Research Article

Artificial Neural Network analysis of EEG waves in focal seizures

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Abstract

Background: Brain dynamics associated with epilepsy remains limited. EEG-based epilepsy diagnosis and seizure detection is still in its infancy. The problem is further amplified for the design and development of automated algorithms, which requires a quantitative parametric representation of the qualitative or visual aspect of the markers. This study proposes an automatic classification system for epilepsy based on neural networks and EEG signals.
Material and Method: The present study made use of EEG data from 16 controls and 16 temporal lobe epilepsy (TLE) patients in order to comparatively assess neural dynamics in normal healthy young adults and person with epilepsy treated with anti-seizure drugs in the context of resting state during eye closed session. Such tangible differences could be appreciated through artificial neural network (ANN) classifiers.

Results: During eye closed session of EEG in order to diagnose TLE the extracted features of EEG activity are given to the classifier algorithm for training and test performance. Artificial Neural Network (ANN) classifier was used for the diagnosis task. Fractal dimension (Katz, Higuchi and Permission entropy) were analyzed, in which the best results was observed in trained set of data of Katz (93.18%).

Conclusion: Non-linear analysis plays an important role in prediction of complex partial seizure during interictal period, which otherwise currently relies on skillful visual inspection by expert epileptologists during clinical diagnosis. We demonstrated that seizure detection improved when training set was performed using EEG patterns recognition via Katz Fractal dimension at satisfactory level during interictal period in focal seizure patients.

Key words: Artificial Neural network**,** Focal Seizures**,** Non-linear analysis of EEG, Neurodynamics

INTRODUCTION

Epilepsy is a neurological disorder with a prevalence of about 1 – 2%. [1] It is a neurological condition that is characterized by sudden paroxysmal, recurrent and transient seizures (neuronal avalanche), the pathophysiology of which is exemplified by synchrony of electrical activity with abnormal bursts of electrical discharges of distributed cortical neuronal networks in space – phase of the respective neurophysiologically coupled neuronal pools (International League Against Epilepsy). [2]

An epileptic seizure is due to abnormal, excessive and synchronous neuronal discharge in the brain. Focal or partial epilepsy originates in the medial or lateral aspect of the temporal lobe of brain. [3] Seizures originating from temporal lobe are not managed completely by the available anti- seizure drugs as of this dated and surgical resection still remains a viable alternate treatment option for such focal epilepsy. In focal seizures, consciousness is impaired to some extent in which the person's ability to interact with the environment is altered. Focal Seizures usually begins in a small portion of temporal lobe and then spreads to large portion of the temporal lobe and these patients were suffer from different types of diseases like memory impairment, signs of motionless staring, automatic movements (tics) of hands or mouth and altered ability to respond to others.[4]

EEG is a signature of underlying neural dynamics in health and disease states. It is widely accepted that EEG analysis could be employed for early detection of varied dysfunctions of the human brain such as depression, epilepsy, autism and Alzheimer's disease.[5] The human mind, the neurophysiological correlate of human brain, observes and obeys the principles of chaos with stochastic trajectory sub-serving a particular defined function.[6] Subsequently, EEG analysis and interpretation need to be done along the axes of non – linear chaotic principles. There are varied non – linear methods presently available and so such EEG analytical assays aim to reconstruct the mental phase – space and characterize the resulting attractor along with the stochastic trajectory, [7] some of which are auto – regression, correlation dimension, lyapunov exponent, entropy, fractal dimensions and other indices of chaotic trajectory.[6]

Seizures are identified by epileptologists who read extensive EEGs, which is a time consuming task requiring experience. [7] Automatic seizure detection is therefore a key technology to save time and effort associated with EEG readings. These types of methods of seizure detection during interictal period open a new therapeutic avenue for future treatments of focal seizures. [8]

EEG signal features have been considered to represent seizures; [9] eg time frequency analysis, wavelet transform and nonlinear analysis. [10] The actual patterns of epileptic EEG signals vary from patient to patient, so the efficacy of most of these traditional methods is patient-specific.[11]

Dynamical analysis of EEG recordings from patients with epilepsy has provided novel perspectives regarding epileptogenesis. Studies on partial seizures of temporal lobe origin have demonstrated the presence of limit cycles in the seizure discharges recorded from subdural electrodes overlying the epileptogenic focus. [12] Dynamical changes in EEG have preceded the seizure activity several minutes before seizure onset in which large area of cortex are dynamically entrained. [13] Fractal dimensions value is usually a non-integer fractional number; hence this dimension is referred to as fractals helping in the process of pattern – recognition. [14]

The dynamic phenomena of fractal theory in the human body or in nature, is considered as a valid and useful tool that allows an approximation to complexity and the absence of linearity which exists in those processes. [15]

EEG pattern learning technology has emerged, by which relevant features are automatically learnt in a supervised learning framework.[16] Although a number of recent studies demonstrated the efficacy of pattern recognition of EEG signals, yet seizure detection by this technique still requires improvement.

The present study has been undertaken to assess the underlying neural dynamics of the human brain in patients of TLE suffering from focal seizures in basal resting state, so as to propose a useful diagnostic tool for seizure prediction during interictal period of TLE patients.

MATERIALS AND METHODS

The present hospital based, observational comparative case control study was conducted on a sample population of 16 temporal lobe epilepsy diagnosed patients (selected through random sampling technique from outdoor of Departments of Neurology and Medicine and diagnosed on the basis of Magnetic Resonance (MR) Protocol and Electroencephalography findings and in the age range of 20 to 30 years at 95% confidence and 80% power to verify the expected minimum difference of 0.66 [± 0.64] of mean working memory task score of temporal lobe epileptic patients along with age and sex matched healthy controls. The temporal lobe epileptic (TLE) patients so included in the present study were in interictal phase and seizure free from last one year and were on anti-seizure drugs. A detailed clinical and family history of epilepsy along with informed written was recorded. The study was approved by the ethical committee of the institution. All the patients and controls EEG data was analyzed by Artificial Neural Network (ANN) by using Matlab Neural Network Tool version 2014. Our results were presented in "Classifier Performance or Accuracy", of ANN classifier on confusion Matrix.

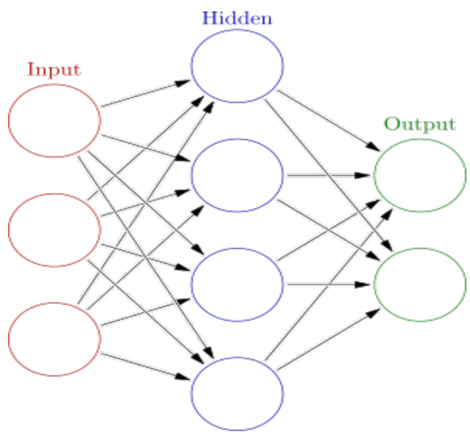
EEG recording

In the present study, 21 channels scalp electroencephalography times series tracing was acquired as per norms of International 10-20 system with biauricular reference. [17] Electrode impedance was kept <5kΩ electrical activities, amplified with a band pass filter of 0.1-30.0 Hz, digitalized at sampling rate 256 Hz. QEEG (Quantitative Electroencephalography) was done for all the subjects and controls using **BESS** (Brain Electro Scan Software) of the **Axxonet System**. EEG was recorded using a Stretchable cap and positioned on the subject's head according to the known anatomical landmarks. [18]

EEG was recorded from frontal (Fz/ Fp1/ Fp2, F3/F4, F7/F8), temporal (T3/T4/T5, T6), central (C3/C4/ Cz), parietal (P3/P4/Pz) and occipital (O1/O2/Oz) regions.

Artificial Neural Network Analysis

Neural Network is an adaptive system that is capable of changing its structure and synaptic weights in real time. In artificial neural networks, the burden of making assumptions about the structure of data is transferred the training of hidden layers that solve "subproblems" of the given input that allows to explore nonlinear relationship of features along and between channels with a propensity to offer an appreciable predictive power. The number of inputs depends on size of the feature vector used. [19]



Artificial neural networks (ANNs) or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains. Such systems learn (progressively improve performance) to do tasks by considering examples, generally without task-specific programming. [20]

The cortically generated EEG is usually contaminated through several non-cerebral artifacts originating from varied sources namely, eye blinks, ocular moments, random noise such as electrical disturbances, instrumentation noise, external electromagnetic activity and other yet unknown factors. EEG signal pre-processing removes such artifacts that enhance the usability of such signals.

The feed forward network was trained through use of a scaled conjugate gradient back propagation to update the weights and measure using cross entropy. Neuronal network consisting 35 hidden layers was trained on samples of epochs 50 on each patient (16*50=800) and control (16*50=800) for each 3 seconds and the results were calculated on 85% training data and 15% for testing evaluation.

Confusion matrix

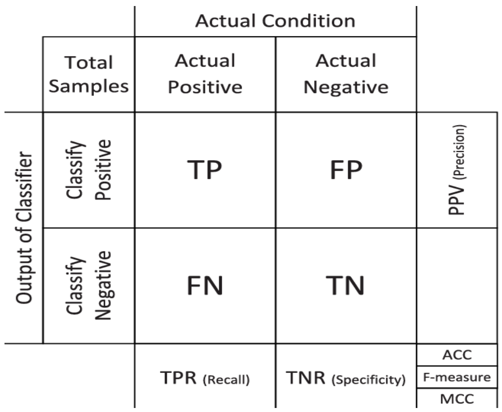
Confusion matrix technique mainly used for summarizing the performance of a classification algorithm. For more accurate observation and conclusion, confusion matrix can make the number of correct and incorrect predictions are summarized with count values and broken down by each class (key to confusion matrix). [21]

Sensitivity it is the ability of a test to correctly identify patients with a disease. **Specificity**: the ability of a test to correctly identify people without the disease. **True positive (TP)**: the person has the disease and the test is positive. **True negative (TN)**: the person does not have the disease and the test is negative. **False positive (FP)**: the person does not have the disease and the test is positive. **False negative (FN)**: the person has the disease and the test is negative. [21]

$$\boldsymbol{Sensitivity = \frac{TP}{TP + FN} \times 100,}$$

$$\boldsymbol{Specificity = \frac{TN}{TN+FP} \times 100,}$$

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100}$$



Nonlinear Parameters

3 different analyses were carried out viz. Higuchi's, Katz's and Permutation Entropy (PE) from the EEG data of the samples (16 patient and 16 controls) for the EEG manoeuvre of eye closed session. 50 epochs were selected and corresponding fractal dimensions were calculated for each class of EEG monomer for each patient and control.

1. Permutation Entropy (PE): PE was first introduced by Bandt and Pompe (2002). [22] It is tool for computing complexity of time series through comparison of neighbouring values.[23]
2. Katz's Fractal Dimension: It was suggested by Mandelbrot (1982). [24] Katz combined a unit of measure or 'yardstick' definition with Mandelbrot's (1982) original work and figured out to compute fractal dimension with discretization of space. [25]
3. Higuchi's Fractral Dimension: Higuchi FD algorithms were based on curve length estimation. [26]

Pre-processing of EEG Data

The cortically generated EEG is usually contaminated by several non-cerebral artefacts that have varied origins namely, eye blinks, ocular moments, random noise such as electrical disturbances, instrumentation noise external electromagnetic activity etc. and such artefacts were removed through EEG signal pre-processing that tends to enhance quality of the signals. [21]

Feature Extraction

To remove various types of noise contents from EEG signal is called Pre-processing. The second stage in EEG signal processing is feature extractions, which signify an important role in pattern recognition and classification. These features characterize the type of EEG signal. Due to multi-resolution approach, artificial neural network is a popular technique to extract point from EEG signals and it is able to localize time and frequency domain features, simultaneously. [21]

RESULTS

The results were calculated on 85% training data and 15% for testing evaluation via Matlab Neural Network Tool version 2014.

Classifier performance /accuracy	Katz	Higuchi	Permutation entropy
Correct	93.18%	88.00%	83.81%
Incorrect	6.81%	12.00%	16.18%

Table 1: Fractal dimension during eye close session of EEG in trained data set

Classification accuracy is the ratio of correct predictions to total predictions made. It is often presented as a percentage by multiplying the result by 100. Table 1 shows the maximum percentage value for katz fractal dimension than higuchi and permutation entropy in trained data set. Out of 800 samples of trained dataset of patients, 93.18% was found positive with epileptogenic discharge during interictal period than compared to Higuchi (88%) and Permutation entropy (83.81%).

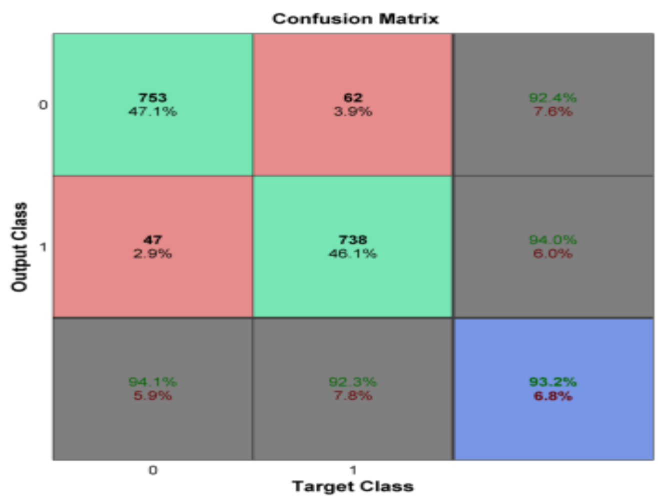


Figure 1.1: Eye Close Katz in Trained Data.

From the above figure 1.1, it concludes that the proposed neural network-based classifier achieved classification accuracy of 93.2% in classifying two classes, attained sensitivity and specificity of 92.4% and 94%, respectively.

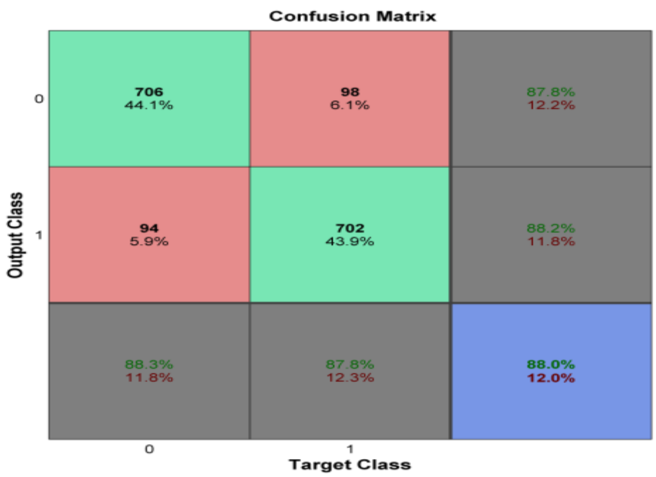


Figure 1.2: Eye Close Higuchi in Trained Data
From the above figure 1.2, it concludes that the proposed neural network-based classifier achieved classification accuracy of 88% in classifying two classes, attained sensitivity and specificity of 87.6% and 88.2%, respectively.

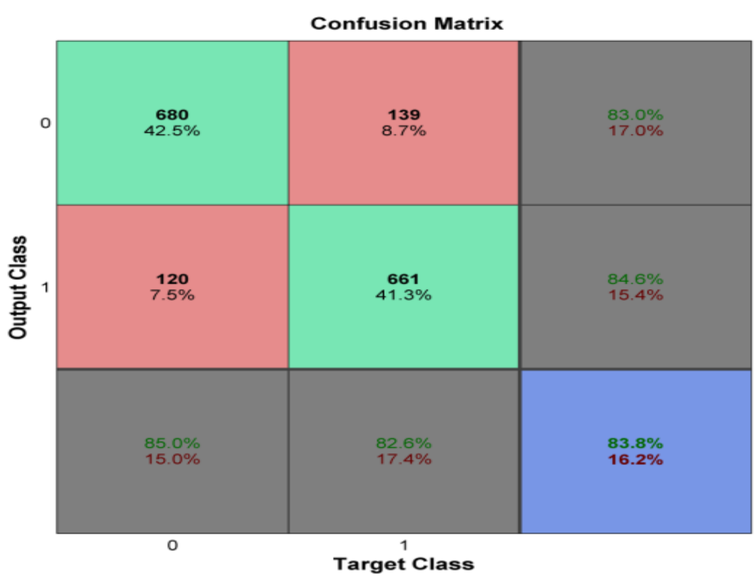


Figure 1.3: Eye Close Permutation Entropy in Trained Data
From the above figure 1.3, it concludes that the proposed neural network-based classifier achieved classification accuracy of 83.8% in classifying two classes, attained sensitivity and specificity of 83.0% and 84.6%, respectively.

Classifier performance /accuracy	Katz	Higuchi	Permutation entropy
Correct	96.33%	85.50%	85.00%
Incorrect	3.66%	14.50%	15.00%

Table 2: Fractal dimension during eye close session of EEG in tested data set

Table 2 shows that the classifier accuracy was maximum at katz (96.33%) than Higuchi (85.50%) and permutation entropy (85.00%) in tested set of data.

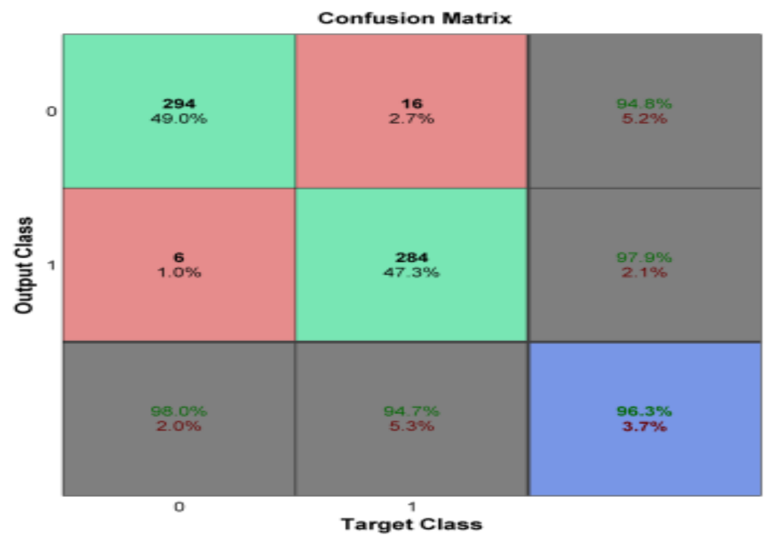


Figure 2.1: Eye Close Katz in Tested Data

From the above figure 2.1, it concludes that the proposed neural network-based classifier achieved classification accuracy of 96.3% in classifying two classes, attained sensitivity and specificity of 94.6% and 97.9%, respectively.

Figure 2.2: Eye Close Higuchi in Tested Data

From the above figure, it concludes that the proposed neural network-based classifier achieved classification accuracy of 85.5% in classifying two classes, attained sensitivity and specificity of 85.1% and 85.9%, respectively.

Figure 2.3: Eye Close Permutation Entropy in Tested Data

From the above figure, it concludes that the proposed neural network-based classifier achieved classification accuracy of 85.0% in classifying two classes, attained sensitivity and specificity of 82.2% and 88.3%, respectively.

DISCUSSION

To our knowledge, the present study is an attempt to automatically evaluate EEG signal pattern recognition of patients suffering from focal epileptogenic discharge during interictal period. With the help of artificial neural network analysis, classifier accuracy of EEG pattern recognition achieves a satisfactory level of epileptogenic discharge during interictal period.

We also demonstrated that the best performance accuracy was obtained in katz analysis with 93.18% than higuchi and permutation entropy, suggesting that adding new data with a variety of seizure patterns should improve the performance of our method that would help in prediction of focal seizures or epileptogenic discharge via EEG at resting state, during interictal period.

Our dataset included subjects with different backgrounds, which made automatic seizure detection challenging; for example, the ages of the subjects ranged from 20-30 years, rural and urban background; educated and non educated; all subjects had focal epilepsy, which makes it more difficult to detect focal seizure states than generalized epilepsy; and each seizure had a different epileptic focus and EEG patterns. For such a wide range of data, the performance of hand-made numerical features may not always be satisfactory. To solve this problem, this particular classifier or non linear techniques are proving more accurate results in patients suffering from focal epileptic discharge.

In the present study the results were calculated on 85% training data and 15% for testing evaluation via Matlab Neural Network Tool version 2014.

The large amount of data (continuous 21-channel EEG data monitoring for 5 minutes from 16 patients) differentiated our work, and was a key success factor in verifying our hypothesis that

EEG signals pattern recognition technique contains universal features of diagnosis of seizure state used by epileptologists. Visual seizure detection requires experience and it's more difficult for inexperienced trainees.[7] To solve this problem it's important for development of a tool that automatically detects the presence of epileptic discharge in brain during the interictal period. Our results suggest that non linear analysis worked as a potent tool in this matter and help in EEG pattern recognition in focal seizers. In present study the results of ANN suggests the higher classifier performance so that we conclude our research benefit in medical field, which involve less time in diagnosis and we achieved the best accurate results in seizure detection.
Several researchers have provided evidence that dynamic of signals with a spectral richness not depleted by the lesion also shows the high level of complexity in time, as shown in present study that maximum accuracy was obtained in patients with epileptogenic discharge during interictal period.[21,22,25,27]

CONCLUSION

The application of nonlinear analysis to neuroimaging allowed obtaining information on scale free properties and modularity, which improve our understanding on brain mechanisms at the systems levels and the dysfunction in neurological diseases. In this light, non-linear analysis seems to be a potentially sensitive instrumentation marker of temporal lobe epilepsy (TLE) and needs to be clinically validated through replication in more such numerous and independent patient cohorts. In brief we have described the process of analysis of EEG signal with ANN and also compare the classifiers performance or accuracy in between Katz, Higuchi and Permutation Entropy and satisfactory results was obtained from katz fractal dimension. The studies on EEG pattern recognition need to be worked on in future with more datasets for focal discharge prediction in TLE patients.

Limitations

The sample was small though the algorithm so proposed and designed in the present study needs to further tested and validated in the field for confirmation of the final outcome and the conclusion of the signature of the disease process that has been so underscored and highlighted in the present study.

Conflict of Interest: None
Source(s) of support: None

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