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***Research paper***

# A comparative study of multi-objective pso- fuzzy optimization with weka classification algorithms to improve the interpretability and accuracy in medical data

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**Abstract**

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. Evolutionary algorithms have been extensively used to resolve problems associated with multiple and often conflicting objectives. The objective of a multi- objective optimization algorithm is to define the collection of best trade-offs between objectives. Among multi-objective evolutionary algorithms proposed in the literature, particle swarm optimization (PSO)-based multi-objective (MOPSO) algorithm has been cited to be the most representative. This paper presents a comparative analysis of Machine Learning (ML) algorithms for Fuzzy Multi-objective evolutionary algorithms (FMOEs) with WEKA Classification algorithms of data using8 publicly available datasets from the Knowledge Extraction based on Evolutionary Learning (KEEL) repository. FMOEs method is evaluated on a popular benchmark data set being used in a medical domain for evaluations. The result obtained shows that the FMOEs method yields an optimum solution in minimizing the trade-off between accuracy and interpretability. These findings add to a better understanding of the trade-offs between accuracy and interpretability in the algorithms under consideration, assisting academics and practitioners in picking the best algorithm for classification tasks.

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

## 1. Introduction

Data mining techniques have recently been used in the medical and healthcare domains to promote public health and assist patient activities. Physicians frequently use statistical approaches to process massive volumes of information such as laboratory screening, diagnosis, treatment, and prognosis. However, these statistical techniques are insufficient for extracting the necessary knowledge from the supplied data and information. This necessitates the investigation of alternate knowledge discovery (KD) methodologies in the medical and health domains [1]. Many academics used Rule-based Systems in a variety of applications, including the medical area. A fuzzy rule-based system (FRBS) is more likely to mimic human reasoning than classical system behavior. Fuzzy sets are used to represent and manage data and information with non-statistical uncertainty. Furthermore, fuzzy sets allow for the use of symbolic models. The Fuzzy rule-based categorization system is the most basic FRBS model (FRBCS). FRBCS design, with if-then statements as their rules, is one area of focus in this field of study. In comparison to other modeling methodologies, it is successful in producing good outcomes. FRBCS can generate information from current data that can be completely utilized.
FRBCS can be created manually by an expert or automatically based on a data set identified as a confident spectacle. Its automation can be viewed as an optimization challenge because it focuses on improving accuracy without taking into account the rules generated [2] [3], [4] is part of the FRBCS. The interpretability and accuracy are important characteristics of a classifier in some fields. Extraction of appropriate fuzzy rules from numeric data has been a prominent concern as part of FRBCs, as documented in the literature, where most of these techniques were utilized for performance enhancement in terms of prediction error with no participation of any interpretability metric. Other strategies, such as evolutionary algorithms (EAs), have addressed the interpretability- accuracy trade-off. [2], [5] – [8]. The application multi-objective evolutionary optimization algorithms (MOEOAs) look to be the best option for multi-objective issues. Multi-objective optimizations may readily optimize several objectives, most of which are in competition with one another. [9]. In the literature, several multi-objective fuzzy classifications have been proposed [2], [4], [5], [7], [8] [10]. Multi-objective PSOs have been effectively recommended to treat accuracy- interpretability trade-offs. In other MOEAs, a non-dominated solution has to be found in each generation and computational effort must be done for Pareto optimal solution. This complicated computational effort is due to less theoretical evidence to Pareto optimal solution. Therefore, PSO is better in many situations due to an intuitively simple representation and relatively low number

of adjustable parameters. In this work will present a comparative analysis of FMOEs with WEKA Classification algorithms to examine which are methods will tackle interpretability-accuracy trade- off and give best result.

The paper is structured as follows: The next part provides a brief examination of the existing MOEAs for general applications, which are typically modified or directly used to generate FRBSs with a good interpretability-accuracy tradeoff. In addition, we provide a brief overview of categorization methods that have been utilized to compare their results with those of the MOEA. In part three, we present the approach provided in this research, followed in section four our by categorization assessment datasets. The section sixth presents the specifics of the obtained results and the comparisons that have been made. Section seventh concludes with some conclusions that we reached in this paper.

## 2. Background

### 2.1. Multi objective evolutionary algorithms

Evolutionary algorithms deal with a set of possible solutions (the so-called population) at the same time, allowing the algorithm to find several members of the Pareto optimal set in a single run. Furthermore, they are not overly sensitive to the shape or continuity of the Pareto front (e.g., they can easily deal with discontinuous and concave Pareto fronts). The first hint about using evolutionary algorithms to solve a multi-objective problem appears in a 1967 Ph.D. thesis [5], [11]. However, no actual MOEA was developed (the multi-objective problem was restated as a single- objective problem and solved with a genetic algorithm). During the mid-1980s, David Schaffer is widely regarded as the first to design a MOEA [5], [12]. Schaffer's method, known as the Vector Evaluated Genetic Algorithm (VEGA), combines a basic genetic algorithm with a modified selection mechanism. VEGA, on the other hand, had a number of issues, the most serious of which was its inability to retain solutions with acceptable performance, perhaps above average, but not outstanding, for any of the objective functions. Following VEGA, the researchers created a first generation of MOEAs that were characterized by their simplicity. The main lesson learned was that successful MOEAs needed to combine a good mechanism for selecting non-dominated individuals (perhaps, but not necessarily, based on the concept of Pareto optimality) with a good mechanism for maintaining diversity (fitness sharing was a choice, but not the only one). The most representative MOEAs of this generation are: Nondominated Sorting Genetic Algorithm (NSGA) [13], Niched-Pareto Genetic Algorithm (NPGA)[14] and Multi Objective Genetic Algorithm (MOGA) [15]. When elitism became a standard mechanism, a second generation of MOEAs emerged. In fact, the use of elitism is a theoretical requirement for ensuring MOEA convergence. During the second generation, many MOEAs were proposed (which we are still living today). Most researchers will agree, however, that few of these approaches have been adopted as a reference or used by others. The Strength Pareto Evolutionary Algorithm 2 (SPEA2) [16] works in this manner and the Nondominated Sorting Genetic Algorithm II (NSGA-II)[17] can be considered the most representative MOEAs of the second generation, with others such as the Pareto Archived Evolution Strategy also being of interest (PAES) [18].

### 2.2. Classification methods

We used classifiers, representatives of different recognition models. These are Jrip, Part and Decision table, which are realized in the Waikato Environment for Knowledge Analysis (Weka) [19].

- JRip (RIPPER): Jrip is a well-known propositional rule learning algorithm that utilizes Repeated Incremental Pruning to Produce Error Reduction (RIPPER). This algorithm generated a detection model comprised of a database of rules designed to identify new instances [20], [21].
- PART: The supervised PART classification method employs the divide-and-conquer tactic. It creates rules recursively, deletes instances affected by these rules, and repeats the process until no instances remain [20], [22].
- Decision Table: A decision table is a programming or organizational tool for representing discrete functions. It can be viewed as a matrix where the upper rows specify sets of conditions and the lower rows specify sets of actions to be taken when the corresponding conditions are met; thus, each column, known as a rule, describes a procedure of the form if conditions, then actions. Given an unlabeled instance, the decision table classifier looks for exact matches in the decision table based solely on the schema features (it is to be noted that there may be many matching instances in the table). If there are no instances, the majority class of the decision table is returned; otherwise, the majority class of all instances that match is returned [23].

## 3. Methodology

### 3.1. A fuzzy rule-based classification systems

In the subject of data mining, data analysts employ a variety of methods to address classification challenges. The FRBCS-based strategy is one of the most extensively utilized techniques for addressing classification-related challenges. Knowledge-based (KB) and rule-based (RB) are two of the primary components of a FRBCS. The KB component of a FRBCS is the region that stores both the RB and the database, whereas the rule-based component is the fuzzy reasoning method that classifies entities based on the information stored in the KB. The knowledge base of a fuzzy rule-based system was built using an algorithm for learning fuzzy rules. The method utilized the following set of P-labeled patterns:

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

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

Each n attribute is represented by a collection of linguistic phrases in addition to its associated functions. Ishibuchi and Nakashima developed fuzzy rule-based systems as a second strategy [24].

$$R_J: IF\ x_1 \text{ is } A_{j1}, \text{ and } x_n \text{ is } A_{jn}, \ then\ Class = C_j \ with \ RW_j \tag{2}$$

Where $R_j$ is the label of the $jth$ rule,
x = (x1. . . xn) is an n-dimensional pattern vector,
$A_{jn}$ is a fuzzy set representing a linguistic term and
$C_j$ is a class label, and
$RW_j$ is the weight of rule.
Consider xp= (xp1, xp2,..., xpn) to be the new categorization candidate pattern. L is the number of rules in the RB, M is the number of classes to classify, and the fuzzy reasoning approach is denoted as follows: xi The Matching degree is the starting strength of the if-part with the pattern for all rules in the RB. T is utilized in the computation.

$$\mu Aj\ (xp) = T\ (\mu Aj1\ (xp1) \ldots\ \mu Ajn\ (xpn)), \tag{3}$$

Where x j= 1, 2..., L
$\mu A\quad (x)$ is the degree of compatibility between the fuzzy rule R j and the input vector. Aji is the membership function of the preceding linguistic value A, I = 1, 2,. $xp$. A degree of Association is employed to calculate the amount of relationship in the pattern with M classes based on each rule in the RB. A combination h operator is employed at this stage to tie a matching degree to a rule weight. This association degree only pertains to the rule's final class when utilizing the shown rule form (i.e., k = Class (Rj )).

$$b\ jk = h\ (\mu A_j\ (x_p), RW_j k), \tag{4}$$

k = 1. . . M, j = 1. . . L.
In the final phase, the aggregation function that combines the positive values of the association and the soundness degree of the Pattern classification is applied as follows:

$$y\ k = f\ (b\ jk,\ j = 1..., L \text{ and } b\ k\ j > 0), \tag{5}$$

k=1.... M.
To apply a function f for determining the level of system soundness, a Classification pattern is applied to each class. This function determines the class label corresponding to an extreme value. The function is denoted by:

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

### 3.2. Multi-objective particle swarm optimization

In Multi-Objective Particle Swarm Optimization (MOPSO), each non-dominant solution was referred to as the new leader when crowding distance was used. Although this strategy has a disadvantage in rapidly merging the leader's size, MOPSO employs the crowding factor to commence a discrimination principle. Based on the missing value, this concept determines which leader should be placed above the binary match. A selected dimension of a set of each leader is equivalent to the dimension of the population for each particle. After each generation, each set of leaders should be changed based on each corresponding crowding value. In situations where the size of a leader exceeds the maximum permissible size, only leaders with the highest crowding value are preserved. Then, each generation's remaining leaders should be terminated. The following equation describes the possible change in velocity vector that can occur for each generation of particles.

$$V_i = (t) = W_{v1}(t-1) + C_1 r_1 \left(X_{pbest} - X_i(t)\right) + C_2 r_2 \left(X_{gbest} - X_i(t)\right) \tag{7}$$

Where,

$W = random\ (0.1, 0.5)\ C_1$, $C_2 = random(1.5, 2)$

$r_1$, $r_2 = random(0.0, 1.0)$

Having updated all particles, the set of leaders must also be updated. It appears that the particles that will enter the set of leaders have the highest value. Whenever the leaders are updated, the general shop is also updated. Finally, the system determines the crowding values in the leaders set and eliminates as many leaders as feasible to prevent the process from exceeding the required size [25] The subsequent algorithm describes the Multi-Objective Particle Swarm Optimization technique (MOPSO).

Algorithm: Multi-Objective Particle Swarm Optimization (MOPSO)

```
Input: maxItr, dataset;
Output: Let NonDom be a non-dominated set of repositions; 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. Classification evaluation datasets

In the present study, eight publicly available datasets were selected from Knowledge Extraction based on Evolutionary Learning (KEEL) repository, a globally well-known benchmark dataset, for evaluation. The datasets have been popularly used in several studies to evaluate the performance of algorithms. The main characteristics of these datasets are presented in Table 1.

**Table 1:** Data Sets Properties

| Dataset | # Variables | # Classes | # Instances |
|---|---|---|---|
| Bupa | 6 | 2 | 345 |
| New thyroid | 5 | 3 | 215 |
| Pima | 8 | 2 | 768 |
| Cleveland | 13 | 5 | 303 |
| Haberman | 3 | 2 | 306 |
| Hert | 13 | 2 | 270 |
| Hepatitis | 4 | 2 | 155 |
| Wisconsin | 9 | 2 | 699 |

The datasets presented several desirable features, such as having a dissimilar number of variables from 3 to 13, and diverse sizes ranging from 155 to 699 patterns.

## 5. Experiment setup

In terms of performance evaluation of algorithms, the basic accuracy measure ACC (X) = Nc / Nt where Nt and Nc are the number of total instances and the numbers of correctly classified instances respectively. The basic measure of interpretability is the complexity, which is based on the number of rules, so that must be minimized. The main experiment used the cross-validation method which minimized some degrees of bias associated with random splitting of a given dataset into learning and test parts. The whole datasets were divided at random into mutually exclusive subsets having an approximately equal number of records and with similar class distributions. The learning process was repeated k times. After every repeat, a subset k is used as the test set, and the remaining as the learning set. In each case, the solution (FMOEs) as characterized by the highest accuracy for the test data and lowest interpretability was selected. The average results from k runs were then computed. The study applied a cross-validation method with similar 10-folds in both methods and baseline systems. Each data set was partitioned randomly into nine folds for the training phase and one- fold for the testing phase.

## 6. Results and Discussion

In many classification rules, algorithms are generally used to generate the classification rules. In the present section, a comparison of three classification techniques: PART, JRip, and Decision Table using the WEKA tool with FMOEs are presented in Table 2.

**Table 2:** Evaluation Result

| Data set | Decision Table | JRip | PRT | FMOEs |
|---|---|---|---|---|
| PIMA | Rules : 63<br>Acc: 74.48% | Rules: 4<br>Acc: 74.48% | Rules: 13<br>Acc: 74.78 % | Rules: 3<br>Acc:<br>77.21% |
| BUPA | Rules: 3<br>Acc: = 59.71 % | Rules: 5<br>Acc:<br>67.8 % | Rules: 5<br>Acc: 64.1 % | Rules: 4<br>Acc:<br>70.40% |
| NEWTHYROID | Rules: 21<br>Acc: 93.4884 % | Rules: 4<br>Acc: 93.% | Rules: 43<br>Acc: 93.95 % | Rules: 3<br>Acc:<br>95.8% |
| HABERMAN | Rules: 2<br>Acc:<br>72.5 % | Rules: 2<br>Acc:<br>73.5% | Rules: 4<br>Acc: 73.8% | Rules: 7<br>Acc: 70.9 |
| WISCONSIN | Rules: 20<br>Acc:<br>93.8 % | Rules: 5<br>Acc:<br>95.6% | Rules: 11<br>Acc: 94.7 % | Rules: 10<br>Acc:<br>98% |
| HEPATITIS | Rules: 29<br>Acc:<br>68.8% | Rules: :3<br>Acc: =67.7% | Rules: 8<br>Acc: 71.2 % | Rules: 4<br>Acc:<br>92.9% |
| HERT | Rules: 16<br>Acc:<br>84.8 % | Rules: 4<br>Acc:<br>77.4 % | Rules: 24<br>Acc: 73.3 % | Rules: 11<br>Acc:<br>91% |
| CLEVELAND | Rules: 8<br>Acc:<br>54.5 % | Rules: 1<br>Acc:<br>54.7 % | Rules: 48<br>Acc: 52.4 % | Rules:33<br>Acc: 5<br>8.4 % |

Results show that for accuracy and interpretability, the FMOEAs outperformed PART, JRip, and Decision most eleven datasets. For PIMA datasets, FMOEAs outperformed the PART, JRip and Decision Table methods in terms of interpretability and accuracy. The results show that the method recorded 77.21% as average accuracy and three rules as interpretability value. For the BUPA dataset, FMOEAs outperformed the Decision Table, PART and JRip methods in terms of accuracy and became competitive in interpretability. The results show that the method recorded 70.40% as average accuracy and four rules as interpretability value. For the NEWTHYROID dataset, FMOEAs outperformed the PART, JRip and Decision Table methods in terms of interpretability and accuracy. The results show that the method recorded 95.8% as average accuracy and three rules as interpretability value. For the HABERMAN dataset, JRip outperformed the FMOEAs, PART and Decision Table methods in terms of interpretability and became competitive in accuracy. The results show that the method recorded 73.5 3% as average accuracy and tow rules as interpretability value. For WISCONSIN datasets, FMOEAs outperformed the JRip, PART and Decision Table methods in terms of accuracy and JRip outperformed the FMOEAs, PART and Decision Table in terms of interpretability. For HEPATITIS dataset, FMOEAs outperformed the Decision Table, PART and JRip methods in terms of accuracy and became competitive in interpretability. The results show that the method recorded 92.9%as average accuracy and four rules as interpretability value. For HEART dataset, FMOEAs outperformed the JRip, PART and Decision Table methods in terms of accuracy and JRip outperformed the FMOEAs, PART and Decision Table in terms of interpretability. For CLEVELAND dataset, FMOEAs outperformed the JRip, PART and Decision Table methods in terms of accuracy and JRip outperformed the FMOEAs, PART and Decision Table in terms of interpretability.

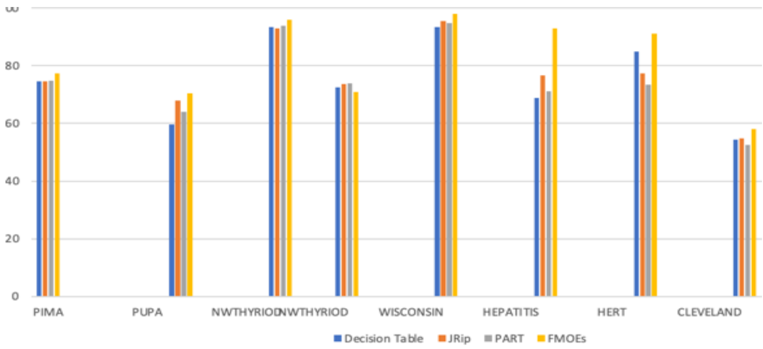

**Fig. 1:** Comparison of Different Algorithms in Accuracy Results.

In terms of Accuracy, the results shown in Figure 1, the FMOEAs is most accurate then Decision Table, PART and JRip. In conclusion FMOEAs outperformed the Decision Table, PART and JRip methods in terms of accuracy and became competitive in interpretability, because Accuracy and Interpretability Trade-off. Which is choose most accuracy in the same time easy to understandable.

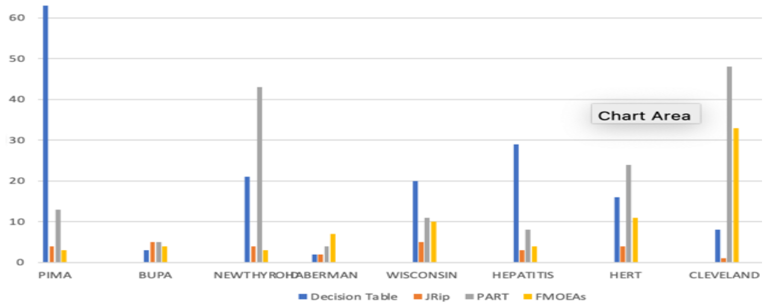

**Fig. 2:** Comparison of Different Algorithms in Interpretability Resu

In terms of Interpretability, the results shown in Figure 2, JRip had significantly lesser interpretability because of its pruning method, whereas Decision Table attained the maximum interpretability and PART came in second then FMOEAs.

## 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 present a comparative analysis of FMOEs (optimal solution) with WEKA (single objective) classification Algorithms to trade-off solution to the problem of accuracy and interpretability 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 FMOEs compared to the WEKA classification Algorithm in the result table.

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