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COMPARISON OF MACHINE LEARNING METHODS FOR PREDICTION OF EPILEPSY BY NEUROPHYSIOLOGICAL EEG SIGNALS

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ABSTRACT

Investigation of brain disorders especially epilepsy and impaired cognitive functions are the most common clinical application of neurophysiologic signals. EEG signals reflect the activity of brain and are capable of assessing the brain condition during abnormalities. In this study we have investigated the potential of two different algorithms (back propagation and radial basis function) of neural network technique for classification of patients suffering from epilepsy through EEG. Classification is based on quantitative parameters obtained from neurophysiologic signals used to train the networks and the performance of the networks is analyzed to confirm the efficacy of the network. Accuracy obtained with multi-layer perceptron NN is 99.6% and with radial basis function is 96.8%. The sensitivity obtained for pre-ictal, ictal and normal conditions are 93.9%, 100% and 97%, respectively in case of back propagation neural network algorithm. The comparative analysis is based on variation in network topology and in feature vector used for training the networks. Results from this study indicate that a classification system based on ANN may help in automation of analysis of neurophysiologic signals and the number and type of parameters used as feature set decide the type of network to be used for the better efficiency of the system.

KEYWORDS: EEG, Machine Learning Methods, Multi-layer Perceptron Neural Networks, Radial Basis Function.

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INTRODUCTION

EEG (Electroencephalogram) is a non-invasive technique of measuring electrical potential on the scalp originating from neuron activities. The signals show patterns of brain activity which is time-varying, non-stationary and varying frequency characteristics. Increasing power of computing and enhanced processing capabilities of the tool has made analysis of EEG signals efficient and effective. It has become a fundamental tool for diagnosing neural problems, and useful for both physiological research and medical applications[1] Epilepsy is a chronic neurological brain disorder, diagnosed by EEG signals. Epilepsy is a syndrome with vastly divergent symptoms resulting in abnormal brain activity, primarily due to hyper synchronous neuronal firing in the cerebral cortex which is manifested as Epileptic seizure. The seizures are sudden, brief and recurrent, depending on the location and extent of the affected brain tissue[2]. In neurology, the main diagnostic application of EEG is in the case of epilepsy. The motivation behind this paper is to predict the presence of epilepsy in human beings employing machine learning methods, which are capable of predicting the behavior accurately based on the previous observations. Main aim of this study is to compare the two machine learning methods (MLM) for prediction of epilepsy with the same dataset. In the field of mathematical modeling, back propagation neural network and radial basis function neural networks have an edge for the classification purposes. In this study, both the algorithms are used for classification and comparative results are tabulated. A variety of different ANN-based approaches are reported in the literature for epileptic seizure detection. Subasi[3] decomposed the EEG signal into time–frequency representations using Discrete wavelet transform (DWT) and applied to different classifiers, such as feed-forward error back-propagation artificial neural network, dynamic wavelet network (DWN), dynamic fuzzy neural network (DFNN), for epileptic EEG classification. Srinivasan et al.[4], employed individually features from the time domain and frequency domain to Elman recurrent neural network for classifying EEG signals. Übeyli [5] classified the EEG signals using Lyapunov exponents. N. Kannathal [6]et al investigated entropy; sample entropy and approximate entropy for discriminating EEG signals. Guo et al.[7] after decomposing original EEG signal into several sub-bands calculated ApEn feature to classify the EEGs using three-layer MLPNN. Artefact extraction and removal from EEG signals using RBF have been taken up by A Saastamoinen et al [8]. Kezban Aslan[9] et al. have classified patients into partial epilepsy patients and as primary generalized epilepsy patients using demographic properties of patients as well. Abdulhamit Subasi[10] applied multi-scale PCA (MSPCA) de-noising method to outperform RBF.

MACHINE LEARNING METHODS

To facilitate physician for accurate online prediction of epilepsy and to design its model, the machine learning approach has gained great popularity. The most often used machine learning methods are support vector machine (SVM), artificial neural network (ANN), and hidden Markov model (HMM), and so on. Among these, ANNs are most popular and efficient as they posses greater accuracy and their capability to handle large data base.

(i) ***Multi Layer Perceptron Neural network (MLPNN)***

Neural network is a model of the human brain and nervous system, composed of interconnected processing units called neurons. Each unit connected to a number of network units' process information, and the network behavior is determined by the relationship between input and output. The most popular neural networks used are multilayer perceptron which are supervised-trained with the error back-propagation algorithm and considered as non-linear statistical method[11]. Figure 1 shows configuration of three layer MLPNN- input layer, hidden layer and output layer. Back Propagation network learns through repeated adjustments of the weights, (a link that signifies the importance of each input to a neuron) and get trained by the inputs given at the input layer and expected output at the output layer. In the back propagation stage, the algorithm checks the error between the expected value and obtained value and modifies the weights to minimize the error. Once trained, the networks can appropriately process data that have not been used for training. A significant improvement in BPNN performance can be achieved by using various high order approaches as Newton's method, conjugate gradient and the Levenberg–Marquardt (LM) optimization technique[12].

(ii) *Radial Basis Function (RBF)*

RBF network is a particular class of multilayer networks in which learning occurs usually in two stages. An unsupervised self-organizing method such as k-means clustering is used for learning in the hidden layer and a supervised method such as least squares estimation is used for learning by the output layer [13]. Amongst the three layers, hidden units provide a set of functions that constitute an arbitrary basis for the input patterns. These functions produce a significant non-zero response only when the input falls within a small region of input space. The basic idea is that a predicted target value of an input is likely to be about the same as other data that have close values of the predictor variables. RBF networks are advantageous as it involves finding the input to output map using local approximations, and rapid learning. A RBF networks may require more neurons than standard feed forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks[14]. In RBFNN, the Gaussian function and the least squares (LS) criterion are selected as the activation function of network and the objective function, respectively.

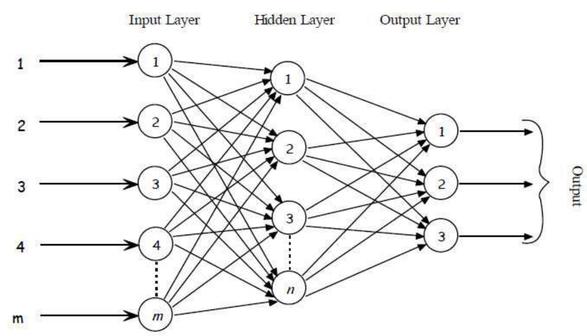


Figure 1
Configuration of a Artificial Neural Network with m input features and n nodes in hidden layer and three nodes in the output layer

MATERIALS AND METHODS

In this study the classification of the patients involve preprocessing, feature extraction, topology selection and classification using ANN techniques and comparison of different techniques.

DATA SET

The EEG database used is obtained from University of Bonn, Germany available in public domain[15]. The complete dataset consist of 500 single-channel EEG signals sampled at 173.61Hz and of 23.6 s duration. The data set is categorized into five different sets (A-E). Sets A and B consist of EEG segments collected from five healthy volunteers in awaken and relaxed state, with their eyes open and closed, respectively. Sets D and C consist of EEG epochs recorded during seizure free intervals and set E is recorded during the seizure period. In this study three cases, seizure state, normal state and pre-ictal state A,D and E respectively are chosen; signal from one of each sets is depicted in Figure 2.

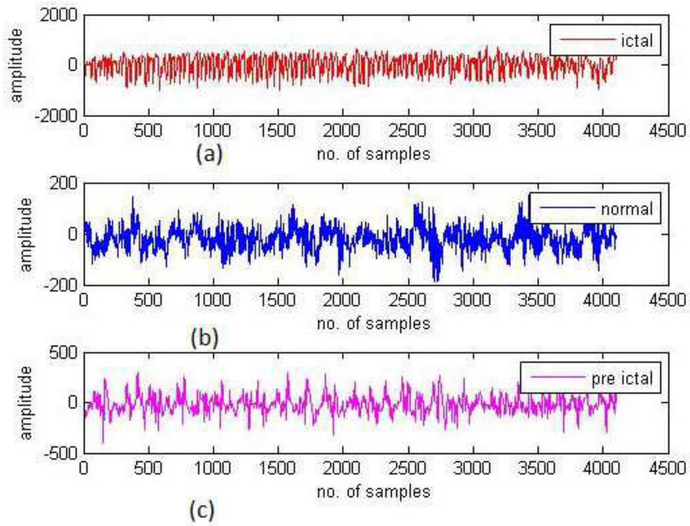


Figure 2
Signals depicting a) EEG of patient in ictal state b) EEG of normal state patient c) EEG of patient in pre-ictal state

DESIGN OF NETWORK

To classify the patients for state of epilepsy using EEG signals and for creation of an effective model following workflow was maintained. After preprocessing the signals for artifact removal, extraction of quantitative features is followed by selection of useful features, forming a feature vector for all the 300 signals.

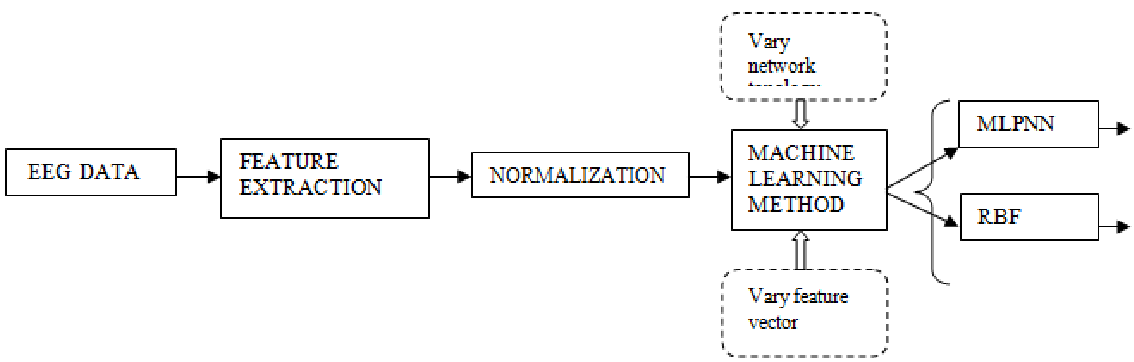


Figure 3
Proposed computational method for classification of EEG signals using MLM.

A. Feature Vector

For designing any classification system, feature extraction plays a vital role as it reduces the dimensionality by reducing the large EEG signal into small set of features. Even if some features do not exactly depict the original signal, they are sufficient enough to examine the accuracy of proposed algorithm. All the extracted features constitute the combined feature index (CFI) = (F_1, F_2, F_3, F4, F5......Fn), which is presented as an input to the ANN network as shown in Fig 3. The features used in evaluating the performance of the proposed scheme are energy, entropy, mean, standard deviation, skew, kurtosis, non linear energy, maxima, minima, in all thirteen features are selected for the present work. Figure 4 represents some of the features chosen for this study.

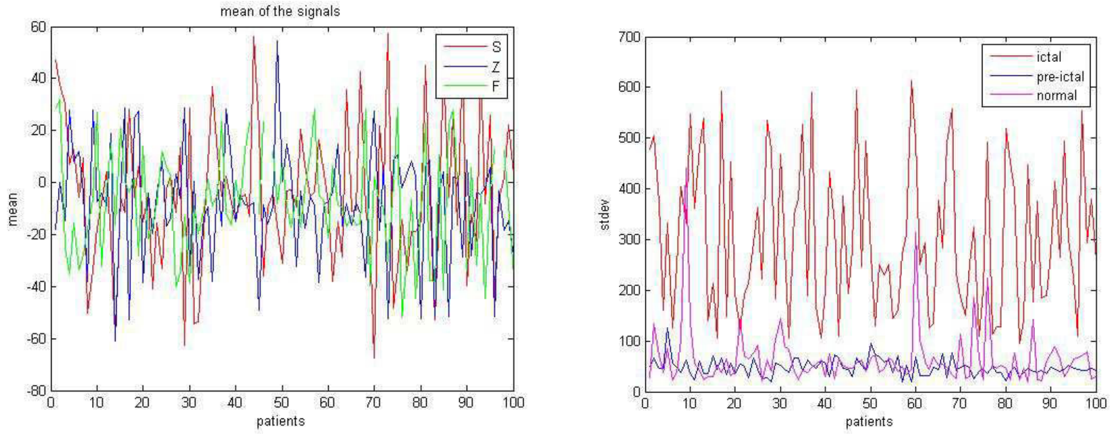


Figure 4
a) Standard deviation b) Mean of the three types of signals (ictal(S), pre-ictal (F) and Z (normal) conditions.)

B. Design of Classifier

The number of neurons in the input layer symbolizes the number of features presented to the network, followed by hidden layer with neurons which transforms the input into nonlinear combinations and passes the signals to the output layer[16]. In our study, the number of neurons in the input layer is thirteen corresponding to CFI and the number of neurons in the output layer is three to classify three different classes. The most challenging task is to select the number of neurons in hidden layer. In our work we varied the numbers of hidden nodes from 5 to 30 to find out the architecture giving the better performance with high accuracy. The same configuration was used for RBF network and the comparison of their performance is reported. The second part of study is based on Brute Force Approach for developing CFI. We have adapted our method by systematically enumerating all combinations of feature vectors and checking all different size CFIs for the optimality of the features. Different features set starting from two are chosen, and performance is evaluated for both MLPNN and RBF. The next part of our work involves exhaustive analysis of the networks by varying feature vectors with same network topology.

C. Performance Parameters

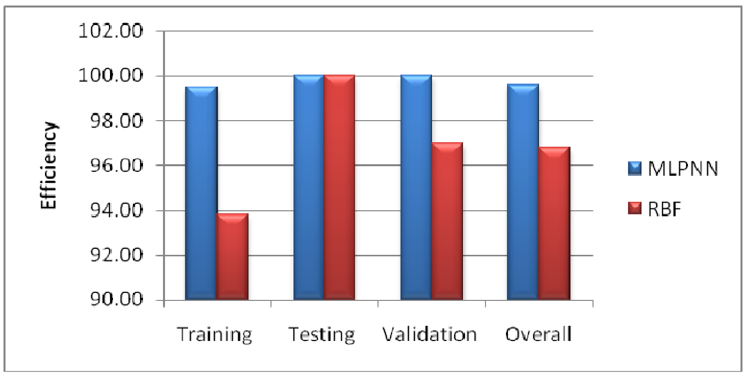
For the performance evaluation of the classification technique, measures used are Sensitivity, and Accuracy, in form of a confusion matrix. Sensitivity measures the fraction of positive cases that are classified as positive. Accuracy measures the overall fraction of samples that are correctly classified. The classification accuracy for all the three classes and separately for training, testing and validating the three classes is the basis of our evaluation.

RESULTS AND DISCUSSION

To validate predictive model with a good generalization performance, dataset is divided randomly into 70% for training the network, 15% for validation and 15% for testing to assess the predictive performance of the model. For each sequence in the training and testing sets, around 20 networks were trained and best five networks were averaged to get the performance parameters. In the proposed system, tan-hyperbolic transfer function was utilized in hidden and output layers, and BFGS (Broyden-Fletcher-Goldfarb-Shanno) method was used for training for MLPNN with sum of squares as the error function. For RBF, training vectors selected as the centres of radial basis function form Guassian model and Softmax function was used for output nodes and RBF Training algorithm for training the weights with Entropy as error function. In all, CFI was formed from thirteen feature namely mean, median, mode, energy, entropy, skew, kurotosis, snr (signal to noise ratio), covariance, amplitude maxima and minima, covariance and nonlinear energy were used for classification with MLPNN and RBF classifiers to compare the capability of both the classifiers to classify the ictal, pre-ictal and normal states of epileptic patient. The performance evaluation was based on classification efficiency in terms of training, testing and validating efficiencies as reported in Graph 1. A highest overall classification efficiency of 99.6% is obtained for the proposed model by using MLPNN and 96.8% accuracy with RBF as machine leaning method. It can be visualized from the graph that training accuracy is better in MLPNN but once training is done, testing accuracy is same for both the networks with small variation in validation efficiency showing that MLPNN is the best prediction model for this experiment. For these networks the network architecture revealed that number of hidden nodes is different for both the methods.

Graph 1

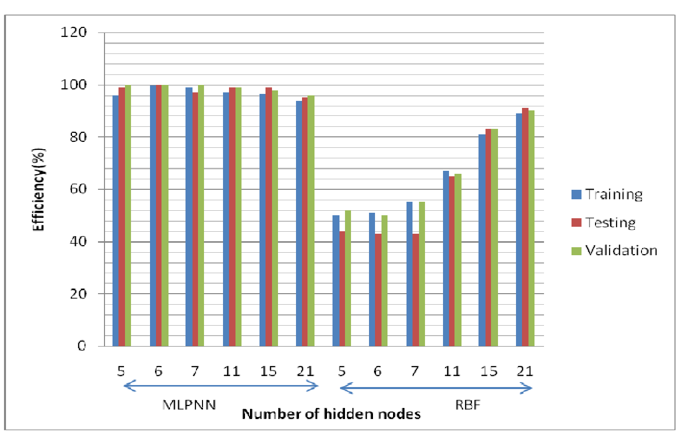
Comparative analysis of prediction performance of both, back propagation multiple layer perceptron (MLPNN) and radial basis function (RBF).



Performance analysis was done for both the networks for different architecture by varying the number of nodes in hidden layer. Varying nodes from five to twenty five in hidden layer, different architectures were trained and their performance was evaluated as shown in Graph 2. Wide variation during training, testing and validating accuracy was observed with two diff types of networks with different topology. It is interesting to note that for all feature set, as number of nodes increases, efficiency increases in case of RBF from 50% to around 95%.

Graph 2

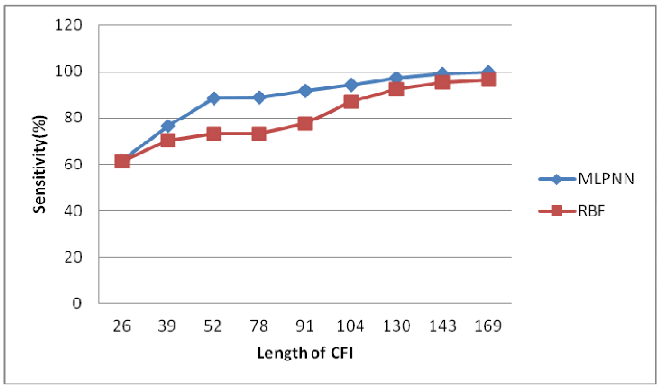
Comparative analysis of prediction performance in terms of classification efficiency of both, back propagation multiple layer perceptron (MLPNN) and radial basis function (RBF).



All the results obtained, used the discrimination ability of all the selected features from all the 300 signals. In our next experiment the discrimination ability of different features sets are investigated. By varying the length of CFI, by varying the number of features (from 26, 39, 52 and so on till169) efficiency and sensitivity of the methods for classification is determined. Graph 3 depicts the comparison of the two methods in terms of sensitivity for predicting the right class by considering different length of CFI. It is observed that combined CFI consisting of all the features has more efficiency but discrimination ability is indicated with less number of features.

Graph 3

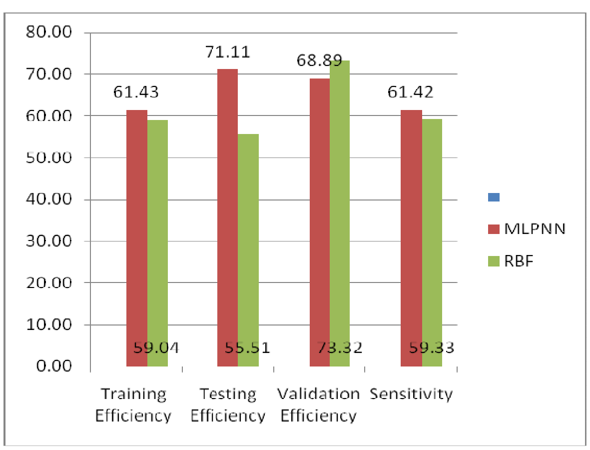
Comparative sensitivity analysis of predictive models (MLPNN and RBF) by varying CFI.

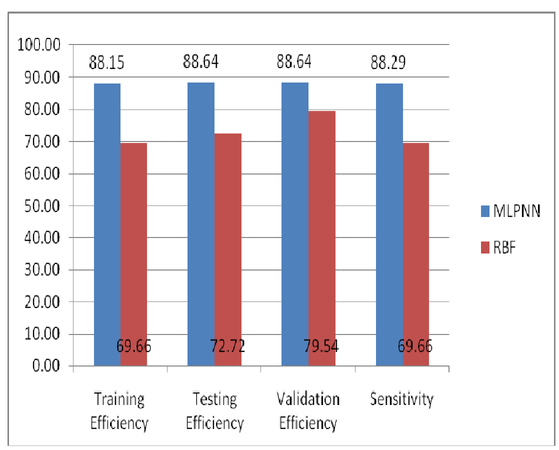


As observed from the previous results, MLPNN has an edge over RBF for this problem of classification; hence another performance analysis was conducted, for RBF network. The efficiencies were calculated by varying number of features but with the same number of hidden nodes as obtained with the MLPNN with the same size of its feature set. The various comparisons for varying length of CFI are reported in Graph 4 in terms of training, testing and validation efficiency and sensitivity of prediction. Selected results of subsets of feature vector sets used for classification are depicted in the Graph 4.

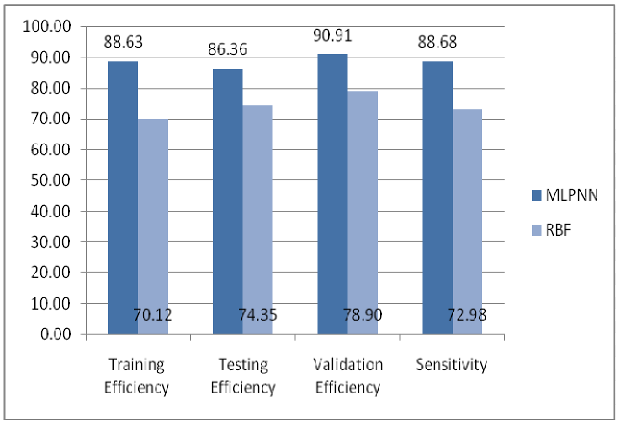
Graph 4

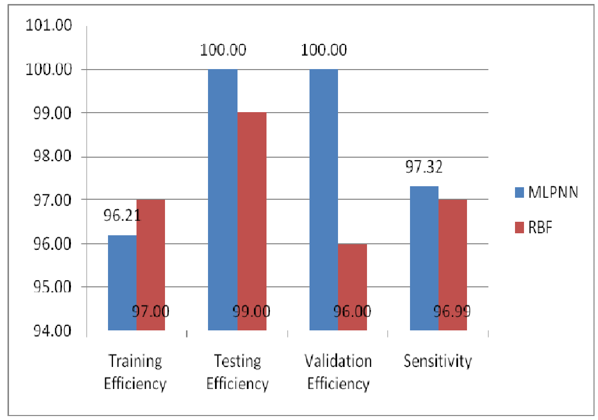
Comparative Performance analysis of both, back propagation multiple layer perceptron (MLPNN) and radial basis function (RBF) for varying length of Combined Feature Index.





(a) Two features with same number of hidden nodes (CFI:26) (b) Four features(CFI:52)

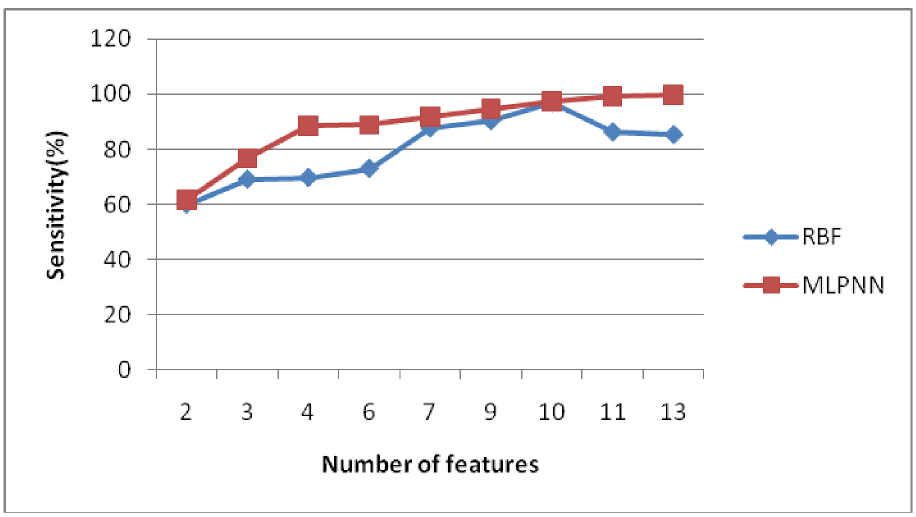




(c) Six features(CFI:78) **(d) Ten features(CFI:130)**

Finally, for the same network topology (13 input nodes, 3 output nodes and 6 hidden nodes) the two networks were analyzed for the sensitivity with varying CFI. Maxima and minima sensitivities obtained are 99.6% and 61.42% for MLPNN respectively and 96.99% and 59.93% respectively for RBF as depicted in Graph 5.

Graph 5
Performance Analysis of MLPNN and RBF in terms of sensitivity with same network topology and varying combined feature index.



RBF gave comparative accuracies in all the works but with larger number of hidden neurons. The evaluation parameters for RBF giving maximum accuracy of classification is tabulated in form of confusion matrix illustrated in Table 1. The highest classification accuracy of 96.8 % was obtained for 30 hidden nodes.

TABLE 1
(a) *Prediction accuracy of neural network model developed in this manuscript.*

Predicted Category	Confusion Matrix		
	Pre- Ictal	Ictal	Normal
Pre-ictal	93	0	3
Ictal	2	100	0
Normal	4	0	97

The ability to make correct predictions, in identifying as many as positive signals as possible is the most important aspect of a prediction method. The performance of classification techniques is measured in terms of Sensitivity and incorrect classification. The sensitivity obtained for developed prediction model for different conditions is 93.9% for pre-ictal condition, 100% (for ictal) and 97% (for normal) with MLPNN method.

(b) *Classification summary for the predictive model for all the three different states with sensitivity and misclassification in %.*

	Pre-ictal	Ictal	Normal
Total	99	100	100
Correct	93	100	97
Incorrect	6	0	3
Sensitivity	93.9	100	97
Incorrect (%)	6.06		

CONCLUSION

In the present work, an elaborative comparison has been performed between two machine learning methods for the classification of ictal, pre-ictal and normal state of epileptic patients.Even as prototype, both the ANNs we implemented have shown practical performance as demonstrative of the efficiency of the machine learning methods. MLPNN could be a very good candidate to achieve the efficiency of 99.6% as compared to 96.8% achieved by RBF with less number of hidden nodes leading to less complexity of the architecture. We have demonstrated the feasibility of choosing number of features for classification and concluded that MLPNN revealed a superior model in terms of higher efficiency and number of hidden nodes. In conclusion, this work can be further improved by optimization techniques for selecting the features and to set CFIs length.

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