Faculty of Engineering and Technology

Master Program of Computing

Modified Binary Cuckoo Search using rough set theory for Feature Selection

حل مشكلة اختيار المعالم باستخدام خوارزمية بحث الوقواق الثنائية المعدلة ونظرية مجموعات الاستقراب

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30/5/2015

Declaration of Authorship

I, Ahmed Fayez Alia, declare that this thesis titled, 'Modified Binary Cuckoo Search using rough set theory for Feature Selection' and the work presented in it are my own. I confirm that:

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- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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Modified Binary Cuckoo Search Using Roughset Theory For Feature Selection

By Ahmad Alia

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Abstract

Modified Binary Cuckoo Search using rough set theory for Feature Selection

by Ahmed Fayez Alia

Feature Selection (FS) for classification is an important process to find the minimal subset of features from original data by removing the redundant and irrelevant features. This process aims to improve the classification accuracy, shorten computational time of classification algorithms, and reduce the complexity of classification model. Rough Set Theory (RST) is one of the effective approaches for feature selection, but it uses complete search to search for all combinations of features and uses dependency degree to evaluate these combinations. However, due to its high cost, complete search is not feasible for large datasets. In addition, RST, as it replies on the use nominal features, it cannot deal efficiently with mixed and numerical datasets [1]. Therefore, Meta-Heuristics algorithms especially nature inspired search algorithms have been widely used to replace the reduction part in RST. In addition other factors such as frequent values are used with dependency degree to improve the performance of RST for mixed and numerical datasets.

This thesis aims to propose a new filter feature selection approach for classification by developing a modified BCS algorithm, and a new objective function based on RST that utilizes distinct values to select the minimum number of features in an improved computational time yet without significantly reducing the performance of classification for nominal, mixed, and numerical datasets with different characteristics.

In the evaluation, our work and baseline approach are evaluated on sixteen datasets that are taken from the UCI repository of machine learning database. Also our work is compared with two known filter FS approaches (genetic and particle swarm optimization with correlation feature selection). Decision tree and naïve bays classification algorithms are used for measuring the classification performance of all approaches that are used in the evaluation. The results show our approach achieved best feature reduction for all mixed, all numerical, and most of nominal datasets compared to other approaches. Also our work achieved less computational time for all datasets compared to the baseline approach.

ملخص

حل مشكلة اختيار المعالم باستخدام خوارزمية بحث الوقواق الثنائية المعدلة ونظرية مجموعات الاستقراب

مشكلة اختيار المعالم في التصنيف هي عملية مهمة لايجاد أقل عدد ممكن من المعالم من مجموعة البيانات الأصلية عن طريق إزالة المعالم التي لا تحوي أو تقدم أية معلومات هامة لخوارزميات التصنيف. هذه العملية تهدف إلى تحسين دقة نموذج التصنيف وتبسيطه وتقليل الوقت المطلوب لبنائه من قبل خوارزميات التصنيف. نظرية مجموعات الاستقراب هي إحدى الطرق الفعالة في اختيار المعالم، ولكنها تستخدم البحث الشامل للبحث في كل الحلول الممكنة، وايضا تستخدم درجة الاعتمادية لتقويم هذه الحلول. ولكن طريقة البحث الشامل مكلفة وغير مناسبة لمجموعات البيانات الضخمة، اضافة الى ذلك فإن درجة الاعتمادية فعالة فقط لمجموعات البيانات من النوع nominal. لذلك فإن خوارزميات الاداء العليا وخصوصا الخوارزميات المستوحاه من الطبيعة اصبحت تستخدم بشكل واسع لتحل محل البحث الشامل في طريقة مجموعات الاستقراب، بالاضافة الى عوامل اخرى مثل القيم المتكررة التي تستخدم مع درجة الاعتمادية لتحسين اداء مجموعات الاستقراب في مختلف انواع مجموعات البيانات.

هذه الاطروحة تهدف الى تقديم طريقة جديدة لمعالجة مشكلة اختيار المعالم في التصنيف من خلال تطوير خوارزمية الوقواق الثنائية وتطوير دالة هدف جديده تعتمد على نظرية مجموعات الاستقراب والقيم المتكرره لاختيار اقل عدد ممكن من المعالم بوقت قليل ومن دون تقليل واضح في كفاءة اداء خوارزميات التصنيف، وان يكون فعالا على انواع مختلفة من مجموعات البيانات المتنوعة في الخصائص.

في مرحلة التقييم، قمنا بتقويم عملنا على 16 مجموعة بيانات ماخوذة من UCI. ثم قمنا بمقارنة عملنا بثلاثة طرق اخرى معروفة من نفس الفئة: خوارزمية الوقواق الثنائية ونظرية الاستقراب قبل تعديلهما(الطريقة الاساسية). وخوارزمية اسراب الطيور والخوارزمية الجينية. ايضا تم استخدام خوارزميات التصنيف (خوارزمية شجرة اتخاذ القرار وخوارزمية naïve Bayes) من اجل تقويم اداء التصنيف في هذه الطرق الاربعة.

اظهرت النتائج ان طريقتنا الجديده حققت افضل النتائج على مستوى عدد المعالم المختارة بالاضافة الى قيم اداء التصنيف مقارنة بالطرق الاخرى التي استخدمت في التجارب في معظم مجموعات البيانات. ايضا الطريقة الجديدة مقارنة بالطريقة الاساسية احتاجت وقت اقل في كل مجموعات البيانات المستخدمة في التجارب.

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Special thanks for DR. Majdi Mafarjeh who helped me to choose the field of this thesis.

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Abbreviations

FS	**F**eature **S**election
NIAs	**N**ature **I**nspired **A**lgorithms
NIA	**N**ature **I**nspired **A**lgorithm
RST	**R**ough **S**et **T**heory
RSTDD	**R**ough **S**et **T**heory **D**ependency **D**egree
CS	**C**uckoo **S**earch
BCS	**B**inary **C**uckoo **S**earch
MBCSFS	**M**odifed **B**inary **C**uckoo **S**earch based on rough set theory for **F**eature **S**election
UCI	**U**niversity of **C**alifornia at **I**rvine
DT	**D**ecision **T**ree
NB	**N**aıve **B**ayes
POS	**P**ositive **R**egion
ACO	**A**nt **C**olony **O**ptimization
ACOFS	**A**nt **C**olony **O**ptimization based on **F**eature **S**election in Rough Set Theory
ACOAR	an efficient **A**nt **C**olony **O**ptimization approach to **A**ttribute **R**eduction in rough Set theory
AntRSAR	Finding Rough Set Reducts with Ant Colony Optimization
RSFSACO	**R**ough **S**et approach to **F**eature **S**election based on **A**nt **C**olony **O**ptimization
PSORSFS	Feature selection based on Rough Sets and Particle Swarm Optimization
ARRSBP	An Attribute Reduction of Rough Set Based on PSO

SPSO-RR	supervised hybrid feature selection based on PSO and rough sets for medical diagnosis
ABC	**A**rtificail **B**ee **C**olony
NDABC	Novel Discrete Artificial Bee Colony Algorithm for Rough Set based fetaure Selection
BeeRSAR	a Novel Rough Set Reduct Algorithm for Medical Domain Based on Bee Colony Optimization
BeeIQR	an Independent Rough Set Theory Approach Hyprid with Artificial Bee Colony Algorithm for Dimensionality Reduction
OPF	**O**ptimum-**P**ath **F**orest
BCSFS	**B**inary **C**uckoo **S**earch based on RST for **F**eature **S**election
3OG	**Three O**bjectives and **G**lobal
CFS	**C**orrelation based on **F**eature **S**election
Recc	**R**ecall average
DA	**D**ifference **A**ccuracy between accuracy of all features and accuracy of feature subset
Prec	**P**recision average
Acc	Acuuracy
CQA	**C**ongressional **Q**uarterly **A**lmanac
MBCSFS_T	**M**odifed **B**inary **C**uckoo **S**earch using **T**raditional objective function for Feature Selection
PCA	**P**rinciple **C**omponent **A**nalysis
CCA	**C**anonical **C**orrelation **A**nalysis
BCOA	**B**inary **C**uckoo **O**ptimization **A**lgorithm for Feature Selection in High-Dimensional Datasets
NKK	**K**-**N**earest Neighbor

This thesis is dedicated to:

My Mother's Soul

My Father

My dearest wife, who leads me through the valley of darkness with light of hope and support

My kids: Oday, and Sham
My Brothers and Sister

Chapter 1

Introduction

This chapter introduces the thesis. It describes the problem statement, motivations, goal and objectives, and organization of the thesis.

1.1 Introduction

The rapid grow of the volume of the data in many fields, such as web, scientific data, business data, presents several challenges to researcher to develop more efficient data mining methods to extract useful and meaningful information [2, 3]. Datasets are often structured as database table which its records are called objects, and its columns are called features which describe each object [4]. Classification is an important example of data mining, which aims to classify each object in the dataset into different groups [5, 6].

There is a large number of features in datasets which causes major problem for classification known as curse of dimensionality [3, 7] . Curse of dimensionality causes exponential increase in the size of search space with adding extra dimensions (features) for learning classification algorithm, and it makes the data sparser. In more details, the curse of dimensionality causes the following problems for classification [3, 7]:

- Reduces the classification accuracy.
- Increases the classification model complexity.

- Increases the computational time.
- Be a problem in storage and retrieval.

Usually, datasets have three types of features [3, 7]: First type is relevant features which provide useful information to learning classification algorithms. Second type is irrelevant features which provide no useful information to classification algorithms. Last type is redundant features that provide no more information than the currently selected features to classification algorithms. Redundant and irrelevant features are not useful for classification, this means removal of these features does not affect the useful information in the datasets for classification, and it helps to solve the curse of dimensionality problem [4, 5]. But usually, determining which features are relevant is very difficult before data collection, and before knowing the effects of redundant/irrelevant on classification algorithms. This means we faced feature selection problem, in other words, the goal of feature selection is that to determine the relevant features [3].

1.2 Problem Statement

Feature Selection (FS) is a general problem for data mining, which aims to select the most relevant features that are necessary and sufficient to the target concept [4]. Nowadays, the amount of data is growing rapidly due to rapid growth in technologies of data collection and storage. This means, the number of datasets is growing rapidly, datasets are larger and more complex. This increases the importance of FS nowadays and the need for data mining algorithms to extract the knowledge automatically from these large and complex datasets. This thesis will study the FS for classification.

Koller and Sahami [6] defined FS as " choose a subset of features for improving the classification performance or reducing the complexity of the model without significantly decreasing the classification accuracy of the classifier built using only the selected features ".

Number of selected features without significantly reducing the classification performance (Features Reduction), computational time, and datasets characteristics are three factors used to evaluate the FS approaches [3]. In general, good FS

approaches are capable to achieve features reduction in short computational time for different datasets with different characteristics such as different number of features, different number of objects, different types(nominal, mixed, and numerical datasets. section 2.1.1 explains these types) , and different number of classes [3, 8]. FS has two conflicting objectives (maximizing the classification performance with minimizing the number of features), for this, FS is multi objective problem [8, 9].

In general, the search strategy which is used to select the candidate feature subsets and objective function which is used to evaluate these candidate subsets are two main steps in any FS approach [3, 10]. Search strategy uses three strategies to search for subset of features which are: complete, heuristic and meta-heuristic search. Complete Search is very expensive because it covers all combinations of features. Heuristic Search is faster than complete search because it makes smart choices to select the near optimal subset without searching in all combination of features. Meta-heuristic needs less number of assumptions to find the near optimal feature subset compared to heuristic search. The objective function is responsible for determining the relevancy of the generated feature subset candidate towards classifier algorithms [3, 10].

Existing FS approaches are categorized into two categories: Filter approaches and wrapper approaches. Filter approaches select the feature subset independently from any classifier algorithms using statistical characteristics (such as dependency degree [11] and information measure [12]) of the data to evaluate these subset of features. But the wrapper approaches include a classification algorithm as a part of the objective function to evaluate the selected feature subsets. Filter approaches are much faster and more general than wrapper approaches [3]. This research is interested in filter FS approaches.

FS is an optimization problem that is the problem of finding the best solution from all feasible solutions [5]. In general, meta-heuristics algorithms are very efficient for optimization problems with very large search space [13]. Meta-heuristics algorithms represent a group of approximate techniques that aim to provide good solutions computed in a reasonable time for solving optimization problems, but does not guarantee the optimality of the obtained solutions [13, 14]. Nature Inspired Algorithms (NIAs) are a population meta-heuristic type that improves multiple candidate solutions concurrently [14], and they are developed based on characteristics of biological systems. NIAs are widely used in search strategy for FS. Also

Rough Set Theory Dependency Degree (RSTDD) is widely used as objective function for FS to measures the dependency between the combinations of features and class labels using dataset alone without complexity [15–17]. [18–26] are examples of filter FS approaches that combine RSTDD and NIAs.

Most approaches that use NIAs and RSTDD suffer from high computational cost, local optimal, slow convergence, weak global convergence, and hence not suitable for different datasets with different characteristics such as sizes, and features types [13, 27]. Therefore the Cuckoo Search (CS) is a powerful search algorithm in many areas, because it uses efficient local and global search mechanism (Hybrid mechanism) [28, 29]. At each iteration, CS uses global search to generate initial solutions for local search that makes a little modification to the solutions to find the nearest optimal feature subset [28].

CS is a NIA from the reproduction strategy of cuckoo birds. The advantages of CS are that it has quick and efficient convergence, less complexity, easier to implement, and fewer parameters compared with other NIAs [28–30]. Recently, two approaches have been reported to use Binary Cuckoo Search (BCS) to solve FS [31, 32], Unfortunately, [31] is a wrapper approach, and [32] is a filter approach with some limitations(see section 3.6 for details). BCS is a binary version of the CS, in which the search space is modeled as a binary string. According to experiments, the BCS algorithm used in [31] provides an efficient search algorithm for datasets that have less than 20 features (see section 4.3), but there is a potential to improve it to become faster, and more efficient for datasets that have large number of features.

According to [33], classification algorithms prefer the feature subsets which have high frequent values and high relevancy. But the RSTDD uses the dependency degree to evaluate the feature subset regardless of the frequent values, for this, most RSTDD objective functions are efficient for nominal datasets only [1]. In other words, RSTDD is inefficient for mixed and numerical datasets.

This thesis aims to develop new filter FS approach called Modified Binary Cuckoo Search based on rough set theory for Feature Selection (MBCSFS) to achieve feature reduction with improved computational time for nominal, mixed, and numerical datasets with different number of features, objects, and number of classes by modifying the BCS and developing a new objective function based on RSTDD, and distinct values.

1.3 Research Motivation

1.3.1 Why Feature Selection is important

As a computer power and data collection technologies grow, the huge amount of data is growing rapidly. This means many large and complex datasets are available that need to be analyzed to extract useful knowledge. Data mining such as classification has been used widely to search for meaningful patterns in datasets to extract useful knowledge. But larger datasets, the more complex the classification algorithms needed to improve the accuracy, and reduce the cost. FS aims to reduce the number of features of datasets by selecting the relevant features to achieve the following benefits[2, 3, 5] :

- Improving the performance of classification.
- Reducing the complexity of classification model.
- Reducing the computational time.
- Reducing the storage requirements.
- Providing a better understanding of the data.
- Help to improve the scalability issues.

1.3.2 Challenges of Feature Selection

- FS is a multi-objective problem which aims to balance between the two conflicting objectives [74]. Two objectives, one of them maximizes the classification performance and the other minimizes the number of selected features. Many FS approaches succeed to find the high classification performance, but they fail to find minimum number of features.
- Datasets have different characteristics, such as number of features, number of objects, features types. This makes it difficult to find an approach suitable for all datasets. Some of FS approaches are not suitable for large datasets [18–20]. Also some approaches are not efficient for mixed and numerical datasets such as FS approaches that use RSTDD only [21, 22].

- The size of the search space grows exponentially. This means the number of possible subsets of features is 2^n, n is the number of features in the dataset, this makes the complete search impractical [4]. To solve this problem, the FS approaches use variety of smart techniques to search for subset of features without searching in all possible subsets of features [4]. Meta-heuristics algorithms especially NIAs are very efficient for optimization problems such as FS [13]. But most existing approaches suffer from high computational time and weak convergence.

1.3.3 Why Binary Cuckoo Search

BCS is a suitable algorithm to address the search strategy in feature selection problems for of the following reasons:

- BCS uses a vector of binary bits to represent a search space and a candidate feature subsets. This is appropriate to feature selection problem. Where the size of a vector is the number of features in the search space, and the value in each bit shows whether the corresponding feature is selected or not (1 means selected, 0 means not) [18, 34].
- The search space of FS is large [3], this often causes high computational cost, slow convergence, and weak global convergence. BCS is less expensive and can converge faster than other approaches and it is able to effectively search in large spaces to find the best solution, because it uses global search and efficient local search [13, 27].
- BCS is easier to implement and it needs fewer parameters compared with other NIAs [31].
- To the best of our knowledge, one filter approach [32], and one wrapper approach[31] used BCS to solve the FS. They have shown that BCS has the potential to address feature selection problem, and that it suffers from some problems especially for large datasets, such as weak convergence, needs extra number of iteration to find the best solution and mostly miss small optimal solution. There is a potential to modify BCS for FS to solve these problems .

1.3.4 Why Rough Set Theory

Rough Set Theory (RST) is a mathematical tool to data analysis and data mining, RST provides RSTDD to measures the dependency between the features [16, 17, 35]. RSTDD is widely used in FS to build objective function to guide the search algorithms to optimal/nearest solution by calculating the dependencies between the feature subsets and class labels. RSTDD is efficient method for the following reasons [16, 17, 35, 36]:

- It does not need any preliminary or additional information about data.
- It allows evaluating the significance of data.
- It is easy to understand.
- Relatively cheaper, when compared to other methods.

1.3.5 Limitations of Existing Work

Filter FS approaches that combine NIAs and RSTDD are efficient approaches, But most of them suffer from some limitations. Slow, weak convergence, and complex implementation problems increase the computational time of search algorithm such as approaches that used ant colony optimization algorithm [17, 18, 20]. Some approaches do not cover all search space (weak convergence) which increases the potential to miss nearest optimal feature subsets, in other words, these approaches generate the feature subsets that have around half number of available features, which means, these approaches miss the small and large optimal feature subset, especially on datasets that have 70 features in the best case, 70 features is selected from experiments results of [21–26, 31] . Also some approaches are affected by poor initial solutions such as [21–23] . Other approaches use hybrid search mechanism to increase the efficiency of convergence, but the local search in this mechanism is weak, and the global search does not cover all search space such as approaches [24–26]. BCS that is used in [31, 32] approach uses hybrid mechanism, but the global search does not cover all search space, while the local search is very strong. There is a potential to improve BCS's global search to make the BCS faster and cover most of the search space.

RSTDD is used in many filter FS to create their objective function [18–26]. But RSTDD has a main drawback which is inefficient for mixed and numerical datasets [1]. Classification algorithms prefer the feature subsets that their features are relevant and have more frequent values [33]. RSTDD measures the relevancy without measuring the frequent values in each subset. Therefore RSTDD is a bad indicator for classification performance in mixed and numerical datasets, because the frequent values in features in these datasets is varies significantly.

1.4 Research Goals

The overall goal of this thesis is to improve the BCS and develop a new objective function to propose a new filter FS approach for classification. We refer to our new approach as is MBCSFS, and it aims to reduce the number of selected features without significant reduction of classification performance in short computational time for mixed, nominal, and numerical datasets with different number of features, objects, and classes. To achieve this overall goal, the following research objectives have been established:

- Developing new initialization mechanism which is dividing the initialization mechanism to three parts to cover most of search space. The first part generates randomly small feature subsets. Second part generates randomly medium feature subsets. Last part generates randomly large feature subsets. This mechanism helps to increase the speed of convergence, and it makes the convergence covers most of the search space.
- Developing new global search which is also divided to three parts as new initialization mechanism to make the convergence more efficient.
- New stopping criterion is proposed to stop the algorithm when in three successive iterations there are no improvement in the current solution. This helps to reduce the computational time.
- New objective function based on RSTDD and distinct values was developed to guide the MBCS to feature subsets that have minimum number of features and maximum classification accuracy. This objective function calculates the quality of feature subsets by balancing between the dependency, distinct

values and their size. The function used RSTDD to measure the dependency between the selected features and class labels. It used distinct values to measure the frequent values for feature subsets.

- In order to examine the performance of the proposed algorithm (MBCSFS), it is compared to BCSFS which is described as the baseline of MBCSFS, and it is the first approach that combines the RSTDD [19] and BCS [31], genetic [37] with correlation feature selection [38], and particle swarm optimization [39] with correlation feature selection [38] these approaches are run on sixteen datasets (UCI repository of machine learning database [40]). To evaluate these approaches, Decision Tree [41], and naïve Bayes [42] classification algorithms are used to measure the precision, recall and accuracy for each approach and each run .

1.5 Research Methodology

This section describes the research methodology that was followed.

- To conduct a literature of filter FS approaches for classification to identify recent approaches in the area, and identify limitations of existing approaches.
- To develop a new filter FS approach using NIA and RSTDD to improve the performance of FS for nominal, mixed and numerical datasets with different characteristics.
- To develop an evaluation methodology for the new approach using the baseline approach, known similar filter FS approaches, classification algorithms, and datasets with different characteristics.
- To select nominal,mixed and numerical datasets with different number of features, different number of objects and different number of classes. And then conduct experiments based on the evaluation methodology by running developed approach, baseline approach and known similar filter FS approaches on selected datasets. And we will use known classification algorithms to evaluate these approaches.
- To analyze experiment's results by comparing the results of developed approach with the baseline approach and known similar filter FS approaches.

Number of selected features, performance of classification(accuracy,precision and recall), and computational time are factors to consider for comparisons.

1.6 Organization of the Thesis

The remainder of this thesis is structures as follows:

Chapter 2: Background. Presents the basic concepts of classification and feature selection.

Chapter 3: Literature Review. Reviews traditional related works in feature selection, and focuses on current filter feature selection which combines the NIAs and RSTDD.

Chapter 4: Proposed algorithm. Proposes new filter feature selection approach that improves the current BCS, and it develops new objective function based on RSTDD and distinct values.

Chapter 5: Evaluation and Results. Examines the performance of our approach, and compared it to three other approaches. First approach is a baseline of our approach (BCSFS). Genetic and particle swarm optimization with correlation feature selection are the second and third approaches. Then, the results are evaluated by decision tree and naive bayes classification algorithms, and results are discussed.

Chapter 6: Conclusion. It discusses the conclusions of thesis, limitations and assumptions, and also suggests some possible future work.

Chapter 2

Background

This chapter aims to provide a general discussion of the concepts needed to understand the rest of the thesis. It covers basic concepts of classification and feature selection.

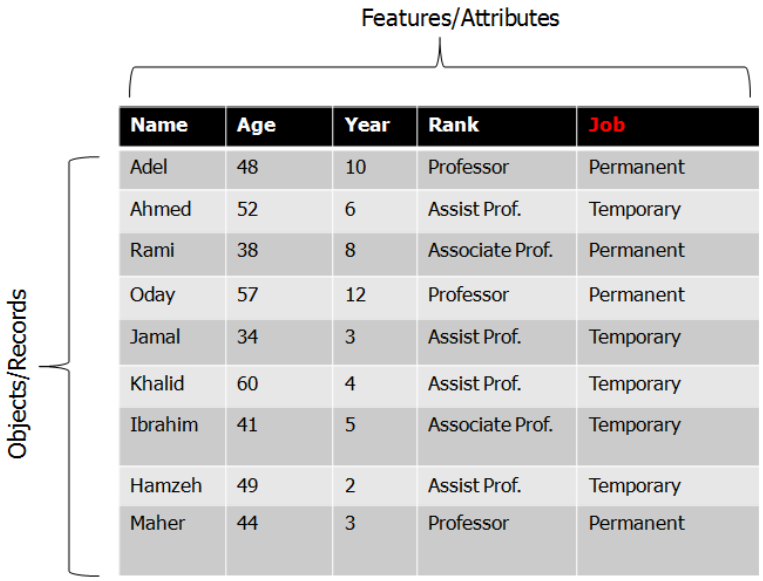
2.1 Classification

The main goal of classification is to classify unseen objects to predefined classes as accurately as possible [2–4]. Classification algorithm uses a group of objects which is each object is classified into classes to build classification model. Classification model takes the values of the features of an unseen object as input and then predicts the classes of these objects [2–4]. The following sections review the data representation, learning and evaluation, classification performance, classification algorithms, and main challenge of classification.

2.1.1 Data Representation

This research focuses on the structured dataset as representation system for classification. Numbers of attributes are defined as properties of an object to help understand and extract hidden useful information from datasets. These attributes are called features. A structured dataset is represented as one database table, where each column represents a particular feature, and every row is an object, See Figure 2.1 [4]. Each object is represented in a vector of values, each value

represents a feature. And there are two types of features: First type is nominal or categorical features that have small number of possible values. Second type is Numerical features that takes any values (can be real or integer numbers.)[4]. In Figure 2.1, Rank and Job are nominal features. Age is a numerical feature. According to types of features in datasets, datasets are categorized to three groups: First group is nominal datasets which their features is nominal. Second group is numerical datasets which their features is numerical. Last group is mixed datasets which some of their features is nominal and other features is numerical features [40].



Name	Age	Year	Rank	Job
Adel	48	10	Professor	Permanent
Ahmed	52	6	Assist Prof.	Temporary
Rami	38	8	Associate Prof.	Permanent
Oday	57	12	Professor	Permanent
Jamal	34	3	Assist Prof.	Temporary
Khalid	60	4	Assist Prof.	Temporary
Ibrahim	41	5	Associate Prof.	Temporary
Hamzeh	49	2	Assist Prof.	Temporary
Maher	44	3	Professor	Permanent

FIGURE 2.1: Example of Dataset.

2.1.2 Learning and Evaluation

To build classification model, classification algorithms need a dataset in which each object is classified into classes. In other words, each object has a set of features, one of them is class [4, 5]. For example in Figure 2.1, each object has five features, but the job feature is class for each object. The given dataset is divided into training and test sets, training set is used to build (learn) the classification model and test set is used to evaluate it.

2.1.3 Classification Performance

Accuracy is one important measure that is used to evaluate the performance of classification [4]. To calculate the classification accuracy, it is applied on test set, then count the number of correct predictions and divide it by the total number of predictions, multiply it by 100 to convert it into a percentage. But the accuracy is not enough to evaluate the performance in some datasets, especially when most objects are assigned to specific class. For this, we need another measures to evaluate a classification performance for each class in dataset in addition to accuracy that evaluates the overall correctness of the classifier [43, 44].

Precision and Recall are very efficient to evaluate the classification model for each class when the accuracy is high. Precision is a fraction of correct predictions for specific class from the total number of predictions (Error + Correct) for the same class. Recall (also known as sensitivity) is a fraction of correct predictions for the specific class from the total number of objects that belong to the same class [43, 44].

Most classification algorithms summarize the results in confusion matrix [45]. It contains information about predicted and actual classifications. Table 2.1 shows the confusion matrix for two classes (A and B), and the entries as follows.

		Predicted	
		Class A	Class B
Actual	Class A	TA	FB
	Class B	FA	TB

TABLE 2.1: Confusion Matrix.

TA: the number of correct predictions that an object is A.
FA: the number of incorrect of predictions that an object is A.
TB: the number of correct predictions that an object is B.
FB: the number of incorrect predictions that an object is B.

$$Accuracy(Overall) = \frac{TA + TB}{TA + FB + FA + TB} \tag{2.1}$$

$$Precision(A) = \frac{TA}{TA + FA} \tag{2.2}$$

$$Recall(A) = \frac{TA}{TA + FB} \tag{2.3}$$

2.1.4 Classification Algorithms

Many classification algorithms have been proposed to build the classification model. Decision Tree and naïve Bayes two different types of classification algorithms that are most common[3, 4, 46]. This section reviews briefly the decision tree and naïve Bayes classification algorithms that will be used in this thesis to measure the classification performance, For more details about Decision Tree and naïve Bayes, you can visit [46].

2.1.4.1 Decision Tree

Decision Tree (DT) is a method for approximating discrete valued functions [4] and it summarizes training set in the form of a decision tree. Nodes in the tree correspond to features, branches to their associated values, and leaves of the tree correspond to classes. To classify a new instance, one simply examines the features tested at the nodes of the tree and follows the branches corresponding to their observed values in the instance. Upon reaching a leaf, the process terminates, and the class at the leaf is assigned to the instance [3].

To build a DT from training data, DT's algorithms use greedy approach to search over features using a certain criterion such as gain and gini index to evaluate the features in order to select the best feature for splitting the input training set(objects) into smaller subsets to create a tree of rules. In more details, if the subsets of objects belong to the same class, then the node is class label. But if the subsets of objects belong to more than one class, then split it to smaller subsets. Recursively apply these procedures to each subset until a stop criterion is met [41, 46].

2.1.4.2 Naïve Bayes

Naïve Bayes (NB) is a simple probabilistic classification algorithm that uses Bayes theorem with independent assumption between the features to predict class membership probabilities. It calculates the probability of unseen instance based on each class, then it assigns this instance to the class with the highest probability. Learning with the NB is straightforward and involves simply estimating the probabilities from the training set. NB is easy to construct and efficient for huge datasets, but it is weak when applied on datasets that have many redundant features, this means, NB is a good classification algorithm to evaluate the FS approaches over redundant features [3, 42].

2.2 Feature Selection

FS studies how to select minimum subset of features from the original set while keeping high accuracy in representing the original features in short computational time [2, 3]. according to[3] FS is " process that chooses an optimal subset of features according to a certain criterion". This section reviews some concepts that is related to FS. The Following section reviews general FS steps, filter FS, and wrapper FS.

2.2.1 General Feature Selection Steps

In general, FS algorithms (approaches) include five basic steps: Initial subset, generation strategy, objective function, stopping criterion, and validation step [3, 10]. See figure 2.2. Generation strategy starts from initial step to generate new subset of features for objective function (evaluation step) to measure the quality of it. Algorithm continues generating new candidate subsets of features until stopping criterion is met. FS steps are discussed as follows.

Initialization: Any FS algorithm (approach) starts from initial subset or subsets of features. There are three types of initial subset. First, empty subset. Second, full subset. And the last is random subset [3, 10].

Search Strategy: is responsible to generate new candidate subset of features to objective function. It starts from one of the initial subsets: Empty subset, features

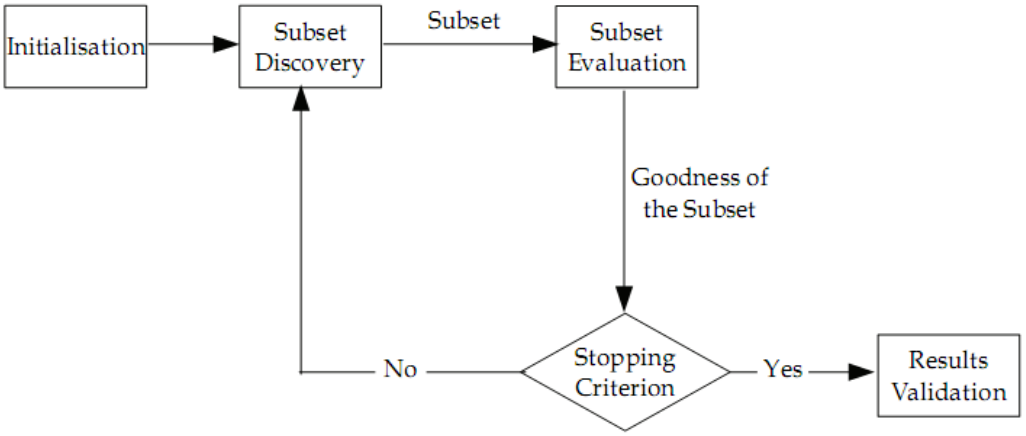


FIGURE 2.2: General FS steps [8].

are added. Full subset, features are removed. Random subset, features are added, or removed or created randomly. Complete, random and heuristic are types to generate the next candidate subset of features [3, 10].

- Complete Search: Searches for all combinations of subsets of features. If the number of features in search space is n, this means the number of subsets of features is 2^n. But this type of search is very expensive and sometimes is impractical.
- Heuristic Search: Makes smart choices to select the near optimal subset without searching in all combination of features. It is fast, but it does find the optimal solution.
- Meta-heuristics Search: Like heuristic Search, but Meta-heuristics Search has faster, and more efficient convergence compared to heuristic Search.

Objective Function: is responsible to determine the quality of subsets of features. This function is very important in any FS algorithms, because it guides the algorithm to find the optimal subset of features.

Stopping criterion: is responsible to stop the algorithm when the candidate of subset features met the objective function (found the best solution), or the number of iterations reached the maximum [10**?**]

Validation: This step is not a part of FS algorithm to search for subset of features. It is responsible to validate/evaluate the FS algorithm by validating the selected subset of features on the test set [3]. The results are compared with previous results to determine the performance of algorithm [3].

All steps are important for FS approaches, but the search strategy, and objective function are two main factors for determining the efficiency of FS approaches.

2.2.2 Filter and Wrapper approaches

According to objective function, FS approaches are generally categorized into filter and wrapper approaches. Filter approaches select the feature subset independently from any classification algorithms, and the subset of features are evaluated using certain criterion such as dependency degree [11], distance measure [8] and information measure[12]. In this type, objective function is indicator for classification performance. FOCUS [47], RELIEF[48], LVF[38], Greedy search[49] are filter FS approaches. Also, [18–26] are filter FS approaches that combine NIAs with rough set theory. These approaches will be reviewed in next chapter.

Wrapper approaches include classification algorithm as part of the objective function to evaluate the selected feature subsets. In other words, classification algorithm performance used objective function to evaluate the subset of features [2, 3]. Sequential forward selection[50], Sequential backward selection[51], linear forward selection[52], PSO[53], ACO[54] are wrapper FS approaches.

Wrapper approaches give high classification accuracy on a particular classification algorithm, because it mixed between the classification algorithm and objective function. But it is very expensive, because each evaluation includes a training processes and testing processes of the classification algorithm[55]. While filter approaches are much faster and more general than wrapper approaches [2, 3]. This thesis focuses on filter approaches.

2.3 Summary

This chapter presented some of the essential background concepts for FS and classification, as a basis for the work in this thesis.

The next chapter reviews typical related works in filter FS.

Chapter 3

Literature Review

This chapter reviews related works in filter feature selection for classification. In general, dimensionality reduction approaches can be categorized into feature extraction (transformation) and FS [1]. Feature extraction approaches apply a transformation to dataset to project it into a new feature space with lower dimension, and they need to make mapping between the original feature space to a new feature space [1, 56]. Principle Component Analysis (PCA)[57] and Canonical Correlation Analysis (CCA)[58] are examples of feature extraction. Where as FS, which the work of this thesis focuses on, selects a subset of features from the original dataset without any transformation and mapping. FS approaches are divided into two main groups: First, ranked approaches which failed to find the nearest optimal feature subset. Second, feature subset approaches which are divided to three groups: Complete, heuristic, and meta-heuristics approaches. Meta-heuristics approaches are capable of finding the nearest optimal feature subset in shortest computational time. NIAs are a very efficient type of meta-heuristics for FS's search strategy. This thesis aims to develop a new filter FS based on NIA and RSTDD, for this, we focus on filter FS approaches that use NIA in their search strategy and use RSTDD in their objective function. Appendix D shows the map of classifications of dimensionality reduction.

3.1 Introduction

In general, chapter two reviews the classification and FS, and it shows the importance of FS for classification. A lot of work of FS has been developed from

70's , and most of these FS approaches try to achieve three goals: First is feature reduction which means select the minimum number of features without significant reduction of classification performance. Second is short computational time. And the last to support different data characteristics, which means the FS is efficient for nominal, mixed, and numerical datasets with different number of features, different number of objects, different number of classes, and different areas [3].

FS approaches are categorized into two groups [59, 60]: First is ranked approaches which depend on single feature evaluation to select the best feature subsets. Ranked approaches measure the score (quality) of each feature, and then these features are ranked according to their score to select the best subset. Relief is a ranked approach [48]. The main problem in these approaches, is that the relevant features cannot be evaluated independently from the other features, therefore the subset of top ranked features, may include high number of irrelevant and redundant features. While the combination of different ranked features may contain low number of irrelevant and redundant features [59, 61–63]. This means, ranked approaches are not capable to achieve the optimal feature reduction, but they are cheap. To avoid this problem, many FS are implemented with feature subset evaluation instead of single feature evaluation, these approaches are a second group which is a feature subset approaches. Also feature subset approaches are categorized into three groups based on search strategy that used in these approaches to complete, heuristic, and meta-heuristics approaches [60].

Complete approaches search for all possible feature subsets to find the optimal feature subset, this means, the number of feature subsets needs to be generated is 2^n, where n is the number of features. These approaches achieve the feature reduction, but they are very expensive (exponential time), practically impossible [3, 60, 64]. Focus approach is example of complete approaches [47]. Heuristic Approaches try to find the best feature subset without searching in all possible feature subsets to reduce the computational time compared to complete approaches. The complexity time of heuristic is quadratic, but the complete is exponential [60, 64]. In general, heuristic approaches apply local changes to the current feature subset to reach to best feature subset. The main drawbacks of heuristic approaches are they do not guarantee the optimal feature subsets, and it stuck to the local optimal which mean the neighbor solutions is worse than the current solution, and the current solution is worse than global optimum [3, 60]. Greedy Search [49] is example of heuristic approaches which are like ranked approaches do not achieve

the feature reduction. Recently, meta-heuristic approaches show more desirable results compared to previous approaches.

FS is optimization problem which is the problem of finding the best solution from all feasible solutions [6], meta-heuristics algorithms are very efficient for this type of problems [13, 14]. Meta-heuristics algorithms represent a group of approximate techniques that aim to provide good solutions computed in a reasonable time for solving optimization problems, but does not guarantee the optimality of the obtained solutions [13, 14]. In general, meta-heuristics algorithms have more efficient, and fast convergence compared to heuristic algorithms [14]. NIAs are powerful type of meta-heuristics algorithms which improve the population of solutions in each iteration, and they are developed based on characteristics of biological systems like ants, bee, swarm of birds to find the source of food, and cuckoo reproduction, therefore some of NIAs can be called biology inspired[65, 66]. The main idea in these systems, agents/particles corporate with each other by an indirect communication medium to discover the food sources, or achieve some things [25]. The advantages of NIAs: They may incorporate mechanisms to avoid getting trapped in local optima. They can be easily implemented. Also these algorithms are able to find best/optimal solution in a reasonable time due to efficient convergence [13].

Recently, many of filter FS that combines NIAs with RSTDD are widely used to develop their objective function such as [18–26], because RSTDD is efficient, easy to implement, no need to any additional information about data, and cheap compared to mutual information and entropy methods [30, 73]. Following sections review nine filter FS that combine NIA with RSTDD [18–26], in addition to two FS approaches that use NIA without RSTDD [31, 32]. To easy reviewing these approaches, firstly, RSTDD is reviewed, then ten approaches are revived according to the NIA which is used in them.

3.2 Rough Set Theory

RST was developed by Zdzislaw Pawlak in the early 1982s [15] as a mathematical tool that deals with classificatory analysis of data table(structured dataset). RSTDD and positive region are two important issues in data analysis to discover the dependency between the feature subsets and class labels. Positive region

(POSp(Q)) contain all objects that can be classified to classes of Q using information in P. The RSTDD can be defined in equation 3.1 [17, 35, 67]. Appendix A contain more details about RST.

$$\gamma_P(Q) = \frac{|pos_P(Q)|}{|U|} \tag{3.1}$$

Where $|U|$ is the total number of objects, $|pos_P(Q)|$ is the number of objects in a positive region, and $\gamma_P(Q)$ is the dependency between feature subset p and classes Q.

In the literature there are two frequently used objective functions that use RSTDD and balancing it with the number of selected features (size of feature subset).

Jensen et al.[19] proposed the first one (equation 3.2) as follows:

$$Objective function(P) = \gamma_P(Q) * \frac{|C| - |P|}{|c|} \tag{3.2}$$

Also Xiangyang Wang et al. [21] proposed a second multi objective objective function(equation 3.3) as follows:

$$Objective function(P) = \alpha * \gamma_P(Q) + (1 - \alpha) * \frac{|C| - |P|}{|C|} \tag{3.3}$$

Where $|C|$ is the total features, $|P|$ is the number of selected features, Q is class, and $\gamma_P(Q)$ is the dependency degree between feature subset and class label Q, α belong to [0,1] and it is a parameter to control the importance of dependency degree and subset size. Normally, the value of α is 0.9 to give most importance to the dependency than the size of subset[21].

RSTDD is an indicator for classification performance, it gives the same importance to all feature subsets that have the same dependency degree, and this is not correct for all feature subsets for classification algorithm. In general, features that have more frequent values and higher relevance are more desirable to classification algorithms, it helps these algorithms to build a classification model in easier and faster way, and better classification performance[33]. For these reasons, RSTDD is efficient for nominal datasets that their features have roughly the small set of values, but inefficient for mixed and numerical datasets that have some features

with large and different number of frequent values, and low frequent values in some other features [1]. RSTDD measures the dependency between the feature subset and class labels without measuring the frequent values. Measuring the dependency in nominal datasets is enough because their features have high frequent values, but in mixed and numerical datasets, it is necessary to measure the frequent values in addition to dependency, because there is a big difference in number of frequent values between features in each dataset, and the number of frequent values in most numerical features is very low which helps to increase the value of dependency degree between the subset and class label regardless of the average of frequent values in these subsets.

Finally, RSTDD is inefficient for mixed and numerical datasets, one goal of this thesis is to develop new objective function based on RSTDD with improved efficiency for nominal, mixed, and numerical datasets. This means approaches [18–26] that use RSTDD in their objective function are inefficient for mixed and numerical datasets.

Before reviewing approaches [18–26] according to the search strategy (NIAs), we define NIAs' search mechanisms which plays an important role in the effectiveness of each NIA. Local, global, and hybrid search are mechanisms that are used in NIAs to update the population of feature subsets to solve the FS [68]. Local Search aims to find the best possible solution to a problem (Global Optimum) by iteratively moving from current solution to better neighbor solution. But sometimes, current solution is better than all neighbors' solutions, and it is worse than global optimum. In this case, the local search suffers from local optimum problem and stops searching. The advantage of local search is that it is relatively efficient (fast), but it is affected by poor initial solutions, and it does not guarantee the global convergence [14, 68]. Global Search searches for the candidate solution in all the search space until it finds the best solution or reaches maximum iterations. But it is slow [14, 68]. Hybrid Search aims to increase the convergence more efficiency (to avoid be trapped in local optimum), and to guarantee the global convergence as soon as possible by using global search to generate initial solutions for local search [68].

3.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a NIA presented by Dorigo et al in 1992 [69], it simulates the behavior of real ants that use chemical material called pheromone to find the shortest path between their nest and the food source. And when each ant finds the food it returns to nest laying down a pheromone trail that evaporate over time, then each ant follows the path that has large amount of pheromone[69].

ACO uses graph to represent the search space, features are represented as nodes, and edges between the nodes determine the best next connected feature. Every ant selects one node then uses a suitable method (Heuristic measures) and amount of pheromone material on each connected edge to select the best connected node to construct the population of candidate feature subsets [69].

We found three approaches in the literature for feature selection based on ACO and RST. The first approach is Ant Colony Optimization based on Feature Selection in Rough Set Theory (ACOFS)[20]. An efficient Ant Colony Optimization approach to Attribute Reduction in rough Set theory (ACOAR)[18] is the second approach. The last approach is Finding Rough Set Reducts with Ant Colony Optimization(AntRSAR) [19].

The three approaches update the pheromone trails on each edge after constructing each solution, but in ACOAR the pheromone values are limited between the upper and lower trail limits to increase the efficiency of algorithm.

The heuristic measure in the AntRSAR approach uses entropy information, but ACOFS and ACOAR use RSTDD which makes ACOFS and ACOAR cost less compared to AntRSAR, because the entropy information is expensive compared to RSTDD.

In general, ACO has some drawbacks. First, complex implementation and slow convergence, because it uses graph to represent the search space [13, 14]. Complex implementation and slow convergence means, these approaches that use ACO are very expensive, and not suitable for large datasets (maximum size of datasets that are used in experiments of these approaches is 69 features [18–20]).

3.4 Particle Swarm Optimization

Particle swarm optimization (PSO) is a NIA developed by Kennedy and Eberhart [70]. In nature, PSO simulates the movements of a flock of birds around food sources, a flock of birds moving over an area where they can smell a hidden source of food. The one who is closest to the food tweets loudly, and the other birds tweet around in its direction. This means the birds closer to the target tweets louder. This work continues until one of the birds find the food [70, 71].

PSO uses Particles as birds to search for the best solution in search space which are represented in binary representation. The position of each particle is a possible solution and the best solution is the closest position of particle to the target (food). Particles move in the search space to search for the best solution by updating the position of each particle based on the experience of its own and its neighboring particles. Each particle has three vectors, first vector represents the current position, second one for the velocity of particle, and the last one represents the best previous position that is called personal best (pbest). But the algorithm stores the best solution in all particles in a vector called global best solution (gbest) [70]. [21–23] are filter FS approaches that use PSO to generate population of candidate feature subsets.

We found three approaches in the literature for solving FS using PSO and RSTDD, the first is Feature selection based on Rough Sets and Particle Swarm Optimization (PSORSFS) [21], the second is An Attribute Reduction of Rough Set Based on PSO (ARRSBP) [22], and the last is supervised hybrid feature selection based on PSO and rough sets for medical diagnosis (SPSO-RR) [23].

Xiangyang Wang, et al (PSORSFS) [21] added limitation to the particle velocity to avoid local optima, and move the particle to near global optimal solution. Because high velocity moves the particle far away from global optimal, and low velocity causes the local optimal.

Hongyuan Shen, et al ARRSBP [22] changed the values of weight parameter from 0.1 to 0.9 to balance between the pbest and gbest in generations.

H. Hannah Inbara, et al (SPSO-RR) [23] developed two algorithms for medical datasets. First, it combines the PSO and quick reduct based on dependency degree. And second algorithm combines the PSO and relative reduct based on relative dependency.

In general, PSO is easy to implement, and cheap. But it has weak convergence, trapped into local optimum when it is applied on large datasets (maximum size of datasets that used in experiments of these approaches is 57 features) [70, 71]. Also PSO is affected by the poor initial solutions [71].

3.5 Artificial Bee Colony

Artificail Bee Colony(ABC) algorithm is a NIA that is inspired by the natural foraging behavior of honey bees. ABC is proposed by Karaboga [72]. In nature the colony consist of three types of bees, employed bees, onlooker bees, and scout bees. The foraging process starts by scout bees that move randomly to discover the food sources. When the scout bees find the food sources, they return to their hive and then start dancing (Waggle dance) to share their information about the quality of food sources with onlooker bees, then depending on this information more bees are recruited (employed bees) to the richness food source, but if any bee finds the food source is poor, the bees call scout bees to discover randomly new source food and so on [72, 73].

The position of a food source represents a possible solution using binary representation, and the nectar amount of food source considered as the quality of the solution. Each bee tries to find the best solution. ABC combines the global search and local search to find the best solution [72, 73]. The ABC algorithm starts with the n scout bees that select randomly population of candidate solutions as initial solutions. Then, these solutions are evaluated, and it selects the candidate solutions that have maximum quality for local search, and the remaining for global search to construct new population of candidate solutions. Then the quality of each solution in new population is evaluated, if the algorithm gets the best solution then the algorithm stops, otherwise it continues searching until it finds the best solution or arrives to maximum number of iterations [72, 73]. [24–26]are filter FS approaches use ABC to generate population of candidate feature subsets.

We found three approaches in the literature for solving FS using ABC and RSTDD, the first is a Novel Discrete Artificial Bee Colony Algorithm for Rough Set based fetaure Selection(NDABC) [24], and second is a Novel Rough Set Reduct Algorithm for Medical Domain Based on Bee Colony Optimization BeeRSAR [25], and

the last is an Independent Rough Set Theory Approach Hyprid with Artificial Bee Colony Algorithm for Dimensionality Reduction (BeeIQR) [26].

Yurong Hu, et al. [24] combined ABC and RSTDD to solve FS in an efficient way. This approach changed one feature by either adding one feature or removing one randomly in local search, a major weakness of this approach. And it uses a random mechanism in global search.

Suguna,et al [25, 26] proposed two approaches that are similar in all things except the initial population started from feature core(Start from set of features) , but [26] started randomly. In local search, more than one feature is randomly changed with some criteria, and random strategy is used in global search.

In general, ABC is a very efficient algorithm that solves the local optimal problem by using hybrid search mechanism. But the local search in this algorithm causes slow convergence [27]. Also these approaches[24–26] are not suitable for large datasets (maximum size of datasets that used in experiments of these approaches is 69 features[24–26]).

3.6 Cuckoo Search

Cuckoo Search (CS) is a new and powerful NIA algorithm that was developed by Yang and Deb in 2009[14]. CS is a search algorithm inspired by the breeding behavior of cuckoos and L'evy flight behavior of some birds and fruit flies which is a special case of random walks [28, 31, 32, 74]. The reproduction strategy for Cuckoo is aggressive. Cuckoos use the nests of other host birds to lay their eggs in, and rely on these birds for hosting the egg. Sometimes the other host birds discover these strange eggs and they either throw these strange eggs or leave their nest and build a new one. Cuckoos lay eggs that look like the pattern and color of the native eggs to reduce the probability of discovering them. If the egg of the cuckoo hatches first, then the cuckoo chick destroys all eggs in the nest to get all the food that is provided by its host bird [28, 75].

Algorithmically, each nest represents a solution, CS aims to replace the "not so good" solution (nest) with a new one that is better. CS uses local and global search (Hybrid search) to update the population of solutions, local search update

the solutions that have highest quality, and the rest of solutions are replaced with new solutions randomly in global search.

Many optimization problems in different domains are solved in by CS to achieve improved efficiency, table 3.1 is repeated here from [76] to show some of these applications for convince. For further details and applications, see [77].

Binary Cuckoo Search for feature selection [31, 87], and Binary Cuckoo Optimization Algorithm for Feature Selection in High-Dimensional Datasets(BCOA) [32] are two approaches that use BCS. But the first approach is a wrapper approach, and the second is a filter approach. To the best of our knowledge, [31, 32] are the only two FS approaches that use BCS alone in their search strategy. The following paragraphs explain these two approaches in details.

Binary representation: Search space is modeled as a binary n-bit string, where n is the number of features [31, 32]. BCS represents each nest as a binary vector, where each 1 corresponds to a selected feature and 0 otherwise. This means each nest represents a candidate solution, and each egg represents a feature.

Initialization strategy: Generating an initial population of n nests randomly by initializing each nest with a vector of binary value. Both [31, 32] use this strategy which does not cover all search space (see section 4.3 for more details).

Objective Function: [31] uses Optimum-Path Forest (OPF) classification algorithm [88] in its objective function. But BCOA[32] uses mutual information (expensive[19]) in its objective function. This step is replaced by a new objective function to develop a new filter FS approach (MBCSFS) to improve the computational time.

Local And Global Search Switching: Existing approaches use threshold value (Value of objective function =25%) to control the nests that are used in local search and global search. Nests that have a quality more than 25% are used for local search, and the remaining nests for global search. But the threshold in [32] is not clearly specified.

Local Search: BCS updates each nest that has a quality more than the predefined threshold using Lévy Flights which is a main point of strength of CS. More details on Lévy Flights can be found in appendix B. Both [31, 32] use Lévy Flights in their local search.

Authors	**Methods**	**Task of CS/Application**
Davar Giveki et.al[78]	Modified Cuckoo Search With SVM	To optimize two parameters C and γ for SVM/ Classification
Miloš MADIĆ et.al[79]	Cuckoo Search With Artificial Neural Networks	Surface Roughness Optimization In CO2 Laser Cutting/ Laser cutting AISI 304 stainless steel
Ivona et.al [80]	Cuckoo Search	Multilevel Image Thresholding Selection/ Segmentation of images
M. Prakash et.al [81]	Cuckoo Search	Optimizing Job Scheduling / Job Scheduling for Grid Computing
Koffka Khan et.al [82]	Cuckoo Search With Neural Network	Optimizing Neural Network Weights/ Compute Health and Safety risk index for employees using NSCS
Moe Moe Zaw et.al [83]	Cuckoo Search	Document Clustering/ Web Document Clustering: 7 sector benchmark data set
Akajit Saelim et.al [84]	Modified Cuckoo Search	Optimizing Path/ To locate the best possible server in distributed systems
Rui Tang et.al [25]	K-Means And Cuckoo Search	Optimize K-Means/Clustering
Ehsan et.al [85]	Improved Cuckoo Search With Feed Forward Neural Network	Optimize Network Weights And Convergence Rate Of Cuckoo Search/ Classification of Iris and breast cancer data sets
Sean P. Walton [86]	Modified Cuckoo Search	Optimization Of Functions/ Applied to aerodynamic shape optimization and mesh optimization
D. Rodrigues et.al [31, 87]	Binary Cuckoo Search	Feature Selection/ Theft detection in power distribution systems for two datasets commercial and industrial obtained from a Brazilian electrical power company
Mahmood Moghadasian et.al [32]	Binary Cuckoo Optimization Algorithm for Feature Selection in High-Dimensional Datasets	Feature Selection/ Search for feature subset on six medical datasets

TABLE 3.1: Applications of CS in different domains[76, 77].

Global Search: [31] uses the same technique in initial strategy to replace the nests that have quality less than the a predefined threshold (25%). But the [32] use Lévy Flights in its global search, this means [32] uses local search only to update the population of solutions.

Stopping Criterion: The algorithm in this approach stops when the number of iterations reaches the maximum predefined by the user. But the Stopping Criterion in [32] is not clearly specified.

In their Evaluation:

[31] approach uses parameters as α =0.1, threshold =0.25, iteration=10, population=30, and applies it on two small datasets obtained from a Brazilian electrical power company. This approach has been compared with some NIAs such as: binary particle swarm optimization and Binary firefly algorithm [89]. Results show that BCS is efficient for FS, and it achieved the maximum accuracy or the same classifier accuracy as other algorithms. But BCS has been found the fastest.

[32] approach uses parameters as α =0.5 to 0.9, maximum number of iteration=1000, and applies it on six numerical and medical datasets. K-Nearest Neighbor (KNN) classification algorithm is selected to measure the classification accuracy. Results show the BCOA achieves better feature reduction compared to other approaches that are used in its evaluation, but its evaluation is not clearly specified, such as the approaches that are used in comparisons.

In general, CS algorithm[28] is a new and powerful NIA, and it uses hybrid mechanism search to find the optimal solution, while its local search is very efficient, not trapped in local optimal, and its implementation is simple. Unfortunately, [31] is a wrapper FS, and its BCS is inefficient for datasets that have more than 20 features and the number of features in optimal features subset is less than 25% from total features(Section 4.3 explains why). [32] is a filter approach that uses expensive objective function(mutual information is expensive[19]), and it uses local search without global search, this means the search mechanism of search algorithm that is used in [32] is not hybrid mechanism, while the main efficient point for CS is the hybrid mechanism[28].

3.7 Comparison

This section shows the general comparison between ACO, PSO, ABC, and BCS for FS. ACO is very complex compared to PSO, ABC, CS, because it uses graph representation compared to other that use binary representation, and ACO needs more parameters than other. This makes the ACO most expensive. PSO, ABC, and BCS use binary representation which makes the implementation of them mostly cheap. The convergence of ABC and BCS is more efficient compared to ACO and PSO, because the ABC and CS use hybrid search mechanism. But the CS has more efficient convergence compared to ABC which its local search is very weak compared to CS that use least number of parameters compared to other. This mean, CS has fastest, most efficient convergence, easiest implementation, and needs less parameters compared to other, and according to my knowledge, No filter FS that use BCS is available.

Unfortunately, approaches [18–26, 31] that are reviewed in this chapter are not efficient for datasets which have more than 70 features in best case (the number of features is determined according to experiments of [18–26]) . Also they [18–26] are not efficient for mixed and numerical datasets because they use RSTDD in their objective function. Also BCS approach[31] is expensive because it is a wrapper approach. But there is a potential to improve the BCS that is used in them to become more efficient and fast by developing new filter FS.

3.8 Summary

This chapter reviewed the related works for filter Feature Selection(FS), and it focuses on filter FS that combines the RSTDD and NIA.

Ranked and feature subset are types of FS approaches, ranked approaches are cheap, but they failed to achieve the feature reduction. In feature subset FS , there are three types: Complete approaches that achieve feature reduction, but they are very expensive. Heuristic approaches are cheap but they do not achieve feature reduction. Recently, meta-heuristics approaches are cheap and mostly achieve feature reduction.

NIAs are efficient type of meta-heuristics algorithms, ACO, PSO, ABC are NIAs that are used in many filter FS approaches. ACO approaches are very expensive

and complex, PSO and ABC are cheap and easy to implement compared to ACO, but ABC has more efficient convergence than PSO, because ABC uses hybrid search mechanism to update the population of solutions, but the main drawbacks of ABC its that it is weak local search. For this, many researchers use CS to solve many optimization problems in several domains, because the CS use hybrid search mechanism, and its local search is very strong. BCS is binary model of CS, and it is used to solve FS.

BCS that is used in approach[31] has some of drawbacks, such as its inefficient for datasets that have more than 20 features. But the performance of BCS can be improved to increase the efficiency and speed of convergence.

The main limitation of the approaches are reviewed, first, they are efficient for datasets that have less or equal 70 features in best case, and most of them that used RSTDD in their objective function are inefficient for mixed and numerical datasets.

Next chapter presents the proposed algorithm .

Chapter 4

Proposed Algorithm

This chapter proposes a new classification filter feature selection approach that is called Modified Binary Cuckoo Search based on rough set theory for Feature Selection (MBCSFS). MBCSFS improves the binary cuckoo search by developing new initialization, global updating, and local updating, switching and termination mechanisms. Also MBCSFS develops new objective function to measure the dependency between the combination of features and class labels using RSTDD, and it measures the average number of distinct values of feature subsets. MBCSFS aims to find the minimum feature subset without significant reduction in classification performance with in best achievable computational time for nominal, mixed, and numerical datasets with different sizes.

4.1 Introduction

FS for classification aims to minimize the number of features and maximize the classification performance, for this FS is called multi objective problem [90]. Two main factors are needed to develop filter FS approach. The first is a search strategy to search in the search space for a candidate feature subsets, and the second is an objective function responsible to evaluate these candidate feature subsets to find the best subset that has less number of features, highest relevancy to class labels, and highest frequent values . NIAs are generally efficient for searching [66], CS is a new and a powerful NIA [28], and BCS is a binary version of the CS [31, 32].

In the literature, filter FS approaches especially that combine NIAs and use RSTDD failed to perfrom well in many datasets, that are mixed and numerical datasets, and datasets that have more than 76 features [18–26]. BCS algorithm used in [31] is a good search algorithm for datasets which have less than 20 features, see section 4.3 . But there is a potential to improve the convergence of BCS algorithm to become faster, and more efficient for datasets that have more than 20 features (experiments in chapter 5 prove modified BCS is more efficient up to 617 features).

MBCSFS is a new classification filter FS approach that has the following contributions:

- According to my knowledge, MBCSFS is the first classification filter FS approach that uses BCS and RSTDD.
- Developed a new objective function that uses RSTDD and number of distinct values to achieve improved efficiency for nominal, mixed, and numerical datasets.
- Improving the BCS
  - New initialization and new global search mechanisms to speed the convergence, and guarantee the global convergence.
  - New local search to decrease the number of iterations needed to find the global optimal solution, and to increase the chance to find this solution.
  - New switching mechanism: guarantee the local and global search in each iteration to increase the efficiency of convergence.
  - New termination mechanism to achieve improved computational time over the baseline BCSFS.

The pseudo code of Basic BCS with the traditional objective function [19](BCSFS) is shown in algorithm 4.1. The main difference between the existing approach that used BCS [31] and the algorithm 4.1, is the objective function shown in step 3.1 in this algorithm. BCSFS is described as the baseline to test the performance of the newly proposed algorithms (MBCSFS).

The remainder of this chapter is organized as follows. The second section presents the new objective function. The third section describes the new initialization

Input:

- *Trainingset*
- *Number of nests n.*
- *Value of P_a .// To control of local and global search*
- *Number of maximum iteration T.*

Output: optimal feature subset g_best.

Step 1: Initialize the population of solutions by random method.

Step 2: t=1.

Step 3: Repeat

Step 3.1: Evaluate the population (n nests/ solutions) by equation (3.2)

Step 3.2: Sort the population of candidate solutions descending according to objective function.

Step 3.3: if g_best< first solution, then g_best=first solution

Step 3.4: (Global Search) Select the worst nests (solutions) which their quality are less than P_a(0.25) and replace them to new solutions randomly.

Step 3.5: (Local Search) Select the best nests (remaining nests/solutions), and update them using L´evy flights.

Step 4: t=t+1.

Step 5: Until (t > T).

Step 6: Output g_best.

ALGORITHM 4.1: Pseudo Code of Basic BCS with traditional Objective function [19] (BCSFS).

mechanism. New updating mechanisms are presented in the fourth section. New stopping criterion mechanism is described in fifth section. The sixth section provides summary of this chapter.

4.2 New Objective Function

In general, feature subset that has high relevancy to class labels, and high frequent values in its features, helps to increase the classification performance in many classification algorithms [33]. High frequent values means the chance to repeat these values which are used to build classification model in future is high, but the high frequent values alone is not enough to give a good indicator for classification

performance, because the dependency between the feature subset and class label may be low. RSTDD is good theory to measure the dependency between the feature subset and class labels, but it is not enough alone as a good indicator for classification performance in all datasets especially datasets that have low and different frequent values(Mixed and numerical datasets).

Objective functions [19, 27] that use RSTDD are good when they are applied on nominal datasets, or the datasets which have the same number of frequent values. But RSTDD is not efficient when applied on mixed and numerical datasets which their features have number of different frequent values.

Therefore it is necessary to develop a new efficient objective function that is capable to evaluate the feature subset by balancing between three objectives (frequent values, dependency degree, and number of selected features). We give Three Objectives and Global (3OG) name for this objective function. We develop 3OG objective function in the following sections:

4.2.1 Frequent values

Feature has high frequent values, means the number of distinct values in this feature is low. We use the number of distinct values and total number of objects to calculate the percentage of distinct values in each feature, and this is indicator for frequent values, see equation 4.1. This equation gives low percentage when the frequent values is high. For example, ZOO dataset [40] has 100 objects, its animal name feature has 100 values, and eggs feature has two values. Eggs feature has high frequent values, equation 4.1 gives 2% as a percentage of distinct values for eggs feature. But the frequent values of animal name feature is very low (no frequent values), and the result of equation 4.1 for animal name feature is 1. Remember the relationship between the frequent values and equation 4.1 is inverse.

$$Distinct\%(R) = \frac{|Distinct \quad values(R)|}{|Objects|} \tag{4.1}$$

Where R is a subset of features, distinct values(R) is the average of number of distinct values for R features, and objects is the number of total objects in dataset.

4.2.2 Dependency Degree

We use RSTDD (equation 3.1) to measure the dependency between the feature subset and class labels.

4.2.3 Balancing between the Percentage of Distinct Values and Dependency Degree

In general, high dependency degree is a good indicator for relevancy between the feature subset and class label. Low distinct percentage for feature subset is a good indicator for high frequent values. In other words, feature subset which has maximum dependency degree and minimum unique values percentage is desirable for classification algorithms [33]. This means, the dependency degree is close to one (100%) and percentage of unique values is close to zero. We develop equation 4.2 to balance between them.

$$Quality\%(R) = DependencyDegree\%(R) - UniqueValues\%(R) \tag{4.2}$$

Equation 4.2 gives high quality when the feature subset is more desirable for classification algorithms. For example, in Zoo dataset, assume there are two feature subsets. First subset is {Animal name, aquatic, domestic}, and distinct % for it is 34%, and dependency degree is 100%Ṡecond subset is {hair, milk, predator, backbone, venomous} and average of distinct % for it is 2%, and dependency degree is 96%. As dependency degree, first subset is the best, because it has higher dependency degree compared to second. But when we measure the classification accuracy of both subsets using decision tree J48 in Weka, the accuracy for first subset is 43%, and 93% for second subset. This means the second subset is better than first subset, because the second subset has high frequent values and high dependency degree. Dependency degree (first subset) gives bad indicator for classification algorithm (Decision tree J48), because it has low frequent values compared to second subset.

When applying our equation 4.2 for both subsets, quality (first subset) is 100% - 34%=66%, but the quality (second subset) =96%-2%=94%. As equation 4.2, second subset achieves better classification accuracy compared to the first subset.

4.2.4 Balancing Between the Quality and Number of Selected Features

FS is multi objective problem, maximum classification performance, and minimum number of selected features are objectives of FS. Equation 4.2 achieves the first objective only, now we modify this equation to achieve two objectives, see equation 4.3.

$$Quality(R) = Equation4.2 * \frac{|C| - |R|}{|C|} \tag{4.3}$$

Where C is the number of available features, R is the number of selected features. The idea of this balancing is taken from equation 3.2.

Following sections explain how the BCS is improved to achieve faster global convergence.

4.3 New Initialization Mechanisms

In BCS [31], in its initialization strategy, each solution (or nest) is randomly initialized, as shown in pseudo code 4.1. Given its binary selection, from a search space, the probability of every feature belonging successfully to the selected features category for search has a 50% chance of being selected [60]. The aim is to maximize the number of different features, to cover a wide range from across the search space, that are selected for each solution search. A good initialization strategy is, thus, one capable of generating initial nests with as many different number of features across the full range as possible, such that the selected features for the search space cover most of the possible numbers of selected features. For example, assume the total number of features in a search space is 50, this means, the possible number of features to select for the search ideally should be from any of 0 to 50. A good initialization strategy is one that allows selecting most of the possible numbers of selected features from across the range from 0 to 50, not one that just perhaps centers its selection of features from around 20-30 of the search space for example.

However, the pseudo code in 4.1 does not guarantee to generate the most possible numbers of selected features, to cover a wide range, from across the search

space. To understand the reason behind that, let's discuss the probability theory of this pseudo code (Traditional initialization strategy). The number of successes in a sequence of n (total number of features) independent selected or not selected experiments is the binomial distribution [60], with each success has probability p (50%), and the n (in our case is the total number of features) play a main role in determining the probability of numbers of successes(selected features). The probability of getting exactly k successes in n trials is given by the probability mass function. Figure 4.1 shows some examples of the probability mass function, first example (n=9 features) shows the initial strategy has a good chance to cover most possible numbers of selected features. But in the second example(n=20 features) show the probability of generating feature subsets that have less than four features or more than 16 features is close to zero. While the third example(n=33) shows the probability of generating feature subsets that have less than 10 features or more than 25 features is close to zero. And in the last example(n=90 features), feature subsets which have less than 30 features or more than 60 features have probability close to zero to select in the initial strategy. In general, Binomial distribution shows the probability is very small to select the feature subsets with a number of features less than 25% or more than 75% of total number of features that is more than 20. In other words, this initialization strategy misses the small and large optimal feature subsets. Also the experiments in chapter 5 shows similar results, table 5.4 in chapter 5 shows the smallest feature subset that can be selected via this initialization strategy with different number of features.

```
For nest=1 to population size do
    For egg=0 to totalFeatures-1 do
     Solution [nest] [egg] =random (0, 1) // 1 means selected, 0 means removed
```

PSEUDO CODE 4.1: Initialization Mechanism for BCSFS .

This strategy does not help the BCS to cover most the the search space (cover most of the possible numbers of selected features), and this causes weak convergence. To investigate the initialization strategy in BCS for FS, new mechanism that divides the initialization strategy to three parts is proposed to increase the efficiency of convergence and speed of BCS. In other words, the main goal of the splitting is

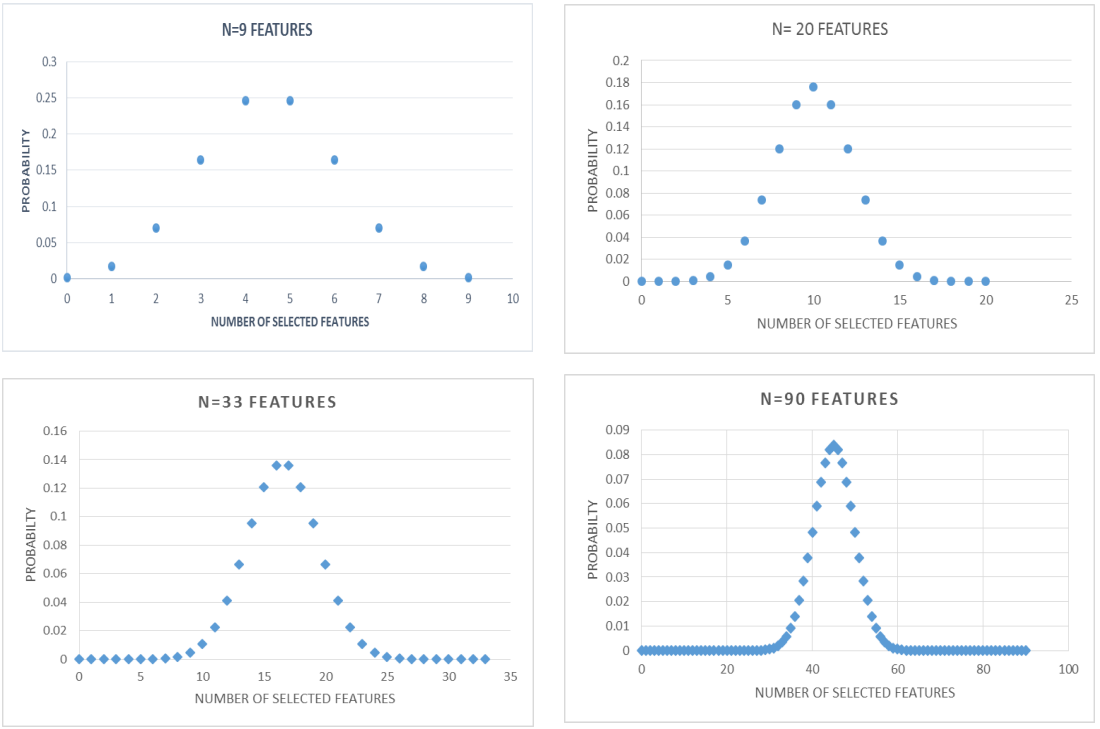


FIGURE 4.1: Probability of Getting Exactly Number of Selected Features in Different n Total Number of Features (Probability Mass Function).

to increase the chance to cover most of the possible numbers of selected features, see figure 4.2, and algorithm 4.3. Nests/solutions are split equally to the following parts:

Small Part: It aims to generate feature subsets that have number of selected around the 25% of the available features. This helps to find optimal solutions that have a small size. Small initialization consists of three steps: First, start from empty set. Second, select randomly number "s" between one and half number of the available features. Third, select randomly "s" of feature from all available features, then add them to empty set. In other words, this part focuses on selecting a number of selected features between 1 and half of the total number of features, according to binomial distribution, the possible numbers of selected features that have around the quarter of available features is greater than others.

Medium Part This mechanism is able to reach and search the area of the feature subsets with medium size. This helps to find the optimal solutions that have a medium size. Also this mechanism starts from an empty set. Then selects randomly features from all available features. Then adds this features to the empty

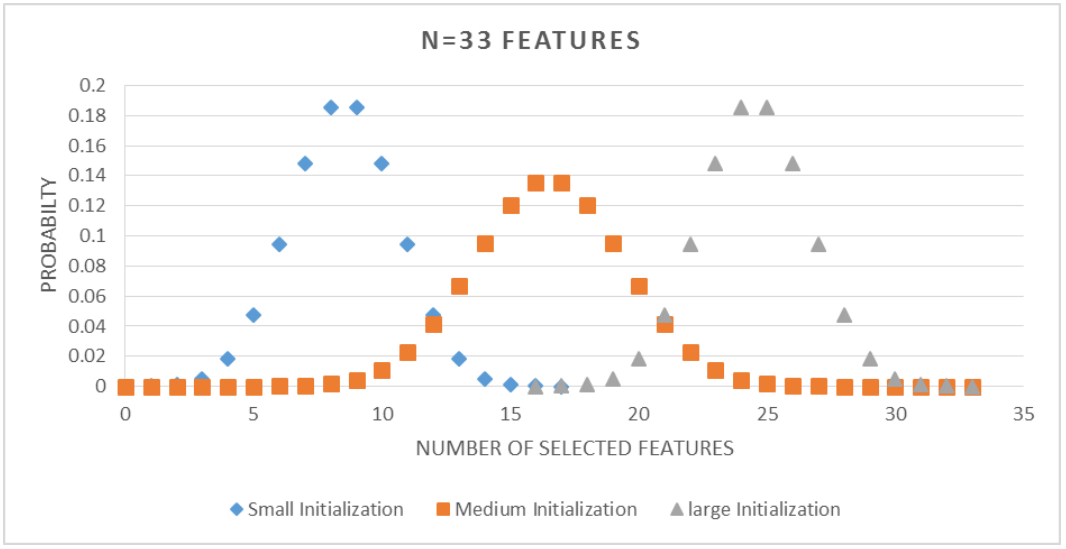


FIGURE 4.2: Probability Mass Function of New Initialization Mechanism.

set. We see this initialization focuses on the feature subsets that have around half number of available features. This part is same as the traditional initialization strategy, see figure 4.1 that shows the possible numbers of selected features that have around the half number of available features is greater than others.

Large Part: This mechanism is capable of searching for the feature subsets that are selected close to the number of available features. This helps to find the optimal solutions that have around 75% of number of available features. Large initialization consists of three steps: First, Start from full set. Second, select random number "s" between the one and half the number of available features, then select randomly "s"' features. Third, remove these features from full set.

4.4 New Updating Mechanisms

In general, local and global search are two mechanisms that are used to update the population of solutions. Local search aims to improve the current solutions by applying small modifications to them in the hope of finding a better one (global optimal) in shorter computation time. But this mechanism (local search) may be unable to prove global optimality, because the initial solutions affect it. Global search does not depend on the initial solutions to find the global optimal, but it needs a large number of iterations to find the global optimal if possible. Many

algorithms combine local and global search in a new mechanism to avoid the disadvantages of them [28, 72]. Global search is used to generate new candidate solutions that are used by the local search to find global or nearest optimal solution. CS is one of these algorithms, and it has very efficient local search mechanism compared to other algorithms. BCS [31] as CS is efficient, but there is a potential to improve the local and global search to BCS to become faster, and guarantee global convergence. Following sections explain how to improve the updating mechanisms.

4.4.1 New Global Search

The main key of global search is to cover all search space as much as possible to guarantee the global convergence, and increases the speed of it. But the global search in BCS and some other approaches does not achieve this key when the search space has more than 20 features, because it uses the same strategy that is used in the initial strategy. Therefore it's necessary to modify BCS's global search to as much of the search space as possible. As a new initialization mechanism, the global search divides the searching into three parts: First part is small search that focuses on feature subsets which size is around the 25% of available features. Second part is medium search that is interested in the subsets which size is around half number of the available features. Last part is large search that focuses on the subsets which size is around the 75% from available features, see algorithm 4.3.

4.4.2 New Local Search

Local search applies small modifications to improve the current solutions to find the local optimal solutions that hopefully lead to global optimal or nearest of it. Remember, the goal of local search is speeding up the convergence to get the global optimal solution in less number of iterations. BCS uses levy flight to move from the current solution to a new one. Step size α in levy flight is main factor in local search. The higher value of α means increasing the size of the modifications. The value of α in BCS is fixed (Typically is 0.25), this means the modification is large and same size in all iterations. Initially we need a large modification to increase the diversity of feature subset, but if this size stays large, this causes going far away from global optimal solution. To improve the local search, according to [85] our approach modifies the value of α to become variable instead of being fixed. In the

early generations, the size of modifications must be large enough to increase the diversity of feature subsets, then the size of modifications must be decreased in the following iterations to avoid going far from the optimal solutions (and reducing the number of iterations) is needed to get the optimal subsets. Therefore, the value of α decreases as the number of iterations increases.

4.4.3 Global versus local Ratio (New Switching Mechanism)

BCS uses the probability P to control the nests for local and global search, Nests that have quality (result of objective function) less than P are updated by global search, and remaining nests are updated by local search. But there is a problem in this mechanism. Assume the quality of all nests is more than P or less than P in some iteration, this means, BCS become local or global search instead of hybrid search. Please note, a hybrid search mechanism helps to increase the efficiency of convergence. We develop a new switching mechanism that guarantees the local and global search are run in each iteration to increase the chance to find the best feature subset in a lesser number of iterations. New switching mechanism divides the population into two parts: first part has the nests that have the highest quality for local search, and the second part has the remaining nests for global search. The ratio of these parts is determined by user.

4.5 New Stopping Criterion

It is very difficult to determine if the algorithm finds the optimal feature subset or not, because the evaluation of feature subset depends on its size and quality. For this reason, most existing approaches uses maximum iterations to stop the algorithm. In most cases, this causes wasting much time without improving the solutions. For example, maximum iteration is 20, third iteration finds the best feature subset, and algorithm continues searching until it reaches maximum iterations without improvement over the feature subset that was found in the third iteration. This means, the time of seventeen iterations is wasted without any use. Therefore, a new stopping criterion is proposed to stop the algorithm before reaching maximum iterations, which is to stop if there was no chance to improve the

best feature subset. The idea of this criterion is when in a number of successive iterations(determined by user) there is no improvement in the best feature subset, the algorithm stops. See algorithm 4.3.

Parameters in algorithm 4.3 has the same values as those used in our experiments.

Input:

- *Trainingset*
- *Number of nests **n**.*
- *Number of maximum iteration **T**.*
- *Number of successive iteration **stopCriterion**.*
- *Local versus global ratio **ratio**.*
- *Total number of features **features***

*Output: optimal feature subset **g_best**.*

*Step 1: Divide equally the population of **n** nests into three parts to initialize them.*

*Step 1.1(Small part): Initialize each nest in this part by selecting randomly number of Features around the quarter of **features**.*

*Step 1.2(Medium part): Initialize each nest in this part by selecting randomly number of Features around the half of **features**.*

*Step 1.3(Large part): Initialize each nest in this part by selecting randomly number of features around the Three quarters of **features**.*

Step2: While (t<T or stop Criterion) do

Step 2.1: Evaluate each nest using 3OG objective function.

Step2.2: Sort the nests descending according to the value of 3OG.

Step 2.3: if (g_best< first nest)

g_best=first nest

*Step2.4: Divide the population of **n** nests according the predefined **ratio** into best nests and worst nests parts.*

Step2.4.1 (local search): Update the best nests using levy flight.

Step 2.4.2(Global search): Update the worst nests as Step 1.

Step2.5: t=t+1.

*Step 3: Print **g_best**.*

ALGORITHM 4.3: Pseudo Code of Modified Binary Cuckoo Search based on Rough Set Theory for Feature Selection(MBCSFS).

4.6 Summary

The goal of this chapter is developing a new filter BCS for FS to improve the performance of the basic BCS, which is expected to achieve feature reduction in short computational time for different datasets with different characteristic (sizes, types, classes). To achieve that goal, all main parts in BCS were modified to speed up the convergence, guarantee the global convergence, and achieve efficient evaluation for feature subsets.

New objective function based on RSTDD and distinct values was developed to guide the MBCSFS to feature subsets that have minimum number of features with maximum classification performance. This objective function calculates the quality of feature subsets by balancing between the relevancy, frequent values and their size. The function used RSTDD to measure the relevancy between the selected features and class labels. And it used distinct values to measure the frequent values of feature subsets.

This chapter shows the new initialization and new global search mechanisms. MBCSFS divides the initialization and global search to three parts to make it suitable for different sizes of datasets and guarantee the global convergence. First part is for small optimal solution. Second part is for medium size. And the last part is for large size of optimal solutions.

Also this chapter shows the modification of local search mechanism that aims to increase the chance to find the global optimal solution in less number of iterations. The main idea is that the size of modifications of the current solutions is decreasing when the number of generations/iterations is increased.

New stopping criterion is proposed in this chapter to stop the algorithm when in three successive iterations there is no improvement in the current solution. This helps to avoid wasting time without any use.

Next chapter shows the design of the MBCSFS and experiments to evaluate it (MBCSFS), and compares it to baseline, particle swarm optimization, and genetic algorithms approaches.

Chapter 5

Evaluation and Results

In order to evaluate the performance of MBCSFS, thesis takes an empirical approach by comparing it to three filter FS approaches after applying them on 16 datasets.Thesis selects filter FS approaches in evaluation, because MBCSFS is a filter approach.

This chapter aims to show the datasets and the methodology evaluation used in the experiments, also it discusses the results of MBCSFS compared to baseline(BCSFS), Genetic[37] with Correlation based on Feature Selection(CFS)[38], and PSO[39] with CFS approaches.

5.1 Evaluation Methodology

This section describes the methodology we detected to evaluate our work.

5.1.1 Datasets selection

In order to evaluate the performance of MBCSFS, a group of experiments have been run on sixteen datasets, where these datasets are taken from the University of California at Irvine, known as the UCI data repository of machine learning database [40]. UCI classifies datasets for classification according to types of their features to three groups: First is nominal or categorical group which contains 28 datasets. Numerical or continuous is the second group which contains 137

datasets, and the last is mixed group which has 37 datasets. These feature types are illustrated in chapter 2.

Our approach aims to achieve feature reduction for nominal, mixed, and numerical datasets with different characteristics especially different number of features in addition to different number of objects and different number of classes. To evaluate this, sixteen datasets that posses these characteristics are selected randomly as follows: Four datasets from nominal group, four datasets from mixed group, and eight datasets from numerical group. Table 5.1 shows these datasets and their characteristics, each dataset is made available as a text file of a CSV format.

#	Dataset	Features	Objects	Class Values.	Domain (Area)
Nominal Datasets					
1	Congressional Voting Records	16	435	26	Social
2	Mushroom	22	8124	2	Life
3	Soybean(small)	35	386	19	Life
4	Lung Cancer	56	32	3	Life
Mixed Datasets					
5	Zoo	17	101	7	Life
6	Hepatitis	19	155	2	Life
7	German Credit Data	20	1000	2	Financial
8	Dermatology	33	366	6	Life
Numerical Datasets					
9	Breast Cancer Wisconsin (Original)	9	699	2	Life
10	Wine	13	178	3	Physical
11	Segment	19	1500	7	Computer
12	Spectf	44	80	2	Life
13	Connectionist Bench (Sonar)	60	208	2	Physical
14	Libras Movement	90	360	15	N/A
15	Musk (Version 1)	168	476	2	Physical
16	ISOLET-test	617	1559	26	Computer

TABLE 5.1: Datasets.

The following is a brief description of the datasets.

Congressional Voting Records. This dataset includes votes for each of the U.S. houses of representatives' congressmen on the 16 key votes identified by the Congressional Quarterly Almanac (CQA). There are 16 nominal features in this dataset, and each one has two distinct values. 435 objects are classified into two classes, 168 objects for the first class, 267 objects for second class.

Mushroom. It contains records drawn from the audubon society field guide to north American mushrooms. This dataset has 22 nominal features with different

number of distinct values(from 2 to 12). Also it has 8124 objects that are classified roughly to two classes.

Soybean(small). The task is to diagnose diseases in soybean plants. It has 35 nominal features that have from 1 to 7 distinct values. There are 47 objects which are classified to 4 classes, one class has 17 objects and each class in remaining classes has 10 objects.

Lung Cancer. It has 55 nominal features with 2 to 4 distinct values. There are 32 objects, 9 objects for first class, 23 objects for second class.

Zoo. It has 17 features (16 nominal features, 1 numerical feature). Most of nominal features have two distinct values, but the numerical feature has 6 distinct values. 101 objects are classified into seven classes, 41 objects for mammal class, 20 objects for bird class, 5 objects for reptile class, 13 objects for fish class, 4 objects for amphibian class, 8 objects for insect class, and 10 objects for invertebrate class.

Hepatitis. It has 19 features, 7 numerical features which have from 30 to 85 distinct values, and 12 nominal features which have 2 distinct values. This dataset has 155 objects, 32 objects belong to one class, and remaining objects belong to second class.

German Credit Data. It has 7 numerical features which have 3 to 921 distinct values, and 13 nominal features which have from 2 to 10 distinct values. 1001 objects are classified into two classes, 701 objects for good class, 300 objects for bad class.

Dermatology. This dataset has 34 features, one feature is numerical which has 60 number of distinct values, and 33 nominal features which have distinct values from 2 to 4. 366 objects are classified into six classes, 61 objects for first class, 112 objects for second class, 72 objects for third class, 52 for fourth class, 49 for fifth class, and 20 objects for sixth class.

Breast Cancer Wisconsin. It is obtained from the university of wisconsin hospitals, it has 9 numerical features, each one has ten distinct values. There are 699 objects, 458 objects classified into benign class, and the remaining objects are classified into malignant class.

Wine. The data of this dataset are the results of a chemical analysis of wines grown in the same region in Italy. It has 13 numerical features with different

number of distinct values (from 39 to 133 unique values). There are 178 objects in this dataset, 59 objects are classified into first class, 71 to second class, and 48 objects are classified into third class.

Segment. This dataset describes diagnosing of cardiac Single Proton Emission Computed Tomography (SPECT) images. It has 44 numerical features with different number of unique values (from 21 to 36 distinct values). Also it has 80 objects which are classified equally into two classes.

SPECTf. This dataset describes diagnosing of cardiac Single Proton Emission Computed Tomography (SPECT) images. It has 44 numerical features with different number of distinct values (from 21 to 36 distinct values). Also it has 80 objects which are classified equally into two classes.

Connectionist Bench (Sonar). It has 60 numerical features with different number of distinct values(from 109 to 208). Also it has 208 objects roughly classified into two classes.

Libras Movement. It has 90 numerical features, and they have number of unique values from 172 to 235. There are 360 objects classified equally into 15 classes.

Musk (Version 1). This dataset describes a set of 92 molecules of which 47 are judged by human experts to be musks and the remaining 45 molecules are judged to be non-musks. The goal is to learn to predict whether new molecules will be musks or non-musks. This dataset has 168 numerical features with different number of distinct values(from 32 to 476). And it has 476 objects are classified into two classes. 207 objects for first class, 269 for second class.

ISOLET-test. This dataset has 617 numerical features with different number of distinct values (from 2 to 1420). Also it has 1559 objects are classified equally to 26 classes.

5.1.2 Evaluation method

To evaluate how effective FS is to a classification algorithms, two general evaluation approaches are commonly employed: direct and indirect [3]. The direct approach is used when the certain relevant features of a dataset are already known, and an algorithm is directly evaluated for FS against them. However, often we do not

have a prior knowledge of the relevant features about the datasets. Hence, most FS approaches use the indirect approach which does not need any prior knowledge about datasets. Indirect approach uses classification algorithms to measure the classification performance (in item of accuracy, Precision, and recall) for selected features [3, 18–26].

Two main comparisons are commonly used in the indirect approach to evaluate the FS. First, before and after comparison which measures the classification performance of all available features and for selected features. Second comparison, checks the efficiency of a specific FS approach by comparing it to other FS approaches. Number of selected features or size reduction (size reduction is the percentage between the number of removed features and all available features), classification performance, and computational time are three factors that may be used in this comparison. To examine whether FS is proper for different classification algorithms, at least two different types of classification algorithms need to be used to measure the classification performance. NB and DT are common algorithms that are used to evaluate FS , they efficient and easy to construct [3]. More details for these classification algorithms were provided in chapter 2 [3, 63, 91].

Given that we do not have prior knowledge of the datasets, the indirect evaluation approach is appropriate for our case. We will employ the indirect evaluation combined with "before and after" comparison to compare our developed approach/algorithm(MBCSFS) with the baseline approach(BCSFS). In addition, it will be compared to genetic [37] with CFS [38] and PSO [39] with CFS [38]. Different two classification types (DT [41] and NB [42]) are used to measure the classification performance for all approaches that are used in the experiments. Classification performance means in this thesis, accuracy, precision, and recall classification measurements, see section 2.1.3.

5.1.3 Benchmarking and Experiment Design

All implementations are run on a personal computer running Windows 7 with (i5) 2.4 GHZ processor and 6GB memory. MBCSFS and BCSFS are implemented with PHP language in same implementation and hardware. Genetic[37] with CFS [38] and PSO[39] with CFS are known filter FS approaches, and they are implemented in Weka tool[104]. We selected the genetic and PSO, because they are common NIAs for FS, and they are implemented in Weka tool [92]. Also CFS is implemented

in Weka tool, it is an efficient objective function for FS, because it measures the redundant and relevant features in each candidate feature subset by evaluating the correlation between each feature and the class labels and between each pair of features using mutual information [38].

Some of parameters in these approaches are selected according to default parameters in Weka tool, some of them are shown as follows: population size is 20, maximum number of iterations is 20. But the number of successive iterations(in new stopping criterion) that is used in our experiments is three, appendix C explains the rational for choosing "three" iterations. The ratio in new stooping criterion is 50% for local search and 50% for global search.

Figure 5.1 illustrates main steps in experiment design.

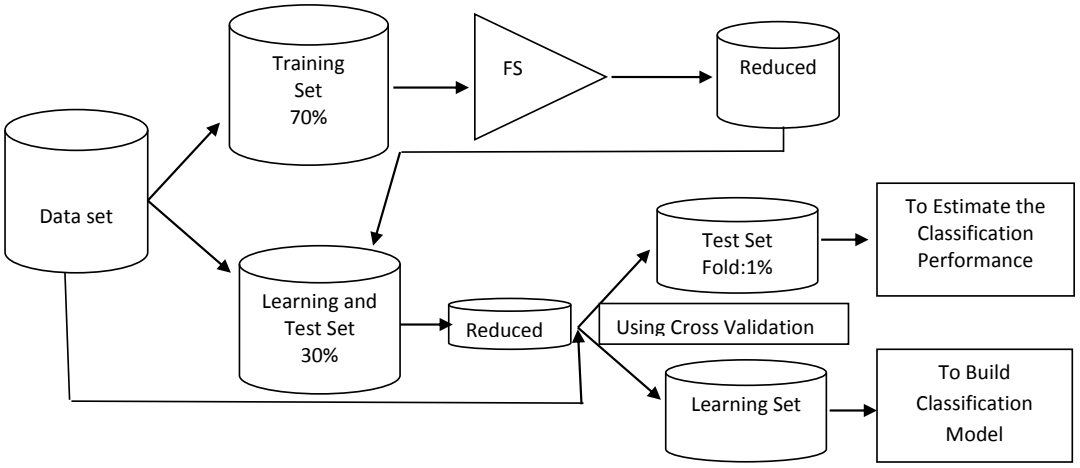


FIGURE 5.1: Experiment Design Steps.

5.1.3.1 Training, Learning and Test Sets

A common way to experiment the FS for classification is to divide each dataset into two datasets randomly, training set, and learning and test set. A training set has about 70% of the dataset objects, and 30% of the dataset objects for learning and test sets [63, 93]. The training set is used by FS approaches to achieve features reduction. And the learning and test set is used to build the classification model and estimates the performance of classification.

In this work, we use K-fold cross-validation [94] that as is implemented in the Weka tool to split the learning and test set into two disjoint sets to build the classification model and estimate the classification performance. When an object belongs to the test set, its class is hidden from the classification model built based on the learning set only. In particular, K-fold cross-validation splits the learning and test set into K subsets, then learning set is created on K-1 subsets, and test set is created on the remaining subset, the size of k is 1% from learning and test set. the process is repeated with several partitions to calculate the classification performance.

5.1.3.2 Feature Reduction

We found, running the experiments five times was sufficient to obtain a good comparison results between the two. Running the experiments longer than five times did not provide additional value of comparison. Number of selected features (features subset), and computational time are recorded for each run. In the next step, run that achieved best classification accuracy is selected. Also PSO and genetic approaches are run for each training set to achieve good feature reduction, the number of selected features are recorded for each run. Remember, MBCSFS is implemented in different environment from PSO [39], and genetic [37] approaches.

According to [3] DT and NB are common classification algorithms that are used to estimate the classification performance, DT and NB are two algorithms from top ten data mining algorithms, and they do not need complex initial parameters [46]. For this, we use DT "J48"[41] and NB[42] classification algorithms which are implemented with Weka tool to measure the classification performance for all approaches that are used in our experiments by applying these classification algorithms on each reduced learning set to build the classification model that is applied on test set to measure the classification performance. Also we measure the classification performance for all datasets before and after FS.

5.2 Results and Discussion

In this section, MBCSFS is compared to BCSFS and other FS approaches, Table 5.2 shows the results of the comparison between the MBCSFS and BCSFS. Table

5.3 shows the computational time for MBCSFS and BCSFS approaches. Table 5.4 shows the smallest feature subset which is converged by BCSFS. Comparison between 3OG and traditional objective functions is found in table 5.5. Table 5.6 compares the performance of MBCSFS for FS to genetic and PSO approaches.

Differences in accuracy is considered significant when it is more than 5% [91], and it is considered the same when it is less than 1%[63].

5.2.1 Comparisons between MBCSFS and BCSFS

Table 5.2 shows the experimental results of MBCSFS and BCSFS with sixteen datasets. We note, no significant difference between average of precision and average of recall, for this, accuracy is enough to evaluate the classification performance for most datasets which are used in experiments. Following paragraphs discuss these results.

Nominal Datasets . Table 5.2, Figure 5.2 show that MBCSFS and BCSFS achieve the same size reduction, DT accuracy, and NB accuracy for congressional voting records dataset. In Mushroom, Soybean (small), Lung Cancer datasets, MBCSFS and BCSFS achieve better or roughly same DT accuracy, and NB accuracy, but MBCSFS achieves significant size reduction compared to BCSFS. The main reasons for these results are: 3OG and traditional objective functions [19] have roughly the same efficiency for nominal datasets. Also MBCSFS convergence is better when the number of available features is more than 20 features, and the best feature subset is less than quarter of available features, see section 5.3.3. For this, MBCSFS achieves better reduction

Mixed Datasets Table 5.2, figure 5.3 show MBCSFS achieves better feature reduction in all mixed datasets compared to BCSFS. In zoo dataset, MBCSFS achieves less size reduction, but it improves the classification accuracy (DT accuracy=13%, NB accuracy=26.7%). MBCSFS achieves the same size reduction, and significantly better classification accuracy according to DT and NB compared to BCSFS in Hepatitis and German Credit Data. But in Dermatology dataset, MBCSFS achieves better size reduction and classification accuracy (DT and NB) than BCSFS. Reasons for these results, 3OG objective function is more efficient than traditional objective function for mixed datasets (number of distinct values

Dataset	Method	Size	SR%	Decision Tree %				Naive Bayes %			
				Acc.	Prec.	Rec.	DA	Acc.	Prec.	Rec.	DA
Nominal Datasets											
Congressional Voting Records	All	16		96.7	96.8	96.8		90.1	90.5	90.1	
	MBCSFS	6	62.50	95.38	95.6	95.4	-1.32	94.6	94.6	94.6	4.5
	BCSFS	6	62.50	95.38	95.6	95.4	-1.32	94.6	94.6	94.6	4.5
Mushroom	All	22		100	100	100		95.8	96	95.8	
	MBCSFS	4	81.82	98.4	98.5	98.4	-1.6	98.3	98.4	98.3	2.5
	BCSFS	6	72.73	99.7	99.8	99.8	-0.3	98.1	98.3	98.2	2.3
Soybean(small)	All	35		95.7	96.5	95.7		97.8	98.1	97.9	
	MBCSFS	4	88.57	85.7	74.6	85.7	-10	100	100	100	2.2
	BCSFS	15	71.43	85.7	75.5	85.7	-10	92.8	94	92.9	-5
Lung Cancer	All	56		50	50	50		56.2	55.3	56.3	
	MBCSFS	7	83.93	66.6	75.6	66.7	16.6	66.6	66.7	66.7	10.4
	BCSFS	18	67.86	37.5	31.3	37.5	-12.5	62.5	39.1	62.5	6.3
Mixed Datasets											
Zoo	All	17		93	95	93		94	94.6	94.1	
	MBCSFS	7	58.8	93	95	93	0	96.7	97.8	96.7	2.7
	BCSFS	5	70.59	80	70	80	-13	70	70.6	70	-24
Hepatitis	All	19		80	80.2	80		83.2	84.1	83.2	
	MBCSFS	4	78.94	84.7	86.9	86.4	4.7	86.9	86.6	86.9	3.7
	BCSFS	4	78.94	71.7	68.4	71.7	-8.3	73.9	72	73.9	-9.3
German Credit Data	All	20		71.2	69.4	71.1		35.1	74.7	35.1	
	MBCSFS	6	70.00	68	67.3	68	-3.2	71.3	69.8	71.3	36.2
	BCSFS	6	70.00	67.3	62.1	67.3	-3.9	68	64.5	68	32.9
Dermatology	All	34		95.9	96	95.9		97.5	97.7	97.5	
	MBCSFS	10	70.59	93.6	94.7	93.6	-2.3	98.1	98.4	98.2	0.6
	BCSFS	12	64.71	88.1	88.8	88.2	-7.8	93.6	94.1	93.6	-3.9
Numerical Datasets											
Breast Cancer Wisconsin (Original)	All	9		93.9	93	93		96.1	96.3	96.1	
	MBCSFS	3	66.67	97.6	97.6	97.6	3.7	98.1	98.1	98.1	2
	BCSFS	3	66.67	97.6	97.6	97.6	3.7	98.1	98.1	98.1	2
Wine	All	13		91.5	91.6	91.6		97.7	97.8	97.8	
	MBCSFS	3	76.92	87.3	87.3	87.1	-4.2	94.4	94.9	94.5	-3.3
	BCSFS	2	84.62	83	82.9	83	-8.5	84.9	84.8	84.9	-12.8
Segment	All	19		96.4	96.4	96.4		81.2	83.3	81.3	
	MBCSFS	3	84.21	92.65	92.9	92.7	-3.75	83.1	82.9	83	1.9
	BCSFS	6	68.42	80.5	80.4	80.6	-15.9	67.8	67.8	67.6	-13.4
Spectf	All	44		66.25	67.1	66.3		80	82	80	
	MBCSFS	6	86.3	75	75.7	75	8.75	83.33	84.3	83.3	3.33
	BCSFS	15	65.91	62.5	65.1	62.5	-3.75	75	75.7	75	-5
Connectionist Bench (Sonar)	All	60		70.2	70.2	70.2		67.3	67.3	66.9	
	MBCSFS	13	78.33	79	78.9	79	8.7	67.7	67.4	67.7	0.4
	BCSFS	22	63.33	72.5	72.3	72.6	2.31	70.9	75	71	3.6
Libras Movement	All	90		64.4	65.8	64.4		62.2	63.6	62.2	
	MBCSFS	7	92.22	60.5	60.6	60.6	-3.9	62.9	63.3	63	0.7
	BCSFS	37	58.89	45.3	43.5	45.4	-19.1	51.8	56.2	51.9	-10.4
Musk (Version 1)	All	168		100	100	100		76.8	77.5	76.9	
	MBCSFS	7	95.83	96.2	97.7	96.2	-3.8	84.6	85.3	84.6	7.8
	BCSFS	71	57.74	56.6	32.1	56.6	-43.4	69.9	69.9	69.9	-6.9
ISOLET-test	All	617		78	78.3	78.1		83.7	84.8	83.8	
	MBCSFS	51	91.73	76.2	76.4	75.9	-1.8	80.3	81.4	80.4	-3.4
	BCSFS	283	54.13	64.3	64.9	64.3	-13.7	73.2	75.8	73.3	-10.5

All: Original Datasets. Size: Number of features. SR: Percentage of size reduction against all features Acc: Accuracy. Prec: Precession Average. Rec: Recall Average. DA: Difference accuracy between accuracy of all features and accuracy of feature subset

TABLE 5.2: Results of BCSFS and MBCSFS.

in their features is different), MBCSFS is more efficient than BCSFS when the number of available features is more than 20 features (dermatology dataset).

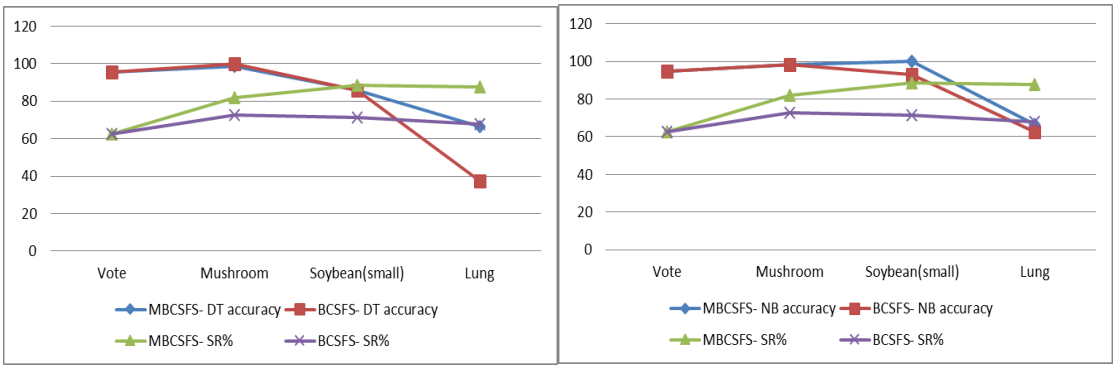


FIGURE 5.2: Comparisons Between MBCSFS and BCSFS for Nominal Datasets(SR% and Classification Accuracy).

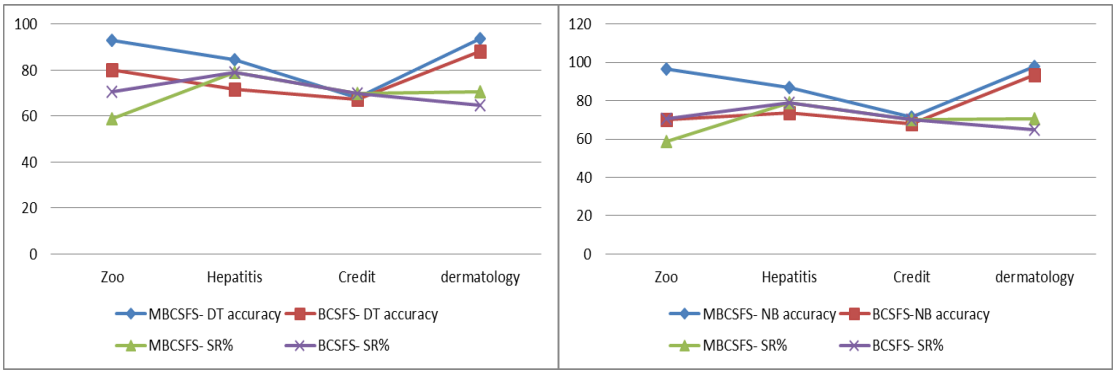


FIGURE 5.3: Comparisons Between MBCSFS and BCSFS for Mixed Datasets(SR% and Classification Accuracy).

Numerical Datasets. According to Table 5.2, figure 5.4, MBCSFS and BCSFS achieve the same feature reduction in Breast Cancer Wisconsin (Original) dataset, because the number of available features is 9 (less than 20 features), and the number of distinct values of its features is the same. In wine dataset, MBCSFS achieves less size reduction, but it achieves significant improvement of classification accuracy (DT and NB) compared to BCSFS. Main reason for this, 3OG objective function is more efficient than traditional objective function for this dataset which its features have different number of distinct values. In ISOLET dataset, BCSFS failed to achieve the feature reduction, it selects around half number of available features compared to MBCSFS which selects 8% from available features without significant classification accuracy reduction. High number of distinct values (close

to total number of objects) for most of this dataset's features, and the BCSFS's weak convergence are two main reasons for this results. High number of distinct values and number of selected features make the RSTDD full dependency (100%) for feature subsets which makes the BCSFS convergence uses local update only to update the population of solutions, and this means, BCSFS is trapped into local optimal.

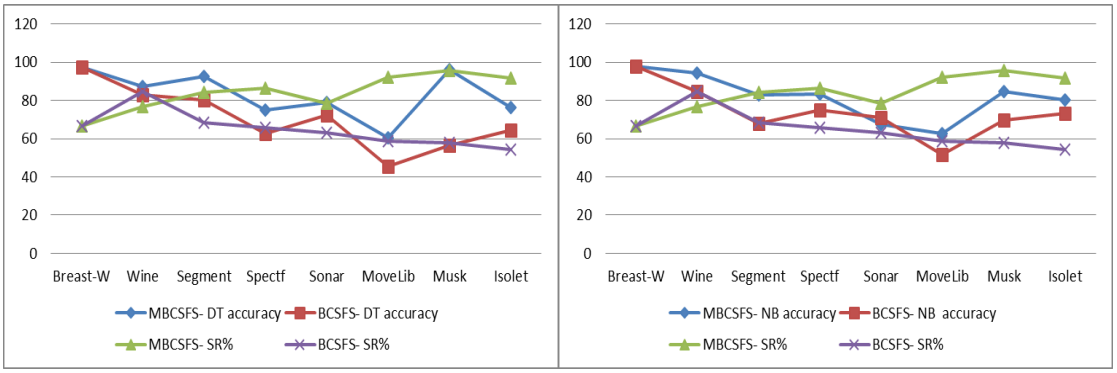


FIGURE 5.4: Comparisons Between MBCSFS and BCSFS for Numerical Datasets(SR% and Classification Accuracy).

In remaining datasets, MBCSFS achieves better significant size reduction than BCSFS (from 15.7% to 38.1%), with significant improvement in the classification accuracy according to DT and NB(except sonar dataset, there is no significant reduction of classification accuracy according to NB). MBCSFS has better efficient convergence than BCSFS, especially when the number of available features for these datasets is more than 20 features. Also 3OG objective is more efficient than traditional objective function when the datasets have different number of distinct values in their features

Finally, MBCSFS and BCSFS have the same efficiency when they are applied on datasets that have less than 20 features, and their features have roughly the same number of distinct values. But MBCSFS is more efficient than BCSFS when they are applied on datasets that have more than 20 features, and their features have different number of unique values. According to balancing between the size reduction and classification accuracy, MBCSFS is more efficient than BCSFS in 14 datasets, and both approaches have the same efficiency in remaining two datasets.

5.2.2 Analysis of Computational Time

Table 5.3 shows the computational time of BCSFS and MBCSFS in seconds for each dataset. Most of their computational time was spent in the objective function procedures such as calculating the number of distinct values and dependency degree. Objective function runs twenty times (population size.) in each iteration. In spite of the extra time needed for the new objective function that is used in MBCSFS, MBCSFS took less time (about 34.4% from BCSFS time) than BCSFS in all datasets, see figure 5.5. The main reason for this difference is that less number of iterations is needed in MBCSFS to reach to best feature subset, because MBCSFS has fast and efficient convergence compared to BCSFS, and MBCSFS stops when three successive iterations do not improve the value of objective function, but the BCSFS continues searching for best solution until it reaches maximum number of iterations (20 iterations).

Dataset	BCSFS			MBCSFS	
	Itr. #	Time(S)	Time(S) For Convergence	Itr. #	Time(S)
Breast Cancer Wisconsin (Original)	7	3.68599	1.682	4	1.4092
Wine	10	1.053916	0.642	6	0.551574
Hepatitis	12	0.95728	0.7490	6	0.440
Congressional Voting Records	4	1.864377	0.6159	2	0.4217
Zoo	13	0.574956	0.532	4	0.240
Segment	18	13.07107	12.78	4	5.010
German Credit Data	7	7.49066	3.31	1	1.644
Mushroom	12	63.00201	50.46	3	19.73
Dermatology	3	5.51263	1.355	2	1.496
Soybean(small)	8	0.696	0.403	4	0.271
Spectf	13	1.45408	1.216	7	0.824
Lung Cancer	5	0.861	0.287	1	0.184
Connectionist Bench (Sonar)	19	3.064	2.93	3	0.894
Libras Movement	9	6.336	3.793	3	2.033
Musk (Version 1)	14	12.624	10.59	9	9.715
ISOLET-test	1	168.7582	16.091	3	55.398

Itr. #: Number of iterations needed to find the solution. Time(S): Time in seconds needed for approach (20iterationas) to find the best feature subset. Time(S) for convergence: Time in seconds for BCSFS needed for number of iterations that found the best feature subset

TABLE 5.3: Computational Time of BCSFS and MBCSFS.

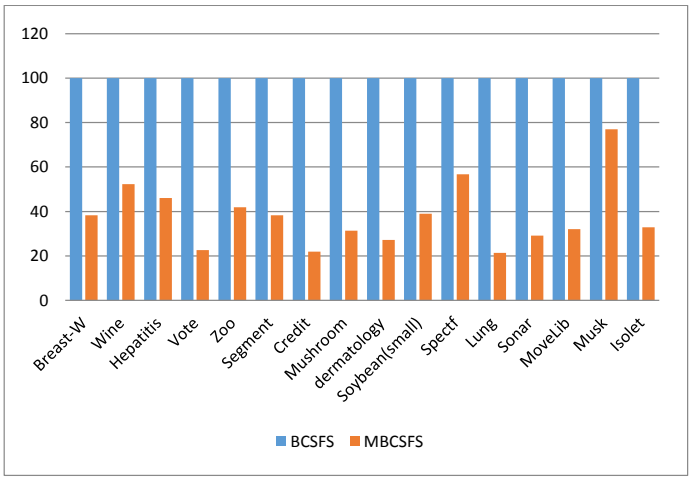


FIGURE 5.5: Time Difference Between MBCSFS and BCSFS (%).

5.2.3 Analysis of convergence

This section discusses the efficiency of MBCSFS convergence, table 5.2 shows that MBCSFS can converge the datasets with different sizes (from 9 features to 617 features), but the BCSFS's convergence efficiency decreases as the number of features increases more than 20, and the best features subset is the one which has less than quarter of available features, see table 5.4. BCSFS can select about the quarter of available features when the size of dataset is less than or equal to 20, for this, we can consider the BCSFS convergence is efficient for the datasets that have less than 20 features. Also 4.3 discussed these results theoreticaly.

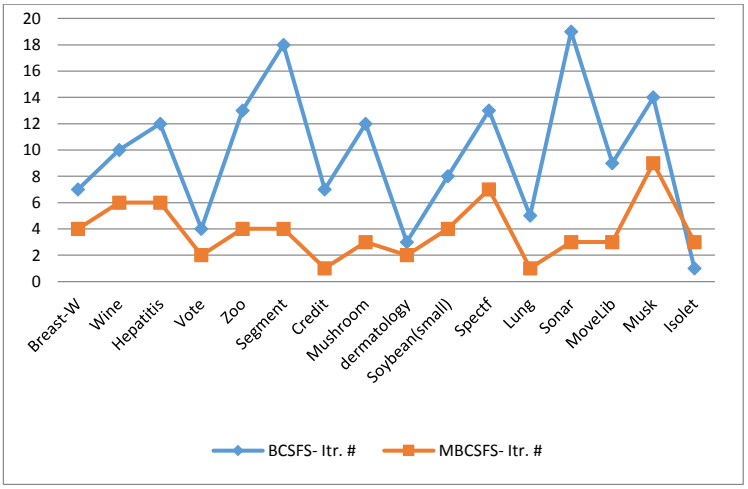


FIGURE 5.6: Number of iterations needed to reach the best features subset

Dataset	Features	Smallest Subset
Breast Cancer Wisconsin (Original)	9	2
Wine	13	2
Hepatitis	19	4
Congressional Voting Records	16	4
Zoo	17	4
Segment	19	5
German Credit Data	20	5
Mushroom	22	6
Dermatology	34	10
Soybean(small)	35	10
Spectf	44	14
Lung Cancer	56	17
Connectionist Bench (Sonar)	60	18
Libras Movement	90	32
Musk (Version 1)	168	67
ISOLET-test	617	281

Smallest Subset: Smallest subset that BCSFS can converge in 20 iterations

TABLE 5.4: Smallest feature subsets for BCSFS.

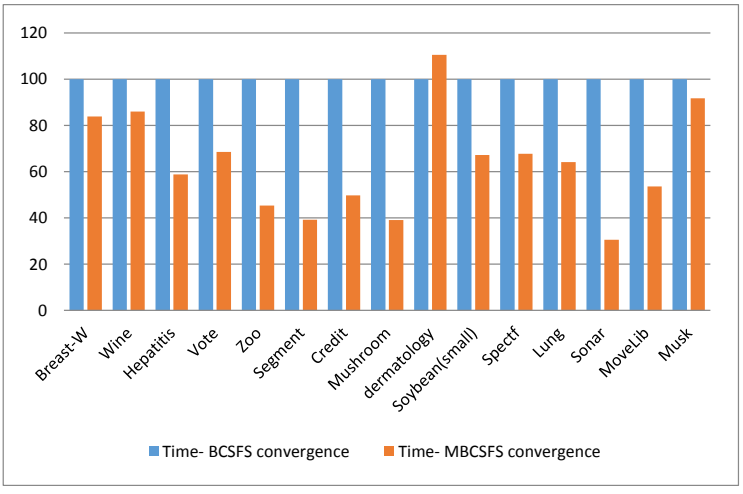


FIGURE 5.7: Time Difference Between MBCSFS convergence and BCSFS convergence (%)

Now we evaluate the number of iterations needed to find the best feature subset. Isolet-test dataset has numerical features that have very high number of distinct values (low frequent values) in its features, and BCSFS selects about the half number of available features. This means, the value of traditional objective function is 100%, which means BCSFS's convergence use local update only to generate new candidate feature subsets after the first iteration (BCSFS trapped into local optimal). Table 5.3, and figure 5.6 show the number of iteration needed to find the best features subset in both approaches. MBCSFS needs 57% iterations from BCSFS iterations to find the best features subset in these datasets. Time for each iteration in MBCSFS needs more time compared to BCSFS, because the 3OG objective function cost more than traditional objective function[19], in general MBCSFS convergence needs less time compared to BCSFS convergence ,because it needs less number of iteration to find the best feature subset.

Figure 5.7 shows the time difference in percentage for convergence for both approaches. MBCSFS convergence needs less time compared to BCSFS convergence in 14 datasets, because MBCSFS needs less significant number of iterations to converge the search space in these datasets compared to BCSFS, but in dermatology, the difference in number of iterations between them is little(one iteration), for this, MBCSFS needs a little bit more time compared to BCSFS to find the best feature subset. But in isolet-test dataset, BCSFS failed to achieve feature reduction

5.2.4 Analysis of New Objective Function "3OG"

To evaluate the new objective function "3OG", traditional objective function[19] is combined to MBCSFS instead of 3OG objective function to construct MBCSFS_T approach which is implemented with PHP language, and it run five times for each training set, then the classification performance are measured using NB and DT that are implemented in Weka tool. Table 5.5 shows the experimental results of MBCSFS and MBCSFS_T.

According to table 5.5, and figure 5.8, 3OG objective function and traditional objective function [19] have the same efficiency when they are applied on the nominal datasets that have the same or roughly same number of distinct values in their features.

Dataset	Method	Size	Decision Tree %			Naive Bayes %		
			Acc.	Prec.	Rec.	Acc.	Prec.	Rec.
Congressional Voting Records	All	16	96.7	96.8	96.8	90.1	90.5	90.1
	MBCSFS	6	95.38	95.6	95.4	94.6	94.6	94.6
	MBCSFS-T	6	94.6	94.8	94.6	93.8	94.1	93.8
Mushroom	All	22	100	100	100	95.8	96	95.8
	MBCSFS	4	98.4	98.5	98.4	98.3	98.4	98.3
	MBCSFS-T	4	99.42	99.4	99.4	97.947	97.9	97.9
Soybean(small)	All	35	95.7	96.5	95.7	97.8	98.1	97.9
	MBCSFS	4	85.7	74.6	85.7	100	100	100
	MBCSFS-T	4	85.7	75.5	85.7	100	100	100
Lung Cancer	All	56	50	50	50	56.2	55.3	56.3
	MBCSFS	7	66.6	75.6	66.7	66.6	66.7	66.7
	MBCSFS-T	7	66.6	75.6	66.7	66.6	66.7	66.7
Zoo	All	17	93	95	93	94	94.6	94.1
	MBCSFS	7	93	95	93	96.7	97.8	96.7
	MBCSFS-T	4	66.6	47.7	66.7	73.3	58.2	73.3
Hepatitis	All	19	80	80.2	80	83.2	84.1	83.2
	MBCSFS	4	84.7	86.9	86.4	86.9	86.6	86.9
	MBCSFS-T	4	84.4	86.6	87	80.4	79.8	80.4
German Credit Data	All	20	71.2	69.4	71.1	35.1	74.7	35.1
	MBCSFS	6	68	67.3	68	71.3	69.8	71.3
	MBCSFS-T	5	63.6	58.3	63.7	66.7	63	66.7
Dermatology	All	34	95.9	96	95.9	97.5	97.7	97.5
	MBCSFS	10	93.6	94.7	93.6	98.1	98.4	98.2
	MBCSFS-T	8	86.3	82.4	86.4	86.4	83.8	86.4
Breast Cancer Wisconsin (Original)	All	9	93.9	93	93	96.1	96.3	96.1
	MBCSFS	3	97.6	97.6	97.6	98.1	98.1	98.1
	MBCSFS-T	3	97.6	97.6	97.6	98.1	98.1	98.1
Wine	All	13	91.5	91.6	91.6	97.7	97.8	97.8
	MBCSFS	3	87.3	87.3	87.1	94.4	94.9	94.5
	MBCSFS-T	2	75.4	74.9	75.9	83	82.7	83
Segment	All	19	96.4	96.4	96.4	81.2	83.3	81.3
	MBCSFS	3	92.65	92.9	92.7	83.1	82.9	83
	MBCSFS-T	2	82.1	82.1	82.1	71.2	70.8	71.2
Spectf	All	44	66.25	67.1	66.3	80	82	80
	MBCSFS	6	75	75.7	75	83.33	84.3	83.3
	MBCSFS-T	2	50	25	50	54.1	54.2	54.2
Connectionist Bench (Sonar)	All	60	70.2	70.2	70.2	67.3	67.3	66.9
	MBCSFS	13	79	78.9	79	67.7	67.4	67.7
	MBCSFS-T	2	67.7	67.2	67.7	67.7	67.7	67.7
Libras Movement	All	90	64.4	65.8	64.4	62.2	63.6	62.2
	MBCSFS	7	60.5	60.6	60.6	62.9	63.3	63
	MBCSFS-T	5	36.1	36.9	36.1	44.4	43	44.4
Musk (Version 1)	All	168	100	100	100	76.8	77.5	76.9
	MBCSFS	7	96.2	97.7	96.2	84.6	85.3	84.6
	MBCSFS-T	4	63.6	63.8	63.6	67.8	68.3	67.8
ISOLET-test	All	617	78	78.3	78.1	83.7	84.8	83.8
	MBCSFS	51	76.2	76.4	75.9	80.3	81.4	80.4
	MBCSFS-T	17	32.2	33.4	32.3	49.7	50.9	49.8

TABLE 5.5: Results of MBCSFS with 3OG and MBCSFS with traditional objective function(MBCSFS_T).

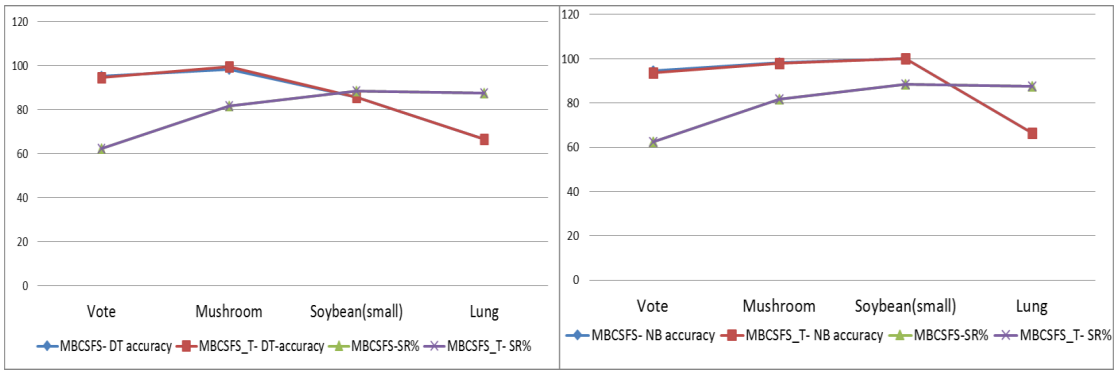


FIGURE 5.8: MBCSFS vs MBCSFS_T for Nominal Datasets (Accuracy, SR%).

Table 5.5 results, and figure 5.9 shows that 3OG objective function is more efficient than traditional objective function for mixed and numerical datasets. 3OG helps the MBCSFS to achieve size reduction without significant classification accuracy reduction, but traditional objective function makes the BCSFS achieve significant size reduction with significant reduction of classification accuracy. But in breast cancer wisconsin (original) dataset, both objective functions have the same efficiency, because the features in this dataset have the same number of distinct values.

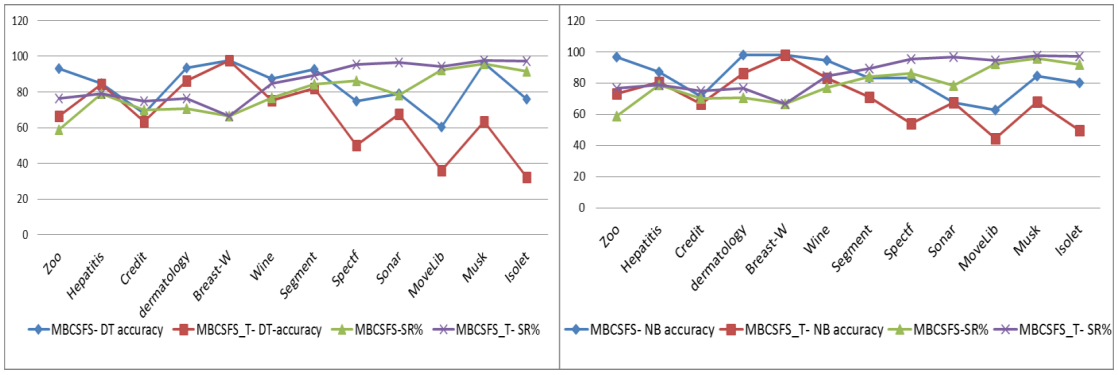


FIGURE 5.9: MBCSFS vs MBCSFS_T for Mixed and Numerical Datasets (Accuracy, SR%).

Generally, 3OG and traditional objective function have the same efficiency for nominal datasets, and the datasets which their features have roughly the same distinct of values. But the 3OG objective function is more efficient for mixed and numerical datasets which their features have different number of distinct values.

5.2.5 Classification Performance Before and After MBCSFS

According to table 5.2, and figure 5.10, MBCSFS achieves significant size reduction(average 79.4%), without significantly reducing or improving the classification performance on all datasets according to DT except soybean(small), and in all datasets according to NB, (difference in accuracy is considered significant when it is more than 5% [91]).

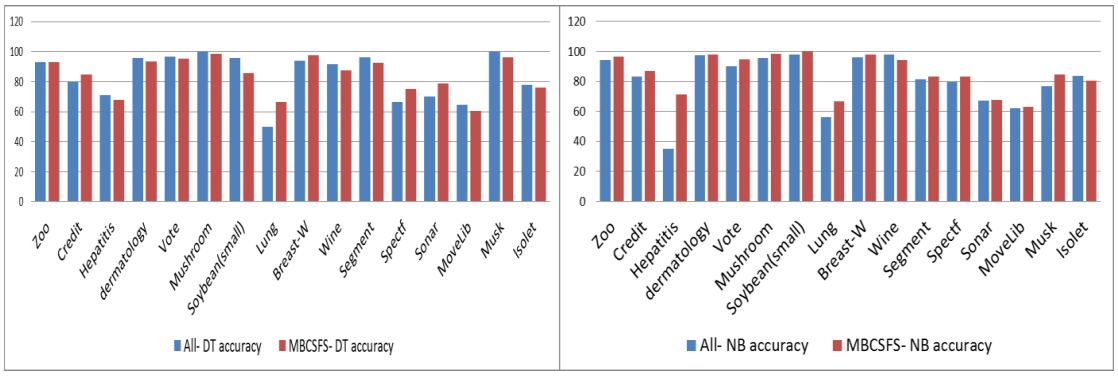


FIGURE 5.10: Classification Accuracy Before and After MBCSFS.

MBCSFS approach is efficient for DT and NB which are different type classification algorithms, according to [3], when MBCSFS is efficient for DT and NB, MBCSFS is general for different type of classification algorithms.

5.2.6 Comparisons between MBCSFS, PSO with CFS, and Genetic with CFS

In general, figure 5.11 shows that MBCSFS achieves best size reduction and classification accuracy (DT and NB) compared to PSO and genetic. MBCSFS removes about 79% from all features with improving the classification accuracy (DT and NB). PSO removes 59.8% from all features with significant reduction of DT classification accuracy (-8.6%), and reduction of the NB classification accuracy (-3.5%). Genetic removes 58.8% from all features with significant reduction of DT classification accuracy (-5.8%), and reduction of the NB classification accuracy (-1.67%).

According to table 5.6, figure 5.12, and figure 5.13, it can be seen that MBCSFS selects smallest feature subsets (MBCSFS, PSO, and genetic remove from all features

Dataset	Method	Size	Decision Tree			Naive Bayes		
			Acc.	Prec.	Rec.	Acc.	Prec.	Rec.
Breast Cancer Wisconsin (Original)	MBCSFS	3	97.6	97.6	97.6	98.1	98.1	98.1
	Genetic	9	92.8	92.9	92.8	97.1	97.2	97.1
	PSO	9	92.8	92.9	92.8	97.1	97.2	97.1
Wine	MBCSFS	3	87.3	87.3	87.1	94.4	94.9	94.5
	Genetic	11	86.7	87.7	86.8	92.4	93.1	92.5
	PSO	11	86.7	87.7	86.8	92.4	93.1	92.5
Hepatitis	MBCSFS	4	84.7	86.9	86.4	86.9	86.6	86.9
	Genetic	8	78.2	75.4	78.3	78.2	76.8	78.3
	PSO	9	78.2	75.4	78.3	78.2	76.8	78.3
Congressional Voting Records	MBCSFS	6	95.38	95.6	95.4	94.6	94.6	94.6
	Genetic	3	95.38	95.6	95.4	96.1	96.2	96.2
	PSO	3	93	95	93	96.7	97.8	96.7
Zoo	MBCSFS	7	93	95	93	96.7	97.8	96.7
	Genetic	10	86.6	80.7	86.7	86.6	81.7	86.7
	PSO	9	86.6	80.7	86.7	76.6	74.7	76.7
Segment	MBCSFS	3	92.65	92.9	92.7	83.1	82.9	83
	Genetic	9	91.9	92	92	80.8	81	80.8
	PSO	8	91.5	98	98	82.14	91.4	91.5
German Credit Data	MBCSFS	6	68	67.3	68	71.3	69.8	71.3
	Genetic	4	65.3	62	65.3	65.3	62	65.3
	PSO	4	65.3	62	65.3	65.3	62	65.3
Mushroom	MBCSFS	4	98.4	98.5	98.4	98.3	98.4	98.3
	Genetic	6	98.7	98.8	98.8	98.7	98.8	98.8
	PSO	6	98.85	98.9	98.9	98.7	98.8	98.8
Dermatology	MBCSFS	10	93.6	94.7	93.6	98.1	98.4	98.2
	Genetic	21	95.4	95.9	95.4	97.2	97.4	97.3
	PSO	20	75.8	76.9	75.9	68.9	68.8	69
Soybean(small)	MBCSFS	4	85.7	74.6	85.7	100	100	100
	Genetic	21	85.7	75.5	85.7	100	100	100
	PSO	21	64.2	55.7	64.3	100	100	100
Spectf	MBCSFS	6	75	75.7	75	83.33	84.3	83.3
	Genetic	6	75	78.1	75	79.16	85.3	79.2
	PSO	6	75	78.1	75	79.16	85.3	79.2
Lung Cancer	MBCSFS	9	66.6	75.6	66.7	66.6	66.7	66.7
	Genetic	2	62.5	39.1	62.5	37.5	15.6	37.5
	PSO	5	62.5	39.1	62.5	37.5	39.6	37.5
Connectionist Bench (Sonar)	MBCSFS	13	79	78.9	79	67.7	67.4	67.7
	Genetic	13	67.7	67.2	67.7	66.1	68.4	66.1
	PSO	13	67.7	68.1	67.7	67.7	68.8	67.7
Libras Movement	MBCSFS	7	60.5	60.6	60.6	62.9	63.3	63
	Genetic	18	43.5	40.5	43.5	43.5	47.5	43.5
	PSO	25	38.8	34.7	38.9	49.2	54	49.1
Musk (Version 1)	MBCSFS	7	96.2	97.7	96.2	84.6	85.3	84.6
	Genetic	62	56.6	32.1	56.6	75.5	75.7	75.5
	PSO	35	56.6	32.1	56.6	72.7	72.8	72.7
ISOLET-test	MBCSFS	51	76.2	76.4	75.9	80.3	81.4	80.4
	Genetic	257	67.3	68.3	67.3	73.7	75.5	73.3
	PSO	236	69.4	69.5	69.4	76.1	77.6	76.1

TABLE 5.6: Results of MBCSFS, Genetic with CFS, and PSO with CFS.

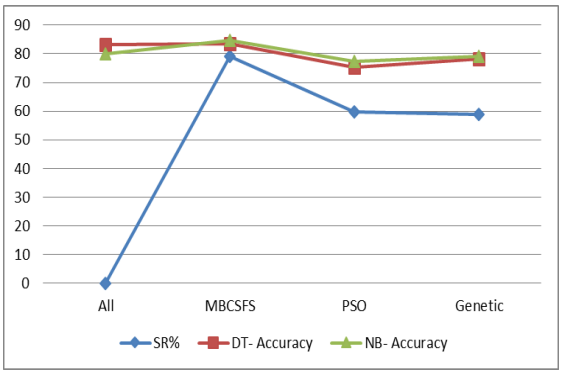


FIGURE 5.11: General Comparison between MBCSFS, PSO, and Genetic approaches .

79.87%, 49.7%, and 46.8% respectively) without significant reduction of classification performance (DT and NB) from available features on breast cancer wisconsin (original), zoo, Hepatitis, mushroom, dermatology,Soybean(small) , libras movement, musk (version 1), wine, segment, and ISOLET-test datasets.

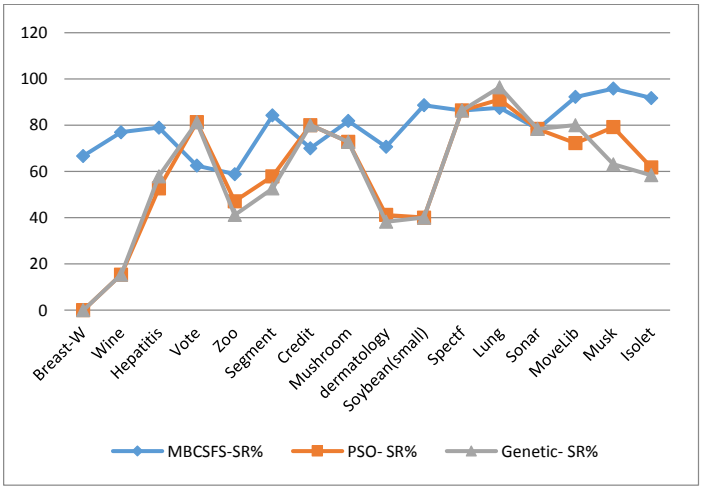


FIGURE 5.12: SR% of MBCSFS, PSO, and Genetic .

In spectf, and connectionist bench (sonar) datasets, MBCSFS, PSO, and genetic achieves the same size reduction, and three approaches achieve the same DT classification accuracy in spectf dataset, while MBCSFS improves the NB classification accuracy, but PSO and genetic achieve reduction of NB classification accuracy in the same dataset. In connectionist bench (sonar) MBCSFS achieves better classification accuracy according to DT and NB.

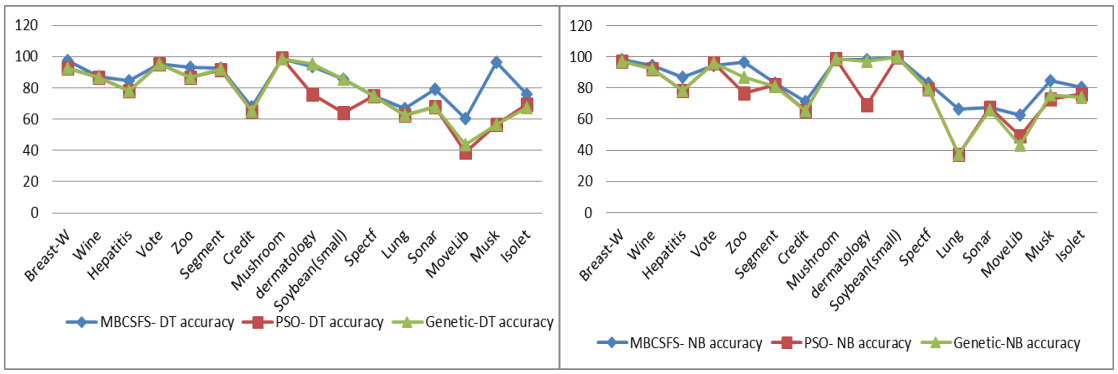


FIGURE 5.13: Classification Accuracy of MBCSFS, PSO, and Genetic .

In german credit data, and lung cancer, PSO and genetic achieve more size reduction than MBCSFS, but MBCSFS achieve better classification accuracy according to DT and NB.

In congressional voting records, MBCSFS achieves less size reduction compared to PSO and genetic, but the classification accuracy (DT and NB) is the same or roughly the same for three approaches.

Generally, MBCSFS achieves better feature reduction than PSO and genetic in 15 datasets.

5.3 Summary

This chapter has examined the proposed algorithm (MBCSFS) by some experiments, and discussed the results for these experiments. All experiments are run on sixteen datasets that are taken from UCI repository database [40], these datasets are selected randomly as follows. Four from nominal datasets, four from mixed datasets, eight from numerical datasets. DT "J48"[41] and NB [42] classification algorithms which are implement in Weka tool are used to measure the classification performance.

Results show that MBCSFS and BCSFS(implemented with PHP) have the same efficiency when they are applied on nominal datasets that have less than 20 features. But MBCSFS is more efficient than BCSFS on two cases: First, when they are applied on datasets that have more than 20 features, because the MBCSFS's convergence is more efficient than BCSFS's convergence. Second, when they are

applied on mixed and numerical datasets, because 3OG objective function in MBCSFS is more efficient than traditional objective function in BCSFS . When balancing between the size of reduction and classification accuracy, MBCSFS is more efficient than BCSFS in 14 datasets, and both approaches have the same efficiency in two datasets.

MBCSFS's convergence is more efficient than BCSFS, and it needs 57% iterations from BCSFS, also MBCSFS has efficient stopping criterion compared to BCSFS. For this, MBCSFS took lesser time (about 34.4% from BCSFS time) than BCSFS.

3OG and traditional objective function have the same efficiency for nominal datasets, and the datasets which their features have roughly the same number distinct of values. But the 3OG objective function is efficient for mixed and numerical datasets which their features have different number of distinct values, compared to traditional objective function which is inefficient for them. Main reason for these results, 3OG measure the frequent values in addition to RSTDD to guide the search algorithm to best subset of features, but the traditional objective function use RSTDD only.

MBCSFS is compared to genetic with CFS, and PSO with CFS which are implementd in Weka tool, MBCSFS achieves better feature reduction compared to PSO and genetic on 15 datasets.

Chapter 6

Conclusion

This chapter conclude the thesis. A summary of literature review is presented with focus on the main contributions, results, limitations and assumptions, and future work.

6.1 Introduction

In our literature review, we focused on meta-heuristic filter FS approaches especially NIAs. Because NIAs approaches have been shown to have faster and more efficient convergence compared to heuristic approaches which have slower and less efficient convergence, and complete approaches which are very expensive. In the exiting literature, there are many filter FS that used RSTDD to evaluate the candidate feature subsets that were generated from NIAs, that RSTDD relatively cheaper, easier to implement, and does not need any preliminary or additional information about data. The main drawback of these approaches is that of the efficiency of convergence decreases as the number of features increases. And these approaches are inefficient for mixed and numerical datasets [18–26]

.

Chapter 4 proposed a new filter FS for classification based on BCS , RSTDD and distinct values to achieve feature reduction for nominal, mixed, and numerical datasets with different characteristics of datasets especially different number of features achieving in shorter computational time.

The rest of this chapter presents the conclusion including contributions, summary of results, limitation and assumptions. Also it presents potential research areas for future work.

6.2 Contributions

The main contributions of this thesis, the development of new objective function, and a modified BCS algorithm (Chapter 4). These contribution are summarized as bellow :

6.2.1 Objective function

A new objective function (3OG) has been developed to select the feature subset that achieve maximum classification performance, and minimum number of features for nominal, mixed, and numerical datasets, by combining RSTDD [19] and distinct values. RSTDD measures the dependency between the feature subsets and class labels. Distinct values measure the average number of distinct values in feature subset to help the 3OG selects the subset that has more frequent values to achieve more efficient results for mixed and numerical datasets as well as nominal datasets. Finally, 3OG selects the minimum feature subset that has maximum dependency to class labels (Maximum RSTDD) and maximum frequent values (minimum number of distinct values) to achieve maximum classification performance for nominal, mixed, and numerical datasets .

6.2.2 Modified Binary Cuckoo Search

The thesis developed a modified BCS algorithm by developing a new initialization, global, local, switching, and stopping criterion mechanisms. Following paragraphs show these points:

Initialization and Global Search: The initialization and global mechanisms can significantly increase the performance of our work (MBCSFS) to reduce the number of features and computational time.

Our work divided the initialization and global mechanism to three parts to make it faster as well as converge for datasets with different number of features. First part converge small optimal solution (about 25% from total features). Second part converge medium size(about 50% from total features). And the last part converge large size of optimal solutions(about 75% from total features).

New Local Search: aims to increase the chance to find the global optimal solution in a lesser number of iterations. The main idea is that the size of modifications of the current solutions decreases as the number of generations/iterations increases.

New Switching Criterion: The switching criterion can improve the performance of our work to solve local optimum problem.

We developed a new switching mechanism by dividing the nests equally for local and global search, to guarantee that local and global searches are run in each iteration. As shown, in chapter 5, this helped significantly improve the performance of the algorithm.

New Stopping Criterion: Similarly the stopping criterion can significantly increase the performance of our work to reduce the computational time.

We developed a new stopping criterion by stopping the algorithm after three successive iterations if there is no improvement in the current solution.

Results show that our work achieved more efficient convergence for datasets that have different number of features (up to 617 features), and it improve the computational time than BCS.

6.3 Results

Our work is evaluated by comparing it to the baseline algorithm (BCSFS), as well as with genetic [37] with CFS and PSO [39] with CFS [38] approaches. Our work and baseline approach were implemented in PHP, for the genetic with CFS and PSO with CFS, the native Weka implementation was used. These approaches were run on 16 datasets taken from UCI, and these approaches were evaluated by DT and NB classification algorithms, using their native Weka implementation.

Results show our work achieved better feature reduction on 14 datasets, and the same feature reduction on two datasets compared to the baseline approach. Our work took lesser time compared to the baseline approach on the datasets. Our work also achieved significant size reduction without significant reduction in accuracy compared to classification accuracy for all features for nominal, mixed, and numerical datasets(except soybean(small) according to DT). It also achieved better feature reduction on 15 datasets compared to genetic and PSO approaches. These results are described in the following points.

- Our work and baseline approach achieved the same size reduction for nominal datasets that have less than 20 features, but ours achieved better feature reduction compared to BCSFS for all datasets that have more than 20 features. This means, our work has better convergence compared to the baseline, and 3OG is more efficient(maximum classification performance with minimum number of features) than the traditional objective function for mixed and numerical datasets.
- Our work took less time (about 34.4% of BCSFS time) than the baseline approach in all datasets, faster convergence, more efficient convergence, and new stopping criterion for MBCSFS are the main reason for it.
- Our work achieved significant size reduction (about 79% on average), without significantly reducing the classification accuracy on 15 datasets(less than 5% from accuracy of all features). Efficient convergence and efficient 3OG objective function are the main reasons for it.
- Our work removed 79% from all features with improve the classification accuracy according to DT and NB . While PSO removed 59.8% from all features with significant reduction of classification accuracy (DT:-8.6%, NB:-3.5%). But genetic removed 58.8% from all features without significant reduction of classification accuracy (DT:-5.8%, NB:-1.67%).

6.4 Limitations and Assumptions

16 datasets with different characteristics were selected to evaluate our work for many characteristics such as difefrent number of features, different types, different

number of classes, and different number of objects, but it is impossible that these datasets cover all characteristics such as all number of features, all number of objects, and all number of classes. This section explains some of assumptions and limitations of our works as follows:

- We assumed all datasets do not have missing values.
- The maximum number of features that is used in the experiments is 617, thus we could not ascertain how the algorithm would scale for datasets with larger number of features.
- Our work achieved feature reduction for datasets that have from 2 to 26 classes, and from 36 to 8124 objects, similarly, we could not ascertain how the algorithm would scale for datasets with larger number of objects or classes.

6.5 Future Work

This section presents the main areas for future work for our work as follows:

- This thesis used distinct values to develop new objective function, but the unique features, and the big difference between the numbers of distinct values for each feature decrease the performance of our work. Therefore we need to investigate the performance of our work by dealing these the two limitations of our objective function.
- Maximum number of features are used in this thesis is 617, to investigate the capability of our work on datasets that greater than 1000 features, alternative initialization and global search would need to be further investigated to develop a more dynamic approach to automatically subdivide the datasets to search groups that provide optimal efficient computation.

Appendix A

Rough Set Theory

Rough Set Theory(RST) was developed by Zdzislaw Pawlak in the early 1982s [15] as a mathematical tool that deals with classificatory analysis of data table. Many researchers are very interested in RST, and applied it in many domains for many reasons. First, it provides efficient methods for finding hidden patterns in data. Second, it allows to reduce original data without additional information about data. Third, It is easy to understand. Fourth, it allows to evaluate the significance of data using data alone[16, 17]. Basic concepts of RST is discussed below.

Information table or information system: Dataset in RST is called information table or information system. Let I=(U,A), where I is information table/system , U is a nonempty set of finite objects and A is a nonempty set of attributes/features. In table A.1, {a,b,c,d,e} are features, but the features consist of four conditional features and one decision feature(Class) D={e}. {0,1,2,3,4,5,6,7} are objects[15–17].

Indiscernibility: Any subset P of A determines a binary relation IND(P) on U, which is called an indiscernibility relation. Indiscernibility(IND) is equivalence relation on the set U, where all the values are identical in relation to a subset of attributes. For example, if P={b,c}, IND(P) creates the following partitions of U: U/IND(P)

Positive region: Let P and Q be equivalence relations over U , then the positive region contains all objects of U that can be classified to classes of U/Q using information in attributes/features P [19,20.30,31]. For example, let P ={b,c} and

X ϵ U	a	b	c	d	e
0	1	0	2	2	0
1	0	1	1	1	2
2	2	0	0	1	1
3	1	1	0	2	2
4	1	0	2	0	1
5	2	2	0	1	1
6	2	1	1	1	2
7	0	1	1	0	1

TABLE A.1: Information System [35].

Q ={e} ,then $pos_P(Q)$= $\bigcup$ {{2,5}, {3}} = {2,3,5}. More details 2,3,5 objects certainly classified into same class. 0,4 objects have the same values{0,2} for {b,c} features , but it is classified into different class (object 0 is classified to 0 class, and object 4 is classified to 1 class), for this reason, 0,4 objects are not included in positive region[6, 28].

Dependency Degree is very important issue in data analysis to discover the dependencies between attributes. For P,Q ⊂A, if all attribute values from Q are uniquely determined by values of attributes from P, this means Q depends totally on P, and partial dependency if some values of Q are determined by values of P, it is said that Q depends on P in a degree K($0 \leq K \leq 1$) . If $0 \leq K \leq 1$, Q depends partially (in a degree k) on P, and if k = 0, then Q does not depend on P. Dependency degree can be defined as equation A.1 [17, 35, 67]:

$$\gamma_P(Q) = K = \frac{|pos_P(Q)|}{|U|} \tag{A.1}$$

Where $|U|$ is the total number of objects, $|pos_P(Q)|$ is the number of objects in a ppositive region, and $\gamma_P(Q)$ is the dependency between feature subset p and classes Q.

For example (table A.1), the degree of dependency of feature {e} upon the {b,c} as follows:

$\gamma_{b,c}(e) = \frac{|pos_{b,c}(e)|}{|U|} = \frac{\{2,3,5\}}{\{0,1,2,3,4,5,6,7\}} = \frac{3}{8}$

Appendix B

Lévy Flights

In nature, many animals and insects search for food by moving to the next location based on the current location. This behavior of search called lévy flight that is a special case of random walks where the step size has a Levy tailed probability distribution to maximize the guarantee and speed of convergence [74]. Step sizes is the main factor of the efficiency of lévy flight search. Lévy flight is modeled in the equation B.1. Remember each solution must be a binary vector, but this equation does not return a binary bit. In order to build a binary vector for each solution, existing study uses equation B.3 and equation B.4 for each feature at each new candidate solution.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \alpha \oplus L'evy(\lambda) \tag{B.1}$$

$$L'evy \sim u = t^{-\lambda} \tag{B.2}$$

Where $x_{(i,j)}^{t+1}$ represents the j_{th} egg(feature) at i_{th} nest(solution) in iteration t , α is the step size($\alpha > 0$) scaling factor of the problem, In most cases, we can use α=1. $\oplus$ means entry-wise multiplications, and λ: Lévy distribution coefficient ($0 < \lambda \leq 3$). Random step length(Lévy(λ) is calculated from power low by the equation B.2.

$$S(x_{(i,j)}^{t+1}) = \frac{1}{1+e^{-x_{i,j}^{t+1}}} \tag{B.3}$$

$$x_{(i,j)}^{t+1} = \begin{cases} 1 \text{ , } S(x_{(i,j)}^{t+1}) > \sigma \\ 0 \text{ , Otherwise} \end{cases} \tag{B.4}$$

Where $\sigma \in [0,1]$, in iteration t .

Appendix C

New Stopping Criterion

It is very difficult to determine if the algorithm finds the optimal feature subset or not, because the evaluation of feature subset depends on its size and quality. For this reason, most of existing approaches uses maximum iterations to stop the algorithm. In most cases, this causes wasting much time without improving the solutions.

Table C.1 shows our work searching for two datasets. First dataset is mushroom which has 22 features and 8124 objects. Second dataset is libras lovement that has 90 features and 360 objects. Our work finds the best feature subset for mushroom dataset in sixth iteration, and in the libras lovement dataset in third iteration, while algorithm continue searching to reach the maximum number of iterations in both datasets. This means, our work wastes much time without any use. According to results in table C.1, when three successive iterations do not improve the current best solution, this means, there is no a chance to improve them, and the algorithm must stop before reaching to maximum number of iterations.

Mushroom Dataset		
Itr#	Number of Selected Features	Values of objective function "3OG"
1	6	0.7264
2	13	0.4086
3	6	0.7265
4	8	0.6358
5	5	0.7718
6	3	0.8627
7	7	0.6809
8	8	0.6355
9	7	0.6810
10	6	0.7263
11	6	0.7263
12	9	0.59014
13	10	0.5447
14	9	0.590
15	4	0.8170
16	5	0.7718
17	5	0.7720
18	11	0.4994
19	19	0.7266

Libras Movement Dataset		
Itr#	Number of Selected Features	Values of objective function "3OG"
1	5	0.3255
2	7	0.3056
3	5	0.3494
4	7	0.3265
5	20	0.2783
6	9	0.33003
7	6	0.3209
8	20	0.26837
9	9	0.3130
10	5	0.31282
11	11	0.3012
12	19	0.278
13	7	0.325
14	4	0.320
15	21	0.279
16	10	0.3344
17	13	0.29368
18	10	0.31023
19	5	0.3426

TABLE C.1: Our Work Searching on Mushroom and Libras Movement Datasets

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Appendix D

Classifications of Dimensionality Reduction

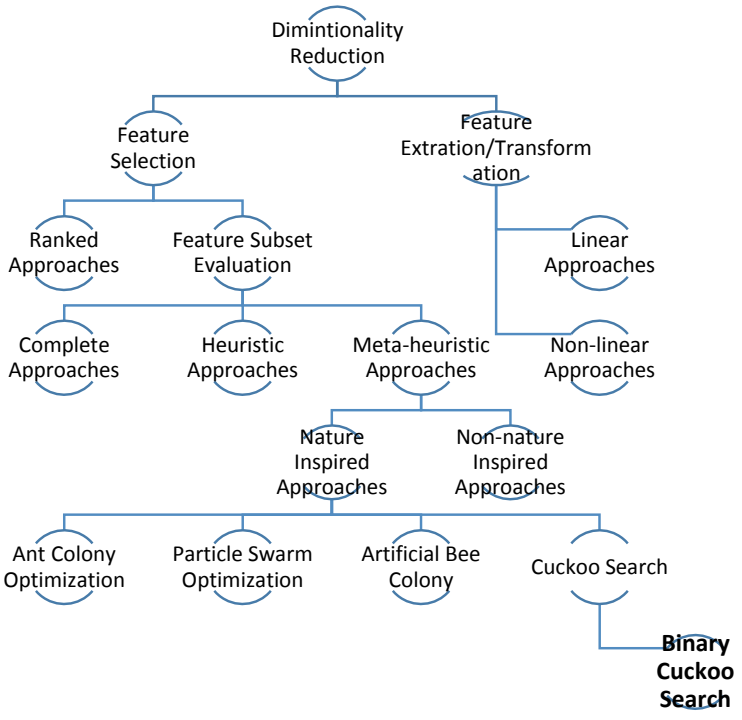

FIGURE D.1: Classification of Dimensionality Reduction.

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