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Diabetes Diagnostic Intelligent Information System

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Abstract:
In the present paper, we deal with the design and development of Soft Computing base Information system using the concept of generating Linguistic Strings through non-linear Fuzzy Membership Functions for detecting the classification criterion of Diabetes. The proposed system, on one hand, will help the patient in adopting a proper strategy to evaluate his present sugar level and follow a balanced lifestyle on the other hand it will provide a quantitative base to medical experts in detecting the disease and suggesting proper action to the patients. The proposed information system is tested on real-life data with a satisfactory result as per the medical experts.

Keywords: *Decision Making, Diabetes, Fuzzy Set, Information System, Medical Diagnosis, Soft Computing*

I. INTRODUCTION

Diabetes is a major challenging health problem of the 21st century it refers to a heterogeneous chronic metabolic disorder caused by genetic, behavioral (Internal factors) and environmental (External factors). It results due to impaired insulin secretion or insulin resistance decrease glucose utilization and increased glucose production [1]. In the Pre-diabetic state the patient meet not all but some of the diagnostic criteria for diabetes. It is often called as the heisted area between normal and diabetic levels. According to International Diabetes Federation (IDF) [2] there were 69.1 million diabetics in India. As per WHO Global Report on Diabetes [3], of April 2016, an estimate of 422 million adults was suffering with diabetes in 2014 with compared to 108 million in 1980. Because of diabetes 1.5 million deaths in 2012 and higher blood glucose level caused an additional risk of 2.2 million death by increasing the risks of cardiovascular as well as other diseases [4,5]. The world today is witnessing an epidemic of Diabetes. It is carrying out the causes of the end stage of such dangerous diseases like renal disease, non-traumatic lower extremity amputations and adult blindness. It is also made expectant to the cardiovascular diseases.

The root cause of the diabetes as it has been observed in recent studies is functioning of Pancreas. Based on functions of pancreas and the development of Insulin diabetes is categorized as Type I and Type II. A very clear line cannot be drawn between pre-diabetic and diabetes of type 1 and type 2. According to "WHO" the maximum number of people who are suffering from diabetes are affected by type 2 diabetes. Type 2 Diabetes can be cured effectively if diagnosed on time and proper treatment is taken. Pre-diabetes is just an indication of diabetes and is result of more of irregular lifestyle and improper food habits [3].

In this article, we deal with the design and development of soft computing base information system using non-linear membership function for detecting the classification criterion of diabetes. In section 2, we have reviewed some literature and discussed about some exiting work. In section 3, discuss about methods and materials, where input and output parameters are taken and design the algorithm. In section 4, based on real data we elaborate some experimental studies. In section 5, we analysis about the sensitivity of this algorithm. Section 6, we make a proper conclusion.

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II. Literature Review and General Discussion

In order to capture the medical thought conventional mathematical techniques are helpless that is why in the present time one of the components of Soft Computing i.e. fuzzy tools [6] are very effective in dealing with uncertainty which is closer to human way of decision-making [7]. This technique is effective especially for diabetes for detecting which criteria of diabetes is pertaining to the patient. Polat, K. and Gvne S. [8] Introduced an expert system using principle component analysis and with the help of neuro-fuzzy inference system to the diagnosis of diabetes. Baskaran, A. et.al [9] briefly studied on the modeling and the automation system for diabetes treatment. Recently, Srivastava Pankaj and Sharma Neerja designed a soft computing-based model for medical diagnosis [10] and with the help of this they developed a classification scheme for the ECG beats [11]. Also, they are developed a soft computing Diagnostic system for Diabetes detection [12] and cardiac analysis [13]. Srivastava et. al. [14] has designed a risk assessment model for measuring the hypertension level. Jang et. al. [15] written a book, where some soft computing approaches has been discussed based on neuro-fuzzy technique.

In 1976, Jain, R. [16] design a decision-making system in the present of various kind of fuzzy variables like Fuzzy Knowledge about the State of the System, Fuzzy Utilities, Fuzzy State and Fuzzy Utility. In this article, only using Fuzzy Knowledge about the State of the System we have developed a Medical Diagnostic Information System that have applied to classify the various level of Diabetics using various criteria.

III. Methods and Material

Various kind of linguistic factors that contribute to the onset of two main kind of diabetes type 1 and type 2 like Hereditary or inherited Traits, Age, poor diet, Obesity, mental stress etc. Doctors mainly use these special tests for diagnosis of diabetes, such of these are Fasting Blood Sugar (FBS), Postprandial Blood Sugar Test (PPBS), Random Blood Sugar Test (RBS), Oral Glucose Tolerance Test (OGTT), HbA1C test etc.

Here we have considered nine main risk factors like **Age, HBA1c, FBS, PPBS, Obesity, Sleeping hour, Stress level, Sensitivity to medical examination and physical exercise**.

3.1. Input Variables

To define the risk factors, we use mainly two types of fuzzy membership functions:

- **Sigmoidal**:$sigmf(x;[a,c]) = \frac{1}{1+e^{-a(x-c)}}$
  Where a and c are constants
- **Gaussian**: $gaussmf(x,[\sigma,c]) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$
  Where σ and c are constants.

3.1.1. Age (Input 1)

It is divided the**age**group into five fuzzy sets which is shown in table 1.

Table 1. Fuzzy variable of Age INPUT Factor

Fuzzy Sets of Age Group	Expected Range	Membership Function
Young (Y)	0-25	$sigmf(x;[-0.25,18])$
Middle Aged (MA)	20-45	$gaussmf(x;[15,32.5])$
Aged (A)	40-65	$gaussmf(x;[15,52.5])$
Very Aged (VA)	60-85	$gaussmf(x;[15,72.5])$
Old (O)	Above 80	$sigmf(x;[0.25,80])$

3.1.2. HBA1c (Input 2)

It reflects glycated hemoglobin which reflects blood glucose level in past 6-8 weeks and do not reflect daily ups and downs. It is classified into five fuzzy sets that has been shown in Table 2.

Similarly, we have taken the input 3 to 9 for **FBS, PPBS, Obesity, sleeping hour, stress level, Sensitivity to medical examination and physical exercise** respectively which has been shown in table

3-9 respectively and its graphical representation is shown in Figure. 1.

Table 2. Fuzzy variable of HBA1c INPUT Factor

Fuzzy Sets of HBA1c	Expected Range	Membership Function
Low (L)	Below 5	$sigmf(x; [-1.5, 5])$
Normal (N)	4-6	$gaussmf(x; [1.5, 5.5])$
Pre-Diabetic (Pre)	5.7-6.5	$gaussmf(x; [1.5, 6.25])$
High (H)	6.25-8	$gaussmf(x; [1.5, 7.25])$
Very High (VH)	Above 8	$sigmf(x; [1.5, 8])$

Table 3. Fuzzy variable of FBS INPUT Factor

Fuzzy Sets of FBS	Expected Range	Membership Function
Very Low (VL)	Below 40	$sigmf(x; [-0.1, 40])$
Low (L)	35-65	$gaussmf(x; [25, 50])$
Normal (N)	60-110	$gaussmf(x; [25, 85])$
Pre-Diabetic (Pre)	105-200	$gaussmf(x; [35, 152.5])$
High (H)	Above 200	$sigmf(x; [0.1, 200])$

Table 4. Fuzzy variable of PPBS INPUT Factor

Fuzzy Sets of PPBS	Expected Range	Membership Function
Very Low (VL)	Below 40	$sigmf(x; [-0.1, 40])$
Low (L)	35-65	$gaussmf(x; [25, 50])$
Normal (N)	60-145	$gaussmf(x; [25, 102.5])$
High (H)	140-250	$gaussmf(x; [35, 195])$
Very High (VH)	Above 250	$sigmf(x; [0.1, 250])$

Table 5. Fuzzy variable of Obesity INPUT Factor

Fuzzy Sets of Obesity	Expected Range	Membership Function
Normal (N)	Below 25	$sigmf(x; [-0.4, 25])$
Over Weight (OW)	20-35	$gaussmf(x; [6, 27.5])$
Obese (OB)	30-40	$gaussmf(x; [6, 35])$
Extremely Obese (EO)	Above 40	$sigmf(x; [0.4, 40])$

Table 6. Fuzzy variable of Sleeping Hour (in hour per day) INPUT Factor

Fuzzy Sets of Sleeping Hour	Expected Range	Membership Function
Very Low (VL)	Below 4	$sigmf(x; [-1.5, 4])$
Low (L)	4-6	$gaussmf(x; [1.5, 5])$
Normal (N)	6.5-8	$gaussmf(x; [1.5, 7])$
High (H)	Above 8	$sigmf(x; [1.5,8])$

Table 7. Fuzzy variable of Stress Level INPUT Factor

Fuzzy Sets of Stress Level	Expected Range	Membership Function
Low (L)	Below 7	$sigmf(x; [-1, 7])$
Moderate (M)	6-16	$gaussmf(x; [4.5, 10])$
Active (A)	15-20	$gaussmf(x; [4.5, 17])$
Hyperactive (H)	Above 20	$sigmf(x; [1, 20])$

Table 8. Fuzzy variable of Sensitivity to Medical Examination (measured in Days) INPUT Factor

Fuzzy Sets of Sensitivity to Medical Examination	Expected Range	Membership Function
Weekly (W)	Below 7	$sigmf(x; [-0.5, 7])$
Fortnightly (F)	6-16	$gaussmf(x; [5, 11])$
Monthly (M)	15-30	$gaussmf(x; [5, 22.5])$
Half-Yearly (H)	28-180	$gaussmf(x; [50, 104])$
Yearly (Y)	Above 180	$sigmf(x; [0.1, 180])$

Table 9. Fuzzy variable of Physical Exercise INPUT Factor

Fuzzy Sets of Physical Exercise	Expected Range	Membership Function
Little Effective (LE)	Below 10	$sigmf(x; [-0.4, 10])$
Slightly Effective (SE)	8-30	$gaussmf(x; [9, 19])$
Very Effective (VE)	25-50	$gaussmf(x; [9, 37.5])$
Very Very Effective (VVE)	45-70	$gaussmf(x; [9, 57.5])$
Extremely Effective (EE)	Above 65	$sigmf(x; [0.4, 65])$

3.2. Output Variables

The output zone is classified in four different alternative layers such as **Normal, Pre Diabetes, Type-1** and **Type-2** Diabetes.

3.3. Linguistic Strings

According as our input variables, we have built 1000000 linguistic strings to describe the state of the patient using his/her **Age, HBA1c, FBS, PPBS, Obesity, sleeping hours, Stress level, Sensitivity to**

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Medical examination and **Physical Exercise**.
Details of these strings are given in table 10.

Figure1. Graphical Representation of the INPUT factors.

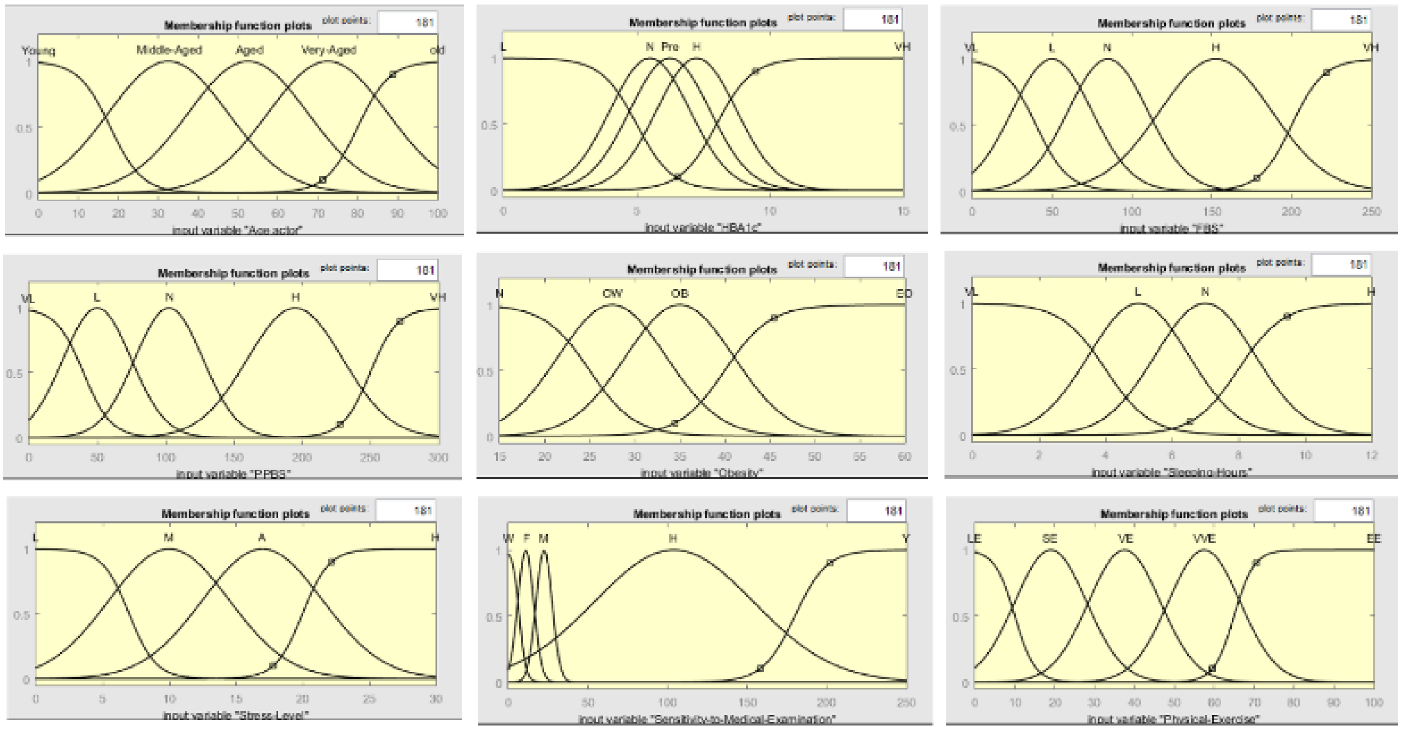

Table 10. List of Generating Linguistic Strings

Weighting Values	W_1 0.0889	W_2 0.2	W_3 0.1778	W_4 0.1111	W_5 0.1556	W_6 0.0667	W_7 0.0444	W_8 0.0222	W_9 0.1333
String No.	Age	HBA1c	FBS	PPBS	Obesity	Slp. Hr.	Stress Lvl.	Sen. Med Exam	Phy. Exr.
J_1	Y	L	VL	VL	N	VL	L	W	LE
J_2	MA	L	VL	VL	N	VL	L	W	LE
J_3	A	L	VL	VL	N	VL	L	W	LE
J_4	VA	L	VL	VL	N	VL	L	W	LE
J_5	O	L	VL	VL	N	VL	L	W	LE
J_6	Y	N	VL	VL	N	VL	L	F	LE
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
J_{40001}	Y	L	VL	VL	N	VL	L	F	LE
J_{40002}	MA	L	VL	VL	N	VL	L	F	LE
J_{40003}	A	L	VL	VL	N	VL	L	F	LE
J_{40004}	VA	L	VL	VL	N	VL	L	F	LE
J_{40005}	O	L	VL	VL	N	VL	L	F	LE
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
J_{999996}	Y	VH	VH	VH	EO	H	HA	Y	EE
J_{999997}	MA	VH	VH	VH	EO	H	HA	Y	EE
J_{999998}	A	VH	VH	VH	EO	H	HA	Y	EE
J_{999999}	VA	VH	VH	VH	EO	H	HA	Y	EE
$J_{1000000}$	O	VH	VH	VH	EO	H	HA	Y	EE

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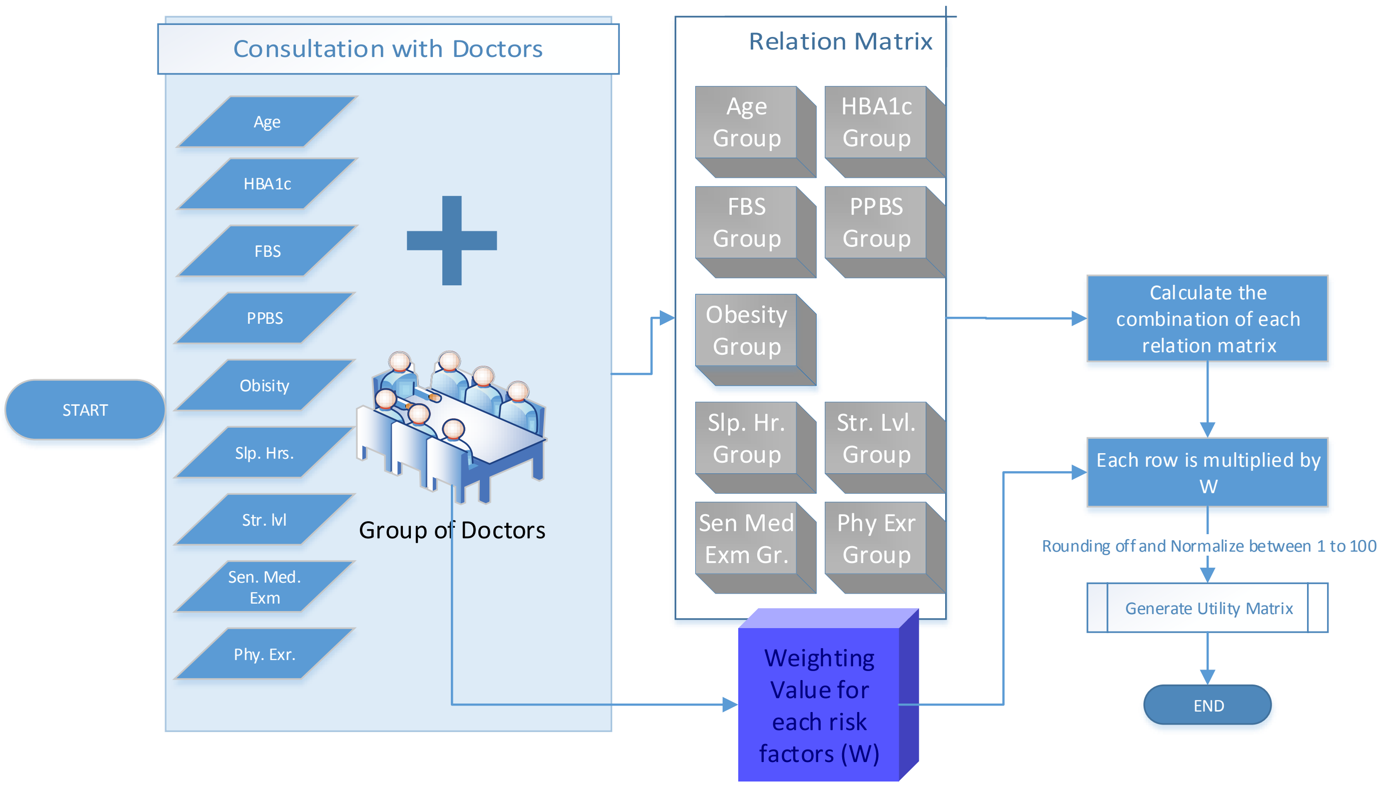
Table 11. Relation Matrix for 9 risk factors

	Age Group					HBA1c Group					FBS Group				
Types	Y	MA	A	VA	O	L	N	Pre	H	VH	VL	L	N	H	VH
Normal	5	4	3	2	1	3	5	4	2	1	2	3	5	2	1
Pre-Diabetes	2	3	5	3	2	1	2	5	3	2	1	2	4	5	4
Type 1	4	3	2	2	1	1	2	4	4	5	1	2	3	4	5
Type 2	1	2	3	4	5	1	2	3	4	5	1	2	4	4	5

	PPBS Group					Obesity Group				Slp. Hrs. Group			
	VL	L	N	H	VH	N	OW	OB	EO	VL	L	N	H
Normal	2	3	5	2	1	5	3	2	1	4	3	5	2
Pre-Diabetes	1	2	4	5	4	3	4	5	4	1	2	3	4
Type 1	1	2	4	4	5	4	4	3	2	2	3	4	3
Type 2	1	2	3	4	5	2	3	4	5	1	2	3	5

	Stress lvl. Group				Sen. Med. Exam. Group					Physical Exr. Group				
	L	M	A	HA	W	F	M	H	Y	LE	SE	VE	VVE	EE
Normal	5	4	2	1	5	4	3	2	1	1	2	3	4	5
Pre-Diabetes	2	3	5	4	2	3	4	4	5	4	3	2	1	1
Type 1	4	4	3	2	3	4	5	4	3	1	1	2	3	5
Type 2	1	3	4	5	1	2	3	4	5	5	4	3	2	1

Flow Chart 1. Process for generating Utility Matrix (U)



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3.4. Generating the Utility Matrix

In our algorithm the above linguistic strings ($J_{i'}s, i = 1, 2, \cdots, 1000000$) are used to represent the every possible the state of patients. Using these linguistic strings and with the help of medical experts, we have constructed the utility matrix U of order 4×1000000. Through the consultations of various medical experts, we have built 9 relation matrices for 9 input risk factors respectively which has been shown in table 11. Here we have taken the rating criteria between 1 to 5 where 5 is max rating and 1 is min rating. If the medical experts are fully satisfied with 'criteria' and 'type' of each group then he/she has rated 5; if fully unsatisfied then rated 1. As an example, if it has considered "HBA1c Group" with criteria 'N' and type 'Pre-Diabetes' then according to medical experts this situation has been rated '2'. Similarly, for "FBS Group" with criteria 'L' and type 'Normal' has been rated '3'.

According to the importance of the input risk factors for diabetic diagnosis with the help of medical experts, we have built the weighting vector. So, among 9 input risk factor highest important risk factor has rated '9' and lowest important risk factor has rated '1'.

Using the knowledge of medical experts rating vector for 9 input risk factors is [4, 9, 8, 5, 7, 3, 2, 1, 6]. Creating the weighting vector through the rating of input risk factors [4, 9, 8, 5, 7, 3, 2, 1, 6], used MATLAB 2018b inbuilt function "*normalize ()*" with norm 1. So, the weighting vector of input variables is [0.0889, 0.2000, 0.1778, 0.1111, 0.1556, 0.0667, 0.0444, 0.0222, and 0.1333] (shown in table 10).

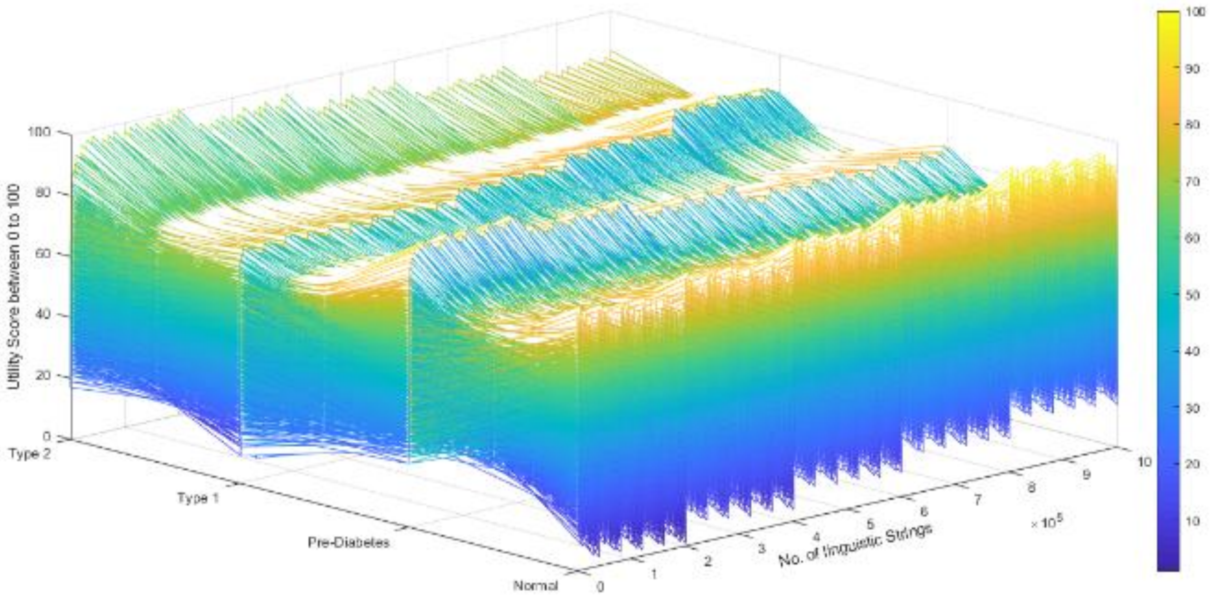
According to the medical experts the weighting criteria for the 9 input risk factors is $W = [0.0889, 0.2, 0.1778, 0.1111, 0.1556, 0.0667, 0.0444, 0.0222, 0.1333]$ respectively.

With help of above flow chart 1, we have built the utility matrix (U) of order 4×1000000, which has been shown in Table 11 and figure 2 has been shown the variation of the utility data for each output factors.

3.5. Methodology

Now with the help of the above linguistic strings (table 10) and the utility matrix (table 11) and using [16], we have developed the algorithm that has been shown in the following flowchart 2 and algorithm 1.

Figure 2. Utility Data of various output layers



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Algorithm 1. Soft Computing Information System for Diabetes Detection

INPUT:
1. Values of Age, HBA1c, FBS, PPBS, Obesity, Sleeping Hour, Stress Level, Sensitivity of Medical Examination, Time of Physical Exercise
2. According to the medical expert utility values for each linguistic Strings.

OUTPUT: Stages of the Diabetes.

METHODOLOGY

1: Construct Fuzzy Sets of each Input Variables

a) For Age	b) For HBA1c	⋯	i) For Physical Exercise
$\begin{bmatrix} Y \\ MA \\ A \\ VA \\ O \end{bmatrix} = \begin{bmatrix} sigmf(x;[-0.25,18]) \\ gaussmf(x;[15,32.5]) \\ gaussmf(x;[15,52.5]) \\ gaussmf(x;[15,72.5]) \\ sigmf(x;[0.25,80]) \end{bmatrix}$	$\begin{bmatrix} L \\ N \\ Pre \\ H \\ VH \end{bmatrix} = \begin{bmatrix} sigmf(x;[-1.5,5]) \\ gaussmf(x;[1.5,5.5]) \\ gaussmf(x;[1.5,6.25]) \\ gaussmf(x;[1.5,7.25]) \\ sigmf(x;[1.5,8]) \end{bmatrix}$	⋯	$\begin{bmatrix} LE \\ SE \\ VE \\ VVE \\ EE \end{bmatrix} = \begin{bmatrix} sigmf(x;[-0.4,10]) \\ gaussmf(x;[9,19]) \\ gaussmf(x;[9,37.5]) \\ gaussmf(x;[9,57.5]) \\ sigmf(x;[0.4,65]) \end{bmatrix}$

2: Find the state of Patient in from of fuzzy sets

a) $[M_V]_{9\times1000000} = Combination\left\{\begin{pmatrix} Y \\ MA \\ A \\ VA \\ O \end{pmatrix}, \begin{pmatrix} L \\ N \\ Pre \\ H \\ VH \end{pmatrix}, \begin{pmatrix} VL \\ L \\ N \\ H \\ VH \end{pmatrix}, \begin{pmatrix} VL \\ L \\ N \\ H \\ VH \end{pmatrix}, \begin{pmatrix} N \\ OW \\ OB \\ EO \end{pmatrix}, \begin{pmatrix} VL \\ L \\ N \\ H \end{pmatrix}, \begin{pmatrix} L \\ M \\ A \\ H \end{pmatrix}, \begin{pmatrix} W \\ F \\ M \\ H \\ Y \end{pmatrix}, \begin{pmatrix} LE \\ SE \\ VE \\ VVE \\ EE \end{pmatrix}\right\}$

b) $C = {M_V}^T . W^T$

c) State of the Patient $= C$

3: Utility Matrix $\boldsymbol{U} = (\boldsymbol{INPUT\ 2})_{\boldsymbol{Output\ Layer} \times \boldsymbol{length}(M_V)}$ **i.e.** $\begin{bmatrix} \boldsymbol{Normal(U_1)} \\ \boldsymbol{Pre\ Diabetes(U_2)} \\ \boldsymbol{Type\ 1(U_3)} \\ \boldsymbol{Type\ 2(U_4)} \end{bmatrix} = (\boldsymbol{U})_{\boldsymbol{4} \times \boldsymbol{length}(M_V)}$

4: Using Decision Making Algorithm on A and U

a) $U_{Max} = Max(U)$

b) $U_i^f = C, i = 1,2,3,4$

c) $U_{im}^f = \frac{U_i^f}{U_{Max}}, i = 1,2,3,4$

d) $U_{i0}^f = Min\{U_i^f, U_{im}^f\}, i = 1,2,3,4$

5: $\boldsymbol{Normal = Max\{U_{10}^f\}, Pre\ Diabetes = Max\{U_{20}^f\}, Type\ 1 = Max\{U_{30}^f\}, Type\ 2 = Max\{U_{40}^f\}}$

6: OUTPUT=$\boldsymbol{Max\{Normal,\ Pre\ Diabetes, Type\ 1, Type\ 2\}}$

IV. EXPERIMENTAL RESULTS

For evolution the performance of the output variables of the proposed information system for diabetic diagnostic, it has been investigated through two experimental results. The used data of these experiments are collected from the local health center "**Narayani Asram Hospital**".

4.1. Experiment 1:

The input variables are:

Age=63 yrs, HBA1c=6.8, FBS=119, PPBS=152, Obesity=24.2, Sleeping hours=7, Stress level=12, Sensitivity to Medical examination=120 days and Physical Exercise=30 min.

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Flow Chart 2. Process for Diabetes diagnostic System

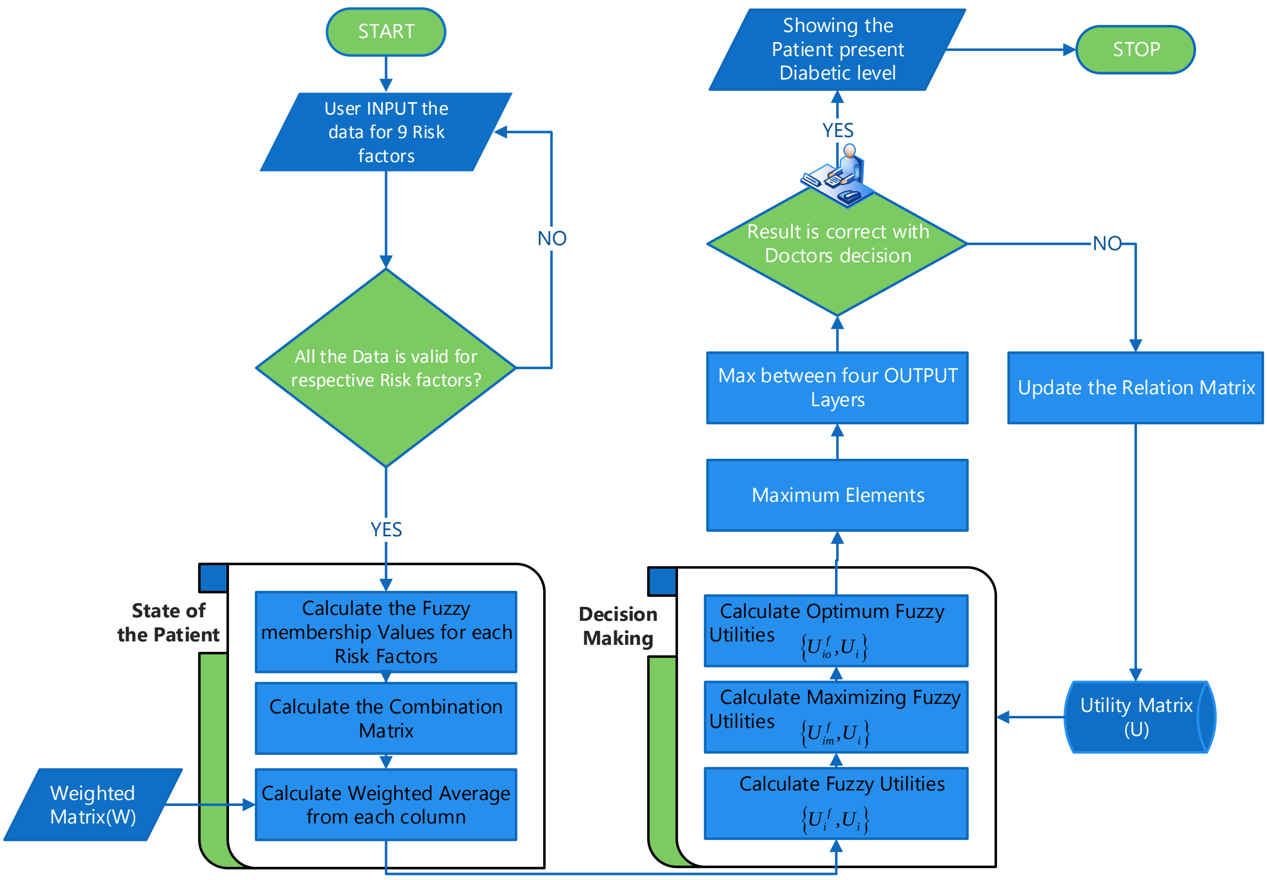

Table 12. Fuzzy sets for the input variables of Experiment 1

INPUT VARIABLE	Corresponding Fuzzy Sets				
Age (63 yrs)	$\frac{Y}{0}$	$\frac{MA}{0.1265}$	$\frac{A}{0.7827}$	$\frac{VA}{0.8183}$	$\frac{O}{0.0141}$
HBA1c (6.8)	$\frac{L}{0.0630}$	$\frac{N}{0.6869}$	$\frac{Pre}{0.9350}$	$\frac{H}{0.9560}$	$\frac{VH}{0.1419}$
FBS (119)	$\frac{VL}{0.0004}$	$\frac{L}{0.0222}$	$\frac{N}{0.3966}$	$\frac{H}{0.6325}$	$\frac{VH}{0.0003}$
PPBS (152)	$\frac{VL}{0}$	$\frac{L}{0.0002}$	$\frac{N}{0.1408}$	$\frac{H}{0.4702}$	$\frac{VH}{0.0001}$
Obesity (24.2)	$\frac{N}{0.5793}$	$\frac{OW}{0.8596}$	$\frac{OB}{0.1979}$	$\frac{EO}{0.0018}$	
Sleeping Hours (7)	$\frac{VL}{0.0110}$	$\frac{L}{0.4111}$	$\frac{N}{1}$	$\frac{H}{1824}$	
Stress Level (12)	$\frac{L}{0.0067}$	$\frac{M}{0.9060}$	$\frac{A}{0.5394}$	$\frac{H}{0.0003}$	
Sensitivity to Med. Exam. (120)	$\frac{W}{0}$	$\frac{F}{0}$	$\frac{M}{0}$	$\frac{H}{0.9501}$	$\frac{Y}{0.0025}$
Physical Exercise (30 mints)	$\frac{LE}{0.0003}$	$\frac{SE}{0.4738}$	$\frac{VE}{0.7066}$	$\frac{VVE}{0.0094}$	$\frac{EE}{0}$

The state of patient in from of fuzzy set is shown in table 13.

For finding the output result of different optimal alternative layers, in 1st step we determine fuzzy utilities $\{(U_i^f, U_i)\}$ associated to each alternative i .In 2nd step ,for finding maximizing fuzzy utility sets $\{(U_{im}^f, U_i)\}$ where $U_{im}^f = \frac{U_i}{Max\{U_1 \cup U_2 \cup U_3 \cup U_4\}}$,for each alternative i and in 3rd step, we calculate optimal fuzzy utility sets $\{(U_{io}^f, U_i)\}$ where $U_{io}^f = U_i^f \wedge U_{im}^f$ and at last for optimal alternative solution(A_O) we calculate $max\{U_{io}^f\}$ for each alternative i.

The details of each step have been shown in table 14. The decision making process yields an alternative optimal(A_O)that provides various phases of diabetes:

Normal= $\boldsymbol{Max\{U_{1O}^f\} = 0.7019,}$

$\boldsymbol{Pre\ Diabetes = Max\{U_{2O}^f\} = 0.7772,}$

$\boldsymbol{Type\ 1 = Max\{U_{3O}^f\} = 0.6904,}$

$\boldsymbol{Type\ 2 = Max\{U_{4O}^f\} = 0.7013.}$

From the above decision layer, it is clearly indicated that Experiment 1 patient is having a close possibility of **Pre-Diabetes.**

4.2. Experiment 2:

Age=36 yrs, HBA1c=8.9, FBS=220, PPBS=350, Obesity=20.3, Sleeping hours=7, Stress level=22, Sensitivity to Medical examination=90 days and Physical Exercise=20 min.

Applying same procedure as above, alternative optimal (A_o) that provides different phases of diabetes: **Normal= 0.6400, Pre-Diabetes= 0.7377, Type 1= 0.7752, Type 2= 0.8100.**

From the above decision layer, it is clearly indicated that Experiment 2 patient is having a close possibility of **Type-2**.

Table 13. Fuzzy set of the state of the Experiment 1 patient

i	1	2	3	⋯	500000	500001	500002	⋯	999998	999999	1000000
$\mu(j_i)$	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422

Table 14. Calculation for Decision Making Algorithm of Experiment 1 patient

i	1	2	3	⋯	500000	500001	500002	⋯	999998	999999	1000000
U_1	53	51	49	⋯	12	55	53	⋯	19	17	14
U_1^f	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_{1m}^f	0.5300	0.5100	0.4900	⋯	0.1200	0.5500	0.5300	⋯	0.1900	0.1700	0.1400
U_{1o}^f	0.1039	0.1151	0.1735	⋯	0.1200	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_2	21	23	28	⋯	52	19	21	⋯	57	53	51
U_2^f	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_{2m}^f	0.2100	0.2300	0.2800	⋯	0.5200	0.1900	0.2100	⋯	0.5700	0.5300	0.5100
U_{2o}^f	0.1039	0.1151	0.1735	⋯	0.1765	0.1900	0.2100	⋯	0.1105	0.1137	0.0422
U_3	24	22	19	⋯	65	27	25	⋯	74	74	71
U_3^f	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_{3m}^f	0.2400	0.2200	0.1900	⋯	0.6500	0.2700	0.2500	⋯	0.7400	0.7400	0.7100
U_{3o}^f	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_4	17	19	21	⋯	90	14	17	⋯	82	84	87
U_4^f	0.1039	0.1151	0.1735	⋯	0.1765	0.2217	0.2329	⋯	0.1105	0.1137	0.0422
U_{4m}^f	0.1700	0.1900	0.2100	⋯	0.9000	0.1400	0.1700	⋯	0.8200	0.8400	0.8700
U_{4o}^f	0.1039	0.1151	0.1735	⋯	0.1765	0.1400	0.1700	⋯	0.1105	0.1137	0.0422

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V. Results and Analysis

In this section we have discussed about the sensitivity of the input risk factors of a respective patient. For small changes of the input risk how much effects the diabetic condition will be discussed here.

First, we consider the Experiment 1 and 2 patient, according to the given input of the respective patients, we have predict that the patients are in **Pre-Diabetic** and **Type 2** condition respectively.

But from the figure 3 we have seen that when the patients age increases then Normal values decrease and Type 2 values are increased. Pre-Diabetes value and Type 1 varies but does not affect so much.

So, we decide that Age factor is more sensitive for Normal and Type 2 diabetic Phase than Pre-Diabetes and Type 1 Phase.
Similarly, in figure 4. If we change the physical exercise times we can see that when the time increases the chances of Normal increases and Pre-Diabetic and Type 2 decreases but Type 1 increases, so Physical Exercises does not affect so much for Type 1 diabetic patients.

Similarly, by changing the values of other risk factors we can decide which risk factor is more sensitive for which type of Diabetic patients.
In figure 5,it is shown that if change HBA1c and Obesity values together then what are the behaviors of the output layers for Experimental 1 patient.

Similarly, if it take Experimental 2 patient, and changing the only values of HBA1c and FBS risk factors when other 7 risk factors are till constant then how the four output variables behave are shown in figure 6.

In figure 7. It is shown that how the output layers changes by changing the HBA1c and Obesity values for Case 1 and HBA1c and FBS for Experiment 2 patient.

Figure 3. Changes the Age Input factor for Experiment 1 and 2 Patients

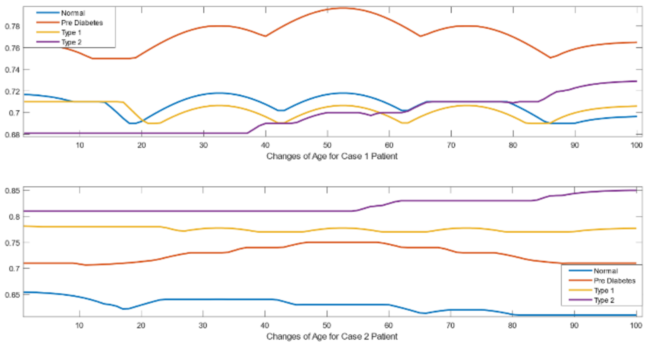
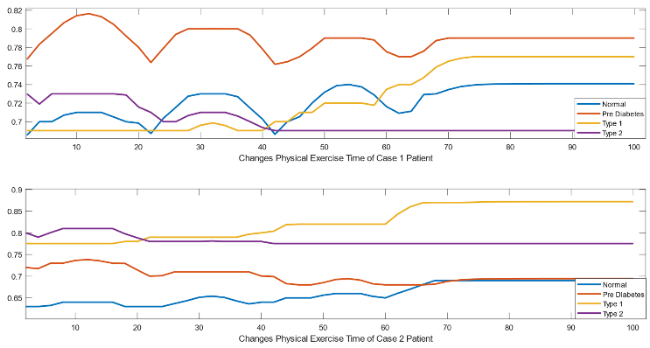


Figure 4. Changes the Physical Exercise Inputfactor for Experiment 1 and 2 Patients



VI. Conclusion

The proposed system will help the patient in adopting proper strategy to evaluate his present sugar level and follow a balanced life style on the other hand it will provide a quantitative base to medical experts in detecting the disease and suggesting proper action to the patients.

This intelligent information system will helpful for design a software that will work as a referral system in between patients and medical experts and it will be beneficial for the patients.

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Figure 5. Changing HBA1c vs. Changing Obesity values of Experimental 1 Patient

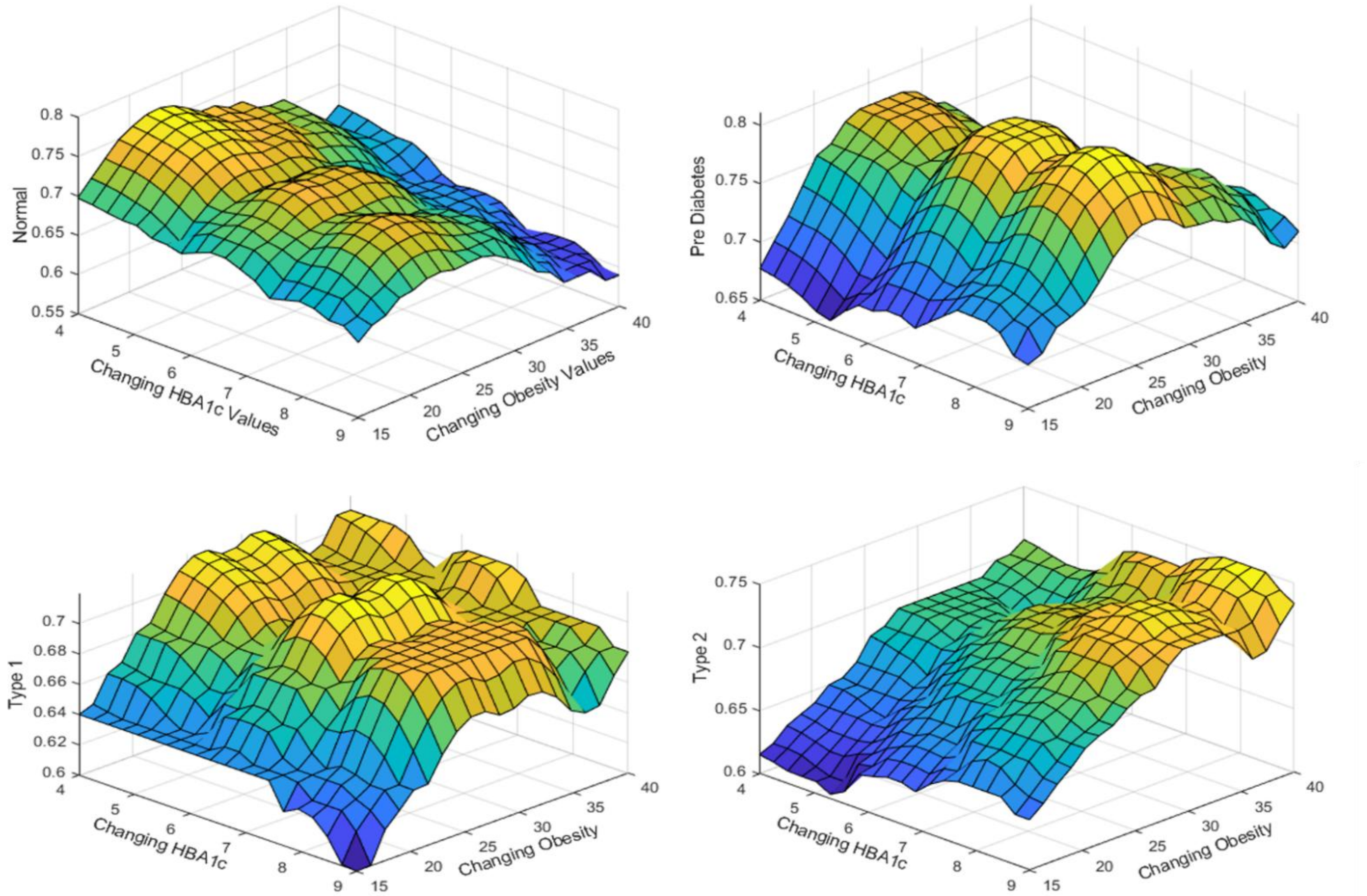


Figure 6. Changing HBA1c vs Changing FBS values of Case 2 Patient

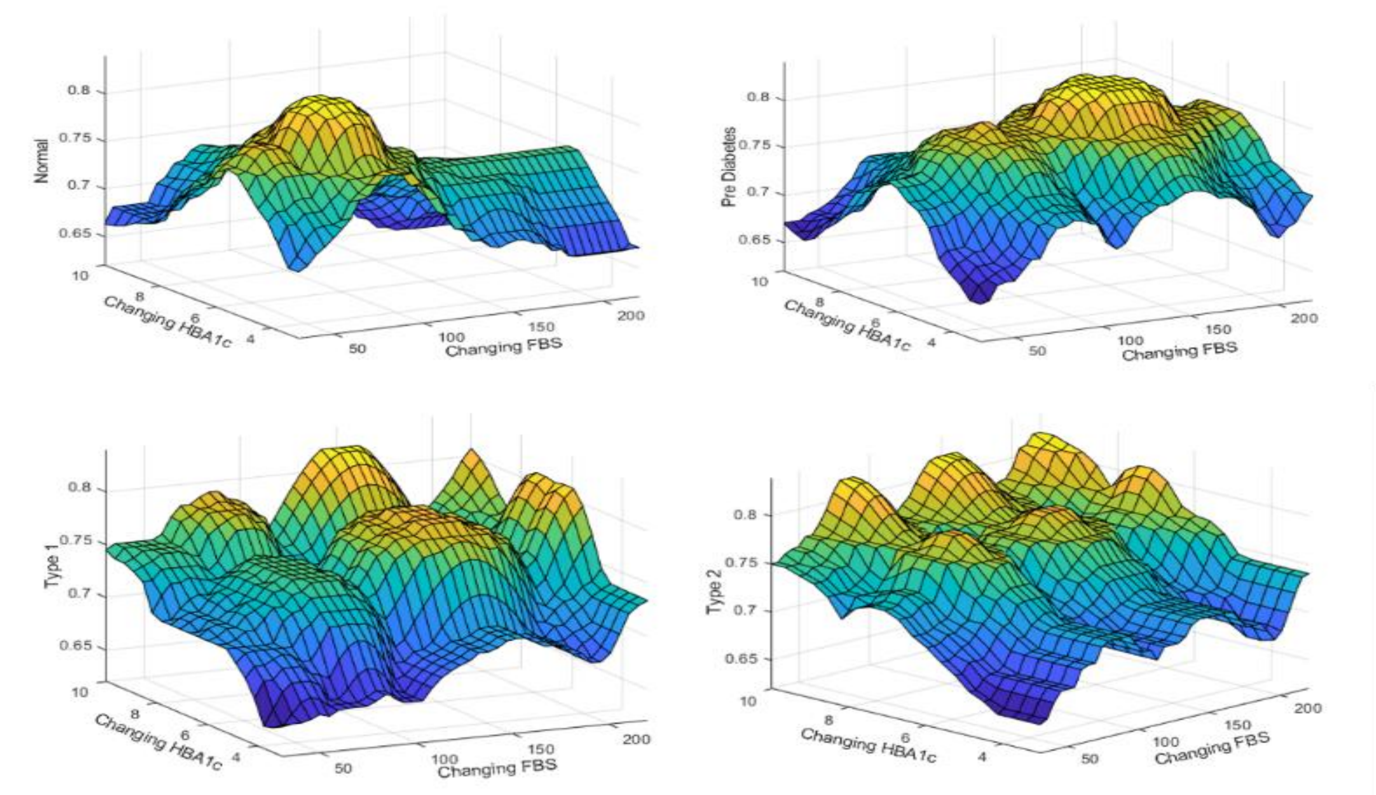
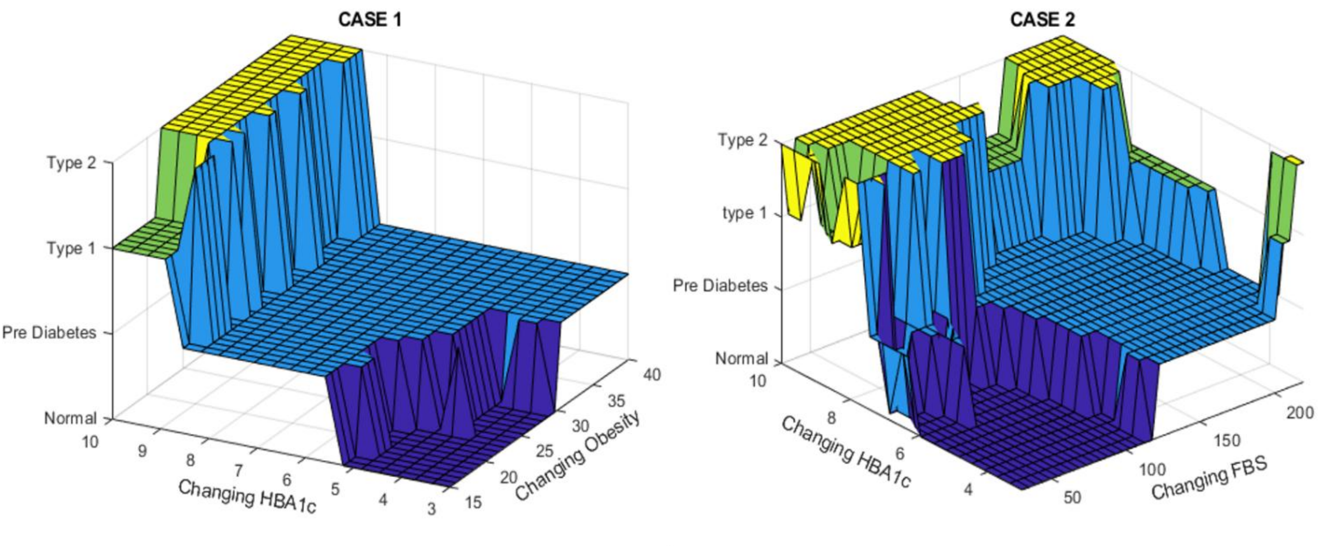


Figure 7. Changes output layers by changing two Risk Factors



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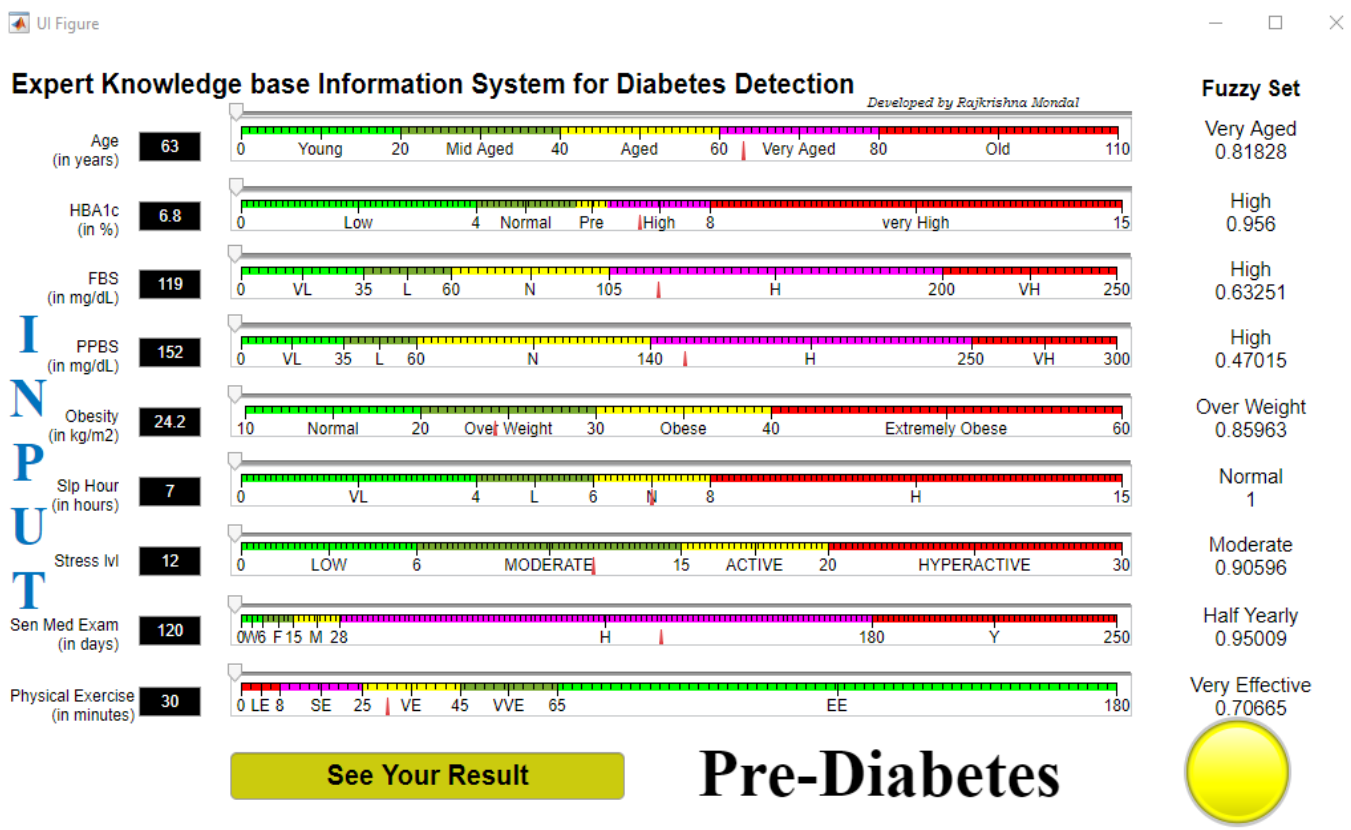
APPENDIX

Screenshot of the Application which is build by MATLAB App Designer



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