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Cardiovascular Dysautonomias Diagnosis Using Crisp and Fuzzy Decision Tree: A Comparative Study

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Abstract. Decision trees (DTs) are one of the most popular techniques for learning classification systems, especially when it comes to learning from discrete examples. In real world, many data occurred in a fuzzy form. Hence a DT must be able to deal with such fuzzy data. In fact, integrating fuzzy logic when dealing with imprecise and uncertain data allows reducing uncertainty and providing the ability to model fine knowledge details. In this paper, a fuzzy decision tree (FDT) algorithm was applied on a dataset extracted from the ANS (Autonomic Nervous System) unit of the Moroccan university hospital Avicenne. This unit is specialized on performing several dynamic tests to diagnose patients with autonomic disorder and suggest them the appropriate treatment. A set of fuzzy classifiers were generated using FID 3.4. The error rates of the generated FDTs were calculated to measure their performances. Moreover, a comparison between the error rates obtained using crisp and FDTs was carried out and has proved that the results of FDTs were better than those obtained using crisp DTs.

Keywords. Cardiovascular dysautonomias, autonomic nervous system, fuzzy logic, fuzzy decision tree, C4.5 algorithm.

1. Introduction

Autonomic nervous system is the part of the nervous system that controls involuntary actions, such as the beating of the heart and the widening or narrowing of the blood vessels. It also controls body temperature, digestion, metabolism, the production of body fluids, and other processes [13]. However, the ANS is frequently subject to malfunctions that are called dysautonomias. This disorder can cause serious problems, including: Blood pressure problems, Heart problems, Trouble with breathing and swallowing and others. Doctors can check for signs of dysautonomias during the physical examination. They measure blood pressure (BP) and heart rate (HR) while a person is lying down or sitting and after the person stands.

Data Mining (DM) is a set of techniques designed to explore large datasets in order to discover hidden and previously unknown patterns, relationships and knowledge. DM can therefore be considered as the kernel of a knowledge discovery process from data [7]. Classification is one of the main tasks of DM. In fact, classification techniques are able of predicting categorical class labels and classify data based on a training set [4]. DTs are considered as one of the popular classification techniques. The goal of DTs is creating a model that predicts the value of a target variable by learning simple decision

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rules inferred from data. There are many algorithms to construct DTs such as ID3 [16], C4.5 [17], and CART [3]. A FDT is a tree structure where every edge is annotated with a condition, and every leaf is annotated with a fuzzy set. It is a generalization of a crisp DT to handle attributes either with numerical or linguistic values.

In our previous work, we performed a case study in the ANS unit of the hospital Avicenne. In this unit, a set of ANS tests is performed to diagnose patients with cardiovascular dysautonomias and provide them the appropriate treatment. These tests include: deep breathing test, hand grip test, mental stress test and orthostatic test. For each test, the specialists analyze deeply the obtained results of HR and BP and provide an interpretation for each result. These interpretations are called preliminary conclusions. Thereby, a decision support system (DSS) was developed to automate the generation of the preliminary conclusion and make it easier for specialists [8, 11]. The developed model was constructed using C4.5 algorithm. However, since our case study is directly related to human lives, we were motivated to extend our research and apply FDTs in order to understand and increase the accuracy rates of decision support systems. Indeed, unlike crisp DTs, FDTs deal with numerical values by transforming them into linguistic ones. According to Zadeh, the use of linguistic values instead of (or in addition to) numbers serves many purposes [21]: (1) They are easier to understand than numerical values; (2) They make allowance for imprecision; (3) They generalize numbers (only when precise information is available) and (4) They accept the finite ability of the human mind to resolve detail and store precise information. For that, we apply in this study FDT techniques to the same dataset used in our previous work. Thereby, a comparison between the results obtained using crisp DTs and FDTs is provided and discussed.

This paper is organized as follow: Section 2 presents an overview of the existing studies in literature applying crisp DTs and FDTs in cardiology. Section 3 provides details about the techniques and the experiment design used in this study. Section 4 presents and discusses the results obtained. Finally, conclusion and future work are presented in Section 5.

2. Related work

DTs are known as one of the most popular classification techniques in medical DM [4]. As a result, data miners have used DM algorithms in different disciplines of medicine including cardiology. To the best of our knowledge, there is no work carried out in applying DTs in an ANS domain. Thus, we have performed a case study in this context using C4.5 DT algorithm [8, 11]. Therefore, we developed a classification model using a dataset collected from the ANS unit of the hospital Avicenne. The classifier obtained presented a high level of accuracy up to 98.5%. On the other hand, since ANS is related to cardiovascular system, a summary of some studies conducted in cardiology using DTs and FDTs is presented in this section. Pecchia et al. proposed a platform to enhance effectiveness and efficiency of home monitoring using CART classifier for early detection of any worsening in patient's condition [15]. The developed system achieved accuracy of 96.39% in detecting heart failure. Karaolis et al. developed a DT based on C4.5 for the assessment of Coronary Heart Disease (CHD) related risk factors targeting in the reduction of CHD events. The DT was applied on a dataset collected from a hospital including 528 cases and has reached an accuracy rate of 75% [12].

On the other hand, FDTs were also getting more interest by researchers in this field. Bohacik and Kambhampati presented a method based on a FDT for prediction of the death of a patient with heart failures. The results showed that this method is a useful technique by reaching a sensitivity of 67.3% and a specificity of 62.6% [2]. Behadada and Chikh implemented a classifier based on a FDT to extract decision rules and classify some cardiac abnormalities. The best classifier in the experiments achieved an accuracy of 71%, and a sensitivity of 100% [1]. Overall, the results obtained by studies applying DTs and FDTs algorithms in cardiology were satisfactory and encouraging.

3. Materials and Methods

In this section, brief presentations of FDTs, experiment design and the medical dataset used in this study are introduced.

Fuzzy decision tree: FDTs combine the DT paradigm with the fuzzy sets theory. They are a generalization of crisp DTs to handle imprecise and uncertain attributes with numeric-linguistic values. FDTs differ from crisp DTs by [9]: 1) They use splitting criteria based on fuzzy restrictions; 2) Their inference procedures are different; and 3) The fuzzy sets representing the data have to be defined. A FDT induction has two major components: a procedure for FDT building and an inference procedure for decision making [14]. In fact, the incorporation of fuzzy logic in building DTs requires a fuzzy partitioning for fuzzy subsets of each input variable. In the FDTs, each node is associated with a variable, and each branch is associated with a fuzzy subset of this variable. Therefore, every path leading to a leaf of the tree will match with a fuzzy rule.

Medical dataset description: The dataset used in this study is the same one adopted in our previous research to provide a comparison between the results obtained by FDTs and crisp DTs. Thereby, a total of 178 records were collected from the ANS unit. This dataset includes records of patients suffering from cardiovascular dysautonomias who went to ANS unit in the period between January 2013 and May 2014. 11 attributes were identified to be required for the generation of the preliminary conclusion and were selected to perform our experiment, including: age, VR_DB, VR_HG, PSR α, CSR α, CSR β, VR_Ort, HRmin, HRmax, BPmin, BPmax. Table 1 provides a brief description and details about input attributes for each ANS test. As can be noticed, the age attribute is considered as the main factor that influences the results interpretation obtained in each ANS test.

Experiment design: In the ANS unit, a patient's diagnosis is based on several dynamic tests. In each test, specific metrics are calculated by means of measuring continuously HR and BP values and a set of mathematical equations. According to the tests results, a set of preliminary conclusions is deduced for each ANS test. These conclusions are analyzed deeply by the specialists to provide a global synthesis and diagnosis of the patient's state. However, the measurement and analysis of the test results are done manually by the specialists which makes it more difficult for the specialists. In this study, the same input data identified in our previous paper were used to generate the FDTs [8, 11]. Thus, for each ANS test, one or two or three FDTs were generated to automate the obtaining of preliminary conclusions. For each FDT, three classes were identified based on the expert's guidelines namely: low, normal and high. As a result, eight FDTs were generated and tested.

Table 1. Description and details about input attributes for each ANS tests

ANS tests	Measured values	Description	Input attributes
Deep Breathing	Vagal response (VR_DB)	Vagal response measured using HR values in Deep Breathing test (DB)	Age VR
Hand Grip	Vagal response (VR_HG)	Vagal response measured using HR values in Hand Grip test (HG)	Age VR
	PSR α	Peripheral sympathetic response α measured using BP values in HG test	Age PSR
Mental stress	CSR α	Central sympathetic response α measured using BP values in Mental Stress test (MS)	Age CSR α
	CSR β	Central sympathetic response β measured using BP values in MS test	Age CSR β
Orthostatic test	Vagal response (VR_Ort)	Vagal response measured using HR values in Orthostatic test (Ort)	Age VR
	SP_HR	heart rate measured in Orthostatic test using supine position (SP)	Age HRmin HRmax
	SP_BP	blood pressure measured in Orthostatic test using supine position	Age BPmin BPmax

In order to build FDTs, we adopt the experiment design presented in Figure 1. This process includes several major phases namely:

- Data pre-processing: It is a critical step which deals with the preparation and transformation of the initial data [6]. Since the dataset adopted in this study is the same as that one used in our previous work, the pre-processing phase was already done and presented in [8, 11]. In fact, a data-cleaning process was performed to fill the missing values that did not exceed 4% of the whole set. Besides, real numbers of the dataset were all transformed to integer values to simplify the generation of crisp DTs.
- Fuzzification process: It aims at transforming numeric values to linguistic ones [20]. For this, membership functions must be built to define the degree of membership of a numeric value to fuzzy sets of linguistic variables. In fact, for each linguistic value, a membership function is defined [20]. The attributes are then described by fuzzy sets and the tree arcs are associated with these fuzzy sets. Moreover, the choice of shapes of membership functions may be subjective. Trapezoidal and triangular shapes for membership functions are generally used.
- FID fuzzy decision tree: It is a classification system, implementing an efficient recursive partitioning technique of DTs, while combining fuzzy representation and approximate reasoning for dealing with noise and language uncertainty [10]. FID has three major components related to partitioning continuous attributes, building an

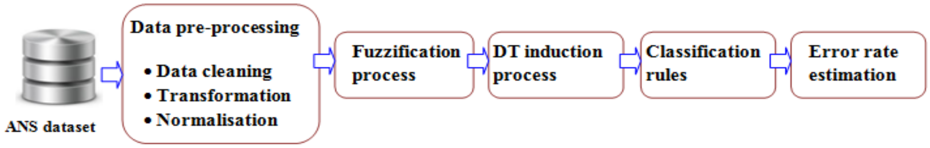

Figure 1. Experiment design process

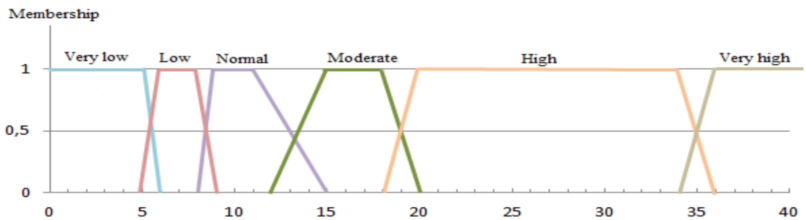

Figure 2. Fuzzy sets defined for VR_HG attribute

explicit tree, and inducing knowledge from the tree [5]. Furthermore, FID includes a pruning algorithm to avoid over-fitting, which balances a tradeoff between the size of the tree and its predictive accuracy.

- Classification rules: With a fuzzy context, an example may belong to several sub-nodes with different degrees of membership [9]. FDTs can be interpreted by a set of fuzzy rules. Each path from the root to the leaf can be converted to a rule where the condition part represents the attributes and the conclusion part represents the classes. The weights of the conclusion of each rule is calculated by means of the membership degrees using the AND operator.

4. Results and Discussion

In order to generate the FDTs, we used the FID 3.4 version which is one of the FID programs [19]. It uses three input files namely: attribute, data, and parameter files. The attribute file contains information about the attributes, definitions of partitioning sets, the corresponding names and the definition of the decision classes. A data file includes information about training examples: the values of each attribute (numeric, linguistic, or missing), the decision value (numeric or linguistic), and weight value (weight of the event). A parameter file contains default values for all of the configurable options. Thereby, these files were generated and were changed in each trial. In fact, in order to measure the efficiency of the generated FDTs, the data set was randomly partitioned into training and independent test sets by means of a 10-fold cross-validation process. Thus, the data set was split into ten equal sized blocks with similar class distributions [18]. Moreover, the error rate metric was used to evaluate the performance of the generated classifiers [4]. Figure 2 presents the membership functions associated to the VR_HG attribute. As can be seen, six fuzzy sets were defined for this attribute. These fuzzy sets were identified based on the empirical knowledge of ANS experts since the data used in this study are very critical and each system error may risk a human life. For this reason, we preferred in this work to rely on the specialists expertise when identifying the fuzzy sets rather than using fuzzy algorithms such as fuzzy C-means.

Table 2 presents the results obtained when measuring the mean error rate and standard deviation for each generated crisp DT and FDT using the training and test sets and 10-fold cross-validation method. The error rate was computed by FID3.4 depending on the degrees of membership. In fact, an example is considered to be incorrectly classified when the “Delta:Best” feature (which contains the decision class having the highest membership) is different from “Class” feature (which contains the actual classwhere the error rates obtained by FDTs were better than those obtained by crisp DTs. Thereby, we notice a reduction in error rates obtained using FDT techniques in

Table 2. Comparison of mean error rate obtained by crisp DTs and FDTs on training and test sets

ANS tests	Phase	Learning phase				Test phase			
		Mean error rate		Std deviation		Mean error rate		Std deviation	
		Crisp DT	FDT	Crisp DT	FDT	Crisp DT	FDT	Crisp DT	FDT
Deep Breathing	Vagal response	3.05%	**2.69%**	1.97	0.89	2.43%	**1.75%**	2.33	1.62
Hand Grip	Vagal response	3.72%	**2.99%**	1.53	1.13	2.98%	**2.07%**	1.18	1.05
	PSR α	1.11%	**1.02%**	0.89	1.22	3.21%	**2.72%**	2.19	1.79
Mental stress	CSR α	1.02%	1.13%	0.76	0.91	0.93%	1.31%	0.88	0.84
	CSR β	0.34%	**0.11%**	1.88	0.83	1.99%	**1.08%**	1.21	1.58
Orthostatic	Vagal response	0.27%	0.41%	0.91	0.97	1.07%	1.91%	0.91	0.99
	SP_FC	1.68%	**1.19%**	1.21	1.42	7.81%	**5.02%**	0.94	1.03
	SP_TA	2.14%	**1.83%**	2.36	1.65	2.31%	**1.94%**	0.80	0.78

most ANS tests (6 of 8 tests) which contributes to the improvement of the generated classifiers performance. Overall, the error rates obtained using FDTs techniques in learning phase were very low reaching a maximum value of 2.99%. Thus, the accuracy rates recorded in all ANS tests exceeded 97.01% which is very promising and encouraging. As for the test phase, the maximum average value of error rates recorded was 5.02%. Thus, the minimum average value obtained for accuracy rates is 94.98% which is a very acceptable accuracy. Moreover, the comparison between the results obtained in the test phase showed an improvement in the error rates of FDTs. Six of eight generated FDTs have reached error rates lower than those of crisp DTs. On the other hand, we can notice that the standard deviation values are close to 0 which indicates that the error rates of the different trials tend to be very close to the average error rate.

Using the 10 fold cross-validation method, 10 trials were carried out for each ANS test. Thus, since eight FDTs were generated in this study, a total of 80 trials were performed. According to the results obtained for both techniques FDTs and crisp DTs, we noticed that using the training sets, FDTs recorded low error rates comparing to crisp DT in 92% of cases (74 of 80 trials). Regarding the test sets, in 89% of cases (71 of 80 trials), the error rates obtained by FDTs were lower than those obtained by crisp DTs. These results may be explained by the fact that FDT techniques are based on modeling uncertainty around the split values of the features which results in soft splits instead of hard splits of crisp DTs techniques; which contributes to the generation of a set of rules with simple conditional parts and relative high accuracy rates.

Moreover, the classification rules generated by FDTs facilitate the results interpretation by the experts. In fact, as aforementioned, the numerical data of the dataset were transformed into linguistic values. By this way, the extracted rules included linguistic forms instead of numerical ones which made them more readable and interpretable. As an example, the rule 1 and rule 2 present two classification rules extracted respectively from the generated FDT of Figure 3 and the crisp DTs regarding Hand grip test and expressing the same decision. Thus, we notice that rule 1 is easier to interpret than rule 2. Besides, based on our observations in the ANS unit, we noticed that the specialists prefer using linguistic values when interpreting the obtained results which can be suitable to the results provided by the generated FDTs. Therefore, the use of FDT techniques was beneficial and more appropriate in this case (*Rule 1:* **IF** Age=”Young” **AND** VR_HG=”High” **THEN** Class=”High”; *Rule 2:* **IF** 25<Age <= 35 **AND** VR_HG=25 **THEN** Class=”High”)

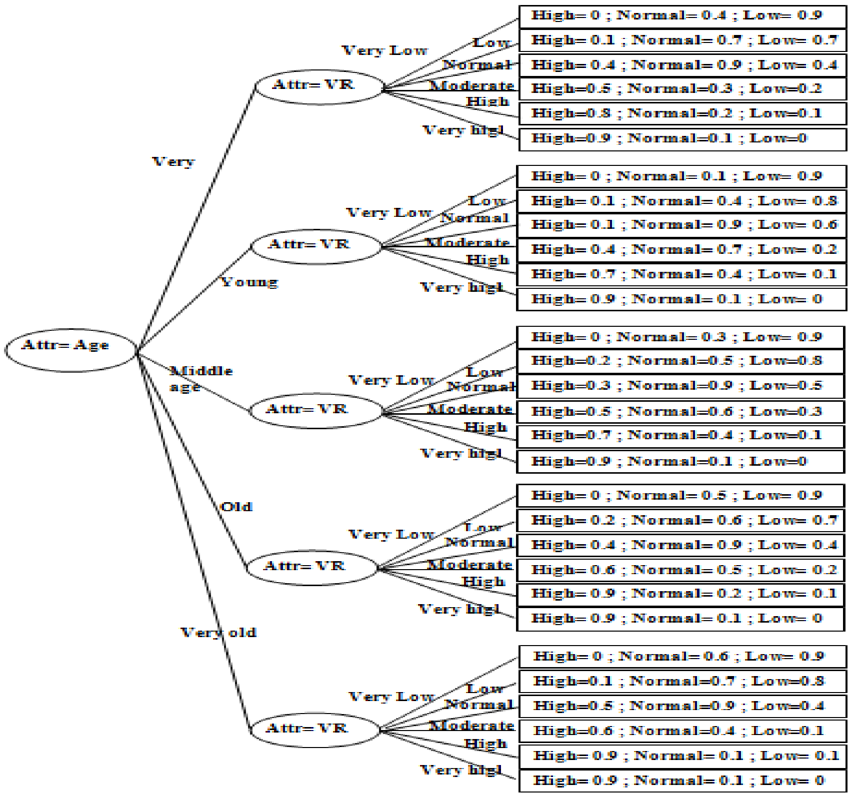

Figure 3. Example of a generated FDT regarding Hand grip test

Overall, this study has shown that FDT classifiers were more efficient and have achieved low error rates. These results may be explained by the fact that combining comprehensibility of DTs with the expressive power of fuzzy sets allowed to handle uncertainties and thus increase the performance of the generated classifiers. However, the complexity of FDTs was slightly higher than the complexity of crisp DTs. In fact, the number of nodes and leafs was higher in FDTs than crisp DTs while the depths of FDTs and DTs were slightly the same. For example, the generated FDT regarding HG test includes 6 nodes and 30 leafs (Figure 3) while the generated crisp DT for the same test contains only 4 nodes and 9 leafs.

5. Conclusion and future work

In this paper, FDT techniques were applied on a dataset extracted from the ANS unit of university hospital Avicenne. This study aimed at providing a making decision system to help doctors in the analysis procedure of the ANS's test results and improving the accuracy rates. This work used the results obtained in a previous case study so as to provide a comparison between the results obtained using crisp DTs and FDTs. Thereby, we used FID 3.4 algorithm to generate FDTs. The error rates recorded in each trial were very low which contributes to the increase of accuracy rates. These results were compared with the error rates obtained using the crisp C4.5 algorithm. Thus, the generated FDTs were proved to be more accurate than those obtained using crisp DTs. However, as a limitation of this research, we may mention the small size of the dataset used which requires performing more validation tests over large data sets. For future work, we intend to conduct a research on evaluating the quality of DM based DSS in medical fields, especially in cardiology, since the data processed by these systems are very important and critical so as not to threaten the patient lives.

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