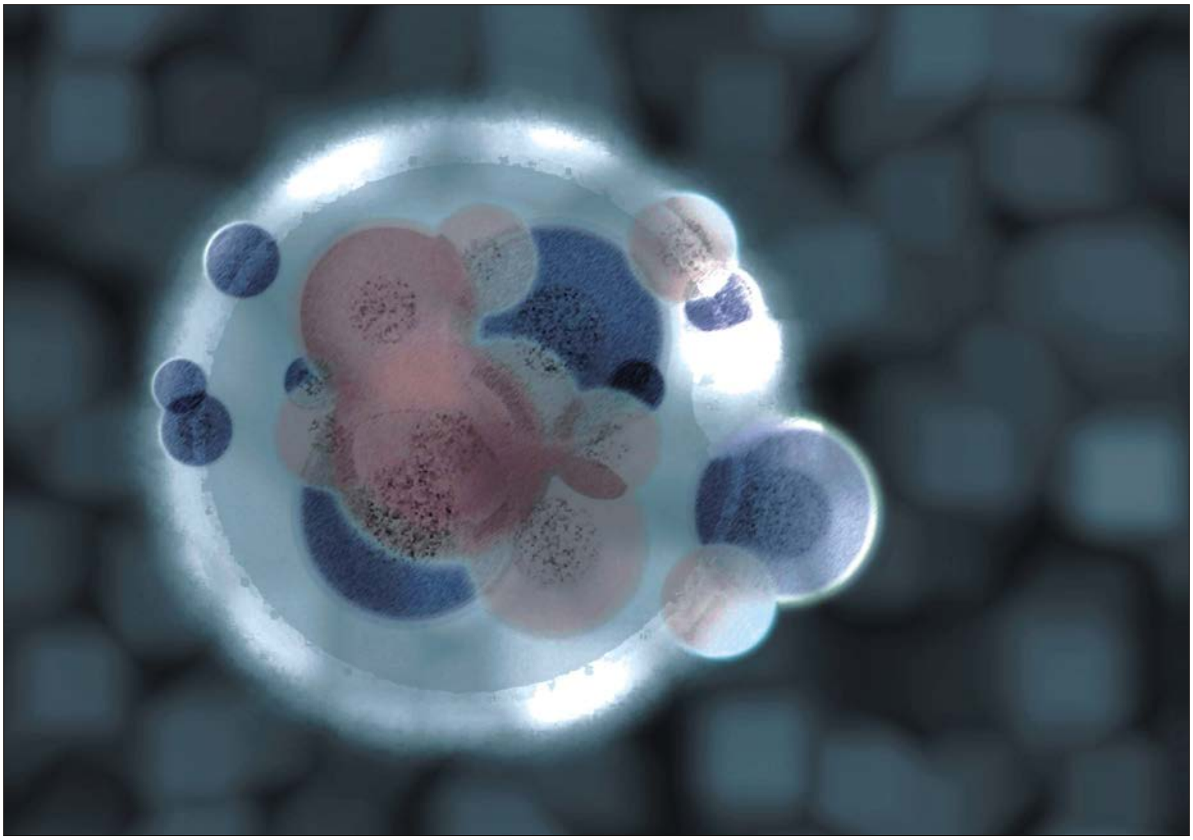

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Diagnosis of Epilepsy By Artificial Neural Network

[1]M.I. EL-Gohary, [2]A.S.A. Mohamed, [3]M.M. Dahab, [4]M.A. Ibrahim, [5]A.A. El-Saeid and [4]H.A. Ayoub
[1]Biophysics Branch, Faculty of Science, Al-Azhar University (Boys), Cairo, Egypt
[2]Department of Biomedical Engineering and Systems, Faculty of Engineering, Cairo University, Cairo, Egypt
[3]Department of Neurology, Faculty of Medicine (Boys), Al-Azhar University, Cairo, Egypt
[4]Department of Physics, Faculty of Science, Suez Canal University, Egypt
[5]Biophysics Branch, Faculty of Science (Girls), Al-Azhar University, Cairo, Egypt

Abstract: A common feature of epilepsy in EEG signals is an excessive electrical discharge which is appeared as electrical potentials of high amplitudes and frequencies with abrupt onset and rise in amplitude, rhythmicity and abnormal synchronization. These potential discharges were termed Seizure patterns. Although several details concerning the cellular basis of these seizure patterns are unknown, numerous experiments led to the general agreement that they reflect a spontaneous and uncontrolled firing of a large number of neurons within a certain region of the brain. Artificial Neural Network (ANN) was proposed in this research as a decision-making tool supported by experimental data to differentiate between healthy and epileptic EEG signals, with accuracy up to 90.2%. This was done by teaching the ANN to perform this function i.e., by Artificial Intelligence (AI) of ANN. The performance of the ANN was calculated for each model's node to obtain the performance of the node. ANN approach is a powerful tool which is promising to give available results in analysis of bioelectric signals.

Key words: Epilepsy, artificial neural network, artificial intelligence

INTRODUCTION

With regard to the diagnosis and localization of pathological processes involved in epilepsy, the recording of brain activity by means of EEG have becomes widely important. The first EEG recording by Berger (1969) from epileptic brains showed that their potentials deviate significantly from normal pattern. This fact was confirmed by the results of magnetoencephalogram (MEG) recordings by SQUID system (Nicolas *et al*., 1983; Barbanera *et al*., 1983; Anninos and Murthy, 1977).

Artificial Neural Network (ANNS) can be defined as information processing systems designed with inspiration taken from the nervous system, in most cases from the human brain. Artificial neural networks are input-output systems which are designed to simulate some of the characteristics of biological neural networks (Yueh and Cheng, 2006). Currently, most workers on ANNS place particular emphasis on problem solving (Fausett, 1994; Zurada, 1995; Bishop, 1996; Haykin, 1999; Kohonen, 2000; De Castro, 2007).

More recently, artificial neural networks have been considered the state-of-art technique for modeling and predicting non-linear system behavior. ANN can learn from examples and therefore can be trained using a series of typical input and their corresponding expected outputs, to establish an implicit non-linear and multi-dimensional correlation between them (Bezerra *et al*., 2007).

Learning is the ability of a system to make predictions and take decisions based on its past experience. Among the many models for learning, there are three main cases, namely; unsupervised, supervised learning models and problem solving model. These learning models are applicable to artificial intelligence AI (Pal, 1989). While human learning is difficult to define, a machine learns when it changes its structure, date or program in response to external information. In such a manner the machine is expected to improve future performance. Machine learning can be applied to any situation in which repetitive system data can be obtained whether biological or mechanical. Learning can be used to train machine, so that it optimizes its rule base in a model and then new parameters may be tested in that model. The application of machine learning is termed AI (Abbod *et al*., 2007).

The primary objective of this study is to illustrate how medicine can benefits from applying learning process to achieve AI for ANN as decision making tool supported by experimental data, to differentiate between EEG signals of healthy people and patients.

Corresponding Author: A.A. El-Saeid, Biophysics Branch, Faculty of Science (Girls), Al-Azhar University, Cairo, Egypt
Tel: 0223694639

MATERIALS AND METHODS

Selection of patients and control persons: The patients in the present work divided into two groups:

- The first group is the control one, it includes 30 persons (15 males and 15 females), these patients have some complains but their EEG showed that they are normal (Fig. 1a).
- The second group, includes 30 epileptic patients (15 males and 15 females), they suffered from brain disorder characterized by convulsions and sometimes absence of consciousness (Fig. 1b).

Recording of EEG signals: EEG signals delt which in the present study were recorded by using the Neurotravel WIN archive system, which is composed of two sections, acquisition and print. In this way, it is possible to archive encephalic and polygraphic signals using a completely digital technology. The recording was done by 10-20 system.

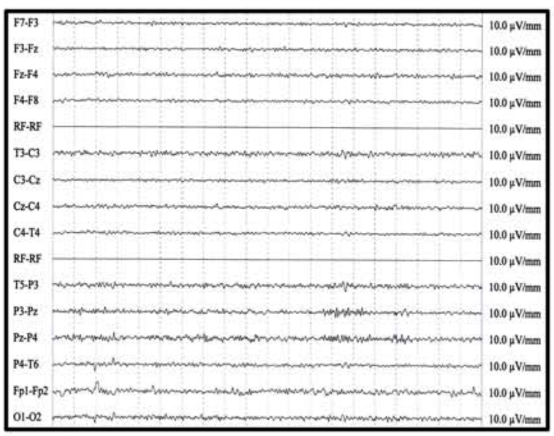

Fig. 1a: Represents EEG signals from normal male

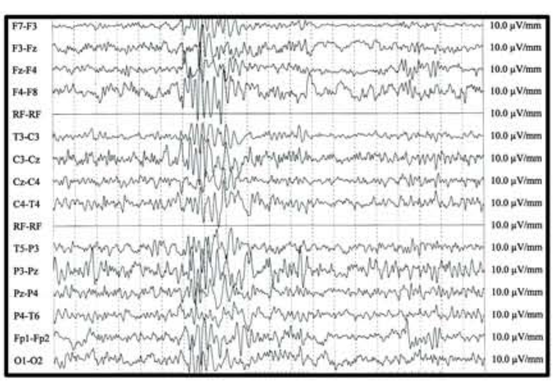

Fig. 1b: Represents EEG signals from male patient suffers from Epilepsy

Learning process: The learning process was designed to fined the coefficients or weights that provide the best fit between the mapping function and data consisting of examples for the target function.

In the present study, learning process was made by using 19 healthy persons and 11 epileptic patients by using supervised learning and the Mean Square Error (MSE) was calculated for each node number, to know the limit of neural network error after learning process.

Testing process: The strategy of AI was to take the object of study to the highest cognitive processes such as logic, rational thought and problem solving.

Testing process was done by feeding the network data records that it never learn before and watching the output results which varied mostly between -1 and 1. The network output was approximated to -1 and 1. The testing process was carried out on the artificial neural network by feeding the information of 6 healthy persons and 4 epileptic patients to evaluate learning process.

RESULTS AND DISCUSSION

Autoregressive (AR) model definition and properties: If a model can be successfully fitted to data, it can be transformed into the frequency domain instead of data upon which it is based, producing a continuous and smooth spectrum. This is the basic promise of the spectra produced using AR model. In an AR model, a value at time (t) is based upon linear combination of prior values (forward prediction), up on a combination of subsequent values(backward prediction), or both (forward- backward predictions). The linear model gives rise to rapid and robust computations. The AR coefficients can be computed in a variety of ways:

- They can be calculated by autocorrelation estimates
- Partial autocorrelation (reflection coefficients) and lastly, by least square matrix procedures (Durbin, 1989)

Autoregressive moving average model (ARMA): In some applications, biomedical signals may not be modeled by AR model, where there is another one will be suited to analysis is called Auto-Regressive Moving Average (ARMA) model. It is evident that the ARMA models calculate the AR and MA coefficients from non-linear equations. Chen *et al.* (1990) proposed that adaptive

ARMA methods should be utilized also to model the biomedical signals, whose frequency spectra are characterized by sharp peaks and deep valley.

AR modeling of seizure EEG (Epilepsy): The analysis of EEG measurements has become a very attractive tool for non-invasive diagnosis of epileptic seizures. Gath *et al.* (1992) proposed a multivariable autoregressive analysis method, combined with adaptive segmentation, to analyze multichannel seizure EEG recording from rats with focal epilepsy. The Power Spectrum Density (PSD) function of the AR method proposed by Gath *et al.* (1992) may be used as a powerful tool in diagnosing dynamic changes in EEG recording during epileptic seizures. The investigation of Gath *et al.* (1992) suggests that the results from parameter modeling of EEG recording taken from both rats and patients with epilepsy are more accurate and reliable than the results obtained by periodogram (FFT method of analysis). Therefore the AR model was applied to the present research.

Network architecture: The present network consists of AR coefficients for 19 healthy and 11 epilepsy patients. The performance characteristics of the AR method were found extremely variable in EEG signal analysis (Gath *et al.*, 1992; Tseng *et al.*, 1995). The output layer which gives only two answers either control or epilepsy and the hidden layer were made in 1, 2, 3, to 30 nodes. As shown in Fig. 2, every node in the network gets its inputs along the connection coming to it, every input line has a weight on it, that's to be multiplied with the input value coming from the lower side of the connection line. All products (of inputs and their corresponding weights) are summed and this sum is considered to be the input of the node (processing element), then, this sum of product is fed to the transfer function of the node and the result of the application of this transfer function on the sum of products is the output of the node being considered. The node's output will flows to the next upper node along another connection and so on.

The input data include AR coefficients of 19 control and 11 epileptic patients, represented as a matrix (15 electrodes×30 coefficients) from which the coefficients are calculated. Orders were tried to choose suitable one and error was calculated for every data file. The best order with lowest Mean Squared Error (MSE) value was selected to be the model representing this file and the number of coefficients resulting is dependent on the order (n).

Table 1 shows the relationship between number of nodes in the hidden layer, the performance of the Artificial Neural Network (ANN) and the Mean Square Error (MSE) of learning process at each node.

Table 1: The number of nodes for the hidden layer, the mean square error (MSE) and the neural network performance

No. of nodes	Mean squared error (MSE)	Performance (%)
1	0.000225	94.75
2	0.000384	57.44
3	0.000489	53.07
4	0.000330	75.00
5	0.000308	68.50
6	0.000236	40.20
7	0.000620	52.73
8	0.000638	88.90
9	0.000511	64.70
10	0.000747	90.24
11	0.000112	90.25
12	0.000614	66.72
13	0.000447	54.95
14	0.000871	70.42
15	0.000427	70.87
16	0.001074	72.87
17	0.000722	47.72
18	0.000637	40.21
19	0.000456	87.48
20	0.000708	39.00
21	0.000308	88.41
22	0.000914	43.12
23	0.001074	64.51
24	0.000770	76.02
25	0.000810	81.71
26	0.000701	79.64
27	0.000664	96.65
28	0.000655	79.24
29	0.000497	57.99
30	0.000710	50.18

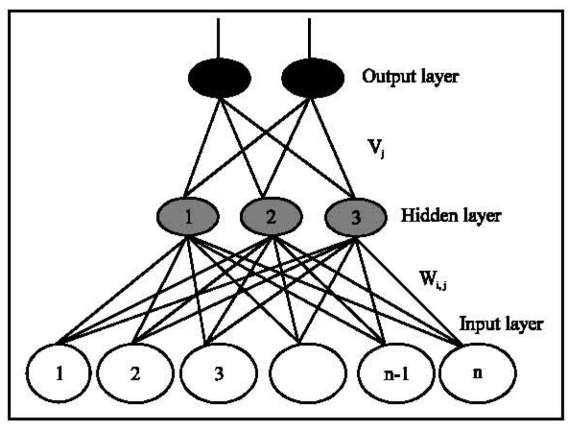

Fig. 2: Feed forward neural network architecture with nodes from 1 to 30 hidden layer and (n) input nodes layer where (n) varies according to each case under investigation

Table 1 and Fig. 3 show the number of nodes of the hidden layer and the performance of ANN at each node. Table 1 shows the performance of ANN at nodes (1, 10, 27) is approximately about 94.7, 90.2 and 96.65%, respectively and in spite of the high performance of the ANN at these nodes, it was failed to recognize a record or more as shown in Fig. 3 for node No. 1 and Fig. 4 and 5 for nodes 10, 27, respectively, so nodes, (1, 10, 27) are not

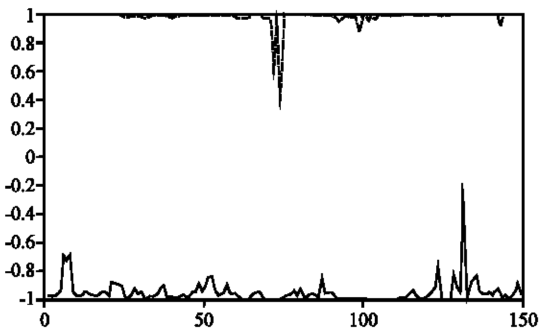

Fig. 3: The performance of ANN at node No. 1

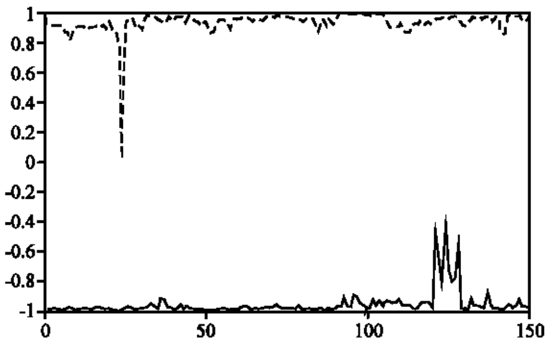

Fig. 4: The performance of ANN at node No. 10

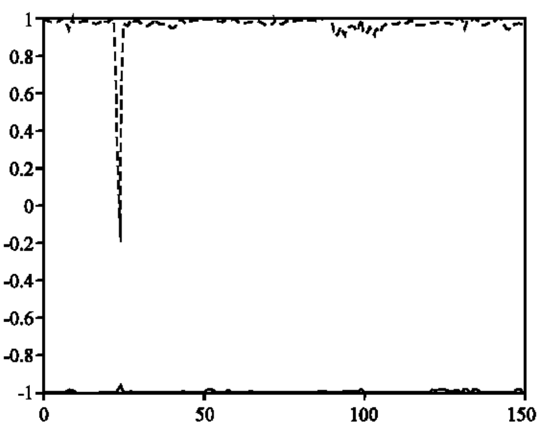

Fig. 5: The performance of ANN at node No. 27

preferred to be used in the ANN because the MSE was enlarged at these nodes and this error is showed by sharp peaks in Fig. 3-5. Mean-while Fig. 6 shows the performance of the ANN at node No. 11 and it is found that, the ANN succeeded to recognize all the records almost correct by performance up to (90.2%) that is why node No. 11 is the best node for differentiating between healthy and impaired signals by ANN.

El Gohary *et al.* (2000) showed that good performance of ANN which was reached (88.02%) in discrimination

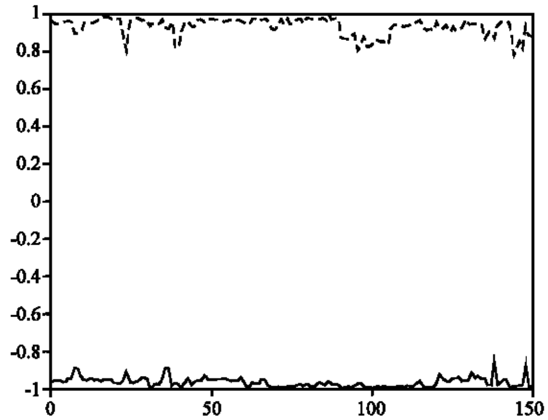

Fig. 6: The performance of ANN at node No. 11

between afferent and efferent patterns, when authors used a single recording technique, but they suggested that accuracy will be higher if multiple recording is carried out in the localization of interest.

AR modeling is the most appropriate and accurate method for analysis of EEG signals with epileptic seizures. ANN had been designed to differentiate between control and epileptic patients. The best node for hidden layer was found to be at node 11 because the artificial neural network succeeded to recognize all the records almost correctly by 90.2%. Artificial neural network approach is a powerful tool which is promising to give good results in biological signal analysis. Many applications in medicine can apply this methodology, such as diagnosis in myoelectric signals and ECG, also in prosthesis equipment design (Goodman *et al.*, 1992).

CONCLUSION

- AR model is more accurate for analysis of EEG recording during epileptic seizures.
- ANN had been made to differentiate between healthy and epileptic patients, with accuracy up to 90.2%.
- ANN approach is a power tool which is promising to give valuable results in analysis of different bioelectric signals.
- Many fields in medicine can apply this methodology as non-invasive diagnostic mean.

REFERENCES

Abbod, F.M., J.W.F. Catto, D.A. Linkens and F.C. Hamdy, 2007. Application of AI to the management of urological cancer. J. Urol., 178: 1150-1156.

Anninos, P.A. and V.K. Murthy, 1977. Statistical analysis of brain waves from randomly interconnected neural nets. Applied Math. Comput., 3: 85-94.

Barbanera, S., G.B. Ricci and I. Modena, 1983. Localization of epileptic foci by means of biomagnetic measurements. IL Nuovo Cimento 2D, pp: 547-557.

Berger, H., 1969. The EEG of Man. Collected Papers, Elsevier Verlag.

Bezerra, E.M., A.C. Ancelotti, L.C. Pardini, J.A.F.F. Rocco, K. Iha and C.H.C. Ribeiro, 2007. Artificial neural networks applied to epoxy composites reinforced with carbon and E-glass fibers: Analysis of the shear mechanical properties. Mater. Sci. Eng., A, 464: 177-185.

Bishop, C.M., 1996. Neural Networks for Pattern Recognition. Oxford University Press.

Chen, J., J. Vandarwalle and J. Jansen, 1990. Adaptive spectral analysis of cutaneous electro gastric signals using ARMA modeling. Med. Bol. Eng. Comput., 28: 531-536.

De Castro, 2007. Fundamental of natural computing: An overview. Phys. Life Rev., 4 (1-36).

Durbin, R., 1989. On the Corresponding Between Net Work Models and Nervous System, in the Computing Neuron. Miall, C. (Ed.). Reading, Mass: Addison-Wesley Publishing Co.

El Gohary, M.I., S.A. Abdallah Mohammed and A.M. Eissa, 2000. Discrimination between afferent and efferent patterns by artificial neural network. Egypt J. Biomed. Eng., 1: 49-57.

Fausett, L., 1994. Fundamentals of Neural Networks: Architectures, Algorithms and Applications. Prentice Hall.

Gath, I., C. Feuerstein, D.T. Pham and G. Rondouin, 1992. The tracking of rapid dynamic changes in seizure EEG. IEEE. Trans. Biomed. Eng. BME., 39 (9).

Goodman, Y.M., C.M. Higgins and J.W. Miller, 1992. Rule based neural networks for classification and probability estimation. Neural Comput. J., 4: 718-804.

Haykin, S., 1999. Neural Networks: A Comprehensive Foundation. 2nd Edn. Prentic Hall.

Kohonen, T., 2000. Self-Organization Maps. Springer.

Nicolas, P., D. Duret, D. Tenzener and T. Tuomisto, 1983. Neuromegnetic measurement at hospital: Instrumentation and preliminary testes. IL Nuovo Cimento 2D, pp: 184-194.

Pal, R., 1989. Learning and Architectures of Neural Networks, in Models of Brain Function. Cambridge University Press, New York, pp: 517-537.

Tseng, S.Y., R.C. Chen, F.C. Chong and T.S. Kuo, 1995. Evaluation of parametric methods in EEG signals analysis. Med. Eng. Phys., 17 (1): 71-78.

Yueh, W.Ch. and S.S. Cheng, 2006. Synchronization in an artificial neural network. Chaos, Solitons and Fractals, 30: 734-747.

Zurada, J.M., 1995. Introduction to Artificial Neural Systems. Text Book, pp: 26-55.