A Fuzzy Association Rule Mining Expert-Driven (FARME-D) approach to Knowledge Acquisition

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ABSTRACT

Fuzzy Association Rule Mining Expert-Driven (FARME-D) approach to knowledge acquisition is proposed in this paper as a viable solution to the challenges of rule-based unwieldiness and sharp boundary problem in building a fuzzy rule-based expert system. The fuzzy models were based on domain experts' opinion about the data description. The proposed approach is committed to modelling of a compact Fuzzy Rule-Based Expert Systems. It is also aimed at providing a platform for instant update of the knowledge-base in case new knowledge is discovered. The insight to the new approach strategies and underlining assumptions, the structure of FARME-D and its practical application in medical domain was discussed. Also, the modalities for the validation of the FARME-D approach were discussed.

Keywords: Fuzzy Expert System (FES), Fuzzy Association Rule Mining, Knowledge-base acquisition, Rule-base, Coronary Heart Disease (CHD)

1. INTRODUCTION

The Fuzzy Association Rule Mining Expert-Driven (FARME-D) approach to knowledge acquisition is the proposed solution to the challenges of the sharp boundary problem, rule-base unwieldiness and instant knowledge-base update in building an expert system especially in medical domain. This paper presents FARME-D as an approach which incorporates domain experts' opinion factors (where experts determine the rules consequences) into the existing Fuzzy Association Rule Mining technique to extract relevant rules which correspond with the expert perception of the domain. The proposed approach is committed to the extraction of interesting knowledge from domain experts' past experiences based on the experts' perception of the data. Instead of using data-driven approach (where data partitions are generated automatically from the data table), this proposed solution uses expert-driven approach which involves the domain expert's opinion in calibrating fuzzy membership functions and determining the mined rules' consequences. This is used for modelling a compact fuzzy rule-based expert system. This paper provides insight to the proposed solution strategies and underlining assumptions..

The extensive review of related works is presented in section 2. The structure of FARME-D architecture in section is presented 3. Also, the modalities for the validation of the FARME-D approach and expected results are discussed in section 4. The paper closes with conclusion and further research areas in section 5.

2. RELATED WORKS

An Expert System (ES) is an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solutions [1]. One of the approaches of modelling expert systems is the rule-based approach [2]. The rule-based expert systems collect the small fragments of human knowledge into a knowledge-base in form of if–then rules, used to reason through a problem, by knowledge that is appropriate [3]. Rule-based expert systems are easy to formulate; they emulate human cognitive process and decision-making ability; and finally, they represent knowledge in a structured homogeneous and modular way [2]. To enhance rule-based system fuzzy logic has provided a framework to model uncertainty, the human way of thinking, reasoning, and the perception process [3,4].

Fuzzy rule-based expert system (FES) is simply an expert system that uses collection of fuzzy membership functions and rules instead of the Boolean logic to reason about data in the inference mechanism [5,6]). A fuzzy expert system consists of fuzzification process, inference mechanism, knowledge-base, and defuzzification subsystems. Fuzzy if-then rules and fuzzy reasoning are the backbone of fuzzy expert systems, which are the most important modelling tools based on fuzzy set theory.

However, there are several limitations to these systems, which include large numbers of rules in the knowledge-base that causes the system to become unwieldy because of the presence of rules that might not be relevant to the application domain [2]. For instance, using standard rule-base formulation, such that given M dimensions where each dimension is partitioned into N subspaces, there exist up to N^M rules in the fuzzy system [7]. The larger the N the larger the number of rules and, according to [7], if all the possible rules are used, then the system is not compact because of the redundant rules (rules that are not relevant to the application domain). These have three negative effects on expert system: 1) it increases the knowledge-base memory usage, since extra space is needed to store the redundant rules; 2) the existence of large number of rules reduces the rule access rate which ultimately slows down the response time of the ES; 3) it also makes the knowledge-base unwieldy which inevitably complicates the system maintenance especially in the case of subtle updates [2]. Therefore, the problem now is, how do we evolve a knowledge-base that is complete, void of Sharp boundary problem and with minimize redundant rules.

2.1 Knowledge Acquisition

Knowledge acquisition is a crucial part of the knowledge engineering processes in modelling a rule-based expert system. It is the process of gathering the relevant information about a domain from human experts for an expert system [8]. The information gathering could be deductively from the human experts or inductively by learning from examples. The knowledge acquisition represents the extracting, structuring and organizing process of knowledge, out of one or many sources, so that the solving expertise of a matter can be stored in an expert system, in order to be used in solving the issues [9].The method of knowledge acquisition can be divided into manual, semi-automated and automated [8,9].

Automated knowledge acquisition uses an induction system with case histories and examples as input to derived knowledge-base. This is also known as machine learning. Automated knowledge acquisition eliminates the role of knowledge engineer and minimizes the role of domain expert in the knowledge extraction [10]. In most existing rule-based expert systems, the knowledge-base rules are generated by experts in the area, especially for control problems with only a few inputs. With an increasing number of variables, the possible number of rules for the system increases exponentially, which makes it difficult for human experts to define a complete rule set for good system performance. Therefore, an automated way to design fuzzy systems might be preferable [11]. Also automated method of knowledge acquisition becomes more important especially where some domain experts are not available and there are case histories and examples.

Different techniques have been introduced in the literature to actualize the automated knowledge acquisition approach. These include clustering [12], classification [13,14], neural network [5,11], hybrid system of fuzzy and neural [15,16], rough set [17], and fuzzy evolutionary [18]. In most other cases, such as in [19] rules were generated by standard rule-base formulation as described in [7].

In [20], the Fuzzy logic concept and data mining approach was implemented to improve intrusion detection system. The improved Kuok fuzzy data mining algorithm which modified apriori algorithm was used to generate the fuzzy rules for the knowledge-base that reflect common way of describing security attacks. The report shows that the approach performed efficiently based on data driven-approach (where data interval boundaries and rule concequences were automatically generated from the data tables). The limitation of this approach is that rules extracted using data-driven approaches could not correspond intuitively to human perception of the domain [21].

Some other approaches that have been used to evolve knowledge-base are not free from sharp boundary problem, which could either overestimate the boundary values or underestimate them because of quantitative nature of some databases [22]. Some exhibited rule inconsistency, membership function not corresponding with the intuitive human perception and some evolve large number of rules in the knowledge-base. All these shortcomings intimate the context of this paper where fuzzy association rule mining based on expert-driven approach is introduced to knowledge acquisition process in modeling a compact fuzzy expert system.

3. OVERVIEW OF PROPOSED FARME-D APPROACH

FARME-D incorporates domain experts' opinion into existing fuzzy association rule mining process. Domain expert determines data interval partitions for calibrating fuzzy membership functions and the mined rules' consequences. FARME-D is committed to modelling of Fuzzy Rule-Based Expert System simply called Fuzzy Expert System (FES). It is a specialized pattern discovery technique that involves domain experts' opinion. It excels in extracting interesting knowledge in form of rules which correspond to the domain expert perception and void of sharp boundary problem. FARME-D enhances FES comprehensibility while accuracy is maintained; it also aims at providing a platform for instant update of the knowledge-base in case new knowledge is discovered. The integration of FARME-D with FES standard architecture would enhance the expert system instant update. Further details on FARME-D approach structure are presented next.

3.1 Limitations And Assumptions
The application of FARME-D in modelling fuzzy expert systems is constrained by a set of preconditions that guarantees its practicability in knowledge acquisition.

These are:
1. Data and technical description of the problem domain is used as stated by the domain expert and literature.
2. In modelling expert systems, the simplicity advantage of production rule knowledge representation is adopted.
3. Only structure historical database is accommodated in the mining process.

In addition, FARME-D is based on the following assumptions:
1. The determinant factors for solving problems are known and predetermined in advance by domain experts.
2. Data stored in organizations are quantitative in nature and growing in an increasingly rapid way with increasing number of variables.
3. Organizations have structured historical data bank where the past human experts' experiences could be retrieved.

FARME-D is designed for specialized automated knowledge acquisition for modelling FES. It does not address the entire structure of FES. As such, the limitations and assumptions of FARME-D are all directed from the principle that governs the practice of automated knowledge acquisition and fuzzy association rule mining processes [9, 22]. The limitations are meant to provide a guide on how the knowledge acquired could be managed to enhance the ES knowledge-base. The set assumptions, on the other hand, are those that facilitate the most utilization of fuzzy association rule mining technique and specify the scenario when FARME-D is optimally applicable.

3.2 Components of Farme-D Knowledge Acquisition
FARME-D adopted the CRISP-DM (Cross Industry Standard Process for Data Mining) model framework for the mining process [24]. It focuses on the extraction of interesting knowledge from past examples based on domain expert perception of the data. FARME-D comprises of application domain historical database, fact from domain experts, fuzzification engine, and expert-driven data mining engine and rule interpretation process. The framework for FARME-D knowledge acquisition is shown in Figure 1.

3.2.1 Historical Database
The historical database is an important component of FARME-D approach, since the proposed approach is acquiring knowledge from the domain experts' past experience. One of the assumptions of FARME-D as stated in section 3.1 is that every organisation has historical database for the human experts' past experiences from solved problem instances.

The database is in a structured form which includes the description of the data stored, input variables and the result variable. The database model platform supported by FARME-D is Relational Data Based (RDM) model.

3.2.2 Domain expert
The expert here refers to the domain human expert who is ready to supply every piece of information (fact) necessary for mining and fuzzification process. Information collection could be achieved through an oral interview, questionnaire approach, or literature. The information includes the description of each attribute in the historical database and the application domain business rules and features. This information would help in fuzzification process to calibrate fuzzy membership models for each attribute and to determine the rules' consequences in mining process. This is to avoid over estimation or under estimation of boundary values, simply called sharp boundary problem and enable the rules to correspond to human perception.

3.2.3 Expert-Driven Fuzzification Process
Prior to the mining process fuzzification is very important to avoid sharp boundary problem. The information gathered from the domain experts is put together to determine the dimensions and the subspaces (fuzzy set) for both the input and output variables (linguistic variables). Also, the membership function for each linguistic fuzzy set was calibrated following the expert's opinion about the data description to enhance the effectiveness of the fuzzy models. Using expert-driven and data-driven approach (where data intervals are generated automatically from the data table), one may expect rules obtained to be significantly different. Hence, the membership functions obtained from data-driven approach such as clustering may not correspond with the most intuitive human perception of concept. So, this introduced approach engages the expert-driven approach to enhance the mining capacity of the existing fuzzy association rule mining algorithm.
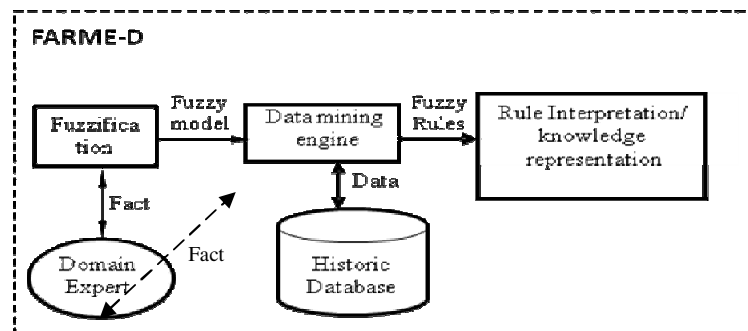

Figure 1 The Framework for FARME-D Knowledge Acquisition Approach

3.2.4 Data Mining Engine

The data mining processes start from data pre-processing and end with Fuzzy Association Rule Mining (FARM). The activity involved in this section is termed rule elicitation. To evolve the interesting knowledge-base, with least amount of redundant records, there is need for mining application domain historical database. This is very crucial in order to access different domain human experts' knowledge for enriching the knowledge-base. To achieve this, Fuzzy Association Rule Mining (FARM) algorithm has proved sufficient over the years. FARM is a data mining technique that hybridizes the fuzzy concept and association rule mining in order to enhance the functionality of the traditional association rule mining algorithm for mining quantitative data attributes. The concept of Fuzzy Association Rule Mining is based on the measure of support and confidence. Any rule that could not maintain support and confidence value above zero is obvious not relevant in the application domain. So, such rule is eliminated during the mining process. The input to the algorithm is the crisp data set from the application domain historical database, and the fuzzy models. The intermediate output is the fuzzy database got as a result of data transformation (fuzzification process). The final output is the set of rules in the form:

$$Young, Low, Middle, Normal \rightarrow LowRisk$$

3.2.5 Rule Interpretation/Knowledge Representation

After extracting all the relevant rules (interesting rules) within the context of the application domain, the next thing is to interpret the rules according to the domain expert perception. Also there is need to represent the rules in a standard knowledge representation format that will support the choice of the programming language and tools for building the expert system.

4. PRACTICAL APPLICATION OF FARME-D KNOWLEDGE ACQUISITION APPROACH IN MEDICAL DOMAIN

In order to validate the applicability of the proposed knowledge acquisition approach a fuzzy expert system to determine CHD risk ratio is designed. The system knowledge-base is evolved using FARME-D. The existing fuzzy association rule mining Apriori-like algorithm proposed in [25] was adopted. The algorithm was adjusted such that only the 4th order rules were extracted (rules with 4 attributes antecedent and one attribute consequence). Also unlike data-driven approach (where data interval boundaries and the rules consequences are automatically generated from the data tables) the data interval boundaries and the rule consequences are determined by the experts' opinion according to ATP III (Adult Treatment Panel) Guidelines for CHD risk ratio determination by National Cholesterol Education programme [22,26].

The Cleveland Clinic Foundation and Hungarian data-set from University of California, Irvine (UCI) repository were integrated for the mining process. The data-set was used in conjunction with ATP III. The Framingham CHD risk point score was used to determine the percentage risk for each record in the sample data-set [26]. For this work 7 attributes of Age, Sex, Blood pressure, Cholesterol, Smoke status, Family History of CHD, History of Diabetes were used to determine the risk. The data description of the seven attributes is shown Table 1.

For the mining process, the data-set of 389 records of non-smoking men with no diabetes history from the two databases was used with 5 attributes as a pivot test. The 5 attributes are quantitative in nature. The input attributes are age: year; cholesterol: mg/dL; high density lipoprotein cholesterol: mg/dL (HDL-C); and systolic blood pressure level: mm/Hg. The output attribute is CHD risk ratio. These attributes were selected based on determinant factors for CHD risk according to experts and literature [19,26,27]. The fuzzy sets for each attribute are described in Table 2. The minimum support and confidence values are set to zero so as to allow for the expert system's knowledge-base completeness. The mining process yielded 79 rules as against 108 rules generated by standard rule-base formulation in [19]. The snapshot for the mining process is shown in Figure 2.

Table 1: Description of Coronary Heart Disease determinant factors

Attribute	Description	Value description
Age	Age (year)	Numerical
Sex	Sex	Categorical
Bp	Systolic blood pressure (mmHg)	Numerical
Cholesterol	• Total Serum Cholesterol (mg/dl) • High density Cholesterol (HDL-C) (mg/dl)	Numerical
Smoke	Smoke status	Categorical
FH	Family History of CHD	Categorical
HD	History of Diabetes	Categorical

Table 2: Linguistic variables and their fuzzy sets

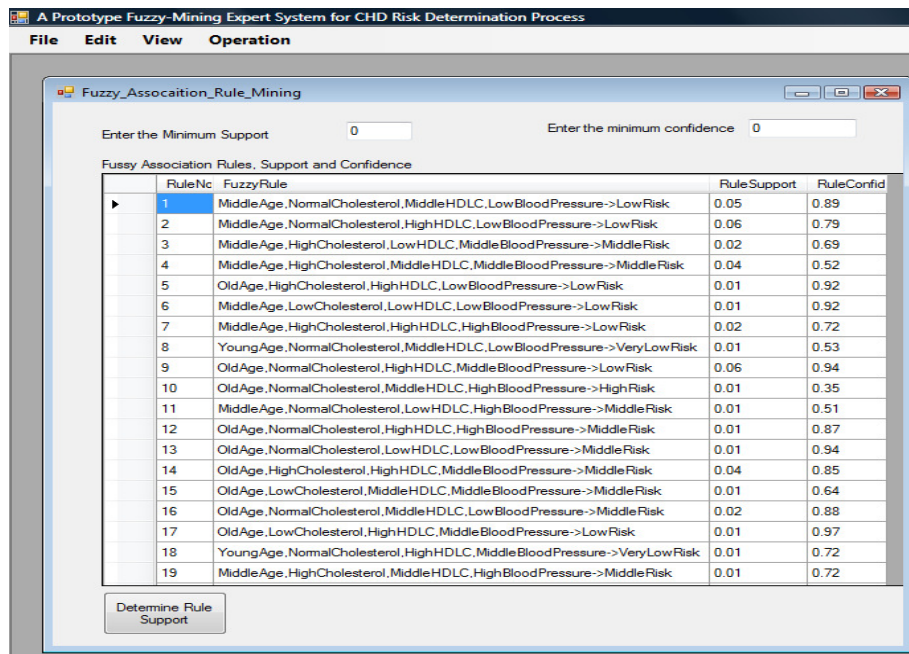| Linguistic variable	Domain	Fuzzy set	Membership function
Age	Input	YoungAge, Middle Age, Old Age	trapmf
Cholesterol	Input	Low, Normal, High	trapmf
HDL-C	Input	Low, Middle, High	trapmf
Blood Pressure	Input	Low, Middle, High, Very High	trapmf
CHD risk ratio	Output	VeryLow, Low, Middle, High, Veryhigh	trimf

Figure 2 The Snapshot for FARME-D Output

4.1 Application Result and Discussion

The prototype system was tested using test case approach. The test cases are 20 records from non-smoking men outside the mining data set to examine the completeness of the knowledge-base. The essence of these test cases is to determine the accuracy similarity percentage between the result we are going to have from our proposed approach with 79 rules and 108 rules knowledge-base.

The linguistics values represent the fuzzy values for each approach. The fuzzy value is more appropriate for medical decision interpretation compare to the actual values.

It was observed that for the test cases, the 79 rules and 108 rules fuzzy systems gave the same risk ratio value except in one instance regardless of the number of rules. This implies that there exist 29 redundant rules among 108 rules which could make the

Table 3:   Non-Smoking men Test Case

Patient no	Age	Cholesterol	HDLC	Blood Pressure	ATP III	FES With 108 Rules	FES With 79 Rules	ATP III CHD risk Linguistic value	FES CHD risk Linguistic value with (108 rules)	FES CHD risk Linguistic value with (79 rules)
1	30	180	37	160	0	1.5	1.5	VeryLow	VeryLow	VeryLow
2	35	190	45	145	0	4.4	4.4	VeryLow	VeryLow	VeryLow
3	48	260	33	120	8	10.1	10.1	Low	Low	Low
4	57	300	67	110	8	9.3	9.3	Low	Low	Low
5	65	250	54	170	18	19.9	19.9	Middle	Middle	Middle
6	75	290	25	135	30	31.5	31.5	High	VeryHigh	VeryHigh
7	30	160	49	160	0	1.5	1.5	VeryLow	VeryLow	VeryLow
8	40	310	33	140	8	15.5	15.5	Low	Middle	Middle
9	55	300	26	200	30	26.9	25.5	High	High	High
10	60	230	39	110	11	11.2	11.2	Low	Low	Low
11	70	210	45	130	16	15.5	15.5	Middle	Middle	Middle
12	30	240	50	150	0	1.5	1.5	VeryLow	VeryLow	VeryLow
13	35	180	65	160	0	5	5	VeryLow	Low	Low
14	45	300	47	155	9	15.5	15.5	Low	Middle	Middle
15	55	300	49	160	16	18.9	18.9	Middle	Middle	Middle
16	65	250	41	140	18	15.6	15.6	Middle	Middle	Middle
17	70	260	38	190	30	28	28	High	High	High
18	44	210	37	180	5	9.2	9.2	Low	Low	Low
19	55	250	30	200	11	18	18	Middle	Middle	Middle
20	66	250	26	200	28	24.6	24.6	High	High	High

All other factors remain constant. The results of the test cases are shown on Table 3. Columns 6 shows the ATP III result, which represent the domain expert result. Column 7 and 8 show the actual crisp values for each record according to the two approaches investigated FES with 108 rules represents the standard rule-base formulation knowledge acquisition approach and the FES with 79 rules represent the proposed approach. Columns 9,10,11 show the linguistic values for the three experiment.

knowledge-base unwieldy and negatively affect the system response time.   The graphical interpretations of the result are shown in Figure 3 and 4. Figure 3 shows the graphical comparative expression of actual crisp result got from the two approaches. Also, the graphical comparative expression of the linguistic values is shown in Figure 4.

The statistical evaluation of the Colum 6, 7 and 8 using ANOVA indicates that with significance level $\alpha = 0.05$, the f statistic < f critical $(0.246< 3.16)$ and *p value > a (0.78> 0.05)* , therefore the hypothesis that the three means are the same at 95% confidence is
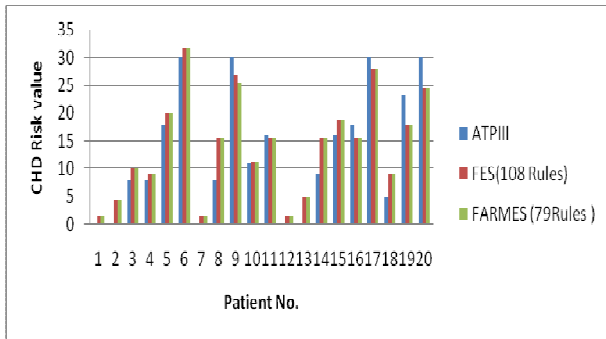
accepted. This confirms the similar performances of the three approaches regardless of the number of rules.

Figure 3   ATPIII, FES with 108 rules and FES with 79 rules CHD %
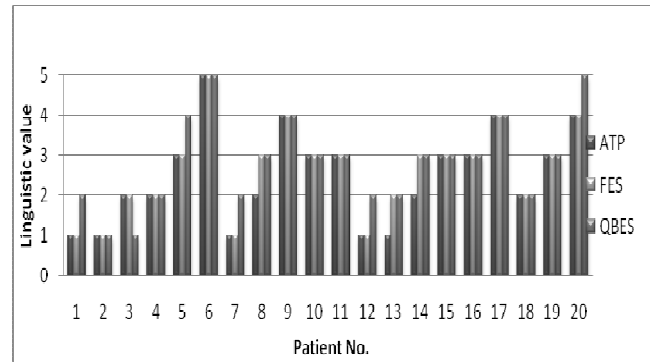**risk value diagrammatic representation**

Figure 4: The linguistic % CHD risk diagrammatic representation
for ATP III,FES and QBES

5. CONCLUSION

In this paper Fuzzy Association Rule Mining Expert-Driven approach was proposed as a viable technique for knowledge acquisition in modelling a compact fuzzy expert system. The involvement of experts' opinion in the mining process makes the extracted rules to correspond more intuitively to expert's perception and enhances the system accuracy. The mining process eliminates the rule that is not relevant in the application domain based on the experts' past experiences. This in turn reduces the number of rules and makes the prototype system more compact according to [7]. The integration of the proposed approach into the standard fuzzy expert system architecture also would provides for knowledge-base instant update as new knowledge is discovered and validated by the experts.

FARME-D was able to achieve 27% *reduction* in the number of rules evolved for the prototype system at a reduced storage usage of 20% while the system accuracy is maintained.. Therefore, the case study scenario has proved the viability of FARME-D knowledge-base acquisition approach in medical domain with fewer number of rules void of Sharp boundary problem and correspond with domain expert perception.

6. FUTURE WORKS

The paper provides several opportunities for further research in the immediate future. The FARME-D approach, as modeled and implemented in this paper, directly inherited some limitations from its parent concept of fuzzy association rule mining. Notably, there exist ample of research possibilities to enhance the concept in the following areas:

- Mining process: extension of the mining process to involve text mining, image mining, voice mining and web mining in order to extend the scope of knowledge acquisition which will turn out to enrich the knowledge-base.
- Knowledge representation: extending the knowledge representation beyond production rule representation to semantic net and case bases.

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Authors' Briefs

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