NEURAL NETWORKS FOR THE DIAGNOSIS OF EPILEPTIC SEIZURES

Katherine Robles Martínez de la Vega

Cognitive Systems: Theory and Models: CSIM

Universitat Pompeu Fabra

ABSTRACT

Epilepsy is a common disease that, according to the World Health Organization, affects around 50 million people of any age around the world. It is characterized by epileptic seizures that are debilitating and disrupt daily living causing a severe feeling of helplessness in the patient. But epileptic seizures are hard to predict. Electroencephalogram (EEG) has become an effective diagnostic tool for epilepsy and the subsequent epileptic seizures. So through a visual analysis of an EEG chart, a specialist can identify seizures, their duration and the place where it manifests, but this method is time-consuming due to the length of EEG recordings and the manual task. Previous researches have shown successful results of ANN as classification systems to differentiate automatically the existence or not of ES in EEG signals. In this project it is proposed the implementation of machine learning based on MLP using the *Backpropagation* algorithm to be able to classify and identify EEG recordings showing or not epileptic seizures from EEG signals. The dataset used was obtained from the Department of Epileptology of the University of Bonn and consisted of subsets of EEG recordings from healthy volunteers with closed and opened eyes, as well as intracranial EEG recordings from epilepsy patients during the seizure free interval and during ictal period. Two models were implemented with the difference that in the second model, the cross-validations method was used. Results showed that both models worked well as classifiers. The model that used the Cross-validation method showed better results.

KEYWORDS: epilepsy; electroencephalography; classification; neural networks; data preprocessing

1. INTRODUCTION

According to the World Health Organization (WHO) (2019), epilepsy is a neurological disorder that affects around 50 million people of any age worldwide. It is characterized by recurrent seizures that are debilitating and disrupt the day-to-day activities, and are associated with an increased risk of premature mortality, as suggested by Rasheed et al., (2021). Seizures can vary from the briefest lapses of attention or muscle jerks to severe and prolonged convulsions (WHO, 2019). However, not all seizures are epileptic since convulsions and seizures may also occur due other neurological diseases such as stroke or brain trauma (Rasheed et al., 2021).

An epileptic seizure (ES) is a result of a sudden abnormal excessive electrical discharge in a group of brain cells and usually lasts for less than a few minutes (Rasheed et al., 2021). Apart from the risk of serious injury, ES consequences depend on the place in the brain when it happens and the case of each individual. Nevertheless, there is often a severe feeling of helplessness that has a strong impact on the everyday life of the patient (Mormann et al., 2005).

But ES are hard to predict as well as its severity and duration which cannot be anticipated (Rasheed et al., 2021). In spite of that, there is evidence (Litt & Echauz, 2002) of long digital intracranial electroencephalographic (EEG) recordings from patients being evaluated for epilepsy surgery that ES develop minutes to hours before the ictal period. These findings mean that an ES can be predicted and anticipated in order to control and even avoid it (Litt & Echauz, 2002). Hence, developing a method capable of early predicting of ES would significantly improve the therapeutic possibilities and the individual's quality of life counteracting its adverse consequences.

The main method used in epilepsy diagnosis is EEG as an effective diagnostic tool to study the functional anatomy of the brain during an ES. EEG signals, that are non-linear, measure the electrical activity in the brain. A trained specialist can identify seizures and its features (when it begins and ends or where it manifests) through a visual analysis of an EEG chart. However this method is time-consuming due to the length of EEG recordings and the fact that the specialist has to analyze it manually (Costa et al., 2008).

The analysis of EEG data allows the detection, classification and prediction of ES (Delgado, Ledesma, & Rostro, 2019). Following this line, the usage of Artificial Intelligence (AI) techniques is helpful for the treatment of

EEG recordings. In fact, in ES detection, one of the most interesting methods is the development of Artificial Neural Networks (ANN) as classifiers to detect automatically and successfully ES from EEG signals (Costa et al., 2008). ANN allow the treatment of non-linear data and can establish complex relations between variables, contributing models with classification properties and pattern recognition depending on data structure and parameters to consider (Delgado et al., 2019).

Some researches (Guo et al., 2010; Srinivasan et al., 2007; Costa et al., 2008; and) have proposed ANN as classification systems to differentiate automatically the existence or not of ES in EEG signals, showing successful results. Especially the studies conducted by Özkan et al. (2016) and Çetin et al. (2015), demonstrate the effectiveness of ANN in the classification of EEG signals through real datasets.

In this project it is proposed an automatic classification system for epilepsy based on supervised training of an ANN with *Backpropagation* algorithm, as suggested by the research line explained above. The aim is to implement a method to support the clinic diagnosis developing a model that can solve the problem of classification of EEG recordings in two groups: non-ES and ES, to do the diagnostic faster and more efficiently, in order to build in future research a prediction system of ES to minimize the impact and improve quality of life.

2. METHODS

For this study, the dataset was obtained from the study conducted by Andrzejak et al. (2001) in the Department of Epileptology of the University of Bonn. And the model was implemented in the Google Colaboratory platform. It was necessary some preprocessing of data before training the model. The following is the methodology described in more detail.

2.2 Data selection

The dataset has been obtained from the Department of Epileptology of the University of Bonn in Germany. The dataset consists of five sets (denoted A–E) each one containing 100 single channel EEG segments of 23.6-sec duration. These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts (e.g., due to muscle activity or eye movements) (Andrzejak et al., 2001). EEG recordings were carried out on five healthy volunteers using a standardized electrode placement scheme (image 1). Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from an EEG archive of pre-surgical diagnosis of epilepsy patients, where intracranial electrodes were implanted (image 2). Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain, both sets were recorded during seizure free intervals. But only set E contained seizure activity from all recording sites exhibiting ictal activity.

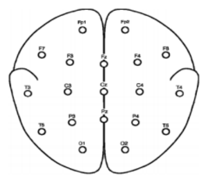

Image 1. Standardized electrode placement scheme (taken from Andrzejak et al.., 2001)

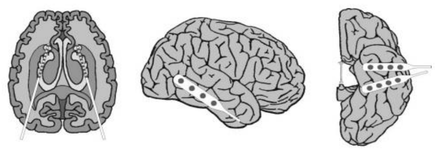

Image 2. Scheme of intracranial electrodes implanted for pre-surgical evaluation of epilepsy patients (taken from Andrzejak et al.., 2001)

According to Andrzejak et al. (2001), all EEG signals were recorded with the same 128-channel amplifier system, using an average common reference [omitting electrodes containing pathological activity (C, D, and E) or strong eye movement artifacts (A and B)]. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. The next image shows recording examples of each set:

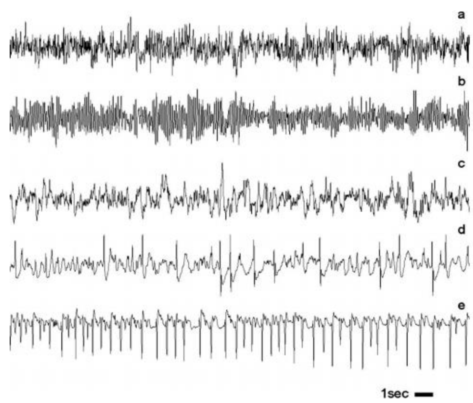

Image 3. Examples of recordings of each set (A-E) (taken from Andrzejak et al.., 2001)

Each data set counts with 100 *.txt extension files with 4097 data. In order to do the processing of the signals it is required to create a matrix that will allow the realization of classifying each class mentioned before.

2.3 Data pre-processing

Data must be pre-processed prior to being used to train and evaluate both models. The steps are importing data and visualizing, filtering, transforming from a temporal domain to a frequency domain, splitting data for training, validation and testing, and cross-validation. All of these steps are detailed below:

First, it is necessary to import the data and visualize it in a data frame, which is useful to see the data in organized columns and the amount of data available to work with. In this case, each column represents a segment of an EEG recording. The next image shows examples of EGG recordings from a patient. The first one shows a normal signal (non-ES) whereas the second one shows the ictal period.

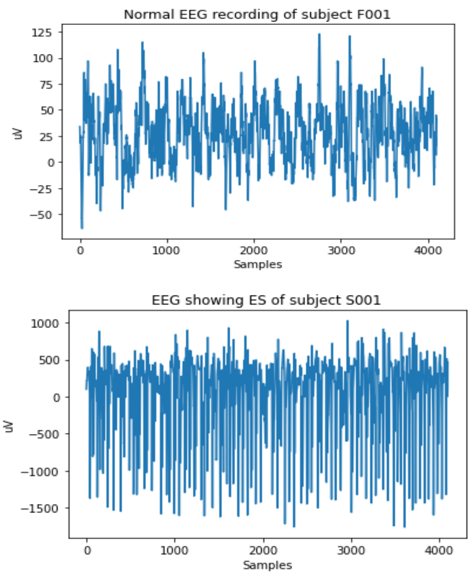

Image 4. Examples of EEG recordings of non-ES and ES. Both signals are from the same patient. The name changes due to the signals are classified in different subsets.

Second, the filter *band-pass* is applied to clean noisy signals that could disturb the model's performance. The filter will isolate frequencies that lie within the band or range between 0.5 and 40 Hz. Also, it is necessary to specify the grade in which the slope will start to ascend and descend in the curve, 3dB and 20 dB respectively.

Third, since Power Spectral analysis is a well-established method for the analysis of EEG signals, Power Spectral Density (PSD) is applied to each EEG segment in order to measure the signal's power content into frequency. This is a way to transform the data from temporal domain to frequency domain. So it is possible to see the amplitude in which an amount of frequency of neurons is acting.

The next image shows how the EEG signal of a patient is before and after the filter is applied.

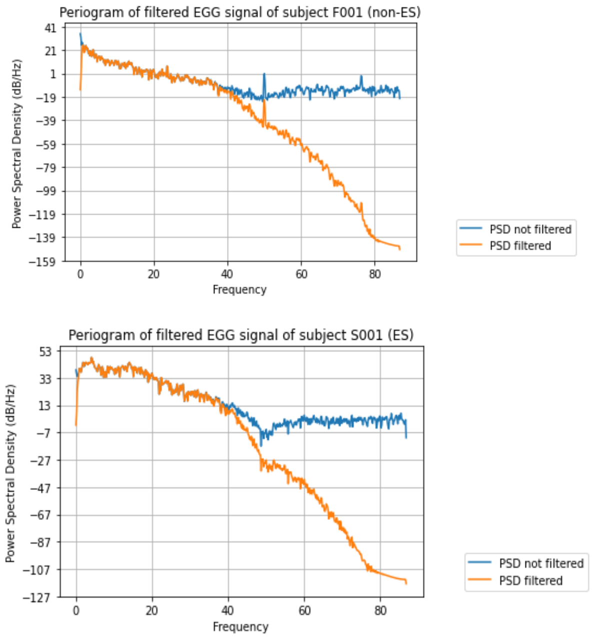

Image 5. Examples of EEG signals from only one patient before and after filter

2 data frames are obtained with 100 columns each one corresponding to the 100 segments of EEG signals, the first of the non-ES group (D) and the second one of the ES group (E). Here, periograms are presented after the filters applied to the data.

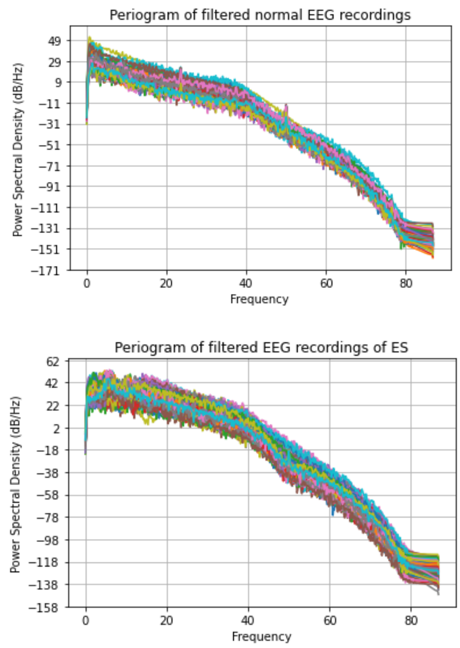

Image 6. Periograms showing all filtered signals of both subsets: non-ES and ES

It is required to turn into rows the data shown in columns previously since the ANN analyzes the rows. Here, both data frames created above are joined in order to create a single data frame in such a way the final data frame will have 200 rows with 513 values as columns.

Four, it is necessary to split the data of D and E datasets into subsets for training (80 from D subset and 80 from E subset), evaluation/validation (15 from D subset and 15 from E subset), testing (5 from D subset and 5 from E subset) and for use the Cross-validation method (95 from D subset and 95 from E subset). So, 4 different subsets are obtained.

Five, the normalization step is very important in order for the model to relate all of the data and treat with them in the same way. Here, the data is transformed to data between 0 and 1.

Before training the model, it was required to designate the corresponding output label to each EEG signal, being that 0 means non-ES and 1 means ES.

2.4 Training

ANN get and process the knowledge through a learning algorithm. For this project, the Multilayer Perceptron (MLP) has been used to solve classification problems with the *Backpropagation* algorithm. MLP was created twice with the difference of that in the second one the objective was to use the k-fold Cross-validation method. Both of the models are the same, they were created with Keras and they have the same amount of layers as well as the same method to compile them.

Both MLP consisted of 1 input layer with 513 artificial neurons, 2 hidden layers with 16 and 8 artificial neurons respectively, and 1 output layer with 1 artificial neuron, the same amount of input layers. The input layer coordinates the EEG data that enters to the ANN, then, the data are distributed to the hidden layers where the main process occurs, and finally, the ANN returns something through the output layer.

To compile, the ‘binary_crossentropy’ loss was used since there are only two label classes (0: non-ES and 1: ES); the optimizer ‘adam’ is used by default; the ‘accuracy’ metric was reported, which will indicate the accuracy at the end of each training epoch.

In order to avoid the overfitting, it was necessary the ‘callbacks’, which means that although 2000 epochs in total have been described to train the model, if it reaches a high percentage of success and is repeated for 100 times in a row, then the training will have to stop.

To train the model, the arguments were the dataset, epochs, callbacks, batch_size and verbose. In the ‘batch_size’ part that refers to the number of samples that will be propagated through the network, the algorithm takes the first 40 samples from the training dataset and trains the network; next, it takes the second 40 samples and trains the network again. And it keeps doing that procedure until all samples have been propagated through the network. This is necessary since it requires less machine’s memory. And the ‘verbose’ is simply the mode that provides additional details about the training progress for each epoch, being that 0 will show nothing, is silent; 1 will show a progress bar ([=========]); and 2 will just mention the number of each epoch (e.g., Epoch 1/10).

The second MLP was created to use the Cross-validation method. Here, the difference was creating the model inside a function. Moreover, here 200 epochs were defined since the training takes 10 subsets of total data and trains them 200 times each one, in such a way the total of epochs would be 2000. Also, a random seed parameter was defined in order to ensure reproducible results, meaning that the data is divided in the same way every time the code is run.

2.5 Evaluation/Validation

To evaluate the first model, the subset obtained before for evaluation (PSD_eval) is needed, as well as the dataset of output labels for each EEG signal. Here, a percentage of accuracy is gotten. The model works at 93.33%.

For the second MLP, the model evaluation k-fold cross-validation is used. Cross-validation is a statistical method used to estimate the skill of a model, it provides sample data to train the model and also leaves sample data for validation (Rodriguez et al., 2009). The k refers to the number of groups that a given data sample is to be split into, in this case, 10 was the specific value for k, becoming 10-fold cross-validation, this means that the holdout method was repeated 10 times from which, every subset gets to be in a validation set exactly once and gets to be in the training set the remaining times. The error estimation is averaged over all 10 trials to get total effectiveness of the model. Here, the bias is reduced as the method is using most of the data for fitting as well as for validating. The model works at 98.42%.

2.6 Testing

The dataset (PSD_test) destined to testing both models was used to predict if each EEG signal is 0: non-ES or

1: ES. The models could predict all the signals perfectly, given an accuracy of 100%. of all data presented.

EEG 1	EEG 2	EEG 3	EEG 4	EEG 5	EEG 6	EEG 7	EEG 8	EEG 9	EEG 10
non-ES	non-ES	non-ES	non-ES	non-ES	ES	ES	ES	ES	ES

Image 7. The same resultant prediction in both models

4. DISCUSSION & CONCLUSION

Epilepsy is a common disorder since ancient times, affecting about 50 million people of any age worldwide. The main characteristic of epilepsy is the sudden seizures. A seizure is an abnormal electrical activity in the brain that expresses itself in motor, psychic, sensorial and sensitive manifestations most commonly associated with spasms. Apart from the risk of serious injury, ES consequences lead to a severe feeling of helplessness that has a strong impact on everyday life.

Previous researches have proposed ANN as classification systems to differentiate automatically the existence or not of ES in EEG signals, showing successful results.

This project proposed an automatic classification system for epilepsy based on MLP using the *Backpropagation* algorithm. The dataset was obtained from the study conducted by Andrzejak et al. (2001) in the Department of Epileptology of the University of Bonn. The classification method was implemented to diagnose EEG recordings with ES or non-ES.

Two models were developed with the only difference that, in the second one, the Cross-Validation method was used to evaluate it. It was expected that both models can classify efficiently a large amount of EEG signals to support the clinical diagnostic and do it faster. The results showed that it is possible to find a good classifier based on ANN, and showed better results in the second model evaluated with Cross-validation. So both models demonstrated an accuracy of 93.33% and 98.42% respectively.

In conclusion, the classification problem of EEG recordings has been successfully solved through MLP proving its efficacy to deal with non-linear data. After analyzing both models, it has shown that the Cross-validation method is more robust and complete than other ways to evaluate a model since it takes into account all data for training and validation.

5. LIMITATIONS AND FUTURE WORK

ANN as classifiers have a lot of potential since they can compute in real time a large amount of data. But this project used only one class of ANN and other ways to classify EEG recordings were not explored. So, further research is needed to find more elaborated ANN's classes and their appropriate training algorithms.

On the other hand, the dataset used to do this project has no continuous data recorded in time. Instead of that the subsets are well differentiated into normal recordings and recordings showing ES, which has been a limitation in order to achieve a better classification of the different periods (pre-ictal, during ictal, and post-ictal) of ES. So, for future research, the methodology presented in this work can be implemented in the same way but with different datasets recorded during time to analyze the different periods of an ES. The performance of the classifier has to intend to be used to give the patient an alarm of an approaching seizure.

Finally, since ANN act in real time, it would be possible to implement them in wearable devices, so patients could have more control of their sudden ES and improve substantially the quality of life. But more research is needed as well as the validation in large-scale of the efficacy of these devices.

BIBLIOGRAPHY

Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, *64*(6), 8. https://doi.org/10.1103/PhysRevE.64.061907

Çetin, G. D., Çetin, Ö., & Bozkurt, M. R. (2015). The detection of normal and epileptic EEG signals using ANN methods with matlab-based GUI. *International Journal of Computer Applications, 114*(12), 45-50.

Costa, R. P., Oliveira, P., Rodrigues, G., Leitão, B., & Dourado, A. (2008). Epileptic seizure classification using neural networks with 14 features. In Knowledge-Based Intelligent Information and Engineering Systems. In: Lovrek, I., Howlett, R. J., & Jain, L. C. (eds) *Knowledge-based Intelligent Information and Engineering Systems*, *5178*. 281-288. Springer: Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-85565-1_35

Delgado, K., Ledesma, S., & Rostro, H. (2019). Electroencephalogram analysis using artificial neural networks. *Acta Universitaria*, *29*, 1–24.

https://doi.org/10.15174/au.2019.1672

Guo, L., Rivero, D., Dorado, J., Rabuñal, J. R. & Pazos, A. (2010). An automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. *Journal of Neuroscience Methods, 191(1)*, 101-109. https://doi.org/10.1016/j.jneumeth.2010.05.020

Litt, B. & Echauz, J. (2002). Prediction of epileptic seizures. *The Lancet Neurology*, *1*(1), 22-30. https://doi.org/10.1016/S1474-4422(02)00003-0

Mormann, F., Kreuz, T., Rieke, C., Andrzejak, R. G., Kraskov, A., David, P., … Lehnertz, K. (2005). On the predictability of epileptic seizures. *Clinical Neurophysiology*, *116*(3), 569–587. https://doi.org/10.1016/j.clinph.2004.08.025

Özkan, C., Doğan, S., Kantar, T., Akşahin, M., & Erdamar, A. (2016). Detection of epilepsy disease from EEG signals with artificial neural networks. *24th Signal Processing and Communication Application Conference (SIU)*, 693-696. https://doi.org/10.1109/SIU.2016.7495834

Rasheed, K., Qayyum, A., Qadir, J., Sivathamboo, S., Kwan, P., Kuhlmann, L., … Razi, A. (2021). Machine Learning for Predicting Epileptic Seizures Using EEG Signals: A Review. *IEEE Reviews in Biomedical Engineering*, *14*, 139–155. https://doi.org/10.1109/RBME.2020.3008792

Rodriguez, J. D., Perez, A., & Lozano, J. A. (2009). Sensitivity analysis of k-fold cross validation in prediction error estimation. *IEEE transactions on pattern analysis and machine intelligence*, *32*(3), 569-575. https://doi.org/10.1109/TPAMI.2009.187

Srinivasan, V., Eswaran, C., & Sriraam, N. (2007). Approximate entropy-based epileptic EEG detection using artificial neural networks. *IEEE Transactions on Information Technology in Biomedicine, 11*(3). https://doi.org/10.1109/TITB.2006.884369

World Health Organization (WHO) (2019). *Epilepsy*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/epilepsy