the EEG signals quantified in the form of the correlation dimension (system complexity) and the largest Lyapunov exponent (system chaoticity).

In order to reduce the number of features, some techniques such as the Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) were used [28].

After the feature extraction, a classification module must discriminate between the different classes. Support Vector Machines (SVM) have been used extensively for the classification of focal and non-focal EEG signals [17,18]. Xie et al. [29] used a k-Nearest Neighbors (kNN) with k = 1. Acharya et al. [30] evaluated the performance of six classifiers: a decision tree, a fuzzy sugeno classifier, a gaussian mixture model, kNN, SVM and a radial basis probabilistic neural network. Subasi et al. [31] used a modular neural network architecture using a double-loop Expectation-Maximization algorithm to train the architecture. SVMs have been also investigated [32,33] widely for seizure detection. Direito et al., [34] proposed a classification system based on Markov modeling to identify four states — preictal, ictal, postictal, and interictal – in the process of a seizure. Dono et al. [35] analyzed the performance of the random forest algorithm using intracranial EEG signals. Other studies have used Bayesian Linear Discriminant Analysis (BLDA) [36], Quadratic Discriminant Analysis (QDA) [37], and artificial neural networks [38].

Deep learning algorithms are attracting a lot of attention due to their good performance in many machine learning applications such as video processing [39], early diagnosis of the Alzheimer's disease [40] or the freezing of gait detection in Parkinson disease [41]. Recurrent Neural Networks (RNN) have been used in EEG analysis to learn temporal patterns for epileptic seizure detection [42]. Long Short-Term Memory (LSTM) is an evolution on the RNNs that include gates to deal with the vanishing gradient problem. LSTM has been used recently for the prediction of epileptic seizures using EEG signals [26]. Convolutional Neural Networks (CNNs) have also attracted significant interest in EEG signal processing. For the classification of epileptic EEG signals, CNNs have been applied to both the raw data [43] and the wavelet space [44] obtaining very good performance in other datasets. The main advantage of CNNs is the possibility to learn new features automatically, providing better results than hand-crafted features when the amount of data for training the CNNs is big enough [41].

Our paper proposes the use of a DNN based on CNNs for epileptic EEG classification and evaluates several signal transformations to generate the inputs to the DNN. The best previous results on the Bern-Barcelona EEG dataset were obtained by Sriraam and Raghu [18] while the best previous results on the Epileptic Seizure Detection dataset were presented by Fasil and Rajesh [17] and Wang et al. [45], using SVMs in all cases. These previous works are our baseline in this paper.

3. Methodology, materials and methods

This section presents an overview of the methodology and describes the datasets used in this study, the signal transforms analyzed in this work and the deep learning structure used for epileptic EEG signal classification.

3.1. Methodology overview

Many previous studies have already reported results on the two public datasets considered in this paper. These studies proposed and analyzed hand-craft features using traditional machine learning algorithms for classifying, but there is a lack of analyses applying deep learning algorithms to classify EEG signals using these datasets. This paper contributes to this aspect by analyzing the performance of a DNN made up of two main parts: the first one for feature extraction and the second for the EEG signal classification. Deep learning algorithms have demonstrated a good performance, not only for classification but also for feature extraction. The inputs to this DNN were obtained from several signal transforms. Several signal transforms were evaluated independently and considering all together for the two classification problems described in the introduction: differentiating signals recorded from epileptic and non-epileptic brain areas, and detecting epileptic seizures. The experimental procedure consisted of a five-fold cross-validation approach: The EEG signals from the dataset being analyzed were randomly divided into training, validation and testing subsets. The validation subset was used to define the number of epochs considered to train the DNN, and the test subset was used to estimate the accuracy of the classification.

3.2. Datasets

We used two public datasets: the Bern-Barcelona EEG [12] and the Epileptic Seizure Recognition [13]. Both datasets were used to evaluate the classification performance when differentiating EEG signals from epileptic and non-epileptic brain areas, and only the Epileptic Seizure Recognition dataset was used for the detection of epileptic seizures.

The Bern-Barcelona EEG dataset includes two categories of intracranial EEG recordings from five epilepsy patients. The first category is called focal (F) and the signals were recorded from the epileptic area of the brain. The second class is non-focal (N) and includes EEG recordings from the non-epileptic area of the brain. Each class contains the same number of examples: 3750 pairs of signals. For the focal class (F), the two signals were obtained from the channel in which the epileptic signals originated and from another neighboring channel. The non-focal signals (N) were recorded from two neighboring channels situated in the non-epileptic area of the brain. All EEG signals were digitally band-pass filtered between 0.5 and 150 Hz using a fourth-order Butterworth filter (forward and backward filtering to minimize phase distortions). In the original dataset, the EEG signals were recorded for 20 s at a sampling rate of 1024 Hz and then down-sampled to 512 Hz. Finally, the median was subtracted in all channels. Recordings of the seizure activity and those 3 h after the last seizure were excluded from the original dataset. Because of this, we used this dataset only for the first classification problem addressed in this paper: identifying EEG signals recorded from epileptic (focal) and non-epileptic (non-focal) brain areas. According to the best results obtained in previous works [17,46], we segmented every recording of 20s into ten non-overlapping segments containing 2 s of data each (1024 samples). The classification decision was made for every single segment. Using the same segmentation as previous works enables us to make a fair comparison with them.

The Epileptic Seizure Recognition dataset contains 500 recordings of 23 s from 500 different patients. These recordings were obtained from surface electrodes with a sampling rate of 173.61 Hz. In the original dataset, every recording of 23s was segmented into 23 non-overlapping segments containing 1 s of data each (173 samples), not being able to consider other segmentation strategies. This aspect is a dataset limitation but allows a fair comparison with previous works than that used in the same segmentation. In total, there are 11,500 recordings of 1 s. This dataset is seven times smaller than the Bern-Bacerlona EEG dataset. The 11,500 recordings are organized into five classes with the same number of examples in each class. The first one corresponds to recordings from healthy subjects with their eyes open (Z). The second class contains recordings from healthy subjects with their eyes closed (O). The third category (ictal group) includes signals from epileptic subjects during a seizure (S). The fourth group contains interictal activity from the hippocampal location (N). And the last class corresponds to interictal activity from the epileptogenic zone (F). For a better comparison with previous works, we considered the same notation described in Fasil and Rajesh [17]. We used this dataset to evaluate the two classification problems considered in this work. Firstly, we classified EEG signals between classes N (interictal activity from the hippocampal location) and F (interictal activity from the epileptogenic zone) similar to the focal vs. non-focal classification considered in the Bern-Barcelona EEG dataset. For seizure detection, we distinguished four different scenarios. These scenarios tried to simulate different situations for seizure detection including interictal signals from healthy and epileptic patients (including signals recorded from epileptic or non-epileptic areas of the brain):

1. The first scenario consisted of classifying signals from healthy people (Z) and seizure signals (S, ictal). The target of this scenario is to evaluate the system in the easiest classification task. This result can be seen as an Oracle result. This scenario was also addressed by Fasil and Rajesh [17].
2. The second scenario is a more realistic scenario and it focuses on classifying signals both from epileptic patients having a seizure (S, ictal group) and the rest of the classes (NS, non-ictal) including classes Z, O, N and F. This situation was also addressed by Wang et al. [45] and Kumar et al. [47].
3. The third scenario was to classify three types of signal: signals from healthy people (Z, healthy group) and signals from epileptic patients considering non-focal signals (N, interictal activity from the hippocampal location) and seizure signals (S, ictal group). The main target is to analyze the confusion in non-focal EEG signals from epileptic patients with those of healthy or seizure recordings. This task was also addressed by Abualsaud et al. [48].
4. The fourth scenario was similar to the third one but replacing non-focal signals with focal signals. The classes to separate were signals from healthy people (Z, healthy group), focal signals (F, interictal activity from the epileptogenic zone) and seizure signals (S, ictal group). This task was also evaluated by Sadati et al. [49].

The main reason for analyzing these different scenarios was to provide a more complete analysis in different situations and a better comparison with previous works that also included these evaluations.

3.3. Signal transforms

In order to process the EEG signals and generate the inputs to the DNN, we analyzed several signal transforms. Fig. 1 shows examples of focal and non-focal signals from the Bern-Barcelona EEG dataset with the corresponding transforms. The first approach consisted of using the raw signal directly (labeled as RAW) without any transform. This was the same strategy used by Rajendra et al. [43].

Secondly, the EMD was considered. Every signal was broken down into 6 IMFs, generating a pool of six signals and a residuum. These signals were sent to the DNN directly in a 2 D structure (labeled as IMFs 1, 2, 3, 4, 5, 6). The EMD process breaks down a signal $x(t)$ into n IMFs $x_n(t)$ and a residuum $r(t)$. The original signal can be represented as:

$$x(n) = \sum_n x_n(t) + r(t) \quad \text{(Equ.1)}$$

The EMD algorithm consists of the following steps [50]:

- Step 0: Initialize: $n := 1$, $r_0(t) = x(t)$
- Step 1: Extract the n-th IMF:
  - Set $h_0(t) := r_n - 1(t)$
  - Identify all local maxima and minima of $h_{n-1}(t)$.
  - Construct for $h_{n-1}(t)$, by the interpolation of the cubic splines, the envelope $U_{n-1}(t)$ defined by the maxima and the envelope $L_{n-1}(t)$ defined by the minima.
  - Determine the mean $m_{n-1}(t) = (U_{n-1}(t) - L_{n-1}(t))/2$ of both envelopes of $h_{n-1}(t)$.
  - Form the $n-th$ component $h_n(t) := h_{n-1}(t) - m_{n-1}(t)$. Then set $x_n(t) := h_n(t)$ and $r_n(t) := r_{n-1}(t) - x_n(t)$.
- Step 2: Repeat step 1 until the desired number of IMFs, six in our case, is reached.

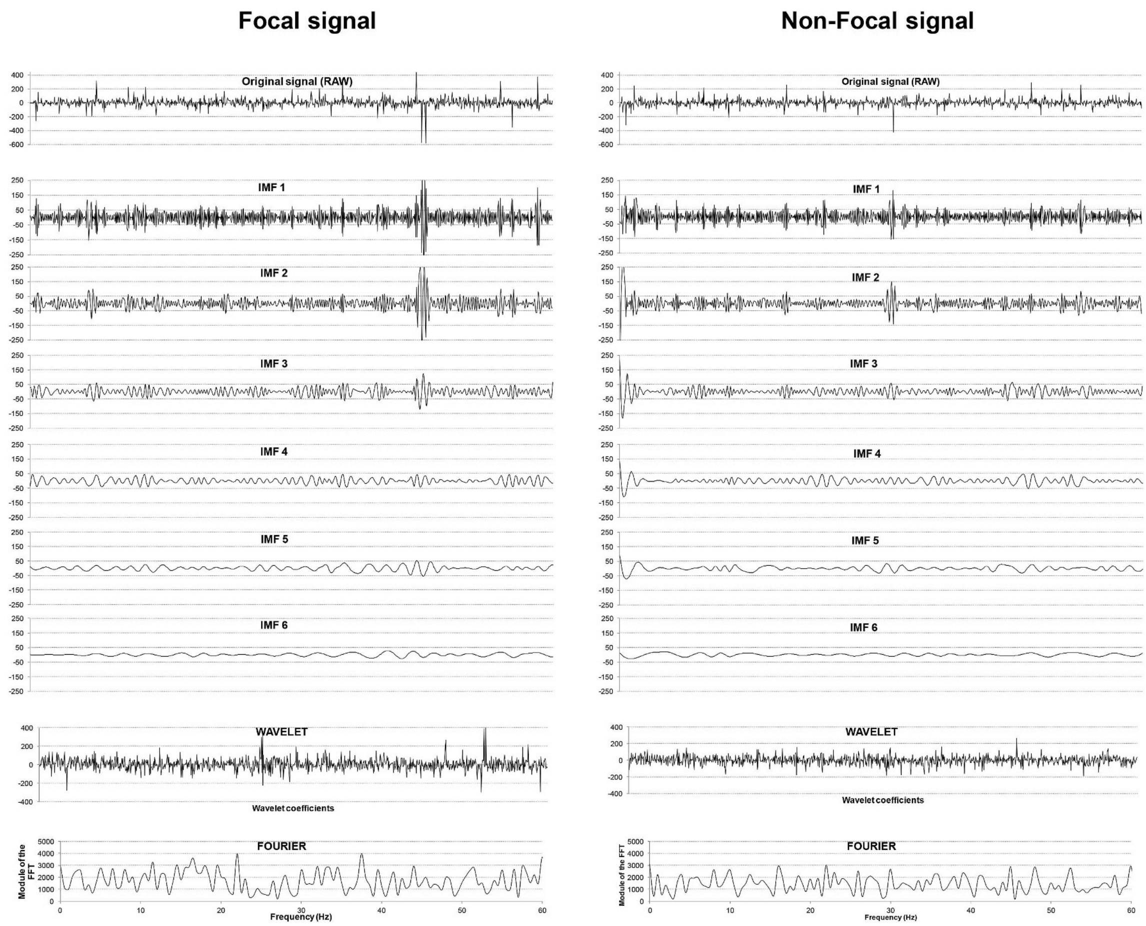

Fig. 1. Examples of focal and non-focal signals with the corresponding signal transforms.

The EMD algorithm was implemented in the Octave program [51].

The third strategy was the wavelet transform (labeled as WAVELET), similar to the proposal by Khan et al. [44]. The inputs to the DNN were the wavelet coefficients. These coefficients were obtained using the Fast Wavelet Transform (FWT) implemented in an Octave script using the *fwt()* command. We used Daubechies Wavelets [52] with 8 vanishing moments and 5 filterbank iterations.

Finally, the Fourier transform (labeled as FOURIER) was used. In this case, the inputs to the DNN were the module values of the Fourier transform. This transform was computed using the *fft*() function of the *signal* library in the Octave program. For a segment of N samples, the *fft* () function outputs N/2 points due to the spectrum symmetry of real signals. The module values of these N/2 spectral points were the inputs to the DNN.

Similar to baseline systems, before transforming the signals, the frequencies beyond 60 Hz were removed using a sixth order Butterworth filter implemented in Octave using *butter()* and *filter()* functions.

3.4. Convolutional neural networks

Fig. 2 shows the DNN used in this paper and Table 1 includes the configuration details and the number of parameters for all layers. This DNN is made up of several layers organized into two parts: The first part learns the main features from the inputs and includes two convolutional layers with an intermediate maxpooling layer, and the second part integrates three fully connected layers for classification. This structure is inspired by architectures proposed in previous works [43,44]. In this case, there are only two convolutional layers with a lower number of filters (32) in order to reduce the number of parameters necessary to be trained. The success of training a DNN depends on the balance between the number of parameters to be trained and the number of examples in the training dataset. Defining a small DNN allows using datasets with different sizes offering a higher flexibility. Previous architectures proposed kernel sizes of between 1×6 and 1×4. For simplicity, we decided to use an intermediate kernel size (1×5) in both convolutional layers. The padding parameter was set to 'same' resulting in padding the input such that the output has the same length as the original input. The use of three fully connected layers for classification, with a decreasing number of units, is very common in previous works [43,44]. The number of units in these layers depends on the size of the tensor after the convolutional layers (flatten layer). There are dropout layers (deactivating 20% of the weights) after convolutional and full connected layers to avoid overfitting during the training process. All of the intermediate layers use ReLU as an activation function because in ReLU there is a reduced likelihood of the gradient vanishing. With this activation function, the gradient has a constant value.

The inputs are organized in a 2 D matrix with N x M dimensions. These dimensions depend on the signal transform applied before the DNN and the number of signals. This number of signals is different depending on the dataset: two for the Bern-Barcelona EEG dataset and one for the Epileptic Seizure Recognition dataset. Table 2 summaries the input dimensions depending on the signal transform and the dataset. When several signal transforms are combined in the same DNN, the feature extraction part is different for each signal transform, and then, all features are combined at the flatten layer.

At the last layer, the number of outputs depends on the number of classes considered in the classification problem. When classifying between two classes, the last layer has only one output (1 focal, 0 non-focal signals). In this case, the output layer uses a sigmoid activation function and the binary cross-entropy as the loss metric. When

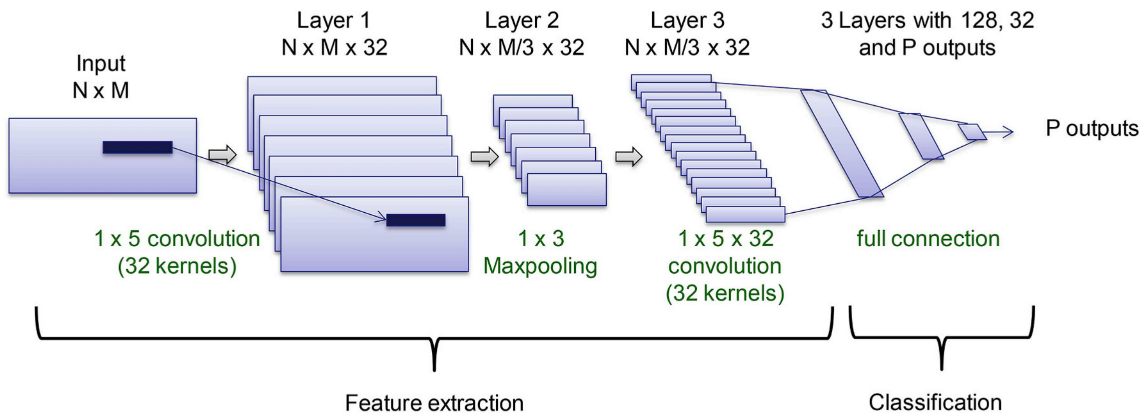

Fig. 2. Deep learning structure including convolutional and fully connected layers.

considering more than two classes, the last layer has P outputs (P being the number of classes). In this case, the output layer uses a softmax activation function and categorical cross-entropy as a loss metric. The softmax function is used to normalize the DNN outputs that sum up one. Thus, the DNN outputs model a probability distribution. After the softmax activation function, it is necessary to consider cross-entropy metrics because they minimize the distance between two probability distributions: predicted and actual. The batch size is 50 for small- and medium-sized datasets as in this paper. The optimizer is the root-mean-square propagation method [53] using the default characteristics: lr = 0.001, rho = 0.9, epsilon = None, decay = 0.0. In this optimization method, each unit keeps its own mean gradient feedback throughout the learning process and the given gradient value is normalized by this mean at each step. This normalization avoids fluctuating weight updates in the deep learning structure, thus obtaining a more stable learning process.

The number of epochs in every experiment was adjusted using a validation set. Keras platform [54] was used to define and train the DNN.

4. Experiments and discussion

The analysis described in this paper was carried out using two different epilepsy datasets (see Section 3.2). In order to compare our results with the results provided by previous works [17,18,45 on these datasets, we used the same experimental procedure: a five-fold cross-validation [55] approach. In this approach, the EEG signals were randomly divided into five equal portions. Three out of five portions of EEG signals were considered to train the DNN, one portion for validation and the remaining portion was used for testing (Fig. 3).

The experimental methodology consisted of the following steps:

- Step 1: Considering the distribution of the subsets shown in the first row of Fig. 3, we trained the DNN using the three training subsets and evaluated the network using the validation subset. From this analysis, the number of epochs with the highest accuracy was selected.
- Step 2: We trained the DNN using the three training subsets and the validation subset with the number of epochs defined in the previous step. We used the testing subset for calculating the accuracy of the classification. This step was repeated three times to reduce the influence of the DNN initialization.
- Step 3: Steps 1 and 2 were repeated for the distribution of the subsets in the rest of the rows of Fig. 3. The accuracy and the specificity vs. Sensitivity curves presented in this paper are the average of all experiments throughout the five different subset distributions.

4.1. Results on classifying between focal and non-focal EEG signals

Fig. 4 and Fig. 5 show accuracy (mean and standard deviation) and specificity vs. Sensitivity curves obtained for the first classification problem (distinguishing between focal and non-focal EEG signals) depending on the signal transform applied at the DNN input. They also show the results when combining all the transforms (labeled as ALL). In both datasets, the convolutional layers were able to extract better features from the raw signals and the EMD analysis. When combining all of

Table 1
Configuration details and number of parameters to train for all the layers considering an input with shape N = 1 x M = 178.

Layer	Output shape	Param #	Activation function	Other characteristics
Input	(-, N, M, 1)	–	–	–
Feature extraction				
Convolution 2D	(-, N, M, 32)	192	ReLU	# Filters = 32, Kernel size = 1 × 5, Strides = 1, Padding = 'same'
Max Pooling 2D	(-, 1, 59, 32)	–	–	Pool size = 3 × 3, Strides = None, Padding = 'valid'
Dropout	(-, 1, 59, 32)	–	–	Dropout = 0.2
Convolution 2D	(-, 1, 59, 32)	5152	ReLU	# Filters = 32, Kernel size = 1 × 5 x 32, Stride = 1, Padding = 'same'
Dropout	(-, 1, 59, 32)	–	–	Dropout = 0.2
Classification				
Flatten	(-, 1888)	–	–	
Full connected	(-, 128)	241792	ReLU	Units = 128, Kernel_initializer = 'glorot_uniform', Bias_initializer = 'zeros'
Dropout	(-, 128)	–	–	Dropout = 0.2
Full connected	(-, 32)	4128	ReLU	Units = 32, Kernel_initializer = 'glorot_uniform', Bias_initializer = 'zeros'
Dropout	(-, 32)	–	–	Dropout = 0.2
Full connected	(-, P)	33 x P	Sigmoid (P = 1) or Softmax (P > 1)	Units = P, Kernel_initializer = 'glorot_uniform', Bias_initializer = 'zeros'
Output	(-, P)	–	–	–

Table 2
N x M dimensions for the DNN inputs depending on the signal transform and dataset.

Signal transform	Bern-Barcelona EEG dataset	Epileptic Seizure Recognition dataset
RAW	N x M = 2 × 1024: 2 signals and 1024 samples (2 s at 512 Hz)	N x M = 1 × 178: 1 signal and 178 samples
EMD	N x M = 12 × 1024: 6 IMFs of 2 signals and 1024 samples (2 s at 512 Hz)	N x M = 6 × 178: 6 IMFs and 178 samples
WAVELET	N x M = 2 × 256: 2 signals and 256 wavelet coefficients	N x M = 1 × 256: 1 signal and 256 wavelet coefficients
FOURIER	N x M = 2 × 128: 2 signals and 128 points of the module of FFT	N x M = 1 × 128: 1 signals and 128 points of the module of FFT

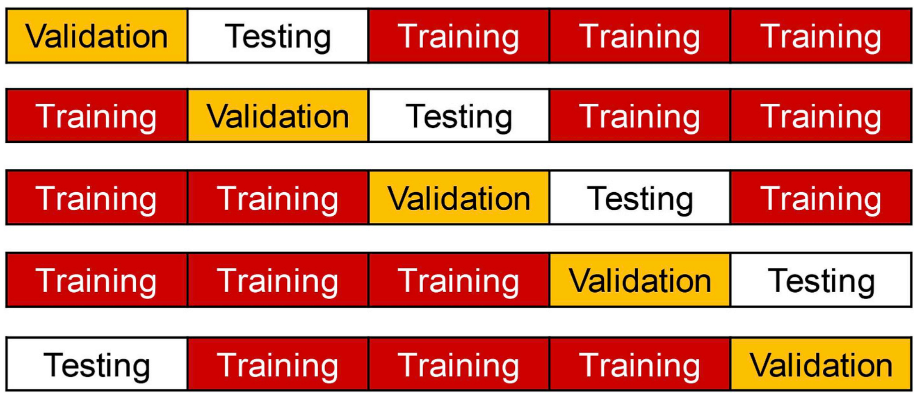

Fig. 3. Subset organization for the five-fold cross-validation approach.

the transforms, we obtained slightly better results but without significant differences. In the case of the Bern-Barcelona EEG dataset (left-hand side), we obtained accuracies higher than 95% in all experiments. When using the Epileptic Seizure Recognition dataset (the right-hand side in Figs. 4 and 5), the performance was considerable lower, obtaining accuracies around 70%.

4.2. Discussion of results on classifying between focal and non-focal EEG signals

By analyzing the intracranial EEG signals in the Bern-Barcelona EEG dataset, we observed a significant energy difference between focal and non-focal signals. Fig. 6 shows the average energy distribution throughout the different frequencies for the focal and non-focal signals in this dataset. Although, we cannot see different patterns throughout the frequencies, there is a consistent higher energy in the focal signals compared to the non-focal signals in all frequencies. This big difference facilitates the classification.

The decrease in performance when using the Epileptic Seizure Recognition dataset was due to the different characteristics between both datasets. The Bern-Barcelona EEG dataset was recorded using intracranial sensors from only five patients, showing a consistent higher energy for focal signals. The Epileptic Seizure Recognition dataset includes recordings from 500 patients from surface electrodes that introduce a higher level of noise and a different frequency pattern compared to intracranial sensors. Fig. 7 shows the average energy distribution the different frequencies for the focal and non-focal signals in the Epileptic Seizure Recognition dataset. We can see a higher energy for the focal signals between 0 a 10 Hz but this difference is smaller than in the Bern-Barcelona EEG dataset.

4.3. Results on detecting epileptic seizures

Fig. 8 shows the accuracy (mean and standard deviation) obtained in the Epileptic Seizure Recognition dataset for the second classification problem addressed in this paper, seizure detection, differentiating the four scenarios described in section 3.2. We also show the results when combining all of the transforms (labeled as ALL). The Fourier transform was the best transform in the four scenarios for seizure detection, obtaining similar results to the case of combining all of the transforms.

4.4. Discussion of results on detecting epileptic seizures

The significant better performance obtained when using the Fourier

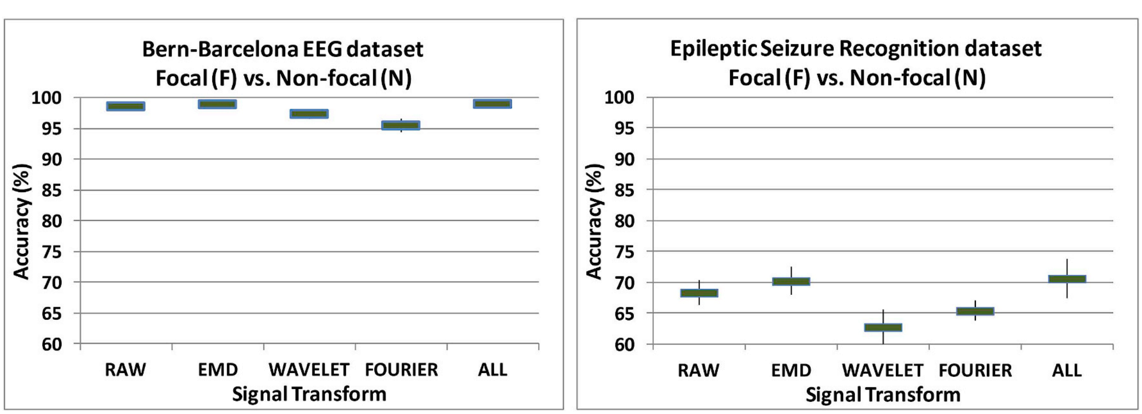

Fig. 4. Accuracy (mean and standard deviation) when classifying focal and non-focal signals for both datasets depending on the signal transform applied at the DNN input. The accuracy of a Zero Rule classifier is 50% (balanced distribution of examples in both datasets).

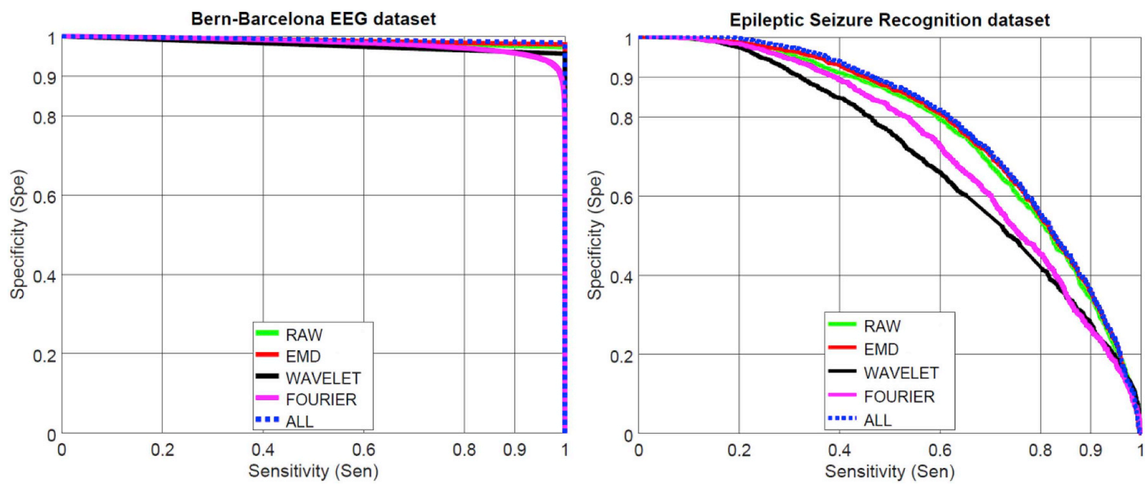

Fig. 5. Specificity vs. Sensitivity curves when classifying focal and non-focal signals for both datasets depending on the signal transform applied at the DNN input.

transform is due to the big difference in the energy distribution throughout the frequencies observed in the ictal (S) recordings compared to the other classes (Fig. 9). Ictal recordings show a higher energy in all frequencies of between 0 and 40 Hz with a marked peak of energy at around 6 Hz. When including ictal (S) signals in the classification tasks, the Fourier transform reported the best results. The wavelet transform also obtained better results than RAW or EMD but worse than Fourier. This is because when dealing with signal segments, the maximum resolution in the frequency domain is obtained by computing the Fourier transform throughout the whole segment. The Wavelet transform carries out a time-frequency analysis with different resolutions. This analysis can be robust in some applications but in these experiments the Fourier transform showed a better performance.

Table 3 includes confusion matrices for seizure detection including the focal and non-focal signals. The non-focal signals in epileptic patients showed a higher confusion with the signals from healthy people (Z) than with seizure signals (S, ictal): 7.3% vs. 0.7%. But, when considering the focal signals from epileptic patients, the confusion with the seizure signals (S, ictal) increased (3.0%) similar to the confusion with healthy signals (4.1%).

4.5. Comparison with previous studies

Table 4 compares our results with previous works for the task of classifying the focal and non-focal signals in the Bern-Barcelona EEG dataset (Fasil and Rajesh [17], Sriraam and Raghu [18] and Sharma et al. [46]). Sharma et al. [46] proposed the use of several entropy features (Shannon entropy, Renyi entropy, approximate entropy, sample entropy and phase entropies) extracted from 10 IMFs (EMD analysis) and selecting 13 main characteristics. After feature extraction, they used a Least Squares SVM classifier, reporting an accuracy of 87.0%. Fasil and Rajesh [17] analyzed different features from several types of entropy and different energy-based metrics. They used SVMs for classification obtaining an accuracy of 89.0%. These works have several limitations; the first being the amount of data used in the experiments. These two previous works [17,46] used only a subset of the original dataset, reducing the data to train the classifier considerably. The second aspect is the use of an SVM using a linear kernel [17]. Non-linear kernels can improve the performance in complex classification problems. These two aspects were improved by Sriraam and Raghu [18]. They used the whole dataset and evaluated several non-linear kernels for an SVM classifier, obtaining the best results with the quadratic kernel. Sriraam and Raghu used 26 different features from time and frequency domains including mean, median frequency, root mean square, entropy, zero crossing, quartiles, skewness, kurtosis, first and second derivatives of mean, variance and standard deviation. The most significant features were selected from these metrics using the Wilcoxon rank sum test by setting a p-value of $< 0.05\%$ and a z-score at a 95% significance level. They reported an accuracy of 92.15%. All of these studies analyzed hand-crafted features, but deep learning algorithms have demonstrated a better performance not only for classification but also for feature extraction from time or frequency domains.

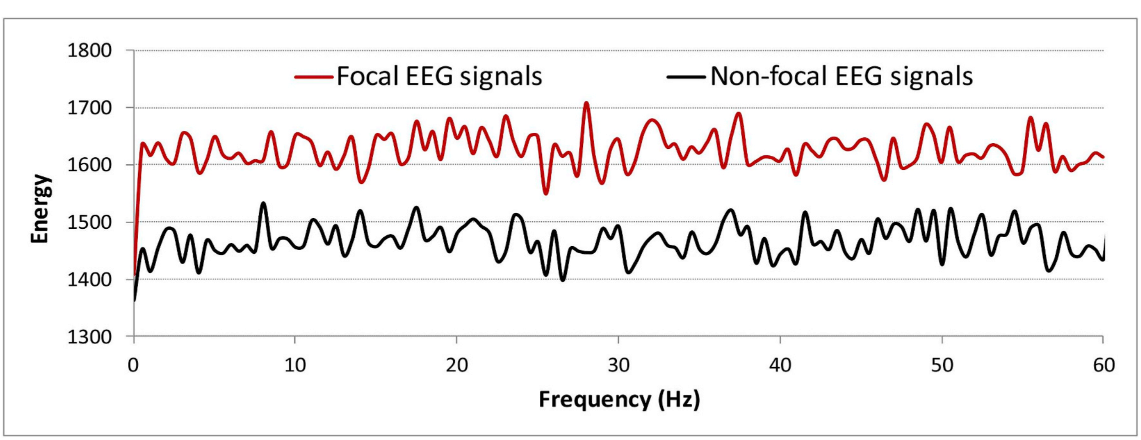

Fig. 6. Average energy distribution throughout the different frequencies for the focal and non-focal signals in the Bern-Barcelona EEG dataset.

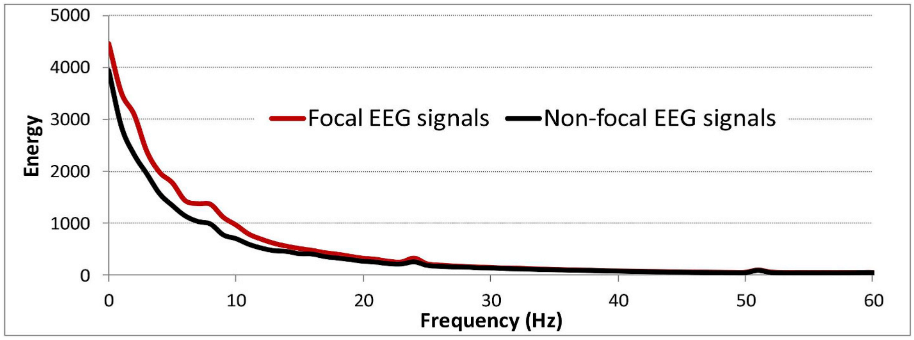

Fig. 7. Average energy distribution throughout the different frequencies for the focal and non-focal signals in the Epileptic Seizure Recognition dataset.

In this paper, we analyzed the use of a DNN including several convolutional layers for feature extraction. The results obtained in this paper significantly improved the accuracy reported in previous works for all of the signal transforms studied. Table 4 also shows the confidence intervals of the accuracy with 95% confidence. These confidence intervals were computed using equation (2) [56], where ACC is the accuracy as a percentage, and N is the number of examples used to test the DNN. These confidence intervals help us to determine whether the two experiments were significantly different (no overlap between confidence intervals).

$$ACC\ (95\%) = ACC\ \pm 1.96\sqrt{\frac{ACC\ \cdot(100 - ACC\ )}{N}} \quad \text{(Equ.2)}$$

Table 5 compares the results obtained in this paper with other previous studies using the Epileptic Seizure Recognition dataset for seizure detection only (considering the four scenarios described in section 3.2). We do not provide a comparison in the focal vs. non-focal classification task because we did not find any previous work addressing this task with this dataset. Wang et al. [45] provided a very interesting analysis comparing several classifiers and obtaining the best accuracy of 99.0% using a radial basis function (RBF), kernel-based

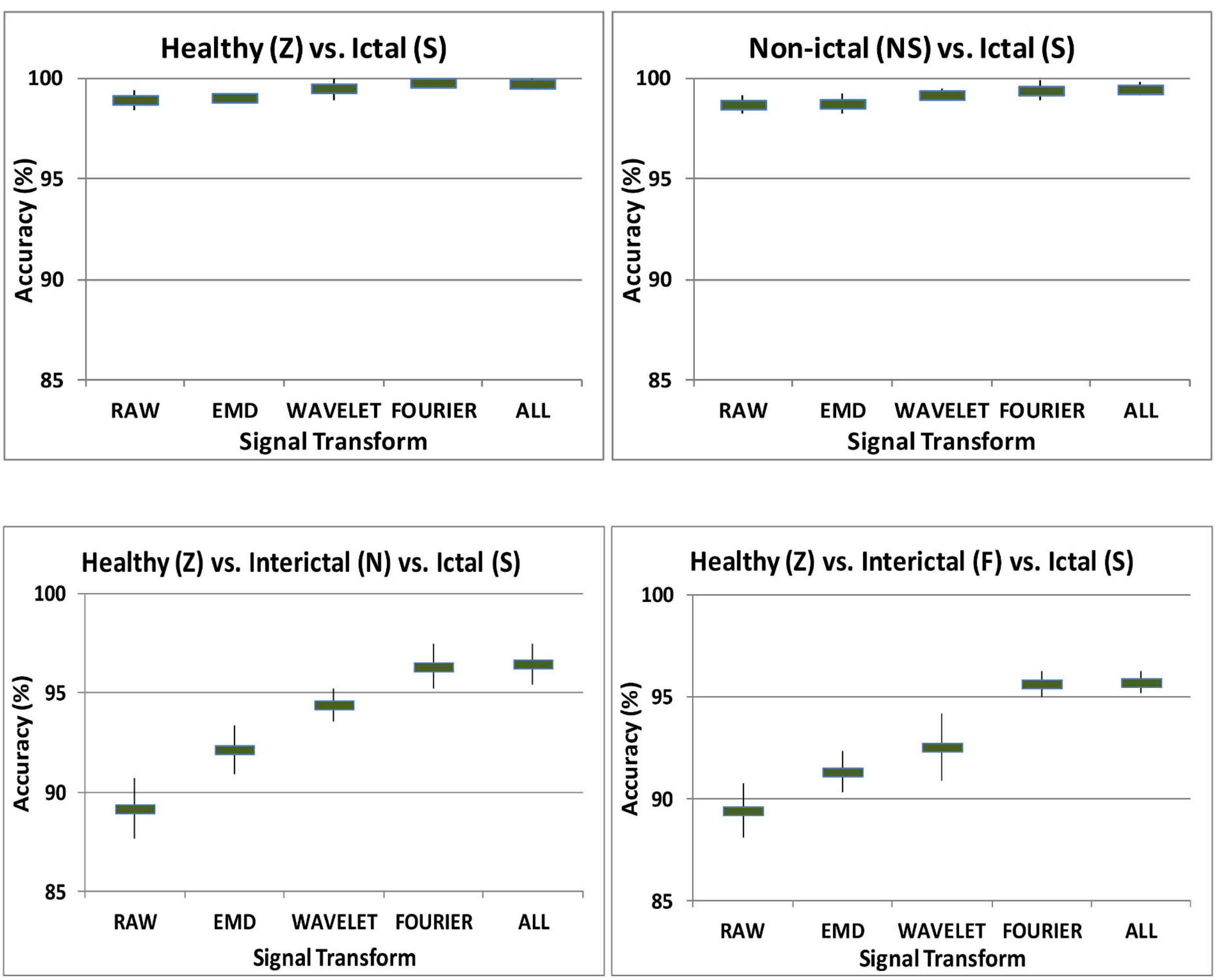

Fig. 8. Accuracy (mean and standard deviation) for the three classification tasks defined in previous studies with the Epileptic Seizure Recognition dataset. The accuracy of a Zero Rule classifier is 50% for Z vs. S, 80% for NS vs. S and 33% when considering three classes with the same number of examples per class.

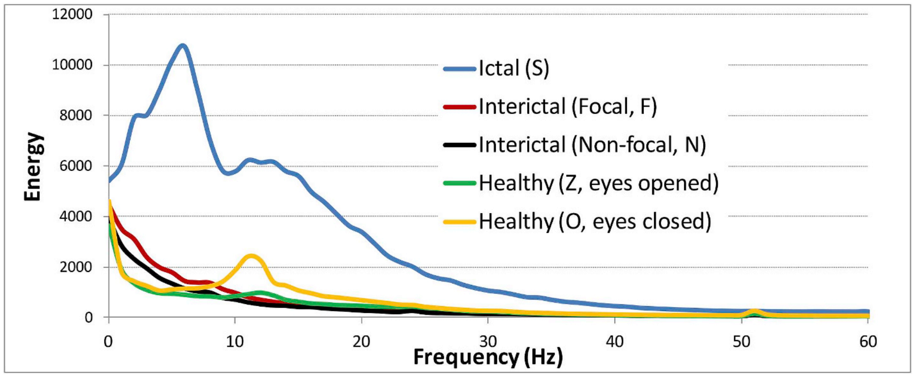

Fig. 9. Average energy distribution throughout the different classes in the Epileptic Seizure Recognition dataset.

Table 3
Confusion matrices for seizure detection including the non-focal (first part of the table) and focal (second part of the table) signals.

	Predicted labels		
Actual Labels	Healthy (Z)	Interictal (N)	Ictal (S)
Healthy (Z)	99.0%	1.0%	0.0%
Interictal (N)	7.3%	92.0%	0.7%
Ictal (S)	0.2%	1.4%	98.3%

	Predicted labels		
Actual Labels	Healthy (Z)	Interictal (F)	Ictal (S)
Healthy (Z)	97.6%	2.4%	0.0%
Interictal (F)	4.1%	92.8%	3.0%
Ictal (S)	0.2%	3.0%	96.8%

Table 4
Accuracy comparison with previous works using the Bern-Barcelona dataset.

System		Focal (F) vs. Non-focal (N) EEG signals
Entropy features from 10 IMFs + least squared SVM [46]		87.0 ± 0.26%
Entropy and energy metrics + linear SVM [17]		89.0 ± 0.24%
Feature selection from time and frequency domain + Quadratic SVM [18]		92.2 ± 0.21%
This paper	**Fourier transform + DNN**	95.5 ± 0.16%
	Wavelet transform + DNN	97.4 ± 0.12%
	Raw data + DNN	98.6 ± 0.09%
	6 IMFs from EMD + DNN	**98.9** ± 0.08%
	All transforms + DNN	**98.9** ± 0.08%

SVM (RBF-SVM) algorithm when classifying seizure (S) and non-seizure (Z, O, N and F) recordings. Wang et al. extracted 83 features from various domains (time, frequency, time-frequency and EMD- Phase Space Reconstruction) and they used a PCA to reduce the feature vector to 14 components. Kumar et al. [47] used histograms of the one-dimensional local binary pattern (1D-LBP) and a kNN classifier, achieving a lower accuracy (98.33%) in the same scenario. Wang et al. also reported lower accuracy in this dataset when using a kNN classifier. Abualsaud et al. [48] used the sixth order Daubechies wavelet transform for feature extraction and evaluated several classification algorithms for classifying Healthy (Z), Interictal (N) and Ictal (S) signals. They proposed a noise-aware signal combination ensemble classifier that combines four classification models reporting an accuracy of 90.0%. Sadati et al. [49] compared several traditional classifiers obtaining the best results when using an adaptive neural fuzzy network. They reported an accuracy of 85.9% when classifying Healthy (Z), Interictal (F) and Ictal (S) signals. Sadati et al. used the wavelet transform for feature extraction. None of these previous works used a deep learning algorithm on this dataset. This paper deals with this lack of analysis in evaluating a DNN with several signal transforms. The results obtained in our paper significantly improve the accuracy obtained in previous works. Unlike the results obtained using the Bern Barcelona EEG dataset, in this case, we did not improve the previous results independently of the signal transform. The Epileptic Seizure Recognition dataset has seven times fewer examples than the Bern Barcelona EEG dataset, so the improvement achieved thanks to the deep learning algorithm is less relevant with a smaller amount of data for training.

5. Conclusions

In the accurate detection of epileptic brain areas and epileptic seizures from EEG signals, it is very important to design focused therapies

Table 5
Accuracy comparison with previous works using the Epileptic Seizure Recognition dataset.

System		Healthy(Z) vs. Ictal (S)	Non-Ictal (NS) vs. Ictal (S)	Healthy (Z) vs. Interictal (N) vs. Ictal (S)	Healthy (Z) vs. Interictal (F) vs. Ictal (S)
Wavelets + adaptive neural fuzzy network [49]		–	–	–	86.0 ± 0.82%
Wavelets + noise-aware signal combination ensemble classifier [48]		–	–	90.0 ± 0.71%	–
Histograms of the one-dimensional local binary pattern (1D-LBP) + a kNN classifier [47]		–	98.3 ± 0.24%	–	–
Features from time and frequency domains + radial basis function (RBF) kernel-based SVM [45]		–	99.0 ± 0.15%	–	–
Entropy and energy metrics + linear SVM [17]		99.5 ± 0.20%		91.7 ± 0.65%	89.0 ± 0.74%
This paper	**Raw data + DNN**	99.0 ± 0.29%	98.8 ± 0.20%	89.2 ± 0.73%	89.4 ± 0.73%
	6 IMFs from EMD + DNN	99.1 ± 0.27%	98.8 ± 0.20%	92.1 ± 0.64%	91.3 ± 0.67%
	Wavelet transform + DNN	99.5 ± 0.20%	99.2 ± 0.16%	94.4 ± 0.54%	92.5 ± 0.62%
	Fourier transform + DNN	**99.8** ± **0.13%**	**99.4** ± **0.14%**	**96.3** ± **0.45%**	**95.6** ± **0.48%**
	All transforms + DNN	**99.8** ± **0.13%**	**99.5** ± **0.13%**	**96.5** ± **0.44%**	**95.7** ± **0.48%**

adapted to each patient and their seizure patterns. The main contributions of this paper lies on the analysis of a DNN for epileptic EEG signal classification and the evaluation of several signal transforms to generate the inputs to the DNN. The deep learning architecture evaluated was made up of two convolution layers for feature extraction and three fully connected layers for classification. As regards the signal transforms, we analyzed Fourier, wavelet and EMD transforms. This analysis was carried out using two public datasets obtaining significant improvements in epileptic EEG signal classification and seizure detection compared to previous works. For the Bern-Barcelona EEG dataset, we obtained an improvement in accuracy from 92.2% to 98.9% for the focal vs. non-focal signal classification. For the Epileptic Seizure Recognition dataset, the accuracy for seizure detection increased from 99.0% to 99.5% when considering non-seizure (non-ictal) and seizure (ictal) recordings, from 91.7% to 96.5%, when using healthy, non-focal (from the hippocampal location) and seizure signals, and from 89.05 to 95.7% when distinguishing between healthy, focal (from the epileptogenic zone) and seizure recordings. Using the raw data (without any transform) or EMD gave the best results for the focal vs. non-focal signal classification due to the energy difference between both types of signal. The Fourier transform performed the best for seizure detection because seizure signals showed a different pattern in the energy distribution throughout the frequencies compared to the rest of the signals. When combining all transforms, we obtained slightly better results but not statistically different from the best result obtained using individual transforms.

Conflicts of interest

Authors have no conflict of interest to declare.

Acknowledgements

The work leading to these results has been supported by AMIC (MINECO, TIN2017-85854-C4-4-R), and CAVIAR (MINECO, TEC2017-84593-C2-1-R) projects. We gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan X Pascal GPU used for this research.

Authors also thank Mark Hallett for the English revision of this paper.

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