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Correlation-Based Analysis and Hybrid Neural Network Training Algorithm For Heart Disease Diagnosis

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Abstract

Heart Disease is one of the most dangerous diseases caused due to various health problems. To virtually support the busy physician and to enhance the diagnosis of heart disease, intelligent systems are increasingly being deployed in medicine and healthcare. In the previous research, the automatic detection of heart diseasesare done using neural network that was trained depending on hybrid algorithm which was designed based on ABC (Artificial Bee Colony) algorithm and GSO (Group Search Optimizer) algorithm. In order to further improve the effectiveness, the GSO-ABC training algorithm is hybridized with the Back Propagation algorithm which is one of the benchmark algorithms for neural network training. The weight values are hybridized using some operations after receiving the weights from GSO-ABC training algorithm and Back Propagation algorithm. At first, the input data is given to pre-processing, and thenfeatures are selected using correlation-based analysis. The important features selected from the previous steps are then given to neural network to detect the heart disease. Here, the training algorithm is designed by combining the weight values of both, GSO-ABC and Back Propagation Algorithms. The proposed technique was implemented in java and three heart disease databases which are UCI Repositories, named asCleveland, Hungarian and Switzerland, used to analyze the performance in terms of sensitivity, specificity and accuracy.

Keywords: Heart Disease, GSO, GSO-ABC, Neural Network

Introduction

To improve the diagnosis of patientsheart disease and to virtually support the busy physicians, Intelligent systems are increasingly being deployed in medicine and healthcare [7- 13]. The need for a novel methodology for evaluating such systems is widely recognized [9, 10] [14-18]. In medicine and healthcare where safety is the utmost priority, it is important that the techniques such as medical expert systems and neural systems are to be commonly recognized in clinical practice. The diagnosis of a disease is a major and tiresome task in medicine. The detection of heart disease from a group of different factors or signs is a multi-layered issue which is not free from unwantedassumptions often accompanied by an unpredictable effects. With the complexity of information available from health care domain, human intelligence alone is not good enough to determine the proper diagnosis for heart disease [1].

In this paper a correlation-based analysis and hybrid neural network training algorithm is proposed for heart disease diagnosis. In [6], the GSO-ABC algorithm was proposed to train the neural network. In the proposed methodology, the Back Propagation algorithm is hybridized with GSO-ABC algorithm to select a best solution that contains the weight values to be assigned to neural networkin order to train the neural network.

The paper is organized as follows: Section 2 describes some of the related works of neural networks.Section 3 brieflydiscusses the proposed methodologyof correlation based hybrid algorithm followed by the brief analysis of the experimented results in Section 4. Then section 5 concludes the proposed methodology.

Related Works: A Brief Review

K.S.Kavitha*et al.* [1] proposed methodology for recognition of heart disease based on feed forward neural network architecture and genetic algorithm. Hybridization is applied to train the neural network by means of Genetic algorithm and demonstrated that their proposed learning is more stable when compare to Back Propagation. Detailed analysis has given with respect to genetic algorithm behavior and its association with learning performance of neural network. Effect of tournament selection has been analyzed to obtain more detailed information that is happening internally. With this system, design of diagnosis for heart disease detection is easy, cost effective, reliable and efficient.

Koushal Kumar and Abhishek [2] proposed a method to diagnose kidney stone disease by using three different neural network algorithms which have different architecture and characteristics. They used Learning Vector Quantization (LVQ) a two layers feed forward perceptron trained with back propagation training algorithm and Radial Basis Function (RBF) networks for diagnosis of kidney stone disease. In this work, Waikato Environment for Knowledge Analysis (WEKA) version 3.7.5 is used as simulation tool which is an open source. This helps in early identification of kidney stone in patients and reduces the diagnosis time.

QeetharaKadhim Al-Shayea [3] proposed a method to evaluate artificial neural network in disease diagnosis. In this methodology, two cases are examined. The first one is acute nephritis disease where data is the disease symptoms. The second is the heart disease where data is on cardiac Single Proton Emission Computed Tomography (SPECT) images. Each patient classified into two categories: infected and non-infected. The results of applying the artificial neural networks methodology to acute nephritis diagnosis based on selected symptoms showed the abilities of the network to learn the patterns corresponding to symptoms of the person.

RanjanaRaut and Dr. S. V. Dudul [4] have proposed an Intelligent Diagnosis of Heart Diseases using Neural Network Approach. The classifiers based on various neural networks namely MLP, PCA, Jordan, GFF, Modular, RBF, SOFM, SVM NNs and conventional statistical techniques such as DA and CART are optimally designed,thoroughly examined and performance measures are compared in this study.

Luo Zaifei*et al.* [5] proposed a hybrid learning algorithm based on simplex method and particle swarm optimization to train the feed forward neural. In the given hybrid algorithm the simple method which has expansion function and contraction function is embedded in the particle swarm optimization as an operator. Using cross-training mode to train neural network, this hybrid algorithm selects limited elitist particles and executes simplex operator for local searching during each generation of particle swarm optimization. This made the neural network learning approximate to the global optimum region rapidly and find more excellent solution. The simulation experiments show that comparing with some traditional learning methods this hybrid algorithm enhances the convergence speed and training precision and improves network performance. It is an effective neural network learning method.

Proposed Correlation-Based Analysis and Hybrid Neural Network Training Algorithm

This section briefly describes the proposed Methodology that is a correlation based analysis using the hybrid neural network training algorithm for heart disease diagnosis. This proposed technique consists of two processes that is Back Propagation and GSO-ABC to select the best weight values and to train the neural network. In [6], the GSO-ABC algorithm is used to choose the best weight values to train the neural network. Generally to train the neural network,Back Propagation algorithm would be used. Thus, both the Back Propagation algorithm and the GSO-ABC algorithm proposed to choose the best weight values as to train the neural network.

The Fig.2 represents procedure of the proposed technique. In this,the initial solutions with weight values for neural network are generated randomly by setting the upper bound and lower bound. The initial solutions are then assigned to the neural network separately and the input data is given to the neural network to calculate the fitness of each solution. The top ten solutions based on the fitness calculation are then given to the GSO-ABC and Back Propagation algorithm separately. Due to which, the weight values of each solution changes based on Back Propagation and GSO-ABC algorithm independently. The fitness is then calculated for newly formed solutions based on both algorithms where the best algorithms is considered and compared to choose a best solution between them. The obtained best valueis used to update the solutions based on GSO-ABC algorithm for next iteration. The process is repeated until specified number of iterations are reached and the best solution in the final iteration are set as the weight values for the neural network to train the system.

Fitness Evaluation

Initially a set of solutions are generated randomly by setting the upper limit and lower limit to process the hybrid Back Propagated GSO-ABC algorithm. A best solution is to be chosen which is perfect to assign the neural network to make the system works effectively. Here the best solution is identified using the proposed hybrid Back Propagated GSO-ABC algorithm. Each solution generated is applied to the neural network separately and it is processed by applying the input data to calculate the fitness for each solution. Let us assume the solutions generated are $S = \{S_1, S_2, \ldots S_i, \ldots S_I\}$ and the dataset contain N number of data as $D = \{D_1, D_2, \ldots D_n, \ldots D_N\}$. The fitness for i^{th} solution S is calculated as follows:

$$fitness(S_i) = \sum_{n=0}^{N} (tgt - o/p)$$

In the above equation tgt represents the target which is the class of n^{Th} data in the dataset and o/p is the output from the neural network for n^{Th} data in the dataset. The best solution is identified based on the minimum value which is given below:

$best\ fitness = \min\{fitness(S_i)\}$

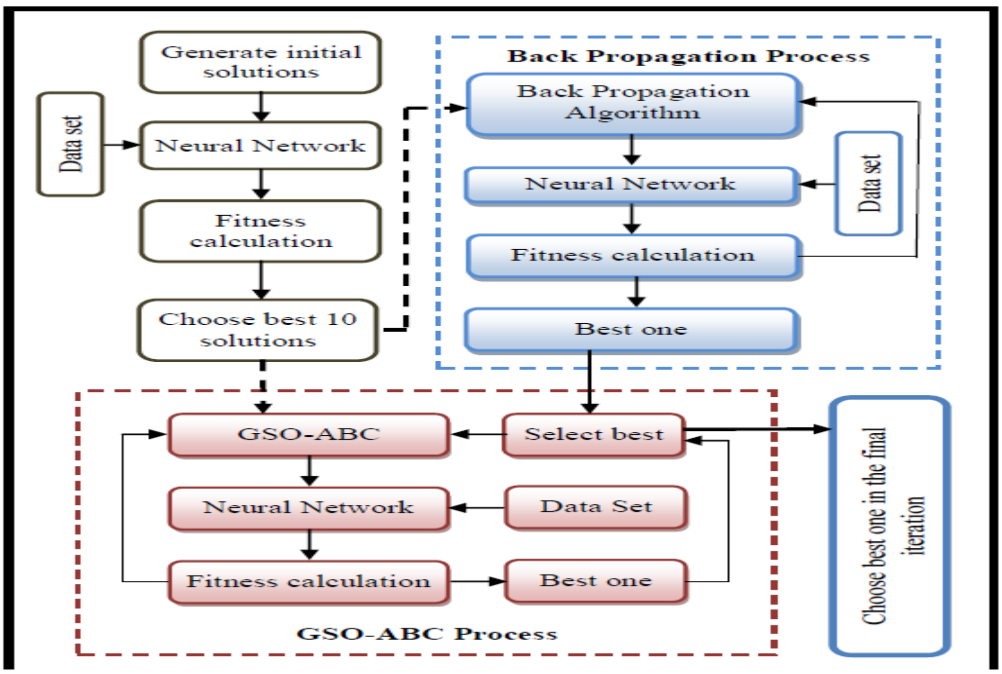

Figure 1: Process of The Proposed Technique

Back Propagation Algorithm

In Back Propagation algorithm, the weight values are altered from the output layer to the input layer based on the error value between the neurons of corresponding layer. Initially the weight values in each solution are applied to the neural network separately and the output from the neural network for the given input is based on the weight values. The Fig.2 shows a sample connection in neural network to perceive the Back Propagation algorithm.

In Fig.2, the output of node (neuron) C is formed from the neurons A and B. Consider, C is the neuron in output layer and A, B are the neurons in hidden layer. First, the error obtained from the output neuron C is evaluated. It is shown by the equation below:

$$Error_C = O_C(1-O_C)(T-O_C)$$

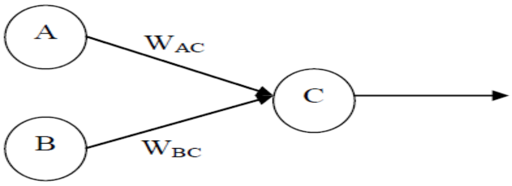

Figure 2: Sample Connection In Neural Network

$Error_C$ is the error from the output neuron C and O_C is the output from the neuron C T is the target based on the class of each data. Using $Error_C$ the weight value between the hidden layer neuron A, output neuron C, the weight value between the hidden layer neuron B and output neuron C would get changed as shown below:

$$W_{AC}^{+} = W_{AC} + (Error_C * O_A)$$

$$W_{AC}^{+} = W_{AC} + (Error_C * O_A)$$

W_{AC}^{+} And W_{BC}^{+} are new weight values and W_{AC} and W_{BC} are the initial weights. Thereafter, the errors from the neurons in the hidden layer have to be evaluated to alter the weight values between the neurons in input layer and neurons in the hidden layer. Unlike output layer, calculation cannot be done directly. Thus, back propagated from the output layer. It is shown by the equations below:

$$Error_A = O_A(1-O_A)(Error_C * W_{AC})$$

$$Error_B = O_B(1-O_B)(Error_C * W_{BC})$$

After obtaining the error for the neurons in the hidden layer, the new weight values are given in between the neurons in input layer and neurons in hidden layer. So eventually, a new solution is obtained. Similarly, each solution is applied to the neural network and a new solution would be obtained for the corresponding solutions.

GSO-ABC Algorithm

The obtained solutions in GSO-ABC algorithm are categorized for doing Producer operation, Scroungers operation, Rangers operation that depends on GSO algorithm [19]. The ABC operator and Error based operator are applied based on the fitness values of each solution (member).

$$catagorize = \begin{cases} \text{Producer} & ; \text{if } fitness\left(S_i^c\right) \text{ is best} \\ \text{Error based op} & ; \text{if } fitness\left(S_i^c\right) \text{ is worst} \\ \text{ABC op} & ; \text{if } fitness\left(S_i^c\right) = fitness\left(S_i^{c-1}\right) \\ \text{Scrounger} & ; \text{if } fitness\left(S_i^c\right) < threshold \\ \text{Ranger} & ; \text{else} \end{cases}$$

In the above equation, $fitness\left(S_i^c\right)$ represents the fitness value of a solution in current iteration and $fitness\left(S_i^{c-1}\right)$ represents the fitness value of the same solution in the previous iteration. The operation of the GSO-ABC is as follows:

Producer Operation

In a q-dimensional search space, the b^th solution at the c^th iteration has current position as $S_b^c \in R^q$, head angle as $\delta_b^c = \left(\delta_{b1}^c, \ldots\ldots, \delta_{b(q-1)}^c\right) \in R^{q-1}$ and head direction as $H_b^c\left(\delta_b^c\right) = \left(h_{b1}^c, \ldots\ldots., h_{bq}^c\right) \in R^{q-1}$ that can be evaluated from δ_b^c .

$$h_{b1}^c = \prod_{p=1}^{q-1} \cos\left(\delta_{bp}^c\right)$$

$$h_{bg}^c = \sin\left(\delta_{b(g-1)}^c\right) * h_{b1}^c$$

$$h_{bq}^c = \sin\left(\delta_{b(q-1)}^c\right)$$

The scanning field of vision is generalized to q-dimensional space which is characterized by maximum pursuit angle $\phi_{\max} \in R^{q-1}$ and maximum pursuit distance $e_{\max} \in R^1$. The behavior of producer S_p at c^th iteration is as follows: the producer S_p initially scans at zero degree and then scans laterally by randomly sampling three points in the scanning field. The scanning is shown by the equations below:

$$S_Z = S_p^c + r_1 e_{\max} H_p^c\left(\delta^c\right)$$

$$S_R = S_p^c + r_1 e_{\max} H_p^c\left(\delta^c + r_2 \frac{\phi_{\max}}{2}\right)$$

$$S_L = S_p^c + r_1 e_{\max} H_p^c\left(\delta^c - r_2 \frac{\phi_{\max}}{2}\right)$$

The S_Z in the above equation denotes zero degree scan and S_R denotes right hand side hypercube scan, denotes left hand side hypercube scan. $r_1 \in R^1$ is a normally distributed random number that has mean value as zero and standard deviation as one. $r_2 \in R^{q-1}$ is a random sequence between the range of zero and one. The producer will then recognize the best point with best resource. If the best point has better resource than its current position, then it will shift to that point or else it will stay in the same position and turn its head to a new angle as shown below:

$$\delta^{c+1} = \delta^c + r_2 \alpha_{\max}$$

In the above equation, $\alpha_{\max}$ is the maximum turning angle. If the producer cannot identify a better area after a number of iterations, it will turn its head back to zero degree and it is shown by an equation below:

$$\delta^{c+a} = \delta^{c}$$

Scroungers Operation

The scroungers will look for the opportunities to bond the resources found by the producer. The rudimentary scrounging strategies are area copying, following and snatching. The area copying is a strategy to look for an instant area around the producer. The following strategy is that it pursues another animal around without revealing any searching behavior. Snatching is a strategy that takes a resource directly from the producer. The common scrounging strategy in sparrows is area copying. The area copying strategy of the bth scrounger at cth iteration is as follows:

$$S_b^{c+1} = S_b^c + r_3 \left(S_p^c - S_b^c\right)$$

In the above equation, $r_3 \in R^q$ is a uniform random sequence in a range (0, 1).

Rangers Operation

Usually, the group members frequently have diverse searching and competitive abilities. The subordinates who have less efficient foragers than the leading will be isolated from the group and it results in ranging behavior. The searching strategy of the rangers includes random walks and methodical search strategies to identify resources efficiently. The ranger generates a random head angle and chooses a random distance and move to a new point. The ranger behavior of bth solution at cth iteration is as follows: initially it generates a random head angle and it is shown below:

$$\delta_b^{c+1} = \delta_b^c + r_2 \alpha_{\max}$$

In the above equation, $\alpha_{\max}$ is the maximum turning angle and it chooses a random distance which is given below:

$$e_b = a \cdot r_1 e_{\max}$$

It then moves to a new point and it is shown by an equation below:

$$S_b^{c+1} = S_b^c + e_b H_b^c \left(\delta^{c+1}\right)$$

ABC Based Operation

The ABC operation is based on the ABC algorithm. If the same fitness value is obtained for a solution in consequent iterations, then that solution is applied to perform ABC operation. The ABC operation is shown by an equation below:

$$S_b^{c+1} = S_b^c + \lambda * dif$$

$$dif = (S_b^c - S_p^c)$$

In the above equation, S_b^{c+1} represents new solution for next iteration and S_b^c represents the solution chosen for ABC operation and S_p^c represents the solution chosen for producer operation in the current iteration and λ is a randomly generated number between zero and one.

Error Based Operation

The solution that has worst fitness is taken for the error based operation. The error based operation is shown below:

$$S_b^{c+1} = S_p^c * err$$

$$err = \beta \frac{fit(S_b^c)}{T}$$

Here, S_p^c is the solution chose as producer in the current iteration and $fit(S_b^c)$ is the fitness value obtained for the solution taken for error based operation and T is the total number of weight values in a solution and β is a randomly generated value between zero and one.The Fig.3 shows the algorithm of our proposed technique.

Proposed Algorithm

Input: Initial solutions
Output: Best Solution

1. Start
2. Generate initial solutions contains weight values by setting the upper and lower bound
3. *For* each solution
4. Apply the weight values to neural network
5. Calculate fitness
6. End for
7. Select best n solutions based on fitness
8. Give the best n solutions as input to back propagation algorithm and GSO-ABC algorithm [6]
9. Set the number of iterations
10. *For* each iteration
11. *For* each solution
12. Apply back propagation algorithm
13. New solution would be formed
14. Calculate fitness for new solution
15. End for
16. Take the best solution $best_{BP}^{current}$ based on back propagation algorithm
17. *For* each solution
18. Apply GSO-ABC algorithm [6]
19. New solution would be formed

20. Calculate fitness for new solution
21. *End for*
22. Take the best solution $best_{GSO-ABC}^{current}$ based on GSO-ABC algorithm
23. Compare $best_{BP}^{current}$ and $best_{GSO-ABC}^{current}$
24. Choose the best one and give as producer to the GSO-ABC algorithm for the next iteration i.e. $current+1$
25. *End for*
26. Compare $best_{BP}^{final}$ and $best_{GSO-ABC}^{final}$
27. Choose the best and assign the weight values to the neural network to train it
28. ***Stop***

Results and Discussions

This section outlines the results obtained for the proposed technique (BP & GSO-ABC) compared to GSO-ABC [6] and GSO [19] algorithms in terms of sensitivity, specificity, accuracy and execution time using three different datasets which are Cleveland, Hungarian and Switzerland. The previous work GSO-ABC [6] is comparedwith the proposed technique. The experimentation is implemented in java (jdk 1.7) that runs on the system that has the configuration as follows: windows 7 32bit, core 2 duo with clock speed of 2.94GHz and has 2GB of RAM.

Dataset Description

The experimentation is done using three different heart disease datasets which are Cleveland, Hungarian and Switzerland. The datasets are taken from UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/) which contains standard benchmark datasets. The dataset characteristics of all the three datasets are multivariate and have fourteen used attributes and the datasets are numeric valued. The number of instances in Cleveland dataset is 303 and in Hungarian dataset it is 294 and in Switzerland dataset it is 123.

Evaluation Metrics

This section explains the metrics user for our evaluation. The metrics used to compare the performance are sensitivity, specificity, accuracy and execution time. The evaluation of sensitivity, specificity and accuracy is explained as follows: The sensitivity is the ratio of true positive to the sum of true positive and false negative. It is denoted by an equation below:

$$Sensitivity = \frac{TP}{TP+FN}$$

In the above formula, TP represents true positive where sick people are correctly diagnosed as sick and FN represents false negative where sick people are wrongly identified as healthy. The specificity is the ratio of true negative to the sum of true negative and false positive. It is denoted by a formula below:

$$Specificity = \frac{TN}{TN + FP}$$

In the above formula, TN represents true negative where healthy people correctly identified as healthy and FP represents false positive where healthy people wrongly identified as sick. The accuracy is the ratio of sum of true negative and true positive to the sum of true negative, true positive, false negative and false positive.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}}$$

Performance Comparison

The performance of the proposed hybrid back propagation and GSO-ABC (BP & GSO-ABC) technique is compared with the GSO-ABC [6] and GSO [19] in terms of sensitivity, specificity, accuracy and execution time using three different heart disease datasets which are Cleveland, Hungarian and Switzerland. The comparisons are as follows:

Comparison Using Cleveland Dataset

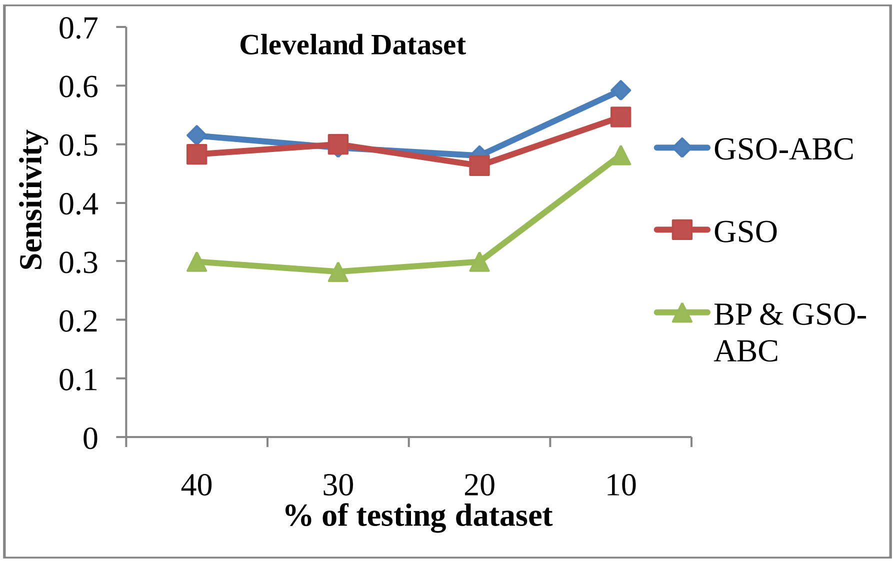

Figure 3: Sensitivity Comparison Using Cleveland Dataset

This section shows the performance comparison using Cleveland dataset. Initially the Cleveland dataset is given to the neural network to train depending on the weight values of the best solution obtained using respective techniques. To test the system based on respective techniques the percentage levels of testing data are varied and given as input to neural network. The Fig.3 shows the sensitivity comparison using Cleveland dataset. In Fig.3, the sensitivity values of respective techniques are taken by changing the percentage level of testing dataset. Here, the proposed (BP & GSO-ABC) technique obtained less sensitivity values for all the varied percentage level of testing data compared to the other technique. The Fig.4 shows the specificity comparison using Cleveland dataset.

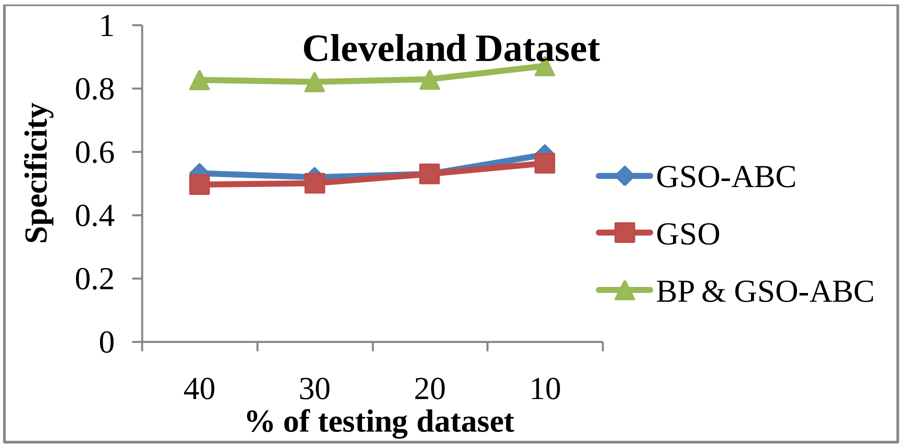

Figure 4: Specificity Comparison Using Cleveland Dataset

In Fig.4, the specificity of the proposed (BP & GSO-ABC) technique is better compared to all the other techniques for all the varied percentage levels of testing dataset. The Fig.5 shows the accuracy comparison using Cleveland dataset. In Fig.5, the accuracy values shows that the accuracy of the proposed (BP & GSO-ABC) technique is better for all the varied percentage levels of testing dataset compared to the other techniques using Cleveland dataset.

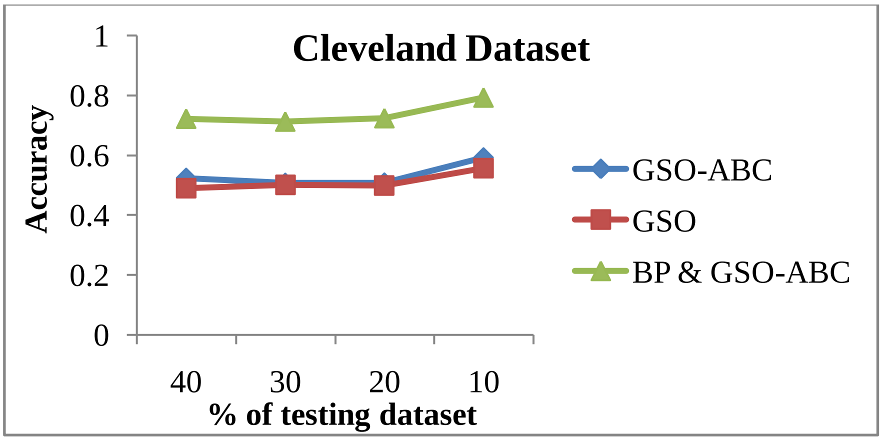

Figure 5: Accuracy Comparison Using Cleveland Dataset

Comparison Using Hungarian Dataset

This section shows the performance comparison using Hungarian dataset. The Hungarian dataset is initially given to the neural network as input and the neural network is trained based on the weight values of the best solution obtained using respective techniques. Thereafter the performances of the respective techniques are tested by giving certain percentage of data as input to the system. The Fig.6 shows the sensitivity comparison using Hungarian dataset.

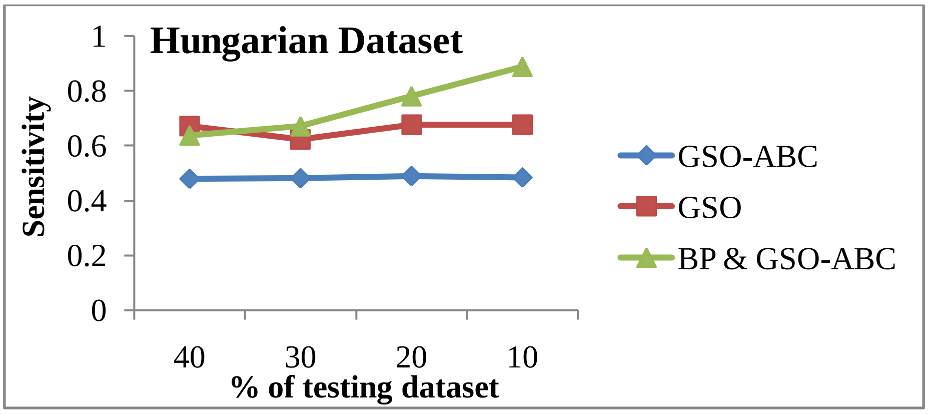

Figure 6: Sensitivity Comparison Using Hungarian Dataset

In Fig.6, the sensitivity values of the proposed (BP & GSO-ABC) technique is better compared to other techniques for all the varied percentage levels of testing dataset except when the percentage level of testing dataset is forty. When the percentage level of testing datasets is forty, the GSO algorithm performed better. The Fig.7 shows the specificity comparison using Hungarian dataset. In Fig.7 the specificity of the proposed (BP & GSO-ABC) technique is better compared to other techniques for all the varied percentage levels of testing dataset using Hungarian dataset. The Fig.9 shows the accuracy comparison using Hungarian dataset. In Fig.8 the accuracy comparison shows that the accuracy of the proposed (BP & GSO-ABC) technique is better compared to other techniques taken for comparison for all the varied percentage levels of dataset.

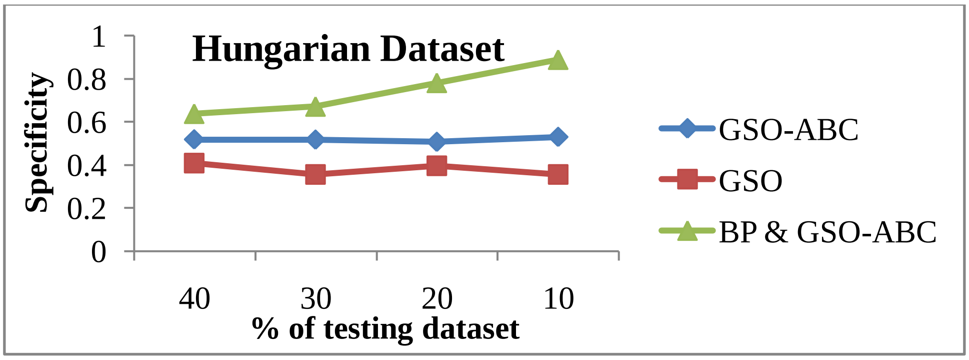

Figure 7: Specificity Comparison Using Hungarian Dataset

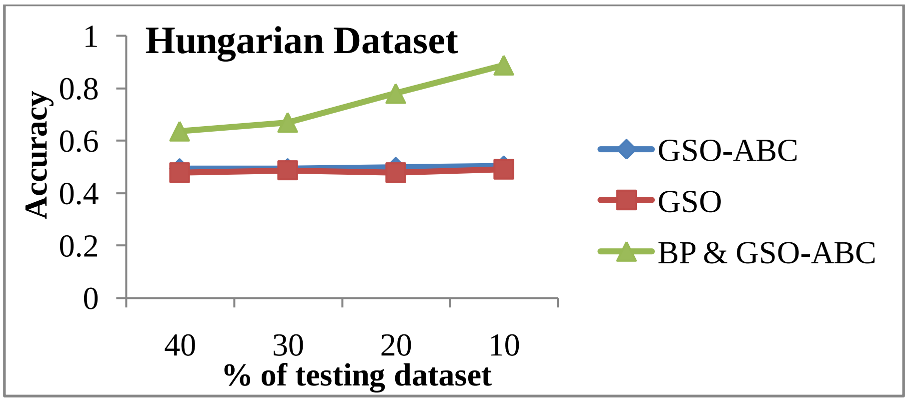

Figure 8: Accuracy Comparison using Hungarian Dataset

Comparison Using Switzerland Dataset
This section shows the performance comparison using Switzerland dataset. Initially the neural network is trained by giving the Switzerland dataset as input and by assigning the weight values of the best solution identified by respective algorithms. The performance is then checked for the respective algorithms by giving different percentage of data as input to the system. The Fig.9 shows sensitivity comparison using Switzerland dataset.

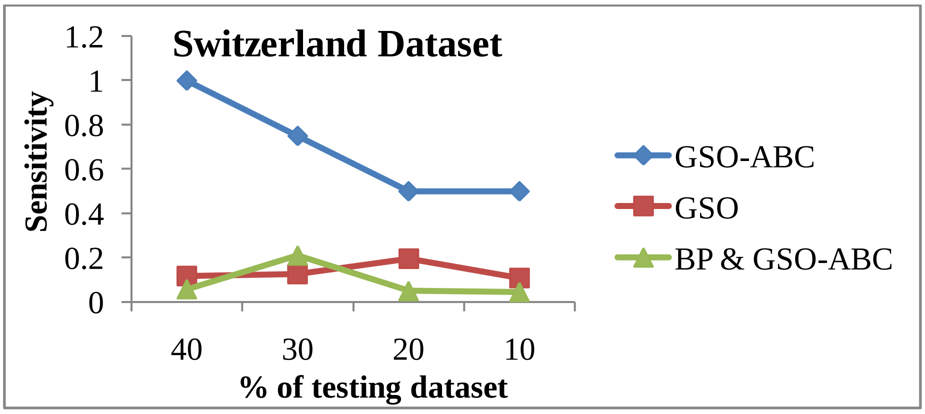

Figure 9: Sensitivity Comparison using Switzerland Dataset

In Fig.9 the sensitivity of the proposed technique is less than the GSO-ABC algorithm for all the varied percentages levels of testing data and it is less compared to the GSO algorithm for all the varied percentages levels of testing data except when the percentage level is thirty. The Fig.11 shows the specificity comparison using Hungarian dataset.

In Fig.10 the specificity of the proposed technique is better compared to the GSO-ABC algorithm and it is less compared to the GSO algorithm for all the varied percentage levels of testing dataset. The Fig.11 shows the accuracy comparison using Switzerland dataset.

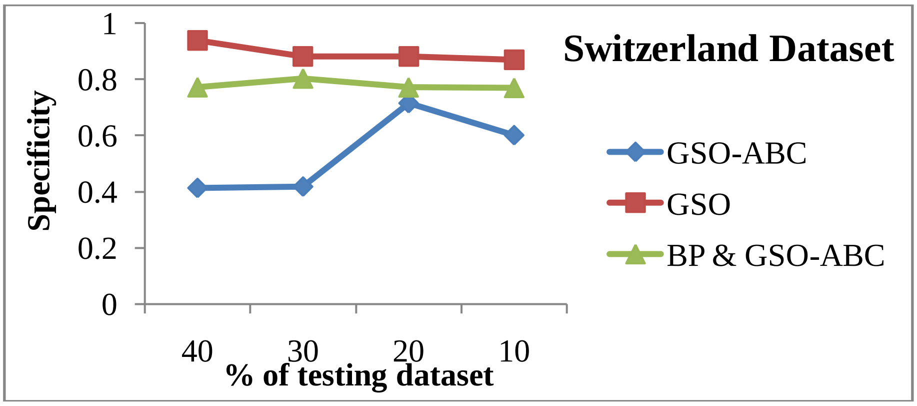

Figure 10: Specificity Comparison using Switzerland Dataset

In Fig.11 the accuracy of the proposed technique is better compared to the other techniques for all the varied percentage levels of testing dataset except when the percentage level is twenty. When the percentage level of the testing data is twenty, the performance of the GSO-ABC algorithm performed better compared to other algorithms.

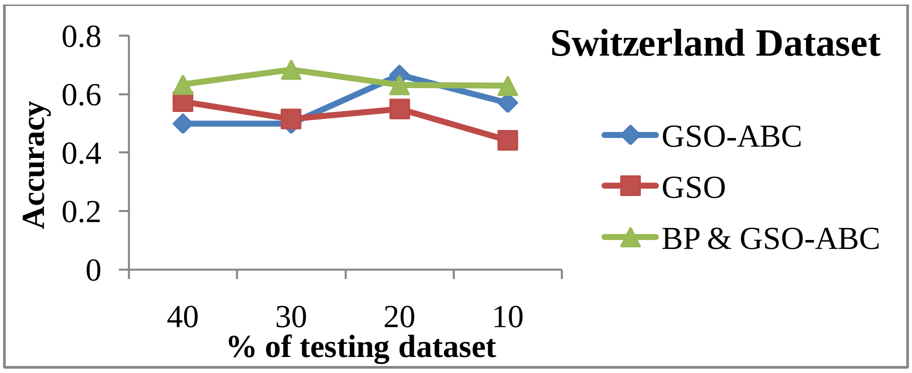

Figure 11: Accuracy Comparison using Switzerland Dataset

Conclusions

In this paper a correlation-based analysis and hybrid neural network training algorithm has been proposed for heart disease diagnosis. Here hybrid back propagation algorithm and GSO-ABC algorithm is used to assign the weight values to the neural network to train it. Both the algorithms are processed separately and the best solution between them is chosen as producer for the GSO-ABC algorithm process of next iteration. The best solution between them in the final iteration is chosen to fix the weight values for the neural network to train it. The performance of the proposed technique (BP & GSO-ABC) is compared with the GSO-ABC and GSO algorithms in terms of sensitivity, specificity and accuracy using three different heart disease datasets which are Cleveland, Hungarian and Switzerland. While comparing the performances, overall the proposed technique performed better than the other algorithms.

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