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Utilization of Rough Set Reduct Algorithm and Evolutionary Techniques for Medical Domain using Feature Selection

T.Keerthika[1], Dr.K.Premalatha[2]
[1] Assistant Professor, Department of Information Technology, Sri Krishna College of Engineering and Technology, Tamil Nadu, India
[2] Professor, Department of Computer Science and Engineering, Bannari Amman Institute of Technology, Tamil Nadu, India

ABSTRACT: *With the real time data, results in increasing in size. Feature selection (FS) has been considered as the problem of selecting these input features that are most predictive of a given outcome. Also current methods are inadequate. By considering this scenario, this paper proposes the incremental techniques; in fact this has found unsuccessful application in tasks that involve datasets contain huge number of features, which could be impossible to process further. For achieving this, these evolutionary techniques such as Genetic Algorithm, Particle Swarm Optimization Algorithm and Ant Colony Algorithm are considered for comparative performance analysis in which the experimental results shows that feature selection is best for minimal reductions.*

Keywords: Feature selection, rough set theory, Genetic Algorithm, Particle Swarm Optimization, Ant Colony Algorithm

1. Introduction

The solution to the dimensionality reducing problem has been of prior importance and worked in a variety of fields like statistics, pattern recognition, discovery through knowledge and machine learning. two major techniques done for reducing the input dimensionality are:

- feature extraction
- feature selection.

The concept behind feature extraction is that the lower dimensionality is used when a primitive feature space is mapped onto a new space. Principle component analysis, partial least squares are the two important approach for the process of feature extraction. The various applications of feature extraction is applied in variety of fields that include literature, where image processing, visualization and signal processing plat an important role.

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Unlike the feature extraction process, feature selection(FS)involves the selection methods of t-statistic, f–statistic, correlation, reparability correlation measure, or information gain which chooses the most appropriate and informative features from the original one using the methods above. The low accuracy and slow learning difficulties occurs because of redundancy and irrelevancy in the dataset. Finding the subset of features that are informative enough is NP complete. Heuristic algorithm is administered to invoke a search process through feature space. The complexity of learning an algorithm and defining its accuracy are some issues used for evaluating the selected subset.

The rough set(RS) [12,13,14] is a helping tool that reduces the problem of input dimensionality and finds a better solution for correcting the vague and uncertain datasets. The reduction of attributes is based on data dependencies. The RS theory partitions a dataset into some equivalent (indiscernibility) classes, and approximates uncertain and vague concepts based on the partitions. A function of approximation is used to calculate the measure of dependency. The measure of dependency is regarded as a heuristic in order to guide the process of FS. Proper approximations of concepts are very essential to obtain a significant measure which makes the initial partitions to be vital in this matter. For a given number of discrete dataset, finding the indiscernibility classes are feasible ,but in the case of real-valued attributes, one can't be sure if the two objects mentioned are the same, or by what relation they are same using the above mentioned indiscernibility relation. A team of research persons extended this RS theory by the usage of tolerant or similarity relation (termed tolerance-based rough set).

The similarity measure between two objects is delineated by a distance function of all attributes .when the similarity measure is exceeding a similarity threshold value, the objects are said to be similar. The important and challenging job is to find the best threshold boundary.

2. RELATED WORKS

A. ROUGH-SET BASED INCREMENTAL APPROACH:

In this approach [1], the approximations of a concept by a variable precision rough-set model (VPRS) usually vary under a dynamic information system environment. It is thus effective to carry out incremental updating approximations by utilizing previous data structures. This paper focuses on a new incremental method for updating approximations of VPRS while objects in the information system dynamically alter. It discusses properties of information granulation and approximations under the dynamic environment while objects in the universe evolve over time. The variation of an attributes domain is also considered to perform incremental updating for approximations under VPRS. Finally, an extensive experimental evaluation validates the efficiency of the proposed method for dynamic maintenance of VPRS approximations.

B. Novel Dynamic Incremental Rules Extraction Algorithm Based on Rough Set Theory:

In this paper, a novel incremental rules extraction algorithm which is called "RDBRST" (Rule Derivation Based on Rough Set And Search Tree) is proposed. It is one kind of width first heuristic search algorithms. The incremental rules are extracted and the existing rule set is updated based on this algorithm [2]. Incremental Induction of Decision Rules from Dominance-Based Rough Approximations. It is extended to handle preference-ordered domains of attributes (called criteria) within Variable Consistency Dominance-based Rough Set Approach. It deals, moreover, with the problem of missing values in the data set. The algorithm has been designed for medical applications which require: (i) a careful selection of the set of decision rules representing medical experience and (ii) an easy update of these decision rules because of data set evolving in time, and (iii) not only a high predictive capacity of the set of decision rules but also a thorough explanation of a proposed decision. To satisfy all these requirements, we propose an incremental algorithm for induction of a satisfactory set of decision rules and a post-processing technique on the generated set of rules.

C. A DISTANCE MEASURE APPROACH TO EXPLORING THE ROUGH SET BOUNDARY REGION FOR ATTRIBUTE REDUCTION

This paper examines a rough set FS technique which uses the information gathered from both the lower approximation dependency value and a distance metric which considers the number of objects in the boundary region and the distance of those objects from the lower approximation. The use of this measure in rough set feature selection can result in smaller subset sizes than those obtained using the dependency function alone. This demonstrates that there is much valuable information to be extracted from the boundary region [5].

D. INCREMENTAL LEARNING OF DECISION RULES BASED ON ROUGH SET THEORY

In this paper, based on the rough set theory, the concept of ∂-indiscernibility relation is put forward in order to transform an inconsistent decision table to one that is consistent, called ∂-decision table, as an initial preprocessing step[4]. Then, the ∂-decision

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matrix is constructed. On the basis of this, by means of a decision function, an algorithm for incremental learning of rules is presented. The algorithm can also incrementally modify some numerical measures of a rule.

3. PROPOSED SYSTEM

The Proposed system idea is to develop a new feature selection mechanism based on Ant Colony Optimization to combat this difficulty. It also presents a new entropy based modification of the original rough set-based approach. These are applied to the problem of finding minimal rough set reducts, and evaluated experimentally.

- Feature selection methods, the Importance Score (IS) which is based on a greedy-like search and a genetic algorithm-based (GA) method, in order to better understand.
- This proposed work is applied in the medical domain to find the minimal reducts and experimentally with the Quick Reduct, Entropy Based Reduct, and other hybrid Rough Set methods such as Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).

Advantages:

- Reducing the dimensionality of the attributes reduces the complexity of the problem and allows researchers to focus more clearly on the relevant attributes.
- Simplifying data description may facilitate physicians to make a prompt diagnosis.
- Having fewer features means less data need to be collected, result in time-consuming and costly.

The proposed work can be explained with the help of the system flow diagram in Figure-1as below,

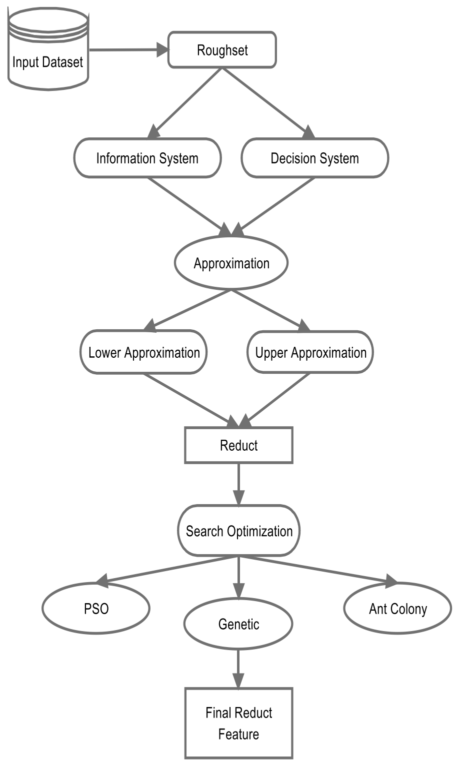

FIGURE 1. SYSTEM FLOW DIAGRAM

4. FEATURE SELECTION APPROACH

The main objective of FS (feature selection) is to pick out from the problem domain the minimal feature subset, such that it represents the original features with an outstanding accuracy given. FS plays a predominant role in real world issues and problems because of the irrelevant, noisy and misleading features of the data that are plenty in numbers. In case of reducing these irrelevant data's, the process of learning from the data technique can be beneficial for the users. The work of FS is to search a feature subset that is the most optimal(that varies depending on the problem to be solved) from the given n size of feature set by competing with candidate subset of size n. But this method is not feasible even though an exhaustive methodology is used.

The searching for the datasets are done randomly in order to cease this complexity. But in that case the extent of getting an optimal solution is drastically brought down.

The degree to which a feature subset or may be a feature may be useful is based on two important factors: 1. relevancy 2.redundancy. Relevancy depends on its ability to predict the decision feature(s), if not the datas are said to be irrelevant. Redundant feature must be

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correlating with other features. So an optimal search to find the best feature subset must be its ability to have a correlation between the decision features but must not be correlating apart from that.
When it comes to subset minimality and subset suitability, a tradeoff occurs with these non-exhaustive techniques and it becomes likely to choose between the two so that one will benefit over the other. Choosing this optimality is a challenging one. Involving situations when the inspection of many features is not possible, it is better to switch on to a subset feature that is much smaller and has a lesser accuracy amount.
For instance , classification rate that is a feature of modeling accuracy should be very high when the user is using selected features, by taking the expense of a non-minimal feature subset.
On the basis of evaluation procedure,there are two important classification in feature selection algorithm.the first one is the filter approach where the FS works independently and which is a separate pre-processor to any learning algorithm. This approach is applied in all the domains as they are very effective in filtering all irrelevant attributes before induction and no any specific induction algorithm is used.
The next is wrapper approach which involves tying up of evaluation procedure to a task of any learning algorithm as in the case of classification. This method employs an accuracy estimation that can search through the spaces of feature subset with the help of an induction algorithm that measures suitability of subsets. Wrapper are the ones that produce good results when compared with the other but faces the difficulties of a break down when large number of features are fed into it and also makes it expensive to run because of the learning algorithm used, that invokes the problem when large datasets are used.

5. ROUGH SET-BASED FEATURE SELECTION APPROACH

Rough set theory (RST) can discover data dependencies. They can curtail the attributes found in the dataset by using only the data and not any additional information. this is a topic in trend that lures many researches to work on it and has been applied in various domains and fields over the past decade. Using RST it is possible to search for the right subset that is often termed as reduct when discretized attribute values are given in a dataset; the rest of the attributes can be taken out from the dataset with minimal loss of information. From the view of dimensionality, the one with the predictive nature of class attribute are often called the informative feature. Finding rough set reducts are put into two approaches: One for to estimate the degree of dependency and the other for discemibility matrix consideration. This section describes the fundamental ideas behind both of these approaches There are two main approaches to finding rough set reducts: those that consider the degree of dependency and those that are concerned with the discernibility matrix. This section describes the fundamental ideas behind both approaches. To illustrate the operation of these, an example dataset (Table 1) will be used.

Table 1. An example dataset

*x***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

A. Rough Set Attribute Reduction

Central to Rough Set Attribute Reduction (RSAR) is the concept of indiscernibility. Let $I = (U, A)$ be an information system, where U is a non-empty set of finite objects (the universe) and $A$is a non-empty finite set of attributes such that $a:U \rightarrow V$a for every $a \in A$. Va is the set of values that attribute a may take. With any $P \in A$ there is an associated equivalence relation $IND(P)$:

B. Information and Decision Systems

An information system can be viewed as a table of data, consisting of objects (rows in the table) and attributes (columns). In medical datasets, for example, patients might be represented as objects and measurements such as blood pressure, form attributes. The attribute value for a particular patient is their specific reading for that measurement. Throughout this paper, the terms attribute, feature and variable are used interchangeably.
An information system may be extended by the inclusion of decision attributes. Such a system is termed a decision system. For example, the medical information system mentioned previously could be extended to include patient classification information, such as whether a patient is ill or healthy. A more abstract example of a decision system can be found in table 1. Here, the table consists of four conditional features (a; b; c; d), a decision feature (e) and eight objects. A decision system is consistent if for every set of objects whose attribute values are the same, the corresponding decision attributes are identical.

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6. A. ANT COLONY OPTIMIZATION FOR FEATURE SELECTION

Swarm Intelligence (SI) is the property of a system whereby the collective behaviors of simple agents interacting locally with their environment cause coherent functional global patterns to emanate. This provides a basis with which it is possible to explore collective (or distributed) problem solving without centralized control or the provision of a global model. Particle Swarm Optimization is one area of interest in SI, a population-based assumptive optimization technique. Here, the system is initialized with a population of random solutions, called particles. Optima are searched for by updating generations, with particles moving through the parameter space towards the current local and global optimum particles. The velocities of all particles are changed depending on the current optima, at each time step.

Ant Colony Optimization (ACO) is another area of interest within SI. In nature, it can be observed that real ants are capable of finding the shortest route between a food source and their nest without the use of visual information and hence possess no global world model, adapting to changes in the environment. The deposition of pheromone is the main factor in enabling real ants to find the shortest routes over a period of time.In this chemical, each ant probabilistically prefers to follow a direction. Over time the pheromone decays, which results in much less pheromone on less popular paths. Provided that over time the shortest route will have the higher rate of ant traversal, this path will be reinforced and the others will be diminished until all ants follow the same, shortest path (the "system" has converged to a single solution). There is a possibility that there are many equally short paths. In this situation, the rates of traversal of ants over various the short paths will be roughly the same, which results in these paths being maintained while the others are ignored. In addition, if there is a sudden change to the environment (e.g. a large obstacle appears on the shortest path), the ACO system responds to this and will eventually converge to a new solution. Based on this idea, artificial ants can be deployed to solve complex optimization problems via the use of artificial pheromone deposition.

ACO is particularly attractive for feature selection as there seems to be no heuristic that can guide search to the optimal minimal subset every time. Additionally, it can be the case that ants discover the best feature combinations as they proceed throughout the search space. This section discusses how ACO may be applied to the difficult problem of finding optimal feature subsets and, in particular, fuzzy-rough set-based reducts.

The ACO-suitable problem is formulated from feature selection task. ACO represents the problem as a graph where the nodes represent features and hte edges between them denote the choice of the next feature. The search for the optimal feature subset is an ant traversal through the graph where a minimum number of nodes are visited which satisfies the criteria for stopping the traversal. Illustrates this setup - the ant is currently at node *a* and has a choice of which feature to add next to its path (dotted lines).Next feature *b* is choosed based on transition rule, followed by c and *d*. With the arrival at *d*, the current subset *fa; b; c; dg* is determined to satisfy the traversal stopping criteria (e.g. a suitably high classification accuracy has been achieved with this subset, based on the assumption that the selected features are used to classify certain objects).The ant outputs this feature subset as a candidate for data reduction by terminating its traversal.

C. GENETIC ALGORITHM FOR FEATURE SELECTION

Genetic algorithm (GA) is a search heuristic, used to generate solutions to optimization problems following the techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. In the genetic algorithm,

- A population of strings (called chromosomes), which encode candidate solution to an optimization problem is taken.
- A proper fitness function is then constructed, and the fitness of the current population is evaluated.
- Two fittest chromosomes are chosen as the parents and (a) crossing over between them or (b) mutation of a parent is performed to produce new children and a new population.
- Again the fitness function for the new population is estimated.
- The process recurs as long as the fitness function keeps on improving or until the termination condition is attained.

The algorithm of a genetic programming begins with the population which is a set of randomly created individuals. Each individual represents a potential solution which is further represented as a binary tree. Each binary tree is constructed by all the possible compositions of the sets of functions and terminals. A fitness value of each tree is calculated by a suitable fitness function. According to the fitness value, a set of individuals with better fitness will be selected. These individuals are used to generate new population in next generation with genetic operators. Genetic operators generally also include reproduction, crossover, mutation and others that are used to evolve functional expressions.

After the evolution of multiple generations, we can obtain an individual having good fitness value. If the fitness value of such individual still does not satisfy the specified conditions of the solution, the process of evolution will be repeated until the specified conditions are satisfied.

D. PSO FOR FEATURE SELECTION

Particle swarm optimization (PSO) is an evolutionary computation technique the original intent was to graphically simulate the graceful but unpredictable movements of a flock of birds. The original version of PSO was formed from the modified initial simulation. To produce the standard ISO, later she introduced inertia weight into the particle swarm optimizer.A population of random solutions which is also called 'particles' was initialized by PSO. In S-dimensional space each particle is treated as a point. The *I*th particle is represented as $a_i=(a_{i1},a_{i2},a_{i3}\ldots a_{in})$. The best previous position (pbest, the position giving the best fitness

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$b_i=(b_{i1},b_{i2},\ldots b_{in})$. The symbol 'gbest' is used to represent the index of the best particle among all the particles in the population. $E_i=(e_{i1},e_{i2},\ldots e_{in})$ represents the rate of the position change(velocity) for the particle i. The following equation manipulates the particles value) of any particle is recorded and represented

$$e_{id}=w*e_{id}+c1*rand()*(b_{id}-a_{id})+c2*Rand()*(e_{gd}-a_{id})$$

$$a_{id}=a_{id}+e_{id}$$

Where $d = 1,2,\ldots, S$, w is the inertia weight, it denotes a positive linear function of time changing according to the generation iteration. The balance between global and local exploration is provided by suitable selection of inertia weight and it also results in less iteration on average to find a sufficiently optimal solution. The constants c1 and c2 in equation are known as acceleration constants which represent the weighting of the stochastic acceleration terms that pull each particle toward pbest and gbest positions. High values result in target regions, abrupt movement toward, or past while low values allow particles from target regions to roam far before being tugged back. The two random function in the range are rand () and Rand ().On each dimension, particle's velocities are limited to maximum velocity, Vmax. Maximum velocity determines how large steps through the solution space is allowed to take for each particle. The particles may not explore sufficiently beyond locally good regions if Vmax is too small and it could become trapped in the local optima. Where as if Vmax is too high particles might fly past good solutions.

The first part of equation provides the "flying particles" with a degree of memory capability allowing the exploration of new search space areas. The second part represents the private thinking of the particle itself called as "cognition". The third part provides the collaboration among the particles and it is called as "social". PSO is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. Then according to the equation the particle flies toward a new position.

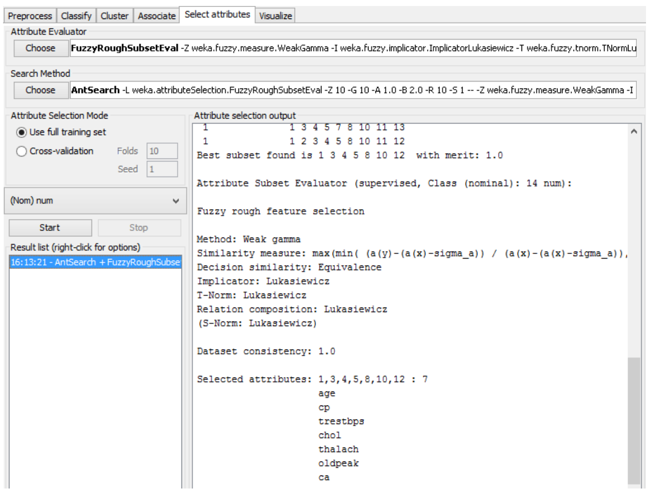
7. EXPERIMENTAL STUDY:

The performance of the reduct calculation approaches discussed in this paper has been tested with different medical datasets obtained from UCI machine learning data repository, [2] to evaluate the performance of proposed algorithm. Weka tool is being used for experimental purpose. Table 2 shows the details of datasets used in this paper.

Table 2. Detail of Data Sets Used for Experiment

Data Set Name	Total Number of Instances	Total Number of Features	Feature Reduction
Cleveland Heart	303	14	7
Lung Cancer	32	57	5

Sample screen shots:



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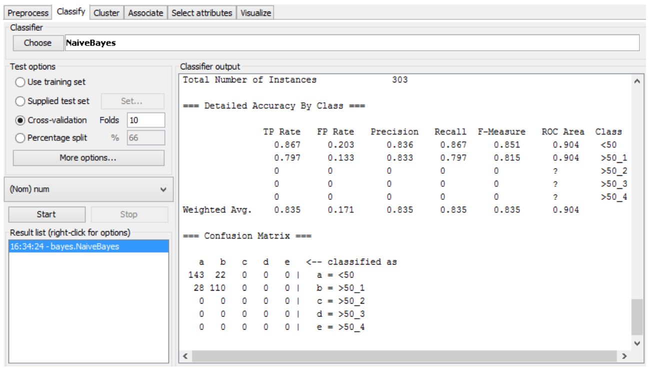
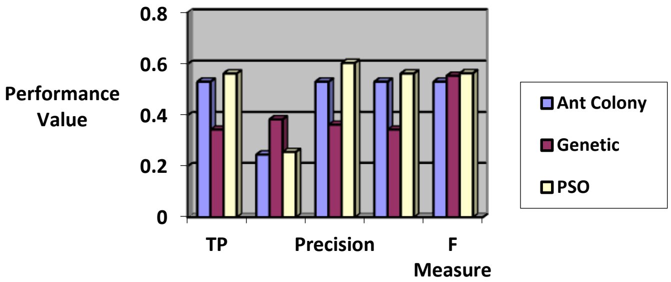


PERFORMANCE ANALYSIS:

In order to obtain the optimal data reductions here, in this paper three types of optimization algorithms such as Genetic algorithm, PSO Algorithm, Ant colony optimization algorithm were used to analyze the performance as follows,



CONCLUSION AND FUTURE WORK

Feature selection is a most valuable preprocessing technique for applications involving huge amount of data. It mainly deals with the problem of selecting minimal attribute set that are most predictive to represent the original attributes in data set. This paper discussed the strengths and weaknesses of various existing feature selection methods. Rough Set Reduct algorithm used as a major preprocessor tool for feature selection. This paper starts with the fundamental concepts of rough set theory and explains basic techniques: Quick Reduct. These methods can produce close to the minimal reduct set. The swarm intelligence methods have been used to guide this method to find the minimal reducts. Here three different computational intelligence based reducts: Genetic algorithm, Ant colony optimization and PSO. Though these methods are performing well, there is no consistency since they are dealing with more random parameters. All these methods are analyzed using medical datasets. Experimental results on different data sets have shown the efficiency of the proposed approach. Comparative performance analysis in which the experimental result shows that feature selection is best for minimal reductions. When compare to other optimization algorithm, PSO algorithm produces higher performance value. As shown in the results, our proposed method exhibits consistent and better performance than the other methods. As an extension of this work the following may be done in future as comparing the results with some other evolutionary algorithm and performing disease prediction.

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