Multi-objective metaheuristic optimization algorithms for wrapper-based feature selection: a literature survey

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ABSTRACT

In the data mining and machine learning (ML) discipline, feature selection problem is considered among many researchers in the recent times. Feature selection process targets to minimize feature set number and maximize performance accuracy by identifying optimal features. Multiple objectives are considered while identifying the optimal feature hence multi-objective metaheuristic optimization algorithms (MOMOAs) are applied. In this study, literature review is performed MOMOAs-for solving wrapper based feature selection problem (WFS). The literature review for solving WFS problem and discuss the challenges faced by the researchers in solving the feature selection problem. The literature review is performed on all relevant studies published in the last 12 years [2009-2022]. A detailed overview of the feature selection preliminaries, MOMOAs-WFS, role of the classifier in feature selection problem are presented. The outcome of this literature review is to highlight the existing works related to WFS problem using MOMOAs. Finally, the research areas for improvement are identified and emphasized for the scientists to survey in the field of MOMOAs.

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1. INTRODUCTION

A massive number of data are involved in all the real time problems were managing the data becomes extremely complex and noticeable process. The dataset consists of vast amount of features or attributes and the dataset contents does not contain usable information. Some attributes or features can be unrelated, redundant that reduces the performance of the model. It is always recommended to minimize the dataset size while maintaining the performance accuracy is the goal of the feature selection problem. The aim of the study is to solve the challenging feature selection problem by applying machine learning (ML) techniques with the help of multi-objective metaheuristic optimization algorithms (MOMOAs). For example, if there are n number of features in a set, then totally 2n subsets are possible from that the optimal subset is chosen. It is complex when the 'n' size is huge in number and the evaluation model for each subset is chosen. To manage these kind of situation, various search techniques such as exhaustive search, random search, and greedy search are applied to solve the feature selection problem and chose the optimal subset. These techniques have drawbacks such as complexity, premature convergence, maximum computational cost and time. Hence, MOMOAs are used to handle these kinds of conditions. This literature survey about multi-objective meta-heuristic optimization algorithms developed in the last 12 years [2009-2022] on various applications to solve the wrapper feature selection (WFS) problem.

The various applications involved in feature selection problem are image and text mining, bioinformatics, computer vision, medical, and industrial applications. The features selection enhances the classification accuracy by selecting a wide range of appropriate features by eradicating the unrelated and repetitive features thus reducing the dimensionality of the data [1], [2]. Feature selection is considered as an NP hard problem consisting of 2n stares consisting of 'n' features. The problem's complexity is enhanced when the N size is increasing daily. These kinds of features extraction and selection approaches are considered such as principal component analysis (PCA) [3] and linear discriminant analysis (LDA) [4]. A new feature is produced from the original feature by minimizing the search space with the help of functional mapping process. The two goals of feature selection process is to maximize the classification performance and minimize the number of features. Multi-objective optimization algorithms aids in selecting the features. This literature review provides the up-to-date work related to the feature selection in multi-objective perspective, discusses the challenges and forthcoming scope of the work. The main contributions of this study are given: i) the basic concepts of feature selection problem definition, search technique, evaluation measures and multi-objective metaheuristic algorithms are elaborated, ii) a detailed survey on the multi-objective metaheuristic algorithms for feature selection are classified and listed, iii) review on the WFS using meta-heuristic algorithms are presented, and iv) research gap is identified and suggestions are given for future work to improve the research on WFS.

The paper is structured as follows: section 2 presents the preliminary details of feature selection problem such as vital definitions, search techniques and evaluation measures. Section 3 discusses the multi-objective metaheuristic algorithms for solving WFS. Section 4 illustrates the role of classifiers in feature selection. Section 5 presents the conclusion and scope for future work in WFS approach.

2. FEATURE SELECTION PRELIMINARIES

This section describes about the feature selection definition, mathematical model of the feature selection problem and the concepts of feature selection. In ML techniques, feature selection is considered as the most essential pre-processing step. The model performance can unfavorably affect the features that are irrelevant or redundant [5]. In case of irrelevant feature, the exactness of the model can be reduced [6]. The original feature is attained from the subset by choosing suitable featureis referred as feature selection [2]. The various advantages of feature selection are: i) decreasing the redundant and over fitted data aids in decision making easier, ii) the precision is enhanced by reducing the misleading data, and iii) minimizes the time, data points, algorithm complexity and quicken the training of the algorithm.

Feature selection can be mathematically framed as follows. Let us assume that a dataset 'S' with features denoted as 'd'. Related features are selected among'd' features with dataset S={f1,f2,f3,…fd}.Ideal subset of feature from 'S' is selected. The subset D={f1,f2,f3,…fn}where n<d and f1,f2,f3,…fn represents the attributes. The overall feature selection process working mechanism is that there is a dataset with whole featureset. Feature selection algorithm aids to extract the feature subset, then based on the selection criteria the results are validated. The five elements of the feature selection process are original dataset, feature subset selection, evaluation, selection criteria and validation. The three categories of feature selection are filter, wrapper and embedded methods [1], [2], [7], [8]. The filter methods are independent and it focuses on the overall characteristic of the data [9]. The wrapper method comprises of classification algorithm and interacts with the classifier. It is expensive than the filter method and provides accurate results compared to filter method. Hybrid methods combine the filter and wrapper approaches. The training process is part of the classifier and this method uses the learning algorithm and it's considered as the wrapper method [10]. Wrapper method obtains better results than the other method and the wrapper method depends on the modelling algorithm for every subset that is generated.The various search strategies are used for the wrapper methods. Jovic *et al.* [11] came up with different search approaches in random, sequential and exponential categories.

The size of the feature increases exponentially with the number of features evaluated. Accurate results are produced in this approach but it's impossible to apply due to high computational cost. Exhaustive search, branch and bound method are few of the examples [12], [13]. The features are added or removed sequentially in the sequential algorithm category. Once the feature is added or removed from the subset it cannot be changed that causes local optima. Linear forward selection, floating forward or backward selection are few of the sequential algorithms [14]. Random algorithms explore the search space randomly. These algorithms do not get trapped in the local optima. Simulated annealing, metaheuristic algorithms, random generations are few of the random population based search approaches.

The vital factors of feature selection problem are search technique, number of objectives and evaluation measures. The bio-inspired algorithms like genetic algorithm (GA) [15], [16], particle swarm optimization(PSO) [17], [18], ant colony optimization (ACO) [19], [20], and grey wolf optimizers (GWO) [21]–[24] are various efficient techniques used to solve the feature selection problem. The various limitations of these techniques are getting stuck in the local optimal and high computational costs. Many single objective techniques were adapted hence multi-objective techniques for solving the feature selection problem was introduced by multi-objective (MOGA) [25], [26], MOPSO [27], MOGWO [28], [29].

The wrapper and filter approaches are grouped generally and the subsets of features are evaluated for classifiers. Wrapper method is expensive by considering computational cost and filters. Produces better results considering the performance of filters for classification. Other researchers classify the feature selection methods into filters, wrappers and embedded methods [30]. Embedded combines classifier and feature selection in one process [7], [31]. In the multi-objective approach, aims in coding the Pareto frontier solutions over the other solutions produced by single objective problem [32]. In the solution group of non-dominated solution consists of subset of all solutions that have all feasible decision space. The boundary is set of all points mapped by the Pareto optimal set [33]. An optimal feature selection process is formulated by identifying the key attributes of the set and the relationship between the data classes. MO can be used to overcome the challenges [34]. The minimization problem multi-objective function is mathematically represented as:

$$\text{Minimize } F(x) = [f_1(x), f_2(x), \ldots, f_k(x)] \tag{1}$$

$$\text{Subject to } g_i(x) \leq 0, \; i = 1, 2, 3, \ldots, m \tag{2}$$

$$h_i(x) = 0, \; i = 1, 2, 3, \ldots, l \tag{3}$$

Where $f_k(x)$ is a function of x, i denotes objective functions number and the constraint functions are $g_i(x)$ and $h_i(x)$.

This feature selection review focuses on the use of wrapper method using random algorithms and its method especially all metaheuristic algorithms are reviewed. In particular, multi-objective optimization algorithms are reviewed. The swarm intelligence-based algorithms, physics-based algorithms and human related algorithms are the various kinds of metaheuristic algorithms present in the literature for various applications.

3. MULTI-OBJECTIVE META-HEURISTIC OPTIMIZATION ALGORITHMS AND ROLE OF CLASSIFIERS IN WRAPPER FEATURE SELECTION

This section discusses few of the various method, experimental results and the findings of MOMOAs-WFS. Table 1 illustrates the search technique, evolution metrics and the multi-objective idea of all the research studies related to WFS.

Table 1. Literature review related to method

Publication	Search method	Evaluation metrics	Objectives	Results and findings
[35]	MOFS-BDE technique	Wrapper and k-nearest neighbors (KNN)	Attribute number and error classification minimization	MOFS-BDE is superior than existing DE, PSO, GA, ABC and MOEA methods at 0.05 level
[36]	MO-ABC algorithm	Wrapper method and KNN	Minimization: attribute number and error classification	Numeric and binary version of MO-ABC is performed and the results outperform NSSABC
[37]	MO-Bat algorithm	Wrapper method and KNN, SVM	Minimization: attribute number and error classification	MOBA is superior performance than the existing
[38]	MOFS Rank	Wrapper method, linear SVM	Attribute number and error classification minimization	MOFS rank is superior and the LETOR datasets were used
[28]	MOGWO algorithm	SVM, Wrapper method	Minimization: attribute number and error classification	MOGWO and MOFA results are processes and superior in terms of accuracy and feature reduction
[39]	MOGA algorithm	Wrapper method and KNN	Minimization: attribute number and error classification	MOGA provides few features and accuracy rate is more compared to single target GA
[40]	MOGA (NSGA-II) algorithm	Wrapper method and SVM	Attribute number and error classification minimization	MOGA (NSGA-II) is superior to AUC and provide better classification accuracies
[41]	MOUFSA algorithm	Wrapper method k-means and KNN	Minimization: attribute number and error classification	MOUFSA is superior than MOFSA1, MOFSA2, FMOFSA
[42]	Deep Belief network	Wrapper method, deep belief network	Attribute number and reconstruction error	The proposed result outperforms baseline method
[43]	Deep Boltzmann	Wrapper method and Deep Boltzmann	Minimization: attribute number and reconstruction error	The results demonstrate the proposed approach by selecting features without reducing the accuracy

This section discusses the various classifiers and the performance of these classifiers using wrapper approach. Table 2 illustrates the classifiers using the wrapper approach. Figure 1 illustrates the various number of classification approaches used. SVM classifier is used maximum number of times in the previous studies.

Table 2. Classifiers using wrapper approach

Publication	Classifier	Description	Performance
[44]	SVM	Hyperplanes for large scale dimensional space are built supervised learning	Performance of SVM is good in terms of accuracy. It's computationally expensive
[45]	SVM	The classifier is used for reducing the generalized error	Performance of SVM is good in terms of accuracy. It's computationally expensive
[46]	KNN	Used for supervised learning. Scans to find the nearest match with the test information	Best performance in dealing with classification compared to SVM and computationally expensive
[47]	Naive Bayes (NB)	NB is a basic algorithm to produce great outcomes which classifies straightforward presumptions with attributes restricted	NB performs well for small datasets. Performance degrades when dealing with large datasets
[48]	Decision tree (DT)	Classification and regression model. If-then for classification. It's equally exhaustive and exclusive	Performance of DT is not well for large datasets
[49]	Random forest (RF)	In ML one of the finest algorithms for classification with high accuracy	When the dataset size is small then it works well

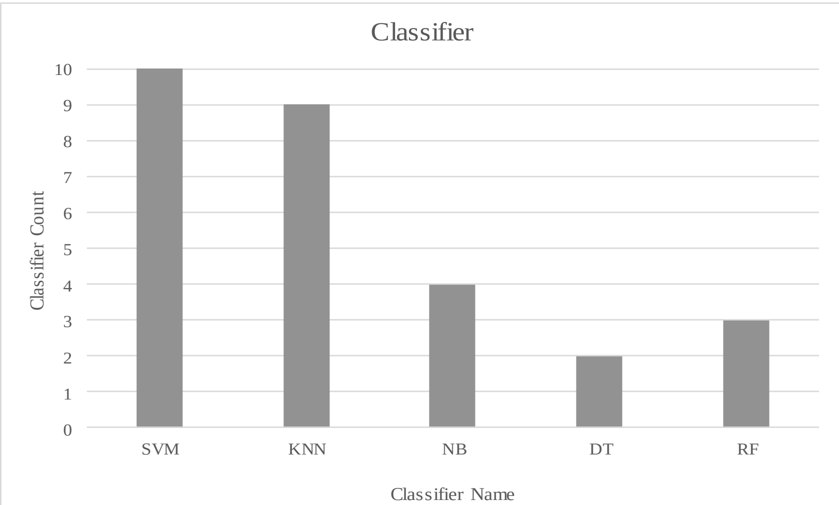

Figure 1. Various classification approaches

4. CONCLUSION

The literature review on meta-heuristic optimization for solving the wrapper based feature selection problem. The detailed description of the feature selection definitions, the search techniques, evaluation measures and the role of the classifier in feature selection are discussed. A detailed survey on the wrapper feature selection based on multi-objective metaheuristic algorithms is done. Multi-objective feature selection key components such as search mechanism, the number of objectives and the applications are presented. The efficiency of the multi-objective feature selection problem using the wrapper method and the SVM classifier is efficiency for dealing with high dimensional data instances. The performance is measured in terms of accuracy and the number of attributes. Hybridization approaches related to multi-objective feature selection are discussed. The research gap is identified and suggestions for future work to improve the research on WFS can be performed in binary feature selection and human related search algorithms for optimization can be studied in future. Further, the exploration of random search techniques, with SVM classifier and WFS model can be performed.

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