

APRENDIZAGEM COMPUTACIONAL

DEPARTAMENTO DE ENGENHARIA INFORMÁTICA

UNIVERSIDADE DE COIMBRA

Prediction and detection of epileptic seizures



Autores:
João Costa
Miguel Fernandes

Professor:
Prof. António Dourado

Contents

1	Abstract	2
2	Introduction	2
3	Dataset Description	2
4	Pre-processing Dataset	3
5	Used formulas	3
6	Neural Networks used	4
6.1	Feed Foward	4
6.2	Recurrent	4
6.3	LSTM	5
6.4	CNN	5
7	Results	6
8	Conclusion	8

1 Abstract

Training neural networks with the goal of predicting and detecting epilepsy crises in the exploration of brain signals is the main focus of the project. We used different types of neural networks (Feed Forward, Layer Recurrent, LSTM and CNN) with the objective of comparing the performances of each in different conditions.

2 Introduction

Many people around the world are affected by epilepsy, just in Portugal there are nearly 100,000 cases, which represents 1% of the total population. An attack can occur at any moment, it can go from a few seconds to several minutes, affecting many parts of the brain. Nowadays, with the help of EEG, the possibility of predicting or detecting an epilepsy attack becomes a research challenge. If it would be possible to develop an algorithm to detect on time a seizure, new strategies for disarming the seizure could eventually be developed. On the other side seizure prediction would allow the patient to take action for his/her own safety and social exposition during the seizure. As a starting point we collected EEG of patients at the previous, during, post and between seizures.

3 Dataset Description

In this project the set of features to be used exploit the different frequency bands of the electrical signals, and have been extracted by Doctor Mojtaba Bandarabadi, during his PhD studies in our Department. They refer to one EEG invasive channel placed in the epileptic focus (the place in the brain where the seizure starts). The characteristics were extracted using 2 seconds segments of EEG with 50% overlap. In practical terms each second a vector with 29 frequency bands is obtained. Because of this, we obtain a matrix where the columns represent extracted characteristics and the rows a vector of characteristics. Each value of this vector represents different states:

- 0, representing a non-ictal state. This means that contains interictal, pre-ictal and post-ictal states
- 1, represents only the ictal state. This means that a seizure is happening.

Each group of students were given two patients to analyze (two databases), and in our case, they had these characteristics:

Table 1: Datasets

ID	Number of crisis	Dataset duration	Average crisis duration
54082	31	142	118.4
112502	14	155	122.7

4 Pre-processing Dataset

In order to predict the crises we had to divide the target matrix, that only has two states (non-ictal and ictal), into four states. For this we consider that 10 minutes (equivalent to 600 points) before each crisis as a state of Pre-Ictal "state in which the crisis is about to happen" and 5 minutes after the end of each crisis (equivalent to 300 points) as one state of Post-Ictal state in which the crisis has just happened". The remaining points at 0 are now represented as Inter-Ictal state "normal patient state" and points at 1 remain as Ictal state "state in which the patient is having a crisis." With this breakdown we have obtained a new target matrix with the following possible columns:

- Inter-Ictal state, (1,0,0,0)
- Pre-ictal state, (0,1,0,0)
- Ictal state, (0,0,1,0)
- Pos-Ictal state, (0,0,0,1)

For the CNN was prepared a 29x29 matrix based on the dataset, with a respective target.

5 Used formulas

The performance of the classifier is calculated through three main formulas given by the professor.

1. Sensivity(SE), representing how many real crises were predicted or detected.

$$SE = \frac{TruePositives}{TruePositives - FalseNegatives} \quad (1)$$

2. Specificity (SP), how many false crises were predicted or detected

$$SP = \frac{TrueNegatives}{TrueNegatives - FalsePositives} \quad (2)$$

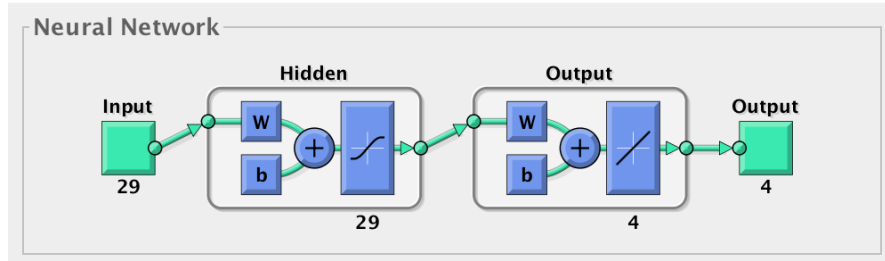
3. Precision(AC), the proportion of correct states.

$$AC = \frac{True}{True - False} \quad (3)$$

6 Neural Networks used

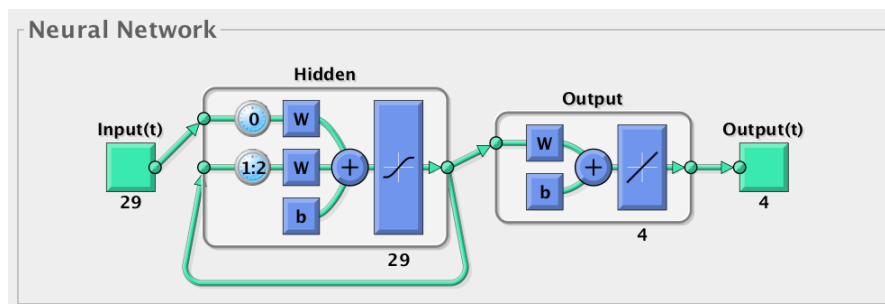
6.1 Feed Foward

The feed forward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. This means that each next layer has the connection to the previous layer. The last layer produces the output of the neural network.



6.2 Recurrent

Similar to the previous one with the exception that each layer has a recurring connection with an associated delay. This allows an infinite dynamic response to the time series input data.



6.3 LSTM

Long short-term memory (LSTM) networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the exploding and vanishing gradient problems that can be encountered when training traditional Recurrent networks. The implemented LSTM has a sequence input layer with 29 features followed by a LSTM layer with 290 hidden units, in which the output mode is a sequence. After this one, we have another LSTM layer with a 174 hidden units. It has a fully connect layer with 4 outputs, because of the number of classes, followed next by a soft max layer and a classification layer.

6.4 CNN

Convolutional neural network (CNNs) use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. The implemented Cnn has a convolutional layer with a pool size of 5x5, having 29 filters, with padding of 2, followed by a max pooling layer with a pool size 3x3 and stride of 2 and a relulayer. The second convolutional layer has the same pool size, padding and filters of the previous one, and its followed by a relulayer and a average pooling layer with a pool size of 3x3 and a stride of 2. The third convolutional layer also has 5x5 pool size, 2 padding, but has 58 filters, followed by a relulayer and a average pooling layer with 2x2 pool size and a stride of 2. Then we have a fully connect layer with 58 outputs, also followed by a relulayer and another fully connect layer with 4 outputs, this because the number of outputs must be equal to the number of classes of the dataset, followed by a soft mat layer and a classification layer.

7 Results

For this experimentation we used Matlab, on which we implemented several scripts to modify the selected database. The class balancing will make sure that the number of points of different states will be the same of Ictal points, for example, if we have a 100 points Ictal points then the Inter-Ictal, Pre-Ictal and Pos-Ictal have 100 points each. To see the performance of neural networks, were made several tests with training 70%, testing 30% and were analyzed the following attributes:

- SE, sensivity
- SP, specifity
- PIA, pre-ictal accuracy
- IA, Ictal accuracy
- AC, General accuracy

Table 2: Feed Foward

TrainingFunc	SE	SP	PIA	IA	AC
traincgp	22%	82%	0%	25%	66%
traincgp	24%	77%	0%	30%	61%
traincgp	27%	81%	0%	27%	65%
traincgp	27%	83%	0%	24%	67%
traincgp	28%	80%	0%	29%	64%
traincgp	28%	81%	0%	27%	65%
trainscg	31%	80%	0%	30%	64%
trainscg	32%	78%	0%	30%	62%
trainscg	32%	80%	0%	29%	65%
traincgb	10%	78%	3%	24%	57%
traincgb	23 %	71%	13%	26%	31%
traincgb	8%	77%	1%	27%	44%
traincgb	8%	78%	2%	26%	52%
traincgb	9%	77%	1%	28%	45%

Table 3: Recurrent

SE	SP	PIA	IA	AC
36%	74%	0%	35%	55%
33%	78%	0%	31%	62%
31%	83%	0%	28%	68%
28%	80%	0%	29%	64%
27%	83%	0%	26%	68%
24%	84%	0%	24%	69%
23%	83%	0%	25%	68%
19%	85%	0%	25%	70%
25%	79%	0%	28%	63%
19%	82%	0%	24%	67%
33%	78%	0%	31%	62%

Table 4: CNN

SE	SP	PIA	IA	AC
77%	57%	50%	76%	25%
75%	60%	52%	76%	32%
58%	61%	33%	76%	33%
82%	58%	39%	76%	26%
68%	60%	42%	88%	32%
64%	60%	31%	88%	31%
61%	57%	30%	82%	24%
61%	60%	39%	76%	32%
53%	60%	31%	82%	31%
77%	57%	50%	76%	25%
58 %	61%	33%	76%	33%

Table 5: LSTM

SE	SP	PIA	IA	AC
67%	58%	34%	82%	25%
69%	57%	37%	96%	24%
62%	58%	31%	96%	22%
74%	62%	36%	91%	35%
64%	61%	43%	85%	32%
59%	61%	29%	85%	32%
58%	62%	30%	89%	31%
54%	64%	28%	78%	39%
52%	60%	32%	89%	30%
50%	62%	20%	89%	37%
44%	63%	20%	75%	34%

8 Conclusion

The best Neural Network was made with 54802.mat, and the possible reason is that it's the dataset with the most Ictal phases. The other patient had very bad results because of the low number of seizures. Was verified that the dataset set treatment is very important, and also, for having a good classifier we must have a long dataset, to provide the best results possible. Its really hard having good results for the prediction and detection of epileptic seizures. As we can see in the results provided the best neural networks are CNN and LSTM. In terms of sensivity the highest values appear on CNN (Table 2), with a maximum value of 82 %, and an average of 65%; this neural network also presents the best values in terms of prediction(pre-ictal accuracy). In detecting seizures (ictal accuracy) LSTM is the one with the highest values, reaching a maximum efectiveness of 96 %. Finally the best way to predict and detect a seizure is to make sure that the Neural Network used was trained with the same type of seizure as the patient in question.