Leafcutter Ant Colony Optimization Algorithm for Feature Subset Selection on Classifying Digital Mammograms

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ABSTRACT

Ant Colony Optimization (ACO) has been applied in wide range of applications. In ACO, for every iteration the entire problem space is considered for the solution construction using the probability of the pheromone deposits. After convergence, the global solution is made with the path which has highest pheromone deposit. In this paper, a novel solution construction technique has been proposed to reduce the time complexity and to improve the performance of the ACO. The idea is derived from the behavior of a special ant species called ‘Leafcutter Ants’, they spend much of their time for cutting leaves to make fertilizer to gardens in which they grow the fungi that they eat. This behavior is incorporated with the general ACO algorithm to propose a novel feature selection method called ‘Leafcutter Ant Colony Optimization’ (LACO) algorithm. The LACO has been applied to select the relevant features for digital mammograms and their corresponding classification performance is studied and compared.

Keywords: Ant Colony Optimization (ACO), Digital Mammograms, Feature Subset Selection, Leafcutter Ants, Leafcutter Ant Colony Optimization (LACO)

1. INTRODUCTION

Breast cancer continues to be a significant public health problem in the world. Early detection is the key to improving breast cancer prognosis. Mammography is one of the reliable methods for early detection of breast cancer. Computer Aided (CA) diagnosis systems have been developed to aid radiologists in detecting mammographic lesions, characterized by promising performance. Various CA diagnosis algorithms have been proposed for the characterization of Microcalcifications (MCs), an important indicator of malignancy (Cheng et al., 2003, 2006; Thangavel et al., 2005). These algorithms are based on extracting image features from regions

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of interest (ROIs) and estimating the probability of malignancy for a given MC cluster. One of the most important steps for the classification task is extracting suitable features capable of distinguishing between classes. There have been great efforts spent on extracting appropriate features from microcalcification clusters (Shen et al., 1994). In order to reduce the complexity and to increase the performance of the classifier the redundant and irrelevant features are to be eliminated from the original feature set (Mohanty et al., 2013).

The objective of feature selection is to choose a subset of presented features by eradicating unnecessary features. To extract as much information as potential from a given image set while using the nominal number of features, we should eradicate the features with modest or no predictive information, and ignore the redundant features that are strongly correlated (Zhang 2000, Guyon & Elisseef, 2003). As a result, a great total of computation time can be saved. The chosen subset of features used to characterize such classification function influences numerous aspects of image classification, including the time requested to learn a classification function, the precision of the learned classification algorithm, the time-space cost coupled with the features, and the number of samples required for training.

Much progress has been made on feature subset selection these years. There are several viewpoints to categorize such techniques: filter, wrapper and embedded (Muni et al., 2006; Zhu et al., 2007), unsupervised (Liu & Yu, 2005) and supervised (Bhatt & Gopal, 2005; Neumann et al., 2005; Hu et al., 2008a, 2008b), etc (Liu & Yu, 2004). In the wrapper approach, the feature subsets are evaluated using a classifier to justify the performance of the selection (Guyon & Elisseeff, 2003), whereas in the filter approach, the subset is evaluated with a statistical measure (Dash & Liu, 1997). The embedded approach could use the strengths of both wrapper and filter approaches. (Huang et al., 2007). Sometimes, the dataset might have imbalanced data where the class distribution is not uniform among the classes; a special kind of attentions has to be taken on such datasets. Dash et al., (2013) used information gain theory (filter approach) for eliminating the irrelevant features and differential evolution for tuning center and spread of radial basis functions on both balanced and imbalanced data. Further these methods could be either supervised or unsupervised learning, the wrapper approaches mostly follows the supervised model as because they employ a classifier. For an unsupervised model, the filter approach is widely used. The major step in feature selection is searching for the features for subset construction, there are number of ways to solve this.

- In first approach, the search process could be started with an empty set and incrementally add features, called Sequential Forward Search (SFS). (Guan et al., 2004; Peng et al., 2003)
- Otherwise, start with a complete set and remove features successively. This method is known as Sequential Backward Search (SBS). (Gasca et al., 2006; Hsu et al., 2002)
- Bidirectional selection, starts on both the end, adds or removes features simultaneously. (Caruana & Freitag, 1994)
- Random Selection, selects the subsets in random and keep track of the best subset so far. (Lai et al., 2006; Straceezzi & Utgoff, 2004)
- Complete Search, evaluates all the possible combination of subsets to find the best subset. Though this approach could find the actual solution, it is not feasible for large number of features. (Liu & Yu, 2005)

This article follows the random selection based subset construction while following the wrapper approach. The utilization of Evolutionary Algorithms to perform dimensionality reduction based on random selection procedure has become an efficient approach to enhance the performance of classification algorithms. Derrac et al., (2010) presented a survey on the application of Evolutionary Algorithms to Instance Selection and Generation process. Most of search approaches in the literature
Gravitational Search Algorithm: Concepts, Variants, and Operators

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Advancing Malware Classification With an Evolving Clustering Method

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