Automated Brain Disorders Diagnosis through Deep Neural Networks

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Abstract

In most cases, the diagnosis of brain disorders such as epilepsy is slow and requires endless visits to doctors and EEG technicians. This project aims to automate brain disorder diagnosis by using Artificial Intelligence and deep learning. **Brain could have many disorders that can be detected by reading an Electroencephalography**. Using an EEG device and collecting the electrical signals directly from the brain with a non-invasive procedure gives significant information about its health. Classifying and detecting anomalies on these signals is what currently doctors do when reading an Electroencephalography. **With the right amount of data and the use of Artificial Intelligence, it could be possible to learn and classify these signals into groups like (i.e: anxiety, epilepsy spikes, etc)**. Then, a trained Neural Network to interpret those signals and identify evidence of a disorder to finally automate the detection and classification of those disorders found.

Introduction

This work explores the use of a supervised machine learning approach to automate the detection of specific disorders on the brain by reading the EEG signals. Primarily it focuses on a type of disorder called Epilepsy.

Epilepsy is a chronic disorder caused by an imbalance in the electrical activity of neurons in one or several areas of the brain. In most epilepsies, an anomaly in electrical activity can be observed thru EEG by registering spikes in the affected areas.

These spikes have a unique pattern that can be seen with the naked eye on an electroencephalogram (spikes or peaks are registered with some frequency associated in the amplitudes of the electrical signals recorded). These marks are indicators of the presence of the disorder.

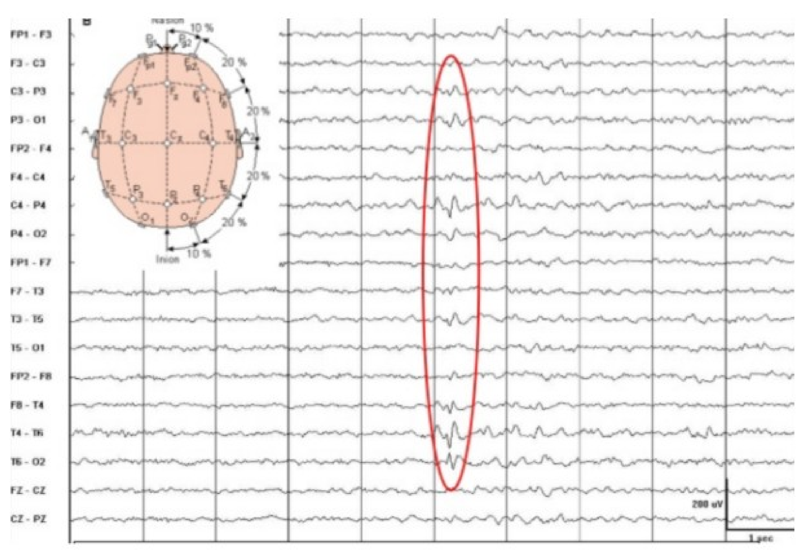

Figure 1. Representative abnormal EEG waveforms.

Patients carry this pattern of spikes almost all the time. In other hand, seizures or epileptic seizures are events of short duration, being the spikes the catalysts thereof. This anomalous brain activity generates an observable mark. That footprint can be learned through a deep neural network.

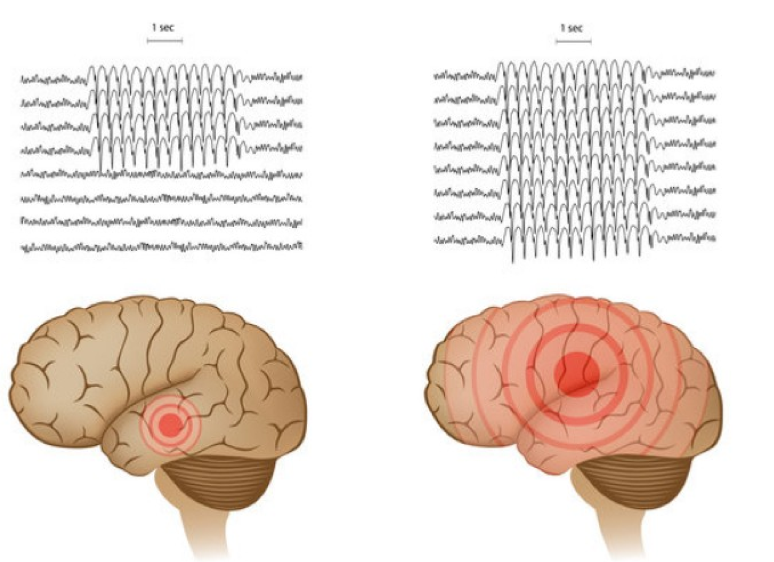

Figure 2. Partial and Generalized seizure

Dataset Processing

Data Set [1],[2] supported by 11500 measurements from a total of 500 individuals with each has 4097 data points for 23.5 seconds. Then divided and shuffled every 4097 data points into 23 chunks, each chunk contains 178 data points of 1 second, and each data point is the value of the EEG recording at a different point in time, 23 x 500 = 11500 pieces of information(rows), each information contains 178 data points for 1 second(columns), the last column represents the labels, zero represent non-epilepsy seizure and one epilepsy seizure.

Feature scaling method called standardization has been applied.

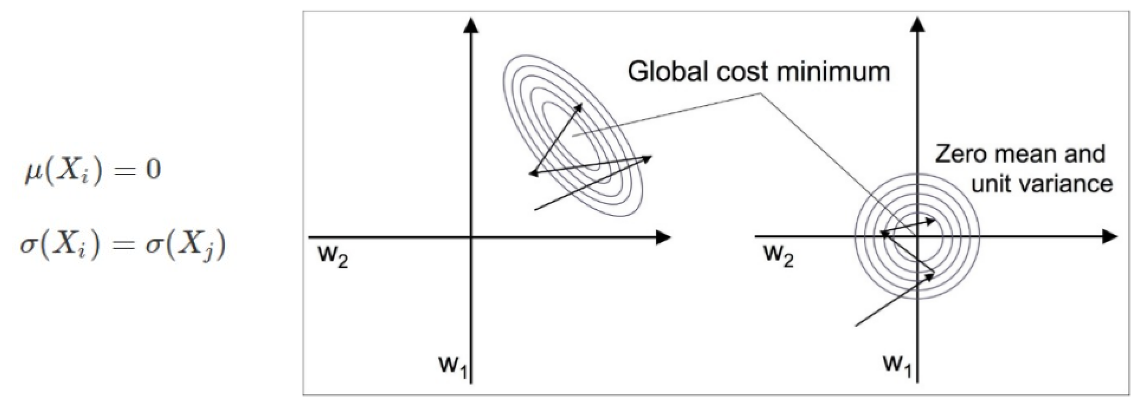

Figure 3. Representative Feature scaling is a method used to standardize the range of independent variables or features of data. In data processing, it is also known as data normalization and was performed during the data preprocessing step.

Theoretical Motivation

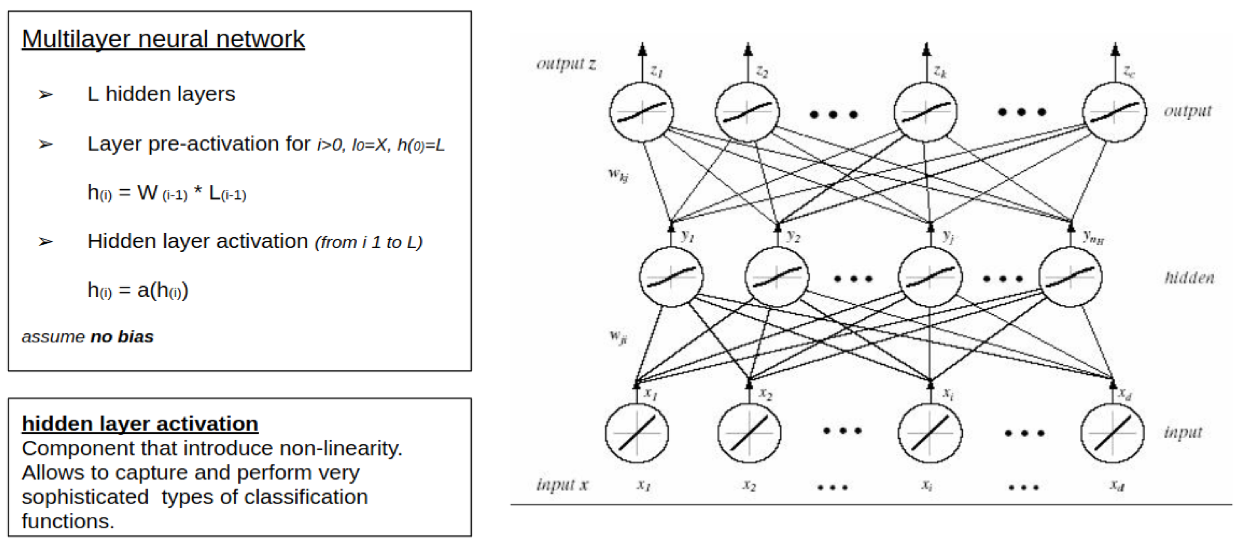

Figure 4. Architecture for a four layer fully connected Neural Network.

- Algorithm that performs update for each example

$$initialize\ \theta \Rightarrow \theta = \{W_0, W_1, W_2 \ldots, W_L\}$$

- For N epochs, for each training example X_i, Y_i
  - Pre-activation layer

$$g(x)^{i+1} = \sum_i^n (w_i * x_i) \Rightarrow W^i \times X^i$$

  - hidden layer activation

$$L^{i+1} = sigmoid(g(x)^{i+1})$$

- Back propagation

$$\nabla_{n-1} = \nabla_n * W_{n-1}^T \qquad \nabla = \frac{\partial E}{\partial w}$$

- Use the chain rule to efficiently compute gradients, top to bottom

$$Error = \frac{1}{2}\sum_i^n (y - \hat{y})^2 \qquad \hat{y} = Sigmoid(x_i \times w_i)$$

$$\frac{\partial E}{\partial w} = \frac{\partial}{\partial w}\frac{1}{2}\sum_i^n (y - \hat{y})^2$$

$$\frac{\partial E}{\partial w} = \sum_i^n (y - \hat{y})(-\frac{\partial E}{\partial w}\hat{y}) \qquad \Rightarrow (-\frac{\partial E}{\partial w}\hat{y}) = \hat{y}(1 - \hat{y})$$

Results

Validation set, 1150 rows of information, was isolated from the the dataset. The set was used to test the trained model, running it in each of the 1150 rows and comparing predictions with corresponded labels. After 100 iterations, 99.96% was reached.

Hyper-parameters used: learning rate 0.001, L2 Regularization with beta of 0.001, dropout with keep prob of %50, Mini-batch / SGD[3] - batch size 100; 1000 epochs; 11000 samples; 90% for training set and 10% for validation set; improve of gradient descent through feature scaling; Sigmoid as activation function; also random weights and biases set to zero

Figure 5. Error using one layer and four layers fully connected Neural Networks trained through 1000 epochs.
1 layer error: 0.175971; **4 layers error: 0.012657**

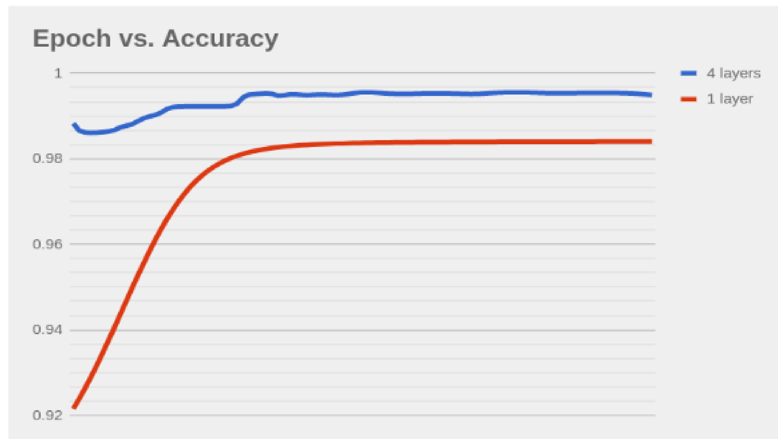

Figure 6. Accuracy on test set using one layer and four layers fully connected Neural Networks trained through 1000 epochs.
1 layer accuracy: 0.981064; **4 layers accuracy: 0.996806**

Conclusions

A successful automated detection and prediction of disorders introduce new innovative opportunities for diagnosis and preventive health care. This paper propose a fast and light way learning procedure for building a predictive model that satisfy the assignment. The use of deep neural networks in the subject turned out to be an excellent solution that presents high accuracy.

The results are prominent and suggest that the model with existing clinical systems and practices may enable clinicians to make a diagnosis of epilepsy and start an earlier treatment

Moreover, it opens a door to extend the work on other areas like diagnosis of dementias, brain damage, brain diseases, psychiatric disorders, tumors, stroke, seizure forecasting from the study of interictal, preictal and ictal states and other focal brain disorders.

Another area of interest would be Electrocardiogram signals. Further works can also be done on predicting heart attacks from ECG signals (people carrying holter monitors).

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