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Multimodal Feature Selection using Invasive Weed Optimization and Improved BAT for high dimensional Imbalanced datasets

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Abstract
Real world optimization problems demand multiple optima within a search space. Feature selection is a combinatorial high dimensional optimization problem in which alternative optimal solutions could be provided. Multimodal optimization in contrast to unimodal optimization aims at providing multiple optima in a single run. This paper uses a multimodal optimization technique to discover solutions. A two phase optimization technique is proposed in which nature inspired Invasive weed optimization (IWO) is used to create sub population and metaheuristic BAT algorithm is enhanced to find optimal solutions in each sub population. Performance of the proposed method Invasive Weed optimization_Improved BAT is experimentally verified on three high dimensional datasets.

KEYWORDS: Multimodal optimization, feature selection, BAT algorithm, Invasive Weed Optimization, multiple optima, high dimension, Imbalanced datasets.

INTRODUCTION

Complex real world optimization problems can be solved by evolutionary algorithms which are stochastic in nature [1]. High dimensional dataset includes redundant and irrelevant features for the classification process. This slows down the learning phase and tends to overfit the training data. Dimensionality reduction is one of the basic steps in pre-processing. It can be done via feature selection or feature extraction. Feature selection aims at finding relevant subset of features that describes the target. The selected subset of features from the whole feature space does not affect the accuracy of classifier. Feature selection methods are categorized into filter, wrapper, embedded and hybrid methods. Filter methods are independent of the classifier it relies only on the intrinsic properties of the data to select the features. These approaches uses measures like distance, dependency or consistency to choose the features then trains the classifier with training data and tests the classifier with test data. In [2] feature selection is carried out using a filter method in which distance measure weighs each feature based on relevancy with the target class. Pang et al. used mutual information as a measure to identify the feature relevancy and to identify feature redundancy mutual exclusive is used [3]. Wrapper method uses a learning algorithm for subset evaluation followed with the classifier to learn from the training data and tested with the test data. Dy & Brodley introduced a wrapper based approach for unsupervised learning by recognizing the number of clusters in the data with expectation maximization clustering algorithm using maximum likelihood criterion [4]. Embedded method embeds the feature selection procedure into the learning algorithm. Hybrid method is a combination of both filter and wrapper method to select the feature subsets. In hybrid methods, the features are reduced using the filter method and then wrapper method is applied on the reduced set to choose the features. This proposed work uses a wrapper approach in which SVM classifier is used as a predictor and selected feature subsets are evaluated using K-Nearest Neighbor, Neural Network and Support Vector Machines.

Evolutionary algorithms with their population based structure could be a suitable method for finding the feature subsets in a reasonable time. Evolutionary algorithms perform well for finding single solution but fail to provide multiple solutions [5]. When there is more than one optimal solution for a single objective optimization problem then it is called as multimodal optimization problem. The main drawback in Evolutionary algorithms is that their populations converge to its best found solution [6]. This could be avoided by controlling the diversity of population. Niching methods incorporated with evolutionary algorithms can be applied to multimodal optimization problems. Niching methods help in forming sub population within a population and they aim at finding multiple optimal solutions within each sub population which result in multiple optima in a single run. They achieve this by forming a neighborhood structure around the optima. Many niching techniques had been used with evolutionary algorithms to solve multimodal problems [7-9]. Most popular niching methods used in combination with evolutionary algorithms include crowding [10], restricted tournament selection [11], fitness sharing [12], and speciation [13]. This article proposes a new IWO_IBAT method to find multiple solutions for feature selection in high dimensional datasets. This method uses Invasive Weed Optimization algorithm to form weed colonies, then a grouping method is used to form subpopulation which avoids overlapping of subpopulations followed by enhanced BAT algorithm which finds multiple optimal solutions. The proposed method assures to achieve a balanced exploration and exploitation behavior of the population.

The rest of the paper is organized as follows. The next section presents the unimodal optimization followed by multimodal optimization for feature selection. Further the paper proceeds with overview of IWO and BAT algorithm followed by proposed method, experimental analysis and conclusion.

UNIMODAL OPTIMIZATION FOR FEATURE SELECTION

Evolutionary algorithms are well suited for feature selection problems which are guaranteed with an exhaustive search in the search space. Metaheuristic algorithms in turn attain good solutions without exploring the whole solution space. Evolutionary algorithm based metaheuristic methods when applied to feature selection do not suffer from nesting effect which is faced by traditional feature selection approaches like Sequential backward Search (SBS) and Sequential Forward Search (SFS). Nesting effect is a problem faced during feature selection process in which the selected features cannot be discarded and discarded features cannot be reselected. Researchers investigated and proved that evolutionary algorithms are effective for feature selection by using Genetic algorithms, particle Swarm Optimization, Differential Evolution and Ant Colony Optimization algorithms and others too. Huang etl al. in [14] proposed a two stage hybrid genetic algorithm for feature selection. The first stage uses a wrapper approach in which the mutual information between the predictive labels of a trained classifier and the true classes serves as the fitness function for the genetic algorithm. The second stage uses a filter method where conditional mutual information is used as a measure for feature ranking. Artificial Intelligence based genetic algorithm to software productline feature selection was introduced by Jianmei Guo et al. [15]. Wang et al. proposed a new optimal feature selection technique based on rough sets and particle swarm optimization [16]. A hybrid ant colony optimization (ACO) algorithm for feature selection called ACOFS was proposed by Monirul Kabir and M.S Md Kazuyuki Murase. The authors in this paper introduced new sets rules for pheromone update and heuristic information measurement. While constructing subsets, the ants are also guided in right direction using bounded scheme. This work provided a high quality solution in feature selection[17]. Khushaba et al. in [18] proposed a novel feature selection method using a combination of differential evolution optimization method and a repair mechanism based on feature distribution measures. Chuang et al. proposed a CatFishBPSO algorithm for feature selection. This algorithm increases the exploration power and diversity of population by introducing catfish particles at the extreme positions of the search space when the fitness of gbest cannot be improved over a number of consecutive iterations [19]. Srividhya.S and Mallika.R proposed unimodal feature selection technique using a hybridization of fisher score and shapley value [20].

MULTIMODAL OPTIMIZATION FOR FEATURE SELECTION

In Unimodal Optimization, the found optimal solution might be impossible to implement due to cost or domain constraints. This led the way for the multimodal optimization in which multiple optimal solutions are obtained. Multimodal optimization methods aim at finding multiple optimum solutions for an optimization problem. Multimodal problems can be solved by introducing niching techniques in evolutionary algorithms. Various niching techniques have been proposed by many researchers with an aim to provide multiple solutions by introducing high exploration and exploitation power. Niching methods involves in creating sub-population within a population. Each sub-population finds an optimal solution which locates multiple optima in a single run. Fitness sharing [21-23], Crowding [7], deterministic crowding, restricted tournament selection [24], speciation [25] and few more are the commonly used niching techniques for multimodal optimization problems. Shima Kamyab and Mahdi Eftekhari used Genetic Algorithm based self adaptive neighborhood scheme with crowding replacement memory (GA_SN_CM) for feature selection and proved that the proposed GA_SN_CM method significantly improved the feature selection process compared with the unimodal optimization [26]. Eric et al. proposed multimodal cuckoo search in which the cuckoo search algorithm is incorporated with a memory mechanism to store the local optima and included a depuration procedure to cyclically eliminate duplicated memory elements [27]. In [28] Weigo et al. proposed Niching Memtic Algorithm for clustering and feature selection (NMA_CFS). In this method, feature selection is made as an integral part of clustering without prior assumptions of the number of clusters.

ANCESTORS OF THE PROPOSED IWO_IBAT: CONVENTIONAL IWO AND BAT ALGORITHM

This section reviews the traditional IWO and BAT algorithms.

Invasive Weed Optimization Algorithm

IWO is an evolutionary metaheuristic algorithm that imitates the colonizing behavior of weeds. The four steps in IWO algorithm are Initialization, Reproduction, Spatial Dispersion and Competitive exclusion. The four steps mentioned below are repeated until maximum number of iterations are reached.

1) Initialization

A fixed number of random weeds are spread over n-dimensional search space as an initial population. This is referred as X= ($\vec{x}_1, \vec{x}_2, \vec{x}_3, \vec{x}_4 \ldots\ldots \vec{x}_m$).

2) Reproduction

Seeds are produced by the members in the population based on their fitness. The number of seeds produced ranges from $seed_{min}$ to $seed_{max}$. Worst member in the population produces $seed_{min}$ and the best member produce $seed_{max}$.

3) Spatial Dispersion

The produced seeds are spread out randomly around the parent weed by normal distribution with mean equal to 0 and varying variance. Standard deviation ranges from σ_{max} to σ_{min}. In each iteration it is obtained using

$$p1 = \sigma_{max} - \sigma_{min}$$

$$\sigma_t = \sigma_{min} + \left(1 - \frac{t}{tmax}\right)^{nmi} .(p1) \qquad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

t_{max} = maximum number of iterations
t = current iteration
nmi= non linear modulation index

4) Competitive Exclusion

Since the reproduction step is faster, the number of plants in the colony grows virally and reaches its maximum limit within fewer iterations. To eliminate undesired plants, a competitive mechanism is introduced in which the weeds and plants are ranked where the weeds with high fitness survive and reproduce. Therefore, the population in every generation should be less or equal to the maximum limit.

BAT Algorithm

BAT algorithm mimics the behavior of bats while catching prey. BAT algorithm was proposed by Yang in [29]. A set of interactive parameters like position, velocity, pulse rate, loudness and frequency is assigned to each bat that affects the quality of solution and time to obtain the solution which makes the algorithm complicated compared to other metaheuristic algorithms [30].

Principles of BAT algorithm

A swarm of bats searches for its prey by flying randomly with velocity V_i at position X_i with fixed frequency f, varying wavelength λ and A_0 as loudness. Rate of pulse (r) emission determines the closeness of the target. r ϵ [0,1] where rate of pulse increases when the bat is closer to the target. The loudness varies from A_0 to A_{min}. Frequency and wavelength varies from $[f_{min}, f_{max}]$ and $[\lambda_{min}, \lambda_{max}]$ respectively [31]. The simulated bats will update their positions and velocity in a D dimensional space. The new solutions x_i^t and velocity v_i^t at time t is given by

$$f_i = f_{min} + (f_{max} - f_{min})\,\beta \qquad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where β ϵ [0,1] is a random vector drawn from uniform distribution.

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*)\, f_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

x_* is the global best solution which is found after comparing all the solutions among all n bats.

$$x_i^t = x_i^{t-1} + v_i^t \qquad \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

After obtaining the global best solution, a new solution for each bat is generated using a random walk with the following equation.

$$x_{new} = x_{old} + \epsilon A^t \qquad \ldots\ldots\ldots\ldots\ldots(5)$$

Where Є ϵ [-1,1] is a random number and A^t is the average loudness of all the bats at time t. As the iterations proceed, loudness and rate of pulse emission have to be updated.

$$A_i^{t+1} = \alpha A_i^t \qquad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

$$r_i^{t+1} = r_i^0 [1-\exp(-\Upsilon t)] \qquad \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where α, ϒ are constants.

PROPOSED IWO_IBAT

The important aspect of Multimodal optimization is exploration and exploitation. A balanced exploration and exploitation is achieved by the proposed IWO_IBAT. The two phase optimization algorithm IWO_IBAT is presented in this section. First a definite number of weeds are spread over an n-dimensional space. Weeds produce seeds by a small perturbation around them. Seeds are then spread out randomly with mean zero and standard deviation varies from max to min with the subsequent iterations. So generated seeds have a low probability of converging towards single optimal solution. The proposed work adopts the competitive exclusion step of

IWO from [32] to make it feasible for multimodal optimization. Selection step adopted is as follows. The best seed produced by each plant is identified. This is done by using the fitness value of the seeds. Then the nearest plant from each of the best seed is identified and the next colony would use only the fitter member between the best seed and the corresponding nearest plant. This selection mechanism is slightly modified from the traditional selection mechanism in which when the weeds in the colony reaches the allowed population, the seeds and the plants are ranked together. Then, the weeds with high fitness are chosen to reach the allowable population in the colony. Subpopulations are formed within the population using distance measure to avoid overlapping.

This is followed by finding the best features among the subpopulation using IBAT algorithm which results in multiple solutions. An improved BAT algorithm is applied to the sub-populations formed by the phase I. The features in each sub population are clustered using k-means clustering algorithm. Signal to noise ratio (SNR) is calculated for each feature and the top ranked features are chosen from each cluster. All the top ranked features from all clusters of the subpopulation are given as input to IBAT algorithm which results in multiple optimal solutions. In IBAT algorithm, a new bat position is obtained by calculating the GCD between the previous position and the current best solution x_*.

$$v_i^t = v_i^{t-1} + \gcd(x_i^{t-1}, x_*) f_i \quad \text{……………..(8)}$$

$$x_i^t = x_i^{t-1} + v_i^t \quad \text{……………..(9)}$$

This method yields a good exploitation so naturally the solutions move towards local and global optima. GCD is calculated using extended Euclidean algorithm.
pseudocode of the proposed IWO_IBAT is given below.

Pseudocode of the proposed IWO_IBAT

PHASE I :
Begin
Initialize the population ps
t=0
While (termination condition not met) do
t=t+1
find the spatial distribution σ_t for the current iteration t using eq. 1
for i=1 to ps
for j=1 to seeds
for all dimensions k
$y_{seedj} = x_{ij} + \text{random}(\sigma_t)$
end for
end for
end for
for i=1 to ps
q= best (seeds)
r= near(q)
while fitness(q) > fitness (r)
r is replaced by q
end while
end for
t=t+1
end while
form subpopulation ($1 – g_{max}$) of features by grouping
for g=1 to g_{max}
Form clusters using Kmeans algorithm
Calculate SNR for each feature in each cluster
Select top ranked features and pass to phase II.
PHASE II :
Initialize x_i (i=1,2,3…….n) and velocity (v_i) of all n bats
Define pulse frequency f_i at x_i
Initialize r_i (pulse rate) and A_i (loudness)
For i= 1 to n
Calculate the fitness of all bats
End for
Find the current best position x_i^{best} according to the fitness value
iter=1
while termination condition not met
iter = iter +1
For_each bat in population:
$v_i^t = v_i^{t-1} + \gcd(x_i^{t-1}, x_*) f_i$
$x_i^t = x_i^{t-1} + v_i^t$
if rand(0,1) > r_i^t
select a solution among the best solutions
Generate a local solution around the best solution
End if
Fly randomly to generate a new solution
If(rand(0,1) < A_i and $f(x_i) < f(x)$)
Accept new solutions
Update pulsation rate and loudness using 6 and 7
Rank the bats and find the current best xi^{best}
End For
End For

EXPERIMENTAL ANALYSIS

The proposed IWO-IBAT is evaluated using three high dimensional imbalanced datasets namely Lung Cancer, Prostrate Tumor and SRBCT. The imbalanced nature of the dataset is found to be complex when selecting the prominent features for classification. The imbalanced datasets are balanced using Cluster Concentric Circle based Under Sampling C3BUS proposed by S.Srividhya and R.Mallika in [33]. The balanced datasets are involved in feature selection process using IWO_IBAT optimization algorithm. The proposed algorithm is compared with multimodal optimization proposed by Subharajit Roy in [32]. Table 1 describes the datasets used.

Table 1: Dataset Description

Dataset	# Features	# Samples	# Classes
Lung_Cancer	12600	203	5
Prostrate_Tumor	12533	102	2
SRBCT	2308	83	4

Lung Cancer and SRBCT are multi class datasets. To adapt these dataset to binary classification one class is taken into consideration versus the rest. Classifiers used for evaluation are Neural Network (NN), K-Nearest Neighbor (KNN) and Support Vector machine (SVM). Table 2,3 and 4 depicts the average accuracy, average precision, average recall and average Fmeasure obtained from all the subsets for the three chosen datasets with Neural network, KNN and SVM Classifiers.

Table 2: Comparison of Average Accuracy , Average Precision, Average Recall and Average Fmeasure for the existing IWO- δ -GSO and proposed IWO_IBAT with NN Classifier

Methods	Datasets / Metrics	Lung Cancer (in %)	Prostrate Tumor (in %)	SRBCT (in %)
IWO-δ-GSO	Accuracy (avg)	87.90	88.23	88.70
	Precision (avg)	87.97	88.40	88.92
	Recall (avg)	87.89	88.20	88.71
	Fmeasure (avg)	87.93	88.30	88.82
IWO_IBAT	Accuracy (avg)	91.97	91.82	92.64
	Precision (avg)	91.95	92.00	92.46
	Recall (avg)	92.04	91.83	92.74
	Fmeasure (avg)	91.99	91.92	92.60

Table 3: Comparison of Average Accuracy , Average Precision, Average Recall and Average Fmeasure for the existing IWO- δ - GSO and proposed IWO_IBAT with KNN Classifier

Methods	Datasets / Metrics	Lung Cancer in (%)	Prostrate Tumor in (%)	SRBCT in (%)
IWO-δ-GSO	Accuracy (avg)	81.77	82.57	81.48
	Precision (avg)	81.81	81.61	81.68
	Recall (avg)	81.77	81.37	81.38
	Fmeasure (avg)	81.79	81.49	81.53
IWO_IBAT	Accuracy (avg)	86.69	87.90	87.28
	Precision (avg)	86.69	87.93	87.23
	Recall (avg)	86.66	87.92	87.29
	Fmeasure (avg)	86.67	87.93	87.25

Table 4: Comparison of Average Accuracy, Average Precision, Average Recall and Average Fmeasure for the existing IWO- δ -GSO and proposed IWO_IBAT with SVM Classifier

Methods	Datasets / Metrics	Lung Cancer (in %)	Prostrate Tumor (in %)	SRBCT (in %)
IWO-δ-GSO	Accuracy (avg)	93.10	93.24	93.22
	Precision (avg)	93.18	93.27	93.29
	Recall (avg)	93.11	93.32	93.17
	Fmeasure (avg)	93.14	93.29	93.23
IWO_IBAT	Accuracy (avg)	98.24	98.03	97.99
	Precision (avg)	98.22	98.09	97.95
	Recall (avg)	98.24	98.01	98.01
	Fmeasure (avg)	98.23	98.05	97.98

CONCLUSION

This work adopts a multimodal optimization technique for feature selection process. The main advantage of using multimodal optimization technique is the ability to find multiple solutions. The proposed IWO_IBAT optimization algorithm uses the aspects of IWO and BAT algorithm with little modification to find multiple optimal solutions. IWO_IBAT is tested against three high dimensional imbalanced datasets and compared with NN, KNN and SVM classifiers. The results obtained from the experiments proved that IWO_IBAT provides a consistent and superior performance than IWO-δ-GSO. Among the all three classifiers used SVM shoots out the best performance. As further enhancement, the proposed method can be implemented for multiclass datasets and also with other niching methods. In addition to it, different optimization algorithms could be enhanced to obtain better results.

REFERENCES

[1] J.Kenneny, R.Eberhart, Swarm Intelligence. San Mateo, CA:Morgan Kaufmann, 2000.

[2] Kira K and Rendall LA, “A practical approach to feature selection”, Proceedings of ninth International Workshop on Machine Learning, Aberdeen, Scotland, UK. (pp. 249-256), 1992.

[3] Peng H, Long F & Ding C , “Feature Selection based on mutual information criteria of max dependency, max-relevance and min-redundancy”, IEEE transactions on Pattern Analysis and Machine Intelligence, vol.27,n o.8,pp.1226-1238, 2005.

[4] Dy, JG & Brodley, CE, “Feature subset selection and order identification for unsupervised learning”, Proceedings of the Seventeenth International Conference of Machine Learning, pp.247-254, 2000.

[5] S.Dasa, S.Maity, B.Y. Qu, P.N Suganthan, “Real parameter evolutionary multimodal optimization- a survey of the state of art,” Swarm and Evolutionary Computation, vol.1, no.2, pp.71-78, 2011.

[6] Jian ping Li, Xiao Dong Li, Alastair Wood , “ Species based evolutionary algorithms for multimodal optimization: A brief Review ”, IEEE Congress on Evolutionary Computation, 2010.

[7] S.W Mahfoud, “Niching methods for Genetic algorithms”, Urbana 51(95001) 62.94, 1995.

[8] N.N Gilbovets, N.M Gulayeva, “ A review of niching genetic algorithms for multimodal function optimization”, Cybern, Syst. Anal. 49(6) pp. 815-820, 2013.

[9] M.Preuss, “Niching methods and multimodal optimization performance. in multimodal optimization by means of evolutionary algorithms”, Springer Intl. Publications. pp. 115-137, 2015.

[10] S.W Mahfoud, “Crowding and preselection revisited”, “Parallel problem solving from nature 2” pp. 27-37, 1992.

[11] E.L Yu, P.N. Suganthan, “Ensemble of niching algorithms”, Information Sciences 180 , 2815-2833, 2010.

[12] D.E. Goldberg, J.J.Richardson, “Genetic algorithms with sharing for multimodal function optimization. Genetic algorithms and application, in: Proceedings on 2nd

International Conference on Genetic algorithms. Pp.41-49, 1987.

[13] Jian-Ping Li, Marton E.Balazs, Geoffrey T.Parks. P.John Clarkson, A species conserving genetic algorithm for multimodal function optimization. Evolutionary Computation 10 (3) , (207-234), 2002.

[14] J.Huang, Y.Cai, X.Xu, "A hybrid genetic algorithm for feature selection wrapper based on mutual information". Pattern Recognit. Lett.28 pp.1825-1844, 2007.

[15] J.W.Jianmei Guo, Guangxin Wang, Jian Li, Wang Yinglin, " A genetic algorithm for optimized feature selection with resource constraints in software product lines, j. Syst. Softw. 84. pp. 2208-2221, 2011.

[16] Xiangyang Wang, J.Yang, Xiaolong Teng, Weijun Xia, Richard Jensen, "Feature selection based on rough sets and particle swarm optimization. Pattern Recognition Letters. 28. pp.459-471, 2007.

[17] Monirul Kabir, M.S Md Kazuyuki Murase, "A new hybrid ant colony optimization algorithm for feature selection. Expert Syst. Appl. 39 , 3747- 3763, 2012.

[18] Khushaba, N.Rami, Ahmed Al-Ani. Adel Al-Jumaily, "Feature subset selection using differential evolution and a statistical repair mechanism". Expert syst. Appl. 38.9. pp. 11515-11526, 2011.

[19] Chuang, Li-Yeh, T.Sai Sheng Wei, Yang-Cheng-Hong, "Improved binary particle swarm optimization using catfish effect for feature selection. Expert systems with applications 38.10 pp.12699-12707, 2011.

[20] S.Srividhya, R.Mallika, " Feature selection for high dimensional Imbalanced dataset using game theory and fisher score" Journal of Advanced Research in Dynamical and Control Systems, Vol.9, No 8. pp.195-202, 2017.

[21] X.Yin, M.germay, "A fast genetic algorithm with sharing scheme using cluster analysis methods in multi-modal function optimization. In proceedings of the International Conference on Artificial Neural Networks and Genetic algorithms. pp.450-457, 1993.

[22] B.L Miller, M.J Shaw, "Genetic algorithms with dynamic niche sharing for multimodal function optimization". In proceedings of IEEE International conference of Evolutionary computation. New York, USA. pp.786-791, 1996.

[23] D.E Goldberg, L.Wang, "Adaptive niching via co evolutionary sharing, Genetic algorithms and Evolution strategy, in Engineering and Computer Science . pp.21-38, 1997.

[24] E.L Yu, P.N Suganthan, "Ensemble of niching Algorithms", Information Sciences 180, 2815-2833, 2010.

[25] Jan Ping Li, Marton E.Balazs, Geoffrey T.Parks, P.John Clarkson, "A species conserving genetic algorithm for multimodal function optimization", Evolutionary computation 10(3) pp.207-234, 2002.

[26] S.Kamyab, M.Eftekhari, "Feature selection using multimodal optimization techniques, Neuro computing, vol 171, pp-586-597, 2016.

[27] Eric Cuevas, Adolfo Reyna-Orta, "A cuckoo search algorithm for multimodal optimization", Hindawi publishing corporation, Article ID 497514, pp.1-20, 2014.

[28] Weigo Sheng, Xiaohui Liu and Micheal Fairhurst, " A niching memtic algorithm for simultaneous clustering and feature selection", IEEE transactions on Knowledge and data engineering, vol 0, No 7, pp.868-878, 2008.

[29] X.S Yang, "A new metaheuristic bat-inspired algorithm" in Nature Inspired Cooperative Strategies for Optimization (NICSO' 10), J.Gonzalez, D.Pelta, C.Cruz, G.Terrazas, and N.Krasnogor, Eds., pp.65-74, Springer, Berlin, Germany, 2010.

[30] Parpinelli, R.S. and Lopes, H.S., "New inspirations in swarm intelligence: a survey", Int. J. Bio-Inspired Computation, Vol. 3, No. 1, pp.1–16, 2011.

[31] Ahmed Majid Taha, Soong-Der Chen, Aida Mustapha, " Natural Extensions : Bat algorithm with memory", Journal of theoretical and applied Information Technology", Vol 79, No 1, 2015.

[32] Subhrajit Roy, Sk. Minhazul Islam, Swagatam Das, Saurav Ghosh, " Multimodal optimization by artificial weed colonies enhanced with localized search optimizers", Applied soft computing 13 pp.27-46,2017.

[33] S.Srividhya, R.Mallika, "Cluster concentric circle based under sampling to handle imbalanced data" Middle East Journal of Scientific Research, Vol. 24, pp.314-319, 2016.