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Hybrid Bio-inspired Approach for Feature Subset Selection

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Abstract

In this paper a methodology for feature selection is proposed. We have used the Ant Colony, Artificial Bee and Firefly Algorithms to select the most relevant features in a dataset. A Genetic Algorithm can create a new population of chromosomes using as initial population the populations generated by the three algorithms used (ACO, ABC and FA) instead a random one. The main objective of this selection is to reduce the features number, by eliminating redundant and irrelevant attributes, while trying to maintain or improve the classifier performance using neural network algorithm. The goal of our study is to achieve a balance between the classification accuracy and the size of the feature subsets selected using new hybrid algorithm based on bio-inspired algorithms.

Keywords: Ant colony optimization, Artificial bee colony, Feature selection, Firefly algorithm, Genetic algorithm.

INTRODUCTION

The feature selection algorithms have been widely investigating due to its importance to a number of disciplines such as pattern recognition and knowledge discovery. Feature selection allows the reduction of feature space, which is crucial in reducing the training time and improving the prediction accuracy. This is achieved by removing redundant, irrelevant, and noisy features.

Different methods have been developed and used for feature subset selection using several search strategies and evaluation functions. In [1] a correlation measure is applied to evaluate the goodness of feature subsets based on the hypothesis that a good feature subset is one that contains features highly correlated to the class, yet uncorrelated to each other. In 2005 Liu has developed three dimensions to categorize feature selection methods:

- Search strategies (complete, sequential and random),
- Evaluation criteria (Filter, Wrapper, and Hybrid)
- Data mining tasks (classification or clustering) [2].

Some other approaches use machine learning approaches, such as Support Vector Machines (SVMs) [3] [4], decision trees, and genetic algorithms [5]. In [6] Al-ani proposed an ACO approach to solve FS problem. His iterative algorithm starts by the selection of random starting point for each ant, and then uses pheromone to guide network exploration to make a final subset of features. Khushaba has proposed a hybrid system based on ACO and DE. The DE crossover and mutation were applied at the end of each iteration and the newly generated solutions will replace those resulting from the ants search. The resulting subsets are then used to update pheromone trails and the process restarts [9]. Based on PSO, Unler [30] proposed a feature selection algorithm with an adaptive selection strategy, where he used the features already selected to select a new feature so a feature is chosen not only according to the likelihood calculated by PSO but also to its contribution to the features already selected.

In our study, we were particularly attracted by the hybridization of bio-inspired methods for feature selection. We propose to use different metaheuristics algorithms: ant colony optimization (ACO), artificial bee colony (ABC) and firefly algorithm (FA) simultaneously to explore the search space then we use genetic algorithm (GA) to select the best feature subset which include a small number of features and achieve a lower classification error rate than using all available features.

The rest of this paper is organized as follows: section 2 reviews feature selection algorithm. Section 3 introduces swarm optimization algorithms: ant colony optimization, artificial bee colony, firefly algorithm and genetic algorithm. Section 4 presents bio-inspired algorithms for feature selection. In section 5, we present the hybrid approach proposed. The experimental results obtained are presented and discussed in section 6. Finally, section 7 concludes the paper.

FEATURE SUBSET SELECTION

The identification of useful and informative attributes for a given dataset, broadly referred to as Feature Selection (FS), is an attractive and challenging research topic for several domains including predictive data mining, pattern recognition, machine learning and information retrieval. One of the fundamental motivations for feature selection is to reduce the dimensionality. In fact, the presence of useless features may not only deteriorate the performance of learning algorithms but also obscure information behind data. Considered as a fundamental problem in machine learning, the role of FS is critical, especially in a context deemed with irrelevant features (*i.e.* redundant and noisy features) [6].

In literature, the authors state a list of three objectives of using feature selection for classification:

To reduce the task of extraction of characteristics;

To improve the precision of the classification module;

To improve the reliability of the performance estimation.

Existing feature selection algorithms can be broadly classified into two categories: wrapper approaches and filter approaches. Wrapper approaches include a learning/classification algorithm in the evaluation procedure, while filter approaches do not include such algorithm. Filter approaches are argued to be computationally less expensive and more general, while wrapper approaches can usually achieve better results. Figure 1 illustrates the generic process that could summarize the different steps by any feature selection approach.

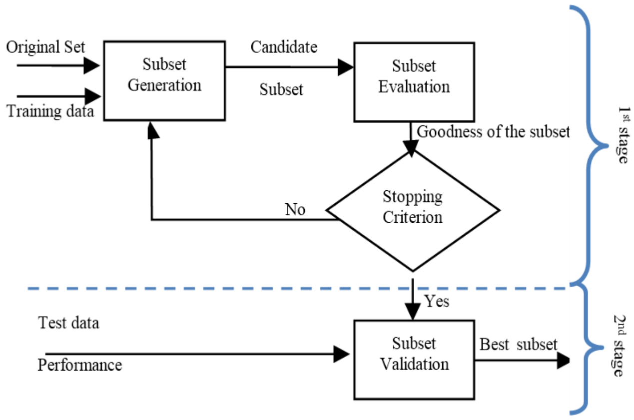

Figure 1. Feature selection process.

As input the feature selection process requires the dataset for which the relevant features will be identified. The outcome should include the retained features. Generally, such process consists of two stages: search and validation. Each candidate subset is evaluated according to certain criterion and compared to the best solution found. Generation and evaluation is repeated until a given stopping criterion is satisfied. The best subset resulting from the first stage is provided as input for the second stage where it is usually, validated on a different data set.

BACKGROUND

Ant colony optimization (ACO)

Ant colony optimization (ACO) is an algorithm that can be used to solve combinatorial optimization problems. It is a metaheuristic in which a colony of artificial ants cooperates in finding good solutions to difficult discrete optimization problems. In real ant colonies, a pheromone, which is an odorous substance, is used as an indirect communication medium. When a source of food is found, ants lay some pheromone to mark the path. The quantity of the laid pheromone depends upon the distance, quantity and quality of the food source. While an isolated ant that moves at random detects a laid pheromone, it is very likely that it will decide to follow its path. This ant will itself lay a certain amount of pheromone, and hence enforce the pheromone trail of that specific path. Accordingly, the path that has been used by more ants will be more attractive to follow. After all ants have completed their solutions, the pheromone produced during the tour will have to be managed [22].

There are two procedures involves in pheromone management, namely pheromone evaporation and pheromone deposit. Both procedures are comprised in one main procedure, pheromone update. The function of pheromone evaporation is to make sure that the ants are not traversing on the same path, constructing the same solution. Then all ants can update the pheromone level on the features they have visited and the best ant with the best solution will get the chance to deposit more pheromone than others [22].

Artificial bee colony (ABC)

In the ABC algorithm, an artificial bee moves in a multidimensional search space choosing sources of nectar depending on its past experience and its companions of beehive or fitting its position. In order to find the best solution, three classes of bees are used: employed bees, onlooker bees and scout bees. These bees have got different tasks in the colony. Some bees (exploratory) fly and choose food sources randomly without using experience. When they find a source of major nectar, they memorize their positions and forget the previous ones. Thus, ABC combines methods of local search and global search, trying to balance the process of the exploration and exploitation of the search space [18].

Firefly algorithm (FA)

Firefly algorithm is a type of swarm intelligence algorithm based on the reaction of a firefly to the light of other fireflies [9]-[10].

Firefly Algorithm (FA) was first developed by Xin-She Yang in late 2007 and 2008 at Cambridge University, which was based on the flashing patterns and behavior of fireflies. In essence, FA uses the following three idealized rules:

- Fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
- The attractiveness is proportional to the brightness, and they both decrease as their distance increases. Thus for any two flashing fireflies, the less bright one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly.
- The brightness of a firefly is determined by the

landscape of the objective function [9]-[10].

According to the above three rules, the degree of attractiveness of a firefly is calculated by the following equation:

$$\beta=\beta_0 e^{-\gamma r2} \quad (1)$$

Where β is the degree of attractiveness of a firefly at a distance r, β0 is the degree of attractiveness of the firefly at r= 0, r is the distance between any two fireflies, and γ is a light absorption coefficient.

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i^{t+1} = x_i^t + \beta_0\ e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha_t e_i^t \quad (2)$$

Where the second term is due to the attraction, the third term is randomization with *t* being the randomization parameter [9]-[10].

Genetic algorithm (GA)

Genetic algorithm (GA) is inspired by the process of natural evolution from parents to their offspring. An initial population of possible solutions is randomly selected and then operated on by GA operators. Three key GA's operators are crossover, mutation, and selection operators. The crossover operator exchanges genes between a mating pair and creates an offspring. The mutation operator randomly changes the genes of an offspring, and the selection operator selects a group of offspring to be the next generation of population [22]-[23]. The processing procedure of GA is as follows:

- Initially, generate the initial gene population.
- Calculate the fitness value for all the population.
- Select the parent gene in the next generation using fitness value.
- Operate crossover and mutation to the population, and generate the next generation gene population.

Repeat Steps 2 to 4 until number of generations=maximum of generations.

ACO, ABC, FA AND GA BASED FEATURE SELECTION

Many methods have been implemented for feature selection and mostly involved statistical approaches. However, with the advancement of knowledge and technology, many other methods from different fields have also been applied for feature selection. Population based optimization algorithms have attracted much interest. In such approaches, a given feature subset representing, a solution is coded in a binary string of length N (total number of features). Zero or one are possible values, respectively denoting the absence or the presence of the attributes at the i^{th} position. Each algorithm randomly initializes features subset selected. During the search process, candidates' solution move and collaborate to find the optimal subset of features. Fitness, reflecting the classification accuracy of the solution is assigned to each solution [18]-[23].

In the literature, many successful bio-inspired based feature selection algorithms have been proposed.

Al-ani proposed an ACO approach to tackle FS problem. The iterative swarm process starts by the selection of random starting point for each ant, initial feature added to the solution subset, and then uses pheromone to guide network exploration [6].

Aghdam et al. used the ACO to tackle the FS problem in text categorization where subset size was taken into account with classification accuracy in the pheromone update stage. The selection of the next feature to add to the subset which was materialized with ant move used the classification accuracy of the subset [7].

Banati and Bajaj proposed FA_RSAR algorithm that combines FA together with RST (Rough Set Theory) to ensure the success in less time without compromising the degree of optimality in terms of size of subset and corresponding dependency degree. The algorithm proposed was evaluated using medical datasets [8].

Tan and Bourgeois used a genetic algorithm to fuse multiple feature selection, for microarray gene expression data, criteria to find the optimal or near optimal subset of informative features. The proposed algorithm search a pool of hypotheses (population) containing complex interacting parts. Each hypothesis (individual) of the current population is evaluated according to a specified fitness function. A new population is generated by applying genetic operations (selection, crossover, and mutation) [24].

PROPOSED APPROACH

Hybrid bio-inspired approaches for feature selection

Recently, another kind of hybridization where the combination is not limited to wrappers and filters or the use of local search to enhance exploitation performance but extended to metaheristics combination, is explored. Several bio-inspired hybrid methods were proposed to tackle FS problems.

Khushaba and Al-ani proposed a hybrid system based on ACO and DE where DE evolves solutions provided by ants. The DE crossover and mutation were applied at the end of each iteration. The newly generated solutions will replace those resulting from the ants search. The resulting subsets are then used to update pheromone trails and the process restarts [9].

Sivagaminathan et al. presents an hybrid method based on ACO and artificial neural networks (ANNs) to find the optimal feature subset . The proposed hybrid model is evaluated using medical diagnosis data sets [10].

Another hybrid approach combined a SA with GA in [11]. The devised hybrid scheme involves three components: SA, GA, and local search based on hill climbing. The search starts with a Simulated Annealing, then followed by a Genetic Algorithm, and terminates with local search solution refinement. The GA starts the evolution process with the best solution returned by SA.

Proposed hybrid ACO-ABC-FA/GA based feature selection

The idea of our hybrid approach is to absorb useful information from different feature selection algorithms to find feature subsets that can have smaller size and/or better classification performance than those individual algorithms.

As shown in figure 2 the proposed method works as follows:

Firstly we train each algorithm (ACO, ABC and FA) to produce best sets of features then we apply a genetic algorithm (GA). A genetic algorithm can create a new population of chromosomes using as initial population the populations generated by the three algorithms used (ACO, ABC and FA) instead a random one. A new population is generated by applying genetic operations (selection, crossover, and mutation). Our genetic algorithm is designed to maximize classification accuracy and minimize the size of feature subsets. The algorithm follows the same procedure for new groups generated in previous iteration and determines the accuracy of each group of features selected until the stopping criterion is satisfied (number of iterations).

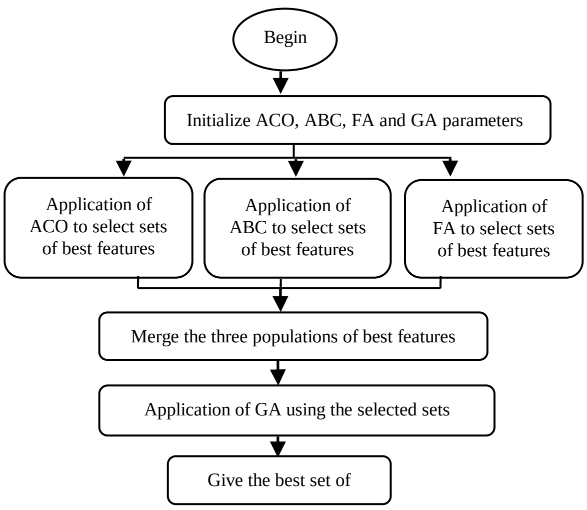

Figure 2. Hybrid proposed approach (ACO-ABC-FA/GA).

The main steps of our algorithm are as follows:

Step 1: Initialization.

- Initialize the ACO parameters and determine the population of ants.
- Initialize the ABC parameters and determine the population of bees.
- Initialize the FA parameters and determine the population of fireflies
- Initialize the GA parameters.
- Determine the maximum of allowed iterations.

Step 2: Run ACO, ABC and FA in the same time

➢ **ACO**: Generation of ants and evaluation of each one.

- Each ant (Ai, i = 1, 2, ..., p) is randomly assigned to one feature and it should visit all features and build solutions.
- In this step, the classifier error is used as an evaluation measure.
- At each iteration, the ants build subset using ACO equations.

➢ **ABC**: Generation of bees and evaluation of each one.

- Each bee (Bi, i = 1, 2, ..., p) is randomly assigned to one feature and it should visit all features and build solutions.
- In this step, the classifier error is used as an evaluation measure.
- At each iteration, the bees build subset using ABC equations.

➢ **FA**: Generation of fireflies and evaluation of each one.

- Each firefly (Fi, i = 1, 2, ..., p) is randomly assigned to one feature and it should visit all features and build solutions.
- In this step, the classifier error is used as an evaluation measure.
- At each iteration, the fireflies build subset using FFA equations.

Step 3: Application of GA

- Merge the three populations of best features
- Calculate the fitness value for all the population.
- Select the parent gene in the next generation using fitness value.
- Operate crossover and mutation to the population, and generate the next generation.
- Repeat Steps 2 to 4 until number of generations=gmax
- Evaluation of the selected subset of features.

EXPERIMENTAL RESULTS

In this section, the datasets as well as the number of features are described. On the other hand, the results of the evaluation are also presented, which relate the number of selected features, the error rates and CPU times.

Selected datasets

In order to make our evaluation results comparable to the most of the published results in feature selection evaluations, we have chosen datasets from the UCI machine learning repository:

Table I. Selected datasets
(number of features, classes and instances)

Data set	Number of Features	Number of Classes	Number of instances
Spect Heart (Binary)	23	02	187
Spect Heart	44	02	187
Parkinson'Diseace	22	02	96
Parkinson 2	26	02	1040
Glass dataset	10	06	214
Breast tissue	09	06	106
Ionosphere	34	02	351
Musk1	166	02	476
Word Breast Cancer	09	02	699
Word Breast Cancer Diagnostic	31	02	569

RESULTS AND DISCUSSION

In this section, the experimental results obtained for the different approaches on datasets are presented.

- Results of Ant colony optimization algorithm

Table II. Results of ACO feature selection algorithm

Data set	Before Selection		ACO		
	Number of features	Error	Number of features	Error	CPU time
Spect Heart (Binary)	23	0.1537	19	0.1111	243.39
Spect Heart	44	0.1491	34	0.0804	189.04
Parkinson's Disease	22	0.0804	14	0.0230	245.19
Parkinson 2	26	0.1795	20	0.1702	431.24
Glass dataset	10	0.6949	9	0.4438	240.14
Breast tissue	9	0.5106	9	0.5106	248.37
Ionosphere	34	0.0678	26	0.0353	334.36
Musk1	166	0.0516	61	0.0414	816.17
Wbc	9	0.0212	8	0.0190	302.05
Wbcd	31	0.0176	26	0.0107	400.81

Table 2 lists the experimental results of error classification rate using an artificial neural network. ACO could reduce the number of features and achieved a good error rate. In general, the recognition rate decreases when the number of features decreases. However, the recognition rate does not decrease when appropriate features are chosen. In this experiment, ACO has improved the recognition rate conversely with only few features.

- Results of Artificial bee colony algorithm

Table III. Results of ABC feature selection algorithm

Data set	Before Selection		ABC		
	Number of features	Error	Number of features	Error	CPU time
Spect Heart (Binary)	23	0.1537	9	0.1026	224.45
Spect Heart	44	0.1491	34	0.0625	174.44
Parkinson's Disease	22	0.0804	15	0.0229	209.38
Parkinson 2	26	0.1795	16	0.1694	395.54
Glass dataset	10	0.6949	7	0.4644	225.26
Breast tissue	9	0.5106	7	0.3327	246.08
Ionosphere	34	0.0678	20	0.0292	290.60
Musk1	166	0.0516	166	0.0516	3803.56
Wbc	9	0.0212	7	0.0171	260.83
Wbcd	31	0.0176	21	0.0100	353.88

According to the above experimental results, when the number of features is small, we can choose the better part of the characteristics, the accuracy of ABC feature selection is higher than other feature selection algorithm.

- Results of Firefly algorithm

Table IV. Results of FFA feature selection algorithm

Data set	Before Selection		FA		
	Number of features	Error	Number of features	Error	CPU time
Spect Heart (Binary)	23	0.1537	15	0.0889	382.85
Spect Heart	44	0.1491	19	0.0568	458.59
Parkinson's Disease	22	0.0804	13	0.0279	495.09
Parkinson 2	26	0.1795	17	0.1666	904.17
Glass dataset	10	0.6949	7	0.4263	493.17
Breast tissue	9	0.5106	7	0.2901	529.70
Ionosphere	34	0.0678	19	0.0333	599.52
Musk1	166	0.0516	85	0.0272	5657.0
Wbc	9	0.0212	7	0.0163	573.76
Wbcd	31	0.0176	18	0.0099	766.78

In Table 4, we also compared the time costs of the feature selection methods. Compared to ABC and ACO, FFA is the most cost algorithm, when the number of all available features is n, the time complexity of FFA generally corresponds to a large amount of time when n is big.

- Results of Genetic algorithm

Table V. Results of GA feature selection algorithm

Data set	Before Selection		GA		
	Number of features	Error	Number of features	Error	CPU time
Spect Heart (Binary)	23	0.1537	9	0.1388	296.58
Spect Heart	44	0.1491	19	0.0884	546.32
Parkinson's Disease	22	0.0804	12	0.0296	412.27
Parkinson 2	26	0.1795	13	0.2188	854.17
Glass dataset	10	0.6949	4	0.6120	174.92
Breast tissue	9	0.5106	5	0.3869	206.53
Ionosphere	34	0.0678	23	0.0316	194.86
Musk1	166	0.0516	91	0.0285	770.72
Wbc	9	0.0212	6	0.0181	179.94
Wbcd	31	0.0176	21	0.0105	239.77

The performance of GA is better when the characteristics are increasing. When taking 166 features (Musk1 dataset), the error rate value of the other three algorithms is similar except FFA algorithm.

Proposed approach

In order to evaluate the performance of the proposed hybrid feature selection approach, a comparison is made with the ACO, ABC, FFA and GA based feature selection performances obtained in this study. Table 6 present the results in terms of number of selected features and classification error for the ten databases.

Table VI. Results of Proposed algorithm (ACO-ABC-FFA/GA)

Data set	Before Selection		Hybrid Approach	
	Number of features	Error	Number of features	Error
Spect Heart (Binary)	23	0.1537	8	0.0941
Spect Heart	44	0.1491	20	0.0601
Parkinson's Disease	22	0.0804	11	0.0208
Parkinson 2	26	0.1795	17	0.1576
Glass dataset	10	0.6949	8	0.3922
Breast tissue	9	0.5106	7	0.2829
Ionosphere	34	0.0678	19	0.0309
Musk1	166	0.0516	84	0.0296
Wbc	9	0.0212	8	0.0165
Wbcd	31	0.0176	20	0.0082

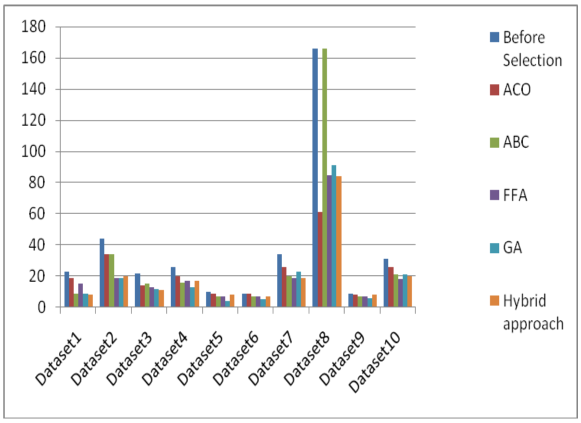

Figure 3. Number of selected features with algorithms used.

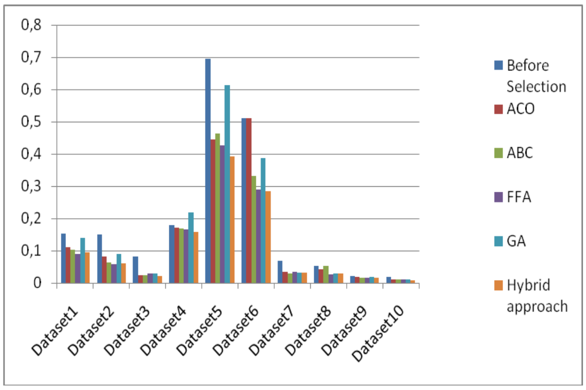

Figure 4. Error rates with algorithms used.

We can notice that solutions describe the datasets using both traditional and hybrid approaches are good well. The hybrid approach produces significant results both in terms of reduction of the selected features number and improvement of classification performance on the used databases. The hybrid approach has achieved the best results in terms of classification performance with the majority of databases.

Comparative study

In Table 7, we put different results (number of features selected and error classification rates) on the selected UCI machine learning datasets.

- PSO: Particle Swarm Optimization.
- ACO-C4.5: Ant Colony Optimization-Decision tree C4.5.
- CSA-SVM: Clonal Selection Algorithm- Support Vector Machine.

- GSBS: greedy stepwise backward selection.
- BPSOWFSS: Binary Particle Swarm Optimization Wrapper Feature Selection Subset.

Table VII. Previous works

		Glass Dataset	Musk1	wbc	Wbcd
Proposed approach	NF	8	84	8	20
	Err	0.3922	0.0296	0.0165	0.0082
PSO [27]	NF		26	2	
	Err		0.2277	0.3483	
ACO-PSO1 [27]	NF		52	2	
	Err		0.2474	0.2550	
ACO-PSO2 [27]	NF		28	2	
	Err		0.2309	0.3033	
ACO-PSO3 [27]	NF		41	2	
	Err		0.2527	0.3033	
ACO-C4.5 [28]	NF	5		6	3
	Err	0.264		0.24	0.241
GA-C4.5 [28]	NF	6		6	5
	Err	0.269		0.046	0.044
CSA-SVM [26]	NF			1	
	Err			2.800	
GSBS [3]	NF		86		13
	Err		15.42		6.61
BPSOWFSS [24]	NF			9	
	Err			0.2315	
Fast BPSOWFSS[24]	NF			9	
	Err			0.2308	

Tab. 7 depicts the error classification rate and number of selected features of the proposed system when comparing with the existing methods.

CONCLUSION

In this work, a way to evaluate Feature Selection algorithms was proposed in order to understand their general behavior on the particularities of relevance, irrelevance, redundancy and size sample of synthetic datasets. Thereafter, the results using the Genetic Algorithm with the Firefly, Ant colony optimization and Artificial bee colony Algorithms for feature selection were presented. Thereby, the aim of this study was to propose a new method for feature selection based on bio-inspired algorithms, and its application in optimization systems. Simulation results demonstrated the superior performance of the proposed algorithm over the traditional ones. As future work, this study can be extended in many ways to carry up richer evaluations, including the use of combined evaluation measures.

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