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Diabetes Diagnostic Model Based on Truth-value Restrictions Method Using Inference of Intuitionistic Conditional and Qualified Fuzzy Propositions

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***Abstract:** Diabetes is a challenging problem nowadays. Not only in India, but it also spreads over worldwide, In the present research paper a novel scheme based on intuitionistic fuzzy propositions to explore the knowledge base rule system with uncertainty has been developed and for the extension of fuzzy propositions to the domain of factors causing diabetes. In this paper, we have constructed the conditional and qualified intuitionistic fuzzy proposition mathematically for the diabetes diagnostic model. We have also developed an algorithm for Truth-value restriction method using the conditional and qualified intuitionistic fuzzy proposition;with the help of developed algorithm for truth-value restriction method we will give a scheme to check this severity of the diabetes. Numerical computations have also been carried out to demonstrate our approach.*

***Keywords:**Diabetes, Intuitionistic fuzzy set, Intuitionistic fuzzy relation, Intuitionistic fuzzy propositions, PIDD, Truth-value restrictions method.*

I. INTRODUCTION

Logic means the rules for the approximate reasoning and its all possible forms. Classical logic with its propositions plays a vital role in theformthat the propositions are assumed to be true or false. Every proposition has its counterpart, which is usually represented in the form of its negation. The propositions and its counterparts are required to assume the oppositional values. The other aspect of the logic, referred to be the propositional logic, deals with the combinations of arbitrary propositions. But the bitter truth of this concept is its form in the bi-valued logic with the drawback that the propositions cannot play a contingent role in the future events. Propositions about the future events are neither actually true nor actually false; hence their truth value identification is undetermined. Therefore the two valued logic may be extended into three valued logic. But when a finite set preserving the characteristic of an early stage in the evolutionary propositions is either the truth or falsity of proposition is known as fuzzy proposition and it is a matter of degree. Considering the truth and falsity are represented by values one and zero and the truth of every fuzzy proposition is represented by a number in the interval [0, 1]. In this paperwe have proposed a Truth-value restrictions method for the conditional and qualified proposition based to the diagnosis of diabetes.

Mathematically the fuzzy proposition can also be viewed as follows:

Let X is a non-empty set, and A is a subset of X. Then a fuzzy set A on X is a mapping which defined as, A: X → [0, 1]. Let "F(X)" denote the set of all fuzzy sets on X. For two non-empty sets X and Y, a fuzzy rule 'IF–THEN' is usually given as follows:

IF "x is A THEN y is B"

Where the antecedent $A \in F(X)$and the consequent$B \in F(Y)$ Further for a given fuzzy observation x isA', where$A' \in F(X)$, a corresponding output fuzzy set$B' \in F(Y)$, which means that y is B', is deduced using an inference. Thus, an inference may generally be viewed as a mapping from F(X) to F(Y). When we talk about the major health problems, then diabetes comes under this study. There are millions of people, who were dying every year because of diabetes. Especially in India, people are not aware about their physical fitness and diet plan. So this is one of the major reason that India having more diabetic patients. Zadeh [1] gave the concept of linguistic fuzzy model to express human way how to think and also introduce the compositional rule of inference but later on the bankler-kohout sub product [2] based on fuzzy rational inference was proposed which was as effective as compositional rule of inference. Later a relational inference system with the fuzzy implication [3] was introduced and this study shows the availability of residuated implications. Zimmermann [4] gave the Fuzzy Set Theory-and Its Applications which focus on the approximate reasoning and expert systems. Hájek and Kohout [5] gave concept of Fuzzy implications and generalized quantifiers in the form of fuzzy qualifier. However in real life this linguistic negation does not satisfy the logical negation, therefore while selecting the membership, there may be some type of hesitation. So due to the hesitation, non membership is less than or equal to the complement of the membership degree. This is the reason why different results may be obtained for the different membership function.

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Due to this, Atanassov in 1985 [6, 7] suggested an intuitionistic fuzzy sets (IFS) where the non-membership degree is not equal to the complement of the membership degree, due to the fact that some kind of hesitation or lack of knowledge is present while constructing the membership function. Later on Atanassov in 2006 [8] introduced Intuitionistic fuzzy negation in which a new negation was described and its specific properties were discussed. So many efforts have already been done for diabetic diagnosis. The expert system and fuzzy logic have an important technique to explore the machine reasoning. There are many fuzzy expert systems developed for diabetic analysis [9, 10]

In this present work, first we will show especially the conditional and qualified intuitionistic fuzzy propositions with the condition on lukasiewicz implication. Fuzzy set theory, takes into account membership degree. But when fuzzy set theory takes into account membership degree and the non-membership value is the complement of the membership degree. However in real life this linguistic negation does not satisfy the logical negation. Many types of inference mechanisms that deal with fuzzy knowledge base systems and fuzzy implications have been proposed and have been used in many applications of several fuzzy inferences.

The present research paper has been divided into seven sections; in the second section of the research paper we have defined some basic concept on Fuzzy set, Intuitionistic fuzzy relation, Fuzzy and lukasiewicz implication, Intuitionistic fuzzy propositions and Pima Indian Diabetes Database [11]. In the third section of the paper we have proposed an algorithm based for Truth Value Restriction Method (TVRM) for the diagnostic model of diabetes using the inference from conditional and qualified intuitionstic fuzzy proposition. In fourth section of the research paper we have constructed membership and non-membership function for input and output variables (as shown in Table-I). In this section, we have also categorized the PIDD data for diabetes into linguistic category for input and output the stages of the risk and the sickness for diabetic patients. In fifth section we have formed the fuzzy rules based on the input variables and the fuzzy propositions used in the inference system and also gave architecture for proposed algorithm. In sixth section we have elaborated our technique by giving the numerical computation with the help of the PIDD data to get the output values by giving some input value for applying Truth-Restriction Method and in the seventh and the last section we have discussed our numerical results and have given the concluding remarks about the proposed algorithm for Truth Value Restriction Method for Intuiotionstic conditional and qualified Fuzzy Propositions.

Notations

I : Fuzzy implication

τ : Lukasiewicz implication

R : Intuitionistic Fuzzy relation

P Intuitionistic Fuzzy proposition

RT (A/B) : Relative fuzzy and Intutionistic fuzzy truth value of A with respect to B.

μ_L, μ_M, μ_H: Membership functions corresponds to linguistic terms low, medium and high.

ν_L, ν_M, ν_H : Non-Membership functions corresponds to linguistic terms low, medium and high.

$\mu_Y, \mu_O, \mu_{LS}, \mu_N, \mu_S, \mu_A$: Membership functions corresponds to linguistic terms young, old, less-severe normal, severe and adult respectively.

$\nu_Y, \nu_O, \nu_{LS}, \nu_N, \nu_S, \nu_A$: Non-Membership functions corresponds to linguistic terms young, old, less severe, normal, severe and adult respectively.

II. BASIC DEFINITIONS

A. Fuzzy Set

If X is a universal set then a fuzzy [1] set A on X is defined as: A= {(x, μ_A(x)): x∈X,
where μ_A(x): X→ [0,1] is called the membership function.

B. Fuzzy and Lukasiewicz Implication

A function I: $[0, 1]^2 \rightarrow [0, 1]$ is called a fuzzy implication [12] if it satisfies, for all x, x_1, x_2, y, y_1, y_2 ∈ [0, 1], if it satisfies the following:
If $x_1 \le x_2$, then I(x_1, y) ≥I(x_2, y), i.e., I (·, y) is decreasing,
If $y_1 \le y_2$, then I(x, y_1) ≤I(x, y_2), i.e., I(x, ·) is increasing and result into the form
I (0, 0) = 1, I (1, 1) = 1 and I (1, 0) = 0.
Łukasiewicz implication:
Lukasiewicz implication is defined as
τ (a, b)= min (1, 1-a+b) a, b ∈[0, 1]

C. Intuitionistic Fuzzy Set

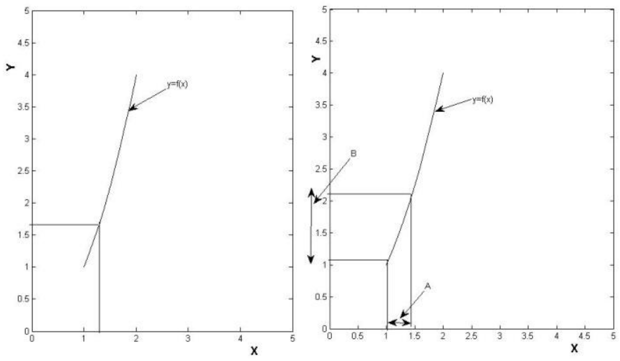
Let X is a universal set then Intuitionistic fuzzy set B in X is defined as
$B = \{(x, \mu_B(x), \nu_B(x))\}: x \in X$,
where $\mu_B(x): X \to [0,1] and \nu_B(x): X \to [0,1]$ called membership and non-membership functions respectively with and $0 \le \mu_B(x) + \nu_B(x) \le 1, \pi_B(x) = 1 - [\mu_B(x) + \nu_B(x)]$ with $0 \le \pi_B(x) \le 1$, called hesitation part.

D. Intuitionistic Fuzzy Relation

Let A and B be any two Intuitionistic fuzzy sets defined on universal sets X and Y respectively, then A×B is the Cartesian product of A and B the fuzzy relation on A×B defined [13] as; R = {((x, y), μ_R(x, y),ν_R(x, y))} for (x, y)∈ A ×B, μ_R andν_R are called membership and non-membership function on R respectively with
μ_R, ν_R: A × B → [0, 1] and $0 \le \mu_R + \nu_R \le 1$.

E. Intuitionistic Fuzzy Proposition

The basic arguments that differentiate the Intuitionistic fuzzy proposition and classical proposition are the range of their truth value. Truth value of proposition P for the case of membership value is denoted by T (P) = $\mu_A(x)$ where $0 \le \mu_A(x) \le 1$, and truth value for the case of non-membership value is denoted by T (P) =1- $\nu_A(x)$ where $0 \le \nu_A(x) \le 1$, with
$0 \le \mu_A(x) + \nu_A(x) \le 1$.
Let X and Y are two sets and assume that if $x \in X$ then,



(a) (b)

Fig.1: Relationship between two variables and sets

$y \in Y$, these two variables are related by a function $y = f(x)$. So for any given $x \in X$ we can infer $y \in Y$ with the help of $y = f(x)$

Similarly if $A \subseteq X$ and $B \subseteq Y$ and if $x \in A$ then we can infer [14] the value of $y \in B$ as shown in Fig.1(a)

where $B = \{y \in Y / \mathrm{y} = \mathrm{f(x)}, x \in A\}$

If we assumes that these two variables related by an arbitrary relation R on $X \times Y$, this will not necessarily be a function. So for any given $x \in A$ then we can infer $y \in B$ with the help of relation R. i.e. $\forall x \in A$ we can conclude $y \in B$ as shown in Fig.1(b)as

$$B = \{y \in Y : < x, y > \in R\}$$

If we replace the given set A and B by fuzzy sets $A' and B'$ and relation R by fuzzy relation as shown in Fig.2 we can conclude that

$$B'(y) = \sup_{\mathrm{x} \in \mathrm{X}} \min\left(A'(\mathrm{x}), \mathrm{R}(\mathrm{x},\ \mathrm{y})\right) \qquad (1)$$

So, we can conclude that if we have a fuzzy set A' and a fuzzy relation R(x, y) we can conclude a fuzzy set B' by equation (1)

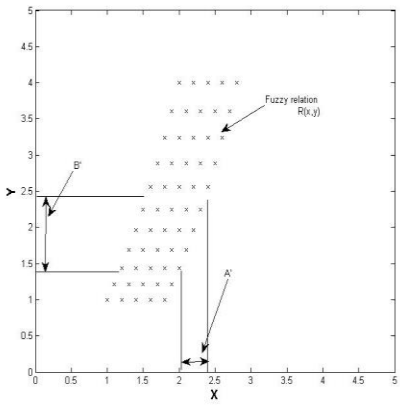


Fig.2: Compositional rule for inference

In this research paper we have extended the fuzzy proposition to the intuitionistic fuzzy proposition. In the intuitionistic fuzzy proposition, we have considered the non-favourable cases. In the present research paper let we have a proposition based on two propositions p and q defined as

p: IF X is A, THEN Y is B and q: X is A'

Now by taking relation of proposition p and assumes proposition q as a fact we can infer or conclude another fact that B' by compositional rule of inference called generalized modus ponens. Fuzzy relation in (1) not usually given, so R embedded in fuzzy proposition p by formula $R(x, y) = \tau\left(\mathrm{A(x)}, \mathrm{B(y)}\right)$, called fuzzy implication now if we have a conditional and qualified proposition P: IF X is A, THEN Y is B is S, where S stands for truth and S (τ (a, b)) denotes the truth value of τ (a, b).

F. Pima Indian Diabetes Database

PIDD is the online database provider by national institute of diabetes and digestive kidney disease, our aim is to predict whether or not the patient has diabetes on the bases of certain diagnostic measurements. PIDD included the data of 700+ female patients.

III. PROPOSED ALGORITHM FOR THE DIABETES DIAGNOSTIC MODEL BASED ON THE TRUTH VALUE RESTRICTION METHOD

In this section of the paper we have developed an algorithm for the solution of our model by creating intuitionistic fuzzy sets based on the available data

Suppose that we have two Intuitionistic fuzzy sets A={x, $\mathrm{A_1(x)}, \mathrm{A_2(x)}$} and B= {x, $\mathrm{B_1(x)}, \mathrm{B_2(x)}$} for inputs and outputs respectively. First, we will develop a truth-value restriction method for conditional and qualified fuzzy propositions, which is of the form

P: IF X is A, THEN Y is B is S

where "S" denotes fuzzy -truth qualifier, for a given fact "X is A'", and we need to develop an another fact "Y is B'" involves the following three steps:

Step1:

Calculate relative truth value of A' with respect to A, which is a fuzzy set on unit interval and denoted by the relative truth value that RT (A'/A) and is defined ∀ a ∈ [0 , 1]as

$$\mathrm{RT\ (A'/A)\ (a)} = \sup_{\mathrm{x:\ A_1(x)\ =\ a}} \mathrm{A'\ (x)} \qquad 2(a)$$

(For favourable cases)

$$\text{And RT (A'/A) (a)} = \inf_{\mathrm{x:\ A_2(x)\ =\ a}} \mathrm{A'\ (x)} \qquad 2(a)$$

(For non-favourable cases)

RT (A'/A) represent the degree to which the fuzzy proposition is true given the available fact "X is A'"

Step2:

The value of S stands for the fuzzy qualifier and role of S is to modify the value of τ(a, b) and S stands for truth value (S (a) =a^2) then S (τ (a, b) =$(\tau\ (\mathrm{a, b}))^2$, then the relative fuzzy truth value of B' with respect to B, denoted by RT (B'/B) for corresponding to the membership and the non membership values, which will be defined as follows:

$$\mathrm{RT\ (B'/B)\ (b)} = \sup_{\mathrm{a} \in [0,1]} \min\ [\mathrm{RT\ (A'/A)\ (a)},\ \mathrm{S}\ (\tau\ (\mathrm{a, b}))], \quad \mathrm{b} \in [\,0, 1\,]$$

$$\mathrm{RT\ (B'/B)\ (b)} = \inf_{\mathrm{a} \in [0,1]} \max\ [\mathrm{RT\ (A'/A)\ (a)},\ \mathrm{S}\ (\tau\ (\mathrm{a, b}))], \quad \mathrm{b} \in [\,0, 1\,]$$

Step3:

Calculate the set B' involved in the inference "Y is B'", which will be given by

$\mathrm{B_1'(y)} = \mathrm{RT(B'/B)}B_1(\mathrm{y})), \mathrm{y} \in \mathrm{Y}$ 3(a)

$\mathrm{B_2'(y)} = 1 - \mathrm{RT\ (B'/B)}(B_2(\mathrm{y}))$, $\mathrm{y} \in \mathrm{Y}$ 3(b)

Finally we get $\mathrm{B'(y)} = \{(\mathrm{x}, \mathrm{B_1'(y)}, \mathrm{B_2'(y)})\}$

IV. FACTORS AFFECTING THE DIABETES WITH THEIR CATEGORICAL DIVISION WITH THEIR LINGUISTIC RANGES OF LOW, MEDIUM HIGH

Table- I: Including the factors and their linguistic ranges

Factors	Linguistic ranges	PIDD Numeric values
Insulin	low, medium and high	[0- 586]
Glucose	low, medium and high	[56-198]
Body Mass Index (BMI)	low, medium and high	[18-67]
Diabetes Pedigree Function (DPF)	low, medium and high	[0.08-2.4]
Age	young, adult and old	[24-30]
Diabetes Mellitus (DM)	less severe, normal and severe	[0-1]

We will construct the membership and non-membership function for linguistic ranges via; low, medium and high for all the input and output factors on the behalf of Membership and Non-Membership function given below:

$$\mu(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0, & x < a \text{ and } x > c \end{cases}$$

(For membership function)

$$\nu(x) = \begin{cases} \dfrac{b-x}{b-a'} & a' \le x \le b \\ \dfrac{x-b}{c'-b} & b \le x \le c' \\ 1 & x < a' \text{and } x > c' \end{cases}$$

(For non-membership function)

Where $a' < a < b < c < c' and a', a, b, c, c' are all real.$

On the basis of this procedure we can constructed the membership function as well as the non-membership functions for all the linguistic ranges, which we have categorized for the including factor(see in"Table- I") in the diabetes.

V. FUZZY RULES FOR INFERENCE BASED UPON THE CONDITIONAL AND QUALIFIED PROPOSITION

By involving five factors as input and their outcome to be in the form of three output factors, there are fifteen fuzzy rules taken for inference based on single input and single output variable shown below as:

#1: If insulin is low Then diabetes mellitus/DM is severe is true
#2: If insulin is medium Then diabetes mellitus/DM is normal is true
#3: If insulin is high Then diabetes mellitus/DM is less severe is true
#4: If glucose is low Then diabetes mellitus/DM is less severe is true
#5: If glucose is medium Then diabetes mellitus/DM is normal is true
#6: If glucose is high Then diabetes mellitus/DM is severe is true
#7: If BMI is low Then diabetes mellitus/DM is less severe is true
#8: If BMI is medium Then diabetes mellitus/DM is normal is true
#9: If BMI is high Then diabetes mellitus/DM is severe is true
#10: If DPF is low Then diabetes mellitus/DM is less severe is true
#11: If DPF is medium Then diabetes mellitus/DM is normal is true
#12: If DPF is high Then diabetes mellitus/DM is severe is true
#13: If age is younger Then diabetes mellitus/DM is normal is true
#14: If age is adult Then diabetes mellitus/DM is less severe is true
#15: If age is old Then diabetes mellitus/DM is severe is true

A. Architecture of the proposed algorithm

We have also provided architecture for numerical computation as given below:

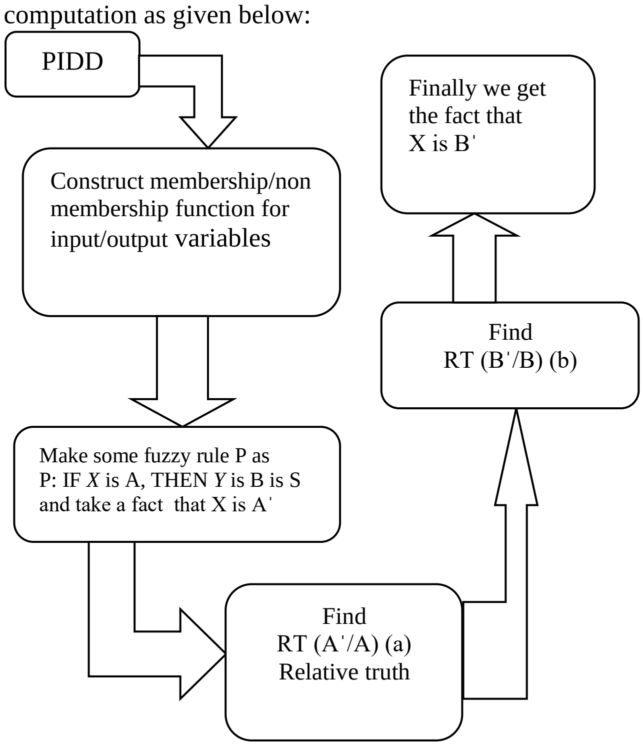


Fig.3.Architecture for numerical computations procedure

VI. NUMERICAL COMPUTATION

For describing our methodology we will use our proposed algorithm for a fuzzy inference rule and try to set the output result as:

#1: If insulin is low Then diabetes mellitus/DM is severe is true

$$A_1(x) = \begin{cases} \dfrac{36-0.4x}{40} & 0 \le x \le 40 \\ \dfrac{18-0.2x}{20} & 40 \le x \le 60 \\ \dfrac{21-0.2x}{30} & 60 \le x \le 90 \end{cases}$$

$$A_2(x) = \begin{cases} \frac{4+0.3x}{40} & 0 \le x \le 40 \\ \frac{0.2x}{20} & 40 \le x \le 60 \\ \frac{12+0.1x}{30} & 60 \le x \le 90 \end{cases}$$

$$B_1(x) = \begin{cases} x-0.2 & .6 \le x \le .8 \\ 2x-1 & .8 \le x \le 1 \end{cases}$$

$$B_2(x) = \left\{ \frac{0.1-0.1x}{2} \quad 0.6 \le x \le 1 \right.$$

$$A_1'(x) = \begin{cases} \frac{32-0.1x}{40} & 0 \le x \le 40 \\ \frac{18-0.1x}{20} & 40 \le x \le 60 \quad \text{and} \\ \frac{0.3x}{30} & 60 \le x \le 90 \end{cases}$$

$$A_2'(x) = \begin{cases} \frac{8+0.1x}{40} & 0 \le x \le 40 \\ \frac{10-0.1x}{20} & 40 \le x \le 60 \\ \frac{12-0.1x}{30} & 60 \le x \le 90 \end{cases}$$

Let us take some points as

A: {(0, .9, 0.1), (40, 0.5, 0.4), (60, 0.3, 0.6), (90, 0.1, 0.7)}

A': {(0, 0.8, 0.2), (40, 0.7, 0.3), (60, 0.6, 0.2), (90, 0.9, 0.1)}

Take S (a) $=a^2$ for all a $\in$[0, 1]

B: {(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)}

STEP1:

We calculate RT (A'/A) (a) = sup {A'(x); x: $A_1(x) = a$}

RT (A'/A) (0.9) = A' (0) = 0.8

RT (A'/A) (0.5) = A' (40) = 0.7

RT (A'/A) (0.3) = A' (60) = 0.6

RT (A'/A) (0.1) = A' (90) = 0.9

And

Calculate RT (A'/A) (a) = sup {A'(x); x: $A_2(x) = a$}

RT (A'/A) (0.1) = A' (0) = 0.2

RT (A'/A) (0.4) = A' (40) = 0.3

RT (A'/A) (0.6) = A' (60) = 0.2

RT (A'/A) (0.7) = A' (90) = 0.1

STEP2:

We calculate, RT (B'/B) (b) = sup {min [RT (A'/A) (a), S (τ(a, b))]} $\quad a \in [0,1]$

RT (B'/B) (b) = max {min (0.8, S (τ(0.8, b)), min (0.7, S (τ(0.7, b)), min (0.6, S (τ(0.6, b)), min (0.9, S (τ(0.9, b))}

= max {min (0.8, S (min (1, 0.2+b)), min (.7, S (min (1, 0.3+b)),min (0.6, S(min (1, 0.4+b)), min (0.9, S (min (1, 0.1+b)) }

(By using $\tau(a,b) = \min(1, 1-a+b)$)

$= \max\{\min(0.8, (0.2+b)^2), \min(0.7, (0.3+b)^2)), \min(0.6, (0.4+b)^2)), \min(.9, (.1+b)^2))\}$

$$= \begin{cases} (0.4+b)^2 & b \in [0, .04721) \\ 0.6 & b \in [.04721, 0.4745) \\ (0.3+b)^2 & b \in [0.4745, 0.5366) \\ 0.7 & b \in [0.5366, 0.6367) \\ (0.2+b)^2 & b \in [0.6367, 0.6944) \\ 0.8 & b \in [0.6944, \quad 0.7944] \\ (0.1+b)^2 & b \in [0.7944, 0.8740) \\ 0.9 & b \in [0.8740, 1] \end{cases}$$

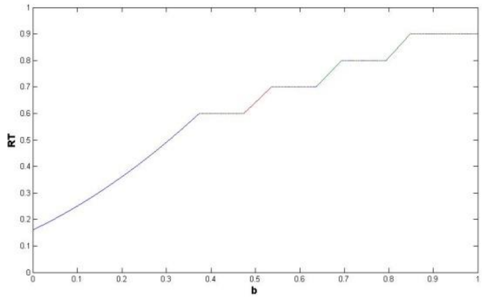


Fig.4. Graph between b and RT (B'/B)

Now we calculate,

RT (B'/B) (b) = inf{max[RT (A'/A)(a), S(τ(a, b))]} $\quad a \in [o, 1]$

RT (B'/B)(b) = min {max(0.2, S(τ(0.2, b)), max(0.3, S(τ(0.3, b)), max (0.2, S (τ(0.2, b)), max (0.1, S (τ(0.1, b))}

= min {max (0.2, S (min (1, 0.8+b)), max (0.3, S (min (1, 0.7+b)), max (0.2, S(min (1, 0.8+b)), max (0.1, S (min (1, 0.9+b))}

(By using $\tau(a,b) = \min(1, 1-a+b)$)

$=\min\{\max(0.2, (0.8+b)^2), \max(0.3, (0.7+b)^2)), \max(0.2, (0.8+b)^2)), \max(0.1, (0.9+b)^2))\}$

$=\{(0.7+b)^2$

STEP3:

We calculate the value of B' by B'(y) = RT (B'/B) (B_1(y)): y $\in$B

And B'(y) = RT (B'/B) (B_2(y)): y$\in$B

B' (0.4) = RT (B'/B) (0.4) = 0.6

B' (0.8) =RT (B'/B) (0.8) = 0 .81

B' (0.5) =RT (B'/B) (0.5) = 0.64

And B' (0.2) = 1- RT (B'/B) (0.2) = 1- 0.81=0.19

B' (0.2) = 1- RT (B'/B) (0.1) = 1- 0.81=0.19

B' (0.3) = 1 - RT (B'/B) (0.3) = 1-1=0

So we conclude "*Y* is B'", where B' = {(0.6, 0.6, 0.19), (0.8, 0.81, 0.19), (1, 0.64, 0)}

By using the same procedure for the calculation of the other factors using different rules from the inference for Intuitionistic conditional and qualified fuzzy proposition we can conclude the following numerical values:

Table- II: Numerical computational for all 15 rules

1.Insulin low	**2.Insulin medium**
A ={(0, 0.9, 0.1), (40, 0.5, 0.4), (60, 0.3, 0.4), (90, 0.1, 0.7)} A'={(0, 0.8, 0.2), (40, 0.7, 0.3), (60, 0.6, 0.2), (90, 0.1, 0.7)} B: {(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)} B'={(0.6, 0.6, 0.19), (0.8, 0.81, 0.19), (1, 0.64, 0)}	A ={(90, 0.5, 0.4), (120, 0.6, 0.3), (150, 0.8,0.1), (200, 0.9, 0.1)} A'={(90, 0.6, 0.3), (120, 0.8, 0.2), (150, 0.6,0.2), (200, 0.9, 0.1)} B ={(0.3, 0.5, 0.3), (0.5, 0.7, 0.2), (0.6, 0.6, 0.3)} B'={(0.3, 0.5, 0), (0.5, 0.8, 0.19), (0.6, 0.64, 0)}

3.Insulin high A ={(200, 0.5, 0.3), (280, 0.7, 0.3), (360, 0.8,0.1), (586, 1, 0)} A'={(200, 0.6, 0.2), (280, 0.8, 0.2), (360, 0.6,0.3), (586, 0.9, 0.1)} B ={(0, 0.8, 0.2), (0.2, 0.6, 0.3), (0.3, 0.4, 0.2)} B'={(0, 0.81, .19), (0.2, 0.6, 0), (0.3, 0.4, .19)}	**4.Glucose low** A ={(50, 0.5, 0.4), (72, 0.7, 0.3), (90, 0.8,0.1), (106, 1, 0)} A'={(50, 0.6, 0.1), (72, 0.6, 0.3), (90, 0.7,0.2), (106, 1, 0)} B ={(0, 0.8, 0.2), (0.2, 0.6, 0.3), (0.3, 0.4, 0.2)} B'={(0, 0.64, 0.19), (0.2, 0.36, 0), (0.3, 0.6, 0.19)}
5.Glucose medium A ={(106, 0.4, 0.2), (120, 0.6, 0.3), (146, 0.5, 0.3)} A'={(106, 0.5, 0.3), (120, 0.6, 0.4), (146, 0.8, 0.2)} B ={(0.3, 0.5, 0.3), (0.5, 0.7, 0.2), (0.6, 0.6, 0.3)} B'={(0.3, 0.6, 0), (0.5, 0.8, 0.19), (0.6, 0.64, 0)}	**6.Glucose high** A: {(146, 0.5, 0.3), (166, 0.6, 0.2), (198, 1, 0)} A': {(146, 0.8, 0.2), (166, 0.7, 0.3), (198, 0.9, 0.1)} B: {(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)} B'={(0.6, 0.5, 0.19), (0.8, 0.81, 0.19), (1, 0.64, 0)}
7.BMI low A ={(18, 0.9, 0.1), (26, 0.7, 0.2), (30, 0.6,0.3)} A'={(18, 0.6, 0.3), (26, 0.9, 0.1), (30, 0.9,0.1)} B ={(0, 0.8, 0.2), (0.2, 0.6, 0.3), (0.3, 0.4, 0.2)} B'={(0, 0.81, 0.19), (0.2, 0.6, 0.36), (0.3, 0.6, 0.19)}	**8.BMI medium** A ={(30, 0.4, 0.5), (40, 0.5, 0.5), (50, 0.7, 0.2)} A'={(30, 0.6, 0.3), (40, 0.8, 0.2), (50, 0.7, 0.2)} B ={(0.3, 0.5, 0.3), (0.5, 0.7, 0.2), (0.6, 0.6, 0.3)} B'={(0.3, 0.64, 0), (0.5, 0.8, 0.19), (0.6, 0.7, 0)}
9.BMI high A= {(50, 0.5, 0.3), (58, 0.6, 0.2), (67, 1, 0)} A'={(50, 0.8, 0.2), (58, 0.7, 0.3), (67, 0.9, 0.1)} B={(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)} B'={(0.6, 0.6, 0.19), (0.8, 0.81, 0.19), (1, 0.64, 0)}	**10.DPF low** A ={(0.08, 0.9, 0.1), (0.5, 0.7, 0), (1, 0.6,0.2)} A'={(0.08, 1, 0), (0.5, 0.6, 0.3), (1, 0.5,0.1)} B ={(0, 0.8, 0.2), (0.2, 0.6, 0.3), (0.3, 0.4, 0.2)} B'={(0, 0.64, 0.19), (0.2, 0.6, 0), (0.3, 0.6, 0.19)}
11.DPF medium A ={(1,0.5, 0.2), (1.5, 0.6, 0), (2, 0.5,0.5)} A'={(1, 0.6, 0.4), (1.5, 0.5, 0.5), (2, 0.7,0.3)} B ={(0.3, 0.5, 0.3), (0.5, 0.7, 0.2), (0.6, 0.6, 0.3)} B'={(0.3, 0.64, 0), (0.5, 0.7, 0.19), (0.6, 0.7, 0)}	**12.DPF high** A ={(2, 0.6, 0.2), (2.2, 0.9, 0), (2.4, 1,0)} A'={(2, 0.8, 0.2), (2.2, 0.7, 0.3), (2.4, 1,0)} B={(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)} B'={(0.6, 0.36, 0.19), (0.8, 0.8, 0.19), (1, 0.49, 0)}
13.Age young A ={(24, 0.5, 0.2), (25, 0.6, 0.4), (26, 0.5,0.3)} A'={(24, 0.6, 0.3), (25, 0.7, 0.2), (26, 0.8,0.1)} B ={(0.3, 0.5, 0.3), (0.5, 0.7, 0.2), (0.6, 0.6, 0.3)} B'={(0.3, 0.6, 0), (0.5, 0.8, 0.19), (0.6, 0.7, 0)}	**14.Age adult** A ={(26, 0.5, 0.2), (27, 0.7, 0.3), (28, 0.8, 0.2)} A'={(26, 0.8, 0.2), (27, 0.6, 0.3), (28, 1, 0)} B ={(0, 0.8, 0.2), (0.2, 0.6, 0.3), (0.3, 0.4, 0.2)} B'={(0, 0.8, 0.19), (0.2, 0.64, 0), (0.3, 0.6, 0.19)}
15.Age old A= {(28, 0.5, 0.2), (29, 0.7, 0.3), (30, 1, 0)} A'={(28, 0.6, 0.3), (29, 0.5, 0.3), (30, 1, 0)} B={(0.6, 0.4, 0.2), (0.8, 0.8, 0.2), (1, 0.5, 0.3)} B'={(0.6, 0.5, 0.19), (0.8, 0.81, 0.19), (1, 0.64, 0)}	

VII. RESULTS AND CONCLUSION

In the present paper a novel scheme based on intuitionistic fuzzy propositions to explore the knowledge base rule system with uncertainty has been developed for the extension of fuzzy propositions to the domain of factors causing diabetes. In addition with the development of an algorithm for diagnosis of the diabetes and the architecture of the diagnostic model has been given in this work. We have taken a data set, from PIDD and have categorized the diabetes causing factors into the linguistic categories. The intuitionistic fuzzy propositions execute the relative intuitionistic fuzzy truth inference rule to make the decisions and the possibility of individual factors causing the diabetes. The whole works done in this research paper explain the following points:

1) The development of this work for an inference has been madebyusing the truth value restriction method for intuitionistic conditional and qualified fuzzy propositions. The numerical computations have been carried out for the knowledge base rule system for the different linguistic categories of the factors.
2) Although the proposed algorithm based on intuitionistic fuzzy proposition for truth value restriction method for the relative truth value for the rule base knowledge system for diabetes. Fuzzification approach has been applied to the factors for intuitionistic fuzzy inference system for the solution of the model.
3) The reasoning mechanism of the Truth Value Restriction Method based on the features characterized by fuzzy rule base system based on the inference of intuitionistic conditional and qualified fuzzy proposition which contains system rules for the fuzzy inference system.

On the basis of the values obtained in numerical computation we may conclude the following facts:

First rule of rule base system that the diabetes mellitus (DM) is severe; when the insulin is low and it has to be noted after applying truth value restriction method for the membership value for output factor that severity increases and the non-membership value decreases, results in, that the patient is going under critical condition. For the second rule, the membership value of output factor increasesasshown in Table-II as compare to the previous one and non-membership decreases, results in; that the patient is going under better condition. For the third rule of rule base system when diabetes mellitus is less severe and the insulin level is high; in this case the value of membership function remains same. But there is slightly decrement in non membership value of output factor, that results in, the patient is going under normal condition.

Similarly for all the other rules of rule base system we have given ascheme based on the intuitionistic fuzzy proposition for the truth value restriction method that the patient either going under critical condition or his/she slightly recovering from his/her illness. And in some cases patient almost recovers his/her condition.

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