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 machine learning models 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.

1 Introduction

This paper 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. A further ongoing research could indicate that the same approach can be extrapolated to other brain conditions.

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.

Patients carry this pattern of spikes almost all the time. Seizures or epileptic seizures are events of short duration, being the spikes the catalysts thereof.

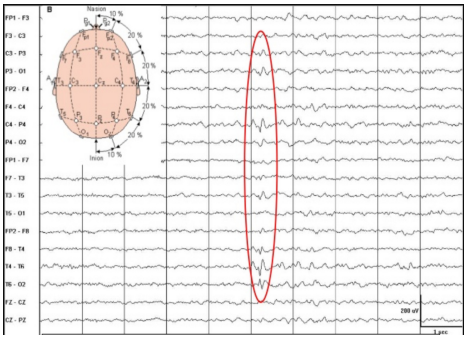

Fig. 1. Representative abnormal EEG waveforms.

This anomalous brain activity generates an observable mark or pattern. That footprint can be learned through a deep neural network. The following section will elaborate the whole process of data extraction, processing as well as the proposed four layers fully connected Neural Network architecture for feature extraction. Furthermore, the process of training the network with a training-set followed by a validation of the results using a testing/validation set.

2 References on the subject

In the past, there has been previous studies on epileptic seizure detection using pure EEG datasets. The following are the most relevant works on the subject (taken from [4]). The most common classifier used was support vector machine (SVM) and for dataset the CHB-MIT database.

Related references using ANN with poor results [5], [6], [11]. No works found on the subject related with the use of deep neural networks.

Webber, 1996 [5] ANN classification system SEN of 76% and FPR of 1 event/h

Pradhan, 1996 [6] Wavelet transformation feature acquisition, ANN classification SEN of 97% and SPEC of 89.5%

Gabor, 1998 [7] Self-organizing neural network with unsupervised training SEN of 92.8% and FPR of 1.35 events/h

Wilson, 2004 [8] matching pursuit,small neural networks, and clustering algorithm SEN of 76% and FPR of 0.11 events/h

Wilson, 2005 [9] Used a trained probabilistic neural network SEN of 89% and FPR of 0.56 events/h

D'Alessandro, 2005 [10] Genetic algorithm for signal processing, probabilistic neural network for classification

Arabi, 2006 [11] Used linear correlation feature selection methods and ANN. SEN of 91% and FPR of 1.17 events/h

Chan, 2008 [12] SVM system SEN of 80-98%, FPR of 38%

Netoff, 2009 [13] Cost-sensitive SVM system SEN of 77.8%, no false positives detected

Chua, 2009 [14] Data processing by higher-order spectra analysis and classification by the Gaussian mixture Acc=93%

Mirowski, 2009 [15] Variable feature extraction methods used SEN71% Sorensen, 2010 [16] Features classified by matching pursuit algorithm and classified by SVM SEN of 78-100%

Chisci, 2010 [17] Least-squares parameter estimator for extraction followed by SVM classification SEN of 100%

Peterson, 2011 [18] Wavelet transform followed by SVM classification EEG SEN of 99.1% and PPV of 94.8%

Temko, 2011 [19] Fast Fourier transform used for feature extraction and SVM classification. SEN 89%

Acharya, 2011 [20] Higher-order spectra-based feature extraction followed by SVM, Detection accuracy of 98.5%

Kharbouch, 2011 [21] Multistep feature extraction system followed by SVM classifier 97% of seizures, FPR of 0.6 events/day

Liu, 2012 [22] Wavelet decomposition-based feature extraction and by SVM SEN of 94.5% and SPEC of 95.3%

Direito, 2012 [23] Markov modeling classification system. Identified four states - accuracy of 89.3%

Rabbi, 2012 [24] Used fuzzy algorithms for feature extraction for classification SEN of 95.8%

3 Methodology: Dataset Processing

Dataset used was taken from The University of California Irvine [1]. UCI contains a Epileptic Seizure Data Set 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 for 1 second, and each data point is the value of the EEG recording at a different point in time. So now we have 23 x 500 = 11500 pieces of information(rows), each information contains 178 data points for 1 second(columns), the last column represents the labels. Labels 2,3,4,5 has been changed to 0 as measurements of individuals with no epilepsy seizure. Those with label 1 represent individuals with epilepsy seizure.

To avoid saturation on the activation function and to make the gradient descents converge faster, the features were normalized to a range of values between -1 and 1 so that all features have a similar scale. The method used was standardization, which makes every feature have a zero mean value and unit variance. It is calculated for each feature as follows:

$$x' = \frac{x - \hat{x}}{\sigma} \tag{1}$$

$$\mu(x_i) = 0 \tag{2}$$

$$\sigma(x_i) = \sigma(x_j) \tag{3}$$

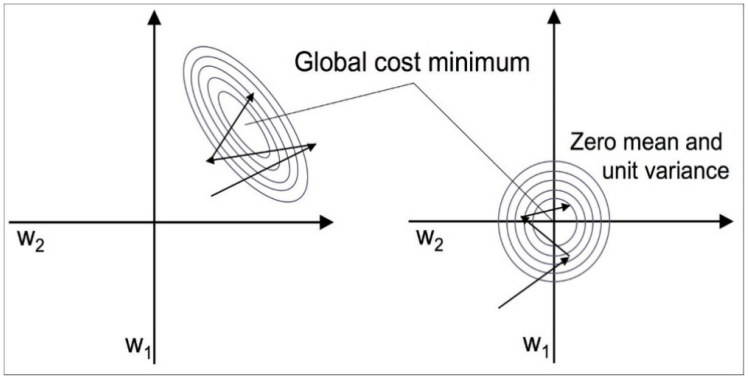

Fig. 2. Feature scaling is a method used to standardize the range of independent variables or features of data. In data processing, it is also known as data normalization and is generally performed during the data preprocessing step.

Lastly, the dataset will be further split into training, test and validation sets. It is very important that dataset is shuffled well to avoid any element of bias before training the ML model.

4 Method / The Solution

Deep learning algorithms are composed of multiple processing levels that learn data representations with multiple levels of abstraction. Using a deep learning network (DNN) implemented in Python (TensorFlow library), we classified the

subjects based of each label. Design a four layers fully connected Neural Network to capture the non-lineality of the signals.

The proposed architecture consists of five layers of fully connected neural networks (Fig. 1.b) to capture data nonlinearity. An Adam optimizer50 was used because it is an efficient extension of stochastic gradient descent optimizers. The Adam optimizer achieves good results faster than other approaches51 and is used for objective function minimization by iteration. It computes individual adaptive learning rates from estimates of the first and second moments of the gradients.

Parameter initialization included assigning random values between 0 and 1 to the weights and zero values to the biases. However, for the dataset with all features and after feature selection, Xavier initialization was applied to the weights following Eq. 1 to obtain a global minimum of the cost function faster and more efficiently:

$$\theta \Rightarrow \theta = \{W_0, W_1, W_2..., W_L\} \tag{4}$$

$$Xavier = \sqrt{\frac{2}{features}} \tag{5}$$

The weights were still random, but positive and negative values close to 0 are assigned to produce outputs that follow a similar distribution across all neurons. Supplementary Table 4 shows the initialization of the learning rates and the Xavier values for each dataset.

The nonlinear sigmoid function was applied as the activation function of hidden layers. The objective function used measures the error between the neural networks output and the actual target, as shown in Eq. x:

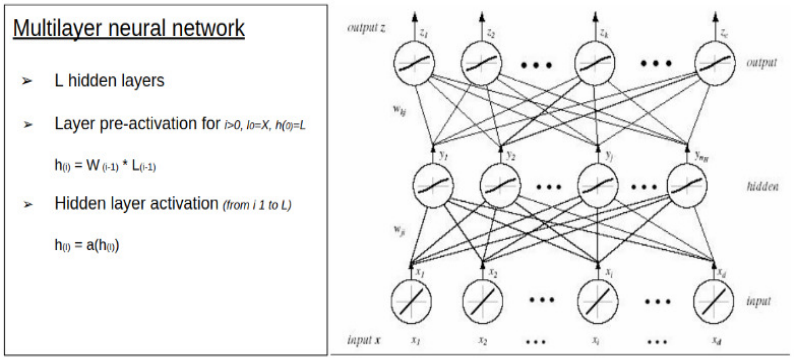

Fig. 3. Architecture for a four layer fully connected Neural Network

Iterate for N epochs, for each training example Xi, Yi

$$g(x)^{i+1} = \sum_{j}^{n}(x_j * w_j) \Rightarrow X^i * W^i \tag{6}$$

Hidden activation layers are components that introduce non-linearity to the system. That Allows to capture and perform very sophisticated type of classification functions.

$$L^{i+1} = sigmoid(g(x)^{i+1}) \tag{7}$$

Calculate the error comparing the output of the NN with the actual target

$$Error = \frac{1}{2}\sum_{i}^{n}(y - \widehat{y})^2 \tag{8}$$

$$\widehat{y} = Sigmoid(x_i \times w_i) \tag{9}$$

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

$$\frac{\partial E}{\partial w} = \frac{\partial}{\partial w}\frac{1}{2}\sum_{i}^{n}(y - \widehat{y})^2 \tag{10}$$

$$\frac{\partial E}{\partial w} = \sum_{i}^{n}(y - \widehat{y})(-\frac{\partial E}{\partial w}\widehat{t}y) \tag{11}$$

$$\Rightarrow (\frac{\partial E}{\partial w}\widehat{y}) = \widehat{y}(1 - \widehat{y}) \tag{12}$$

Back propagation of errors using the chain rule

$$\nabla = \frac{\partial E}{\partial w} \tag{13}$$

$$\nabla_{n-1} = \nabla n * W_{n-1}^T \tag{14}$$

As a regularization procedure for avoiding overfitting, a dropout approach was employed in the fourth hidden layers with a keep probability of 0.560. The optimization procedure was iterated until the minimum error on the training set and the maximum accuracy on the validation set (the number of observations that were correctly classified) were reached (Fig. 1ac and Supplementary Figure 4) and 5).

5 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.

Fig. 4. Error using 1 layer and 4 layers fully connected Neural Networks trained through 1000 epochs. 1 layer error: 0.175971; 4 layers error: 0.012657

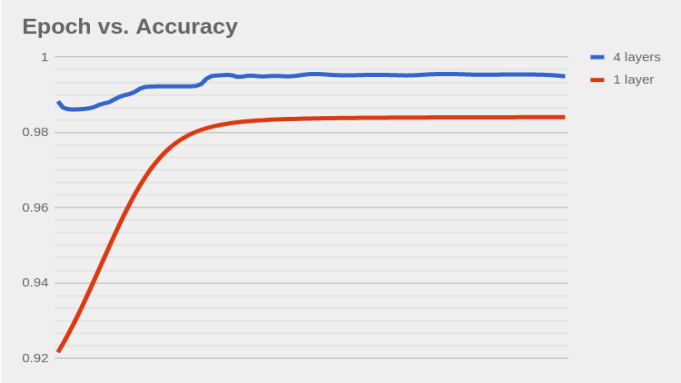

Fig. 5. Accuracy on test set using 1 layer and 4 layers fully connected Neural Networks trained through 1000 epochs. 1 layer accuracy: 0.981064; 4 layers accuracy: 0.996806

Hyper-parameters used: learning rate 0.001, L2 Regularization with beta of 0.001, dropout with keep_prob of %50, Mini-batch / SGD - 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

6 Conclusion and Future Directions

A successful automated detection and prediction of disorders introduce new innovative opportunities for diagnosis and preventive health care. This paper propose a fast and lightway 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).

References

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