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Fuzzy inference systems for predicting and evaluating diabetes likelihood and severity

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Abstract
Since the prevalence of diabetes continues to increase across the globe, there exists an increased demand of accurate and convenient methods of predicting and determining the severity of this chronic illness. This analysis explores why Fuzzy inference system (FIS) is such an informative and flexible tool that can be used to predict and determine the seriousness of diabetes. The standards of fuzzy rationale are employed by FIS to prove the innate susceptibility and laxity of clinical data pertaining to diabetes. The research starts with the establishment of a complete dataset comprising of the relevant clinical variables such as the level of blood glucose, age and body mass index (BMI). Then a predictive model is developed using FIS which considers the complex relationships between these variables. The functioning of the membership and fuzzy rules have been well structured to replicate the knowledge of a professional medical worker in finding out the chances of having diabetes and the severity. The suggested FIS model is comprehensive in its approval using verifiable clinical data on a variety of patient groups. The analysis of the displayed model is conducted on the bases of awareness, specificity, and, to a greater extent, accuracy in the prediction of the seriousness of diabetes. The shortcomings and advantages of the FIS approach are also characterized by near investigations using existing analytic strategies. FIS model is also expanded to analyze the efficiency of different treatment choices to decrease the severity of diabetes. The FIS demonstrates its real potential as a choice help device when it comes to making medical care specialists fit customized therapy plans by consolidating the dynamic sources of data and changing according to the changing circumstances of the patients. The post-exploration consequences contribute to the emerging collection of writing on shrewd frameworks of diabetes the board. FIS is an encouraging instrument of forecasting and assessing the level of diabetes because of its flexibility and deciphering, which will lead to a more accurate and tailored treatment in the global struggle against the health problem.

Keywords: Fuzzy inference system, Body mass index, interpretability, clinical boundaries

Introduction
Diabetes mellitus, a complicated metabolic issue characterized by increased levels of glucose in the blood is an enormous and emerging health care issue in the world. The varied concept of diabetes demands extensive and accurate symptomatic and prognostic equipment to guide clinicians evaluate its severity and initiate potent treatment regimens. Recently, foreseeing and evaluating the gravity of diabetes via Fuzzy inference system (FIS) has emerged as a promising direction to follow, to provide a subtle methodology to address the inherent weaknesses and inaccuracies of clinical data. Fuzzy rationale is excited by human dynamic cycles which often involve obscure or equivocal data that provide a framework of showing the complicated relationships using phonetic factors and the principle of fuzziness. FIS is especially well-adapted to the use in the area of healthcare since it can be applied to develop intelligent systems, which could capture the complexities and peculiarities inherent in the medical diagnosis. The commonly applied demonstrative methods of surveying diabetes severity often rely on the limit based methodology that might fail to adequately encompass the variability of the consistent information and the interaction of a vast number of influencing variables. FIS, in its turn, manages to address the uncertainties, and this is why it is a powerful tool to decipher the multifaceted relationships between clinical limits such as blood glucose levels, HbA1c values, and weight file (BMI) and the severity of diabetes.

Mansourypoor and Asadi (2017) [6] developed a determination framework of diabetes mellitus using a support learning based transformative fuzzy rule- based framework. Birjais *et al*. (2019) [5] have tried to focus more on the diagnosis of diabetes that is one of the chronic diseases increasing at an alarming rate globally as per world health organization in 2014. Naz and Ahuja (2020) [7] examined the different machine learning methods of classification in a bid to predict diabetes. ANN, NB, DT and deep learning (DL) were compared. Pradhan *et al*. (It was proposed to detect diabetic patients with a model based on artificial neural networks (ANNs) in 2020) to detect them. The functioning of the proposed model was tested with the assistance of Pima Indian Diabetes (PID) dataset. The article by Tigga and Grag (2020) [10] developed an algorithm to categorize type 2 diabetes through machine learning. The model was oriented to the achievement of the gamble of diabetes in the minds of individuals in regards to their lifestyle and family background. In order to spearhead the study, an on the web and disconnected based poll was conducted to obtain 952 instances of diabetes.

The Akpado *et al*. (2021) [3] developed a model of a fuzzy logic-driven expert system that would be used in diabetes type 2 diagnosis. The developed expert system contained the four steps of Mamdani fuzzy inference system namely fuzzification, rule evaluation, output aggregation and difuzzification. Arora *et al*. (2021) [4] suggested the use of fuzzy-based system to predict Covid-19 is rooted in the symptoms and the parameters of an individual. It receives input limits such as fever, hack, breathing difficulty, muscle sore, sore throat, traveling history, age and clinical history in the form of different enrollments works and generates one output which estimates the possibility of an individual being infected with coronavirus using Mamdani fuzzy inference framework.

Aamir *et al*. (2021) [1] applied fuzzy rationale to foster an interpretable model and to play out an early determination of diabetes. Fuzzy rationale has been joined with the cosine plentifulness strategy and two fuzzy classifiers have been built. Thakkar *et al*. (2021) [9] proposed a method that provides a pipeline of various tasks, such as selecting the dataset and preprocessing the data using standardization, normalization, and other techniques.

Aggarwal *et al*. (2022) [2] proposed a coronavirus risk expectation model for diabetic patients utilizing a fuzzy surmising framework and AI draws near. Their study sought to estimate the level of COVID-19 risk in diabetic patients who did not receive prompt medical advice and overcome the multifold COVID-19 mortality rate in diabetic patients. In this review study, Yazdani *et al*. Machine learning (ML) methods were developed and validated using the data of 784 elderly people in 2023 [11].

In this paper, we dig into the development and approval of a FIS model for diabetes seriousness expectation. We examine the choice of significant clinical boundaries, the plan of fuzzy guidelines, and the foundation of participation capabilities to catch the innate vulnerability in clinical information. In addition, we investigate the potential of FIS for assessing the impact of various treatment strategies on diabetes severity, contributing to ongoing efforts to improve diabetes care's precision and individualization.

2. Membership Plot Functions of Input and Output Variables

By defining how input values relate to fuzzy sets and, consequently, how these fuzzy sets contribute to the overall fuzzy logic model, membership functions play a crucial role in Fuzzy Inference Systems (FIS). A participation plot outwardly addresses these capabilities and gives bits of knowledge into the fuzzy rationale framework's way of behaving.

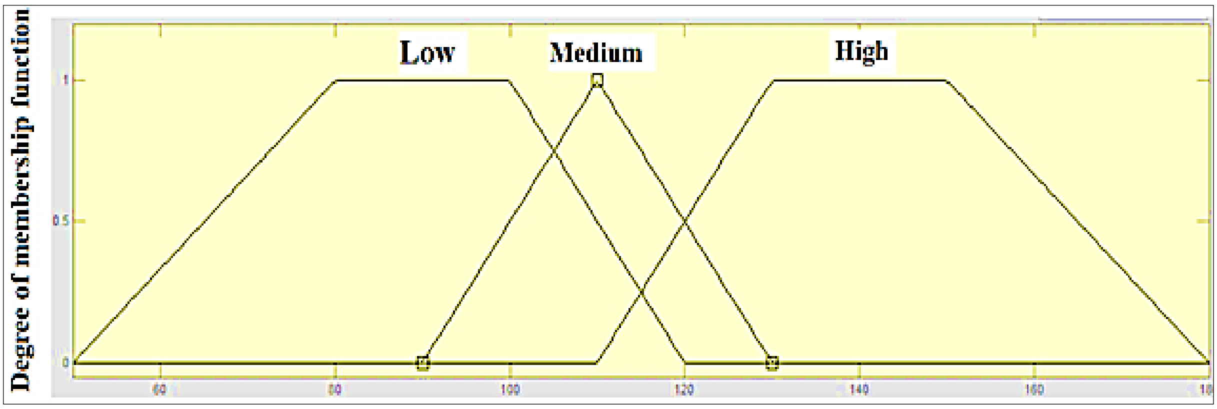


Fig 1: Membership function plot of blood glucose level (Input variable '1')

$$\mu_{low}(x) = \begin{cases} \frac{x-50}{30} & 50 \le x \le 80 \\ 1 & 80 \le x \le 100 \\ \frac{120-x}{20} & 100 \le x \le 120 \end{cases} \qquad (1)$$

$$\mu_{medium}(x) = \begin{cases} \frac{x-90}{20} & 90 \le x \le 110 \\ \frac{130-x}{20} & 110 \le x \le 130 \end{cases} \qquad (2)$$

$$\mu_{high}(x) = \begin{cases} \frac{x-110}{20} & 110 \le x \le 130 \\ 1 & 130 \le x \le 150 \\ \frac{180-x}{30} & 150 \le x \le 180 \end{cases} \qquad (3)$$

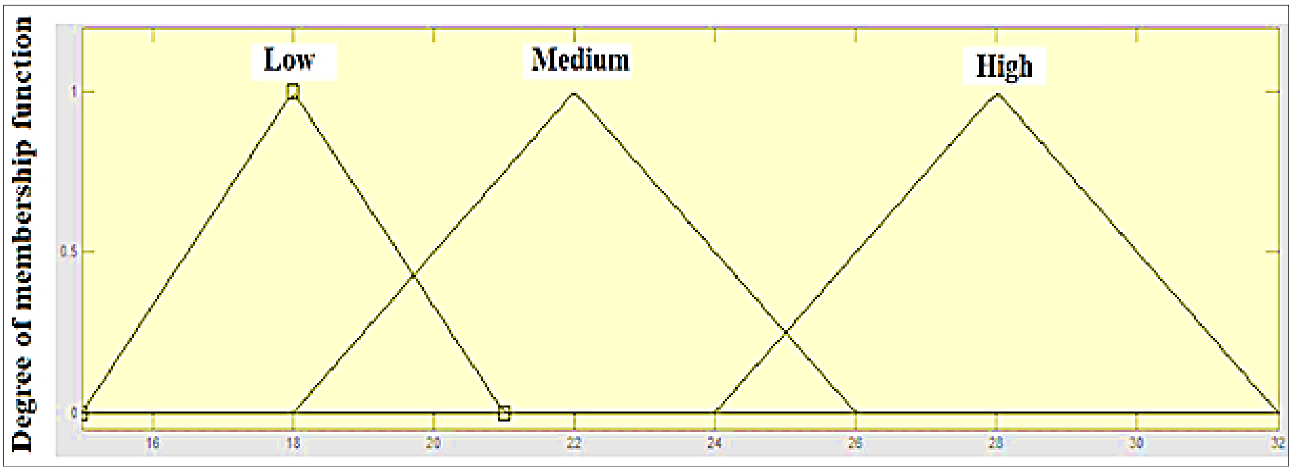


Fig 2: Membership function plot of body mass index (Input variable '2')

$$\mu_{low}(y) = \begin{Bmatrix} \frac{y-15}{20} & 15 \le y \le 18 \\ \frac{21-y}{20} & 22 \le y \le 21 \end{Bmatrix} \tag{4}$$

$$\mu_{medium}(y) = \begin{Bmatrix} \frac{y-18}{4} & 18 \le y \le 22 \\ \frac{26-y}{4} & 22 \le y \le 26 \end{Bmatrix} \tag{5}$$

$$\mu_{high}(x) = \begin{Bmatrix} \frac{y-24}{4} & 24 \le y \le 28 \\ \frac{32-y}{4} & 28 \le y \le 32 \end{Bmatrix} \tag{6}$$

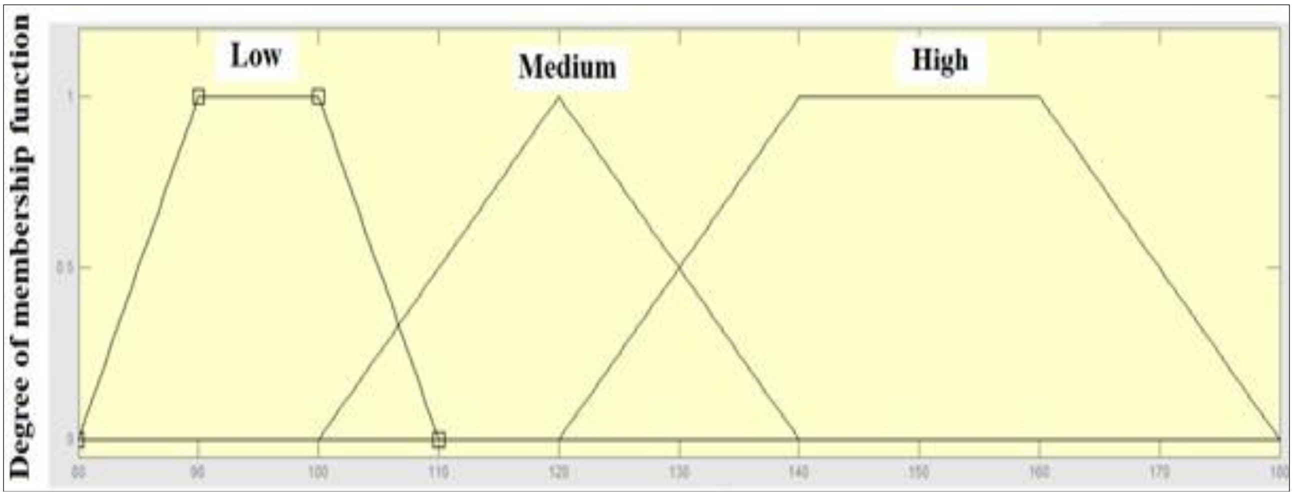


Fig 3: Membership function plot of blood pressure (Input variable '3')

$$\mu_{low}(z) = \begin{Bmatrix} \frac{z-80}{10} & 80 \le z \le 90 \\ 1 & 90 \le z \le 100 \\ \frac{110-z}{10} & 100 \le z \le 110 \end{Bmatrix} \tag{7}$$

$$\mu_{medium}(z) = \begin{Bmatrix} \frac{z-100}{20} & 100 \le z \le 120 \\ \frac{140-z}{20} & 120 \le z \le 140 \end{Bmatrix} \tag{8}$$

$$\mu_{high}(z) = \begin{Bmatrix} \frac{z-120}{20} & 120 \le z \le 140 \\ 1 & 140 \le z \le 160 \\ \frac{180-z}{20} & 160 \le z \le 180 \end{Bmatrix} \tag{9}$$

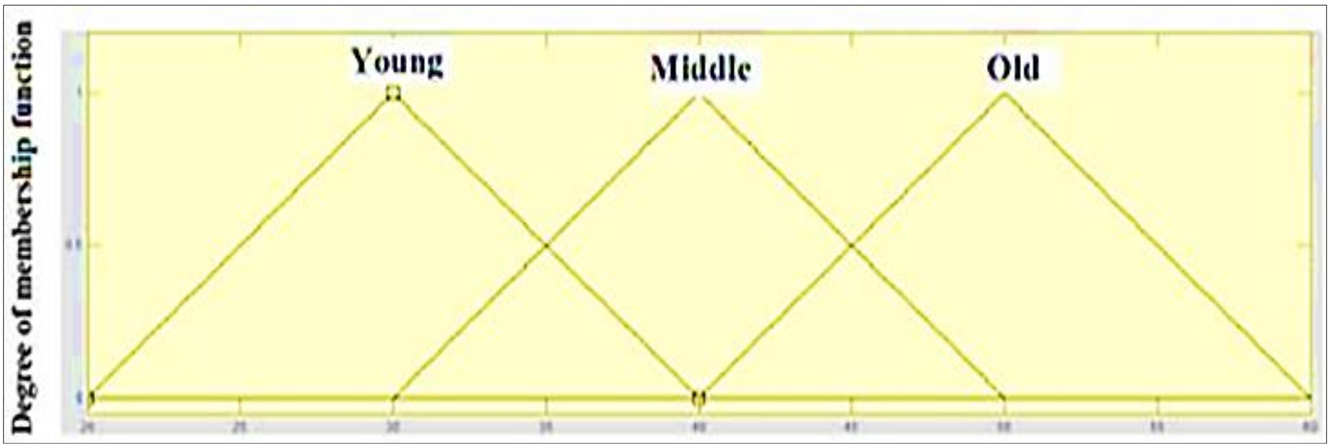


Fig 4: Membership function plot of age (Input variable '4')

$$\mu_{young}(u) = \begin{Bmatrix} \frac{u-20}{10} \; 20 \le u \le 30 \\ \frac{40-u}{10} \; 30 \le u \le 40 \end{Bmatrix} \tag{10}$$

$$\mu_{middle}(u) = \begin{Bmatrix} \frac{u-30}{10} \; 30 \le u \le 40 \\ \frac{50-u}{10} \; 40 \le u \le 50 \end{Bmatrix} \tag{11}$$

$$\mu_{old}(u) = \begin{Bmatrix} \frac{u-40}{10} \; 40 \le u \le 50 \\ \frac{60-u}{10} \; 50 \le u \le 60 \end{Bmatrix} \tag{12}$$

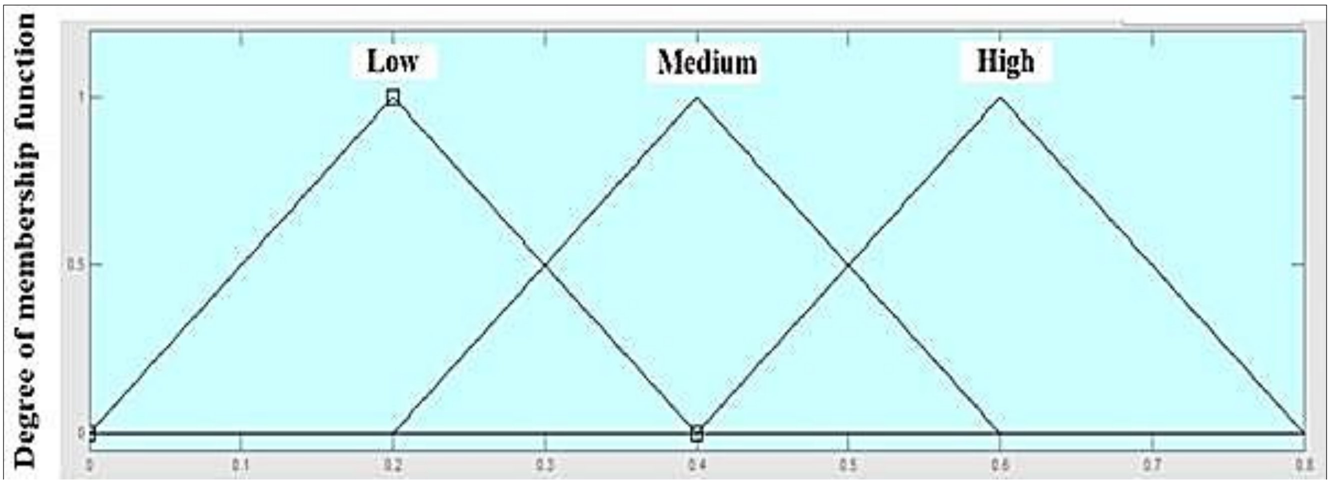


Fig 5: Membership function plot of likelihood of diabetes (Output variable '1')

$$\mu_{low}(v) = \begin{Bmatrix} \frac{v}{0.2} \; 0 \le v \le 0.2 \\ \frac{0.4-v}{0.2} \; 0.2 \le v \le 0.4 \end{Bmatrix} \tag{13}$$

$$\mu_{medium}(v) = \begin{Bmatrix} \frac{v-0.2}{0.2} \; 0.2 \le v \le 0.4 \\ \frac{0.6-v}{0.2} \; 0.4 \le v \le 0.6 \end{Bmatrix} \tag{14}$$

$$\mu_{high}(v) = \begin{Bmatrix} \frac{v-0.4}{0.2} \; 0.4 \le v \le 0.6 \\ \frac{0.8-v}{0.2} \; 0.6 \le v \le 0.8 \end{Bmatrix} \tag{15}$$

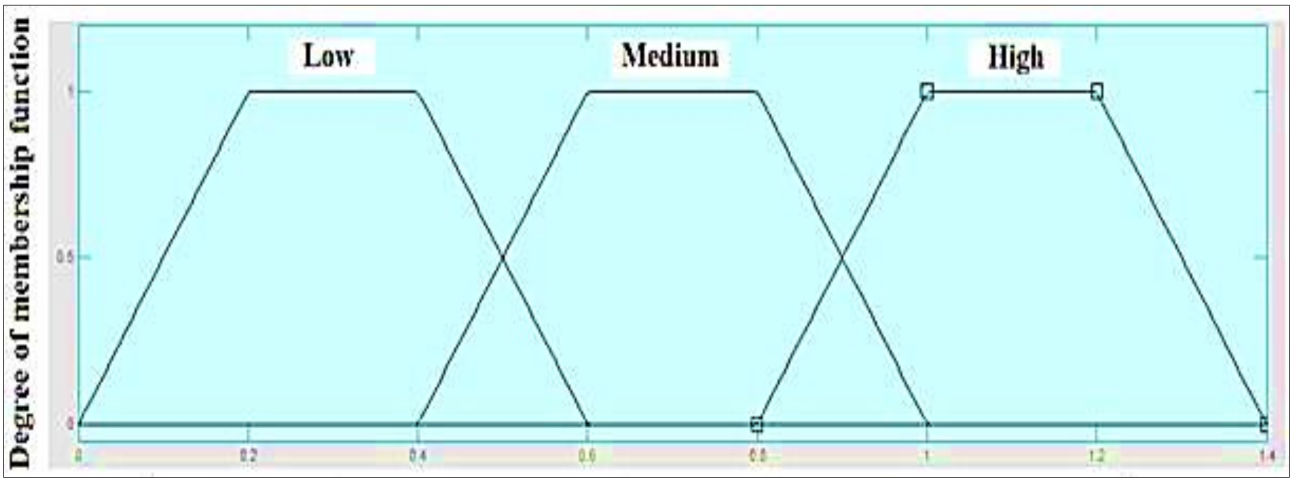


Fig 6: Membership function plot of likelihood of diabetes (Output variable '2')

$$\mu_{low}(w) = \begin{Bmatrix} \frac{w}{0.2} \; 0 \le w \le 0.2 \\ 1 \; 0.2 \le w \le 0.4 \\ \frac{0.6-w}{0.2} \; 0.4 \le w \le 0.4 \end{Bmatrix} \tag{16}$$

$$\mu_{medium}(w) = \begin{Bmatrix} \frac{w-0.4}{0.2} \; 0.4 \le w \le 0.6 \\ 1 \; 0.6 \le w \le 0.8 \\ \frac{1-w}{0.2} \; 0.8 \le w \le 1 \end{Bmatrix} \tag{17}$$

$$\mu_{high}(w) = \begin{Bmatrix} \frac{w-0.6}{0.2} \; 0.6 \le w \le 0.8 \\ 1 \; 0.8 \le w \le 1 \\ \frac{1-w}{0.2} \; 1 \le w \le 1.2 \end{Bmatrix} \tag{18}$$

3. Rule Base

The fundamental elements that establish the relationships between the input variables, fuzzy sets, and the output variable are the rules of a fuzzy inference system (FIS) for predicting and evaluating the severity of diabetes. The system's decision-making logic is defined by these rules, which direct how input data is processed to make accurate predictions.

Table 1: Rules regarding the model

Rules	GL	BMI	Blood Pressure	Age	Likelihood of Diabetes	Severity of Diabetes
1	Low	Low	Low	Young	Low	Low
2	Medium	Medium	Low	Young	Medium	Medium
3	High	High	Low	Young	High	High
4	Low	Low	Medium	Young	Low	Low
5	Medium	Medium	Medium	Young	Medium	Medium
6	High	High	Medium	Young	High	High
7	Low	Low	High	Young	Low	Low
8	Medium	Medium	High	Young	Medium	Medium
9	High	High	High	Young	High	High
10	Low	Low	Medium	Young	Low	Medium
11	High	Low	Medium	Young	High	Medium
12	Low	Medium	Low	Young	Low	Low
13	High	High	High	Young	High	High
14	Low	High	Low	Young	Low	Low
15	Medium	Medium	Medium	Young	Medium	Medium
16	Low	Medium	Medium	Young	Low	Low
17	Medium	Low	High	Young	Medium	Medium
18	High	High	Medium	Young	High	High
19	Medium	Medium	High	Young	Medium	Medium
20	High	Low	High	Young	High	High
21	Low	Low	Low	Middle	Low	Low
22	Medium	Medium	Low	Middle	Medium	Medium
23	High	High	Low	Middle	High	High
24	Low	Low	Medium	Middle	Low	Low
25	Medium	Medium	Medium	Middle	Medium	Medium
26	High	High	Medium	Middle	High	High
27	Medium	Medium	High	Middle	Medium	Medium

28	Low	High	High	Middle	Low	Low
29	High	Low	High	Middle	High	High
30	Medium	High	Medium	Middle	Medium	Medium
31	High	Low	Medium	Middle	High	High
32	Medium	Medium	Low	Middle	Medium	Medium
33	High	High	Low	Middle	High	High
34	Low	Medium	High	Middle	Low	Low
35	High	Low	Medium	Middle	High	High
36	Medium	High	Medium	Middle	Medium	Medium
37	Low	Medium	Low	Middle	Low	Low
38	Low	High	High	Middle	Low	Low
39	Medium	Low	High	Middle	Medium	Medium
40	Medium	High	Low	Middle	Medium	Medium
41	High	Low	High	Middle	High	High
42	High	Medium	Medium	Middle	High	High

Table 2: Contd.: Rules regarding the model

Rules	GL	BMI	Blood Pressure	Age	Likelihood of Diabetes	Severity of Diabetes
43	Low	Low	Low	Old	Low	Low
44	Medium	Medium	Low	Old	Medium	Medium
45	High	High	Low	Old	High	High
46	Low	Low	Medium	Old	Low	Low
47	Medium	Medium	Medium	Old	Medium	Medium
48	High	High	Medium	Old	High	High
49	Low	Low	High	Old	Low	Low
50	Medium	Medium	High	Old	Medium	Medium
51	High	High	High	Old	High	High
52	Medium	Low	Medium	Old	Medium	Medium
53	High	Low	High	Old	High	High
54	Low	Medium	Low	Old	Low	Low
55	High	Medium	High	Old	High	High
56	Low	Medium	Low	Old	Low	Low
57	Medium	High	Medium	Old	Medium	Medium
58	Low	Medium	Medium	Old	Low	Low
59	Low	High	Medium	Old	Medium	Medium
60	Medium	Low	Medium	Old	Medium	Medium
61	Medium	High	High	Old	High	High
62	High	Low	High	Old	High	High
63	High	Medium	Medium	Old	High	High

4. Defuzzification

4(i). Likelihood of Diabetes

The centroid can be calculated by $C_r = \frac{\int_a^b r\mu(r)dx}{\int_a^b \mu(r)dx}$ (19)

$$C_{low} = \frac{\int_0^{0.4} v\mu_{low}(v)dv}{\int_0^{0.4} \mu_{low}(v)dv} = \frac{\int_0^{0.2}\frac{v^2}{0.2}dv + \int_{0.2}^{0.4}\left(\frac{0.4v-v^2}{0.2}\right)dv}{\int_0^{0.2}\frac{v}{0.2}dv + \int_{0.2}^{0.4}\left(\frac{0.4-v}{0.2}\right)dv} = \frac{\frac{1}{75}+\frac{2}{75}}{\frac{3}{10}+\frac{1}{10}} = \frac{\frac{1}{25}}{\frac{2}{5}} = \frac{1}{10} = 0.1 \quad (20)$$

$$\boldsymbol{C_{medium}} = \frac{\int_{0.2}^{0.6} v\mu_{medium}(v)dv}{\int_{0.2}^{0.6} \mu_{medium}(v)dv} = \frac{\int_{0.2}^{0.4}\left(\frac{v^2-0.2v}{0.2}\right)dv + \int_{0.4}^{0.6}\left(\frac{0.6v-v^2}{0.2}\right)dv}{\int_{0.2}^{0.4}\frac{0.4v-0.2}{0.2}dv + \int_{0.2}^{0.4}\left(\frac{0.6-v}{0.2}\right)dv} = \frac{\frac{1}{30}+\frac{7}{150}}{\frac{1}{10}+\frac{1}{10}} = \frac{\frac{12}{150}}{\frac{1}{5}} = \frac{60}{150} = \frac{2}{5} = \mathbf{0.4} \quad (21)$$

$$C_{high} = \frac{\int_{0.4}^{0.8} v\mu_{high}(v)dv}{\int_0^{0.4} \mu_{high}(v)dv} = \frac{\int_{0.4}^{0.6}\left(\frac{v^2-0.4v}{0.2}\right)dv + \int_{0.6}^{0.8}\left(\frac{0.8v-v^2}{0.2}\right)dv}{\int_0^{0.2}\frac{v-0.4}{0.2}dv + \int_{0.2}^{0.4}\left(\frac{0.8-v}{0.2}\right)dv} = \frac{\frac{4}{75}+\frac{1}{15}}{\frac{1}{10}+\frac{1}{10}} = \frac{\frac{9}{75}}{\frac{1}{5}} = \frac{9}{15} = \frac{3}{5} = 0.6 \quad (22)$$

Crisp likelihood of diabetes $= \frac{0.1+0.4+0.6}{3} = \frac{1.1}{3} = 0.37$ (23)

4(ii). Severity of Diabetes

$$C_{low} = \frac{\int_0^{0.6} w\mu_{low}(w)dw}{\int_0^{0.4} \mu_{low}(w)dw} = \frac{\int_0^{0.2}\frac{w^2}{0.2}dw + \int_{0.2}^{0.4} w\,dw + \int_{0.4}^{0.6}\left(\frac{0.6w-w^2}{0.2}\right)dw}{\int_0^{0.2}\frac{w}{0.2}dw + \int_{0.2}^{0.4} dw + \int_{0.4}^{0.6}\left(\frac{0.6-w}{0.2}\right)dw} = \frac{\frac{1}{75}+\frac{3}{75}+\frac{7}{150}}{\frac{1}{10}+\frac{1}{5}+\frac{1}{10}} = \frac{\frac{18}{150}}{\frac{4}{10}} = \frac{180}{600} = 0.3 \quad (24)$$

$$C_{medium} = \frac{\int_{0.4}^{1} w\mu_{medium}(w)dw}{\int_{0.4}^{1} \mu_{medium}(w)dw} = \frac{\int_{0.4}^{0.6}\frac{w^2-0.4w}{0.2}dw+\int_{0.6}^{0.8} wdw+\int_{0.8}^{1}\left(\frac{w-w^2}{0.2}\right)dw}{\int_{0.4}^{0.6}\frac{w-0.4}{0.2}dw+\int_{0.6}^{0.8} dw+\int_{0.8}^{1}\left(\frac{1-w}{0.2}\right)dw} = \frac{\frac{4}{75}+\frac{7}{50}+\frac{13}{150}}{\frac{1}{10}+\frac{1}{5}+\frac{1}{10}} = \frac{\frac{42}{150}}{\frac{4}{10}} = \frac{420}{600} = 0.7 \quad (25)$$

$$C_{high} = \frac{\int_{0.6}^{1.2} w\mu_{high}(w)dw}{\int_{0}^{0.4} \mu_{high}(w)dw} = \frac{\int_{0.6}^{0.8}\frac{w^2-0.6w}{0.2}dw+\int_{0.8}^{1} wdw+\int_{1}^{1.2}\left(\frac{1.2w-w^2}{0.2}\right)dw}{\int_{0.6}^{0.8}\frac{w-0.6}{0.2}dw+\int_{0.8}^{1} dw+\int_{1}^{1.2}\left(\frac{1.2-w}{0.2}\right)dw} = \frac{\frac{11}{150}+\frac{9}{50}+\frac{8}{75}}{\frac{1}{10}+\frac{1}{5}+\frac{1}{10}} = \frac{\frac{54}{150}}{\frac{4}{10}} = \frac{540}{600} = 0.9 \quad (26)$$

Crisp severity of diabetes $= \frac{0.3+0.7+0.9}{3} = \frac{1.1}{3} = 0.6$ (27)

5. Estimated Values of Likelihood and Severity of DIABETES for Different Input Parameters

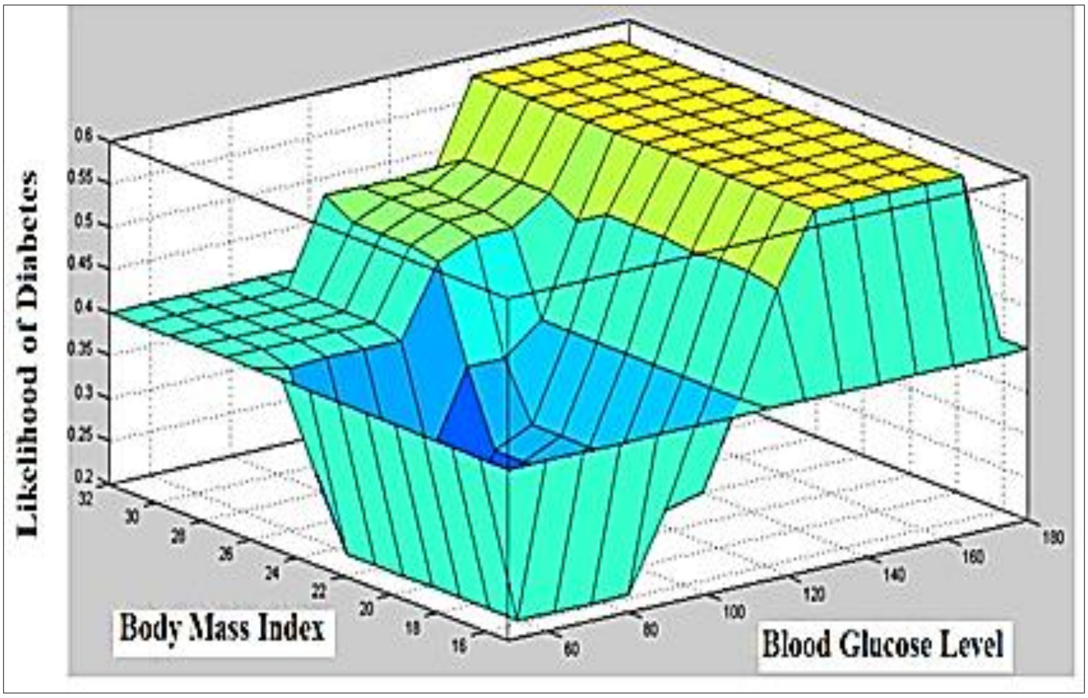
The assessed upsides of probability and seriousness of diabetes for various information boundaries in a fuzzy inference system (FIS) give significant bits of knowledge into the potential results in light of the fuzzy rationale model.

Table 3: Estimated values of outputs

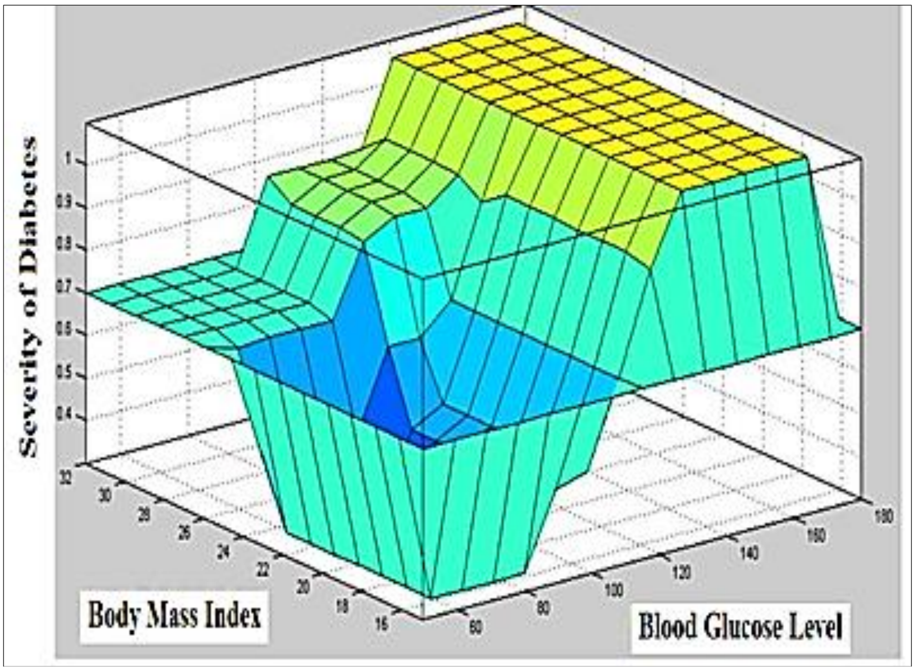
GL	BMI	Blood Pressure	Age	Likelihood of Diabetes	Severity of Diabetes
115	23.5	130	40	0.4	0.7
140	25.8	146	42.9	0.6	1.1
63.4	16.8	100	27.8	0.2	0.3
173	31.4	177	57.7	0.6	1.1
95.5	29	94.3	50.1	0.2	0.3
108	27.1	151	40.8	0.506	0.917
81.6	29.2	113	26	0.4	0.7
117	28.1	118	29.7	0.477	0.849
132	29.1	162	32.1	0.6	1.1
119	24.7	130	37.9	0.476	0.852
101	23.6	132	36.3	0.314	0.53
109	24.4	114	39.5	0.3	0.5
105	26.8	128	27.5	0.487	0.87

6. 3D Surface Visualization of Fuzzy Inference Output for DIABETES Risk

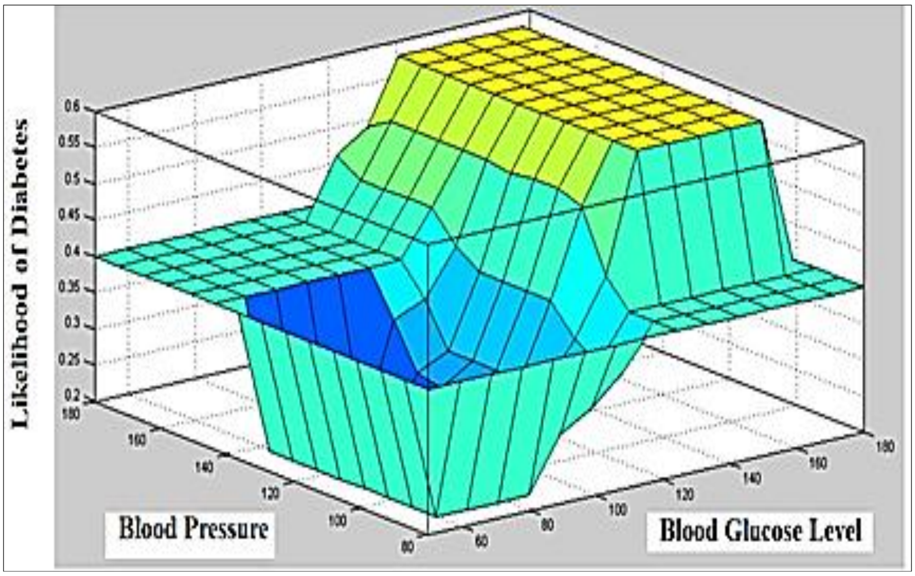
A 3D surface perception of fuzzy induction yield for diabetes risk gives a strong means to investigate and figure out the intricate connections between input factors, fuzzy principles, and the subsequent gamble evaluations.



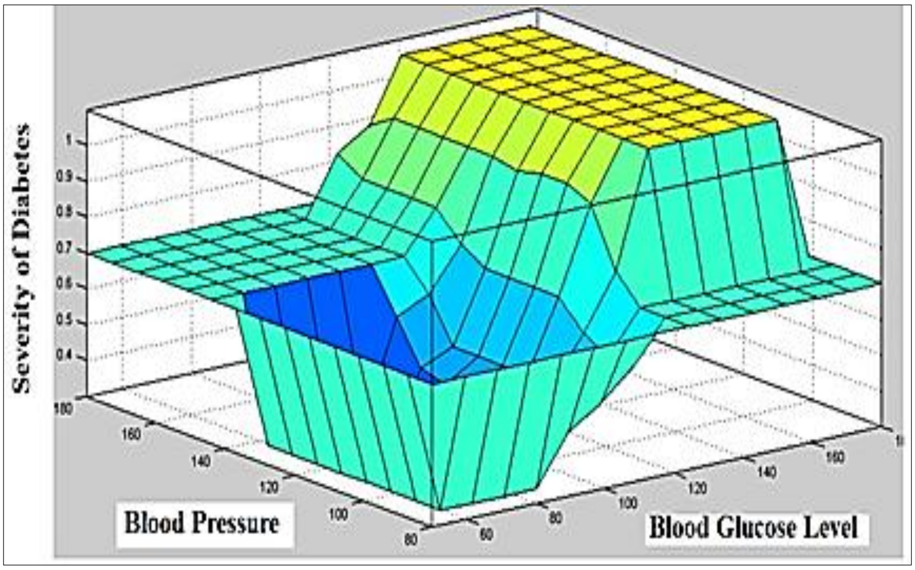
Graph 1: 3D variation in likelihood of diabetes for different values of blood glucose level and body mass index



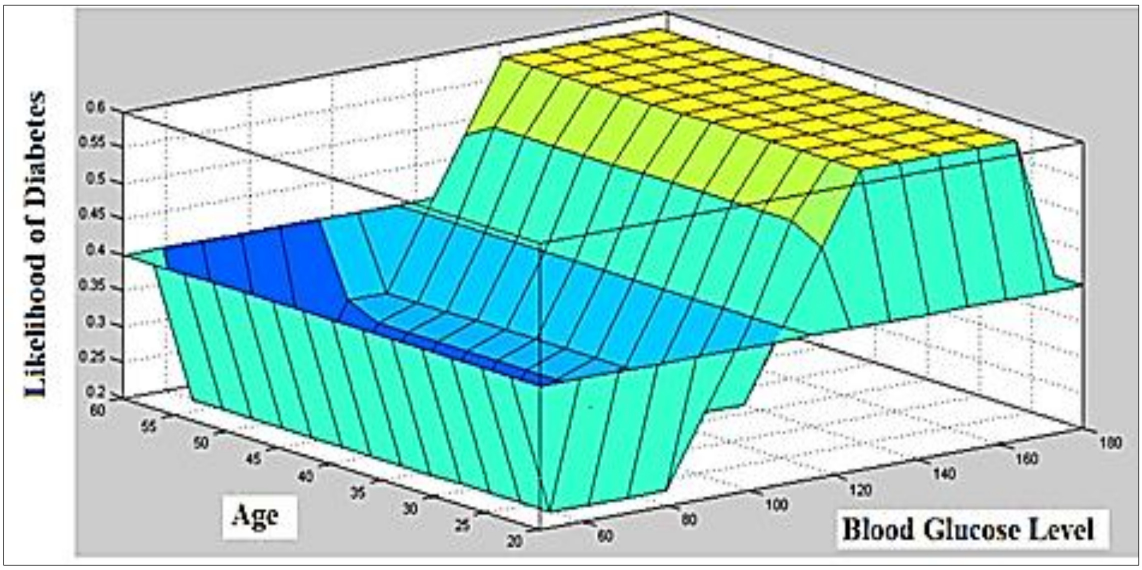
Graph 2: 3D variation in Severity of diabetes for different values of blood glucose level and body mass index



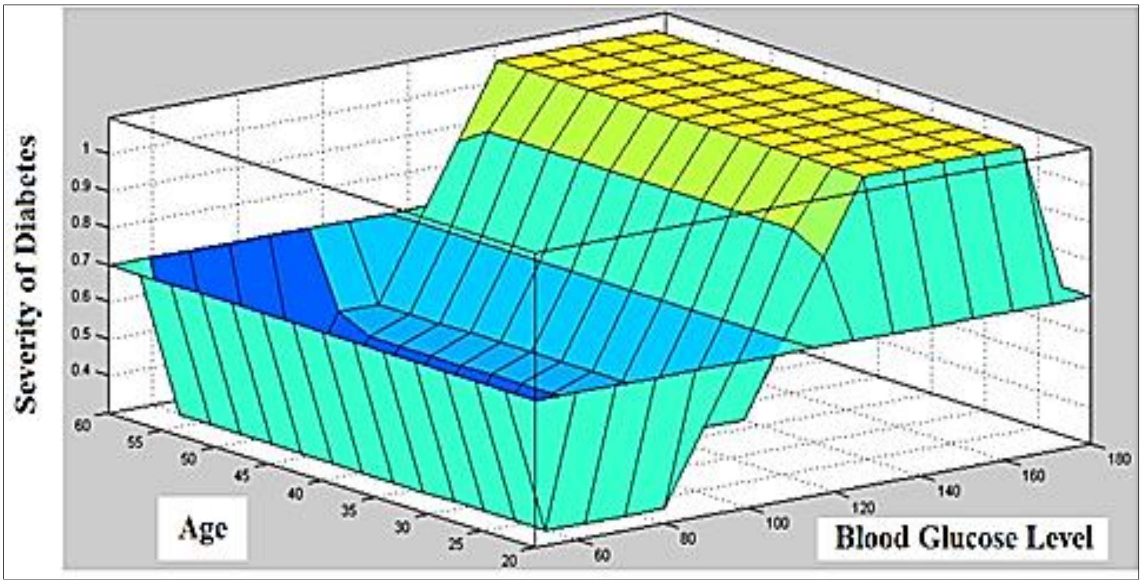
Graph 3: 3D variation in likelihood of diabetes for different values of blood glucose level and blood pressure



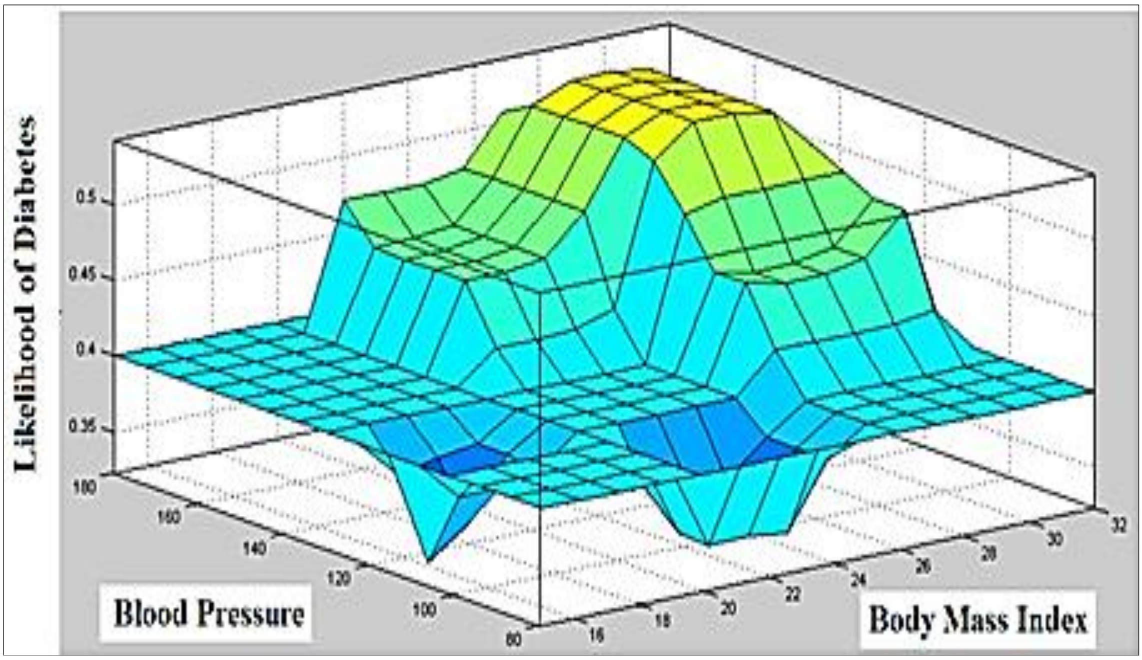
Graph 4: 3D variation in Severity of diabetes for different values of blood pressure and age



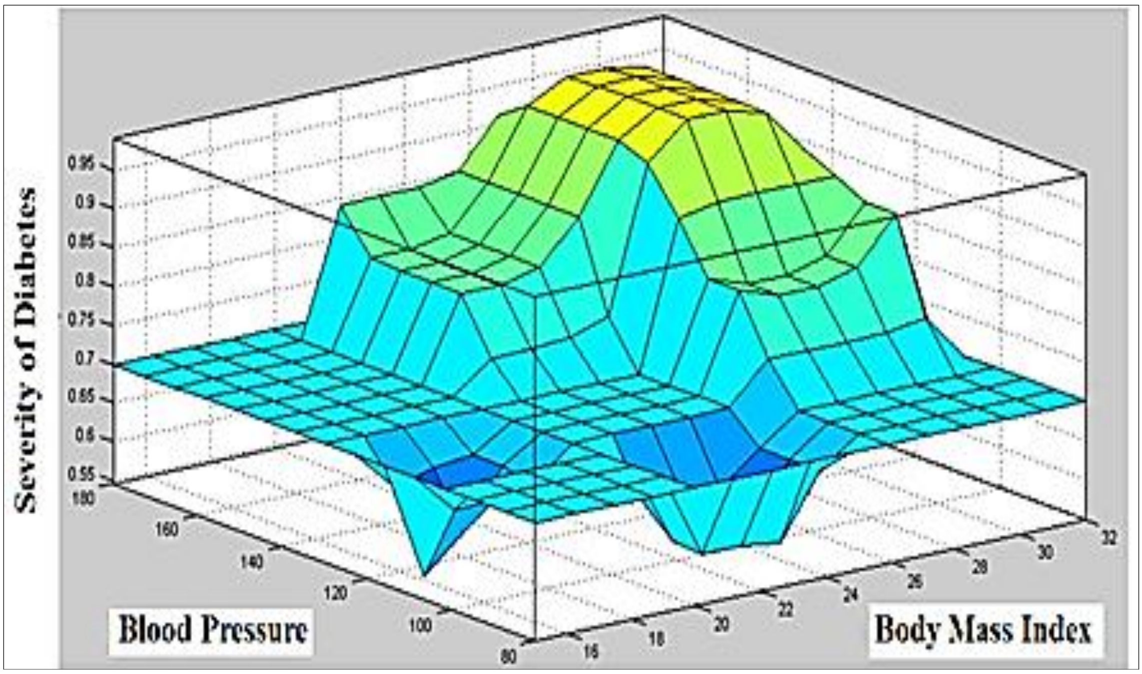
Graph 5: 3D variation in likelihood of diabetes for different values of blood glucose level and age



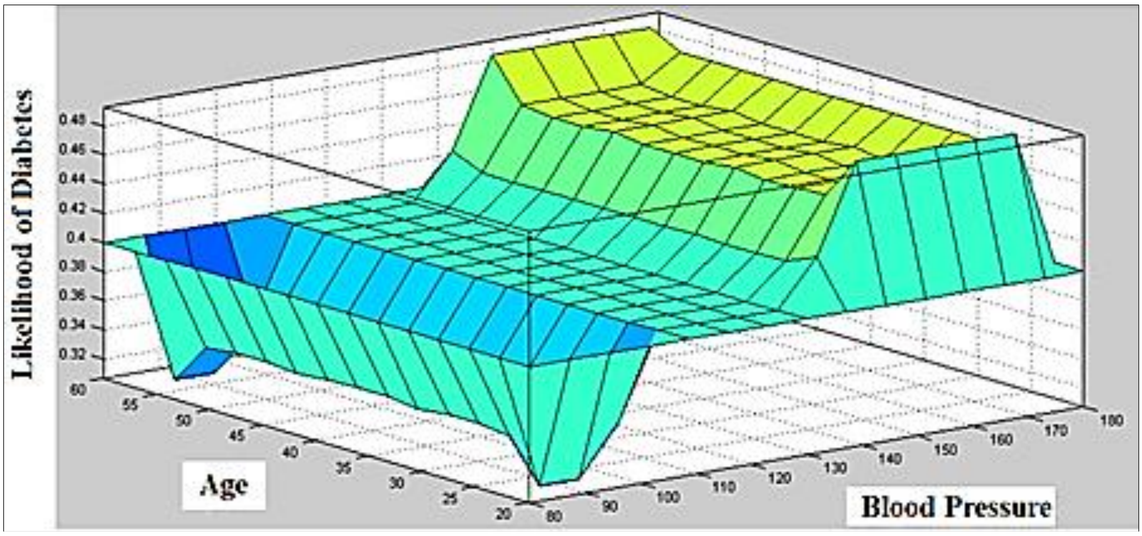
Graph 6: 3D variation in severity of diabetes for different values of blood glucose level and age



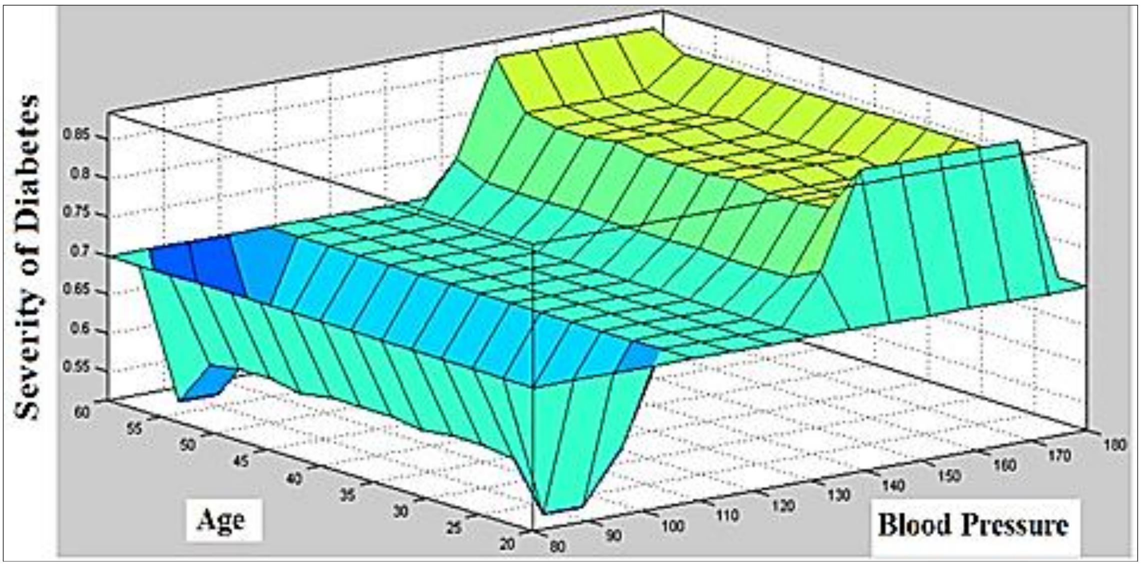
Graph 7: 3D variation in likelihood of diabetes for different values of body mass index and blood pressure



Graph 8: 3D variation in severity of diabetes for different values of body mass index and blood pressure



Graph 9: 3D variation in likelihood of diabetes for different values of blood pressure and age



Graph 10: 3D variation in severity of diabetes for different values of blood pressure and age

The graphs (1) and (2) indicate that the points are the combinations of the BMI and the level of blood glucose. The surface height at the point is a measure of the possibility and the severity of diabetes respectively. Places of the drawing where the area is elevated or more opaque can evince an increased gamble of diabetes. Risk, on the contrary, is reduced in lower areas. The patterns, trends, or clusters of the graphs illuminate the interaction between the body mass index (BMI) and the blood glucose level in the prediction of the risk and intensity of diabetes. The graphs (3) and (4) can be unraveled using the association of different combinations of blood glucose level and circulatory strain with the likelihood of diabetes and its severity. This could help illuminate trends and possible risk factors related to the probability and the intensity of diabetes. In the figures (5) and (6), data points correspond to a person or group of people sharing specific values of the degree of blood glucose, age, and probability/severe of one having it. Aspects that are critical are those where both the probability and the extent is high. Patterns, clusters, or trends which provide light on such insights as what age groups are more prone to develop diabetes or what blood glucose level is correlated with an increased risk. Surveillance plot on diagrams (7) and (8) reveal the effect of the combination of BMI and pulse on the probability or severity of diabetes. Every point on the superficial level deals with a specific combination of a BMI and a pulse and the level of a surface by that point indicates the value of likelihood or severity.

As we travel along the X-hub (varying BMI esteems), the graphs indicate the variation of probability or seriousness. Equally, the charts illustrate the effect on likelihood or severity that would occur as we traverse the Y axis (varying blood pressure values). Two surface plots, one of the likelihood of diabetes and the other of the severity have been plotted in graphs (9) and (10), respectively. This involves matching the fragments of information with surfaces to demonstrate how the factors alter with the different mixes with old enough age and circulatory strain. When we observe these 3D diagrams, we observe examples and trends in the probability as well as the severity of diabetes. It is observed that with increasing age, the likelihood of diabetes will in most cases increase and the severity can also increase.

7. Performance Metrics of the Model

The estimations of F1 score, exactness, particularity (true negative rate), and accuracy (positive predictive value) from a disarray framework for a fuzzy inference system (FIS) anticipating and assessing diabetes seriousness are as per the following:

Table 3: Confusion Matrix

	Predicted Negative	Predicted Positive
Actual Negative	***TN***	***FP***
Actual Positive	***FN***	***TP***

Let's denote these values

$TN = True\ Negatives = 120$

$FP = False\ Positives = 20$

$FN = False\ Negatives = 30$

$TP = True\ Positives = 80$

(i). Accuracy: Accuracy gives a general proportion of how frequently the model's forecasts are right.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{80+120}{80+120+20+30} = \frac{200}{250} = 0.8$$

(ii). Precision: Precision centers around the precision of the positive forecasts. It is the proportion of accurately anticipated positive perceptions to the all-out anticipated up-sides.

$$Precision(Positive\ Predictive\ Value) = \frac{TP}{TP+FP} = \frac{80}{80+20} = \frac{80}{100} = 0.8$$

(iii). Sensitivity: Recall estimates the capacity of the model to catch every one of the positive occurrences. It is the proportion of accurately anticipated positive perceptions to the all-out genuine up-side.

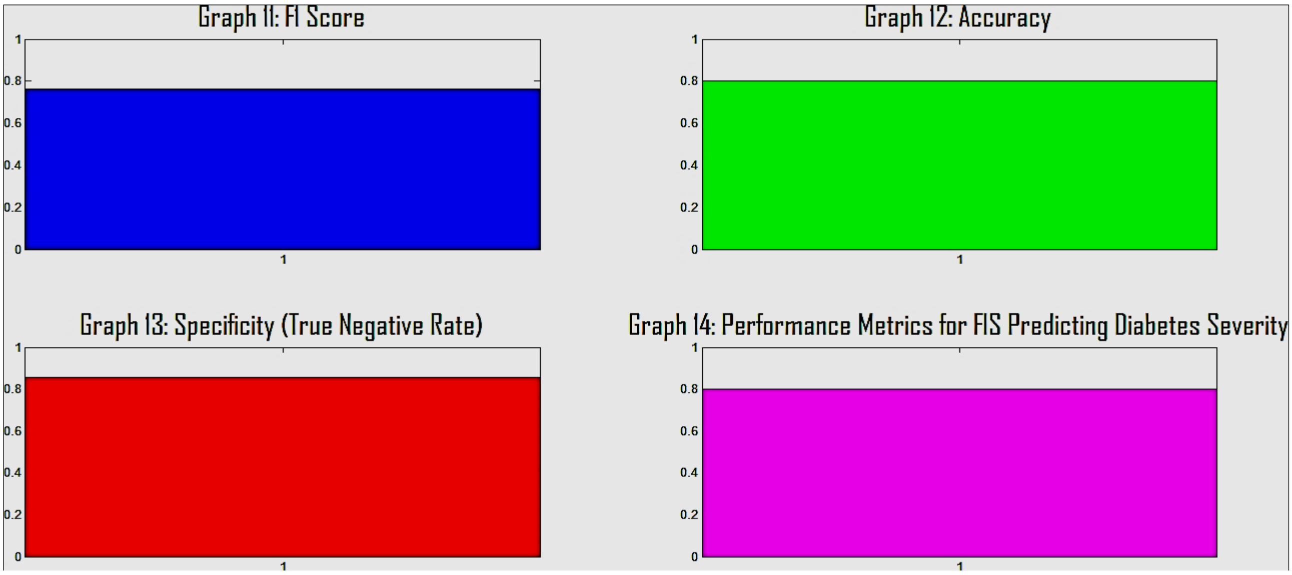
$$Sensitivity\ (Recall) = \frac{TP}{TP+FN} = \frac{80}{80+30} = \frac{80}{110} = 0.727273$$

(iv). Specificity: The capacity of the model to capture all negative instances is measured by its specificity. It is the proportion of accurately anticipated negative perceptions to the complete real negatives.

$$Specificity(True\ Negative\ Rate) = \frac{TN}{TN+FP} = \frac{120}{120+20} = \frac{120}{140} = 0.857143$$

(v). F1 score: The F1 score is the symphonious mean of accuracy and recall. It gives a harmony among precision and recall.

$$\text{F1 Score} = 2\frac{Precision \times Sensitivity}{Precision + Sensitivity} = 2\frac{\left(\frac{80}{100}\times\frac{80}{110}\right)}{\left(\frac{80}{100}+\frac{80}{110}\right)} = 2\frac{\frac{64}{110}}{\frac{80\times210}{1100}} = 2\frac{640}{80\times210} = 2\frac{8}{210} = \frac{8}{105} = 0.07619$$



8. Conclusion

Overall, the introduction of fuzzy inference system (FIS) to predict and detect the seriousness in diabetes is one major step to overcoming the limitations of the traditional symptomatic approach. The natural complexity of diabetes, which is illustrated by its multi factorial complexity and varying degrees of severity in individuals, demands innovative approaches which are able to capably investigate the intricacies of clinical data. By committing the vulnerabilities and the intrinsic inaccuracy in the clinical data, FIS is a promising path towards achieving this accuracy since it is built on the fuzzy rationale standards.

FIS makes a unique range of features visible in the situation of defining the severity of diabetes as discussed earlier. FIS can be used to obtain the nuances of patient data through the use of linguistic variables, fuzzy rules, and well-crafted membership functions. Consequently, it is able to give a more context sensitive and finer analysis of the severity of diabetes. Such flexibility is an emergency in an area where individual types and progressive shifts in wellbeing status play crucial roles in illness circulation. The FIS ability is able to extend further beyond being anticipatory of seriousness; It is capable of determining the efficacy of different treatment modalities. FIS is a valuable resource to medical practitioners as it can receive dynamic inputs and adapt to evolving conditions of patients. It is this flexibility that ensures that the FIS model can progress at the side of the patient and help in enhancing personalized and receptive treatment strategies.

Such introduction is a prelude to a deeper exploration of the subject matter because it presents a general review of the principles on which FIS is based and how it is applied to predicting the severity of diabetes. The lessons learnt in this line can greatly enhance the quality and customized approach to managing diabetes as researchers keep on refining and verifying FIS models on the basis of actual clinical information. The inclusion of FIS into the process of assessing the severity of diabetes, in its turn, is the testimony to the shifting nature of healthcare technology. It clears pathways to more precise, multifaceted, and tailor-made intercessions, to the general aim of attending to ongoing outcomes and individual contentment to the affected individuals by diabetes. The anticipated impact of FIS in altering the healthcare of diabetes continues to emerge as the examination moves forward, providing a ray of hope in the ongoing effort to manage the global epidemic of diabetes.

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