ISSN 0975-2366
https://doi.org/10.31838/ijpr/2018.10.04.046

Review Article

Epileptic Seizure Classification Using Feed Forward Neural Network Based on Parametric Features

RAJENDRAN T[1], SRIDHAR K P[2]
[1]Research Scholar,[2]Associate Professor
[1,2]Department of Electronics & Communication Engineering, Faculty of Engineering, Karpagam Academy of Higher Education (Deemed to be University), Coimbatore, India.
Email id ::rajendran.thavasimuthusamy@gmail.com &capsridhar@gmail.com
Received: 09.05.18, Revised: 15.08.18, Accepted: 29.09.18

ABSTRACT
Globally, epilepsy is a severe neural disorder occurring among 0.6-0.8% of the population. The formation of pattern-change from normal to disturbed factors that all gets triggered at once is called seizure. Many researchers introduced different techniques, but the problem of detecting epileptic seizures remains unsolved. This paper presents a new technique for detection of epileptic seizure-based Electroencephalogram (EEG) signals. The detection scheme adapts the non-invasive measure of the brain's electrical activity by placing the electrodes on the scalp. The collection of such electrical activity and diagnosing is a complex task because the brain is composed of numerous classes with numerous overlying features. Feature extraction based on parametric and non-parametric method is employed to extract the features vectors from EEG signals. The extracted features are forwarded to machine learning algorithms. Feed Forward Neural Network (FFNN) is implemented to detect the epileptic seizure. The performance results are evaluated by comparison of previous Modified Back Propagation Neural Network, Multilayer perceptron neural network, combined neural network, Probabilistic Neural Network and FFNN methods with respect to feature extraction in terms of accuracy, specificity and sensitivity. The FFNN has the higher classification accuracy as 97.23% demonstrates that it has a great potentiality of the real-time epileptic seizure detection.

Keywords: Epilepsy Seizure, Electroencephalogram, Feature Extraction, Neural Network and Auto Regressive.

INTRODUCTION
Epilepsy is a severe neurological brain disorder and many people are affected it. The term seizures are caused when there is rapid and persistent failure of the brain by epilepsy disorder. It reflects the clinical indications of an extreme and hyper synchronous movement of neurons in the brain. An epileptic seizure happens when the normal pattern of the brain's driving force is disturbed by the neuron which quickly terminatesat the same time. It can cause changes in sensation, mindfulness and normal human behavior, muscle spasms or loss of consciousness based on starting stage and spreading conditions of seizure [1].Seizures are of two types: they are Partialand Generalized. The Partial seizures areminor or unusual, and sometimes ignored. They occur in a small portion of the brain and can occasionally spread to other regions. If they spread, then they will be classified as generalized seizure normally called as tonic clonic seizure. Generalized seizures occur when there is seizure activity spread to the whole portion of the brain and leads to unconsciousness. The treatment of epilepsy disorders is undertaken by monitoring the brain activity using a tool through the Electroencephalogram (EEG). EEG machine records the brainwaves by placing electrodes on the human head region based on the golden standard of 10-20 electrode placement system [13]. The recorded EEG information is frequently twisted by different signs, called ancient rarities, whose sources are of both physiological and specialized nature. For diagnosing epilepsy, machine learning algorithms are to be introduced based on feature extraction. Several methods have been proposed for handling EEG signal-classification in which FFNNis implemented in this research. The NN has the capacity to sum up data, and its resilience to noise. The parametric and non-parametric methods are employed for feature extraction and the extracted features are forwarded as input to the NN for detecting epilepsy disorder [27-30].

Literature Survey
Karlıket *al.*[9] introduced machine learning techniques for diagnosing epileptic seizures. The EEG signals were extracted by using the Discrete Wavelet Transform (DWT) and Auto Regressive (AR) model and then forwarded to machine learning methods. The experimental results proved that Artificial Neural Network (ANN) and SVM were effective in extracting the EEG features. Sakkaliet *al.*[10] projected a technique for determining the epilepsy in young children by EEG signal based on parametric and non-parametric methods. It built up reliable techniques for testing epilepsy from the EEG signal. The feature extraction was done by parametric and non-parametric methods. The results were compared between children of two matching age groups with exact control epilepsy, and the features were extracted by demonstrating the EEG signals and it showed that it was more efficient with linear

discriminate classifier. Wang *et al.*[4] proposed an epilepsy diagnosis framework based on the integration of multi-domain feature extraction and nonlinear analysis to detect seizure and non-seizure EEG signals. Numerous methodologies were proposed for detecting epileptic seizure, based on Fourier spectral analysis. The EEG signals were extracted based on time and frequency domain. It applied to eliminate the noise from EEG signals with respect to feature extraction and by employing a discrete wavelet transforms and the nonlinear analysis for extracting the multiple features. The performance results proved that it achieved high accuracy and increased classification robustness for detecting the epileptic seizure. It removed the burden of doctors by processing a large number of datasets for identification. Alam*et al.* [21] analyzed the epileptic seizures based on chaotic and statistical features to distinguish EEG signal. The integration of numerical and disordered features was separated from the input samples and transferred to neural network to categorize the EEG signals which underwent training and testing. Finally, each case was evaluated by certain performance metrics such as accuracy, sensitivity and specificity which indicated that the proposed method achieved efficient classification when equated with other techniques. Hassan *et al.* [22] proposed an Ensemble Empirical Mode Decomposition with Adaptive Noise for effective feature extraction. Statistical features were extracted from the EEG signal segments disintegrating by EEMDAN and ANN were utilized for seizure sorting. Adeli*et al.* [23] made an outline of the DWT and computing spikes, sharp waves and waves based on wavelet transform to examine and illustrate epileptic from discharges in the form of 3-Hz spike and wave complex in patients with absence seizure. The performance results proved that temporary features were captured and analyzed with both time and frequency domain. Mostly diseases are recognized bygenetic, behavioral and environmental factors which are analyzed by several statistical methods and regression models. To overcome these limitations, an approach called Multifactor Dimensionality Reduction (MDR) was proposed by Gola*et al.* [3]. It was employed for feature extraction process to determine the imbalanced data and missing value for large datasets. The obtained results were implemented on a large scale which aimed to process large data by integrating a genetic and clinical data. Husain *et al.*[5] introduced a Fourier Bessel functions for predicting an epileptic seizure. This method was employed for predicting a seizure to improve the human lifetime based on EEG signals which were recorded from patients. The Fourier–Bessel(FB)series coefficients were consideredto extract the feature vector for segmentation of the EEG signal. Classifying the Interictal (seizure free)and preictal (before seizure)transition was based on machine learning algorithms such as neural network. Finally, it was efficient in terms of accuracy and sensitivity. A multichannel epilepsy detection system was proposed by Thanaraj*et al.*[6] based on Higher Order Statistics (HOS) and complexity analysis on the signal for input signals of 8 channels. To extract the feature vector by ANIOVA test the features were trained by SVM classifier. Singular Value Decomposition was then used to reduce the dimension of the feature vector. The results were computed for test accuracy and error rate which showed better efficiency than traditional methods.

Eeg Signal Frequency Bands Of Epileptic Seizure

Generally, the frequency range of brain waves according to rhythms of the EEG are categorized into five signals which are shown in table 1 [11].

Table 1 Frequency of the EEG wave

Delta	0.4-3Hz	This is the frequency achieved at deep sleep and serious brain disorder.
Theta	3-7 Hz	It occurs when the people is in emotional and unconscious. In some cases, the creative inspiration and deep mediation are included in this range
Alpha	7-12 Hz	It occurs if a person is in relaxation state.
Beta	12 - 29 Hz	If the brain is in active attention and some intellectual activities.
Gamma	> 29 Hz	It occurs due of various reasons like cognitive and motor functions.

Eeg Epileptic Seizure Database

The databases (EEG signal) for this research were collected from the Karunya University. The performance results are compared with K-means, Navies Bayesian and Neural Network with respect to parametric and non-parametric method. The collected database is extracted by applying feature extraction methods and the extracted features are classified by implementing the proposed Feed Forward Neural Network.

Discrete Wavelet Transform Based Noisy Filtering

Discrete Wavelet transform is more advantageous than other spectral analysis methods on non-stationary signals. Most of the researchers prefer DWT because of its unique characteristics that are localized in both time and frequency. Mainly it is employed for detecting the noisy signal in EEG signals and applicable for low and high frequency that is narrow for the window size. The whole processes are carried out with various frequency ranges,and some optimal results detected. The main reason to select DWT-based filtering is the efficient scaling and high speed when compared with the continuous wavelet. The process of wavelet is divided into x[n] terms with the multi resolution decomposition. It decides the overall accuracy, frequency level and strength of the signal. The applications of DWT have been huge and vast in recent years. Various research methodologies followed this concept and achieved good results. The major applications of the DWT are utilized in data and medical/signal processing areas.

Feature extraction

The reduction of input data into a set of features represents feature extraction and it comprises simplification of the amount of resources to demonstrate a large set of data exactly. It will extract the significant data from the input data to perform the task using the algorithm instead of a full-size input. Dealing with huge data requires a large amount of memory and calculation power or classification algorithm which over fits the training sample. The extracted coefficients provide a compressed representation that shows the energy distribution of the EEG signal in time and frequency [2]. The features used to represent EEG signals in terms of time and frequency are

Maximum and minimization of the coefficients in each dataset

Mean of the coefficients in each dataset

Standard deviation of the coefficients in each dataset

Auto Regression (AR) Features

Auto regression is one of the parametric methods mainly used for AR feature extraction [19]. It is characterized based on input streamx(n) harvested at the linear system output. It is progressed in-between the range $0 \leq n \leq N-1$). It is initially designed by resolving the linear equations. Data can be modeled as output of a causal, all-pole, discrete filter whose input is white noise in the AR method for obtaining stable and high performance. AR method can be characterized such as optimum estimation method, selection of the model order, the length of the signal and the level of stationary data[14]. Estimated auto aggressive extracts the feature vectors from the given EEG signal, and the extracted features are forwarded to neural network for classification.

Feed forward neural network

The feature extracted features are forwarded as input to the NN. FFNN is one of the machine learning techniques[20] that is inspired by the organization and functioning of biological neurons. When the nonlinear processing neurons are given as input, NNs can learn from familiarity and evaluate any complex functional relationship with high accuracy. ANN is a way to deal with calculation or is the model of a processor in the light of human mind. A pervasive perspective of human mind is that it is a kind of neural system. The neural system comprises around 100 billion neurons, every neuron being associated with up to 10000 other neurons. There is one layer for the input variables and another layer for the output. The layers include:

Input Layer - Input layer includes input units indicating the unrefined information provided for the network. It is liable for getting data, signals, features or measurements from the external environment. These input samples are usually normalized within the limit values produced by activation functions.

Hidden Layer – These layers are composed of neurons which are responsible for extracting patterns associated with the process or system being analyzed. These layers perform most of the internal processing from a network. It includes the hidden units which are affected by the conduct of the input units and the weights that interface the information and the hidden units.

Output Layer - This layer is made out of neurons, which are in charge of delivering and displaying the last system yields, which result from the processing performed by the neurons in the past layers. The layer conduct is subject to the specificity of the concealed units and the weighted neuron which interface with the covered up and yield units. Figure1 demonstrates the general model of FFNN.

The measure of neurons forming the main concealed layer is generally not the same as the quantity of signs making the information layer out of the system. Actually, the quantity of hidden layers and their particular measure of neurons rely upon not only the nature and complexity of the issue being mapped by the system, but also the amount and nature of the accessible information about the issue. Similarly, for basic layer feed forward systems, the measure of output signs will dependably coincide with the quantity of neurons from the individual layer [16].Here, the interconnected nodes are grouped with respect to the layers which contain an activation function. Patterns are represented via the input layer and it is represented as X_1, X_2, X_3.....X_n which interconnects with at least one shrouded layer where the genuine handling is finished by arrangement of weighted associations. The concealed layers at that point connect to a yield layer, then the outcome yield is demonstrated as out1, out2… … outm. There can be one or a few computation nodes between these

two layers referred to as concealed layers [12]. The flag or information given to one neuron is passed to every one of the neurons with which it is associated in portions equal to the weight between these neurons. Every neuron computes its yield in light of a capacity which can be sigmoid, advance or some such appropriate capacity. The quality of neural systems is their ability to gain from designs. The two key components of neural network structure are neurons and weighted direct relations, which connect one layer of neurons with another layer of neurons. In the training phase, certain weights of the layer connections are adjusted. FFNN models can be trained for these features from sample data, and this information can be used to predict or categorize data in a dataset.

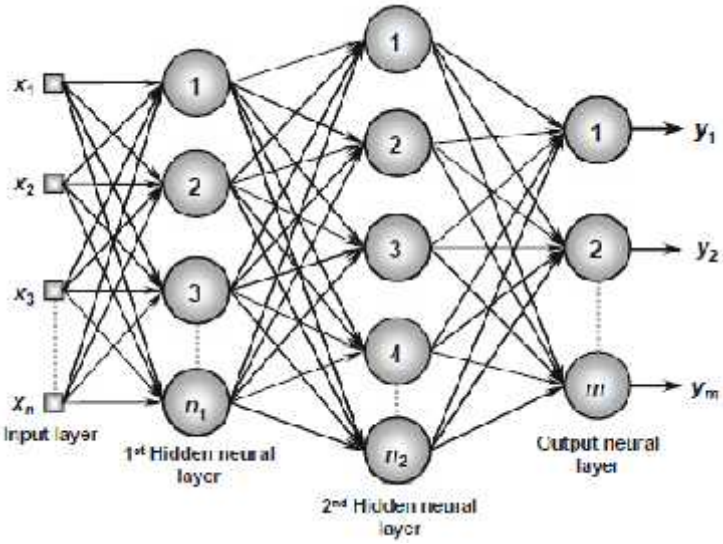

Figure1:Model of FNNN Network

Some steps are considered here to build and train the network, which is listed below

Step-1: Initialize number of hidden units in neural network, h = 1.

For the general ANN model shown in figure 1, the net input can be calculated as follows:

$$Y_{in} = X_1W_1 + X_2.W_2 + \cdots \ldots \ldots X_m W_m \quad (10)$$

Step-2: Determine the Number of input and output neurons Hidden neurons and layers

$$N \qquad Y_{in} = \sum X_i W_i M_i \quad (11)$$

The output can be calculated by applying the activation function over the net input.

Step-3: Fix all the initial weights randomly within a certain range.

Step-4: Add the algorithm that train the network based on the number of epochs that minimizes the error function.

Step-5:Choose the learning rate

Step-6: Compute the error function

Step-7: If the error function ξ on given set is acceptable, then immediately the network must classify desired number of patterns on test set and then stop.

Step-8: If the error function ξ on given set is rejected then go to step -1 and continue

Step- 9: Add a one hidden unit to hidden layer.

(Set h = h + 1)

Step-10 Randomly initializes the weights by linkingit with the new hidden unit on input nodes and output unit(s).

$$Y = f(Y_{in}) \quad (12)$$

Output = function (net input calculated)

Step-11 Continue the process until it get accepted.

Results And Discussion

The performance for finding the epilepsy disorder based on feature extraction and NN are carried out by collecting EEG data of patients as epileptic seizure data and normal data. The feature extractions are performed on Auto Regressive model and Multifactor dimensionality reduction. Training and testing the information has been chosen by cross validation Extract of the information,and the extracted features are forwarded to neural network for detecting the

epilepsy data. The dataset is selected with the following specifications. The details of the dataset are considered here to display the exactness of research. It is acquired with 10-20 electrodes, which is determined by the international standard. The metrics are collected from the 16 scalp channels and two periocular electrodes. Some important metrics are shown in table 2.

Table 2: EEG dataset parameters

Content	Parameters
Sampling rate	256Hz
Analog pass band	0.01 to 100 Hz
Contact impedance	Below 5k
Each EEG data epoch duration	10-second
Comprising 2560 data points	Having 4ms duration each

After removing the features from feature parameter, the examination is carried out. It is continually checked by ordering the information utilizing these two strategies by FFNN [17]. The strategies are compared for execution, before which the information is trained by NN design.The proposed method is compared with the previous methodologies and neural network-based algorithms.

Performance Measurement

The efficiency of the proposed epilepsy detection system is expressed in terms of following parameters. Table 1 shows the training data accuracy for various algorithms with respect to feature extraction methods.

$$A = \frac{T + T}{T + F + T + F} * 100 \quad (13)$$

$$Se = \frac{T}{T + F} * 100 \quad (14)$$

$$Sp = \frac{T}{T + F} * 100 \quad (15)$$

Where TP denotes True Positive, TN denoted True Negative, FP denotes False Positive and FN denotes False Negative.

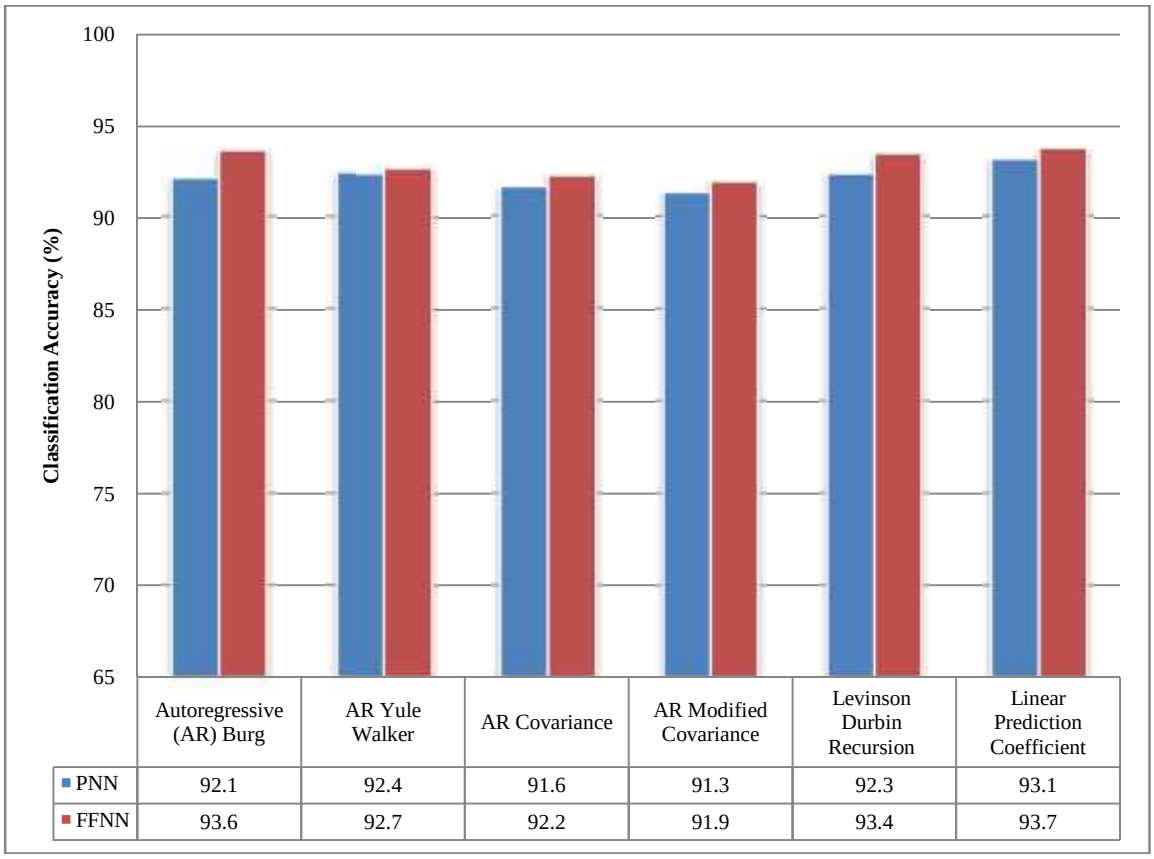

Figure 2: Classification accuracy of a single (A0014) patient

From the training data, an A0014 patient dataare considered to measure the AR features. This concept is adapted by comparing it with the AR feature accuracy with the previous neural network module called PNN. It is concluded that the AR burg has the maximum accuracy as 93.6%, and has the difference of 1.5% of PNN values. Similarly, there is a difference in all other AR feature set with ±1.6. The overall accuracy declares that FFNN is effective in all terms of classifying the lobe seizure. The comparison of different classifiers and their sensitivity, specificity and accuracy are calculated and listed in table 3.

Table 3: Comparison of different classifier

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
Modified Back Propagation Neural Network [24]	74	77	94
Multilayer perceptron neural network (MLPNN) [25]	94.95	96.03	95.60
Combined neural network [26]	94.50	96.00	94.83
PNN	**95.10**	**97.25**	**96.30**
Feed Forward Neural Network	**95.41**	**98.21**	**97.23**

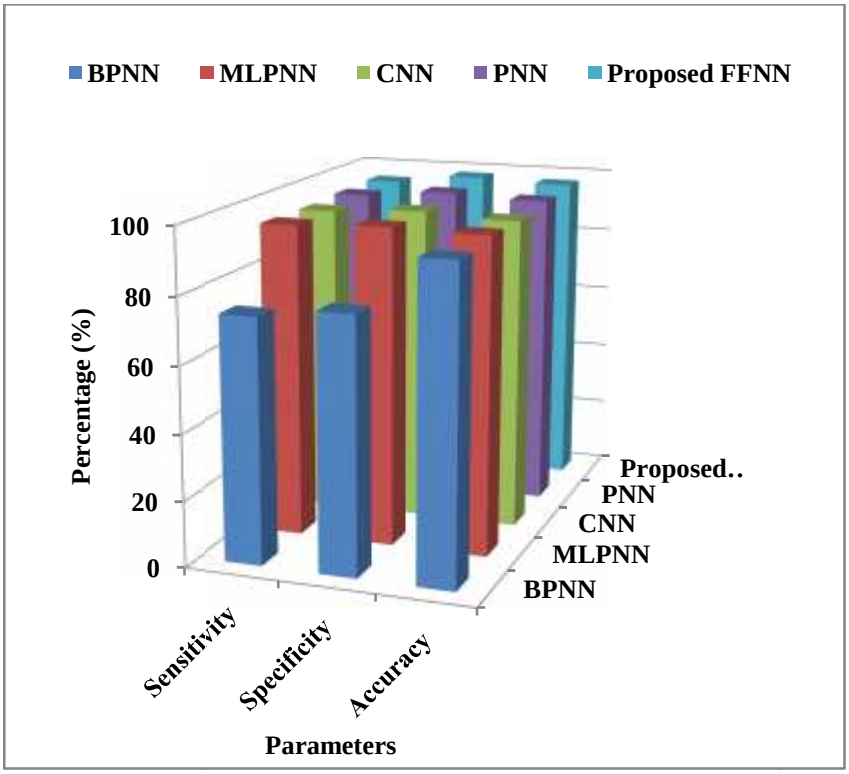

Figure 3: Overall comparison of lobe classification

Figure 3shows the accuracy comparison of the proposed method with respect to feature extraction methods. From the graph it is shown that the proposed neural network performs well for parametric method when compared to existing methods.

Conclusion

In this paper a new epilepsy detection method is implemented based on EEG signal. Features are extracted using Auto Regressive, and statistical features are classified using feed forward neural network. The results are tabulated and the proposed method shows significant results when compared to the existing methods. The Modified Back Propagation Neural Network is the only method that lags beyond 80%. Since, the accuracy is improved to 94%,when compared to Multilayer perceptron neural network (MLPNN) and combinedNN, the proposed method has improved by nearly 2.85% of accuracy. Moreover, these results show that the proposed method, based on parametric for detection of epileptic seizure by using FFNN theAR parametric methods, is faster and has better accuracyat 97.23%. The FFNN desires more iteration time for training. The epilepsy detection by using the proposed methodis faster and offers more effective results than other methods, and is applicable for an early detection of the disease. Furthermore, the research must focus more on adapting the possible training

algorithm for better classification. It is believed that this proposed method is a promising one, since there is a need to explore some real time dataset and test with that to find an accurate prediction.

Acknowledgement

The authors would like to thank the Department of ECE, Karpagam Academy of Higher Education (Deemed to be University), for their constant support and encouragement.

References

1. Song, Y. and Liò, P., 2010. A new approach for epileptic seizure detection: sample entropy based feature extraction and extreme learning machine. Journal of Biomedical Science and Engineering, 3(06), p.556.
2. Wang, F.L., Meng, Q.F., Chen, Y.H. and Zhao, Y.Z., 2014. Feature extraction method for epileptic seizure detection based on cluster coefficient distribution of complex network. WSEAS Trans. Comput, pp.351-360.
3. Gola, D., Mahachie John, J.M., Van Steen, K. and König, I.R., 2015. A roadmap to multifactor dimensionality reduction methods. Briefings in bioinfor
4. Wang L, Xue W, Li Y, Luo M, Huang J, Cui W, Huang C. Automatic Epileptic Seizure Detection in EEG Signals Using Multi-Domain Feature Extraction and Nonlinear Analysis. Entropy. 2017 May 27; 19(6):222.
5. Husain SJ, Rao KS. A Neural Network Model for Predicting Epileptic Seizures based on Fourier-Bessel Functions. International Journal of Signal Processing, Image Processing and Pattern Recognition. 2014;7(5):299-308.
6. Thanaraj KP, Chitra K. Multichannel Feature Extraction and Classification of Epileptic States Using Higher Order Statistics and Complexity Measures. International Journal of Engineering & Technology.:0975-4024
7. Musselman M, Djurdjanovic D. Time–frequency distributions in the classification of epilepsy from EEG signals. Expert Systems with Applications. 2012 Oct 1; 39(13):11413-22. matics, 17(2), pp.293-308.
8. Sakkalis V, Cassar T, Zervakis M, Camilleri KP, Fabri SG, Bigan C, Karakonstantaki E, Micheloyannis S. Parametric and nonparametric EEG analysis for the evaluation of EEG activity in young children with controlled epilepsy. Computational intelligence and neuroscience. 2008 Jan 1; 2008:1.
9. Karlık B, Hayta SB. Comparison Machine Learning Algorithms for Recognition of Epileptic Seizures in EEG.
10. Subasi A. EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications. 2007 May 31; 32(4):1084-93.
11. Singh M, Kaur S. Frequency band separation for epilepsy detection using EEG. International Journal of Information Technology and Knowledge Management. 2012 Dec; 6(1):11-3.
12. Husain SJ, Rao KS. An artificial neural network model for classification of epileptic seizures using Huang-Hilbert Transform. International Journal on Soft Computing. 2014 Nov 1; 5(3):23.
13. Costa RP, Oliveira P, Rodrigues G, Leitão B, Dourado A. Epileptic seizure classification using neural networks with 14 features. InInternational Conference on Knowledge-Based and Intelligent Information and Engineering Systems 2008 Sep 3 (pp. 281-288). Springer, Berlin, Heidelberg.
14. Shiman F, Safavi SH, Vaneghi FM, Oladazimi M, Safari MJ, Ibrahim F. EEG feature extraction using parametric and non-parametric models. InBiomedical and Health Informatics (BHI), 2012 IEEE-EMBS International Conference on 2012 Jan 5 (pp. 66-70). IEEE.
15. Selvaraj TG, Ramasamy B, Jeyaraj SJ, Suviseshamuthu ES. EEG database of seizure disorders for experts and application developers. Clinical EEG and neuroscience. 2014 Oct; 45(4):304-9.
16. Verikas A. and Bacauskiene M., "Feature Selection with Neural Networks. Pattern Recognition Letters", 23(11), Pp.1323-1335, 2002.
17. Turkson R.F., Yan F., Ali M.K.A. and Hu J., "Artificial Neural Network Applications in the Calibration of Spark-Ignition Engines: An overview", Engineering Science and Technology, an International Journal, 19(3), Pp.1346-1359, 2016.
18. Sivagaminathan R.K. and Ramakrishnan S., "A Hybrid Approach for Feature Subset Selection using Neural Networks and Ant Colony Optimization", Expert systems with applications, 33(1), Pp.49-60, 2007.
19. Ouelli A, Elhadadi B, Aissaoui H, Bouikhalene B. Epilepsy Seizure Detection Using Autoregressive Modelling and Multiple Layer Perceptron Neural Network. American Journal of Computer Science and Engineering. Jul 15;2(4):26-31, 2015
20. Sheb A, Guttag J. Application of machine learning to epileptic seizure detection. In2010 the 27th International Conference on machinelearning, Haifa, Israel 2010.
21. Alam, S.S. and Bhuiyan, M.I.H., 2011, December. Detection of epileptic seizures using chaotic and statistical features in the EMD domain. In India Conference (INDICON), 2011 Annual IEEE (pp. 1-4). IEEE.
22. Hassan, A.R. and Haque, M.A., 2015, November. Epilepsy and seizure detection using statistical features in the complete ensemble empirical mode decomposition domain. In TENCON 2015-2015 IEEE Region 10 Conference (pp. 1-6). IEEE.
23. HojjatAdeli, Ziqin Zhou, and NahidDadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform", Journal of Neuroscience Methods, Vol. 123, pp.69-87, 2003.
24. Hemanth, D. J., & Anitha, J. (2018). Brain signal based human emotion analysis by circular back propagation and Deep Kohonen Neural Networks. Computers & Electrical Engineering, 68, 170-180.

25. Vuckovic, A., Radivojevic, V., Chen, A. C., & Popovic, D. (2002). Automatic recognition of alertness and drowsiness from EEG by an artificial neural network. Medical engineering & physics, 24(5), 349-360.
26. Übeyli, E. D. (2009). Combined neural network model employing wavelet coefficients for EEG signals classification. Digital Signal Processing, 19(2), 297-308.
27. Emayavaramban. G, Amudha. A, Ramkumar. S, Sathesh Kumar K. Classification of hand gestures using FFNN and TDNN networks. Int J Pure Appl Math 2018; 118(8): 27-32.
28. Emayavaramban G, Amudha A. Identifying hand gestures using sEMG for human machine interaction. J EngApplSci (Asian Res PublNetw) 2016; 11(21): 12777-85.
29. Emayavaramban G, Amudha A. Recognition of sEMG for prosthetic control using static and dynamic neural networks. International Journal of Control Theory and Applications 2016; 9(24): 205-15.
30. Emayavaramban G, Amudha A, Rajendran T, Sivaramkumar M, Balachandar K & Ramesh T, "Identifying User Suitability in sEMG Based Hand Prosthesis Using Neural Networks". Current Signal Transduction Therapy. 2018. (Article in Press)