Self-Evolving Expert Systems based on Fuzzy Neural Network and RDB Inference Engine

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In this research, we propose the mechanism to develop self-evolving expert systems (SEES) based on data mining (DM), fuzzy neural networks (FNN), and relational database (RDB)-driven forward/backward inference engine. Most researchers had tried to develop a text-oriented knowledge base (KB) and inference engine (IE). However, this approach had some limitations such as 1) automatic rule extraction, 2) manipulation of ambiguousness in knowledge, 3) expandability of knowledge base, and 4) speed of inference. To overcome these limitations, knowledge engineers had tried to develop an automatic knowledge extraction mechanism. As a result, the adaptability of the expert systems was improved. Nonetheless, they didn't suggest a hybrid and generalized solution to develop self-evolving expert systems. To this purpose, we propose an automatic knowledge acquisition and composite inference mechanism based on DM, FNN, and RDB-driven inference engine.

Our proposed mechanism has five advantages. First, it can extract and reduce the specific domain knowledge from incomplete database by using data mining technology. Second, our proposed mechanism can manipulate the ambiguousness in knowledge by using fuzzy membership functions. Third, it can construct the relational knowledge base and expand the knowledge base unlimitedly with RDBMS (relational database management systems) module. Fourth, our proposed hybrid data mining mechanism can reflect both association rule-based logical inference and complicate fuzzy relationships. Fifth, RDB-driven forward and backward inference time is shorter than the traditional text-oriented inference time.

Keywords: Expert systems, Knowledge base, Data mining, Fuzzy neural networks, Relational database, Inference engine, Self-evolving expert systems.

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1. Introduction

The purpose of this study is to develop self-evolving expert system based on hybrid knowledge acquisition (DM and FNN) and RDB-driven high-speed inference mechanism. Expert system has been emerged as a new area of human knowledge management field during several decades. Expert system was a collection of emerging technologies inspired by the intelligent processing of expert knowledge in the human reasoning, decision-making, software engineering, process scheduling, medical diagnosis, and etc. Therefore, most researchers tried to extract the knowledge from human expert and large database. It was commonly regarded as a major obstacle and bottleneck in the process of designing and implementing expert systems. Through the former researches automated knowledge acquisition tools were developed to help the knowledge engineer or even the expert himself to build and maintain the required knowledge systems (Eriksson, 1991; Gruber, 1987; Hong et al., 2002; Rafea et al., 2003).

One of the interesting topic in the filed of knowledge acquisition was data mining. Data mining was introduced in the field of knowledge discovery (or extraction) in database (Bonchi, et al., 2001; Chakrabarti et al., 1999; Changchien & Lu, 2001; Hui & Jha, 2000; Lee et al., 2002; Song et al., 2001), and has been recognized as a new area for database research. The area could be defined as efficiently discovering interesting rules from large collections of data. Especially, association rule extraction mechanism, which was proposed by Agrawal et al.(1993), was a most popular tools to execute the data mining. Given a set of transactions, where each transaction was a set of item, an association rule was an expression of the form X → Y. X and Y means the sets of items. An example of an association rule was: "20% of transactions that contain beer also contain diapers; 10% of all transactions contain both these items." Here 20% is called the *confidence* of the rule, and 10% the *support* of the rule. However, association rules couldn't represent the fuzzy logic embedded in real world knowledge. Therefore, combination of fuzzy logic with data mining was very difficult for general decision makers because they require high expertise in knowledge discovery, artificial intelligence and fuzzy logic (Lee et al., 2002). As a solution to this problem, we proposed FNN and fuzzy rule extraction algorithm, which could extract the implicit fuzzy knowledge from database. Nonetheless, expandability and reusability degree were still remained as tackling points since no one of these tools integrates between task and domain (Allsopp et al., 2002). These issues were critical motivations in developing our mechanism. In this sense, we proposed a hybrid data mining mechanism based on association rule mining, FNN, and fuzzy rule extraction algorithm.

The remainder of this paper is organized as follows. In Section 2 we summarized research background briefly. Then, the research methodology was proposed in Section 3. In Section 4, prototype system and its performance with an illustrative example were presented. Conclusion and some future research topics were finally suggested in Section 5.

2. Research background

Knowledge acquisition

Knowledge acquisition was commonly regarded as a critical problem in designing and implementing knowledge base. Knowledge typically could be acquired through one of two ways: either manual or automatic. Where, manual means the face-to-face knowledge acquisition (Gruber, 1987). Recently, in this area, Rafea et al. (2003) proposed generalized knowledge acquisition architecture as shown in Figure 1.

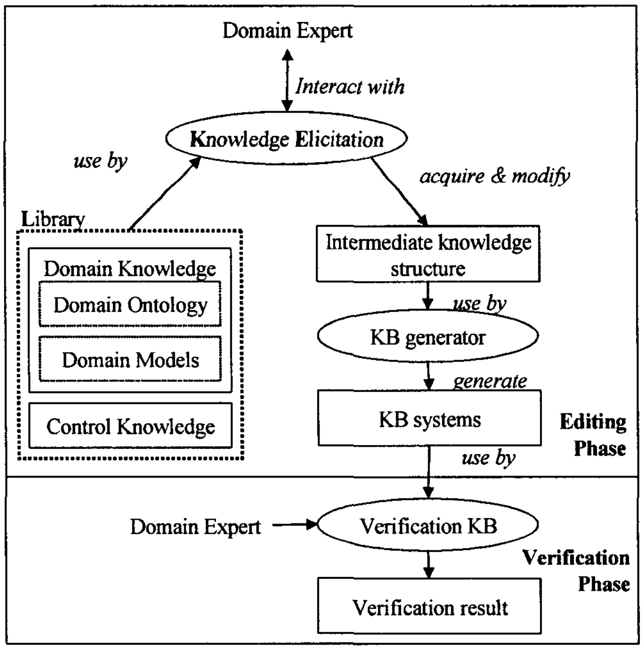


Figure 1 Knowledge acquisition architecture (Rafea et al., 2003)

The proposed tool included four main components namely: knowledge elicitation module, library, knowledge base generator, and verification knowledge base. Ellipses corresponded to modules, whereas rectangles represented input and output for these modules. The objectives of this research was to accelerate and improve the knowledge acquisition process by automatically generating the knowledge base system. As a result, this architecture could propose the generalized view for automatic knowledge acquisition and verification process.

Fuzzy neural network and rule extraction

Artificial neural networks or connectionist model, were massively parallel interconnections of simple neurons that function as a collective system. An advantage of neural nets lies in their high computation rates provided by massive parallelism, so that real-time processing of huge data sets became feasible with proper hardware and software. The utility of fuzzy sets lies in their capability in modeling *uncertain* or *ambiguous* data so often encountered in real life. Information was encoded among the various connection weights (Mitra & Pal, 1994). However, fuzzy neural network had a critical limitation that it couldn't suggest appropriate interpretation about her computation results.

As an alternative for this problem, Mitra & Pal (1994) proposed an application of the fuzzy neural network model, capable of inference and rule generation. The connection weights of the neural net constituted the *knowledge base* for the problem under consideration. The network was capable of handling uncertainty and/or impreciseness in the input representation provided in quantitative, linguistic and/or set forms. The output class memberships were inferred for the input patterns. The user could be queried for the *more essential* feature information in case of partial inputs, when so required. Justification for the decision reached was generated in IF-THEN rule form. The antecedent and consequent parts of these rules were provided in linguistic and *natural* terms. For the linguistic output form they used

1) very likely for $0.8 \le bel_{p1}^{k1} \le 1.0$

2) likely for $0.6 \le bel_{p1}^{k1} < 0.8$

3) more or less likely for $0.4 \le bel_{p1}^{k1} < 0.6$

4) not unlikely for $0.1 \le bel_{p1}^{k1} < 0.4$

5) unable to recognize for $bel_{p1}^{k1} < 0.1$

Note that here the belief (*bel*) was converted to linguistic classes to enable the expression of the consequent part of the rule in a *normal* form (Mitra & Pal, 1994).

Forward and backward Inference

In this section, we introduced forward/backward inference algorithm briefly. First, backward inference use top-down reasoning method. During the backward inference, final goal could be accomplished by satisfying sub-goals. Table 1 shows the sample pseudo code for backward inference algorithm.

Table 1 Sample pseudo code for backward inference

```
Sub Backward-Inference
  For i = 1 To Number of Hypothesis
    Backward-Response = Test-Hypo( i^th Hypothesis)
    If Found Final Conclusion Then Exit For
  End For
End Sub

Function Test-Hypo(Hypothesis) As Boolean
  Do Until End of Rules
    Find Next matched Hypothesis
    If Matched Rule Then Exit Do
  End Do

  For i = 1 To Number of Rules
    Response = Test-Rule(i, Hypothesis)
    If Response Then
      Test-Hypo = Response
      Exit For
    Else
      Find matched Hypothesis in KB
      If No Match and (i = Count of Rules) Then
        Exit For
      End If
    End If
  End For
End Function

Function Test-Rule(RuleNo, Hypothesis) As Boolean
  Find First Hypothesis
  Comparison = Compare New FACT with previous THENs
  If Comparison Then
    Test-Rule = Comparison
  Else
    Comparison = Test-IFs(RuleNo, Hypothesis)
    Remember the RuleNo and it"s THEN
    Test-Rule = Comparison
  End If
End Function
```

Forward inference was well known method in the area of rule-based expert systems. Forward inference begins with known facts to the conclusions, which follow from the facts. In contrast with backward inference, it uses bottom-up reasoning method. Therefore, it reasons from the lower level evidence to the top-level conclusion. All relevant facts were usually known in advance (Durkin, 1994). Figure 2 shows the traditional forward inference process.

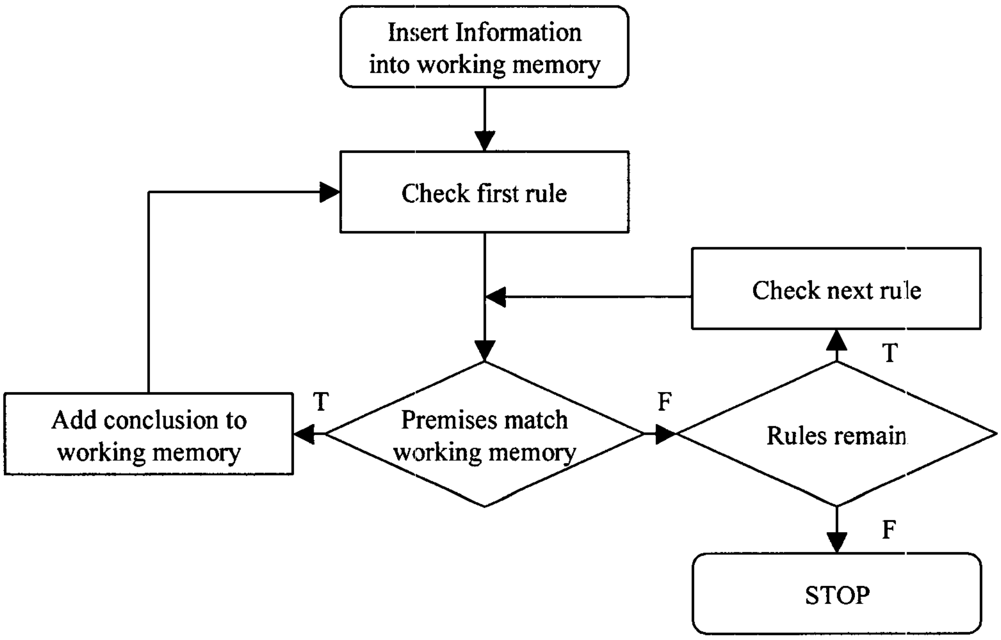


Figure 2 Forward inference process

Generally, forward inference mechanism use text-oriented knowledge base and pattern-matching algorithm to extract relevant rules. Therefore, the speed of inference was still remained as a tackling point to develop an expert system. Table 2 shows the pseudo code for forward inference algorithm.

Table 2 Pseudo code for forward inference

```
Sub ForwardInference
Move to First Rule
Do While Not EOF of KB
  If Empty Rule Then Exit Do
  i = 0
  Do Until Is Null Rule
    For j = 0 To Number of Rules
      If Found Final Conclusion Then
        Exit Do
  End If
  End For

  For j = 0 To Number of FACTs
  If FACTs(j) = Value of IFs in Rule Then
    FiredIF = True
    Exit For
  End If
  End For

  If Not FiredIF Then
  For j = 0 To Number of Newly Inferred FACTs
    If Inferred FACTs(j) = IFs in Rule Then
    FiredIF = True
    Exit For
    End If
    End For
  End If

  If FiredIF Then
  FiredRule = True
  Else
  FiredRule = False
  Exit Do
  End If
  i = i + 1
  End Do

  If FiredRule = True Then
    Add FACT in THENs i = IFsStart
    Do Until IsNull Fired Rule
      Save & Write Fired Rule (IFs and THEN)
    End Do
  End If
  Move to Next Rule
End Do
End Sub
```

3. Methodology

To develop the self-evolving expert system shell, we revised Rafea et al.'s (2003) knowledge acquisition architecture. Our research methodology was graphically shown in Figure 3. The mechanism includes five main components namely: knowledge elicitation, library, ES (expert systems) generator, knowledge expresser, and inference engine. These components are similar to the research architecture of Rafea et al. (2003). However, we expanded the Rafea et al.'s (2003) research architecture with knowledge expresser and inference engine as shown in Figure 3. Detailed description for this architecture was shown in as follows.

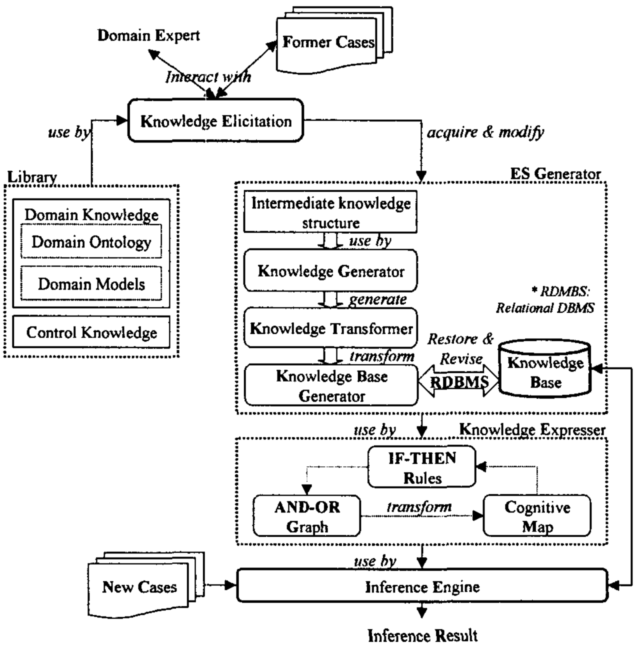


Figure 3. Research Methodology

- *Library*: Library contained reusable domain knowledge, domain ontology, domain models, and control knowledge. Especially domain ontology were used to extract the *essential attributes* for domain knowledge.
- *Knowledge Elicitation*: Its main functions were to create, maintain, and restore knowledge elicited from the various external inputs, fetch the relevant knowledge components from the library, and transform imprecise knowledge into *executable (knowledge acquisition)* knowledge

format.

- *ES Generator*: Automatically generate an executable knowledge, which corresponds to the intermediate knowledge generated above. It contains knowledge generator, knowledge transformer, and knowledge base generator. During this process, ES Generator uses the RDBMS module to restore and revise her knowledge base.
- *Knowledge Expresser*: Support the three knowledge expression methods such as, IF-THEN rules, AND-OR graph, and Relationship matrix. It could help users to understand the knowledge base efficiently.
- *Inference Engine*: Has the SQL-based bi-directional (forward and backward) inference engine. Therefore, its inference speed was faster than other text-oriented inference.

Our proposed ES generator and knowledge generator were based on fuzzy membership function, association rule mining and fuzzy neural networks. Knowledge generator could enrich the adaptability of knowledge base. The proposed knowledge generator consisted of four phases-*association rule extraction, fuzzy neural networks*, and *fuzzy rule extractions*. Figure 4 shows the detailed ES generator.

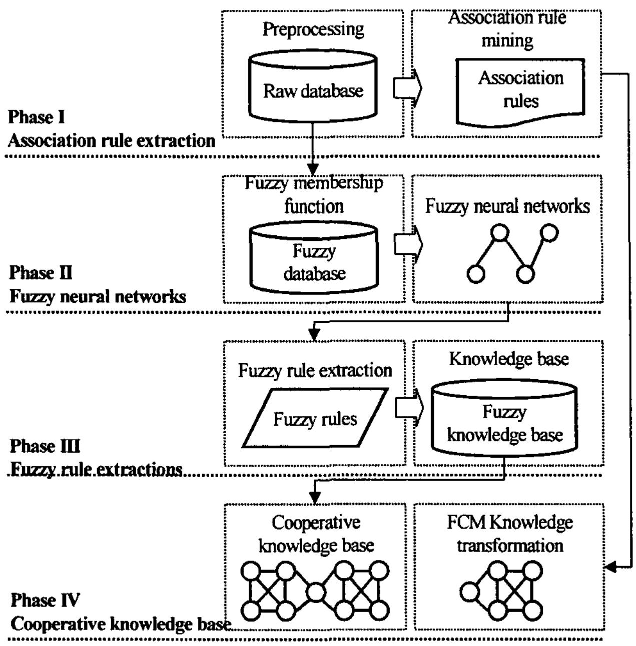


Figure 4. ES generator

• *Phase I: Association rule extractions*

The first phase was to preprocess the raw database and association rule mining. In this phase, we adopted the association rules mining technique to extract the relationships among items and attributes.

• *Phase II: Fuzzy neural networks*

The second phase was to adapt the fuzzy membership function to traditional databases. As a result, raw database was transformed into fuzzy database. Then, we used the fuzzy neural networks to learn the implicit knowledge from the fuzzy database.

• *Phase III: Fuzzy rule extractions*

The fourth stage of the proposed hybrid data mining mechanism was to apply the fuzzy rule extraction algorithm the fuzzy neural networks. Then, initial knowledge base was extended by fuzzy rules.

• *Phase IV: Cooperative knowledge base*

The final stage of our proposed mechanism started with the transformation of association rules into knowledge base. Then, association rule-based knowledge base was combined and with fuzzy rules extracted from fuzzy neural networks.

4. Implementation

To validate our proposed mechanism, we developed the prototype expert system shell SEES (Self-Evolving Expert System Shell) using Visual Basic (VB) and MS Access on Windows-XP environment. The prototype system SEES has five components 1) *Knowledge Elicitor*, 2) *Library*, 3) *ES Generator*, 4) *Knowledge Expresser*, and 5) *Inference Engine*. As a validation set, in the application process, hepatitis data stored in University of California Irvine's machine learning data repository was used (UCI ML Group, 2003).

Library

Table 3 shows the library of hepatitis. Where, the library contained 20 attributes, 6 of which were linear valued and 14 of them were nominal. The diseases in this group were DIE and LIVE. This kind of knowledge for disease, attributes, and other control value of hepatitis were regarded as domain ontology, domain knowledge, domain model, and control knowledge simultaneously.

Table 3 Domain knowledge of hepatitis

No	Attribute	Value
1	Class	DIE, LIVE
2	AGE	10, 20, 30, 40, 50, 60, 70, 80
3	SEX	male, female
4	STEROID	no, yes
5	ANTIVIRALS	no, yes
6	FATIGUE	no, yes
7	MALAISE	no, yes
8	ANOREXIA	no, yes
9	LIVER BIG	no, yes
10	LIVER FIRM	no, yes
11	SPLEEN PALPABLE	no, yes
12	SPIDERS	no, yes
13	ASCITES	no, yes
14	VARICES	no, yes
15	BILIRUBIN	0.39, 0.80, 1.20, 2.00, 3.00, 4.00
16	ALK PHOSPHATE	33, 80, 120, 160, 200, 250
17	SGOT	13, 100, 200, 300, 400, 500
18	ALBUMIN	2.1, 3.0, 3.8, 4.5, 5.0, 6.0
19	PROTIME	10,20, 30, 40, 50, 60, 70, 80, 90
20	HISTOLOGY	no, yes

First, totally 155 data were selected. After the pre-processing such as missing data elimination, however, totally 80 data were used for validation. Which was composed of 19 input variables and 1 output variable (two classes 1: DIE, 2: LIVE).

Knowledge Elicitor

To acquire and modify a meaningful set of knowledge from the database, the first step to be done was to cleanse the original data so that the preprocessed data may become more traceable (Lee et al., 2002). Then, preprocessed data set was transformed into a table format for efficient knowledge elicitation. Table 4 shows the raw database and preprocessed data set of hepatitis check. SPSS and Clementine 6.0.1 were also used to preprocess the raw-data and extract the association rules.

Table 4 Example of raw database and preprocessed data set

(a) Raw dataset of hepatitis check

```
2,2,0,3,0,0,0,0,1,0,0,0,0,0,0,3,2,0,0,0,0,0,0,0,0,0,0,3,0,0,0,1,0,55,2
3,3,3,2,1,0,0,0,1,1,1,0,0,1,0,1,2,0,2,2,2,2,2,1,0,0,0,0,0,0,0,1,0,8,1
2,1,2,3,1,3,0,3,0,0,0,1,0,0,0,1,2,0,2,0,0,0,0,0,2,0,2,3,2,0,0,2,3,26,3
2,2,2,0,0,0,0,0,3,2,0,0,0,3,0,0,2,0,3,2,2,2,2,0,0,3,0,0,0,0,0,3,0,40,1
2,3,2,2,2,2,0,2,0,0,0,1,0,0,0,1,2,0,0,0,0,0,0,0,2,2,3,2,3,0,0,2,3,45,3
```

(b) Preprocessed database of hepatitis check

No	Class	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20
1	2	30	2	1	2	2	2	2	1	2	2	2	2	2	1	85	18	4	?	1
2	2	50	1	1	2	1	2	2	1	2	2	2	2	2	0.9	135	42	3.5	?	1
3	2	78	1	2	2	1	2	2	2	2	2	2	2	2	0.7	96	32	4	?	1
4	2	31	1	?	1	2	2	2	2	2	2	2	2	2	0.7	46	52	4	80	1
5	2	34	1	2	2	2	2	2	2	2	2	2	2	2	1	?	200	4	?	1
6	2	34	1	2	2	2	2	2	2	2	2	2	2	2	0.9	95	28	4	75	1
7	1	51	1	1	2	1	2	1	2	2	1	1	2	2	?	?	?	?	?	1
8	2	23	1	2	2	2	2	2	2	2	2	2	2	2	1	?	?	?	?	1
9	2	39	1	2	2	1	2	2	2	1	2	2	2	2	0.7	?	48	4.4	?	1
10	2	30	1	2	2	2	2	2	2	2	2	2	2	2	1	?	120	3.9	?	1
11	2	39	1	1	1	2	2	2	1	1	2	2	2	2	1.3	78	30	4.4	85	1
12	2	32	1	2	1	1	2	2	2	1	2	1	2	2	1	59	249	3.7	54	1
13	2	41	1	2	1	1	2	2	2	1	2	2	2	2	0.9	81	60	3.9	52	1
14	2	30	1	2	2	1	2	2	2	1	2	2	2	2	2.2	57	144	4.9	78	1
15	2	47	1	1	1	2	2	2	2	2	2	2	2	2	?	?	60	?	?	1
16	2	38	1	1	2	1	1	1	2	2	2	2	1	2	2	72	89	2.9	46	1
17	2	66	1	2	2	1	2	2	2	2	2	2	2	2	1.2	102	53	4.3	?	1
18	2	40	1	1	2	1	2	2	2	1	2	2	2	2	0.6	62	166	4	63	1
19	2	38	1	2	2	2	2	2	2	2	2	2	2	2	0.7	53	42	4.1	85	2
20	2	38	1	1	1	2	2	2	1	1	2	2	2	2	0.7	70	28	4.2	62	1

ES Generator

Phase I: Association rule extraction

The association rule mining algorithm we adopted here was an APRIORI algorithm (Agrawal et al., 1993), which was known to yield a set of association rules. Based on the hepatitis data in Table 4, the corresponding association rules were extracted with a threshold of 80% confidence. Figure 5 shows the association rule extraction process using Clementine.

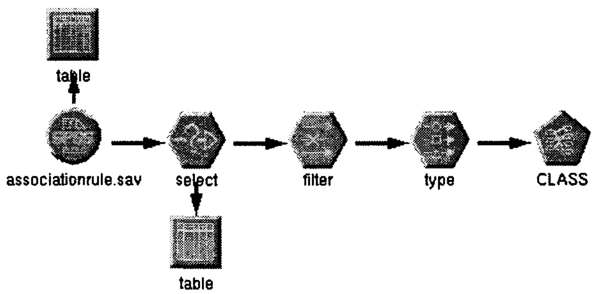


Figure 5 Association rule extraction process using Clementine

Table 5 shows an excerpt of the derived association rules. The association rules shown in Table 3 are straightforward and easy to understand and interpret.

Table 5 Example of association rules from the database

CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V11 = 2 & V20 = 2 (9:22.5%, 0.889)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V5 = 2 & V20 = 2 (13:32.5%, 0.846)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V6 = 1 & V20 = 2 (11:27.5%, 0.909)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V4 = 1 & V20 = 2 (7:17.5%, 1.0)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V7 = 1 & V20 = 2 (9:22.5%, 0.889)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V20 = 2 & V12 = 1 (9:22.5%, 0.889)
CLASS = 2 <= V9 = 2 & V8 = 2 & V14 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 & V8 = 2 & V11 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 & V8 = 2 & V13 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)

Phase II: Fuzzy membership functions and fuzzy neural networks

In this phase, we adapted the fuzzy membership functions to transform the real data into fuzzy sets. Fuzzy membership functions used in this phase was as follows (Mitra & Pal, 1994):

$$\pi(F_j : c, \lambda) = \begin{Bmatrix} 2\left(1-\frac{|F_j - c|}{\lambda}\right)^2, & \text{for } \frac{\lambda}{2} \leq |F_j - c| \leq \lambda \\ 1-2\left(\frac{|F_j - c|}{\lambda}\right)^2, & \text{for } 0 \leq |F_j - c| \leq \frac{\lambda}{2} \\ 0, & \text{otherwise} \end{Bmatrix}$$

$$\lambda_{medium} = \frac{1}{2}(F_{\max} - F_{\min})$$

$$C_{medium} = F_{\min} + \lambda_{medium}$$

$$\lambda_{low} = \frac{1}{fdenom}(c_{medium} - F_{\min})$$

$$C_{low} = C_{medium} + 0.5 * \lambda_{low}$$

$$\lambda_{high} = \frac{1}{fdenom}(F_{\max} - C_{medium})$$

$$C_{high} = C_{medium} + 0.5 * \lambda_{high}$$

Table 6 shows the fuzzified database transformed by fuzzy membership functions.

Table 6 Fuzzified database

No	V2_L	V2_M	V2_H	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15_L	V15_M	V15_H		Class	Class
1	0.96	0.61	0.04	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.98	0.14	0.00		0.90	0.10
2	0.78	0.91	0.22	0.10	0.10	0.10	0.90	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.99	0.40	0.01		0.90	0.10
3	0.99	0.43	0.01	0.10	0.90	0.10	0.10	0.90	0.90	0.90	0.10	0.90	0.10	0.90	0.90	0.99	0.19	0.00		0.90	0.10
4	0.67	0.97	0.33	0.10	0.90	0.10	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.98	0.14	0.00		0.90	0.10
5	1.00	0.28	0.00	0.10	0.90	0.90	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.72	0.95	0.28		0.90	0.10
6	0.83	0.87	0.17	0.10	0.10	0.90	0.10	0.10	0.10	0.90	0.90	0.90	0.90	0.10	0.90	0.81	0.88	0.19		0.90	0.10
7	0.73	0.95	0.27	0.10	0.10	0.90	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.93	0.04	0.00		0.90	0.10
8	0.83	0.87	0.17	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.95	0.06	0.00		0.90	0.10
9	0.83	0.87	0.17	0.10	0.10	0.10	0.90	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.95	0.06	0.00	…	0.90	0.10
10	0.82	0.00	0.00	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.98	0.14	0.00		0.90	0.10

Phase III: Fuzzy rule extractions

After the learning of fuzzy neural networks, we adopted the fuzzy rule extraction algorithm proposed by Mitra & Pal (1994) to fuzzy neural network. Fuzzy rule extraction algorithm was shown in Table 7.

Table 7 Fuzzy rule extraction algorithm

Step 1: Path generation by backtracking
Step 1.1: Find the intermediate node i which has a positive effect on output node j in H(output) layer.
If $w_{ji}^{H-1} > 0$, *Then select node i in H-1 layer*
Step 1.2: Select the connection weights between i and j.
Step 1.3: Select the input node, which has an output value more than 0.5. Then, find the connection weight from the lower layer until there's no connection weight.
Step 1.4: Sort the selected connection weight list.

Step 2: Sentence generation
Adapt two conditions as follows:
Condition 1: Define the conditions for sorting. Then, generate the If-Then rules.
Condition 2: Select the linguistic hedge or real values.

Table 8 shows the fuzzy rules extracted from fuzzy neural networks. Where, each real value means the fuzzy membership value.

Table 8 Sample fuzzy rules extracted from FNN

CLASSS = 1<=V2_L=0.96 & V2_M=0.61 & V3=0.90 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.98 & V15_M=0.68 & V16_L=1.00 & V16_H=1.00 & V17_=0.92 & V17_H=0.82 & V18_L=0.98 & V18_M=0.81 & V18_H=0.87 & V19_L=0.62 & V19_M=0.73 & V19_H=0.91 (95%)

CLASSS = 1<=V2_L=0.78 & V2_M=0.91 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.99 & V16_L=0.99 & V16_M=0.64 & V17_=0.93 & V18_H=1.00 & V19_H=1.00 (95%)

CLASSS = 2<=V2_M=0.95 & V2_H=0.99 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.97 & V15_M=0.56 & V16_L=0.97 & V16_M=0.55 & V16_H=0.66 & V17_=1.00 & V17_M=0.91 & V17_H=0.79 & V18_M=1.00 & V18_H=0.55 & V19_L=1.00 & V19_M=0.88 & V19_H=0.81 & V20=0.90 (90%)

CLASSS = 2<=V2_M=0.95 & V2_H=0.73 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V13=0.90 & V15_L=0.81 & V15_M=0.88 & V16_L=1.00 & V17_=0.89 & V18_M=0.60 & V18_H=0.96 & V19_M=0.96 & V19_H=0.70 & V20=0.90 (90%)

Phase IV: Cooperative knowledge base

After the extraction of association rules and fuzzy rules, we combined two different kinds of knowledge bases into cooperative knowledge base. Table 9 shows the cooperative knowledge base.

Table 9 Example of cooperative knowledge base

CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V11 = 2 & V20 = 2 (9:22.5%, 0.889)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V5 = 2 & V20 = 2 (13:32.5%, 0.846)
CLASS = 1 <= V9 = 2 & V8 = 2 & V3 = 1 & V6 = 1 & V20 = 2 (11:27.5%, 0.909)
CLASS = 2 <= V9 = 2 & V8 = 2 & V14 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 & V8 = 2 & V11 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 & V8 = 2 & V13 = 2 & V20 = 1 & V7 = 2 (16:40.0%, 1.0)

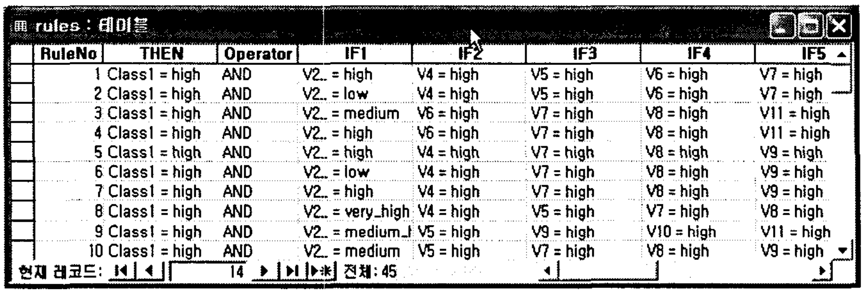
CLASSS = 1<=V2_L=0.96 & V2_M=0.61 & V3=0.90 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.98 & V15_M=0.68 & V16_L=1.00 & V16_H=1.00 & V17_=0.92 & V17_H=0.82 & V18_L=0.98 & V18_M=0.81 & V18_H=0.87 & V19_L=0.62 & V19_M=0.73 & V19_H=0.91 (95%)

CLASSS = 1<=V2_L=0.78 & V2_M=0.91 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.99 & V16_L=0.99 & V16_M=0.64 & V17_=0.93 & V18_H=1.00 & V19_H=1.00 (95%)

CLASSS = 2<=V2_M=0.95 & V2_H=0.99 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V12=0.90 & V13=0.90 & V14=0.90 & V15_L=0.97 & V15_M=0.56 & V16_L=0.97 & V16_M=0.55 & V16_H=0.66 & V17_=1.00 & V17_M=0.91 & V17_H=0.79 & V18_M=1.00 & V18_H=0.55 & V19_L=1.00 & V19_M=0.88 & V19_H=0.81 & V20=0.90 (90%)

CLASSS = 2<=V2_M=0.95 & V2_H=0.73 & V4=0.90 & V5=0.90 & V6=0.90 & V7=0.90 & V8=0.90 & V9=0.90 & V10=0.90 & V11=0.90 & V13=0.90 & V15_L=0.81 & V15_M=0.88 & V16_L=1.00 & V17_=0.89 & V18_M=0.60 & V18_H=0.96 & V19_M=0.96 & V19_H=0.70 & V20=0.90 (90%)

The rule premise part might contain arbitrarily complex conjunctions or disjunctions nested within each clause. Otherwise, a separate rule was written for each clause, instead of writing rules whose premise would be a disjunction of clauses. The ACTION part or THEN part indicated one or more conclusions that could be drawn if the premises were satisfied making the rules purely inferential. Each rule was highly stylized- with an IF-THEN format and a specified set of admissible primitives. These rules transformed into relational database. Therefore, this tightly structured database form makes it possible for SEES to be designed to execute them in a form of SQL-based inference. Furthermore, it could be represented as an AND-OR graph or Relationship matrix. Figure 6 shows the knowledge base (fuzzy rules) restored in relational database.


rules : 테이블

RuleNo	THEN	Operator	IF1	IF2	IF3	IF4	IF5
1	Class1 = high	AND	V2.. = high	V4 = high	V5 = high	V6 = high	V7 = high
2	Class1 = high	AND	V2.. = low	V4 = high	V5 = high	V6 = high	V7 = high
3	Class1 = high	AND	V2.. = medium	V6 = high	V7 = high	V8 = high	V11 = high
4	Class1 = high	AND	V2.. = high	V6 = high	V7 = high	V8 = high	V11 = high
5	Class1 = high	AND	V2.. = high	V4 = high	V7 = high	V8 = high	V9 = high
6	Class1 = high	AND	V2.. = low	V4 = high	V7 = high	V8 = high	V9 = high
7	Class1 = high	AND	V2.. = high	V4 = high	V7 = high	V8 = high	V9 = high
8	Class1 = high	AND	V2.. = very_high	V4 = high	V5 = high	V7 = high	V8 = high
9	Class1 = high	AND	V2.. = medium_l	V5 = high	V9 = high	V10 = high	V11 = high
10	Class1 = high	AND	V2.. = medium	V5 = high	V7 = high	V8 = high	V9 = high

현재 레코드: 14 전체: 45

Figure 6 Knowledge base restored in relational database

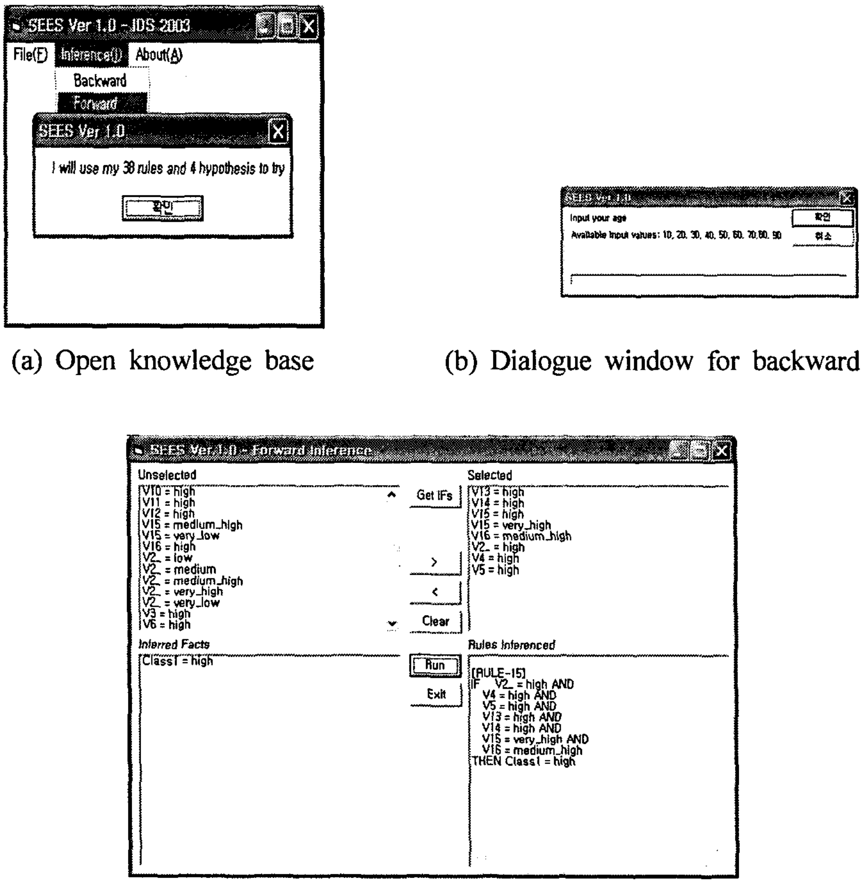
Knowledge Expresser

Totally 38 production rules were extracted by using APRIORI algorithms which are highly efficient techniques developed by Agrawal (1993). SEES could express the knowledge base as OAV type production rules (IF-THEN rules), AND-OR graph, and Relationship matrix (Kim, 2003). Kim (2003) proposed composite knowledge expression mechanism in his research.

However, he didn't use a learning mechanism such as FNN which used in this study.

Inference Engine

Inference engine depended on RDB and SQL-driven forward/backward inference algorithm. Therefore, rule consistency check and incompleteness check was easier than other traditional text-driven works (Kim, 2003). Figure 7 shows the example of inference process and final inference result for a patient's data set.



(a) Open knowledge base (b) Dialogue window for backward inference

(c) Forward inference and result

Figure 7 Inference results of SEES

In the first step, user opened the knowledge base. Then, he might confirm the total number of rules and hypotheses (Figure 7(a)). In the third step, SEES showed the dialog window for backward/forward inference (Figure 7(b), (c)) requiring user's response. Especially, Figure 7(c) showed the unselected and selected IFs, inferred facts, and final conclusions. Then the final conclusion was translated into OAV-typed IF-THEN rules as shown in Figure 7(c).

5. Conclusion

In this study, we introduced the problems of traditional data mining and construction mechanism for ES. Therefore, we suggested an automatic expert systems shell construction and maintaining mechanism. The proposed mechanism consisted of the five main components *Library, Knowledge Elicitation, ES Generator, Knowledge Expresser,* and *Inference Engine*. In the implementation process, we developed a prototype expert system shell SEES and proved the inference ability using hepatitis data set. This mechanism and prototype systems were based on data mining, fuzzy membership functions, fuzzy neural networks, and RDB-driven forward/backward inference algorithm, which were mainly aimed at expand the adaptability, expandability, and reusability of knowledge base. In addition, this study has shown how the knowledge base could be transformed into IF-THEN rules, AND-OR graph, and Relationship matrix to help the user's correct recognition in knowledge base. Nonetheless, our study has some limitations. First, we developed simple prototype expert system shell. Second, effective rule refinement process (such as pruning, conflict resolution, and etc.) was omitted, which was enable to improve the inference ability of that expert systems. Then, further research topics still remain. First, this expert system shell should be improved as an Internet-based system to support the Web-based user's decision-making. Second, other AI (artificial intelligence) technologies (such as fuzzy logic, neural networks, rough set, and etc.) may improve the inference ability of our expert system shell. Third, multiple-decision problem and concurrent decision-making should be supported using other concurrent engineering mechanism. Fourth, the basic technology of association rule mining used for this study needs to be improved so that more fuzzy knowledge can be analyzed. Fifth, fuzzy membership functions need to be integrated with other rule refining and reasoning mechanism.

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