A Comparative Performance Analysis of Artificial Neural Networks and Particle Swarm Optimization based Classification System using Electroencephalogram Signals

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ABSTRACT
The aim of this paper is to develop the classification system using Artificial Neural Network for Electroencephalogram (EEG) signals. A good standard traditional method is to use Electroencephalogram for diagnosing patients brain functioning that corresponds to epilepsy and different brain disorders. This research focused on designing new classification techniques for single channel EEG recordings. This work proposes three classification techniques namely Back propagation feed forward neural networks (BPFFNN) with different training algorithms, Radial Basis Function Neural Network (RBFNN) and Particle swarm optimization (PSO) based neural network to classify from EEG signals whether a person is epileptic or nonepileptic. The first aspects of proposed work is to extract the features from EEG signals based on statistical measures and evaluate the neural networks architecture with various numbers of hidden neurons to reduce the complexity of the system. Feed forward neural networks have trained using different learning algorithms. Particle swarm optimization techniques proposed with optimal parameters to train the feed forward neural network. The performance of proposed method has compared with other commonly used classification techniques. The BPLM, RBFNN and PSONN provide very promising and practical results and required much less time and memory resources and improved classification accuracy and generalization. This study based on EEG benchmark database and it is publically available source.

Keywords
Back Propagation Neural Network (BPNN), Radial Basis Function (RBFNN), Electroencephalogram (EEG), Artificial Neural Network (ANN), Epilepsy, Particle Swarm optimization (PSO)

1. INTRODUCTION
Machine learning methods for classification provide inexpensive means to perform diagnosis and classification of certain outcomes in healthcare research. Classification is one of the important decision making tasks for many real world problems. In this paper, the binary classification tasks for classification of EEG signals have been proposed. In biomedical area for diagnosis the disorder, the EEG is the very important tool to pick up the electrical voltage signal along scalp on which the brains functionality has strong impact. Hence EEG is most often used to diagnose epilepsy. The epilepsy is the brain disorder termed as 'fit'. It is the sudden and recurrent malfunction of brain. The literature focused the most popular method is an Artificial Neural Network based system for epilepsy classification. The recent vast research activities in neural network classification have established that ANNs are promising alternative to various traditional classification methods.

The methods proposed by Kiymik et al. [2] uses artificial neural networks with back propagation neural networks with period gram and autoregressive (AR) features as the input for the automated detection of epilepsy. Paper [3] presented the study and assessment of accuracy of Recurrent Neural Network (RNN) using Lyapunov Exponents in detection seizure in the EEG signals. Kezban Aslan et al. [4] have presented epileptic classification of EEG signals using RBF Neural Network and Multi Layer Percepron Neural Network (MLPNN). The required parameters acquired from the EEG signals and clinic properties of the patients are used to train the neural networks. Radial Basis function Neural Network (RBFNN) produced better classification accuracy than the multi level perceptron neural network (MLPNN) model. Pari Jahankhani et al. [5] uses wavelet transform for feature extraction. The extracted features have proposed as the inputs to MLPNN and RBFNN for epileptic EEG signals classification. Srinivasan [6], presented Approximate Entropy (ApEn) as the statistical parameters for epileptic EEG detection. Two different types of neural networks namely, Elman and Probabilistic neural networks have been considered and achieved 100% overall accuracy. Samanwoy Ghosh Dastidar et al. [7], presented principal component analysis (PCA) based cosine radial basis function neural network classifier and the epilepsy diagnosis model achieved 99.3% classification accuracy.

The second part of this literature study show that the Particle Swarm Optimization (PSO) is popular tool for optimization [8]. The Particle Swarm Optimization (PSO) technique has been used for training the neural network design. This research will investigate the applications of an optimization method, such as Particle Swarm optimization (PSO) in biomedical applications to design artificial neural network based classification system. Natural optimization algorithm, which is stochastic population –based global search methods inspired in nature, such as particle swarm optimization (PSO) are effective for optimization problems with a large number of design variables and inexpensive cost function evaluations.

This paper discussed an automated epileptic classification system using three different neural networks namely, Back propagation feed forward neural networks (BPFFNNs), Radial Basis Neural Network (RBFNN) and Particle Swarm optimization feed forward neural network (PSOFFNN) using statistical features of EEG signals. Back Propagation neural network have proposed with variety of learning algorithms to achieve high speed and good convergence, less simulation time and best classification accuracy. The analyzed EEG signals and statistical features are applied as the inputs to design the neural network based classification system have been proposed first time in this study with reduced number of input attributes.

2. MOTIVATION AND OBJECTIVES

The conventional methods in medicine for classification of signals and images for diagnosis of diseases are based on human inspection. Operator assisted classification methods are impractical for large amounts of data and also non reproducible. Medical data always contains an error caused by operator performance which can lead to serious inaccuracies in classification. Traditional classification systems for biomedical signal processing gives less classification accuracy, so the aim of this research is to design of optimized Artificial Neural Network classifiers with improved performance.

The objectives of proposed research work to make and evolve efficient neural network classifier topology, improve classification accuracy, reliability, robustness and improve the optimization algorithms and design optimal ANN based classification model, to enhance the performance of a classification system for biomedical applications.

3. PROPOSED METHODS

The proposed block diagram of classification system for normal and epileptic EEG signals has depicted in figure 1. An EEG signals have statistically analyzed and statistical features are calculated. The extracted features are applied as input to neural network design. The decision making into two class as normal and epileptic EEG as the output of system.

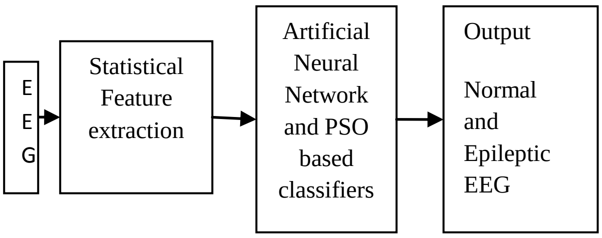

Figure 1: Proposed Model

3.1 Artificial Neural Network

In this work, Artificial neural network is used as the classifier due to their inherent features namely, adaptive learning, robustness, self organization and generalization capability. Two classification schemes are utilized namely, multilevel feed forward Back propagation neural networks (BPNNs), Radial basis function neural network (RBFNN). This section provides the brief description of feed forward back propagation neural network and Radial basis function neural network model.

The Multilayer perceptron network termed as back propagation neural network, which has the ability to learn and generalize , smaller training set requirements, fast training, easy to implement and therefore most commonly used neural network architectures have been adapted for describing the alertness level of arbitrary subject. BPNN consists of three layers (inputs, hidden, output). The activation function for hidden layer is tangent sigmoid and output layer activation function is purelin. We have proposed two design approaches, first to find the optimal number of hidden neurons in hidden layers and secondly use different learning methods to train neural networks.

Radial basis function neural network consists of input, hidden and output layers. The activation of hidden neurons is determined in two steps; the first is computing the distance (usually by using the Euclidean norm) between the input vector and a center Ci that represents the i^{th} hidden neuron. Second, a function h distance to get the final activation of the hidden neurons. In this case the Gaussian function G(x) is used. The parameter spread determined using heuristic rule" global first nearest neighbor". The activation of a neuron in the output layer is determined by a linear combination of the fixed non linear basis function.

3.2 Learning Process

Learning is a process in which the neural network undergoes changes in its free parameters when it is stimulated by the environment. As a results of this learning it structure changes and it responds in a new way to its architecture. Its performance improves through this process. There are many types of learning rules, some of it is mentioned below.

Error –correction learning in which the error signal actuates a control mechanism so as to make adjustments in to synaptic weights. These changes make the output signal come closer to the target value in a step manner. The error signal is the difference between the desired output and the output from the network. The objective in this type of learning is to minimize the cost function or the index performance. The cost function is the instantaneous value of the error.

Backpropation feed forward neural network has been trained using different training algorithm such as Levenberg Marquardt , BFGS quasi newton, Resilient Back propagation, scaled conjugate gradient, conjugate gradient with Powell, Fletcher Powell conjugate gradient, polak –Ribiere conjugate gradient, one step secant, variable learning rate backpropogation.

Memory based learning gives past values of correctly classified input output example are stored. When a new test pattern is applied to the network this learning algorithm responds by retrieving and analyzing the training data in the local neighborhood of the test pattern. Nearest neighbor rule and K-nearest classifier are two popular algorithms in this type of learning.

3.3 Particle Swarm Optimization

PSO algorithm is a recent addition to the list of global search methods. This derivative-free method is particularly suited to continue variables problems and has received increasing attention in the optimization community. The PSO algorithm originally was developed in 1995 by James Kennedy and Russell Eberhart. The PSO algorithm is a population based search algorithm based on social behavior of birds within a flock. PSO requires only primitive mathematical operators and is computationally inexpensive in terms of both memory requirements and speed. The features that derive PSO are social interaction. Individuals (particles) within the swarm learn from each other and based on the knowledge obtained move to become more similar to their neighbors. The structure of the PSO is determined through the formation of neighborhoods. Individuals within the neighborhood can communicate with each other..

A swarm consists of a set of 'N' particles represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors. In the original formulation of PSO, each particle is defined as a potential solution to the problem in a D-dimensional space. The particle i is represented in a D-dimensional space as

$Xi = (x_{i1}, x_{i2}, x_{i3}...., x_{iD})$

And each particle maintains a memory of its previous best position. The best previous position of the ith particle can be represented as

$Pi = (p_{i1}, p_{i2}, p_{i3}, ...p_{iD})$

And the velocity for the particle is represented as

$Vi= (v_{i1}, v_{i2}, v_{i3} ...v_{iD})$

The particle position with the highest fitness value for the entire run is called the global best. The global best particle among all the particles in the population is represented by

$Pg = (p_{g1}, p_{g2}, p_{g3},.p_{gD})$

At each iteration the velocity vector of every particle is adjusted based on its best solution and the best solution of its neighbors. The position of the velocity adjustment made by the particles previous best position is called the cognition component. The updated PSO equations described as below.

Velocity calculation

$$V_{id\ (t)} = w\ V_{id\ (t-1)} + C1\ rand()\ (P_{id}-X_{id}) + C2\ rand() *(P_{gd}-X_{id}) \quad (1)$$

Position update

$$X_{id\ (t)} = X_{id\ (t-1)} + V_{id\ (t)} \quad (2)$$

3.4 EEG dataset description and Feature extraction

Epilepsy is the chronic neurological disorder which is identified by successive unexpected seizures. EEG records the brain's activity which contains valuable information about its normal or epileptic activity. The benchmark EEG database available online [1]. Firstly the dataset used in this research collected from the Epilepsy center in Bonn, Germany by Ralph Andrezejak. The EEG data consists of five groups of EEG records. The free EEG signals both in normal subjects and epileptic patients. The set A and set B is recorded the EEG signals from five healthy subjects with open eyes and closed eyes respectively. The dataset C and dataset D are recorded prior to a seizure from part of the brain with the epilepsy syndrome and from the opposite (healthy) hemisphere of the brain respectively. The last group dataset E is recorded from part of the brain with the epilepsy syndrome during the seizure. Each datasets contains 100 single channel EEG segments of 23.6 seconds duration at the sampling rate of fs =173.61Hz. All EEG signals were recorded with the same 128- channel amplifier system using an average common reference .The data were digitized at 173.61 samples per second using 12 bit resolution. The band pass filters setting was 0.53-40 Hz (12 dB/oct). The signals are recorded in a digital format at a sampling rate of 173.61 Hz. Thus, the samples length of each segment is (173.61* 23.6) 4097, and the corresponding bandwidth is 86.81 Hz.

In this paper, set A (normal EEG) consisted of segments taken from surface EEG recordings that were obtained from five healthy volunteers using a standardized electrode placement and Set E (epileptic EEG) only contained seizure activity , uses for classification task using artificial neural networks. The typical patterns of EEGs are depicted in figure 2.

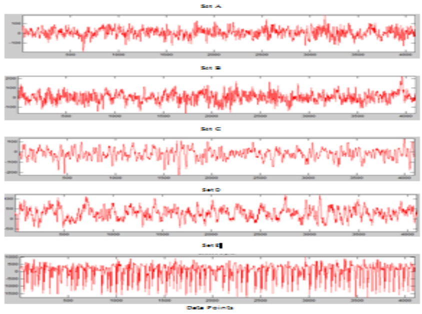

Figure 2: Samples of five sets of EEG from top (a) Healthy subjects with open eyes (b) Healthy subjects with closed eyes (c) ill patients seizure free interval from hippocample formation of the opposite hemisphere of the brain(d) ill patients seizure free interval (e) epilepsy syndrome during the seizure.

The statistical features of EEG signals obtained by analyzed EEG signals from set A and set E. In the feature extraction phase, statistical features values are obtained with the help of software developed by the MATLAB programming language. The four statistical features are presented in Table 1.

Table 1. EEG Statistical Features

No. of Features	Features	Description
1	MIN	Maximum value of variables
2	MAX	Minimum value of variables
3	MEAN	Mean value is the measure of central tendency
4	SD	Standard deviation measures of variability

4. EXPERIMENTAL DESIGN AND RESULTS

For effective design of ANN classifiers, most important element is selection of set of features as the input to neural networks. The extracted features values for both set A and set E are used as inputs to the neural networks. The total data set consists of 200 EEG segments with 4 dimension feature vector. The data set is divided into two sets, namely, 80% training set and 20% testing set. The training dataset uses for training the networks and testing sets uses for validation.

This work is focused on back propagation feed forward neural network (BPFFNN) design to find the optimal architecture by performing the experimentation on adaptive hidden neurons in hidden layer and different training algorithms. Radial basis function neural network (RBFNN) has design with variable spread constant in the range value [0.2 1]. The design parameters of BPNN, RBFNN and PSONN are as shown in Table 2.

Table 2. Design Parameters of classifiers

ANN Model	Parameters	
BPNN	No. of Hidden layers	1
	No. of Hidden neurons	[0 10]
	Train Function	Trainlm
	Activation function for hidden layer	Tansig
	Activation function for output layer	Purelin
	Network Performance	MSE
RBFNN	Spread constant	[0.2 1]
	Network Function	Gaussian
	Network Performance	MSE
PSONN	Inertia weight (w)	0.4 to 0.9
	No. of particles	100
	Cognitive acceleration coefficients (C1,C2)	1.49618
	Train function	Trainpso
	NN layers	2

The performance measure have taken to analyze different ANN models, namely, classification accuracy, Mean Square Error function (MSE) , number of Epochs, simulation time and generalization capability.

% Classification Accuracy = Number of corrected classified samples / Total number of samples (7)

The mean square error (MSE) is measured for varying numbers of hidden nodes and number of training epochs. To decrease the complexity of the network and increase training speed, less nodes in the hidden layer is preferred. The MSE equation is given below.

$$\text{MSE} = 1/N \sum_{n=0}^{N-1} (yn - tn)^\wedge 2 \quad (8)$$

The results found from BPNN, RBFNN and PSONN models are discussed in stages. In first stage, BPNN design is analyze with most important components, namely, the selection of networks inputs, number of hidden layers, number of hidden neurons and training algorithms. In this paper, back propagation neural network is designed with 4 inputs, 8 hidden neurons and 1 output neurons (4-8-1) three layers structure. The BPNN network trained using back propagation Levenberg Marquardt algorithm. This BPNN network has simulated with variable number of hidden neurons in hidden layer in the range [1, 10]. The computation results found that the optimal hidden neurons for this problem are 8, as given in Table 3. The mean square error is 0.00034787, 18 number of epochs and 1.264 seconds simulation time for training the network.

Table 3. Different NN Architecture computation results

NN Classifiers	Hidden Neurons	MSE	No. of Epochs	Simulation Time (secs)	Training Accuracy (%)
4-2-1	2	4.8019e-16	36	1.84	99.3
4-4-1	4	3.7542e-15	24	1.342	99.3
4-6-1	6	1.9854e-06	10	1.139	99.3
4-8-1	8	0.00034787	18	1.264	100
4-10-1	10	1.1806e-09	22	1.357	100

This work has extended based on trial and error methods for experimentation of BPNN (4-8-1) network using different training algorithms. The results obtained as mentioned in Table 4. Back propagation feed forward neural network trained with Levenberg Marquardt and conjugate gradient with Powell algorithm gives 100 % testing accuracy, good generalization. Conjugate gradient with Powell algorithm provided less number of epochs and training time but training accuracy 98%. Variable learning rate backpropogation algorithm (BPGDX) provides worst results as compared to other algorithms.

Table 4. Results of BPNN classifiers

Classifier	Performance Analysis			
	MSE	**Time (sec)**	**Epochs**	**Accuacy (%)**
BPLM	0.0003478	1.264	18	100
BPBFG	0.0098167	1.528	26	100
BPRP	0.018089	1.092	18	98
BPSCG	0.013558	1.202	21	98
BPCGB	0.015819	1.108	9	98.7
BPCGF	0.007173	1.716	42	100
BPCGP	0.012294	1.31	16	100
BPOSS	0.011675	1.435	21	100
BPGDX	0.31183	1.217	31	56.7

In stage II, Proposed RBFNN model trained with Gaussian function and the spread constant value is 1. The Mean Square Error (MSE) for RBFNN has obtained 1.82907e -030. The achieved classification accuracy by RBFNN model 100 %.

In stage III, Proposed particle swarm optimization neural network (PSONN) model trained with particle swarm optimization algorithm. The PSONN (4-2-1) design models with minimum hidden neurons provide good results than other architectures. The mean square error is obtained 0.0055563, training time 10.717 seconds, less number of epochs , 13 NN dimension and training accuracy 98.7% is achived by PSONN model. PSONN results obtained mentioned in Table 5. PSONN models with different hidden neurons have provides equal classification accuracy. The result exhibits the good PSONN model with minimum number of hidden neurons as 2.

While compared the three classifiers performance in terms of classification accuracy. The classification accuracy of investigated BPNN and RBFNN provides 100 % and PSONN gives 98.7% accuracy.

As per literature review, the proposed method has compared with other techniques mentioned in Table 6. The proposed BPLM network has the good classifier for classification of normal and epileptic EEG signals. Compared the paper [16] and proposed method, the results showed that the classification accuracy is equal to 100% but set of input features proposed have been taken differently with the reduced number of features. The backpropagation learning method has used for designing the neural network classifier mode. Backpropagation Levenberg Marquardt has good design classifier for EEG classification task.

The second proposed method, Radial Basis Function Neural Network (RBFNN) model has provided 100 % accuracy as compared with principal component analysis (PCA) enhanced cosine radial basis function neural network classifier [15]. The classification accuracy using proposed LMBP is 100% and 9 features Wavelet chaos LMBP neural network classifier provided accuracy 96.7% is observed from the results that the performance of BPLM and RBFNN classification system is good in term of accuracy has compared to PSONN algorithm.

Table 5. Results of PSOFFNN model

Classifier	**Hidden Neurons**	**No. of Epochs**	**NN Dim**	**MSE**	**Time (sec)**	**Training Accuracy (%)**
PSOFFNN	2	34	13	0.005556	10.717	98.7
	4	34	25	0.021771	11.045	98.7
	6	37	27	0.022012	10.015	98.7
	8	27	49	0.028993	14.43	98.7
	10	34	61	0.02429	11.248	97.3

Table 6. Comparative study of various techniques

Dataset	**Reference paper**	**Features and classifier**	**Accuracy (%)**
EEG set A and EEG set E	Polat et al. [9]	Fast Fourier transform –Decision tree	98.72
	Subhasi et.al.[10]	Discrete wavelet transform- Mixture of expert model	95
	Tzallas et.al [11]	Time frequency analysis –Artificial neural network	99
	Tzallas et.al.[12]	Reduced Interference Dist., ANN	100
	Bedeeuzzaman et.al.[13]	Higher order statistics linear classifier	95.75

	Fathima et.al.[14]	Higher order statistics, Linear classifier	96.9
	Samanwoy et.al [15]	principal component analysis (PCA) enhanced cosine radial basis function neural network classifier	99.3
	Proposed	**Statistical features, Radial Basis Function Neural Network classifier**	**100**
	Samanwoy et.al [16]	9 features -Wavelet chaos LMBP neural network classifier	96.7
	Proposed	**Statistical features, Back propagation Levenberg Marquardt Neural Network classifier**	**100**
	Proposed	**Statistical features, PSO based Feed Forward Neural Network classifier**	**98.7**

5. CONCLUSION

The work demonstrates the uses of statistical method, an artificial neural network and particle swarm optimization technique for a given non-stationary signal classification. These methods can be used for multi class epileptic seizure classification. A robust and computationally low-intensive feature with reduced dimensionality proposed for low computational burden. Experimental results show that overall accuracies as high as 100% can be achieved by this system. The backpropagation Levenberg Marquardt algorithm shows the efficient method for designed neural model for EEG classification. PSO techniques will explore future scope for designing the neural network model with optimal features.

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