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Optimization of Multi-objective ENORA and NSGA-II based on Bio-Inspired Algorithms for Classification Problem

Mohammad Aizat Basir[1], Mohamed Saifullah Hussin[2], Yuhanis Yusof[3]
[1]Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Malaysia,
aizat@umt.edu.my
[2]A Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Malaysia,
saifullah@umt.edu.my
[3]School of Computing, Universiti Utara Malaysia, Malaysia,
yuhanis@uum.edu.my

ABSTRACT

Selecting optimal feature is very hard to be accomplished, especially for classification task. This is due to common feature selection methods that operate independently and caused selection of unnecessary features, consequently affecting the accuracy of the classification task. The objective of this paper is to explore the capability of the wrapper/filtered method with bio-inspired search algorithms in optimizing the multi-objective algorithms namely ENORA and NSGA-II in producing optimal set of features. To idealize the combination of ENORA and NSGA-II with suitable bio-inspired search algorithms is the critical phase in this paper. The following step is to confirm the optimal set of features by performing classification task. The evaluation criteria are established by minimizing the number of selected features with good classification accuracy. Eight (8) benchmark datasets with various sizes were carefully chosen to be experimented. The final output revealed that the ideal combination of multi-objective algorithms namely ENORA and NSGA-II with selected bio-inspired search algorithm promisingly accomplishes better solution (i.e. optimal selected features with good classification accuracy) on the selected datasets. This discovery implies that the combination of wrapper/filtered method with bio-inspired algorithms can improve the performance of ENORA and NSGA-II for feature selection and classification task.

Key words : Feature Selection, Bio-Inspired, Classification, ENORA, NSGA-II

1. INTRODUCTION

Data with large number of attributes are often referred as big dataset. Usually, most model are affected by redundancy of those attributes. By having numerous attributes in rule structure, it has become more complex and harder to interpret. By understanding this problem, reducing the number of insignificant features becomes a vital step for constructing machine learning model. In practical circumstances, it is suggested to eliminate the unrelated and unnecessary features for time efficiency and low labor cost. Large datasets which consists high number of attributes known as high dimensionality dataset [1]. This situation will lead to larger computation time that is an exponential function of the number of the dimensions, resulting in a phenomenon known as the curse of dimensionality. In addition, high dimension of searching space contributes to redundancy of features in the model. The fundamental solution is to shrink the search space while avoiding from losing important features in the dataset.

The risk of losing information become crucial for the complexity of attribute reduction. Two important aspects that should be considered while dealing with attribute reduction, i) attribute optimality degree (subset size and corresponding dependency degree) ii) time needed to obtain attribute optimality. In many situations, fast attribute reduction like Quick Reduct (QR) and Entropy-Based Reduction (EBR) [2] having problem to obtain a subset with minimal size [2]–[4]. On the other hand, hybrid feature selection methods [3] [5] could improve the accuracy yet required more computation time [6].

The selection of relevant features (attributes) subset, also known as feature selection is the process to choose a subset of important features to be used in data mining model. In addition, this process should minimize the complexity of computation and data. To be concise, search problem can be seen as each state in the search space represents a subset of possible features (e.g: minimum time will be required to complete for searching subsets in small search area at any order. However, in common practice the search space is large (e.g: N>20) where 2^N the total number of promising solutions in dimensions N). Therefore, the suitable (best) search strategy become a paramount step to be discovered.

2. RELATED WORKS

A multi-objective method for feature subset selection fuzzy based combined with ACO has been developed by [7]. In this research, fuzzy multi-objective problem has been solved efficiently by applying ACO algorithm. Their research works indicate that the proposed method can generate better subsets and reach higher classification accuracy. ACO also has been applied with genetic algorithm for feature selection pattern recognition [8]. The approach involved dual interesting models which are visibility density model (VMBACO) and pheromone density model (PMBACO) for optimal solution in selecting and deselecting features. Promising result has been obtained where the proposed method displays robustness and adaptive performance compared to other methods. Likewise, ACO was used in medical area to search for important features in breast cancer diagnosis [9]. Experimental results demonstrated that ACO has the capability to improve the diagnostic accuracy of Raman-based diagnostic models. Similarly, ACO has been applied in network security field for detecting intrusion [10].

Artificial Bee Colony (ABC) [11] was used to detect the presence of cervical cancer in Computed Tomography (CT Scan) images. For handling high dimensionality problem, [12] has proposed novel feature selection method based on ABC with gradient boosting decision tree. Research result has shown that the proposed method efficiently reduces the dimensions of the dataset and achieves greater classification accuracy using the selected features. Similarly, a hybrid approach presented by [13] utilized the ABC algorithm with differential evolution algorithm for tackling high dimensionality problem. The developed hybrid method shows the ability to select good features for classification tasks hence improve run-time performance and accuracy of the classifier. A multi-objective artificial bee colony (MOABC) model has been developed by [14]. The developed algorithm was integrated with fuzzy approach to evaluate the relevance feature subsets. Experimental results show significant contribution for finding the good feature subset.

Bat algorithm has been used effectively in engineering [15]. Multi-objective binary bat algorithm (MBBA) proposed by [16] has modified bat position updating strategy which works better with binary problems and also introduced mutation operator to improve the local search ability and help the diversity of algorithm. The experimental results show that the proposed MBBA is a competitive multi-objective algorithm and outperforms NSGA-II. Bat algorithm has also been applied in field of renewable energy in [17] which the proposed algorithm has great potential for application to wind power system. Similarly, in medical area, Modified Bat Algorithm (MBA) for feature selection developed by [18] performed significantly well to eliminate inappropriate and repeated breast cancer data before diagnosis being performed. In [19], hybrid binary bat enhanced particle swarm optimization algorithm (HBBEPSO) has been created and claimed to have the ability to explore the feature space for optimal feature combinations.

A multi-objective algorithm based on Cuckoo Search Algorithm (CSA) has been applied in optimization problem [20]–[22]. In dimensionality reduction problem, new multi-objective CSA has been developed by [23] to search the attribute space with minimum correlation among selected attributes. Experimental results showed that the proposed multi-objective CSA system has successfully outperformed the particle swarm optimization (PSO) and genetic algorithm (GA) optimization algorithms. For instance, adapted cuckoo search algorithms with hybrid rough set based on modified CSA was developed by [24]. This hybrid algorithm managed to decrease number of features in reduction set without compromising the classification accuracy. Furthermore, [25] introduced an algorithm for predicting heart disease based by utilizing Cuckoo Search method. By combining multiple algorithms which are CSA and Cuckoo Optimization Algorithm (COA), it was successfully used in generating the features subset which improving the accuracy on all experimented datasets.

Firefly Algorithm (FA) has been proposed by Yang [26] that was applied in various area of feature selection. Recently in medical area, new FA based on Ada-boost method was developed by [27] for diagnosing liver cancer. The developed hybrid method utilized FA in improving Ada-boost algorithm where the result produced can assist physicians to identify and classify healthy and unhealthy individuals. Furthermore, it can also be used in medical centers to enhance accuracy and speed and reduce costs. In addition, [28] proposed FA-based algorithm to classify text features in Arabic character. The developed algorithm shows promising performance in improving the accuracy value especially in combinatorial problem for Arabic text classification. In multi-objective problem, firefly algorithm has been successfully applied to area of scheduling problem such as in [29]–[31].

Evolutionary non-dominated Radial slots-based Algorithm (ENORA) and Non-dominated Sorted Genetic Algorithm (NSGA-II) are two popular methods in multi-objective feature selection methods. ENORA is commonly used for selection strategy for a random search method [32],[33]. There are two objectives for this selection strategy: i) number of selected features will be minimized ii) root of mean squared error (RSME) will be minimized and learned by Random Forest (RF) [34]. NSGA-II [35] is also known as multi-objective evolutionary computation which in term of statistics of hyper volume for the last population and in terms of the RMSE of the chosen individual. For example, [36] has developed a NSGA-II wrapper to rename entities recognition.

NSGA-II has been used in [37] with logistic regression, and naive Bayes with Laplace correction to handle vast number of objectives to modify the dominance relation. In addition, multi-objective feature selection were applied in medical area [38] and engineering [39]. In general, multi-objective algorithms have been used for classification problem [40]-[42], optimizing error rate and selecting feature subset [43][44].

Inspired by the advantages of various bio-inspired algorithms in feature selection, this paper aims to present an optimized ENORA and NSGA-II algorithms by deploying bio-search algorithms for optimum attributes selection. The details execution steps are described in the next section.

3. METHODOLOGY

Methodology of this paper is represented in form of algorithm in Figure 1. It comprises of four important phases: (i) Dataset collection [various sizes and domain]; (ii) Data handling [missing values]; (iii) Dimensionality Reduction [optimal reduction]; (iv) Production of best combination.

Start
i. Load selected datasets
ii. Managing missing values
- Eliminate irrelevant attributes (column) with majority missing values
- Convert missing values with '0'.
- Discretization all datasets (FILTER: - Instance Supervised filters)

iii. Optimal Dimensionality Reduction
- First Reduction: - ENORA/NSGA-II + (FilteredSubsetEval)
- Second Reduction: - ENORA/NSGA-II + Bio-Search Algorithms
  - ✓ Setting up the parameter: {ant, bat, bee, cuckoo & firefly}.
  - ✓ Search the optimal number of attributes achieved + good accuracy.

iv. Produce the best combination of ENORA/NSGA-II with selected Bio-Search Algorithms.
End

Figure 1: Optimal ENORA/NSGA-II Feature Selection Algorithm

Step (i) – Data Collection: Datasets were selected from online repository (UCI Machine Learning Repository) [45] (refer Table 1 for profile details). These datasets consist of various sizes and mix domains in order to confirm the performance of the model.

Step (ii) – Data handling: Missing values in the dataset has been pre-processed to be ready for experimentation. Dataset that has missing value (symbolized as '?') has been replaced with "0" values.

Step (iii) – Optimal Reduction: In this step, two (2) reduction processes have been applied. First reduction was ENORA and NSGA-II algorithms with filtered method. The output of the first reduction will be further reduced with five (5) bio-search methods for searching near-optimal attributes. This experiment process reflects research done in [46] which claimed that balance of exploitation and exploration need to be accomplished for efficient space searching. Three (3) popular learning algorithms (Naïve Bayes, K-nearest Neighbor and Decision Tree) have been deployed with wrapper methods.

Step (iv) – (Production of suitable/best combination): This is the final and crucial step where different combinations of bio-search algorithms with reduction algorithms were used to optimize ENORA and NSGA-II algorithms. Optimal number of reductions with highest performance accuracy will be measured to choose the best combination list of the ENORA and NSGA-II model.

Table 1:. Profile of the selected datasets

Dataset	Size	#Atr	#Ins	#Cls
Arcene	Large	10000	900	2
Breastcancer	Small	9	367	2
Clean1	Medium	166	476	2
Emails	Large	4702	64	2
Gisette	Large	5000	13500	2
Ozone	Small	72	2536	2
Parkinson	Small	22	197	2
Semeion	Medium	265	1593	2

Table 2:. Details parameter setting

Bio-Algo	Specific setting
Ant	Evaporation (0.9), Heuristic (0.7), Pheromone (2.0)
Bat	Loudness (0.5) & Frequency (0.5)
Bee	Radius Mutation (0.80) & Radius Damp (0.98)
Cuckoo	Sigma (0.70) & Pa (0.25)
Firefly	Absorption Coefficient (0.001) & Beta zero (0.33)

*Setting for all algo: *Iteration:20, Mutation Probability: 0.01, Population: All Algo:20 except for Bee Algorithm: 30.*

5. RESULTS AND DISCUSSION

Table 3:. Comparison of attribute reduction: ENORA vs ENORA + Bio-Search

Dataset	#Attr Ori	1st Rdc	2nd Rdc				
		#Attr ENORA Filtered	# Attr [ENORA + (Wrapper + Bio Search)]				
			Ant	Bat	Bee	Cuc	Fly
Breastcancer	9	9 (0.0%)*	7	7	7	6	7
Parkinson	22	9 (59.1%)*	5	6	6	7	6
Ozone	72	12 (83.3%)*	1	1	1	1	1
Clean1	166	22 (86.7%)*	14	13	14	14	14
Semeion	265	5 (98.1%)*	4	4	4	4	4
Emails	4702	79 (98.3%)*	18	24	11	13	34
Gisette	5000	66 (98.7%)*	23	28	18	15	31
Arcene	10000	391 (96.1%)*	101	37	36	37	133

** % of reduction from original attributes.*

In Table 3, as expected, Filtered approach with ENORA accomplished to diminish number of attributes for seven (7) datasets (Ozone, Parkinson, Clean1, Semeion, Emails, Gisette, Arcene) except for Breastcancer datasets where the original attributes remained. Semeion, Emails and Gisette datasets achieved almost 99% reduction. Nevertheless, the massive reduction of these attributes with filtered approach still does not approve the optimal selection. Extended experiment has been conducted to optimize the ENORA algorithms with five (5) bio-search algorithms and wrapper method. Result shows more reduction for all datasets. Extreme case has been discovered by Ozone dataset where twelve (12) attributes have been reduced to only one (1) attribute in the second reduction. Obviously, bio-search algorithms are more suitable to be used to select the good features compared to filtered technique. This condition confirmed that wrapper techniques with bio-search algorithms is suitable to perform optimal features selection for ENORA algorithms. Besides that, the advantage bio-search algorithms of having random search function contributes more efficient searching especially while dealing with various size of datasets.

Table 4: Comparison of attribute reduction: NSGA-II vs NSGA-II + Bio-Search

Dataset	#Attr Ori	1st Rdc	2nd Rdc				
		#Attr NSGA-II Filtered	#Attr[NSGA-II + (Wrapper + Bio Search)]				
			Ant	Bat	Bee	Cuc	Fly
Breastcancer	9	9 (22.2%)*	7	7	7	6	7
Parkinson	22	6 (72.7%)*	5	3	5	5	5
Ozone	72	19 (73.6%)*	1	1	1	1	1
Clean1	166	7 (95.8%)*	15	17	15	15	14
Semeion	265	40 (84.9%)*	4	6	6	6	4
Emails	4702	49 (99.0%)*	8	11	4	7	14
Gisette	5000	216 (95.7%)*	14	20	13	18	20
Arcene	10000	7 (99.9%)*	93	86	56	80	84

** % of reduction from original attributes.*

Table 4 shows the reduction performance between NSGA-II+filtered verses NSGA-II+bio-algo+wrapper for performing optimal features (attributes) selection. Similar situation with ENORA has been captured in the case of NSGA-II+filtered method where it succeeded to decrease all datasets. NSGA-II performed better to reduce more than 94% attributes almost half of selected datasets (Clean1, Emails, Gisette and Arcene). Even though the performance of NSGA-II is better than ENORA in term of much less selected attributes in first reduction, this condition does not guarantee to obtain get the optimal set of attributes. Further experiment been conducted to optimize the NSGA-II algorithms with five (5) bio-search algorithm and wrapper method. Results shows superior reduction for all datasets compared to ENORA results. Overall, the result confirmed the combined methods of bio-search and wrapper adaptive behavior to search better set features selection for NSGA-II algorithms.

Table 5:. Comparison of classification accuracy of ENORA vs ENORA+Bio-search

Dataset	Acc (%) [Bef Rdc]	1st Rdc	2nd Rdc				
		Acc (%) ENO	Acc (%) [ENO + (Wrapper + Bio Search)]				
			Ant	Bat	Bee	Cuc	Fly
Breastcancer	96.2	96.2	**96.2**	**96.2**	**96.2**	**96.2**	**96.2**
Parkinson	84.8	89.4	87.9	**89.4**	**89.4**	**89.4**	**89.4**
Ozone	93.3	93.7	**93.9**	**93.9**	**93.9**	**93.9**	**93.9**
Clean1	85.8	75.9	**80.9**	**80.9**	**80.9**	**80.9**	**80.9**
Semeion	94.5	92.4	**92.4**	**92.4**	**92.4**	**92.4**	**92.4**
Emails	72.7	77.3	**77.3**	**77.3**	**77.3**	**72.7**	**77.3**
Gisette	91.5	88.2	*84.4*	*87.1*	*86.2*	*83.5*	*87.6*
Arcene	70.6	85.3	**88.2**	**88.2**	76.5	**88.2**	**94.1**

Table 5 displays the comparison of classification accuracy of ENORA vs ENORA+Bio-search. Surprisingly that attributes selected from all datasets by ENORA in the first reduction does not improve the classification accuracy which maintained the same accuracy results of the original datasets. Clearly, attributes selected in second reduction by ENORA+bio-search+wrapper method improved the accuracy of the classifiers. All bio-search algorithms (ant, bat, bee, cuckoo and firefly) demonstrated better classification accuracy for all datasets except Gisette dataset. But it is still considered acceptable since the percentage of reduction achieved is more than 50% (refer to Table 4) while maintaining good classification accuracy for Gisette dataset. Reduction using firefly algorithms achieved good classification results for all sizes of datasets. This result reflects the capability of search features in firefly algorithms I in which the manipulation of absorption coefficient parameter in evaluating the light intensity for new solution to be optimized.

Table 6:. Comparison of classification accuracy of NSGA-II vs NSGA-II + Bio-search

Dataset	Acc (%) [Bef Rdc]	1st Rdc Acc (%) ENO	2nd Rdc Acc (%) [ENO + (Wrapper + Bio Search)]				
			Ant	Bat	Bee	Cuc	Fly
Breastcancer	96.2	96.2	**96.2**	**96.2**	**96.2**	**96.2**	**96.2**
Parkinson	84.8	87.9	**87.9**	**84.8**	**87.9**	**87.9**	**87.9**
Ozone	93.3	93.9	**93.9**	**93.9**	**93.9**	**93.9**	**93.9**
Clean1	85.8	82.1	**84.0**	**83.3**	**83.3**	**83.3**	**83.3**
Semeion	94.5	93.4	92.6	93.4	93.4	93.4	92.6
Emails	72.7	77.3	**77.3**	**77.3**	**77.3**	**77.3**	**77.3**
Gisette	91.5	86.8	**88.2**	**88.2**	**88.2**	**88.8**	**88.2**
Arcene	70.6	85.3	**85.3**	**91.2**	76.5	76.5	82.4

Table 6 shows the comparison of classification accuracy of NSGA-II vs NSGA-II+Bio-search. Interestingly to highlight that attributes selected from all datasets by NSGA-II in the first reduction show inconsistent results which improved the accuracy for the half of the datasets. Another half shows decrement of classification accuracy. Obviously, the first reduction results by NSGA-II algorithm need to be optimized in order to get better classification accuracy. In second reduction, NSGA-II and bio-search algorithms with wrapper method show significant increment for all datasets. All bio-search algorithms show superior dominance which boosted the classification accuracy for all dataset (except Gissette). The parameters in all bio-search algorithms have been utilized for generating the best solution (feature to be selected).

Table 7:. Ideal Bio-search algorithms for ENORA and NSGA-II for feature selection

Multi-objective algorithm	Reduction Algorithm	Bio-search Algorithm
ENORA	WRAPPER	ACO, BA, ABC, CSA, FA
NSGA-II		

Table 7 shows the Ideal Bio-search algorithms for ENORA and NSGA-II for different ranges of datasets. The recommendation of this result can be used for searching task especially for near-optimal solution.

6. CONLUSION AND FUTURE WORK

In summary, impact of this paper can be seen in the area of data mining especially contributing alternative techniques for optimization problem in network security field. This alternative technique provides better understanding of implementing various bio-search algorithms to manipulate the exploitation and exploration of the search space especially for optimizing the multi-objective algorithms. This paper discovers new optimization technique for ENORA and NSGA-II that were compared and tested on eight (8) datasets. The suitable bio-search algorithms for ENORA and NSGA-II have been determined based on optimal selected features with high classification accuracy. Study on various bio-search algorithms and formulating the right setting of parameters for new optimization techniques would be the next research work to be explored.

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