

**A peer-reviewed version of this preprint was published in PeerJ on 18 November 2019.**

[View the peer-reviewed version](https://doi.org/10.7717/peerj-cs.188) (peerj.com/articles/cs-188), which is the preferred citable publication unless you specifically need to cite this preprint.

Hasanpour H, Ghavamizadeh Meibodi R, Navi K. 2019. Improving rule-based classification using Harmony Search. PeerJ Computer Science 5:e188 <https://doi.org/10.7717/peerj-cs.188>

# Improving rule based classification using harmony search

Hesam Hasanpour<sup>1</sup>, Ramak Ghavamizadeh Meibodi<sup>Corresp., 1</sup>, Keivan Navi<sup>1</sup>

<sup>1</sup> Department of Computer Science and Engineering, Shahid Beheshti University, Tehran, Iran

Corresponding Author: Ramak Ghavamizadeh Meibodi  
Email address: r-ghavami@sbu.ac.ir

Classification and associative rule mining are two substantial areas in data mining. Some scientists attempt to integrate these two field called rule-based classifiers. Rule-based classifiers can play a very important role in applications such as fraud detection, medical diagnosis, and etc. Numerous previous studies have shown that this type of classifiers achieves high classification accuracy than traditional classification algorithms. However, they still suffer from a fundamental limitation. Many rule-based classifiers used various greedy techniques to prune the redundant rules that lead to missing some important rules. Another challenge that must be considered is related to the enormous set of mined rules that result in high processing overhead. The result of these approaches is that the final selected rules may not be the global best rules. These algorithms are not successful at exploiting search space effectively in order to select the best subset of candidate rules. We merged the Apriori algorithm, harmony search, and classification based association rules (CBA) algorithm for building a rule-based classifier. We applied a modified version of the Apriori algorithm with multiple minimum support for extracting useful rules for each class in the dataset. Instead of using a large number of candidate rules, binary harmony search was utilized for selecting the best subset of rules that appropriate for building a classification model. We applied the proposed method on seventeen benchmark dataset and compared its result with traditional association rule classification algorithms. The statistical results show that our proposed method outperformed other rule-based approaches.

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Hesam Hasanpour<sup>a</sup>, Ramak Ghavamizadeh Meibodi<sup>a\*</sup>, Keivan Navi<sup>a</sup>

*a. Department of Computer science and Engineering, Shahid Beheshti University, Tehran, Iran*

**\*Corresponding author:**

Dr. Ramak Ghavamizadeh Meibodi, Department of Computer Science and Engineering, Shahid Beheshti University, GC, Tehran, Iran Tel+ 98-21-29904169, Email: r-ghavami@sbu.ac.ir

# Abstract

Classification and associative rule mining are two substantial areas in data mining. Some scientists attempt to integrate these two field called rule-based classifiers. Rule-based classifiers can play a very important role in applications such as fraud detection, medical diagnosis, and etc. Numerous previous studies have shown that this type of classifiers achieves high classification accuracy than traditional classification algorithms. However, they still suffer from a fundamental limitation. Many rule-based classifiers used various greedy techniques to prune the redundant rules that lead to missing some important rules. Another challenge that must be considered is related to the enormous set of mined rules that result in high processing overhead. The result of these approaches is that the final selected rules may not be the global best rules. These algorithms are not successful at exploiting search space effectively in order to select the best subset of candidate rules.

We merged the Apriori algorithm, harmony search, and classification based association rules (CBA) algorithm for building a rule-based classifier. We applied a modified version of the Apriori algorithm with multiple minimum support for extracting useful rules for each class in the dataset. Instead of using a large number of candidate rules, binary harmony search was utilized for selecting the best subset of rules that appropriate for building a classification model. We applied the proposed method on seventeen benchmark dataset and compared its result with traditional association rule classification algorithms. The statistical results show that our proposed method outperformed other rule-based approaches.

# Introduction

The availability of a huge amount of raw data has created an immense opportunity for knowledge discovery and data mining research to play an essential role in a wide range of applications such as industry, financial forecasting, weather forecasting and healthcare. Classification is one of the most important areas in data mining that has applied in many applications such as bioinformatics, fraud detection, loan risk prediction, medical diagnosis, weather prediction, customer segmentation, target marketing, text classification and engineering fault detection. Association Rule Mining (ARM) is another popular and substantial technique in machine learning and data mining that introduced by Agrawal et al (Agrawal et al. 1993), and since that remained one of the most active research areas in machine learning and knowledge discovery. Association rule mining finds interesting relationships among large sets of data items. Association rules show attribute value conditions that occur frequently together in a given data set. Association rules provide information of this type in the form of if-then statements. Unlike the if-then rules of logic, association rules are intrinsically probabilistic and are computed from the data. The ARM is a powerful exploratory technique with a wide range of applications including marketing policies, medical domain(Ilayaraja & Meyyappan 2013; Shin et al. 2010), financial forecast, credit fraud detection(Sarno et al. 2015) and many other areas. There are a number of famous association rule mining algorithms that are accessible to researchers (Agrawal et al. 1993; Burdick et al. 2001; Scheffer 2001a).

There is some evidence that integration benefits of classification and association rule mining together can result in more accurate and efficient classification models than traditional classification algorithms(Ma & Liu 1998). Producing concise and accurate classifier by utilizing association rule mining is one of the attractive domain for data mining and machine learning researchers.

A typical associative classification system is constructed in two stages:

- 1) discovering all the association rules inherent in a database.
- 2) Selecting a small set of relevant association rules to construct a classifier.

In the first step, some algorithms use Apriori algorithm for rule generation and some other algorithms use other approaches such as FOIL (First Order Inductive Learner). Mazid et al. (Mazid et al. 2009) compared the performance between the rule-based classification and association rule mining algorithm based on their classification performance and computational

complexity. They concluded that Apriori is a better choice for rule-based mining task in terms of accuracy and computational complexity.

Usually a lot of rules are generated in the first step and the main issue on second step is that how to efficiently find out a small number of high-quality rules and how to generate a more accurate classifier. It must be noted that some researchers focus on the first step and try to find a minimal class association rule set(Li et al. 2002), but our focus is on the second step.

Traditional algorithms use greedy approaches for selecting a small subset of generated rules for building a classifier. By using this approach, the selected rules are not the best subset of possible rules. Another challenge is that the resulted rules bias to prevalent classes and classification the rare instances is a major problem. consequently, test samples belonging to the small classes are misclassified as prevalent classes(Chen et al. 2012; Sun et al. 2009). Sometimes rules with low support and very high confidence are effective in identifying rare events.

In this paper, we present an association rule-based classification method to obtain an accurate and compact rule-based classifier. We use Apriori algorithm for rule generation and harmony search for selecting the best subset of rules that can build a classifier.

The plan of this paper is as follows: at first, we present the necessary information related to rule-based classification. At the next Section, we describe the proposed method. Result section shows the induced results and finally, discussion section concludes the study.

## Preliminaries

### Apriori algorithm and interesting measures

Apriori is a standard and well-known basic algorithm in association rule mining that is used for mining frequent itemsets in a set of transactions. It was first introduced by Agrawal and Srikant(Agrawal et al. 1993). The APRIORI-C is another Apriori-based algorithm that drives rules according to the parameters minimal confidence and minimal support of a rule (Jovanoski & Lavrač 2001). Predictive Apriori (Scheffer 2001b) is another algorithm motivated by Apriori and unlike the confidence related focus of Apriori tries to maximizes the expected accuracy of an association rule on unseen data. While Apriori sorts the rules based on confidence only, Predictive Apriori considers both the confidence and support in ranking the rules.

Nahar et al. considered three rule generation algorithms – Apriori, Predictive Apriori and Tertius- for extraction the meaningful factors for particular types of cancer(Nahar et al. 2011) and heart disease (Nahar et al. 2013). Their experimental results showed that Apriori is the most beneficial association rule mining algorithm.

Apriori algorithm can produce a lot of rules, but much of them are superfluous. To select appropriate rules from the set of all possible rules, constraints on various measures of interestingness can be used. Support and confidence are two measures of rule interestingness that mirror the usefulness and certainty of a rule respectively(Agrawal et al. 1996). The support is the percentage of the total number of records of transactions that include all items in the antecedent (if) and consequent (then) parts of the rule. Frequent itemsets are those itemsets that their frequency is greater than a predefined minimum support (Minsup). Confidence is the ratio of the number of transactions that include all items in the consequent, as well as the antecedent (the support) to the number of transactions that include all items in the antecedent. In another word, confidence is the accuracy of the rule and usually is used in Apriori for ranking the rules. The task of association rule mining is to generate all association rules from the set of transactions that have a support greater than Minsup and confidence greater than Mincon. Since we need to discover the relationship between input attributes and class label, we need to find all the rules of the form  $A \rightarrow B$  that antecedent part of the rule includes of some item and the consequent part can just be the class items.

High support and high confidence rules are not necessarily interesting. Instead of using only Support and confidence, we also used lift measure as a metric for evaluating the significance and reliability of association rules. Lift is the ratio of Confidence to Expected Confidence. Hence, Lift is a value that gives us information about the increase in the probability of the consequent given antecedent part of a rule. A lift ratio larger than 1.0 implies that the relationship between the antecedent and the consequent is more significant than would be expected and make those rules potentially useful for predicting the consequent in unseen instances. The larger the lift ratio, the more significant the association.

$$Support(X \Rightarrow Y) = P(X \cap Y) \quad (1)$$

$$Confidence(X \Rightarrow Y) = P(Y | X) = \frac{Support(X \cap Y)}{Support(X)} \quad (2)$$

$$Lift(X,Y) = \frac{P(X \cap Y)}{P(x) * P(Y)} \quad (3)$$

Another issue that must be considered is related to the type of dataset that is appropriate for applying the Apriori algorithm. Consider a dataset for supervised learning which contains observations of a class label variable and a number of predictor variables. Such a dataset can be converted into an appropriate format for association rule mining if both the class label and the predictors are of the categorical type. Since our benchmark datasets contain continuous variables, we must use a method for handling numeric attributes. There are some methods for this purpose. A traditional method is discretization that can be static or based on the distribution of data. we use a method that proposed by Tsai et al(Tsai et al. 2008).

#### **Associative rules for classification**

In recent years, some researchers try to combine association rule mining and classification (Cano et al. 2013b; Li et al. 2001; Ma & Liu 1998; Wang et al. 2000; Wang & Wong 2003; Yin & Han 2003). Their experiments show that this approach achieves better accuracy than conventional classification algorithms such as C4.5. The reason is that the associative classifier is composed of high-quality rules, which are generated from highly confident event associations that reflect the close dependencies among events.

Classification Based on Association rules (CBA) algorithm is one of the first efforts for combining of classification and association rule mining(Ma & Liu 1998). This algorithm will describe with details in the next section. Wenmin Li et al. suggested a weighted  $\chi^2$  analysis to perform a classification based on multiple association rules (CMAR)(Li et al. 2001). Unlike the CBA algorithm, the CMAR algorithm uses all the rules that cover the example to be classified instead of using just one rule.

Yin et al(Yin & Han 2003) propose the CPAR (Classification based on Predictive Association Rules) rule-based classification algorithm,. CPAR doesn't generate a large number of candidate rules as in conventional associative classification. It pursues a greedy algorithm to produce rules directly from training data and uses the best k rules in prediction time.



An advantage of associative classifiers is that they are rule-based and thus lend themselves to be more easily understood by humans. As previously stated a classification system is built in two phase. In the first stage, the learning target is to discover the association patterns inherent in a database (also referred to as knowledge discovery). In the second stage, the goal is to select a small set of relevant association patterns to construct a classifier given the predictor attributes. To produce the best classifier out of the entire set of rules, we need to consider all the feasible subsets of rules and selecting the most accurate subset. This is clearly impractical. In the classification phase, some methods such as (Ma & Liu 1998; Thabtah et al. 2004; Wang et al. 2000), simply select a rule with a maximal user-defined measure, such as confidence. If there is no rule covering the example, then usually the prevalent class is taken to be the predicted class. However, identifying the most effective rule at classifying a new case is a big challenge. When classifying a new data object, it may have more rules that satisfy the test conditions and using them may increase the prediction accurately (Li et al. 2001).

#### **CBA algorithm**

Classification Based on Associations (CBA) algorithm is one of the first algorithms to bring up the idea of classification using association rules (Ma & Liu 1998). CBA implements the famous Apriori algorithm (Agrawal et al. 1993) in order to discover frequent items. Once the discovery of frequent items finished, CBA proceeds by converting any frequent item that passes the Minconf into a rule in the classifier. At the rule generation phase, CBA selects a special subset of association rules whose right-hand-side are restricted to the classification class attribute. This subset of rules is called class association rules (CARs). At the next step, the CBA algorithm builds a classifier using CARs. At this step, CBA uses a heuristic approach and sorts the rules according to their confidence and selects top rules that cover the training samples. The algorithm first selects the best rule (rule having the highest confidence), then eliminates all the covered examples. If at least one example satisfied the rule conditions, then that rule is appended to the final rules. This procedure is repeated until there are no more rules to select or there are no more examples to cover. The algorithm then stops and returns the classifier in the form of an IF-THEN-ELSE rule list. One challenge with this approach is that selecting the best rules may be not the best subset of rules.

The CBA system follows the original association rule model and uses a single Minsup in its rule generation. It seems that this is inadequate for mining of CARs because class frequency distributions in many practical classification datasets is unbalanced. We used the CBA algorithm with three little changes. The first change is that we use multiple Minsup than can be useful for imbalanced datasets. The second change is that in the original CBA algorithm once each sample is covered by a rule, it removed from the samples, we define a parameter called Delta. This parameter defined that how many times each sample must be covered to remove from the samples(Li et al. 2001) . This approach leads to generation more rules. The third change occurs in the classification phase. In the classification phase of the original CBA algorithm, the rule with maximum confidence that covers the test conditions defines the class label of a test sample. We select the top k (a predefined parameter) rules from each class that covers the test sample conditions and determine the class label according to the sum of the confidence of selected rules. All data preprocessing and analyses were conducted using Matlab version 2014a (The MathWorks Inc.).

## Proposed method

The proposed method of rule selection based on HS are depicted in Figure 1. At the initial step, we do some preprocessing on each dataset. One of the main preprocessing is discretization of continuous features. We applied a discretization algorithm based on class-attribute contingency coefficient that was proposed by Tsai et al (Tsai et al. 2008). After discretization, we convert each dataset to appropriate format such that the value of each feature can be True (1) or False (0). For this aim, if a feature is converted to N different discrete values, we produce N feature. After the conditions are satisfied for the Apriori algorithm, we run this algorithm for each class with different Minsup and Minconf. The main novelty of our study is in the next step. As previously was mentioned, the Apriori algorithm produces a lot of rules and CBA algorithm uses a greedy algorithm for selecting a subset of produced rules for building a classifier. Using greedy approaches cause that the selected rules are not the best subset of rules. We believe that population-based evolutionary algorithms fit well to the rule selection problem. Harmony search (HS) is a population-based stochastic search algorithm that inspired by the musical process of searching for a perfect state of harmony (Geem et al. 2001). The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are

similar to local and global search methods in optimization techniques. When a musician is improvising, he has three choices: (1) to execute any pitch from memory; (2) to execute a pitch next to any other in his memory; (3) to execute a random pitch from the range of all possible pitches. These three options are employed in the HS algorithm by means of three main parameters: Harmony Memory (HM), Harmony Memory Consideration Rate (HMCR), and Pitch Adjustment Rate (PAR). The HMCR is defined as the probability of selecting a component from the present HM members. The PAR determines the probability of a candidate from the HM to be mutated. The steps in the procedure of HS are as follows:

Step 1. Initialize a Harmony memory (HM). The initial HM consists of a given number of randomly generated solutions to the optimization problems under consideration.

Step 2. Improvise a new harmony from HM.

Step 3. Update the HM. If the new harmony is better than the worst harmony in HM, then include the new harmony in the HM and exclude the worst harmony from the HM.

Step 4. If stopping criteria are not satisfied, go to step 2.

HS has been successfully applied to various discrete optimization problems such as Maximum Clique Problem (Afkhami et al. 2013), traveling salesperson problem (Geem et al. 2001), tour routing (Geem et al. 2005), water network design (Geem 2006), Dynamic relocation of mobile base stations in wireless sensor networks (Moh'd Alia 2017), and others.

In binary HS, the size of each solution equals the number of candidate's rules. For example, if the Apriori algorithm produces 100 rules that satisfy Minsup and Minconf conditions then the size of each solution in HS will be equal to 100. Each solution consists of a binary vector of rule incidences, indicating exclusion (0) or inclusion (1) of the rule in the combination.

The standard harmony search (HS) is not suitable for binary representations. This is due to the pitch adjusting operator not being able to perform the local search in the binary space. Therefore we used the implementation of HS that proposed by Afkhami et al (Afkhami et al. 2013).

We run the HS algorithm with the following parameters: Maximum number of iterations = 20, Harmony memory size = 100, Number of new Harmonies = 20, Harmony memory consideration rate = 0.75.

We used harmony search, a music inspired stochastic search algorithm, for selecting the best subset of rules as a classifier. One of the important section in any meta-heuristic algorithm is the calculation of cost function. For this aim, we apply a modified version of the CBA algorithm on

the selected rules and calculate the error rate of applying the resulted rules on the training and validation data. At final, the solution with minimum cost value is selected and this solution (a subset of rules) applies on the test data. It is obvious that the proposed flowchart is shown for one fold of cross-validation. In K-fold cross-validation, this approach must be repeated for K times, until all the samples in the dataset are used for the test data. The pseudo code of the proposed method is shown in Table 1.

Time complexity of the Apriori algorithm and association rule mining is a critical challenge that must be considered (Cano et al. 2013a; Cano et al. 2014; Luna et al. 2016; Thabtah et al. 2006). As its time complexity is exponential, we can do some preprocessing activity to decrease the running time. First of all, we can apply feature selection before applying Apriori algorithm. Feature selection can be done before or after of discretization. The second thing that we can do is related to the size of the rules. As small rules are favorable, we can limit the size of items that appear in a rule and consequently decrease the running time of Apriori algorithm.

## Results

We applied the proposed method on seventeen benchmark dataset and compare its result with traditional association rule classification algorithms. We compared our proposed method with CPAR, CBA and C4.5 algorithms that are famous algorithms in rule-based classification (Ma & Liu 1998; Quinlan 1993; Yin & Han 2003) The characteristic of the used datasets are shown in Table 2. We selected datasets with a variety of size in samples, attributes and number of classes. To run the experiments, stratified five-fold cross-validation was used to produce a reliable accuracy. Cross-validation is a standard evaluation measure for calculating error rate on data in machine learning. At each run, we split each dataset to five parts, three part for training, one part for validation and one part for testing. To increase reliability, the experiments for each dataset have been repeated 10 times and the average of results were reported.

The result of the proposed method is shown in Table 3. As the results show, at four dataset decision tree gain the best accuracy, CPAR algorithm have the highest accuracy at the five datasets and our proposed method is the best at the seven datasets out of nine datasets. In one dataset, all algorithms are perfect and gain equal accuracy. CBA algorithm is not the best in none of the datasets and in all of the datasets our proposed method outperformed the CBA algorithm.

It must be noted that the results of decision tree, CBA and CPAR algorithms are reproduced on the same partitions.

We used Friedman test(Friedman 1940) as an appropriate choice for comparing multiple classification algorithms(Brazdil & Soares 2000; Demšar 2006). The Friedman test is a non-parametric statistical test developed by Milton Friedman(Friedman 1937; Friedman 1940). Similar to the parametric repeated measures ANOVA, it is used to detect differences between groups when the dependent variable being measured is ordinal. It must be noted that classification algorithms are ranked on each of the datasets and then Friedman test is applied. The last row of table 3 shows the mean rank for each of the algorithms. As the results show, proposed method gained the best position and CBA has the worst one. The results also shows that there is an overall statistically significant difference between the mean ranks of the related algorithms ( $P=0.0005$ ).

The reported accuracy of other studies may be different in some algorithms from our ones. One of the main reason for this conflict is that we had no information about the discretization algorithm, in particularly the number of ranges used to discretize continuous attributes. Using different discretization approaches can result in different outputs.

## Discussion

This research has focused on the application of computational intelligence in association rule mining-based classifiers. Although rule-based classification algorithms have high classification accuracy, but some of them suffer from a critical limitation. They used a heuristic approach for selection a subset of rules for building a classifier. It is obvious that the selected rules may not be the best subset of possible rules. Another challenge of existing algorithms is related to rare class. Using greedy approaches, the resulted rules bias to prevalent classes and classification the rare instances is a major problem.

We combined Apriori, CBA and harmony search algorithms for building a rule based classifier that has a high prediction accuracy. We used Apriori algorithm with multiple Minsup for rule generation. Since the number of rules that satisfy Minsup and Minconf conditions is high and considering all subset of rules is not possible, we applied the harmony search algorithm for finding the best subset of rules that can be used as a classifier. The Harmony search (HS) is a relatively simple yet very efficient evolutionary algorithm. One of the main sections in every

population based algorithms is calculating the cost function. For every solution (subset of selected rules) we applied a modified version of the CBA algorithm on training and validation data and assigned the resulted value to the cost function. The statistical and experimental results of applying the proposed method on seventeen benchmark dataset demonstrate that our proposed method outperformed famous algorithms such as tree search, CBA and CPAR in general. One of the limitations of the proposed method is that it does not gain proper accuracy in datasets with many class number. Another limitation in our study is that we used accuracy measure for comparing the algorithms. Using measures such as precision and recall can better reflects the benefits of the proposed method. Our aim in the future is to tackle these problems.

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# **Table 1**(on next page)

Pseudo code of the proposed method

This pseudo code supposes that we have training input, training output, test input, validation input and validation output. The code shows that how we build a rule-based classifier and determine the test data output.

1 *Table 1: pseudo code of the proposed method*

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*For i=1 to Kfold*

Determine Traininput, Trainoutput, Testinput, Testoutput, Valinput and Valoutput

Finalrules={};

For j=1 to number\_class

Rulesj= apply Apriori algorithm(traininput, Minsupj,Minconj,class j )

Finalrules= append Rulesj to Finalrules

End %for j

Selected\_rules=Apply harmony search algorithm (Finalrules, Traininput, Trtainoutput, Valinput, Valoutput)

Testoutput= apply selected\_rules on Testinput

End %for i

---

2

## Table 2 (on next page)

### Description of used datasets

each row shows the specifications of a used dataset including the name of the dataset, the number of features, the number of classes and distribution of classes.

1 Table 2: description of used datasets

id	Dataset	# of Data items	# of features	# of class	distribution
1	Iris	150	4	3	50-50-50
2	Galaxy	323	4	7	51-28-46-38-80-45-35
3	Wine	178	13	3	59-71-48
4	Tictactoe	958	9	2	626-332
5	SAHeart	462	9	2	160-302
6	Car	1728	6	4	1210-384-65-69
7	Breast cancer	699	19	2	458-241
8	Yeast	1484	8	10	244-429-463-44-35-51-163-30-20-5
9	Balance scale	625	4	3	49-288-288
10	lymphography	148	18	4	2-81-61-4
11	Haberman	306	3	2	225-81
12	Mammographic	830	5	2	427-403
13	phoneme	5404	5	2	3818-1586
14	Pima	768	8	2	267-500
15	German	1000	20	2	700-300
16	Monks-2	432	6	2	142-290
17	Monks-3	432	6	2	228-204

2

# **Table 3**(on next page)

## Experiment results

Each row of the table shows the accuracy of applying four rule-based classification algorithm on a dataset.

1 Table 3: Experiment results based on 20 repetitions of 10-fold cross validation

Id	dataset	Decision tree	CBA	CPAR	Proposed method
1	Iris	91.33	94.6	94.67	<b>96.67</b>
2	Galaxy	<b>68.73</b>	56.66	60.37	61.12
3	Wine	86.52	95.12	94.38	<b>97.19</b>
4	Tictactoe	91.22	80.48	<b>97.39</b>	92.81
5	SAHeart	64.94	66.45	71.21	<b>73.43</b>
6	Car	94.68	73.38	<b>95.78</b>	80.22
7	Breast cancer	92.85	85.69	95.42	<b>96.28</b>
8	Yeast	54.99	52.96	<b>57.61</b>	56.27
9	Balance scale	<b>77.44</b>	72.20	71.36	73.76
10	Lymphography	73.65	57.43	<b>83.11</b>	74.32
11	haberman	71	73	73.84	<b>75.16</b>
12	mammographic	81.08	80.81	81.49	<b>83.20</b>
13	phoneme	<b>85.79</b>	70.65	70.73	77.22
14	pima	71.08	71	64.84	<b>72.01</b>
15	German	<b>73.1</b>	67	71.40	68.7
16	Monks 2	73.61	60.49	<b>80.79</b>	64.58
17	Monk 3	1	1	1	1
Mean Rank		2.55	3.5	2.14	1.79

2

# Figure 1(on next page)

The framework of the proposed method

This figure shows what steps must be done for implementation of the proposed method.

