PSO TUNED RBFNN CLASSIFIER TECHNIQUES FOR THE ANALYSIS OF ELECTROGASTROGRAM SIGNALS

P. Jeba Santhiya[1], Dr.D.Murugan[2]
[1]Research Scholar, [2]Professor, Department of CSE, M.S University, Tirunelveli, India.

Abstract

The main objective of pattern recognition in medical field is to assist the physician to analyze the large amount of data. The necessity to extract most important features from a large volume of data has led to development of new methods for pattern recognition. Numerous methods have been developed to analyze the medical data using wavelet transform, ANN and fuzzy etc. Among these methods, ANN is one of the best and acceptable tool for analyzing the bio signals. ANN has the ability to learn and generalize from the training data. The challenging task of NN is to find the optimal weights and structure of network to analyze the bio signal. In this research work, RBFNN and BPNN are employed to discriminate between normal and abnormal EGG signal.To enhance the performance of both the classifiers, Particle Swarm Optimization (PSO) algorithm is combined with RBFNN and BPNN known as PSO tuned RBFNN and PSO tuned BPNN respectively. PSO is one of the bio inspired computing algorithm used to optimize the parameters of RBFNN and BPNN to achieve the desired target. It is also used to improve the recognition rate of the proposed PSO tuned RBFNN and PSO tuned BPNN classifiers. Performance of the both the classifiers are evaluated using four evaluation parameters including classification accuracy, sensitivity, specificity and precision. Furthermore, efficiency of PSO tuned RBFNN is compared with PSO tuned BPNN to find the suitable classifier for EGG signal

Key word: Bio inspired computing, ANN, Particle Swarm Optimization PSO,

1. Introduction

Bio inspired computing is a field of study that loosely knits together subfields related to connectionism and social behavior. It is closely related to ANN. Bio inspired computing is a subset of major computation. These algorithms have been developed to overcome the drawbacks of ANN. One of the important features of bio inspired computing algorithm is that their working mechanisms are more lifelike a group of organisms or an individual, which can be easily understood. These algorithms also have higher efficiency than traditional ANNs. Due to this property, bio inspired algorithms have been used in many fields such as pattern recognition, forecasting and robot control etc. Different kinds of bio inspired algorithms are available. Each has its own characteristics. Optimization plays an important role in solving very complex problem in engineering. It is the process of finding the best solution for a given complex problem. Optimization algorithms studies behavior of models derived from the observation. These models as a source of inspiration for the design and development of new algorithms for the solution of optimization and distributed control problems[1]. Conventional techniques need more computational efforts to solve complex problem. But, these techniques fail as the problem size increases. To overcome the drawbacks of conventional techniques and find the best solution, a new technique have been developed named as bio inspired computing techniques.

Bio inspired computing is a kind of computation method inspired by brain, nature and evolution are being used to solve more complex problems in computer science, engineering, artificial intelligence and robotics[2]. It is the combination of computational intelligence and collective intelligence. Generally, bio inspired computing techniques are classified into three groups namely bio inspired from organism structures, organism behaviors and evolutions. Some of the techniques base on bio inspired computing are as follows:

- Ant Colony Optimization (ACO)
- Particle Swarm Optimization (PSO)
- Stochastic Diffusion Search (SDS)
- Artificial Bee Colony Algorithm (ABC)
- Cuckoo Search Algorithm (CSA)

In this research work, PSO is used to optimize the parameters of RBFNN and BPNN to classify the EGG signal into normal and abnormal signal.

2. PARTICLE SWARM OPTIMIZATION

PSO is an evolutionary computation technique developed initially by Kennedy and Eberhart in 1995.It is nature inspired algorithm. PSO inspired from the social behavior of bird flocking. Similar to the Genetic Algorithm (GA)[3], the PSO is an optimization algorithm which is based on population, and the system is initialized with a population of random solutions and can search for optimal solution by the updating the generations[4]. In PSO, each solution is denoted as a vector named as particle. Each particle starts with its initial velocity and position, then moves in the solution space to achieve the optimum result. Flow chart of PSO algorithm is shown in Figure 1.

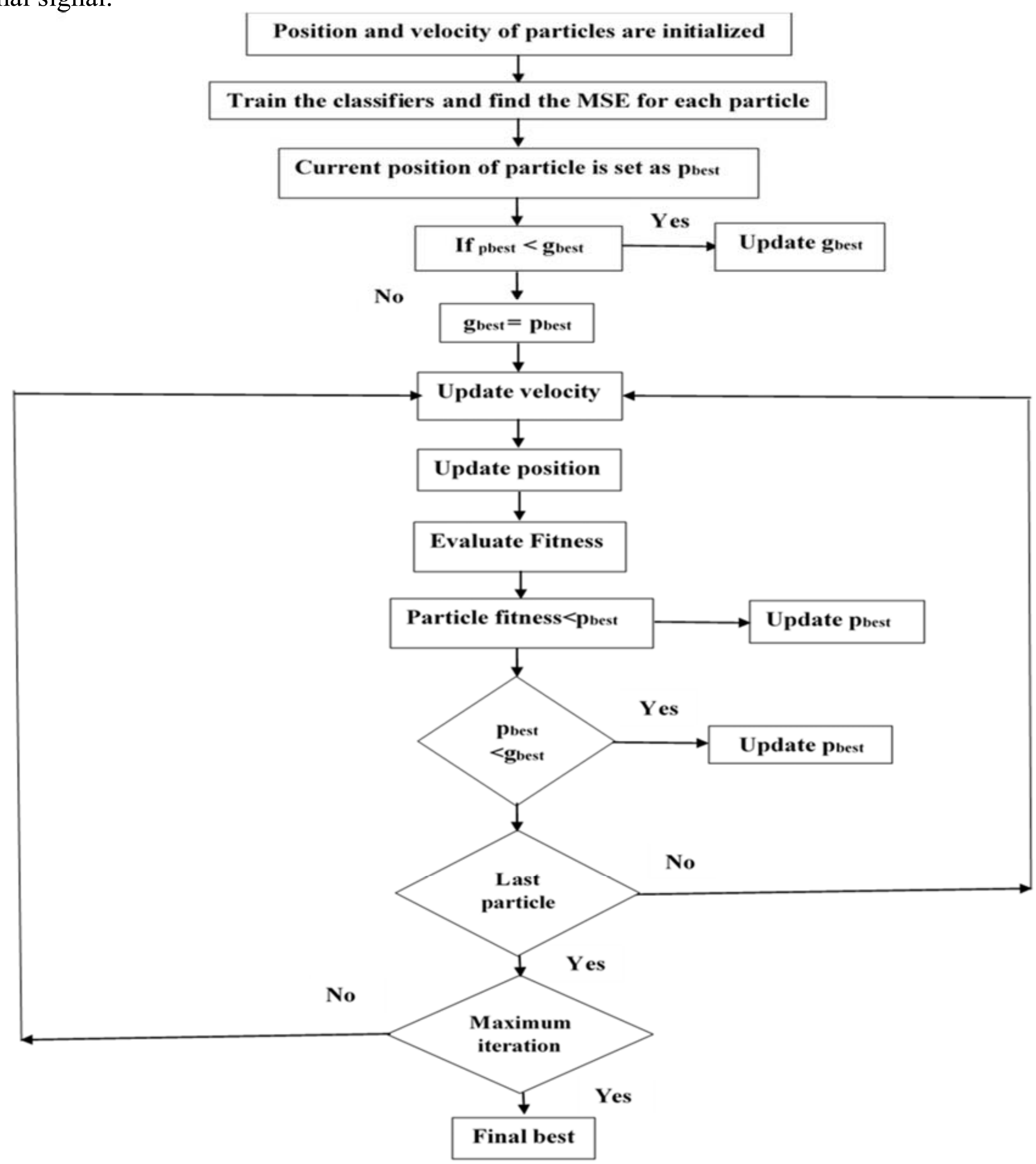

Figure 1 Flowchart of PSO algorithm

The main computational steps of PSO includes generating initial position and velocity of each particle in population, updating position and velocity for a certain number of iterations to find the best solution. Mathematical steps of PSO is given below. Let the particle (solution) p_k in m-dimensional space is given in equation (1)

$$p_k = \{p_{k1}, p_{k2}, p_{k3}, \dots, p_{km}\} \text{ k=1,2,3, ... N} \quad (1)$$

Where

N : Number of particles

Let u is the velocity of each particle and represented in equation (4.2)

$$u_k = \{u_{k1}, u_{k2}, u_{k3}, \dots, u_{km}\} \quad (2)$$

Each particle in PSO[4] maintain its personal best position known as P_{best} and a best solution among all particles named as g_{best}. In each iteration, position and velocity of particles are updated to find the optimal solution according to equation (3) and (4).

$$u_k(t+1) = w * u_k(t) + c1 * r1 * \left(p_{best_k}(t) - p_k(t)\right) + (2 * r2 * (g_{best_k}(t) - p_k(t)) \quad (4.3)$$

$$p_k(t+1) = p_k(t) + u_k(t+1) \quad (4)$$

Where

$u_k(t+1)$: Velocity of kth particle at (t+1) iteration

w : Inertia weight

$u_k(t)$: Velocity of kth particle at iteration t

P_{best} : Personal best

G_{best} : Global best

$p_k(t+1)$: Previous solution of particle k at (t+1) iteration

$p_k(t)$: Present solution of particle k at t iteration

c1 : Self-confidence factor

c2 : Swarm confidence factor

r1,r2: Random numbers [0,1]

3. PROPOSED CLASSIFICATION TECHNIQUES

This section describes the functioning of the proposed PSO tuned RBFNN and PSO tuned BPNN classifiers.

3.1 PSO tuned RBFNN for EGG classification

Figure 2 illustrates the framework of the proposed PSO tuned RBFNN classifier for EGG signal.

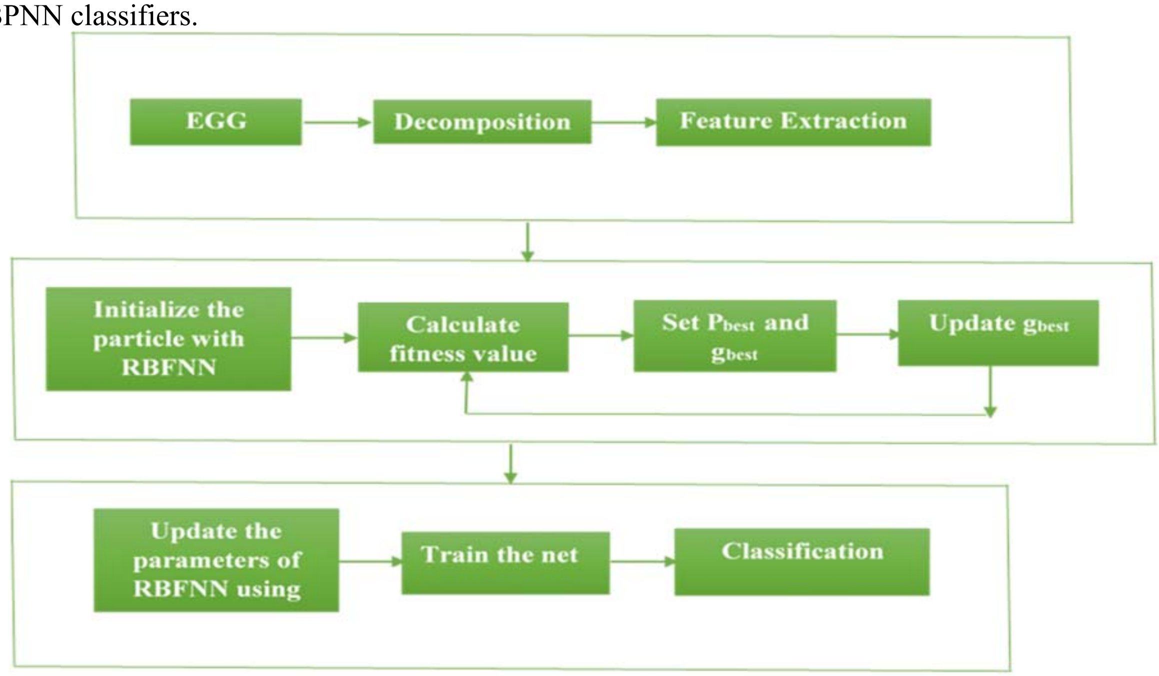

Figure 2 Architecture of proposed PSO Tuned RBFNN classifier

The proposed PSO-RBFNN classifier consists of 3 stages. In stage1, the raw EGG signal preprocessing is carried out. Preprocessing is necessary to remove noise and redundant component from EGG signal. In this research work, wavelet transform employed to perform preprocessing operation. In stage 2,features are extracted from the decomposed signal. These features are used as an input for the RBFNN[5]. Parameters of RBFNN is optimized using PSO algorithms to achieve desiredtarget.In stage 3, the proposed classifier is examined using testing samples. Four statistical measures including classification accuracy, sensitivity, specificity and precision are used to measure the efficiency of the proposed PSO tuned RBFNN classifier.

3.2 PSO tuned BPNN for EGG classification

BPNN is a multilayer feed forward network. In this research work, PSO is used to find the optimal weights of BPNN. The network is trained to classify the EGG signal. PSO is also enhance the performance of BPNN. The procedure for PSO tuned BPNN classifier can be summarized as follows:

Step 1 : Randomly initialize the position and velocity of each particles

Step 2 : Evaluate the fitness value of each particle with initialized value.

Step 3: Current solution is set as P_{best} value.

Step 4: If iteration is equal to maximum iteration, go to step 9, else go to step 5.

Step 5: Best position and velocity values are stored.

Step 6: Velocity and Position of each particle is updated using equation (4.3) and (4.4).

Step 7: Evaluate new p_{best} and g_{best}.If new values are better than previous values, update the position and velocity.

Step 8: If current values are not changed for some iterations, go to step 9,else go to 3.

Step 9: Use BPNN training algorithm to find g_{best} for some epochs, if search result is better than g_{best} output the current search result else output g_{best}.

Step 10: Based on final values, the BPNN is trained with training data.

Step 11: Classify the EGG data using trained network.

Step 12: Measure the statistical parameters.

4. SIMULATION RESULTS

Many simulations were carried out in order to test the efficiency of the proposed classifiers. Four evaluation parameters such as classification accuracy, sensitivity,specificity and precision are employed to measure the performance of the classifiers. All simulations were performed using MATLAB platform.

4.1 Database

For this research work, the EGG data were collected from a hospital.200 samples were used. Database consists of both normal and abnormal subjects of male and female patients of different age groups. The demographic details of subjects are listed in Table.1.

Table 1. Demographic details of the subjects

	Normal (100)	**Abnormal (100)**
Male	35	30
Female	15	20
Age	35-50	33-55

4.2 Performance of PSO tuned RBFNN classifier

To improve the classification accuracy of the RBFNN, PSO is employed to train the RBFNN. The training process includes finding optimal values for RBFNN parameters to minimize the error. Three parameters namely weight, spread and center are trained by PSO. Classification accuracy obtained using PSO tuned RBFNN is shown in Table 2. From the table2, it can be seen that 181samples were correctly classified out of 200 samples by the proposed PSO tuned RBFNN classifier.

Table 2 Classification of EGG using PSO tuned RBFNN

Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
92	89	181	90.5

Table 3 Performance of PSO tuned RBFNNclassifier

Number of samples	Specificity	Sensitivity	Precision	Classification Accuracy (%)
50	0.88	0.89	0.90	87.5
100	0.90	0.89	0.88	89
200	0.94	0.92	0.92	90.5

Performance PSO tuned RBFNN classifier is tested using three different number of samples such as 50,100 and 100.Each set consists of 50% normal and 50% abnormal subjects. Efficiency of PSO tuned RBFNN in terms of four statistical measures are listed in Table 3.From the table 3, it is found that the classification accuracy of 90.5% is obtained using PSO tuned RBFNN. For 200 samples, specificity, sensitivity and precision are 0.94%,0.92% and 0.92% respectively. Classification performance of PSO tuned RBFNN classifier is graphically represented in Figure 3.

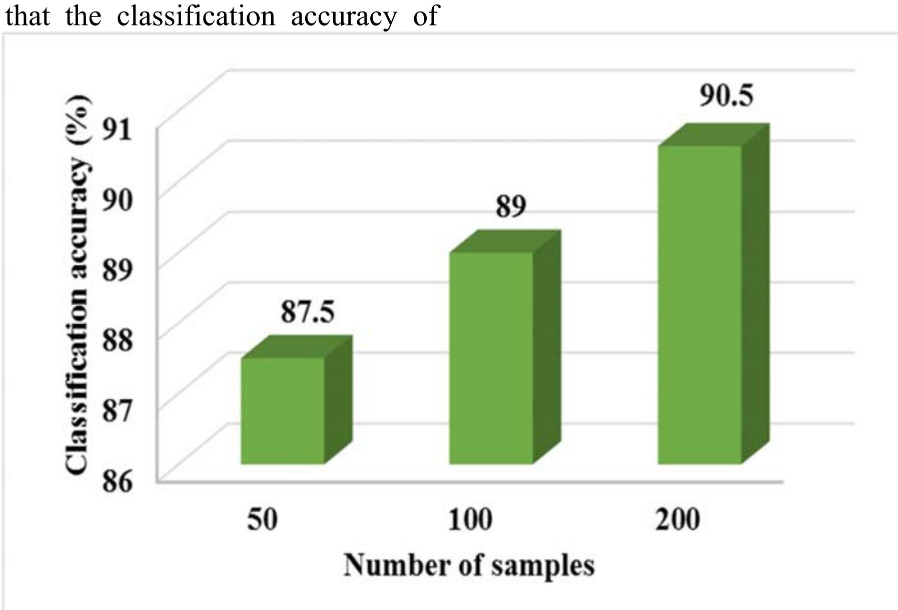

Figure 3Classification accuracy of PSO tuned RBFNN for different number of samples

4.3 Performance of PSO tuned BPNN classifier

In this research work, PSO tuned BPNN is used to distinguish between normal and abnormal EGG signal. PSO is a type of natural inspired algorithm. It has the ability to find the global optimal solution for the given complex problem. To enhance the training speed and convergence rate, PSO is combined with BPNN[6]. In PSO tuned BPNN, when the objective function value changed is smaller than a threshold (predefined) or objective function value has not changed for some iterations, the process control is transferred from PSO to gradient training algorithm.

The challenging task of BPNN is to find the optimal architecture to provide better result in EGG classification. Generally, three main issues are associated with BPNN to classify EGG data such as (i) Number of hidden layer needed for BPNN (ii) Number of neurons in each hidden layer and (iii) To find the suitable training algorithm to achieve high classification rate.

Table 4 Classification of EGG signal using PSO tuned BPNN with 5 hidden neurons

Number of hidden layers	Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
1	85	74	159	79.5
2	90	89	179	89.5
3	77	86	163	81.5

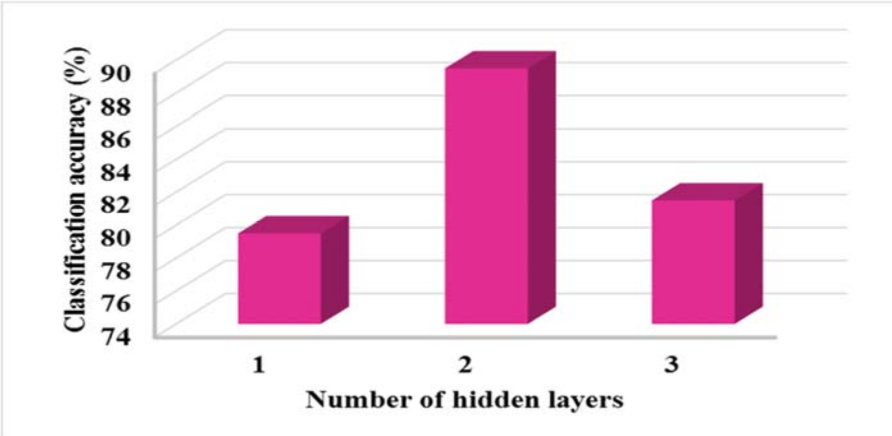

Figure 4 Comparison of classification accuracy of PSO tuned BPNN for different hidden layers with 5 neurons

To address the first two issues, hidden layers are varied from 1 to 3 in this research work. Hidden neurons in each layer is also varied as 5, 10 and 15. The optimum number of hidden layers and hidden neurons in each layer is fixed according to high recognition rate and minimum MSE value.

Table 4 lists the classification accuracy obtained using PSO tuned BPNN for hidden layers 1,2 and 3. Each hidden layer consists of 5 hidden neurons. High classification accuracy of 89.5% is achieved by BPNN with two hidden layers and 5 neurons in each layer. Figure 4 demonstrates the graphical representation of classification accuracy of the proposed PSO tuned BPNN for different number of hidden layers with 5 neurons in each layer.

Table 5 Classification of EGG signal using PSO tuned BPNN with 10 hidden neurons

Number of hidden layers	Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
1	86	85	171	85.5
2	99	98	197	98.5
3	85	88	173	86.5

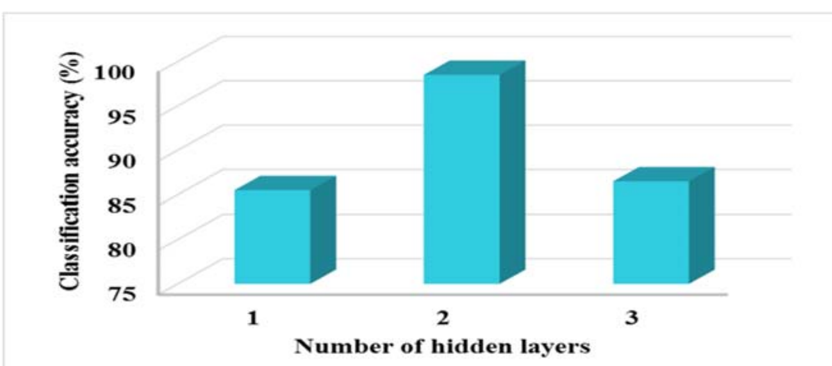

Figure 5 Comparison of classification accuracy of PSO tuned BPNN for different hidden layers with 10 neurons

Classification of EGG data using PSO[7] tuned BPNN with different hidden layers is shown in Table 5. Each hidden layer consists of 10 hidden neurons. From the table 5, it is found that the proposed PSO tuned BPNN with two hidden layer and 10 hidden neurons in each layer provide better result than BPNN with one or three hidden layer. Figure 5 shows the graph representation for classification accuracy comparison of different hidden layers with 10 hidden neurons in each layer

Table 6 Classification of EGG signal using PSO tuned BPNN with 15 hidden neurons

Number of hidden layers	Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
1	75	80	155	77.5
2	95	88	183	91.5
3	70	79	145	74.5

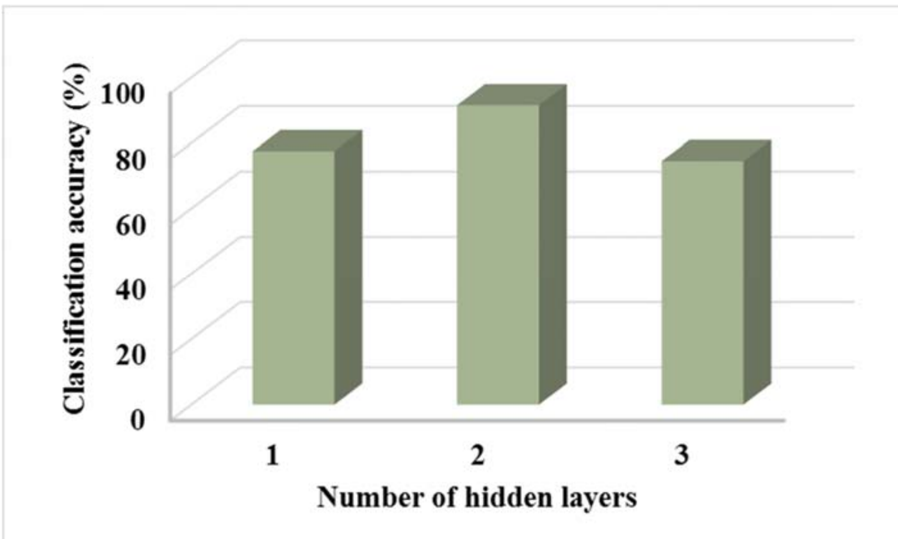

Figure 6 Comparison of classification accuracy of PSO tuned BPNN for different hidden layers with 15 neurons

Table 6 shows the classification performance of proposed PSO tuned BPNN with three different hidden layers such as 1,2 and 3.15 neurons are used in each layer. The performance comparison of different hidden layers with 15 neurons in each layer is graphically represented in Figure.6. The proposed PSO tuned BPNN achieves an accuracy of 77.5%,91.5% and 74.5% for BPNN with single hidden layer, BPNN with two hidden layer and BPNN with three hidden layer respectively.

Table 7 Performance of PSO tuned BPNN with different training algorithms

Training algorithms	Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
RP	87	92	169	84.5
SCG	90	85	175	87.5
OSS	78	73	151	75.5
LM	99	98	197	98.5
GDX	65	80	148	74

To find the suitable training algorithm, proposed classifier is trained with five training algorithms namely RP, SCG, OSS, LM and GDX. Table 7 lists the classification accuracy obtained using

PSO tuned BPNN classifier with different training algorithms. From the table 4.7, it is observed that the classification performance of the proposed classifier is very poor when it is trained GDX.

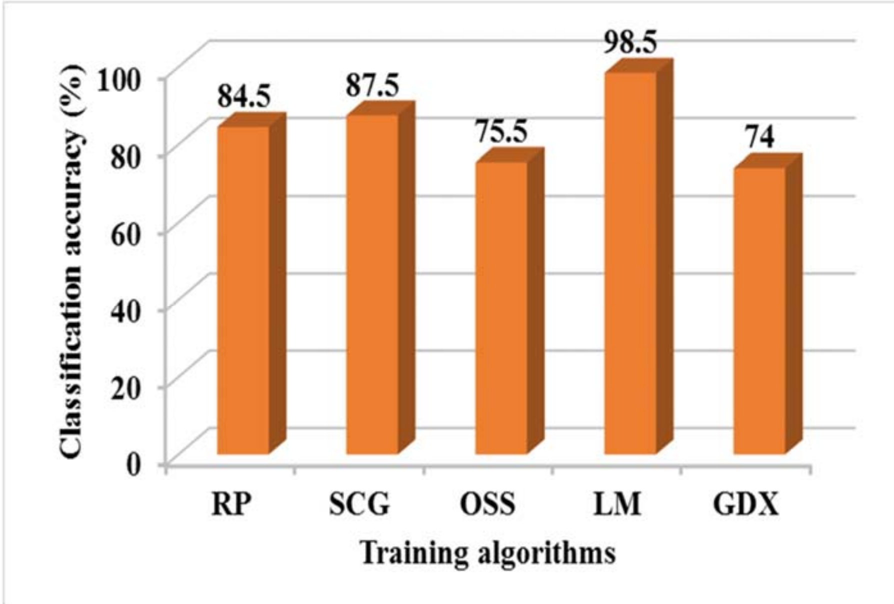

Figure 7 Comparison of classification accuracy of PSO tuned BPNN classifier using different training algorithms

GDX showed an accuracy of 74%.75.5% classification accuracy [8]observed with OSS. The proposed BPNN classifies 169 samples out of 200 samples with RP training algorithm.84.5% classification accuracy is obtained using RP. 87.5 % classification accuracy is achieved by PSO tuned BPNN with SCG training algorithm.

Performance of SCG is better than RP. The proposed PSO tuned BPNN with LM training algorithm outperformed than other training algorithms. Classification accuracy of 98.5 % is observed with LM algorithm. So, it is suggested that the proposed classifier with LM training algorithm offer the potential to classify the EGG data with high recognition rate[9]. Figure 7 shows the graph representation for comparison of different training algorithms for 200 samples.

By comparing the tables from 4 to 7, it is concluded that the proposed PSO tuned BPNN with two hidden layer, 10 hidden neurons in each layer and LM training algorithm is the suitable model to classify EGG data. The topology of the classifier is fixed as 18-10-10-2.

Table 8 Classification performance of PSO tuned BPNN

Number of samples	Specificity[12]	Sensitivity	Precision[11]	Classification Accuracy (%)
50	0.96	0.96	0.96	94.5
100	0.95	0.97	0.96	96
200	0.99	0.97	0.97	98.5

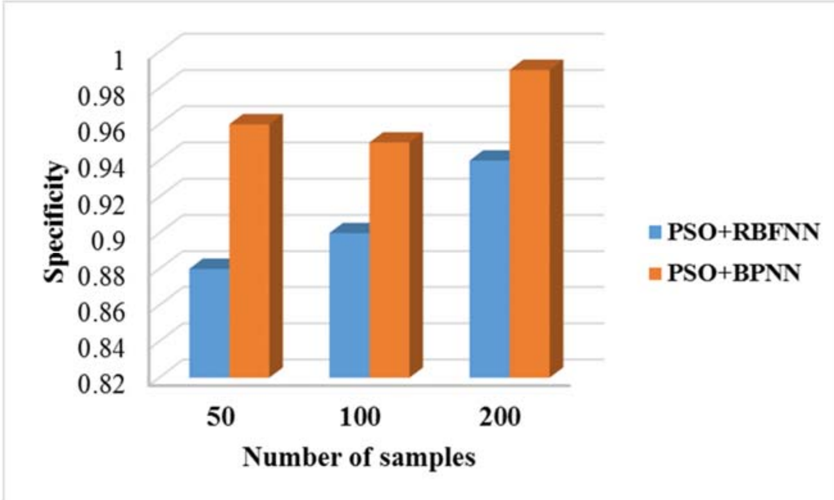

Figure 8 Comparison of specificity for different number of samples using proposed classifiers.

Table 8 compares the performance of the proposed PSO tuned BPNN with three different number of samples such as 50, 100 and 200 samples. An accuracy of 98.5%, specificity of 99%, sensitivity of 97% and precision of 97% is obtained for 200 samples using PSO tuned BPNN classifier.

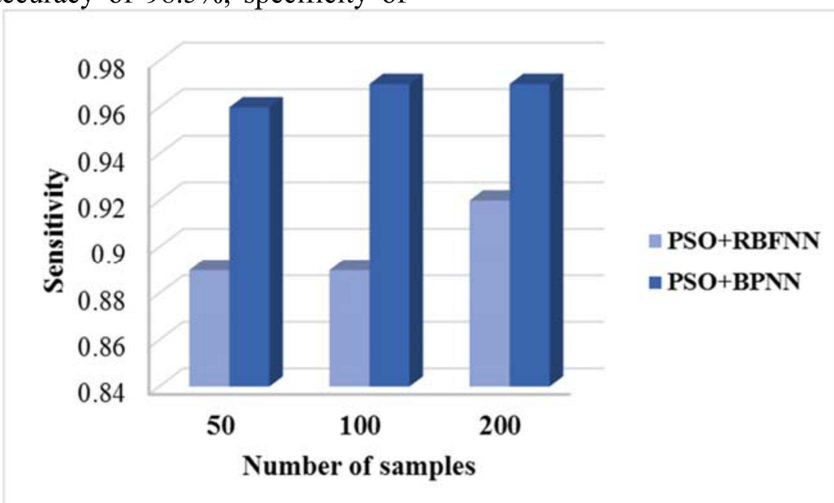

Figure 9 Comparison of sensitivity for different number of samples using proposed classifiers

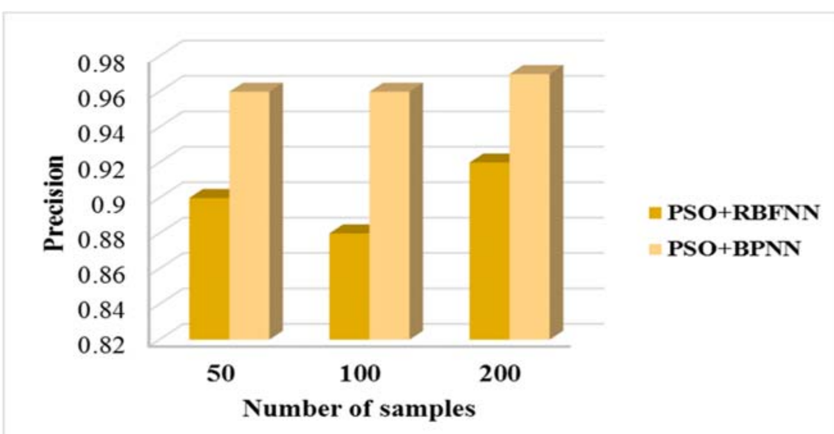

Figure 10 Comparison of precision for different number of samples using proposed classifiers

Figure 8 shows the comparison graph of specificity obtained on different datasets using proposed classifiers. Similarly, Figure 9 and Figure 10 graphically shows the comparison of sensitivity and precision of the proposed classifier on different number of samples.

4.4 Performance comparison the proposed classifiers

Table 9 lists the classification accuracy obtained using PSO tuned RBFNN and PSO BPNN classifier with three different set of samples such as 50, 100 and 200.For comparison, BPNN with two hidden layers and 10 neurons in each layer is considered.BPNN is trained with LM algorithm.

Table 9 Classification performance comparison of the proposed classifier

Number of samples	Classification Accuracy (%)	
	PSO tuned RBFNN	PSO tuned BPNN
50	87.5	94.5
100	89	96
200	90.5	98.5

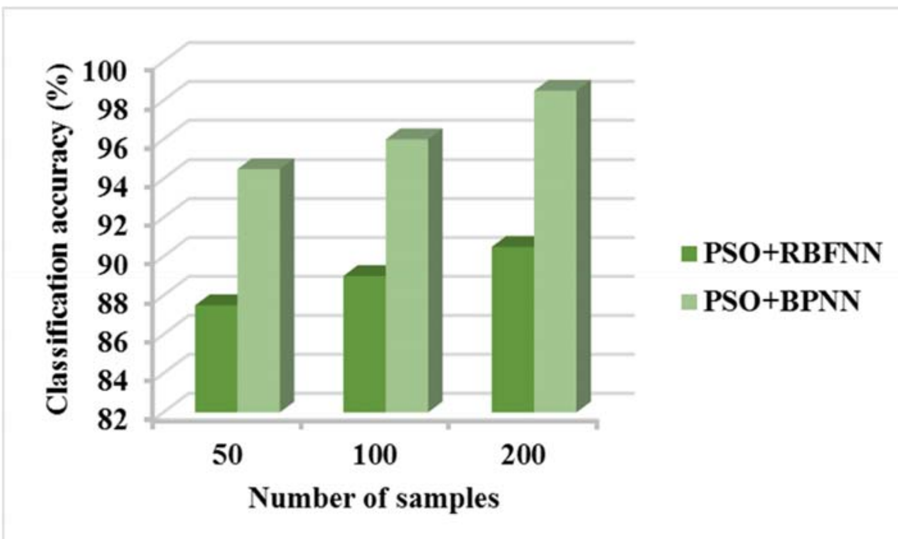

Figure 11 Comparison of classification accuracy using proposed classifiers

From the table 9, it is inferred that the performance PSO tuned BPNN is better than PSO tuned RBFNN.For 200 samples, 98.5% accuracy is obtained by PSO tuned BPNN. But, PSO tuned RBFNN showed an accuracy of 90.5%. Figure 11 compares the classification accuracy of PSO tuned RBFNN with PSO tuned BPNN on different number samples.

Table 10 Performance comparison of RBFNN and BPNN with and without PSO

Number of samples	Classification Accuracy (%)			
	RBFNN	BPNN	PSO tuned RBFNN	PSO tuned BPNN
50	86	95	87.5	94.5
100	87.5	96.5	89	96
200	88	97.5	90.5	98.5

Table 10 compares the classification performance of RBFNN and BPNN with PSO and without PSO algorithm. Performance is compared in terms of classification accuracy.

50,100 and 200 sets of samples were used for comparison. For 200 samples, 90.5% accuracy observed with PSO tuned RBFNN. An accuracy of RBFNN is 88%.97.5% and 98.5 % accuracy obtained using BPNN and PSO tuned BPNN respectively. From the Table 9 and Table 10, it is observed that the proposed PSO tuned BPNN can classify the EGG signal with high classification rate.

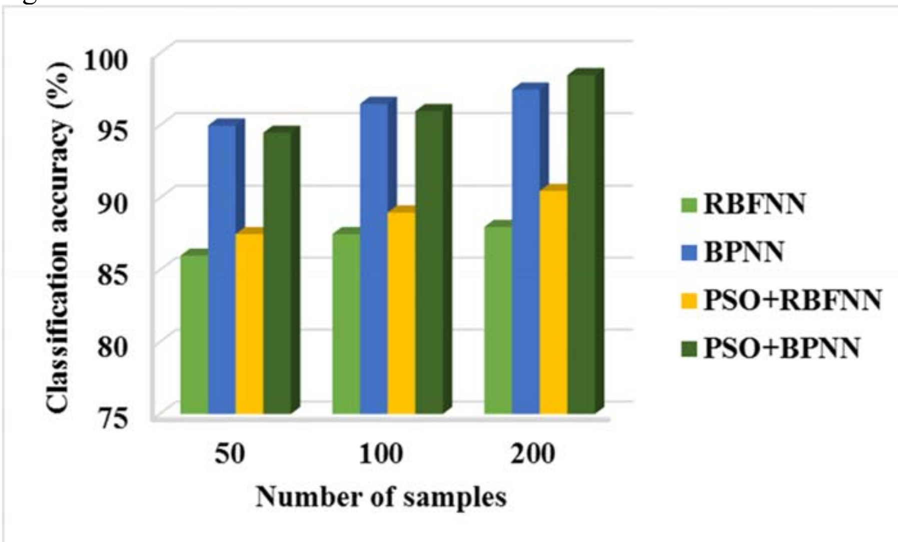

Figure 12Performance comparison of proposed classifiers with the existing classifiers

Figure 12compares the classification accuracy of the proposed classifiers with the existing classifiers. From the detailed simulation evaluation, it can be strongly proved that BPNN with PSO outperforms other classifiers such as BPNN, RBFNN and PSO tuned BPNN for the classification of EGG signal. The advantages of the proposed PSO tuned BPNN is that it can classify the EGG signal into normal and abnormal subjects with high classification accuracy for different number of samples.

4.6 Conclusion

In this paper, RBFNN and BPNN were used to discriminate between normal and abnormal EGG data. Classification performed in three phases. In phase 1, wavelet transform employed to enhance the quality of EGG signal and eliminate the noisy data. During phase 2,18 features were extracted from the decomposed EGG signal. In phase 3, two classifiers namely PSO tuned RBFNN and PSO tuned BPNN are used to classify the signal. PSO algorithm is used to tune the parameters of RBFNN and BPNN. It is also used to improve the performance of the classifiers. Classification performance of both the classifiers were compared in terms of accuracy. From the comparison, it is observed that PSO tuned BPNN outperformed than other classifiers such as BPNN, RBFNN and PSO RBFNN.

References

[1]. Lin ZY, Maris J, Hermans L, Vandewalle J & Chen JDZ (1996)," Classification of normal and abnormal Electrogastrogram using multilayer feedforward neural networks" Medical and Biology Engineering and Computing, Vol.35, No.3, pp.199–206.

[2]. Mario Sansone, Roberta Fusco, Alessandro Pepino& Carlo Sansone (2013),"Electrocardiogram Pattern Recognition and Analysis Based on Artificial Neural Networks and Support Vector Machines: A Review",Journal of Healthcare Engineering, Vol. 4, No. 4, pp.465–504.

[3]. MillarayCurilem, Max Chacón, Gonzalo Acuña& Sebastian Ulloa et al. (2010)," Comparison of artificial neural networks and support vector machines for feature selection in Electrogastrography signal processing", 32nd Annual International Conference of the IEEE EMBS Buenos Aires, Argentina, 2010.

[4]. Pal,S&Mitra,M (2009), "ECG feature extraction by multi resolution wavelet analysis based selective coefficient method. In: Lim C.T., Goh J.C.H. (eds) 13th International Conference on Biomedical Engineering. IFMBE

Proceedings, Vol 23. Springer, Berlin, Heidelberg

[5]. Patel,JL&Goyal,RK (2007)," Applications of artificial neural networks in medical science",Current Clinical Pharmacology,Vol.2 ,No.3,pp.217-226.

[6]. Ramalakshmi&Jeyachandran (2014)," Automatic brain tumor detection in MRI images using neural network based classification", International Journal of Computer Science and Network Security, Vol.11, No.5, pp.38-41.

[7]. Saheb,AR &Meharzad,Y (2011), "An automatic diagnostic machine for ECG arrhythmia classification based on wavelet transform and neural network" International Journal of circuit systems and signal processing, Vol.5, No.3, pp. 255-262.

[8]. Satapathy,SK,Dehuri,S&Jagadev, AK (2017),"EEG signal classification using PSO trained RBF neural network for epilepsy identification",Informatics in Medicine Unlocked, Vol. 6, pp.1–11

[9]. Smout, AJPM & Van der Schee, EJ &Grashuis, JL (1980), "What is measured in Electrogastrography?", Digestive Diseases and Sciences, Vol. 25, No.3, pp.179-87.

[10]. Tokmakci, M (2007), "Analysis of the Electrogastrogram using discrete wavelet transform and statistical methods to detect gastric dysrhythmia", Journal of Medical Systems, Vol.31, No.4, pp.295-302.

[11]. Wang,Z, He,Z&Chen,JD (1999),"Filter banks and neural network-based feature extraction and automatic classification of Electrogastrogram", ANN Biomedical Engineering, Vol.27, No.1,pp.88-95.

[12]. Yan,X& Shi , H (2011), "A hybrid algorithm based on particle swarm optimization and group search optimization", InSeventh Conference on Natural Computing (ICNC), IEEE, Vol. 1, pp.13-17.