

Swarm Approach Combined With Artificial Neural Networks to Constructive Data Organization and Information Extrapolation

K. Kalyani^{1*}, T. Chakravarthi²

¹Dept. of Computer Science, MPC College of Arts and Science, Thanjavur, Tamil Nadu, India

²Dept. of Computer Science, A.V.V.M. Sri. Pushpam College, Poondi, Thanjavur, Tamil Nadu, India

*Corresponding Author: drkkalyanims@gmail.com

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Abstract - Swarm intelligence is a cooperative behavior of collective systems like insects such as ant colony optimization (ACO), fish schooling, birds flocking, bee Colony Optimization (BCO) particle swarm optimization (PSO) and so on. In this paper, a hybrid performances for data organization and information extrapolation is recommended. The Honey Bee Mating Optimization algorithm and Artificial Neural Networks (HBMO-ANN) may also be considered as a distinctive swarm-based optimization, in which the exploration algorithm is encouraged by the development of real honey-bee marital and mimic the iterative mating process of honey bees and approaches to select applicable drones for mating progression through the fitness function enrichment for selection of superlative weights for hidden layers of Neural Network classifiers. Enhanced HBMO with Neural Network (EHBMO-NN) algorithm is now realistic to classify the data proficiently by training the neural network. The classification accuracy of EHBMO is much more compared with other algorithm such as Support Vector Clustering Algorithm (EHBMO-SVC). In this paper, enhanced honey-bee mating optimization algorithm is offered and verified. A developed way of Honey Bee Mating Optimization performance is combined with Neural Network which expands accuracy and moderate time delay in difficulty of various real world datasets.

Keywords - Swarm intelligence, Honey Bee Mating Optimization Algorithm, Support Vector Clustering, Artificial Neural Networks.

I. INTRODUCTION

The various types of swarm based approaches are ant colonies, honey bee colonies, cat swarm optimization, birds flocking, fish schooling, herds of animals and microbial intelligence. Among these swarm based algorithms, the honey bee mating optimization algorithm (HBMO) is used to play a substantial role in data clustering, organization and extrapolation [1]. In which the searching technique imitate the mating process of honey-bee colonies. This algorithm undertakes mating flight, broods establishment and greatest brood selection as various segments. Based on those stages the replacement of weaker queen via fitter brood is done through fitness function evaluated. In this work, University of California, Irvine machine learning database is used. Through the analysis of existing method, based on the achieved results, that it causes Scalability issues, absence of accuracy and time consumption in case of large datasets. To challenge this issue, our work is focused on various methodologies considered and to improve the fitness function evaluation in Enhanced honey bee mating optimization (EHBMO) [2]. Our goals are to solve

complexity and scalability issues in real world datasets and to improve the efficiency in data classification. Thus, the enhanced honey bee mating optimization is combined with Support vector clustering and artificial neural networks. Initially the enhanced honey bee mating optimization combined with Support vector clustering (EHBMO-SVC). It is a fast and scalable support in high dimensional supervised data and improves efficiency in filtering the outlier data. Thus the elimination of outlier data by scaling the contour point in each iteration and analyzing the variations of outlier data, for that it consume more time to identifying the contour in each iteration. It causes the performance degradation, to overcome this drawback the next proposed approach is enhanced honey bee mating optimization with artificial neural network (EHBMO-ANN). The weights are optimized through the evaluation of enhanced fitness function. The results obtained from the Enhanced honey bee mating optimization with Artificial neural network is to avoid scalability issues in large datasets, reduce the time consumption and also provide better accuracy and performance. This work conclude that Enhanced honey bee

mating optimization with Artificial Neural Network is better than the other methods.

In our work, the University of California, Irvine (UCI) Machine Learning database is used. Many more researchers are used this databank for honey bee mating optimization techniques such as Iris flower, wine, heart disease, cancer, diabetes and soya bean etc. The UCI datasets are used here to evaluate the time, accuracy and efficiency in various data and sources of the data are different from each other. Since that time, it has been widely used by students, educators, and researchers all over the world as a primary source of machine learning data sets and it is popularly known benchmark datasets.

II. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks are a people of models motivated the genetic neural systems and used to evaluate or approximate purposes that can depend on a huge amount of contributions. It is commonly presented as systems of interrelated "neurons" which interchange messages among each other. The networks have numeric weights that can be altered based on proficiency and accomplished of learning. It holds three categories of layers such as input, hidden and output layers. Neural systems are related to biological neural networks in the execution of functions cooperatively and in corresponding units, rather than there being a clear description of subtasks to which distinct units are dispensed. The term "neural networks" typically denotes to models engaged in statistics, cognitive psychology, artificial intelligence and swarm intelligence [3].

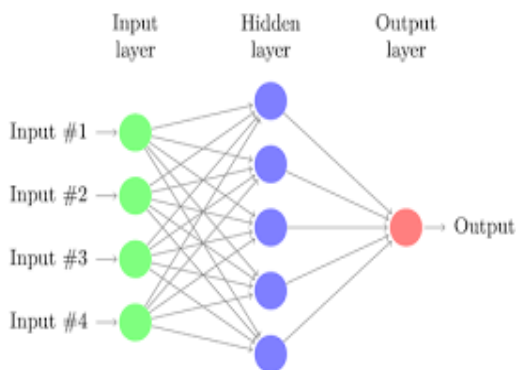


FIGURE-1 Artificial Neural Networks

The system scrutinizes its output reaction to the sample input shape. The output reaction is then associated to the known and desired output and the error value is planned. Based on the error, the connection weights are adjusted [4]. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections. In our work the weight of each node are

optimized that the evaluation of fitness function in honey bee mating optimization algorithm.

Artificial neural networks are known dynamic and intelligent system for output prediction. A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data into a set of appropriate outputs. MLP utilizes a supervised learning technique called backpropagation for training the network. The Learning algorithm is used to minimize the overall error of the network based on optimization method called gradient descent.

The Delta rule is a gradient descent learning rule for updating the weights of the inputs to artificial neurons [5]. It is a special case of the more general back propagation algorithm.

$$\Delta w_{ji} = \alpha(t_j - y_j)g(h_j)x_i$$

Where,

α is a small constant called learning rate, $g(x)$ is the neuron's activation function, t_j is the target output, h_j is the weighted sum of the neuron's inputs, y_j is the actual output, x_i is the j^{th} input. This training process continues till the error between actual output and expected value meets the requirements.

III. HONEY BEE MATING OPTIMIZATION ALGORITHM (HBMO)

In the existing honey bee mating optimization (HBMO) algorithm is a group-based optimization performance in which the exploration procedure mimics the mating process in honey-bee colony [6,8]. The algorithm is related to the general field of swarm aptitude, but the mating procedure which is based on crossover and transmutation operators, strongly relate this algorithm to evolutionary computing excessively. Honey bee mating optimization algorithm may be constructed with the following five main stages.

- The algorithm starts with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermathecal (list of drones). A drone is then selected from the list randomly for the creation of broods.
- Creation of new broods via crossover the drone's genotypes with the queens.
- Use of workers (heuristics) to conduct local search on broods (trial solutions).
- Adaptation of worker's fitness, based on the amount of improvement achieved on broods.
- Replacement of weaker queens through fitter broods.

Crossover Operation

During the mating flight the queen mates with drones to form a genetic pool called spermatheca, which consists of chromosomes received the queen from drones. The second stage of the evolutionary process starts after the genetic pool was filled with chromosomes and consists of breeding eggs with genetic information from the spermatheca, based on crossover operations between chromosomes.

Mutation Operation

Mutation is the simplest genetic operator, it randomly flips bits in a binary string genome from zero to one or from one to zero. This operator improves the algorithm via introducing new solutions that do not exist in the population. The mutation rate has to be low to prevent the algorithm from becoming a simple random search. Some types of mutation are deletion of genes, duplication of genes, inversion of a sequence of genes, and insertion of a portion of a chromosome into another chromosome [7]. The evolution process consists in raising the broods generated during the second stage and creating a new generation of bee based on mutation process.

Broods Replacement

Selection of new queen sort all calculated values of fitness function select the best one and compare it to the queen fitness function [8, 9]. If the best brood value is better than the queen, replace the new best brood with queen. A determined percentage of remained best broods will replace with the worst existing drones

IV. ENHANCED HONEY BEE MATING OPTIMIZATION (EHBMO)

Our Research has primarily two portions i) To Enhance the honey bee mating optimization (HBMO) algorithm through the fitness function evaluation for the efficient data classification ii) To improve the classification accuracy, the Enhanced honey bee mating optimization (EHBMO) is combined with Support vector cluster and Artificial neural networks for efficient data classification and information prediction. In our work, the Honey bee mating optimization concern with

F1 and F2 as Fitness Function whereas Enhanced HBMO consists of four Fitness Functions which are F1, F2, F3, and F4.

Table -1 EHBMO Algorithm

Enhanced Honey Bee Mating Optimization algorithm is implemented as clustering technique.

- The algorithm starts with matting flight, first generate a random cluster, where a queen (best solution) selects drones probabilistically to form the spermatheca. A drone then selected from the list randomly for the creation of broods.

- EHBMO algorithm focus on queen’s speed and energy that it can choose best drone for mating.
- Next queen’s energy is greater than zero then only queen chooses a drone.
- Then randomly generate clusters and set the best separate as the queen.
- After each transition the queen’s speed and energy decays. Update the queen’s energy and speed for every iteration.

Compute the Fitness Function by the following steps:

Table-2 EHBMO Fitness Enhancement

$$\text{Step1: } F = Af1(Br) + Bf2(Br) + Cf3(Br) + Df4(Br) \quad \text{----- (Eq - 1)}$$

Where A, B, C, D are constants with 0.2, 0.5, 0.2, 0.1 consequently.

$$\text{Step2: } f1(Br) = \sum_{j=1}^{\beta} [(\sum_{i=1}^{\alpha_j} d_{w(b),d}) + d_{d,Q(b)}] \quad \text{----- (Eq - 2)}$$

$$\text{Step3: } f2(Br) = \sum_{j=1}^{\beta} \left[\left(\frac{\sum_{i=1}^{\alpha_j} \text{AverageEnergy}(W(b))}{\text{Average Energy}(d)} \right) \right] / k \quad \text{----- (Eq - 3)}$$

$$\text{Step4: } f3(Br) = \sum_{j=1}^{\beta} \frac{[d_{d,Q(b)}]}{1} / \beta \sum_{j=1}^{\beta} \sum_{i=1}^{\alpha_j} [d_{w(b),Q(b)}] \quad \text{----- (Eq - 4)}$$

$$\text{Step 5: } f4(Br) = \sum_{j=1}^{\beta} \sum_{i=1}^{\alpha_j} \alpha_j \beta_j (\text{th}) \quad \text{----- (Eq - 5)}$$

Where

- Br - is a Replacement of Bees in the current round,
- α - is the number of worker bees,
- β - is the number of drone

$d_{w(b)-d}$ is the Euclidean distance from worker bee i in cluster j to its drone,
 $d_{d,Q(b)}$ - is the Euclidean distance from j^{th} drone to the Queen bee.

$f1$ - is the sum of Euclidean distances of worker bees to its drone and drone to the Queen Bee,

$f2$ - is the ratio of the average energy of worker bees with its drone.

$f3$ - is the ratio of the average Euclidean distance of the drone to the $Q(b)$ with the sum of Euclidean distance of all the worker bees to the Queen Bee.

$f4$ - is the input particle is filtered with threshold value of the worker Bees ($\alpha \ 1 \dots n$) and drone ($\beta \ 1 \dots n$),

So that the worker bees are eliminated based on this threshold value which regains minimum iteration and Energy Efficiency. The A, B, C, D are predefined constants used to weight the contribution of each of the sub objectives and $A + B + C + D = 1$.

V. Enhanced HBMO with Support Vector Clustering (EHBMO-SVC)

A novel method for clustering using the Support vector clustering algorithm involves calculating the sphere with insignificant radius which encloses the data points when plotted to a high dimensional feature space [10]. This sphere corresponds to a set of curves which enfold the points in input space. As the width parameter of the Gaussian kernel is decreased, these contours fit the data more tightly and splitting of contours occurs [11]. The algorithm is working in separate clusters according to valleys in the underlying probability distribution and thus clusters can take on arbitrary geometrical shapes. Other support vector clustering algorithms, outliers can be dealt with introducing a soft margin constant leading to smoother cluster boundaries. The structure of the data is explored through varying the two parameters (p and q) and investigates the dependence of our method on these parameters and applied it to several data sets [12,13]. In our research the support vector clustering used for preprocessing the data's and it is responsible for removal of missing and outlier data's in the clusters.

Support Vector Clustering is used to preprocess the input data using support vector values generated by the formation of contour or clusters without Overlapping clusters, this leads to reduce input data by preprocessing stage to the computation stage, in which SVC acts as a preprocessing stage, EHBMO act as a Computation stage [14]. The Elimination of outlier data by scaling the contour point, in each iteration and analyzing the variations of outlier data, it causes the performance degradation, to overcome this

drawback the next approach is proposed as EHBMO combined with ANN.

VI. Enhanced HBMO with Artificial Neural Network (ANN)

Applying the honey bee mating algorithm to training neural networks are relatively straight-forward [14]. The multi-dimensional search space is the space of network connection weights and neuron thresholds and the fitness is a standard measure of network output performance on the training data. With gradient descent training, such as backpropagation, that is typically avoided in stopping training early, or adding a regularization term to the cost function (weight decay), and optimizing those with reference to an independent validation dataset [15]. In neural network training, the artificial bee colony algorithm would be compared with standard backpropagation algorithm. Following the earlier study of using for neural network training, it concentrate on standard fully connected feed-forward classification neural networks with one hidden layer and use sigmoid hidden and output activation functions. Sum squared error will again be used as the training cost function, a simple approach would be used to determine the predicted value. The enhanced honey bee mating optimization is used to Bees Replacement with fitness Evaluated. The ANN is used as a machine learning algorithm, and the network is constructed based on the size of the dataset and it helps to calculate the connected weights of input data, with the bias in neuron for data prediction. The EHBMO is combined with ANN through Hidden Layer for weightage adjustments by fitness worth valued. The results obtained from EHBMO_ANN is avoid scalability issues in large datasets, minimum time consumption and better accuracy and performance.

VII. Experimental Results

Table-3 Input Dataset Statistics

Dataset Used	Iris	Liver	Cancer	Diabetes	Arrhythmia
No of Instances	150	345	32	768	452
No of Classes	3	2	2	2	16
No of Attribute	5	78	57	9	280

Table-4 Illustrates the performance of Enhanced honey bee mating optimization algorithm combined with Support vector clustering algorithm.

Algorithm Performance	Result Analysis

Time	14.5 ms
Accuracy	75 %
Efficiency	70 %

Table – 5 Illustrates the Performance of Enhanced honey bee mating optimization with Artificial Neural Networks.

Algorithm Performance	Result Analysis
Time	9.4 ms
Accuracy	91 %
Efficiency	96 %

The overall performance statistics of our proposed algorithms such as Enhanced honey bee mating optimization with Support vector clustering and Artificial Neural Networks are considered as a feasible and an efficient heuristic to find optimal or near optimal solutions to the classification problems are validated.

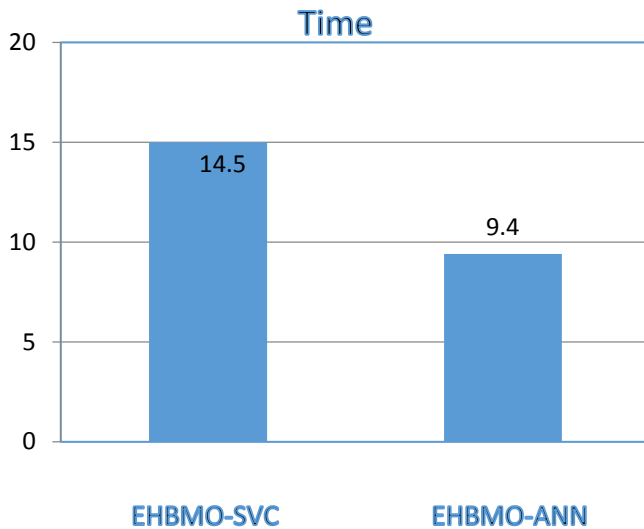


FIGURE-2 Illustrates Time performance of above algorithms.

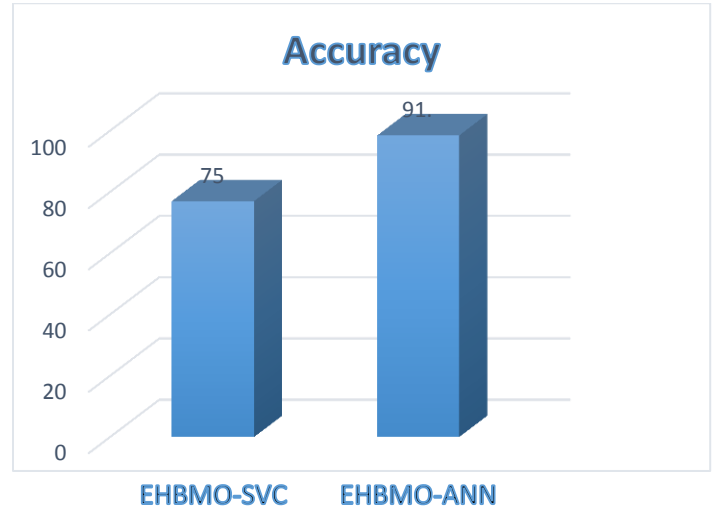


FIGURE-3 Illustrates the Accuracy of above algorithms.

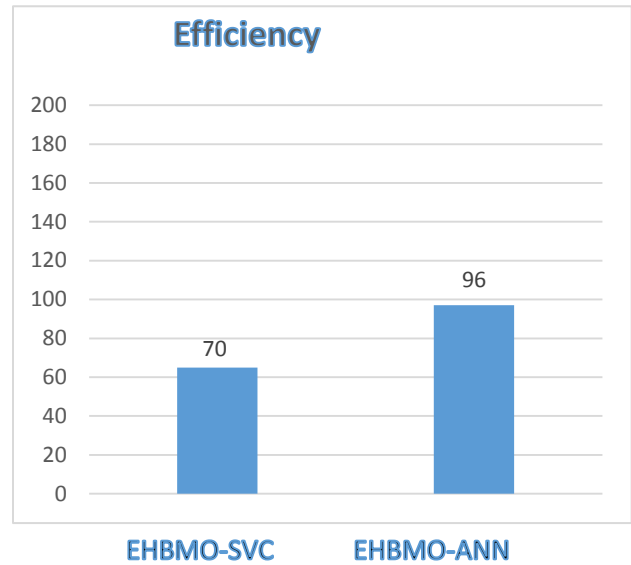


FIGURE-4 Illustrates the Efficiency of above algorithms.

VIII. CONCLUSION

In this paper, examine the efficiency of Honey bee mating optimization in data classification tasks, based on the obtained results, it causes scalability issues in case of large datasets. To tackle this scalability issue, the exploration is focus based on various methods investigated, and improve the fitness function evaluation in Enhanced honey bee mating optimization. Our goals are to solve complexity and scalability issues in real world datasets [16] and to improve

the efficiency in data classification. The results are compared, such as Enhanced honey bee mating optimization with Support vector clustering (SVC) and Artificial neural networks (ANN). From the results, our method conclude that Enhanced honey bee mating optimization with artificial neural networks can obtain competitive results against the real world data sets used.

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