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Optimizing Feed Forward Neural Network Connection Weights Using Artificial Bee Colony Algorithm

Asha Gowda Karegowda * **, Darshan M**
Department of Master of Computer Applications,
Siddaganga Institute of Technology, Tumkur, India

Abstract— Feed forward neural networks (FFN) are one of many data mining analytical tools that can be utilized to make predictions for medical data. Model selection for a neural network entails various factors such as selection of the optimal number of hidden nodes, selection of the relevant input variables and selection of optimal connection weights. This paper presents the application of hybrid model that integrates Artificial Bee colony (ABC) optimization and Feed forward neural network (FFN), where ABC is used to initialize and optimize the connection weights of FFN. Significant features identified by GA-CFS method are provided as input for both BPN and ABC-FFN. The results prove that, ABC optimized FFN approach has outperformed the BPN approach. In addition the hybrid ABC with relevant inputs provided by GA-CFS, lead to further improvised categorization accuracy compared to results produced by ABC-FFN alone for some of data sets.

Keywords— Artificial Bee Colony algorithm, Back Propagation Network, Feed forward neural network, connection weight optimization, Genetic Algorithm

1.0 INTRODUCTION

Medical data mining has great potential for exploring hidden patterns in the data sets of medical domain. These patterns can be used for clinical diagnosis. Neural Networks are one of many data mining analytical tools that can be utilized to make predictions for medical data. BPN uses the gradient based approach which either trains slowly or get struck with local minimum. Instead of using gradient-based learning techniques, one may apply the commonly used optimization methods such as Genetic Algorithm (GA), Particle swarm optimization (PSO), Ant Colony optimization to find the network weights. ABC is a stochastic general search method, capable of effectively exploring large search spaces, and has been used with FFN for determining the various parameters such as number of hidden nodes and hidden layers, select relevant feature subsets, the learning rate, the momentum, and initialize and optimize the network connection weights. This paper presents the application of hybrid model that integrates ABC Algorithm and FFN for classification task for various datasets availed form UCI machine learning datasets by finding the optimal network connection weights. Data sets namely diabetic, Heart stat log , Vehicle, Indian liver and Sonar data set have been availed for UCI machine learning dataset. Section 2 elaborates on the working of the hybrid ABC-FFN model. Results and conclusion are described in section 3 and 4.

2.0 OPTIMIZING FFN CONNECTION WEIGHTS USING ABC

Neural Networks [1,2] are commonly used in pattern classification, function approximation, optimization, pattern matching, machine learning and associative memories. However, the success of the networks is highly dependent on the various parameters namely, the number of hidden nodes, the significant inputs and the training process. Back propagation (BPN) is the most common technique used to train feed forward neural network. But the convergence obtained from back propagation learning is very slow and may get struck with local optima. In this context, to improve the connection weights of single layer feed forward neural network, evolutionary algorithm namely Artificial Bee colony (ABC) optimization [3-8] in addition to Genetic algorithm and particle swarm algorithm have been applied. Authors have used GA for optimizing the connection weights of FFN using GA [10].

The ABC consists of mainly three types of bees namely: employer bees, onlooker bees and the scot bee. The bee is encoded to represent the feed forward connection weights. The dimension of the bee is governed by the topology of feed forward neural network. Initially the user defined size of employee bees is randomly initialized and given as initial feed forward connection weights. For each employee bee the fitness is computed using the mean square error

(MSE), which is difference between the expected output and actual output of FFN. The probabilities of each of the employer bee are computed using fitness of the employer bee, which is turn, is used to initialize the onlooker bee. The fitness of each of onlooker bee is computed. If the performance of bees is not showing any mark able improvement for user specified time, then the scout bee is abandoned and replaced by the randomly initialized employee bee. This process is repeated for user specified number of iterations. The best bee represents the final connection weights of the FFN. Experiments have conducted by varying the population size of bee, number of iterations, and number of nodes in the hidden layer on various benchmark datasets availed from the UCI machine learning datasets. The performance is measured by the percentage of correctly classified test samples. The results of proposed method is compared with the BPN trained FFN. The Pseudo-code of the ABC algorithm is given below.

Pseudo-code of the ABC algorithm

a. Initialize the population of solution X_i .
b. Evaluate the population
c. Set cycle to 1
d. Repeat
e. Produce new solution v_i in the neighborhood of x_i for employed bees and apply the greedy selection process x_i and v_i.
f. Calculate the probability values Pi for the solution xi be means of their fitness values by using the equation

$$Pi = \frac{fit_i}{\sum_{n=1}^{SN} fit_n}$$

g. Produce the new solution v_i for the onlooker from the solution x_i selected depending on p_i and evaluate them and apply the greedy selection process
h. If there is an abandoned solution for scout then replace if with a new solution using equation

$$x_i(i)=lb_i+(ub_i-lb_i)*r$$

i. Memorize the best solution so far
j. Cycle=cycle+1
k. Until cycle=Max_iterations

The working of hybrid ABC for optimizing connection weights is shown in figure 1.

3.0 RESULTS

As part of feature selection, authors have used GA and Correlation based feature selection (CFS) in a cascaded fashion, where GA rendered global search of attributes with fitness evaluation effected by CFS. Genetic algorithm is used as search method with Correlation based feature selection as subset evaluating mechanism[9]. Experiments have been conducted by varying the number of iterations (25-250), population size of ABC (20-100) and number of nodes in input layer used with different number of hidden nodes (1-20) in the hidden layer. Similarly BPN was experimented with different number of hidden nodes and iterations. Results of ABC-FFN were compared with BPN alone with all inputs and with inputs identified by GA-CFS as shown in figure 2. For diabetic dataset the GA-CFS identified features proved to be better for both BPN and ABC-FFN. It was observed that the BPN performance was same with all features and reduced features identified by GA-CFS for heart statlog dataset. For vehicle dataset the performance of BPN with GA-CFS features was less compared to BPN with all features. For Sonar the GA-CFS shown an improved accuracy for ABC-FFN when compared to all features, but did not make difference for BPN performance with all and reduced features. Overall the ABC-FFN performance is found to be better for the four datasets when compared to BPN performance.

4.0 CONCLUSIONS

In this paper, application of hybrid ABC-FFN has been experimented for classification of four datasets availed form UCI machine learning datasets. Back propagation learns by making modifications in weight values by using gradient method starting at the output layer then moving backward through the hidden layers of the network and hence is prone to lead to troubles such as local minimum problem, slow convergence pace and convergence unsteadiness in its training procedure. The optimal network connection weights obtained by using hybrid ABC-FFN showed substantial improvement in classification accuracy when compared to BPN trained FFN for all the four datasets.

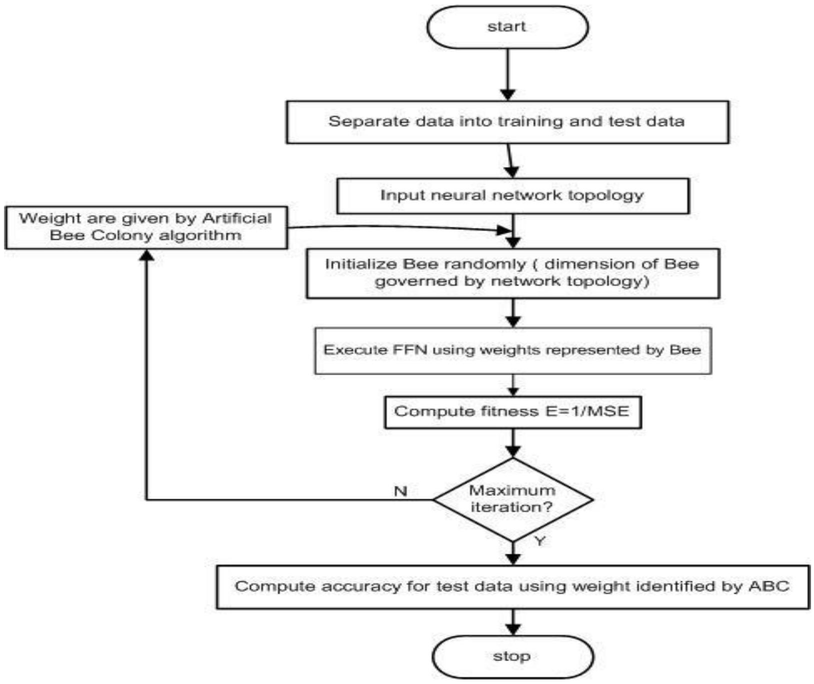

Figure 1. Working of ABC -FFN

References

1. S. Haykin, Neural Networks- A comprehensive foundation, Macmillan Press, New York, 1994.
2. A. Roy, Artificial neural networks – a science in trouble, SIGKDD Explorations, 2000.
3. Asaju La'aro Bolaji, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar and Mohammed A. Awadallah, "Artificial Bee Colony Algorithm, Its Variants And Applications: A Survey", Journal of Theoretical and Applied Information Technology , Vol. 47 No.2, 2013.
4. Pravin Yallappa Kumbhar, Shoba Krishnan, Use Of Artificial Bee Colony (ABC) Algorithm in Artificial Neural Network Synthesis, International Journal of Advanced Engineering and technology, Vol.11, Issue No. 1, pages 162 – 171, 2011.
5. D. Karaboga and B. Akay. A comparative study of artificial bee colony algorithm. Applied Mathematics and Computation, Vol. 214, Issues 1, pages 108–132, 2009.
6. D. Karaboga. An idea based on honey bee swarm for numerical optimization. Techno. Rep. TR06, Erciyes Univ. Press, Erciyes, 2005.
7. D. Karaboga and B. Basturk. A powerful and efficient algorithm for numerical function optimization: Artificial Bee Colony (ABC) algorithm. In Journal of Global Optimization, Vol. 39, Issues 3, pages 459–471, 2007.
8. D. Karaboga and B. Akay. Artificial bee colony (ABC) algorithm on training artificial neural networks. In Signal Processing and Communications Applications, in IEEE, Vol. 15, pages 1–4. 2007.
9. Asha Gowda Karegowda and M.A.Jayaram, "Cascading GA & CFS for feature subset selection in Medial data mining", IEEE International Advance Computing Conference, Patiyala, India, 2009.
10. Asha Gowda Karegowda , A.S. Manjunath , M.A. Jayaram, "Application Of Genetic Algorithm Optimized Neural Network Connection Weights For Medical Diagnosis Of Pima Indians Diabetes", International Journal on Soft Computing (IJSC), Vol.2, No.2, May 2011.

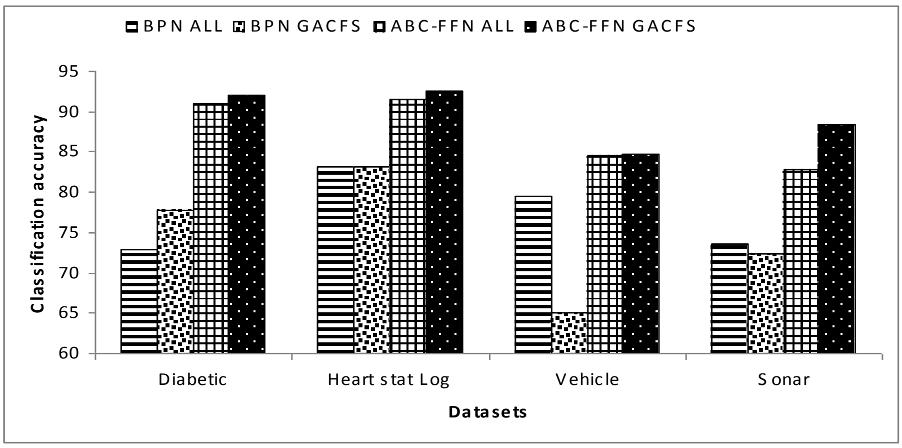

Figure 2. Comparative Performance of FFN trained using BPN and ABC using all features and feature identified by GA-CFS for four different datasets

