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Research paper

Multi-Objective PSO-fuzzy Optimization Approach to Improve Interpretability and Accuracy in Medical Data

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Abstract

Today, Decision Support Systems (DSS) plays a significant role in a medical and healthcare domain. Designing an Automatic Fuzzy Rule-based Classification Systems (FRBCSs) is considered as optimization problem associated to a result of high interpretability and accuracy. Interpretability and accuracy are the two main objectives to be improved in the optimization measurement of FRBCSs. However, improving these objectives is found to be difficult in most of the existing systems due to the conflicting issues between accuracy and interpretability. In this work, we proposed an approach that can effectively handle accuracy- interpretability trade-off in constructing FRBCSs. We designed automated FRBCSs in the form of Multi-objective Particle Swarm Optimization with Crowding Distance. In the approach, there will be a collection of solutions to FRBCSs that deem best global minimum or global maximum with respect to interpretability and accuracy. Our method is evaluated on a popular benchmark data sets being used in a medical domain for evaluations. These datasets are Liver Disorders (BUPA), Pima Indians Diabetes and Thyroid Disease (New Thyroid). The result obtained shows that the proposed method yields an optimum solution in minimizing the trade-off between accuracy and interpretability. Moreover, the result of the comparison shows that our approach outperforms the alternate techniques in terms of accuracy of FRBCSs and also exhibits good result in terms of interpretability objective.

Keywords: *Fuzzy Rule-based Classification, Multi-objective PSO, Particle Swarm Optimization (PSO), Rule-based Systems, Single-objective PSO*

1. Introduction

Recently, data mining techniques are being applied in medical and healthcare domain in order to improve public health and support patient's activities. The huge amounts of information such as laboratory screening, diagnosis, treatment, prognosis, etc. are commonly processed by physicians using statistical techniques. However, these statistical techniques are not capable enough to extract the required knowledge from the available data and information. This necessitated the exploration of alternative techniques for knowledge discovery (KD) in medical and health domain [1].

Many researchers applied *Rule-based Systems* in many applications in various fields including the medical domain. A fuzzy rule-based system (FRBSs) is more probable to be near to human thinking than the behavior of classical systems. Fuzzy sets are represented and handle data and information which have non-statistical uncertainties. Moreover, fuzzy sets let the utilization of symbolic models. The simplest model of FRBSs is the Fuzzy rule-based classification system (FRBCS). An area of interest in this field of study is that of FRBCS design, with *if-then* statements as their rules. It is successful in achieving good results in contrast to other modeling methods. FRBCS is able to give the ability to deduce knowledge from the existing data that can be fully understood by the human.

An FRBCS may be developed by an expert in manual form or be made automatically base on the set of data that labels a confident spectacle. FRBS automation can be considered an optimization problem [2], [3]. Classical based optimization techniques could not present a positive Pareto front solution in a situation where objective function comprises separate Pareto front and is non-convex in nature [4]. To address the problem, other techniques like Genetic Algorithms (GAs) and Evolutionary Algorithms (EAs) were applied [3], [5]–[8]. Application of Multi-objective Evolutionary Optimization Algorithms (MOEOAs) is the most suitable solution to the problem. Multi-objective optimizations are easy to optimize several objectives, usually the objectives in conflict with each other, at the same time. In genetic algorithms based MOEAs, in each generation a non-dominant solution has to be found and also computational effort has to be made for Pareto optimal solution. This complex computational effort is as a result of less theoretical evidence to Pareto optimal solution[9]. Beside the GAs based, numerous MOEAs like Particle Swarm Optimization (PSO) algorithm [10], [11] are being used. Most of the PSOs have been applied to work as a single-objective optimization problem. They are widely convergence to the solution within little stages and they found to be reliable by presenting fast solutions [12]. The nature of execution speed in PSOs motivated researchers to come up with multi-objective optimization methods. Thus, Multi-objective PSOs were recommended to effectively treat accuracy-interpretability trade-off.

In this work, the Multi-objective PSO-fuzzy Optimization method is proposed to improve accuracy and interpretability in analyzing medical data. We have found an optimum solution that can effectively take care of accuracy and interpretability trade-off associated with the FRBCSs decision support systems. Generally, there are key features of FRBCSs' interpretability. One, their rule base complexity and second, the semantics that governs the meaning in their linguistic terms that designate the actual attributes and represented using suitable fuzzy sets categorized by their given membership functions [13]. Complexity-related interpretability is applied, that is, the overall amount of attributes, and the overall amount of rules in the system. The result obtains shows the significant difference between our method and other existing techniques that are based on multi-objective PSOs. Our approach outperforms all the techniques accuracy wise and some remains competitive in interpretability objective.

The rest of this paper is organized as follows: literature review in section two, the methodology in section three, an experimental setup in section four, results and discussions in section five and finally the conclusion in section six.

2. Literature Review

Applications of data mining techniques in medical and healthcare domain become popular recently in knowledge exploration from the existing information and data. However, achieving the best accuracy in the performance of these techniques, defining interpretability and thus the possible strategies to measure these concepts from complexity to semantic problems remain an open issue among data mining community [14]. Many classifications on interpretability, its definitions, methodologies, measurements and views, to solve the trade-off with accuracy have been proposed by different scholars. A dual step approach was proposed by [15] to attain fuzzy model that is based on rule-base performs better in attaining interpretability and accuracy. In its step one, the created model which is rule-based fuzzy is formed via the application of "Fuzzy Modeling Algorithm". In the second step, multi-objective genetic approach is used to improve the prior fuzzy system with accuracy and interpretability objectives. However, this approach requires extra computational power for multiple Pareto optimal solution, and it is based upon GSA-algorithm.

In the work [16], a Fuzzy Association Rule-Based Classification Model that works on high-dimensional issues with genetic rule selection and lateral tuning. It handles the rapid growth of FRBCSs of the fuzzy search space rules. The approach utilizes the priori algorithm to extract association rules and to select the most appropriate ones. However, this algorithm cannot work concurrently and make the process of learning tedious. In [10], the method of designing FRBCSs using MOEAs is proposed. Two types of algorithms exist: Genetic Algorithms (GAs) and Swarm Intelligence (SI). This approach depends heavily on evolutionary quality. Another two stage method is proposed in [17]. In this approach, FastArt and NefProx algorithms generated the base model. The earlier is FBRS algorithm approximation while the later is linguistic algorithm. Both depend on fuzzy models with maximum accuracy but do not focuses on the other aspects. To test the method in different domain, two sorts of base models were created in which each have its performance in fuzzy nature to improve interpretability and accuracy. Stage two of this method consists of post-processing fuzzy rule selection via multi-objective GA for rule selection. Though, in the case of large-scale and high dimensional data sets, rules generation and fuzzy optimization may be complex. Additionally, the method requires high computational effort to achieve better performance.

In another related approach, the authors propose a technique called a "multi-objective evolutionary method for learning granularities based on fuzzy discretization, to improve the accuracy-complexity trade-off of fuzzy rule-based classification systems" [2]. They established a Fuzzy Discretization Algorithm to minimize the hardship of learning by automating the learning process. However, the post-processing in cutting the created rules and optimizing the fuzzy rules used to be complex when handling large-scale, high dimensional datasets. To address such problem, a novel associative classification model based on a fuzzy recurrent pattern mining algorithm is proposed [18], [19]. In multi-objective evolutionary approach, in particular, those based on genetic algorithms, apart from finding the non-dominated solution in each generation, the more computational effort is required for diversity Pareto optimal solutions. This computational complexity lacks theoretical convergence to proof a Pareto optimal front and distribution that a particular MOEA aims to obtain.

For better optimization of non-linear systems, [20] proposed an automatic design technique to build Fuzzy Logic Controller (FLC) that comprises genetic rule-based training. In this approach, regulator algorithm is used to generate fuzzy sets automatically and also to reduce the size of rule base using Genetic algorithm at the same time. This combined method considerably minimizes the size of the rules being used in the fuzzy knowledge-base.

Particle swarm optimization for an adaptive neuron-fuzzy inference system (ANFIS) interpretability and accuracy is developed to learn features in the data set and adjusts the system parameters according to a given error criterion[21]. However, it is a single-objective optimization explores only a limited part of the whole search space and, thus, some interesting solutions are difficult to be found. In [3] a method is proposed that can interpret and provide accurate medical data classification in a multi-objective genetic-fuzzy optimization approach. The method provided a collection of solutions (medical FRBCSs) characterized by various levels of accuracy-interpretability trade-off. This works based on GSA-algorithms, besides finding the non-dominated solution in each group, a more computational effort is required for diversity Pareto optimal solutions.

In work [22], granular rule-based classifiers (GRBCs) are considered. These GRBCs are meant to perform classification and they involve rules with information granules as predecessor chunk. In these systems, rules are generated from data automatically or encoded a domain expert knowledge which will classically manipulate training sample sets that comprises target input pairs. Provided the granulation form is selected, considerable monitoring of automatic rules generation will take effect to elude the trade-off between accuracy and interpretability, such as high number of rules and difficulty in logical partitions of variables involved. In such case, MOEAs may be subjugated successfully. In this article, they would demonstrate how both granulation turning and learning can be applied simultaneously or separately to handle the situation and effect the performance.

Most of the previous works are based on GSA-algorithms, besides discovery non-dominated solution in every generation, a lot of computational work is required for diversity Pareto optimal solutions. These efforts resulted in the lack of theoretical convergence proof to the Pareto optimal front and distribution that a particular MOEA will obtain.

2.1. A Fuzzy Rule-Based Classification Systems

Many techniques are being used to treat classification issue in the data mining field. FRBCSs are broadly employed to handle classification issues. The two main components of FRBCSs are knowledge-base which comprises both rule-based and database, and fuzzy reasoning method which classify entities using the stored information in the KB.

To create the knowledge-base, fuzzy learning rule algorithm is normally used that uses a set of P labeled patterns.

$$x_p = (x_{pi}, x_{p2i}, \ldots x_{pni}),\ p = \{1, 2, \ldots, P\} \quad (1)$$

where, x_{pi} is the ith attribute value $i = \{1, 2, \ldots n\}$.

Each n attributes is defined by a set of linguistic terms alongside their corresponding associate functions.

Another approach considered fuzzy rules in the following form [23]:

$$R_j : If\ x_1\ is\ A_{j1},\ \text{and}\ x_i \ldots x_n\ \text{is}\ A_{jn}\ \text{then}\ Class = C_j\ \text{with}\ RW_j \quad (2)$$

where R_j is the label of the jth rule,
x = (x1. . . xn) is an n-dimensional pattern vector,
A_{ji} is a fuzzy set representing a linguistic term and
C_j is a class label, and
RW_j is the weight of rule
Consider $x_p = (x_{p1}, x_{p2}, \ldots, x_{pn})$ to be the new candidate pattern for classification, L represents the rules number in the RB, M denotes the classes number to classify, then, the fuzzy reasoning method is given as:

1. The strength of start of the *if-part* for all rules in the RB with the pattern x_p called **Matching degree.** *T* is used in order to perform the computation.

$$\mu A_j(x_p) = T(\mu A_{j1}(x_{p1}) \ldots \mu A_{jn}(x_{pn})),\quad j = 1, 2 \ldots, L \tag{3}$$

2. calculate the amount of relationship in the pattern x_p having *M* classes base on each rule in the RB, **Association degree** is applied. At this point, a combine *h* operator is practically used to relate a matching degree to a rule weight. When using rules in the form shown in (1) this association degree only refers to the consequent class of the rule (i.e. k = Class (R_j)).

$$b_j^k = h(\mu A_j(x_p), RW_j^k),\quad k = 1 \ldots M,\ j = 1 \ldots L. \tag{4}$$

3. As can be seen in the last step, the *f* aggregation function that combines positive values of association, ***Pattern classification soundness degree for all classes*** is applied as follows:

$$y_k = f(b_j^k, j = 1, \ldots, L \text{ and } b\, k\, j > 0),\quad k = 1, \ldots, M. \tag{5}$$

4. To apply a function *f* for the decision over the degree of soundness of a system, **Classification** pattern is applied to all the classes. This function will decide the class label that corresponds to the extreme value. The function is given as:

$$F(Y1, \ldots Ym) = arg.\max(Yk), k = 1, 2, \ldots m \tag{6}$$

2.2 An Evolutionary Fuzzy Systems

Numerous techniques were proposed to automatically produce if-then fuzzy rules on the medical data. Evolutionary Computation (EC) is one of these approaches that are widely used due to the complexity of problem. EC uses representation closely related to traditional evolutionary algorithm (EA) which solves a problem in the living environment of individuals. Evolutionary Algorithm (EA) produces potential solutions progressively to the problem, as in the evolution in nature [24].
EC has been successful in learning fuzzy models, this led to different algorithms that are complex to evolutionary fuzzy systems or EFS in short [25], they are specifically used to perform fuzzy classifications. It is hybrid system that combines fuzzy systems approximation reasoning process with the EAs abilities adapted. A Fuzzy systems ought to proven the ability of being formalized in an efficient computational way and human estimated reasoning on one side, and EAs have made a strong method for optimization that is complex in the identification, in both learning, and adaptation issues (classification inclusive) on the other side. Previously, much interest among data mining community has been the system accuracy, but number of papers that concentrated on solving accuracy and interpretability trade-off emerges recently. Application of Multi-objective Evolutionary Algorithms (MOEAs) [2], [3], [7], [11], [16] is among the current research findings solve the trade-off between accuracy and interpretability in fuzzy models.

Multi-objective issues are problems with multiple objectives. Usually, these objectives used to be in conflict with one another. The difference between multi-objective and single-objective optimizations is that there are optimum solutions in multi-objective problems as suggested by the name. In single-objective problems, there is always a single optimum solution. The implementation of multi-objective is based on EA. The basic concept of a multi-objective minimization problem is defined below:

$$\text{Minimize } f(x) = [f_1(x), \ldots \ldots f_k(x)] \tag{7}$$

Subject to the given constraints:

$$g_i(x) \leq 0,\ i = 1,2, \ldots \ldots m \tag{8}$$

$$h_i(x) \leq 0,\ i = 1,2, \ldots \ldots p \tag{9}$$

where, $x = (x_1, x_2, \ldots \ldots \ldots x_n) \in$ population space,
$g_i(x)$ and
$h_i(x)$ defines the constraint functions of the problem,
k is the number of objectives, m and p represent respectively the number of equality and inequality constraints.
Multi-objective optimizations afford the set of optimal solutions non-dominated solutions. The process of dominance can be described as a solution vector x and it is said to be Pareto dominate (represented as X < Y) if and only if X is strictly better than Y in at least one objective, and X is no worse than Y in any objective. It is called Pareto- optimal if it is not subjected to any other solution of an existing population. The pareto-optimal front is regarded as the collection of all of the non-dominated solutions in the objective space [26].
MOEAs are mainly appropriate for multi-objective solutions. They search for manifold solutions that are optimal in a parallel way. MOEAs can find a set of solutions in a single run for its final subjects. Out of the set of solutions, the most suitable solution would be chosen via the criterion preference. Thus, the primary aim of a multi-objective search algorithm is to determine the set of solutions that can best fit the approximation of a Pareto front. However, the serious challenge associated with multi-objective search algorithms is the accuracy-interpretability trade-off.

3. Methodology

3.1. Optimization of FRBCS

The methodology used in this paper composed of two steps: 1) fuzzy model Generation: this model is generated from the data that is trained in a set of fuzzy rules which describes the association between systems and decides the mapping amongst the feature space and the class set. 2) Optimization process of the candidate systems is optimized by means of the MOEAs (MOPSO).

3.2. MOPSO Optimization Objectives

Two fitness functions, f1 (X) and f2 (X), defined in this optimization correspond to the two objectives of the multi-objective optimization model. These are:

$$\begin{cases} f1\ (I) = ACC\ (X) \\ f2\ (I) = INT\ (X) \end{cases}$$

Where,
ACC (X) = $\frac{N_c}{N_t}$ Nc and Nt, the number of correctly classified instances and the number of total instances, respectively is the accuracy of the classifier when the classification is performed using only the attributes in individual X; f1 (X) must be maximized.

INT (X) is The complexity at the rule-based level, interpretability based on two criteria, Number of rules and Number of conditions, so that f2 (X) must be minimized.

3.3. OMOPSO

In OMOPSO with crowding distant referred each non-dominate solution as the new leader. Although, this method has the downside in rapid combining of the leader's size, OMOPSO uses the crowding factor to initiate a principle of discrimination. This principle determines base on the missing value, which leader to be above the binary match. For each particle, a selected dimension of a set of each leader is equivalent to dimension of population. Base on each equivalent crowding value, each set of a leader should be updated after each generation. In a situation whereby the size of a leader is high than the extreme acceptable size, the only leaders to be retained are those with the best crowding value. Then, the remaining leaders of each generation should be eliminated. The equation below explains the probable change in velocity vector that can perform the particle move at each generation.

$$\mathcal{V}_i(t) = \mathcal{W}_{\mathcal{V}_i}(t-1) + C_1 r_1 \left(\mathcal{X}_{pbesti} - \mathcal{X}_i(t) \right) + C_2 r_2 \left(\mathcal{X}_{gbest} - \mathcal{X}_i(t) \right) \quad (10)$$

Where,
$\mathcal{W} = random(0.1, 0.5)$ $C_1, C_2 = random(1.5, 2)$, $r_1, r_2 = random(0.0, 1.0)$

Having all particles updated, the set of leaders should also be updated. Apparently, the particles that will enter the set of leaders are the ones that exhibit the best value. Upon update of the leaders, the general store is also updated. Finally, the system proceeds to apprise the crowding values in the leaders set and as many leaders as possible are eliminated to avoid on the process to prevent exceeding the required size [27]. The following algorithm describes the procedure of Multi-Objective Particle Swarm Optimization (OMOPSO).

Algorithm: OMOPSO

```
Read instances from ARFF file
Spilt instance to test and trine
Generates a classifier based on training instance
Classifies the given test instance.
Initial population of fuzzy set
Initialize swarm
Locate leaders
Send leaders to archive
crowding (leaders)
generation = 0
while generation < max Generations do
for (i = 1 to particles) do
    Select leader, flight, mutation
    Evaluation, update pbest
end for
Update leaders
   Send leaders to archive
    crowding (leaders)
     generation ++
end while
Report results in the archive
```

4. Datasets

In order to obtain an optimum result in performance analyses of our proposed method, we evaluate our technique with three medical data sets, well-known and being used as benchmark data. These are Liver Disorders (BUPA), Pima Indians Diabetes, and Thyroid Disease (New Thyroid). Table 1 summarizes the datasets used base on its properties. All data sets are publicly available from KEEL repository.

Table 1: Data sets Properties

Dataset	# Variables	# Classes	# Instances
Bupa	6	2	345
New thyroid	5	3	215
Pima	8	2	768

5. Experiment Setup

The experimental of the proposed OMOPSO algorithm to the FRBC design methodology is conducted on standard classification datasets. The comparisons done with the baseline approaches [2], [16] ,[22] make a comparative analysis in this work. A cross-validation method is applied with the same 10 folds in both our method and the baseline systems. Each dataset is partitioned randomly into nine folds for the training phase and one fold for the testing phase. In this experiment, the process of learning is carried out via 10 generation with initial population contains100 instances.

Table 2: The parameters values used in the experiment

Generations number to evolve the population = 10
Population number = 100
Maximum similarity value for the fuzzy sets: 0.1
Minimum variance parameter: 30.0
Maximum variance parameter: 2.0
Minimum rules: 2
Maximum rules: 12
Evaluation criteria: accuracy

6. Results and Discussion

The experimental results of our proposed method, the D-MOFARC, the FARC-HD and the GRBCs algorithms that examine the performance of our proposed with other techniques are shown in Table 3. Based on bar chart for accuracy and complexity, our method outperforms baseline methods, which are D-MOFARC, FARC-HD, and GRBCs on all the three data sets. For PIMA dataset, it outperforms the baseline methods in both accuracy and interpretability. The result shows that our approach recorded 77.21% average accuracy for the test data and 24 as complexity value. For BUPA dataset, our proposed method performs better in all data sets with regard to accuracy and became competitive in the complexity value with 70.43 % average accuracy for a test data and 24 for complexity. For NEWTHYROID dataset, our approach has significantly outperformed all compared methods in both accuracy and interpretability with an average of 95.8% accuracy for the test data and 15 for complexity value.

Table 3: Evaluation Result

	PIMA			**BUPA**			**NEWTHYROID**		
Algorithms	#R*#C	P training (%)	P test (%)	#R*#C	P training (%)	P test (%)	#R*#C	P training (%)	P test (%)
Our proposed Method	**24**	**79.81**	**77.21**	**24**	**77.10**	**70.43**	**15**	**99.5**	**95.8**
GRBCs (2016)	29.3	80.9	75.44	35.7	77.27	64.24	36.8	98.19	94.26
D-MOFARC	26	82.3	75.5	20.02	82.8	70.1	16.15	99.8	95.5

(2014)									
FARC-HD (2011)	46.46	82.3	76.2	20.14	78.2	66.4	17.25	99.2	94.4

Note: *#R = fuzzy rules values*
#C = conditions in fuzzy rule value set
#R#C = the complexity*
P = the training phase performance
P = the testing phase performance

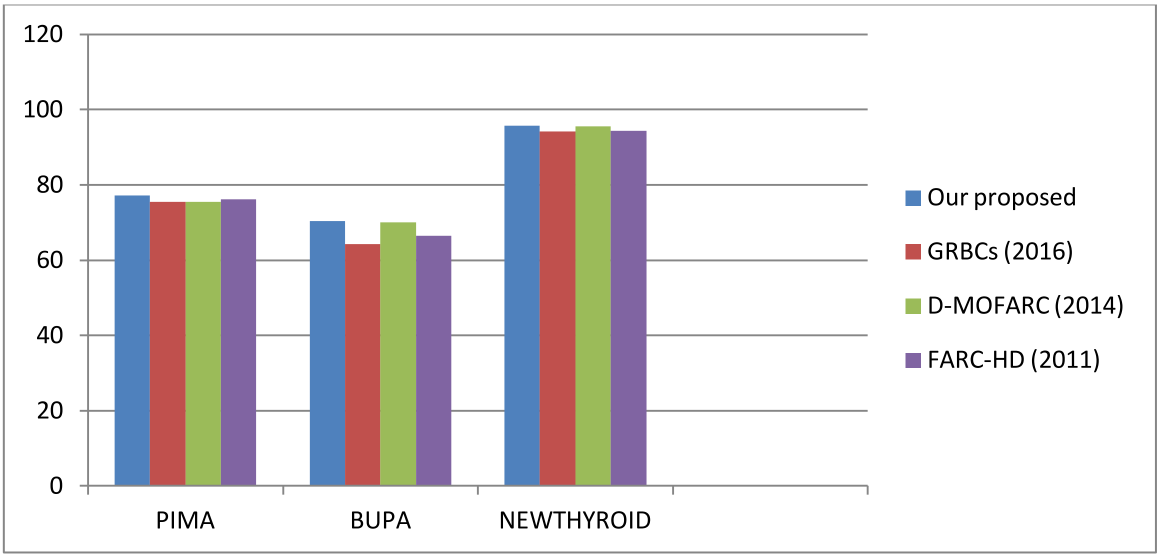

Fig. 1: Comparison of Different Approaches in Accuracy Results

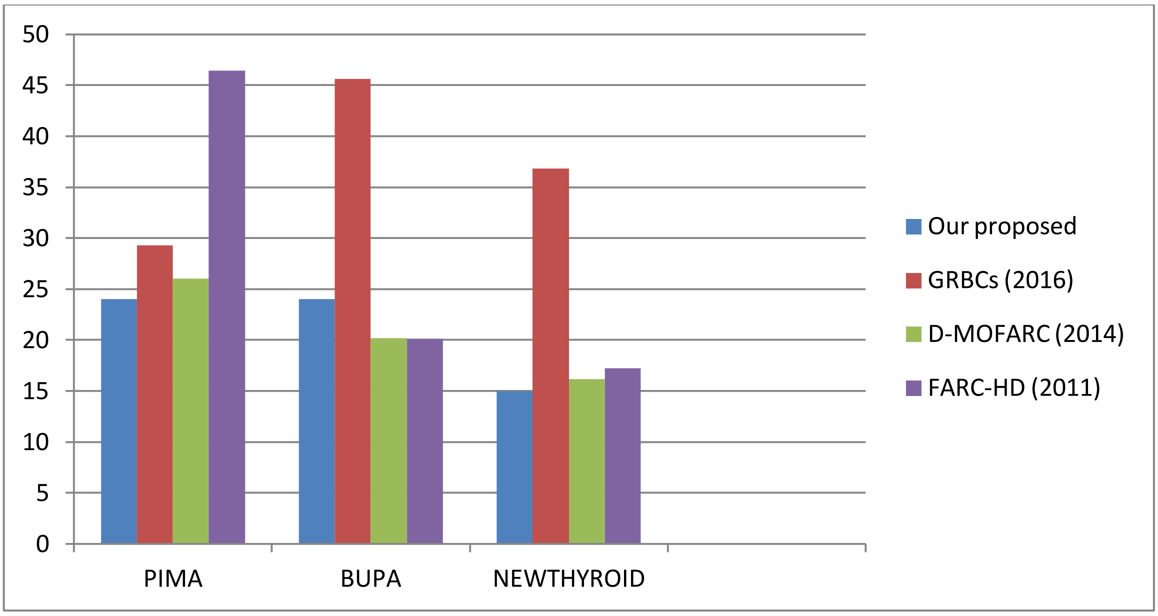

Fig. 2: Comparison of Different Approaches in Interpretability Results

7. Conclusion

Multi-objective EA is applied to find an optimal solution rather than the single objective functions that can provide the only single optimal solution. In this work, we proposed a possible trade-off solution to the problem of accuracy and interpretability through the fuzzy Rule-based Classification tested on the medical data sets. We have determined the set of solutions that are non-determinant in nature rule-based classification format that have different stages of this trade-off. The result recorded significant improvement in both accuracy and interpretability with our method compared to the baseline approaches in the result table. Even though, our technique remain competitive in some test cases; it does not signify low performance in our approach since the average accuracy in FRBCSs of our method outperforms the average accuracy of FRBCSs in the baseline techniques in almost all the affected cases. The collection of these solutions creates better approximation solutions to the Pareto front that are optimal in a medical healthcare domain.

In a near future, we hope to test the efficiency of our method on different data sets that belongs to different decision support systems (DSS) than the medical DSS, so that the technique can be extend for optimization across domain of knowledge. Scalability evaluation is also an open area of improvement for large-scale optimization problems.

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