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Classification of Electrogastrogram Signals Using Soft Computing Algorithms

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ABSTRACT

Electrogastrogram (EGG) is a non-invasive technique to measure and record the electrical activity of digestive system to detect abnormalities. EGG signal is measured by placing many electrodes over the stomach. These electrodes sense the signals originating from stomach muscles. Some of the attributes or features of normal EGG signal differ when compared with the attributes of EGG signal acquired from patients with abnormalities. By investigating such attributes, several digestive system disorders can be diagnosed. This paper proposes two different classifiers namely GSO-PSO based RBFNN and GSO-PSO based BPNN to classify the EGG signal with high accuracy. The weights of both the classifiers employed in this thesis are tuned by the proposed hybrid GSO-PSO algorithm to get high classification accuracy. In addition to, this contribution compares the proposed classifier performance with that of the other existing classifiers like MR-BPNN, RBFNN and BPNN. Empirical findings reveal that the proposed hybrid GSO-PSO based BPNN classifier outperforms in terms of classification accuracy than other classifier considered for comparison in regard that to that of EGG signal classification.

1. INTRODUCTION

EGG is a non-invasive technique to measure and record the electrical activity of digestive system to detect abnormalities. EGG signal is measured by placing many electrodes over the stomach. These electrodes sense the signals originating from stomach muscles. Some of the attributes or features of normal EGG signal differ when compared with the attributes of EGG signal acquired from patients with abnormalities. By investigating such attributes, several digestive system disorders can be diagnosed. An accurate classification of EGG signal is of fundamental important for the patient effective treatment. Henceforth, it is necessary to classify the EGG signal automatically which are helpful for the physician to make decision. From the literatures, it is observed that soft computing approaches like ANN, GA, Fuzzy logic and Support Vector Machine (SVM) etc. are applied for the classification of many bio signals like EGG, Electrocardiogram (ECG) and Electroencephalogram (EEG). Among these approaches, ANNs are highly accurate and well suited for the classification of EGG signal. As discussed in the previous chapters of this thesis, several ANN models are available to carry out classification operation. The key objective of this chapter is to model a hybrid Global Search Optimizer (GSO) – PSO based RBFNN and GSO-PSO based BPNN classifier to enhance the performance of NN and enable better classification. RBFNN and BPNN is used in this research work due to its nature of efficiency and faster convergence. Basic RBFNN and BPNN are get trapped with global and local optima problem. To overcome such limitations of basic RBFNN and BPNN classifier, in this thesis two bio inspired computing algorithms such as GSO and PSO are integrated with basic RBFNN and BPNN classifier. Hybrid GSO-PSO algorithm employed in this chapter is used to tune the weights of the classifiers to achieve high classification rate.

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2. GLOBAL SEARCH OPTIMIZER

GSO is population based optimization algorithm which is inspired by animal behaviour. It imitates the searching behaviour of animal to find the resources such as food, water and nests etc. success of searching behaviour heavily

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depends on the efficiency in locating the resources. GSO follows the Producer- Scrounger (PS) model for the search of solution. GSO uses three types of members to find the solution namely producers, scroungers and rangers. Producers find the ways to reach optimal solution in the resources. Scroungers follow the producers to find the solutions. Rangers trying to escape from local minima by using random walks. In a group, there exists only one producer. The remaining members are either scroungers or disperse members.

During each iteration process, a member is to be present in the location with best solution or fitness value is chosen as the producer. The producer detects the prominent location is the search space and stand in that position. Other group members are selected as rangers or scroungers. Each scroungers makes a random walk towards producers and rangers moves through the space in random manner. The steps are followed in GSO algorithm is given below: Let the m-dimensional search space, the k-th member at j-th iterations has a current position $Y_k^j \in S^m$ and head angle $\emptyset_k^j = \left(\emptyset_{k1}^j, \emptyset_{k2,}^j \emptyset_{k3,}^j \dots, \emptyset_{k(m-1)}^j\right) \in S^{m-1}$. The search direction of k-th member is unit vector and represented by equation (1.1)

$$d_k^j(\emptyset_k^j) = (d_{k1}^j, d_{k2}^j, d_{k3}^j, \dots, d_{km}^j \in S^m \quad (1)$$

The search direction can be computed from $\emptyset_k^j$ via polar to Cartesian coordinate transformation. The behavior of the producer Y^p during j-th generation is as follows:

Step 1: Producer starts scan at zero degree represented in equation (2). Then the producer scan one point at the Right Hand Side (RHS) hypercube is given in equation (2) and one point at Left Hand Side (LHS) hypercube is denoted in equation (3).

At zero-degree scan

$$Y_z = Y_p^j + c_1 N_{max} d_p^j(\emptyset^j) \quad (2)$$

At RHS scan

$$Y_z = Y_p^j + c_1 N_{max} d_p^j(\emptyset^j + c_2 \emptyset_{max}/2) \quad (3)$$

At LHS scan

$$Y_z = Y_p^j + c_1 N_{max} d_p^j(\emptyset^j - c_2 \emptyset_{max}/2) \quad (4)$$

Where

$c_1 \in S^1$: Random number with zero mean 1 standard deviation

$c_2 \in S^{m-1}$: Random number [0-1]

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$N_{max} \in S^1$: Maximum pursuit distance and

$\emptyset_{max} \in S^1$: Maximum pursuit angle

Step 2: Producer will find the best location (value) with the best solution or objective fitness value. If the best value is better than its current location (position), then it will fly to this new value. Else it will stay in its current location. Then it turns head to a new generated angle as represented in equation (5)

$$\emptyset^{j+1} = \emptyset^{j} + c_2\beta_{max} \quad (5)$$

Where

$\beta_{max} \in S^1$: Maximum turning angle

Step3: If the producer does not find any better solution or fitness value for some iterations, it will turn its head back to zero degree as given in equation (6)

$$\emptyset^{j+x} = \emptyset^{j} \quad (6)$$

Where, x $\in S^1$:Constant

The k-th scroungers at j-th iterations walks randomly to the producer is expressed in equation (7)

$$Y_k^{j+1} = Y_p^j + c_3 O\left(Y_p^j - Y_k^j\right) \quad (7)$$

Where

$c_3 \in S^m$: Random sequence [0,1]

O : Hadamard product

Step 4: When a scrounger finds a better point than a current producer point and other scrounger point, then it gets moved as a producer in the next iteration.

Step 5: The group members who are identified as less efficient searches than the dominant, eliminated from the group.

Step 6: When the p-th member is removed, it performs ranging. At j-th iteration, it generates the head angle $\emptyset_R$ and random distance is selected,

$$L_p = bc_1 N_{max} \quad (8)$$

$$Y_k^{j+1} = Y_p^j + L_p d_p^j\left(\emptyset^{j+1}\right) \quad (9)$$

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The flowchart of GSO algorithm is shown in Figure 1. In GSO algorithm, population is called as a group. Each individual in the population is called as a member. GSO algorithm has the nature of random walk in m-dimensional space. The members which are having less efficiency in the group are removed to determine the solution. GSO algorithm tends to have faster convergence due to the effective movement of members in the solution space. Therefore, GSO algorithm is hybridized with PSO algorithm to overcome the drawbacks of basic PSO algorithm.

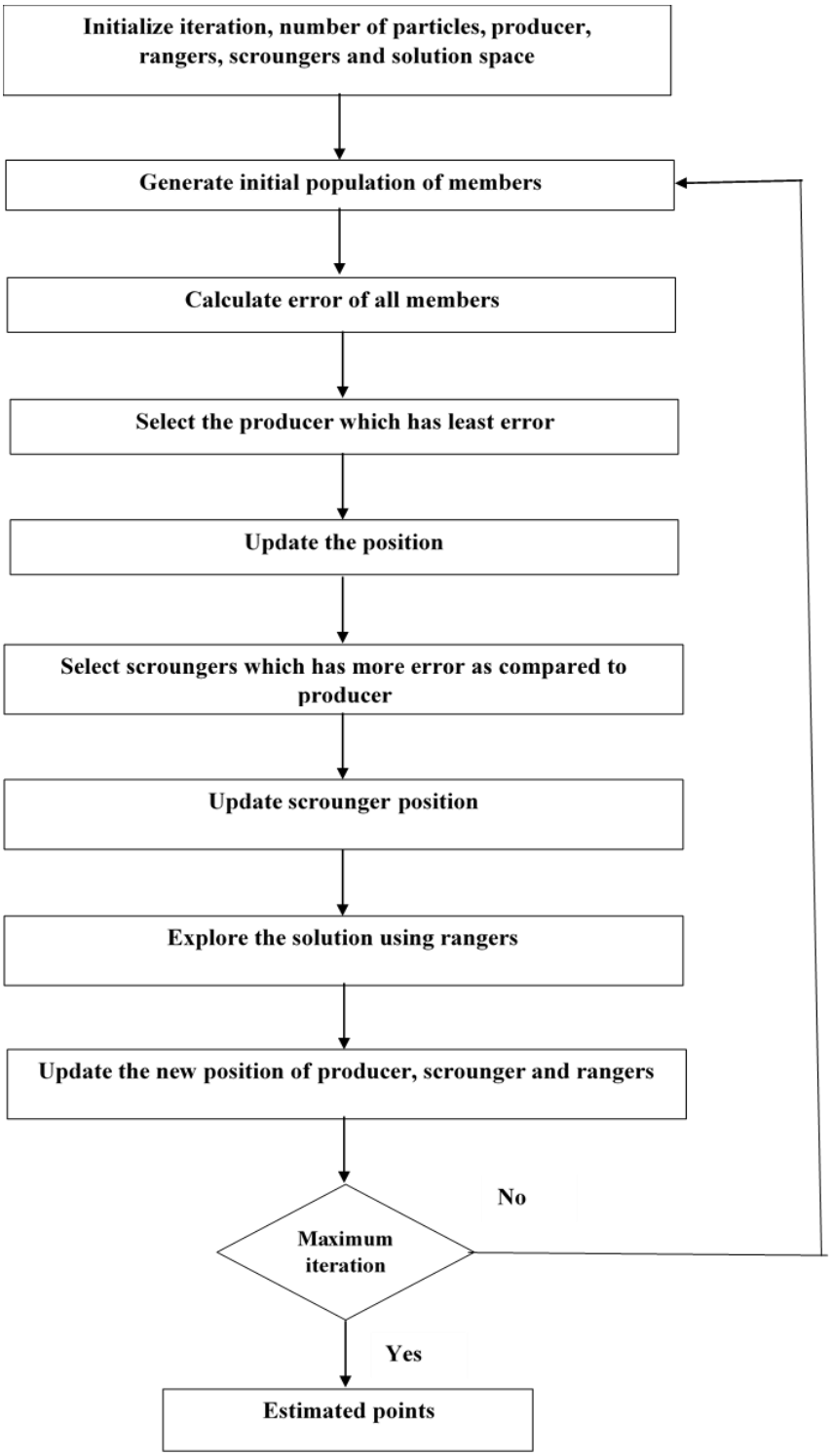

Figure 1 Flowchart of GSO algorithm

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3. PROPOSED HYBRID GSO-PSO ALGORITHM

PSO algorithm is a stochastic population based algorithm inspired by social behavior of fish and birds. Even though, PSO is a best algorithm for finding the optimal solution of complex problem. It has two limitations namely (i) premature convergence and (ii) dimensionality. To overcome the above said two limitations of PSO, GSO is hybridized with PSO. The GSO is invoked when the best solution does not change for some iterations. GSO algorithm employs fly-back mechanism which is used to increase the exploitation rate of search process.

Movement of particles is search space depends on head angle and location of new point. The steps followed in the proposed hybrid GSO-PSO algorithm is given below.

Step 1: Initialize the number of members (particle) positions head angles and acceleration factors.

Step 2: For each iteration, evaluate the value of each member (particle).

Step 3: Calculate the P_{best} and G_{best} value of particle.

Step 4: IfG_{best} is better than P_{best},return the value.

Step 5: Update the position and velocity of particle based on $P_{best}$and G_{best}

Step 6: If P best does not change for some iterations, invoke GSO module.

Step 7: Find the producer Y_p of the search group.

Step 8: The producer scans the search space using equations (5.2), (5.3) and (5.4)

Step 9: Determine the best point with the best fitness values.

Step 10: If best point is better than its current position, it will move to this new point. Else it will stay in the present position and turn its head to new angle using equation (5).

Step 11: 75% of members form the rest of the group selected randomly as a scrounger.

Step 12: Remaining 25% members perform ranging task.

Step13: Return the members of the group at which better fitness value is found.

The proposed hybrid GSO -PSO algorithm [1] is integrated with two ANN including RBFNN and BPNN to make it as a classifier for performing EGG classification.

3.1 Implementation of proposed hybrid GSO-PSO based RBFNN Classifier

This research work focuses on developing hybrid GSO-PSO based RBFNN for classifying EGG signal with high accuracy. In this work, the proposed hybrid GSO-PSO algorithm is utilized to find optimal weights of RBFNN classifier. The objective of combining hybrid GSO-PSO algorithm with RBFNN can escape from local minima problem. Minimization of error is used as an objective function. This research work mainly concentrates on tuning the parameters of RBFNN classifier using hybrid GSO-PSO algorithm and performing clustering task. Hybrid GSO-PSO based RBFNN classifier operates in three phases. During phase 1, features are applied on RBFNN and output is calculated from output layer. In phase 2, phase 1 output is used as an input for hybrid GSO-PSO algorithm. Based on the inputs, new weights are founded. During phase 3, classification task is performed by using new weights.

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3.2 Implementation of proposed hybrid GSO-PSO based BPNN Classifier

This section presents the functioning of proposed hybrid GSO-PSO based BPNN to perform EGG signal classification. BPNN performs the classification task and the internal parameters of BPNN are tuned to achieve high recognition rate, faster convergence and minimum error employing hybrid GSO-PSO algorithm.[2] In BPNN, weights between all the layers are initialized randomly. This random initialization of weights and weight updation leads to premature convergence, local and global minima during the training of the BPNN. Therefore, this chapter focus on hybridizing GSO-PSO algorithm with BPNN to tune weight of BPNN in order to avoid the above mentioned problem.[3] Table 1 presents the pseudo code for proposed hybrid GSO-PSO based BPNN classifier.

Table 1 Pseudo code for hybrid GSO-PSO based BPNN classifier

Phase I
Randomly initialize the bias, weights and learning rate of BPNN
Present the inputs to BPNN
Calculate the output of input layer
Apply activation function on the hidden layer to calculate the output of hidden layer
Carry out the above process from hidden layer to output layer
Calculate the output of BPNN from the output layer
Update weights till stopping condition met
Phase II
Apply the output of phase I to the input of proposed hybrid GSO-PSO algorithm
Invoke hybrid GSO-PSO algorithm
Evaluate the objective function
Update velocity and position
If the values do not change over iterations
Invoke GSO algorithm
Assign the particles to the members
Identify the scrounger, producers and ranges.
Update movement and position trough random walk
Perform iterations until the condition met
Note the points at which best solution is achieved
Present the best value to BPNN classifier
Phase III
Invoke BPNN with inputs from phase II output
Tune the weights of BPNN with hybrid GSO-PSO algorithm
Invoke hybrid GSO-PSO algorithm
Carry out phase I for tuned weights of hybrid GSO-PSO algorithm

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Continue phase II

Repeat until termination condition met

The stopping condition can be error minimization or number of iterations

4. SIMULATION RESULTS

In this section, the developed hybrid GSO-PSO based RBFNN and GSO-PSO based BPNN is applied to classify the EGG signal [4]. Four performance metrics such as classification accuracy, specificity, sensitivity and precision are calculated to evaluate the efficiency of the proposed classifiers.

4.1 Performance of hybrid GSO-PSO based RBFNN Classifier

To enhance the performance of RBFNN and increase the recognition rate, hybrid GSO-PSO algorithm is merged with the RBFNN. Hybrid GSO-PSO algorithm is employed to tune the weights of RBFNN. It is also used to overcome the drawback of PSO. Table 2 presents the classification accuracy achieved by employing hybrid GSO-PSO based RBFNN to classify the EGG signal. From the Table 3, it can be seen that the proposed GSO-PSO based RBFNN can classify the EGG signal with an accuracy of 94.5%.

Table 2. EGG signal classification using hybrid GSO-PSO based RBFNN

Normal (100)	**Abnormal (100)**	**Total**	**Classification Accuracy (%)**
96	93	189	94.5

Table 3 Performance of hybrid GSO-PSO based RBFNN classifier

Number of samples	**Specificity**	**Sensitivity**	**Precision**	**Classification Accuracy (%)**
50	0.93	0.96	0.97	91
100	0.96	0.95	0.95	92.5
200	0.98	0.96	0.96	94.5

Three different number of samples such as 50 ,100 and 200 were utilized to test efficiency of the proposed hybrid GSO-PSO based RBFNN classifier. Table 4 tabulates the efficiency of hybrid GSO-PSO based RBFNN classifier. From the Table 4, it is inferred that the classification accuracy of 91% ,92.5% and 94.5 % is achieved using proposed classifier for 50,100 and 200 samples respectively.[5] For 200 samples, specificity of 98%, sensitivity of 96% and precision of 96% is obtained. Figure 2 presents the classification accuracy of hybrid GSO-PSO based RBFNN with respect to three different number of samples 50, 100 and 200.

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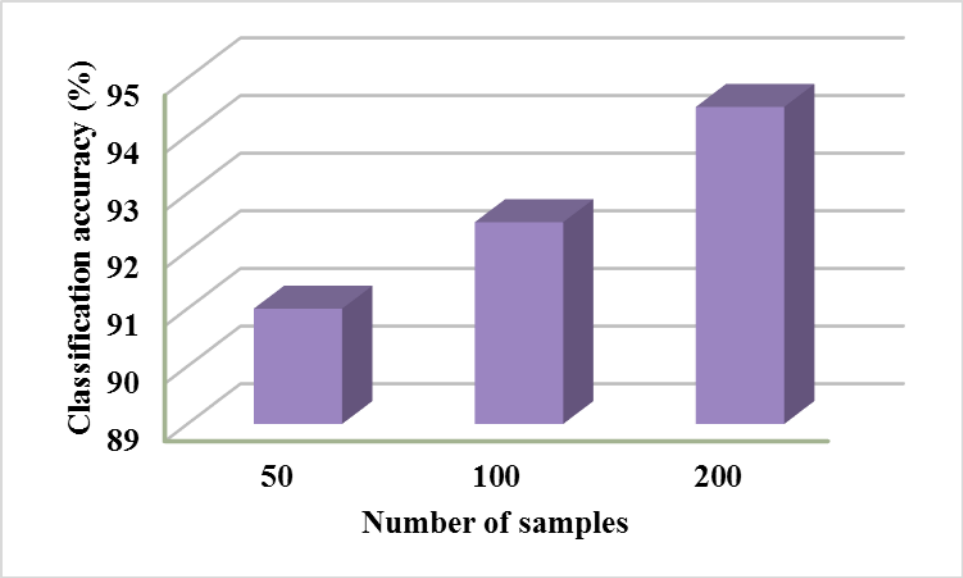

Figure 2 Classification accuracy of hybrid GSO-PSO based RBFNN for different number of samples

4.2 Performance of hybrid GSO-PSO based BPNN Classifier

The developed hybrid GSO-PSO based BPNN classifier is employed to discriminate between normal and abnormal EGG signal. The hybrid GSO-PSO algorithm is used to tune the weights of BPNN classifier during training. Then the trained network is employed to classify the EGG signal. To improve the performance and increase the convergence rate, hybrid GSO-PSO algorithm is combined with BPNN in this research work.

Performance of the proposed hybrid GSO-PSO based BPNN classifier is analyzed by varying three parameters namely number of hidden layer, hidden neurons and training algorithm in order to find the best topology for BPNN.[7]In this research work, hidden layers are varied from 1 to 3. 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. Classification accuracy obtained using hybrid GSO-PSO based BPNN for different hidden layers with 5 hidden neurons in each layer is tabulated in Table 4.

Table 4 Classification of EGG signal using hybrid GSO-PSO based BPNN with 5 hidden neurons

Number of hidden layers	**Normal (100)**	**Abnormal (100)**	**Total**	**Classification Accuracy (%)**
1	90	81	171	85.5
2	96	95	191	95.5
3	85	89	174	87

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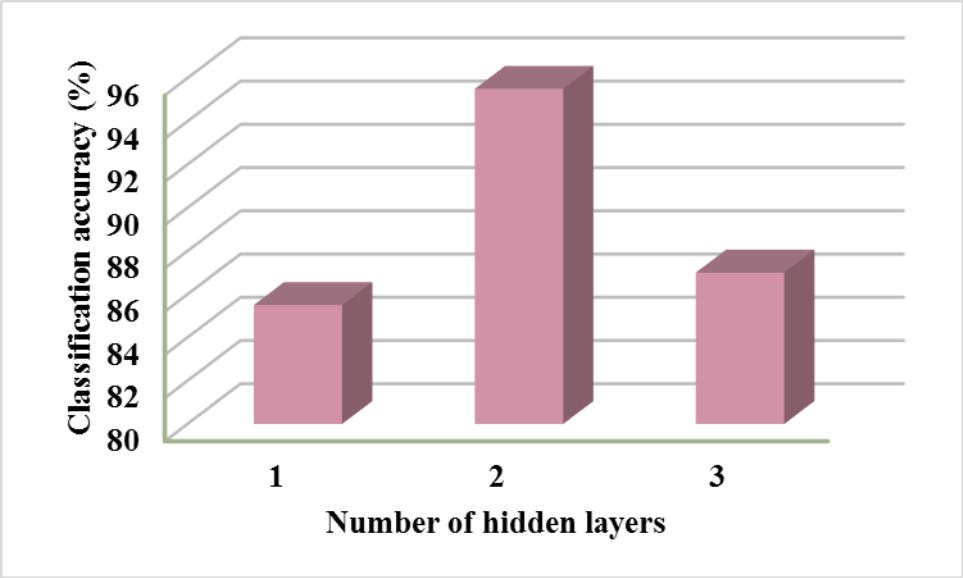

Figure 4 Comparison of classification accuracy of hybrid GSO-PSO based BPNN for different hidden layers with 5 neurons

From the Table 3 it is observed that proposed hybrid GSO-PSO based BPNN provides an accuracy of 85.5%, 95.5% and 87% for single hidden layer, two hidden layers and three hidden layers respectively. Figure 3 demonstrates the performance of the proposed hybrid GSO-PSO based BPNN classifier for varying hidden layers.[8] Each hidden layer consists of 5 hidden neurons. From the Figure 3, it is evident that the hybrid GSO-PSO based BPNN outperforms with two hidden layers than hybrid GSO-PSO based RBFNN classifier.

Table 5 Classification of EGG signal using hybrid GSO- PSO based BPNN with 10 hidden neurons

Number of hidden layers	**Normal (100)**	**Abnormal (100)**	**Total**	**Classification Accuracy (%)**
1	94	91	185	92.5
2	100	99	199	99.5
3	90	96	186	93

Table 5 tabulates the classification accuracy of EGG signal obtained using hybrid GSO-PSO based BPNN classifier for different hidden layers.[9] The graphical representation of classification accuracy is illustrated in Figure 5.Each hidden layer consists of 10 hidden neurons. From the Table 6, it can be seen 99.5% classification accuracy is obtained with the configuration of 18-10-10-2. From the results, it is proved that the proposed hybrid GSO-PSO based BPNN classifier with two hidden layer can classify the EGG signal with high classification accuracy.

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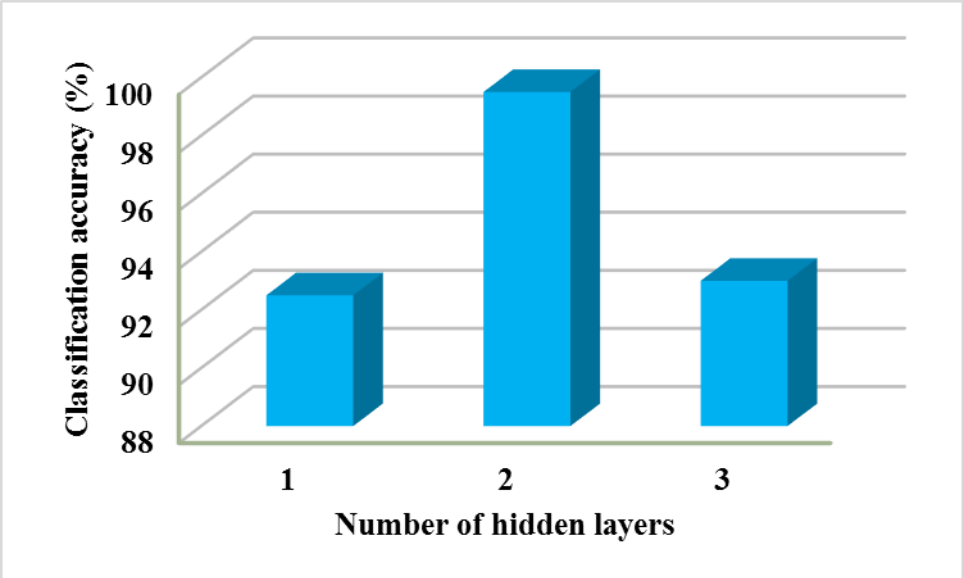

Figure 5 Comparison of classification accuracy of hybrid GSO-PSO based BPNN for different hidden layers with 10 neurons

Table 6 Classification of EGG signal using hybrid GSO- PSO based BPNN with 15 hidden neurons

Number of hidden layers	Normal (100)	Abnormal (100)	Total	Classification Accuracy (%)
1	92	85	177	88.5
2	98	87	185	92.5
3	85	90	175	87.5

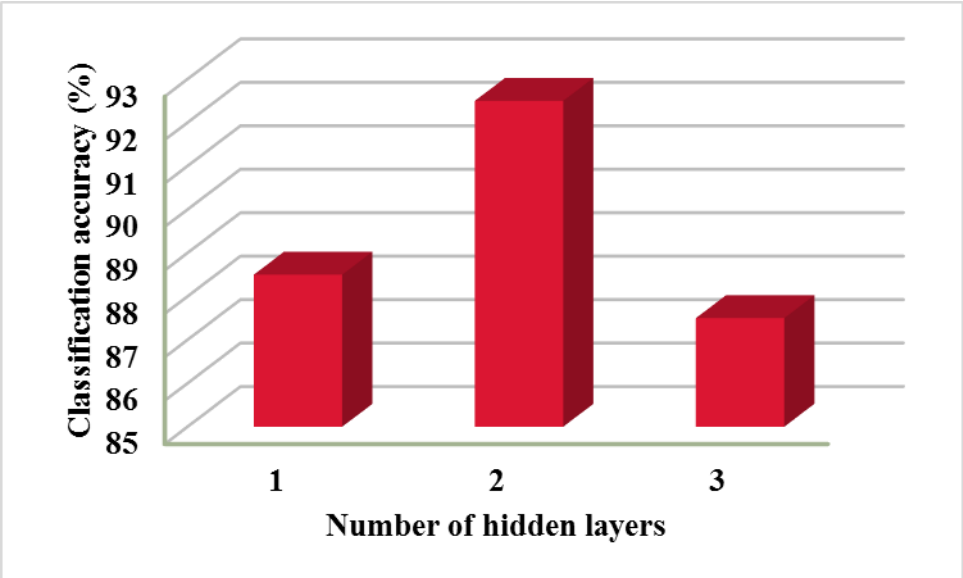

Figure 6 Comparison of classification accuracy of hybrid GSO-PSO based BPNN for different hidden layers with 15 neurons

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Classification performance of proposed GSO-PSO based BPNN for different hidden layers are listed in Table 7. Each layer having 15 hidden neurons. Figure 6 depicts the classification accuracy of hybrid GSO-PSO based BPNN classifier. From the Table 7, it is found that the maximum classification accuracy is achieved using this topology (18-15-15-2) is 92.5% which is lesser than the accuracy obtained using 18-10-10-2 topology.[9] So, it is suggested that the proposed hybrid GSO-PSO based BPNN with two hidden layers and 10 neurons in each layer is the best choice for classifying the EGG signal with high accuracy.

Table 7 Performance of hybrid GSO-PSO based BPNN with different training algorithms

Training algorithms	**Normal (100)**	**Abnormal (100)**	**Total**	**Classification Accuracy (%)**
RP	93	96	189	94.5
SCG	93	89	182	91
OSS	80	87	167	83.5
LM	100	99	199	99.5
GDX	70	85	155	77.5

Selection of training algorithm for BPNN is an important task and it plays vital role to achieve the desired target. To find the most suitable training algorithm, proposed classifier is trained with five training algorithms namely RP[11], SCG[12], OSS[13], LM[14] and GDX.

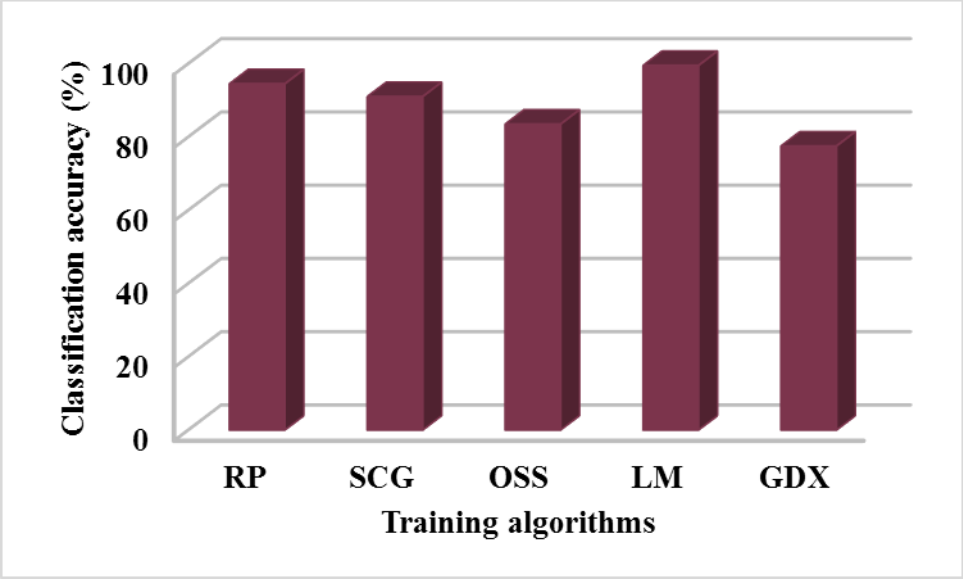

Figure 7 Comparison of classification accuracy of hybrid GSO-PSO based BPNN classifier using different training algorithms

The proposed hybrid GSO-PSO based BPNN classifies 167 samples out of 200 samples with OSS training algorithm with an accuracy of 83.5%.SCG algorithm observed an accuracy of 91%. Performance of SCG is better

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than GDX and OSS.94.5% accuracy is achieved using RP algorithm. LM algorithm gives an accuracy of 99.5%. LM algorithm outperforms than other training algorithms considered for comparison such as RP, OSS, SCG and GDX. Performance comparison of hybrid GSO-PSO based BPNN classifier with 5 different training algorithms are graphically shown in Figure 7.

Table 8 Classification performance of hybrid GSO-PSO based BPNN classifier

Number of samples	**Specificity**	**Sensitivity**	**Precision**	**Classification Accuracy (%)**
50	0.96	0.96	0.96	95.5
100	0.96	0.97	0.97	97
200	0.99	0.98	0.98	99.5

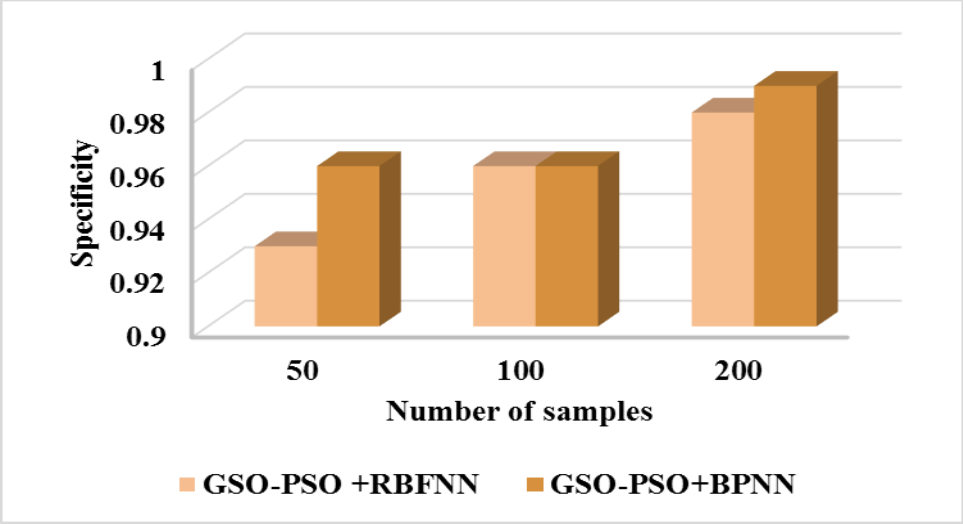

Figure 8 Comparison of specificity for different number of samples using proposed classifiers.

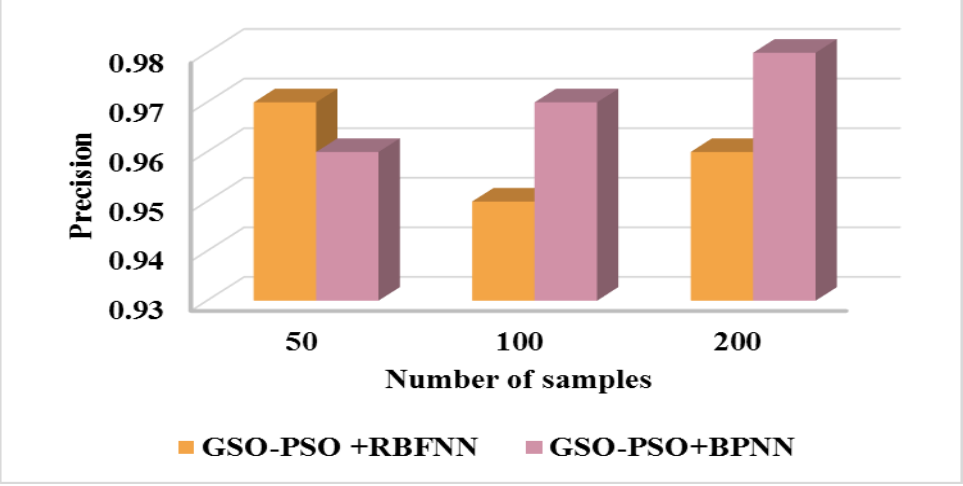

Figure 9 Comparison of precision for different number of samples using proposed classifiers

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Table 8 compares the performance of the proposed hybrid GSO- PSO based BPNN with three different number of samples such as 50, 100 and 200 samples. The topology employed is 18-10-10-2 and the classifier is trained with LM training algorithm. An accuracy of 99.5%, specificity of 99%, sensitivity of 98% and precision of 98% is obtained for 200 samples using hybrid GSO-PSO based BPNN[15] classifier.

Comparison of specificity on different datasets obtained using proposed two classifiers are graphically shown if Figure 7.Similarly, comparison of sensitivity and precision of the proposed classifier on different number of samples achieved employing proposed two classifiers are demonstrated in Figure 8 and Figure 9 respectively. From the above three graphs, it is inferred that the performance of hybrid GSO-PSO based BPNN is better than hybrid GSO-PSO based RBFNN classifier.

5. CONCLUSION

In this chapter the main objective was to classify the EGG signals with high accuracy based on the features extracted from the decomposed signal. The EGG database consists of two groups which are normal and abnormal subjects. This thesis chapter developed two classifiers namely hybrid GSO-PSO based RBFNN and hybrid GSO-PSO based BPNN. Two classifiers developed in this chapter are employed to distinguish between normal and abnormal subjects where in the parameters of the classifier are tuned using proposed hybrid GSO-PSO algorithm. The advantages of hybrid GSO-PSO is merged into RBFNN and BPNN for tuning its parameters (weights) which resulted in minimization of error rate and as well increased convergence speed. The most important features of exploitation and exploration of hybrid GSO-PSO algorithm is invoked to optimize the weight of RBFNN and BPNN classifier. Simulation results demonstrated that the proposed hybrid GSO-PSO algorithm based BPNN proves to be better in terms of classification accuracy than that of the other classify considered for comparison from the existing and as well that of the hybrid GSO-PSO based RBFNN classifier proposed in this chapter.

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