ISSN No. 0976-5697
Volume 3, No. 1, Jan-Feb 2012
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

Diagnosis of Diabetes using Correlation fuzzy logic in Fuzzy Expert System

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Abstract : Fuzzy expert system framework constructs large scale knowledge based system effectively for diabetes. Fuzzy Expert System helps the medical practitioners to solve decision problem. The components of correlation fuzzy determination mechanism are determination logic and knowledge base. The fuzzification interface converts the crisp values into fuzzy values for the diagnosis of diabetes. The determination logic evaluates the effect on the number of membership functions, the shape of membership functions and the effect of fuzzy operators. Correlation fuzzy logic is computed for fuzzy numbers and membership function. Knowledge base is constructed by fuzzy if-then rules. Defuzzification interface converts the resulting fuzzy set into crisp values. The result of the proposed method is compared with earlier method using accuracy as metrics. The proposed fuzzy expert system can work more effectively for diabetes application and also improves the accuracy of fuzzy expert system.

Keywords: Fuzzy Expert System, Correlation Fuzzy Determination Mechanism, determination logic, knowledge base, Diabetes application.

I. INTRODUCTION

Fuzzy expert system formulates the reasoning process of human language by means of fuzzy logic and controls the presence of uncertainty for variety of problem domains.

Chang-Shing Lee[1] designed fuzzy expert system based on the fuzzy decision making mechanism for diabetes application. Ismail Saritas et al. [2] the fuzzy expert system designed can be applied in complex and uncertain fields such as the treatment of illness, to determine the exact dose of medicine, evaluate clinic and laboratory data to determine drug dose in treatment of chronic interstine inflamation using the concept of fuzzification, fuzzy inference mechanism and defuzzification. D. U. Campos-Delgado et al. [3] developed fuzzy logic controller by using mamdani-type fuzzy logic to regulate the blood glucose level that incorporates expert knowledge. Magni and Bellazzi[4] devised a methodology useful in variety of clinical contexts, uses stochastic model to extract time course variability from a self-monitoring blood sugar level time series. Polat and Gunes[5] designed an expert system to diagnose the diabetes disease based on principal component analysis which improves the diagnostic accuracy of diabetes disease.

K. Polat et al.[6] to diagnose the diabetes a cascade learning system based on generalized discriminant analysis and least square support vector machine was developed. Chang and Lilly[7] developed an evolutionary approach to derive a compact fuzzy classification system directly from data. L. B. Goncalves et al. [8] introduced an inverted hierarchical neuro-fuzzy BSP system for pattern classification and rule extraction in databases. Kahramanli and Allahverdi[9] designed a classification of the diabetes database for hybrid neural network system to increase the reliability of the result. Mehdi Fasanghari et al.[10] developed a fuzzy expert system for Tehran stock exchange using the concept of fuzzification. The American Diabetes Association [11] categorizes diabetes into type-1 diabetes, which is normally diagnosed in children and young adults, and type-2 diabetes, i.e., the most common form of diabetes that originates from a progressive insulin secretory defect so that the body does not produce adequate insulin or the insulin does not affect the cells. M. Kalpana and A. V Senthikumar [12] developed fuzzy expert system using fuzzy verdict mechanism for diabetes application using the concept of fuzzification with triangular membership function.

Diabetes treatment focuses on controlling blood sugar levels to prevent various symptoms and complications through medicine, diet and exercise. The structure of the rest of this paper is as follows: Section II deals with the architecture of fuzzy expert system. The experimental results, implemented in MATLAB are presented in Section III and experimental results indicate that the proposed fuzzy expert system can work more effectively than other methods [1], [5], [7], [9],[12],[14],[15]in section IV.

II. ARCHITECTURE OF FUZZY EXPERT SYSTEM FOR DIABETES APPLICATION

This section describes architecture of the fuzzy expert system, including Fuzzification interface, Correlation Fuzzy Determination Mechanism for diabetes application and Defuzzification interface.

A. *Pima Indians Diabetes Database:*

The Pima Indians Diabetes Database is examined from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) [16]. The PIDD is retrieved from the Internet (http://archive.ics.uci.edu/ml/) and it contains the collected personal data of the Pima Indian population. Table I lists the attributes of PIDD.

Table I Atttributes of PIDD

Abbreviation	Fullname	UoM
Pregnant	Number of times pregnant	-
Glucose	Plasma glucose concentration in 2-hours OGTT	mg/dl

DBP	Diastolic blood pressure	mmHg
TSFT	Triceps skin fold thickness	mm
INS	2-hour serum insulin	mu U/ml
BMI	Body mass index	Kg/m^2
DPF	Diabetes pedigree function	-
Age	Age	-
DM	Diabetes Mellitus where '1' is interpreted as "tested positive for diabetes"	-

B. Modeling Fuzzy Expert Systems:

Fuzzy expert system modeling can be pursued using the following steps.

a. Select the relevant input and output variables.
b. Determine the fuzzy number for the fuzzy set.
c. Fuzzification interface.
d. Choose the appropriate family of membership function and fuzzy operators.
e. Design the correlation fuzzy determination mechanism with determination logic and knowledge base
f. Defuzzification interface

The information from PIDD is transformed into the required knowledge. For the PIDD, each case has nine attributes, listed in Table I, and each attribute can be constructed as a fuzzy variable with some fuzzy numbers.

C. Data Preparation:

The data are taken from PIDD, the input variable are Plasma glucose concentration in 2-hours OGTT(Glucose), 2-hour serum insulin(INS), Body mass index(BMI), Diabetes pedigree function(DPF), Age(Age) and the output variable are Diabetes Mellitus(DM). The data with the age group from 25-30 are taken to test the Correlation Fuzzy Determination Mechanism.

D. Fuzzification Interface:

The inputs are crisp numbers which are transformed in to fuzzy set [10]. Each crisp input is converted to its fuzzy equivalent using a family of membership function. Additionally, an interface is offered to tune and validate the parameters of the built fuzzy numbers. In this paper a triangular function as shown in eqn. (1) is adopted as the membership function of the fuzzy number and can be expressed as the parameter set[a,b,c]. The parameter is fixed with Minimum value, Mean, Standard Deviation, Maximum value for each variables [13]. Then the membership function μ (x) of the triangular fuzzy numbers[17] is given by

$$\mu(x) = \begin{cases} 0, x \le a \\ (x-a)/(b-a), a < x \le b \\ (c-x)/(c-b), b < x < c \\ 0, x > c \end{cases} --(1)$$

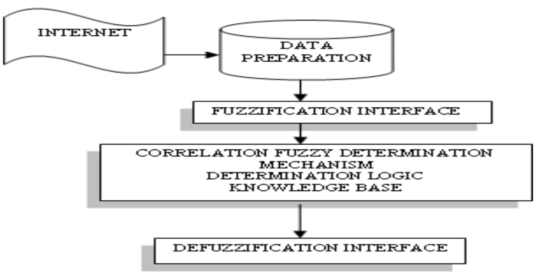

Figure 1 Architecture of the Fuzzy Expert System for diabetes application

The PIDD is first retrieved from the Internet to become the experimental database. By fuzzification the crisp input values, its membership values and degrees are obtained. These obtained fuzzy values are processed in correlation fuzzy determination mechanism. Here, the output values which are also obtained by using rule-base are send to defuzzification unit and from this unit the final crisp values are obtained as output[2]. The fuzzy values are given in Figure 2 and Figure 3. The input fuzzy value Age (let x), that varies from 26 to 30, the fuzzy expression will be

$$\mu_{low}(x) = \begin{cases} \frac{26-x}{26}; 26 \le x \le 27 \\ 0; otherwise \end{cases}$$

$$\mu_{medium}(x) = \begin{cases} \frac{27}{x}; 26 \le x \le 27 \\ \frac{30-x}{27}; 27 \le x \le 30 \\ 0; otherwise \end{cases} --(2)$$

$$\mu_{high}(x) = \begin{cases} 0; x < 27 \\ \frac{x-27}{27}; 27 \le x \le 30 \\ 1; otherwise \end{cases}$$

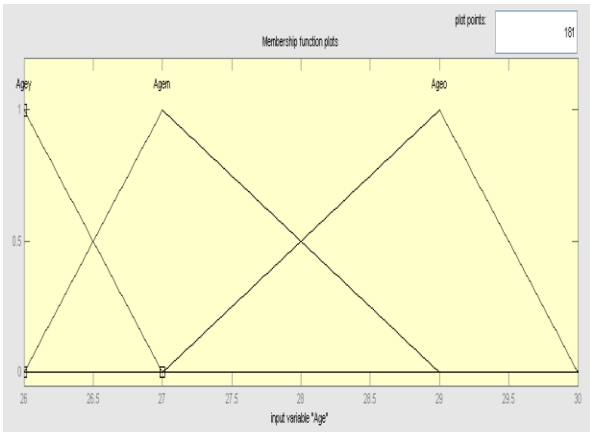

Figure 2 Membership graphics for the fuzzy three values Age

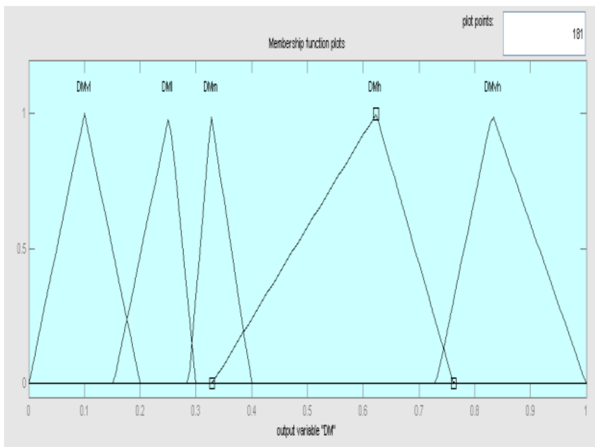

Figure 3 Membership graphics for the fuzzy values DM

E. Correlation Fuzzy Determination Mechanism:

The Correlation Fuzzy Determination Mechanism can take fuzzy inputs, but the outputs produced are always a fuzzy set. With the crisp inputs and output, correlation fuzzy determination mechanism implements mapping from its input variable to output variable through determination logic and knowledge base. Table II represents fuzzy variables and fuzzy numbers. The parameters of the fuzzy numbers are listed in Table III.

Table II Representation of Fuzzy variables and numbers

Fuzzy Variables	Fuzzy Numbers	Representation of fuzzy numbers
Glucose	low	Gl
	medium	Gm
	high	Gh
INS	low	INSl
	medium	INSm
	high	INSh
BMI	low	BMIl
	medium	BMIm
	high	BMIh
DPF	low	DPFl
	medium	DPFm
	high	DPFh
Age	young	Agey
	medium	Agem
	old	Ageo
DM	verylow	DM vl
	low	DM l
	medium	DM m
	high	DM h
	veryhigh	DM vh

Table III Parameters of Triangular Membership Functions

Fuzzy Variables	Fuzzy Numbers	Fuzzy triangular numbers
Glucose	Gl	[71 94.41 121.27]
	Gm	[94.41 121.27 148.12]
	Gh	[121.27 148.12 196]
INS	INSl	[0 15.16 89.82]
	INSm	[15.16 89.82 194.81]
	INSh	[89.82 194.81 579]
BMI	BMIl	[0 24.46 33.24]
	BMIm	[24.46 33.24 42.03]
	BMIh	[33.24 42.03 67.1]
DPF	DPFl	[0.13 0.21 0.44]
	DPFm	[0.21 0.44 0.67]
	DPFh	[0.44 0.67 0.96]
Age	Agey	[26 26 27]
	Agem	[26 27 29]
	Ageo	[27 29 30]
DM	DM vl	[0 0.1 0.2]
	DM l	[0.1524 0.2524 0.3]
	DM m	[0.287 0.327 0.3997]
	DM h	[0.329 0.623 0.762]
	DM vh	[0.731 0.831 1]

The proposed Correlation Fuzzy Determination Mechanism consists of determination logic and Knowledge base.

F. Determination Logic:

Fuzzy set occurs frequently to organize, summarize and generalize the knowledge about the input and output variables. Fuzzy set is applied in Glucose{Gl, Gm, Gh},INS { INSl, INSm, INSh},BMI { BMIl, BMIm, BMIh}, DPF { DPFl, DPFm, DPFh},Age { Agey, Agem, Ageo} and DM{ DMvl, DMl, DMm, DMh, DMvh}. Fuzzy numbers are special type of fuzzy sets restricting the possible types of membership functions. Determination logic step is to take the input variables which are fuzzified thereby the membership functions defined on the input variables are applied to their actual values to determine the degree of the truth of each rule antecedent[18]. Determination logic is invoked by using Mamdani's approach.

G. Evaluate the numbers of membership functions:

Three triangular membership functions (MFs) for each input variable(Glucose,INS,BMI,DPF and Age) and four triangular MFs for the output variable (DM) using eqn (1) with parameters Glucose[Min, Mean-SD, Mean+SD, Max], INS[Min, Mean-SD, Mean+SD, Max], BMI[Min, Mean-SD, Mean+SD, Max], DPF[Min, Mean-SD, Mean+SD, Max] and Age[Min, Mean-SD, Mean+SD, Max].

H. Evaluate the Effect of Fuzzy Operators:

The fuzzy operator makes a sizable difference to the overall performance of the fuzzy expert system. Fuzzy operators are intersection and union. Fuzzy intersections are represented by T-norms and Fuzzy union are represented by T-conorm. In diabetes application T-norm operator used is algebraic product and T-conorm operator used is algebraic sum[18].

I. Correlation Fuzzy Logic:

While plotting the Membership function there occurs an overlapping between each and every function[17]. To overcome this correlation fuzzy logic is adopted. Let fuzzy number and memberships function for Age may be defined for Ageyoung and Agemedium represented as Ageyoung = $\mu_{Agey}(x)$ and Agemedium= $\mu_{Agem}(x)$. Output fuzzy number and memberships function for DM may be defined for DMverylow, DMlow, DMhigh, DMveryhigh represented as DMverylow = $\mu_{DMvl}(x)$, DMlow = $\mu_{DMl}(x)$, DMveryhigh = $\mu_{DMvh}(x)$ and DMhigh = $\mu_{DMh}(x)$. We compute the correlation coefficient using the formula

$$\rho = \mathrm{cov}(\mu_{Agey}(x), \mu_{Agem}(x)) \Big/ \sqrt{\mathrm{var}(\mu_{Agey}(x)).\mathrm{var}(\mu_{Agem}(x))}$$
$$\rho = \mathrm{cov}(\mu_{DMvl}(x), \mu_{DMl}(x)) \Big/ \sqrt{\mathrm{var}(\mu_{DMvl}(x)).\mathrm{var}(\mu_{DMl}(x))} \longrightarrow (3)$$
$$\rho = \mathrm{cov}(\mu_{DMvh}(x), \mu_{DMh}(x)) \Big/ \sqrt{\mathrm{var}(\mu_{DMvh}(x)).\mathrm{var}(\mu_{DMh}(x))}$$

The correlation coefficient for membership function Ageyoung and Agemedium is obtained from eqn(3). If ρ=-1there is no overlap. The membership function Ageyoung or Agemedium and DMverylow or DMlow or DMveryhigh or DMhigh using correlation logic is shown in the figure 4 and figure 5

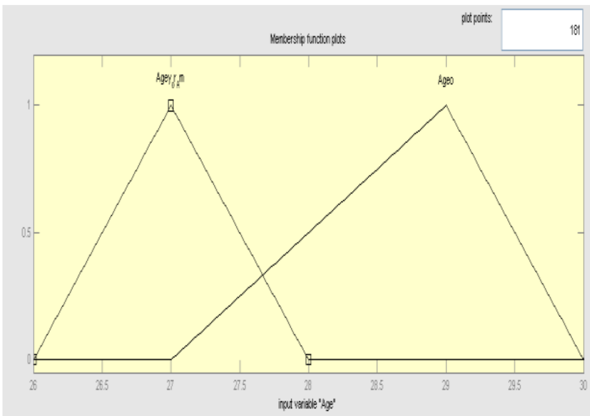

Figure 4 A membership function Ageyoung or Agemedium using correlation logic

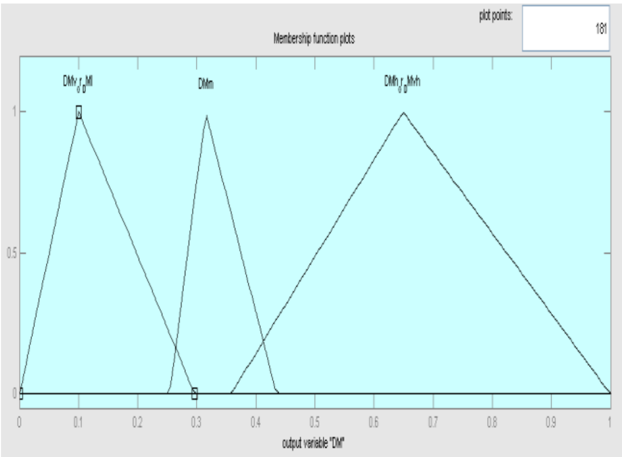

Figure 5 A membership function DMverylow or DMlow and DMveryhigh or DMhigh using correlation logic

J. Knowledge base:

The rule base consisted of nine if-then rules. If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. The OR operator evaluates the antecedent of the rule. The fifteen different pieces of the antecedent (Gl, Gm, Gh, INSl, INSm, INSh, BMIl, BMIm, BMIh, DPFl, DPFm, DPFh, Agey, Agem, Ageo) gives the fuzzy membership values respectively. The developed fuzzy rule has multiple antecedents. Implication is the process of mapping result of the fuzzification from antecedent part into the consequence [19]. The input for the implication process is a single number given by the antecedent and the output is a fuzzy set. For more than one fuzzy rule fired at same time, MIN operation is conducted by the system. Implication results through the aggregation process. The input of aggregation process is the list of developed clipped consequent membership function and the output is one fuzzy set of each output variables[20]. SUM operation is used by the system.

K. Defuzzification:

Defuzzification process is conducted to convert aggregation result into crisp value for DM output. Transforms the fuzzy set obtained in correlation fuzzy determination mechanism into crisp values. The final combined fuzzy conclusion is converted into a crisp value by using the centroid method[2]. Correlation Fuzzy Determination Mechanism analyzes the personal physical data, converts the inferred results into knowledge, and then presents the decision results through descriptions. The patterns of the statement for output descriptions, includes statement analysis and decision statement.

The proposed Algorithm for the Correlation Fuzzy Determination Mechanism is given below.

L. Proposed Algorithm: Correlation Fuzzy Determination Mechanism:

Input:

Input variable are {Glucose, INS, BMI, DPF, Age}

Output:

Output variable is {DM}

Process:

begin

Step 1: Read the crisp values of each variable

While(i>N)

Read the value of $Glucose_i$

Read the values of INS_i

Read the values of BMI_i

Read the values of DPF_i

Read the values of Age_i

Do

Step 2: Calculate the mean and standard deviation of each variable.

Step 2.1: Calculate mean value

$$Mean_{Glucose} = \frac{value_{Glucose1} + value_{Glucose2} .. value_{GlucoseN}}{N}$$

$$Mean_{INS} = \frac{value_{INS1} + value_{INS2} .. value_{INSN}}{N}$$

$$Mean_{BMI} = \frac{value_{BMI1} + value_{BMI2} .. value_{BMIN}}{N}$$

$$Mean_{DPF} = \frac{value_{DPF1} + value_{DPF2} .. value_{DPFN}}{N}$$

$$Mean_{Age} = \frac{value_{Age1} + value_{Age2} .. value_{AgeN}}{N}$$

Step 2.2: Calculate standard deviation $SD_{Glucose}, SD_{INS}, SD_{BMI}, SD_{DPF}, SD_{Age}$

$$SD_{Glucose} = \sqrt{\frac{\sum_{i=1}^{N} Glucose_i^2 - \frac{(\sum_{i=1}^{N} Glucose_i)^2}{N}}{N}}$$

$$SD_{INS} = \sqrt{\frac{\sum_{i=1}^{N} INS_i^2 - \frac{(\sum_{i=1}^{N} INS_i)^2}{N}}{N}}$$

$$SD_{BMI} = \sqrt{\frac{\sum_{i=1}^{N} BMI_i^2 - \frac{(\sum_{i=1}^{N} BMI_i)^2}{N}}{N}}$$

$$SD_{DPF} = \sqrt{\frac{\sum_{i=1}^{N} DPF_i^2 - \frac{(\sum_{i=1}^{N} DPF_i)^2}{N}}{N}}$$

$$SDAge = \sqrt{\frac{\sum_{i=1}^{N} Age_i^2 - \frac{(\sum_{i=1}^{N} Age_i)^2}{N}}{N}}$$

Step 2.3: Sort all the values in descending order to get $Max_{Glucose}$, $Min_{Glucose}$, Max_{INS}, Min_{INS}, Max_{BMI}, Min_{BMI}, Max_{DPF}, Min_{DPF}, Max_{Age}, Min_{Age}

Step 3: Execute Determination logic with Mamdani's approach.

Step 3.1: Calculate Glucose[Min, Mean-SD, Mean+SD, Max], INS[Min, Mean-SD, Mean+SD, Max], BMI[Min, Mean-SD, Mean+SD, Max], DPF[Min, Mean-SD, Mean+SD, Max] and Age[Min, Mean-SD, Mean+SD, Max].

Step 3.2: Construct fuzzy numbers listed in Table III using triangular membership function with equation (1).

Step 3.3: Set the fuzzy operator to T-norm and T-conorms for fuzzy set {Glucose, INS, BMI, DPF, Age} with algebraic product and algebraic sum.

Step 3.4: Compute the correlation coefficient using the eqn.(3) to identify the area overlap between fuzzy numbers and membership. If ρ=-1there is no overlap between the membership function.

Step 4: Knowledge base is invoked with rules. The OR operator evaluate the rules.

Step 4.1: Map the antecedent part of the rule into consequence by MIN operator and SUM operator combines the output of each rule into single set.

Step 5: Defuzzify into the crisp values by

$$DM_i \leftarrow \frac{\sum_{i=1}^{n} Z_i \mu(Z_i)}{\sum_{i=1}^{i=n} \mu(Z_i)}$$

Where Z_i means the weight for $\mu(Z_i)$ and $\mu(Z_i)$ means the number of fuzzy numbers of the output fuzzy variable DM.

Step 6: Present the knowledge in the form of human nature language

end.

M. Statement pattern of output Descriptions

Statement Analysis(SA):

The data exhibit that person is at [Age: Agey, Agem, Ageo], meanwhile the plasma glucose concentration in 2-hour OGIT is [Glucose: Gl, Gm, Gh], 2-hour serum insulin is [INS: INSl, INSm, INSh], body mass index is [BMI: BMIl, BMIm, BMIh], and diabetes pedigree function is [DPF: DPFl, DPFm, DPFh]

N. Decision Statement(DS):

The Decision statement justifies that the possibility of suffering from diabetes for this person as [DM: DMvl, DMl, DMm, DMh, DMvh](Possibility:[0,1]).

III. EXPERIMENTAL RESULTS

The implementation of desired fuzzy expert system has been developed in MATLAB. The experimental environment was constructed to evaluate the performance of the proposed approach; in addition, PIDD was chosen as the evaluated data set. The proposed approach can analyze the data of the PIDD and generate corresponding human knowledge based on the Fuzzification interface, Correlation Fuzzy Determination Mechanism and Defuzzification interface for the parameter very young [1]. The first experiment shows sets of results in Table IV and figure 6, indicating that the proposed approach automatically supports the analysis of the data. The acquired information is then transferred into knowledge, and finally the proposed method presents them in the form of the descriptions of humans.

A. Rule for Fuzzy Expert System in MATLAB:

1. If (Glucose is Gl) or (INS is Il_or_Im) or (BMI is Bl) or (DPF is DPFl) or (Age is Ay_or_Am) then (DM is DMv_or_DMl) (1)
2. If (Glucose is Gl) or (INS is Il_or_Im) or (BMI is Bh) or (DPF is DPFl) or (Age is Ay_or_Am) then (DM is DMv_or_DMl) (1)
3. If (Glucose is Gm) or (INS is Ih) or (BMI is Bh) or (DPF is DPFm) or (Age is Ay_or_Am) then (DM is DMm) (1)
4. If (Glucose is Gh) or (INS is Il_or_Im) or (BMI is Bh) or (DPF is DPFh) or (Age is Ay_or_Am) then (DM is DMh_or_DMvh) (1)
5. If (Glucose is Gl) or (INS is Il_or_Im) or (BMI is Bm) or (DPF is DPFl) or (Age is Ay_or_Am) then (DM is DMv_or_DMl) (1)
6. If (Glucose is Gl) or (INS is Il_or_Im) or (BMI is Bh) or (DPF is DPFl) or (Age is Ay_or_Am) then (DM is DMv_or_DMl) (1)
7. If (Glucose is Gh) or (INS is Il_or_Im) or (BMI is Bh) or (DPF is DPFh) or (Age is Ay_or_Am) then (DM is DMh_or_DMvh) (1)
8. If (Glucose is Gh) or (INS is Ih) or (BMI is Bm) or (DPF is DPFl) or (Age is Ao) then (DM is DMh_or_DMvh) (1)
9. If (Glucose is Gl) or (INS is Il_or_Im) or (BMI is Bm) or (DPF is DPFl) or (Age is Ay_or_Am) then (DM is DMv_or_DMl) (1)

IV. PERFORMANCE EVALUATION

The second experiment evaluates the performance of the Decision statement and the medical practitioner. Accuracy is the measuring scale for performance of this experiment. The True Positive (TP) and the True Negative (TN) denote the correct classification. False Positive (FP) is the outcome when the predicted class is yes (or positive) and actual class is no (or negative). Still, a False Negative (FN) is the outcome when the predicted class is no (or negative) and actual class is yes (or positive). Table V lists the various outcomes of a two-class prediction [16].Accuracy is the proportion of the total number of predictions that were correct. The eqn. (4) show the formula for accuracy.

$$Accuracy = \frac{TN+TP}{TN+FP+FN+TP} X100\% \text{---} > (4)$$

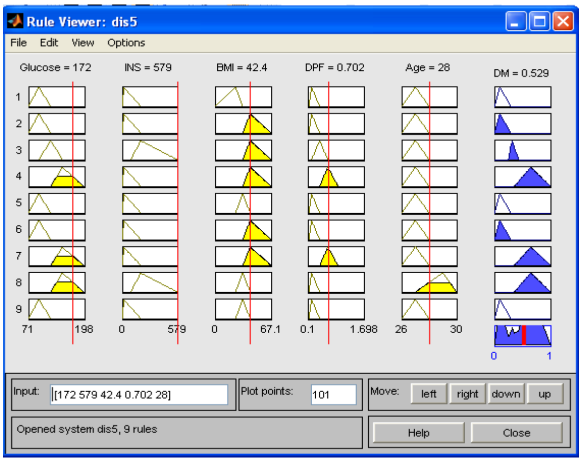

Figure 6 Result Obtained From MATLAB

Table IV Final Result for Medical practitioner

Data	Glucose (mg/dl)	INS (mu U/ml)	BMI (Kg/ m^2)	DPF	Age
	172	579	42.4	0.702	28
SA	If(Glucose is Gh) or(INS is INSm) or (BMI is BMIh) or (DPF is DPFh) or(Age is Agey) then (DM is DMh)				
DS	The Decision statement justifies that the possibility of suffering from diabetes for this person is medium(possibility:**0.529**)				
Justification by Medical Practitioner	Medical practitioner justification is the person is diabetes				

Table V Different Outcomes of a Two-Class Prediction

Actual class	Predicted class	
	Yes	No
Yes	True positive (*TP*)	False Negative (*FN*)
No	False positive (*FP*)	True Negative (*TN*)

Table VI Comparison of Proposed Method Accuracy with Earlier Methods

Method	Accuracy (%)	Author
Our study for Very Young	**89.52**	M.Kalpana and Dr. A.V.Senthil Kumar
FES for Diagnosis of Diabetes Using Fuzzy Determination Mechanism [15]	89.32	M.Kalpana and Dr. A.V.Senthil Kumar
Diagnosis of Diabetes using Intensified Fuzzy Verdict Mechanism[14]	88.35	Dr. A.V.Senthil Kumar and M.Kalpana
Enhanced Fuzzy Verdict for Diabetes using Fuzzy Expert System	87.38	M.Kalpana and Dr. A.V.Senthil Kumar
FES for diabetes using Fuzzy Verdict	85.03	M.Kalpana and Dr. A.V.Senthil Kumar

Mechanism		
A FES for Diabetes Decision very young[8]	81.7	Lee and Wang
HNFB-1[6]	78.26	Goncalves et al.
Logdisc	77.7	Statlog
IncNet	77.6	Norbert Jankowski
DIPOL 92	77.6	Statlog
Linear discr. Anal	77.5-77.2	Statlog, ster and Dobnikar
A FES for Diabetes Decision very very young[8]	77.3	Lee and Wang
VISIT[5]	77	Chang and Lilly
SMART	76.8	statlog
GTO DT(5 X CV)	76.8	Bennet and Blue
ASI	76.6	Ster and Dobnikar
Fisher discr. Analysis	76.5	Ster and Dobnika
MLP+BP	76.4	Ster and Dobnika
LVQ(20)	75.8	Ster and Dobnika
LFC	75.8	Ster and Dobnika

The final experiment compares the accuracy of the proposed method with results of studies involving the PIDD [[1], [5], [7], [9],[12],[14],[15]. Comparing these methods, as listed in Table VI, reveals that the proposed method achieves the first highest accuracy values for "very young" based on the proposed fuzzy expert system. The accuracy values of the proposed method are compared with the earlier methods and represented graphically in figure 7, which shows better accuracy.

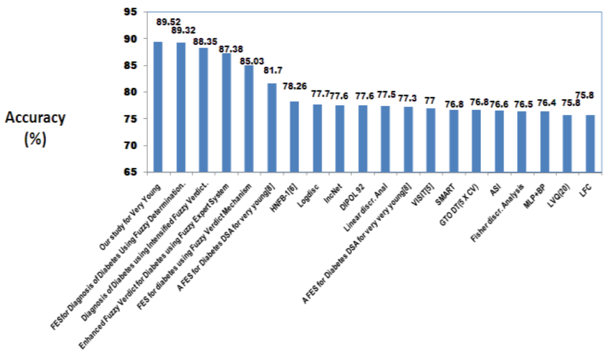

Figure 7 Graphical represent of accuracy

V. CONCLUSIONS AND FUTURE RESEARCH

The fuzzy expert system provides a greater flexibility for the diagnosis of diabetes. The experimental data set, PIDD, is processed and the crisp values are converted into fuzzy values in the stage of fuzzification interface. The correlation fuzzy determination mechanism evaluates the numbers of membership functions, effect of fuzzy operator with rules to make a decision for medical practitioner and to present the knowledge with descriptions. Finally defuzzification interface is adopted to convert the fuzzy output set to a crisp output. Experimental results indicate that the proposed method can analyze data more effectively compared to earlier methods. Future works includes to modify rules and to add rules to fuzzy expert system to perform higher accuracy.

VI. REFERENCES

[1]. Chang-Shing Lee," A Fuzzy Expert System for Diabetes Decision Support Application" IEEE transactions on systems, man, and cybernetics—part b: cybernetics, vol. 41, no. 1, Feb. 2011

[2]. Ismail Saritas · Ilker A. Ozkan · Novruz Allahverdi Mustafa Argindogan," Determination of the drug dose by fuzzy expert system in treatment of chronic intestine inflammation" Springer Science+Business Media J Intell Manuf 20 PP 169–176 Jan. 2009.

[3]. D. U. Campos-Delgado, M. Hernandez- Ordonez, R. Femat, and A. Gordillo-Moscoso, "Fuzzy-based controller for glucose regulation in type-1 diabetic patients by subcutaneous route," IEEE Trans. Biomed.Eng., vol. 53, no. 11, pp. 2201–2210, Nov. 2006.

[4]. P. Magni and R. Bellazzi, "A stochastic model to assess the variability of blood glucose time series in diabetic patients self-monitoring," IEEE Trans. Biomed. Eng., vol. 53, no. 6, pp. 977–985, Jun. 2006.

[5]. K. Polat and S. Gunes, "An expert system approach based on principal component analysis and adaptive neuro-fuzzy inference system to diagnosis of diabetes disease," Dig. Signal Process., vol. 17, no. 4, pp. 702–710, Jul. 2007.

[6]. K. Polat, S. Gunes, and A. Arslan, "A cascade learning system for classification of diabetes disease: Generalized discriminant analysis and least square support vector machine," Expert Syst. Appl., vol. 34, no. 1, pp. 482–487, Jan. 2008.

[7]. X. Chang and J. H. Lilly, "Evolutionary design of a fuzzy classifier from data," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 34, no. 4, pp. 1894–1906, Aug. 2004.

[8]. L. B. Goncalves, M. M. B. R. Vellasco, M. A. C. Pacheco, and F. J. de Souza, "Inverted hierarchical neuro-fuzzy BSP system: A novel neuro-fuzzy model for pattern classification and rule extraction in databases," IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 36, no. 2, pp. 236–248, Mar. 2006.

[9]. H. Kahramanli and N. Allahverdi, "Design of a hybrid system for the diabetes and heart diseases," Expert Syst. Appl., vol. 35, no. 1/2, pp. 82–89, Jul./Aug. 2008.

[10]. Mehdi Fasanghari, Gholam Ali Montazer," Design and implementation of fuzzy expert system for Tehran Stock Exchange portfolio recommendation" Expert Systems with Applications 37 PP 6138–6147 2010

[11]. American Diabetes Association, "Standards of medicalcare in diabetes—2007,"Diabetes Care, vol. 30, no. 1, pp. S4–S41, 2007.

[12]. M.Kalpana and A.V Senthilkumar, "Fuzzy Expert System for Diabetes using Fuzzy Verdict Mechanism", Internationl Journal of Advanced Networking and Applications, Volume: 03, Issue:02, Pages;1128-1134 2011

[13]. M.Kalpana and A.V Senthilkumar, "Enhanced Fuzzy Verdict Mechanism for Diabetes using Fuzzy Expert System", Journal of Computational Intelligence and Information Security, Vol. 2, No. 8 2011.

[14]. A.V Senthilkumar and M.Kalpana ,"Diagnosis of Diabetes using Intensified Fuzzy Verdict Mechanism", A. Abd Manaf et al. (Eds.): ICIEIS 2011, Part III, CCIS 253, pp. 123–135, Springer-Verlag Berlin Heidelberg 2011.

[15]. M.Kalpana and A.V Senthilkumar, "Fuzzy Expert System for Diagnosis of Diabetes Using Fuzzy Determination Mechanism", International Journal of Computer Science & Emerging Technologies IJCSET, Vol-2 No 6 December, 2011

[16]. C. S. Lee and M. H. Wang, "Ontology-based intelligent healthcare agent and its application to respiratory waveform recognition," Expert Syst.Appl., vol. 33, no. 3, pp. 606–619, Oct. 2007

[17]. William Siler and James Buckley,"Fuzzy Expert System and Fuzzy Reasoning" Wiley & Sons,Inc pp,40,49-50,60-62 2005.

[18]. Peter H.Sydenham and Richard Thorn, "Handbook of measuring system Design" John Wiley & sons, Ltd., pp, 912-917, 2005.

[19]. Arazi Idrus, Muhd fadhilg Nuru system to Estimate Iddin, M. arif Rohman, "Development of project cost contingency

estimation model using risk analysis and fuzzy expert system" ,Expert System with applications 38(2011) 1501-1508.

[20]. Tien Ho and vishy Karri, "Fuzzy Expert System to Estimate Ignition timing for Hydrogen car" Springer-Verlag Berlin Heidelberg, Part II, LNCS, pp. 570-579 2008.