Incorporating User Cognitive Profile Information in Intelligent Decision Support Systems

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***Abstract*— Intelligent Decision Support Systems (iDSS) frequently rely in analytical models to improve problem solving capabilities of decision makers. A large number of intelligent algorithms solely focus on accuracy, but this is seldom the only, or even the most important issue to be considered in decision making processes. This work investigates how to incorporate user cognitive profile preferences in the intelligent decision model. Two situations were considered in this study: (i) how to conceive appropriate models when user preferences and constraints are available and (ii) how to optimize a problem solving structure if these models are already available (*i.e.* can be posed by its user - the decision maker). Due to their effective application in many classification problems and their high interpretability, Decision Trees were chosen as the main inference technique and were used in four benchmark databases as our proof of concept for both: conception and optimization of intelligent models. Results suggest that the proposed approach can be useful to better bridge the gap between what the user wants and what can be provided to him, by means of intelligent algorithms. This simple, yet powerful, combination affords high levels of user satisfaction and confidence because they reduce the loss of valuable qualitative information that is readily available in the decision makers' mind. Moreover it is likely to relief the number one plague in DSSs: dismissive attitude by decision makers, leading to quite often systems dismissal.**

***Keywords*— intelligent computing, decision support systems, cognitive profile modeling, analytical model generation, decision trees**

I. INTRODUCTION

In Decision Support Systems the accuracy of an analytical model is seldom the only and most important feature considered when choosing a decision model to help in solving a given problem [1]. Frequently, other issues must be dealt with, namely: (i) urgency of decision, (ii) availability of information and (iii) alignment of model and cognitive stile of the decision maker.

Most intelligent models and training algorithms focus specifically in finding the best partitioning of the space, or the best function approximation, thus providing the highest possible accuracy.

This work proposes a novel method which aims at creating intelligent analytical models, with multi-objective focus, that incorporates cognitive profile information of the decision maker. Accuracy could be one of them, but there would be also an explicit focus on attributes used and their structure, in order to satisfy both objective requirements as well as user preferences modeled via cognitive profiling.

Based on a cognitive profile model two alternatives were considered: (i) conception of an analytical model open to user preferences and constraints, and (ii) optimization of a problem solving structure if this can be posed by the user.

The remainder of this work is organized as follows: Section 2 brings together relevant theoretical information for our approach that is presented in Section 3. Section 4 contains details on the proof of concept presented here, comparative study of structural and preference similarity in the analytical models as well as performance metrics. Section 5 presents simulation results and finally, in Section 6, our conclusion and discussion are disclosed.

II. BACKGROUND

A. *Decision Support Systems*

Decision Support Systems (DSS) aid in solving semi-structured problems which are too complex to be completely specified, have a large number of options to be analyzed and also, impose severe penalties when a bad choice is made. Most important, they require a special kind of supportive tool in order to be properly dealt with [1].

The solution frequently employed is to combine the expertise of a decision maker with the augmented analytical capability provided by a DSS to reduce uncertainty and improve decision quality. Previous works [2][3] have shown that it is viable to introduce Intelligent Computing analytical models in DSS striving to provide DSS with adaptation and generalizing capabilities – the iDSS (Intelligent Decision Support Systems).

This work aims at improving iDSS by providing them with analytical models which are in accordance with the cognitive profile of decision makers.

B. *Decision Trees*

Decision Trees (DT) are well established classification technique in Intelligent Computing, which are very suitable for use into iDSS. Among main reasons, the following ones deserve special attention: (i) training algorithms are usually fast, and (ii) tree structures can be inspected for an easy explanation of how it gets to its conclusions.

When combined, these characteristics allow a convenient way to provide analytical models under specific demands of time and precision. Also, as considered 'white-box' models, it is not uncommon the user to recognize a DT processing structure as his own way to solve a given problem. Besides, DT can be used to directly parameterize decision dialogues [5], to solve a given problem.

In Section 4, DTs are employed as analytical models because of the abovementioned reasons. Those characteristics can be synergistically combined to improve flexibility and confidence in the system usage – and both can be understood as means to reduce the probability of abandoning the iDSS.

C. *Evolutionary Training of Decision Trees*

Aitkenhead [6] proposed an evolutionary approach to perform the training of Decision Trees. This method can be understood as a particular case of Genetic Algorithm [7] with a population composed of a single element (*i.e.* candidate Decision Tree) which is mutated according to some specific rules to keep its validity.

Among its advantages we highlight that: (i) the algorithm speed can be adjusted according to the number of generations allowed for convergence; (ii) the precision of resulting Decision Trees is comparable to other classifiers such as Artificial Neural Networks [8]; and, (iii) the algorithm is capable of automatically select the most relevant attributes for a classification problem.

In this work, the Aitkenhead training algorithm was customized to optimize problem solving structures proposed by decision makers.

III. Cognitive Profile Modelling for Intelligent Decision Support Systems

This section presents the main contribution of this paper that is: (i) an approach to model user cognitive profiles based on preferences, constraints and a possible problem solving structure; (ii) a proposal of how to employ cognitive profile information in analytical model training, either in suggestion or optimization of models and (iii) a proposed customization of an evolutionary method to create Decision Trees for usage in Intelligent Decision Support Systems.

A. *Cognitive Profile Modelling*

The main objective of modeling a user cognitive profile is to make the iDSS aware of what the user wants in a general sense. For example, it is useful to know if the decision maker prefers short interactions used only for validation of its decision or if it likes to use the system to help his reasoning to draw conclusions about the problem. Although similar, from a user perspective these are completely different approaches, and ascribed very different levels of importance.

By considering the relevance of results produced by the system, makes it possible that a more adequate level of support to be generated, this in accordance with the user preferences. Because of that, this gives special attention to two broad cases: (i) General Guideline Cognitive Profile (GGCP) – where the user only informs general characteristics of *what* he thinks would make a good decision and (ii) Specific Guideline Cognitive Profile (SGCP) – where the user informs *what* and *how* he would solve the problem. GGCP and SGCP.

1) General Guideline Cognitive Profile (GGCP): This case is related to situations where the user can only offer general insights about the decision making process. And this can be due to plain inexperience or problem complexity. For example, the user may know which is the most important set of attributes to be considered for solving a problem, but he may not know exactly how to draw a conclusion using them. The GGCP formulation is given in Equation 1, where W is the problem, P stands for a set of Preferences and C stands for Constraints about the given Decision Problem.

$$GGCP = (W, P, C) \tag{1}$$

2) Specific Guideline Cognitive Profile (SGCP): This case is related to situations where the user can offer general insights about the decision making process, including preferences and constraints. Moreover, he is able to inform how (not necessarily in detail) he would solve the problem. This situation is not uncommon with trained decision makers when tackling problems that are completely unknown from others seen in past occasions. In this case, the user knows how to draw conclusions about the problem and is able to formalize this knowledge. In this case the iDSS may use this knowledge to improve its performance and/or to behave more closely to the user reasoning manner. The SGCP formulation is given in Equation 2, where W is the problem, P stands for a set of Preferences, C stands for Constraints about the given Decision Problem Dp and PSM stands for Problem Solving Manner.

$$SGCP = (W, P, C, PSM) \tag{2}$$

The PSM can be informed as a heuristic, a set of rules, a cognitive map [9], or any other way to formally express the knowledge of a decision maker about the problem at hand.

B. *Cognitive Profile Based Training of Intelligent Analytical Models*

In most cases, the training of analytical models is data centered – the only objective is to maximize the model accuracy. This work proposes employing cognitive profile information as a mean to improve the satisfaction and trust of users when interacting with the iDSS. To properly tackle that, the training of the analytical models contained in the iDSS should be multi-objective, considering the two measures below.

- Model-Centric measures: values are obtained directly by inspection of the analytical model or by its interaction with objective data, such as tree height and overall accuracy;
- User-Centric measures: values are obtained by the interaction between user, analytical model, and his understanding about problem solving, such as what attributes should be employed and how similar was the tree structure to his reasoning process. These measures are directly related to his cognitive profile.

Considering the measures proposed above, and the cognitive profiles proposed in the previous section, it is possible to understand the training of analytical models as an optimization problem as stated in Equation 3, where MC stands for Model-Centric measures and UC stands for User-Centric measures.

$$Max(MC, UC) \tag{3}$$

Two cases deserve special attention: (i) without structural knowledge, when dealing with a GGCP and (ii) with structural knowledge, when dealing with a SGCP. In both situations, it is important to identify if objectives are conflicting, then:

- When objectives are not conflicting, it is possible to employ an aggregation method to convert the multi-objective problem into a single-objective. In this case, techniques such as Genetic Algorithms [7] and Simulated Annealing [10] could be readily used;
- When objectives are conflicting, it is highly desirable to use the concept of dominance, try dealing with objectives separately and use Evolutionary Multi-Objective Algorithms as SPEA2 [11] and NSGAII [12].

C. Multi-objective Creation of Decision Trees

Figure 1 shows the evolutionary algorithm for training decision trees, proposed by Aitkenhead [6]. In order to adhere to the principles proposed in the Section 3-B, some experiments were conducted to verify if the Model and User Centric objectives were conflicting in the considered databases shown in Section 4. Preliminary results suggested that it would be viable to aggregate both objectives into one prior to making the optimization. The algorithm shown in Figure 1 was adapted to suggest and optimize decision trees using a multi-objective aggregation described in the following subsections.

```
Input decision tree
Repeat for number of generations
   Measure Fitness F1 of decision tree
   Make x mutations to Boolean questions
   Set F2 = F1
   Repeat for number of mutations to predictions
      Measure fitness F3 of decision tree
      If F3 > F2 accept mutation and set F2 = F3
   End-Repeat
If  F2 > F1, accept mutation to questions and set F1 = F2
End-Repeat
```

Figure 1. Evolutionary training algorithm for decision trees, adapted from Aitkenhead[6].

1) Suggestion of Analytical Models: the main adaptation performed in the basic algorithm was the evaluation of fitness. The rules for mutation of questions and predictions were maintained. The input decision tree is randomly generated. In the basic version, the fitness value considered only model accuracy. We propose employing Equation 4 for fitness evaluation.

$$F = CA + AC \tag{4}$$

In Equation 4, the CA stands for Cognitive Appropriateness and AC stands for Accuracy, and both formulations are presented in Equations 5 and 6.

$$CA = \frac{NRP * 100}{NP} \tag{5}$$

In Equation 5, NRP is the Number of Respected Preferences, contained in the Cognitive Profile and the NP is the Number of Preferences.

$$AC = \frac{NCCP * 100}{NCP} \tag{6}$$

In Equation 6, NCCP is the Number of Correctly Classified Patterns in the database and NP is the total Number of Classified Patterns (*i.e.* considered). The models which do not respect the constraints posed in the Cognitive Profile received the value 0 for CA.

2) Suggestion of Analytical Models: the objective of this adaptation was to improve the input decision tree, contained in the SGCP. The fitness evaluation was done according to Equation 4, but rules for mutation of questions and predictions were slightly altered.

Both situations require selecting a node in the decision tree to be mutated, either a prediction or mutation node. A control parameter ε was assigned to each node, and considered as the probability of mutation. After selecting the node, the mutation will happen only according to the probability ε. This variable allows for controlling how much the resulting decision tree will look like the input decision tree.

The Structural Similarity (SS) was introduced to measure the difference between the input and resulting decision tree. The SS formulation is shown in Equation 7, where NSN is the Number of Similar Nodes, considering the input decision tree and the resulting decision tree. The NNIT is the Number of Nodes in the Input Tree. For the calculation of SS, it was considered only non-terminal nodes.

$$SS = \frac{NSN * 100}{NNIT} \tag{7}$$

IV. EXPERIMENTS

In order to validate the ideas presented in the previous section, three experiments were conducted using four UCI [13] benchmark databases, concerning a comparative study of classifiers, the generation of analytical models considering the user cognitive profile, and the optimization of problem solving structures.

The databases used were: (i) Breast, (ii) Heart, (iii) Wine and (iv) Glass, each one with different number of classes, attributes and patterns according to Table I.

TABLE I. FEATURES OF STUDIED DATABASES

Database	Patterns	Attributes	Classes
Breast	569	30	2
Heart	297	13	2
Wine	178	13	3
Glass	214	9	5

All experiments were conducted using training and test sets for each database. The preprocessing was done as follows:

1. Patterns containing missing values were removed;
2. All remaining lines were randomly sorted;
3. After sorting, the dataset was split into a 2:1 fashion – 2 patterns for training, and the next for test;

When considering the Aitkenhead (Single-objective) and the proposed algorithm (Multi-objective), the experimental configuration was: 30 simulations were performed, where 1000 generations were allowed, with 150 mutations in questions and 150 mutations in predictions in each generation.

Cognitive profiles of subsections A and B are composed of:

- Preferences: the decision maker has an explicit preference for certain attributes in each database, according to Table II.
- Constraints: only decision trees with height smaller than 10 are to be allowed.

TABLE II. COGNITIVE PROFILE PREFERENCES FOR EACH DATABASE

Database	Preferred Attributes
Breast	1, 4, 10, 13, 20, 23, 27, 28, 29
Heart	0, 1, 2, 8, 11, 12
Wine	0,3,5,11,12
Glass	2, 3, 5, 7, 8

The next three subsections present information about each of the three experiments.

A. Comparative Studies of Classifiers

This experiment was designed to check how good the proposed algorithm would perform in relation to established algorithms and the original Aitkenhead algorithm. For this comparison, only the accuracy was considered. As the basis of comparison, it were selected the Artificial Neural Network (ANN) and the Naïve Bayes (NB), implemented in the Weka Data Mining and Machine Learning software [14]. The process was as follows:

- For NB, and ANN, it were used the basic configuration provided by Weka. It were supplied the training and test set. The accuracy result was recorded.
- For the Single-objective and Multi-objective algorithms, maximum accuracy for each simulation was stored. After all 30 simulations, the average value was recorded.

B. Suggestion of Appropriate Intelligent Analytical Models

The objective of this experiment was to check the performance of the Multi-objective algorithm, when compared to its Single-objective counterpart. The studied measures were Tree Height, Cognitive Appropriateness and Accuracy.

Each measure was stored at each 50 generations, over the total of 1000 generations. After the 30 simulations, their average values were recorded; trends are in Figures 2 to 5.

C. Optimization of Problem Solving Structures

This experiment aims at studying how the multi-objective optimization behaves, with and without a problem solving structure provided by the user. To simulate the presence of an experienced decision maker, a decision tree was created using the C4.5 algorithm contained in Weka [14]. Then, a small part of this tree was selected to be used as user input.

Each non-terminal node was assigned a ε = 0 and each leaf-node was assigned ε = 100. This experimental setup guarantees that the resulting trees will keep the maximum Structural Similarity (SS) with the original decision tree.

V. RESULTS

A. Comparative Study of Classifiers

Table III shows comparative results for accuracy in the four databases considered. It is possible to perceive that ANN and Naïve Bayes (NB) achieved the best performances. The Decision Trees created by the Aitkenhead Single Objective Optimization (SOO) algorithm [6] and the Multi-Objective Optimization (MOO) version proposed in this algorithm, were, in the maximum, 16% worse than the best classifier (either ANN or NB) in each database.

Despite this difference is significant, it is worth mentioning that the conventional training algorithms for NB and ANN, and also the SOO do not allow a direct control about the created model, focusing only on accuracy. Furthermore ANN and NB are connectionist models, and it is not straightforward to obtain understandable explanations about how they get to their classifications.

The obtained results are interesting, because they may indicate that trees created by the proposed algorithm are not necessarily worse than classic classifiers. One has to bear in mind that the proposed models, even with inferior accuracy, could provide more valuable contributions for problem solving, in situations where usability and trust in the system are priorities. These qualitative characteristics can be obtained by approximating aspects of the user cognition into the analytical model – main focus of our approach.

TABLE III. COGNITIVE PROFILE PREFERENCES FOR EACH DATABASE

Classifier	Breast	Heart	Wine	Glass
ANN	**97.3684**	73.7374	96.6102	**60.5634**
NB	**97.3684**	**80.8081**	**98.3051**	43.6620
SOO	87.1052	74.3097	80.9604	56.7136
MOO	84.0877	74.5791	82.7683	51.4084

B. Suggestion of Appropriate Intelligent Analytical Models

Figures 2 to 5 show evolutive trends for 30 distinct simulations in the Breast, Heart, Wine and Glass databases respectively. Each figure contains curves illustrating the absolute value of tree height, percentile accuracy and percentile cognitive appropriateness for the Single-Objective Optimization (SOO) and the Multi-Objective Optimization (MOO) algorithms. The X-Axis presents the number of generations recorded at each 50 generations and the Y-Axis presents the tree measures.

In all databases, the MOO algorithm reaches the maximum value for C.A in around 200 generations. The SOO algorithm was always worse in this measure, suggesting that maximizing C.A. is not always the same as maximizing accuracy.

In the Breast database, illustrated in Figure 2, the C.A. for the SOO algorithm is very low when compared to the MOO algorithm. Maybe the attributes desired by the decision maker do not compose the attribute set which would produce the best space partitioning, and thus, the best accuracy. In the remaining databases, the SOO algorithm ranges from 60% to 70% in C.A., suggesting that the attributes desired would be able to produce a moderately good space partitioning in those databases.

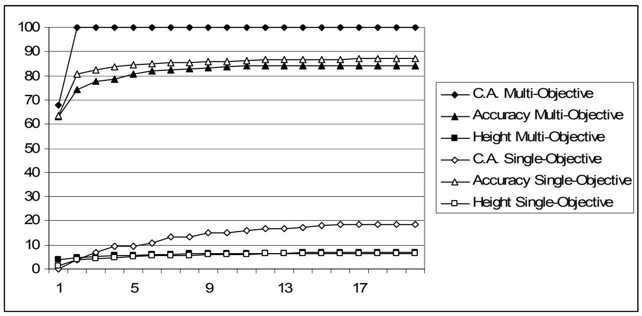

Figure 2. Cognitive Appropriateness (CA), Accuracy and Height for *Breast*.

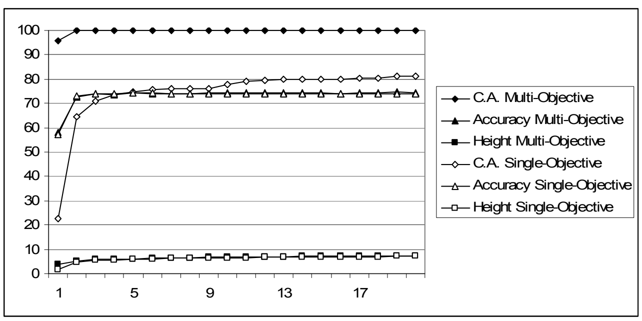

Figure 3. Cognitive Appropriateness (CA), Accuracy and Height for *Heart*.

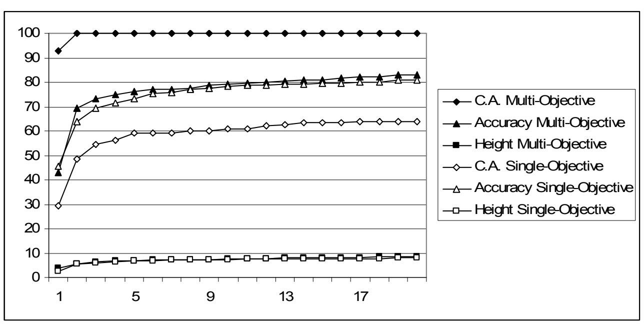

Figure 4. Cognitive Appropriateness (CA), Accuracy and Height for *Wine*.

In all databases, except in the Heart database, as seen in Figure 3, the SOO algorithm presented better results in accuracy due to its data centered approach. However, the difference to the MOO algorithm was in the maximum 5%, suggesting that, it is possible to combine user satisfaction with analytical model accuracy.

We argue that in complex problems, if the decision maker could choose between a model which is completely in accordance with his cognitive profile and another one which is only partially in accordance with him (only 5% more accurate), it is reasonable to expect that the first one would be chosen.

In all databases, the tree height between SOO and MOO algorithm was similar, suggesting that both algorithms could explore tree depth to create more accurate models.

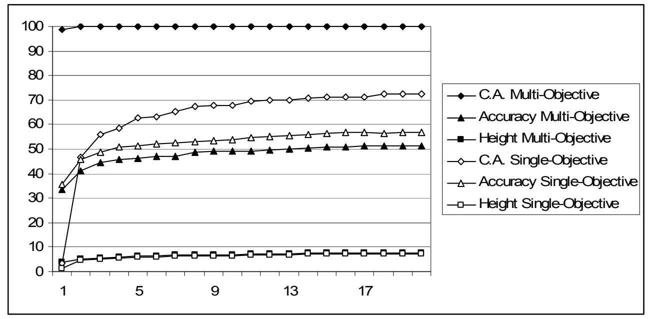

Figure 5. Cognitive Appropriateness (CA), Accuracy and Height for *Glass*.

C. *Optimization of Problem Solving Structures*

Table IV to VII show average results for tree height and values for accuracy, cognitive appropriateness (C.A.) and Structural Similarity (S.S.) for the four databases (problems) considered.

In all databases, it was possible to optimize the decision tree informed by the user (*i.e.* User Structure), improving the accuracy from 28% in the Glass database to 53% in the Wine database.

The proposed algorithm was set up to create a "better" decision tree, growing up the user structure. Thus, in all databases, the Optimized Structure was 100% similar to the user structure.

TABLE IV. AVERAGE RESULTS OF 30 SIMULATIONS FOR BREAST

Method	Height	Accuracy	C.A.	S.S.
User Structure	4	37.3684 %	12.5000 %	100 %
Optimized Structure	5.66	68.4386 %	88.3333 %	100 %
Free Search	6	83.5614 %	99.1666 %	0.8333 %

TABLE V. AVERAGE RESULTS OF 30 SIMULATIONS FOR HEART

Method	Height	Accuracy	C.A.	S.S.
User Structure	5	45.4545 %	50 %	100 %
Optimized Structure	5.16	74.9494 %	96.66 %	100 %
Free Search	7.2	75.4545 %	100 %	5.3333 %

Another interesting result is about S.S. values in the Free Search. When the algorithm had total freedom to create a decision tree, the S.S. ranged from 0.83% in the Breast database to 10% in the Wine database. This result suggests that, it was not possible to find analytical models which behave in a similar fashion as the user itself would solve the problem.

TABLE VI. AVERAGE RESULTS OF 30 SIMULATIONS FOR WINE

Method	Height	Accuracy	C.A.	S.S.
User Structure	1	32.2033 %	20 %	100 %
Optimized Structure	4.7	85.4802 %	97.3333 %	100 %
Free Search	7.83	79.0395 %	100 %	10 %

The tree height was larger in Free Search than in the Optimized Structure. Despite both respected the limit of maximum size, the Optimized Structures, were smaller because the User Structures informed were smaller. This characteristic suggests that, even indirectly, it can be advantageous to improve an informed structure, instead of creating a model without user guidance.

TABLE VII. AVERAGE RESULTS FOR 30 SIMULATIONS USING THE GLASS DATABASE

Method	Height	Accuracy	C.A.	S.S.
User Structure	1	35.2112 %	0 %	100 %
Optimized Structure	4.8	63.2863 %	100 %	100 %
Free Search	7.4	56.0563 %	100 %	3.88 %

VI. CONCLUSION

Frequently, intelligent analytical models training algorithms focus only on accuracy, but in many cases, the most accurate model does not provide the desired support in solving semi-structured problems for decision makers.

This work proposed an approach to incorporate cognitive profile information of decision makers into intelligent analytical models. The primary objective of conceiving this approach was to increase user satisfaction and trust in system use by incorporating user experiences into the decision process.

The main contribution provided were: (i) an approach to model user cognitive profiles based on preferences, constraints and when it is available, problem solving structure; (ii) a proposal of how to employ cognitive profile information into analytical model training, either for suggestion or optimization of models; and, (iii) a proposed customization of an evolutionary method to create Decision Trees to be used in Intelligent Decision Support Systems. The obtained results were promising and encourage further investigation following this proof of concept paper.

The proposed multi-objective algorithm achieved high levels of cognitive appropriateness suggesting that, the in cases where only insights about problem solving is available, the user would be satisfied to perceive that his preferences and constraints were respected.

In cases where the problem solving structure was available, the algorithm was also capable of keeping high levels of structural similarity. This suggests that, in the studied databases, it was possible to combine cognitive alignment and accuracy, mimicking the user reasoning process.

All these contributions, either suggestion of models and optimization of problem solving structure, play a prominent role in the improvement of system trust and satisfaction of use. Based on the results achieved here, employing benchmark databases composed of real data, we are confident to say that the proposed approach might be useful and reliable enough to be employed in real world Intelligent Decision Support Systems.

Future works include: (i) optimization of the multi-objective algorithm to provide better levels of accuracy, without losing cognitive appropriateness; (ii) the extension of this proof of concept to other benchmark databases and study of performance of other techniques such as Naïve Bayes, Nearest Neighbor and Artificial Neural Network in terms of Cognitive Appropriateness; and (iii) apply the modeling approach to real world problems, for example, in the medical domain because of its complexity and high need of reliability.

REFERENCES

[1] E. Turban, J. E. Aronson, TP Liang and R. Sharda, "Decision support and business intelligence systems", 8th. Edition, Prentice Hall, New York, USA, 2006.

[2] F. B. Lima Neto, F. R. S. Oliveira and D. F. Pacheco, "HIDS: Hybrid intelligent suite for decision support", Seventh International Conference on Intelligent Systems Design and Applications (ISDA), Rio de Janeiro, Brazil, October 2007, pp. 90-95.

[3] D. F. Pacheco, F. R. S. Oliveira and F. B. Lima Neto, “Including Multi-objective Abilities in the Hybrid Intelligent Suite for Decision Support”, International Joint Conference on Neural Networks (IJCNN 08), 2008, Hong Kong, China.

[4] S. Russel and P. Norvig, “Artificial Intelligence, A modern Approach”, Prentice Hall, 2002.

[5] F. R. S. Oliveira and F. B. Lima Neto, “An Evolutionary Approach to Provide Flexible Decision Dialogues in Intelligent Decision Support Systems”, 8th International Conference on Hybrid Intelligent Systems (HIS 08), 2008, Barcelona, Spain.

[6] M. J. Aitkenhead, “A Co-evolving Decision Tree Classification Method”, Expert Systems with Applications, n. 34, 2008, p. 18-25.

[7] R. L. Haupt and S.E. Haupt, Practical Genetic Algorithms, 2nd Ed., Wiley Interscience, 2004.

[8] S. Haykin, “Neural networks – a comprehensive foundation”, Prentice-Hall International Editions. New Jersey, USA, 1994.

[9] P. Langley, J. E. Laird, S. Rogers, “Cognitive Architectures: Research Issues and Challenges”, Cognitive System Research, vol. 10, pp. 141-160, 2009.

[10] S. Kirkpatrick, C. D. Gelatt and M. P. Vechi, “Optimization by Simulated Annealing”.Science, New Series, vol. 220, 1983, pp. 671-680.

[11] E. Zitzler, M. Laumanns, and L. Thiele. “SPEA2: Improving the strength pareto evolutionary algorithm”. Technical Report 103, Computer Engineering and Networks Laboratory (TIK), Swiss Federal Institute of Technology (ETH), 2001.

[12] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. “A fast and elist multi-objective genetic algorithm: NSGA-II”. KanGAL technical report 200001, Indian Institute of Technology, Kanpur, India, 2000. Available: http://www.lania.mx/~ccoello/EMOO/deb00.ps.gz

[13] D.J. Newman, S. Hettich, C.L. Blake and C.J. Merz. “UCI repository of machine learning databases”, University of California, Irvine, Dept. of Information and Computer Sciences. USA, 1998. Available: http://www.ics.uci.edu/~mlearn/MLRepository.html

[14] I. H. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques,* 2nd Ed., Morgan Kaufmann, 2005