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Fuzzy Logic-Based Model for Blood Glucose Monitoring and Diabetes Control

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Abstract

This study presents a fuzzy logic-based model for blood glucose monitoring and diabetes control, addressing the inherent uncertainty and nonlinearity in physiological and lifestyle factors affecting glucose regulation. The proposed system utilizes key input variables such as blood glucose level, carbohydrate intake, and physical activity, which are mapped into linguistic terms using triangular and trapezoidal membership functions. A Mamdani-type fuzzy inference system is employed, consisting of fuzzification, rule evaluation, aggregation, and centroid defuzzification to generate an appropriate insulin/control dose. The model incorporates a structured rule base derived from clinical reasoning to ensure safe and effective decision-making. A numerical case study demonstrates the applicability of the system, where realistic patient inputs produce a clinically meaningful insulin recommendation. The results highlight that the proposed approach provides smooth, consistent, and adaptive outputs, making it a promising tool for intelligent diabetes management and decision support systems.

Keywords: Fuzzy Logic, Diabetes Control, Blood Glucose Monitoring, Fuzzy Inference System, Membership Functions, Insulin Dose Optimization, Mamdani Model, Defuzzification, Decision Support System

1. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by abnormal blood glucose levels due to insufficient insulin production or impaired insulin utilization. Effective management of diabetes requires continuous monitoring and precise control of glucose levels, which is influenced by multiple factors such as diet, physical activity, and physiological conditions. Traditional mathematical and statistical models often struggle to handle the uncertainty, vagueness, and nonlinear relationships inherent in such systems. As shown in the proposed framework (page 1, Figure 1), fuzzy logic provides a powerful alternative by incorporating human-like reasoning through linguistic variables and rule-based decision-making. The system processes inputs such as glucose level, carbohydrate intake, and physical activity through fuzzification and applies expert-defined rules to determine appropriate control actions. This approach enables flexible and adaptive glucose regulation, making it particularly suitable for real-world healthcare applications where precision and interpretability are crucial.

Bhandari and Kumar (2015) discussed the usefulness of fuzzy expert systems in diabetic diagnosis by showing that fuzzy logic can manage uncertain clinical symptoms and borderline glucose values more effectively than rigid classification methods. Their work is important because diabetes diagnosis often depends on imprecise medical indicators, and fuzzy rules allow the system to convert patient data into linguistic categories such as low, normal, high, and very high. The study supported the idea that fuzzy expert systems can assist physicians by providing interpretable diagnostic decisions. **Lukmanto and Irwansyah (2015)** emphasized early diabetes detection through a hierarchical fuzzy structure. Their approach showed that dividing the diagnostic process into different fuzzy levels can improve decision-making by gradually processing patient symptoms and clinical parameters. This contribution is useful for diabetes screening because early detection requires careful interpretation of several risk factors rather than dependence on a single glucose value. **Singla (2015)** compared Mamdani and Sugeno fuzzy inference approaches for diabetes diagnosis. The study indicated that both methods are useful, but Mamdani inference is more interpretable because it works with linguistic rules, while Sugeno inference is often more computationally efficient. This comparison is relevant for selecting an appropriate fuzzy model in diabetes control, especially when the system must balance accuracy, simplicity, and clinical interpretability. **Pradini *et al.* (2020)** introduced optimization into fuzzy diabetes prediction by using particle swarm optimization to improve membership functions. Their work showed that manually selected membership parameters may not always provide the best prediction performance. By optimizing fuzzy sets, the system can better classify diabetes risk levels and reduce errors caused by poorly defined boundaries between normal, pre-diabetic, and diabetic conditions. **Aamir *et al.* (2021)** developed a fuzzy rule-based classification approach for diabetes. Their study demonstrated that fuzzy rules can effectively classify patients by combining clinical inputs in an understandable form. The main strength of their work lies in rule transparency, because the decision process can be explained through IF–THEN rules. This makes the model suitable for medical decision-support systems where interpretability is highly important. **Aris (2023)** presented a fuzzy inference-based diagnostic model that strengthened the role of fuzzy logic in healthcare decision-making. The study showed that fuzzy inference can handle incomplete, uncertain, and overlapping patient data. This is especially useful in diabetes diagnosis because clinical symptoms and glucose values may vary across patients. The work supports the use of fuzzy models as flexible tools for assisting diagnosis and reducing dependence on strict threshold-based decisions. **Asghari Varzaneh and Hosseini (2023)** combined fuzzy logic with Harris Hawks optimization for diabetes detection. Their work highlighted the growing trend of integrating fuzzy systems with metaheuristic optimization techniques. The optimized fuzzy system improved the selection of rules and membership parameters, leading to better diagnostic performance. This study is significant because it shows that fuzzy logic can become more powerful when combined with intelligent optimization methods. **Nataala and Goni (2023)** used an adaptive neuro-fuzzy framework for predicting diabetes likelihood. Their contribution connected fuzzy reasoning with neural learning capability. The neuro-fuzzy structure allowed the model to learn patterns from data while still preserving fuzzy interpretability. This approach is useful because diabetes prediction involves both nonlinear relationships and uncertain medical boundaries, which can be better managed through hybrid intelligent systems. **Aris (2024)** extended fuzzy decision-making toward diagnosis and level-of-care classification. The study is important because diabetes management does not end with diagnosis; patients also require suitable care recommendations based on disease severity. By classifying care levels, the fuzzy model provides more practical clinical support and helps guide treatment intensity, monitoring frequency, and intervention planning. **Ganji and Pourgholi (2024)** focused on robust fuzzy control for blood glucose regulation in type 1 diabetes. Their study moved beyond diagnosis and addressed control-oriented diabetes management. The use of fuzzy control is significant because glucose regulation is affected by meal intake, insulin sensitivity, and physiological variation. Their work supports the idea that fuzzy controllers can contribute to artificial pancreas systems and automated insulin delivery. **Tasić *et al.* (2024)** proposed a multilevel fuzzy inference approach for estimating type 2 diabetes risk. Their work showed that multilevel fuzzy systems can organize complex risk factors into structured layers, improving clarity and decision quality. This is useful for risk estimation because diabetes develops through the interaction of lifestyle, physiological, and metabolic factors. The study supports the use of layered fuzzy models for more detailed and systematic risk assessment. **Chiu *et al.* (2025)** introduced a fuzzy deep learning ensemble approach for type 2 diabetes diagnosis. Their work represents a modern development in which fuzzy logic is combined with deep learning to improve flexibility and objectivity. The fuzzy component helps represent diagnostic uncertainty, while the deep learning ensemble improves predictive capability. This study indicates that future diabetes models may increasingly depend on hybrid systems that combine explainability with high computational accuracy. **Ganie (2025)** discussed a lifestyle-based fuzzy-enhanced artificial neural network model for early diabetes prediction. The study emphasized the importance of lifestyle variables in diabetes risk assessment, such as physical activity, diet, and related behavioral factors. By combining fuzzy logic with neural networks, the model improved the interpretation of uncertain lifestyle information. This contribution is relevant because diabetes prevention requires attention not only to clinical measurements but also to modifiable lifestyle conditions. **Jha *et al.* (2025)** developed a fuzzy logic-based diabetes prediction system using clinical data. Their work reinforced the suitability of fuzzy systems for converting medical parameters into meaningful diagnostic outputs. The model showed that fuzzy logic can provide simple, rule-based, and understandable predictions, making it useful for preliminary screening and decision support in clinical environments. **Kulshreshtha *et al.* (2025)** proposed a fuzzy diagnostic system for early diabetes detection. Their study supported the role of fuzzy logic in identifying diabetes at an early stage, where symptoms and clinical indicators may not be clearly defined. The system's ability to handle vague boundaries between normal and abnormal conditions makes it valuable for preventive healthcare and early medical intervention. **Riaz (2026)** applied fuzzy logic to diabetes-related data readability and analysis. Although the focus differs from direct diagnosis or insulin control, the study is relevant because it shows the wider application of fuzzy logic in diabetes-related healthcare information systems. The work highlights that fuzzy models can be useful not only for clinical prediction but also for interpreting uncertain healthcare data and improving patient-centered information analysis.

Figure 1: General Architecture of Fuzzy Logic-Based Diabetes Control System

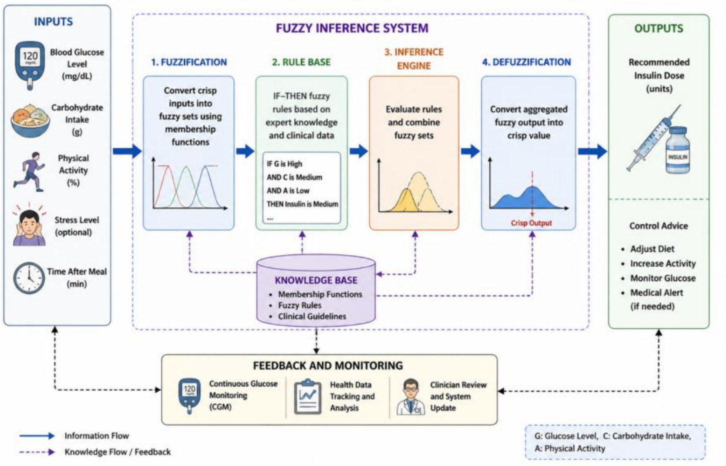


Table 1: Normal, Pre-diabetic, and Diabetic Glucose Ranges

Category	Fasting Blood Glucose (mg/dL)	Postprandial (2-hour) Glucose (mg/dL)	HbA1c (%)
Normal	70 – 99	Less than 140	Less than 5.7
Pre-diabetic	100 – 125	140 – 199	5.7 – 6.4
Diabetic	126 or higher	200 or higher	6.5 or higher

The table (1) classifies blood glucose levels into normal, pre-diabetic, and diabetic categories based on standard clinical guidelines. Fasting glucose reflects baseline metabolic status, while postprandial glucose indicates the body's ability to regulate glucose after meals. HbA1c provides a long-term average of blood glucose levels over approximately three months. These thresholds are essential for defining fuzzy membership functions in the proposed model, as they help map crisp glucose values into linguistic variables such as low, normal, and high, thereby improving decision-making in diabetes control systems.

2. OBJECTIVES OF THE STUDY:

The main objectives may be written as:to develop a fuzzy logic-based model for blood glucose monitoring; to classify glucose status into hypoglycemia, normal, moderate, high, and very high; to recommend insulin/control action using fuzzy rules; and to validate the model through a numerical case study.

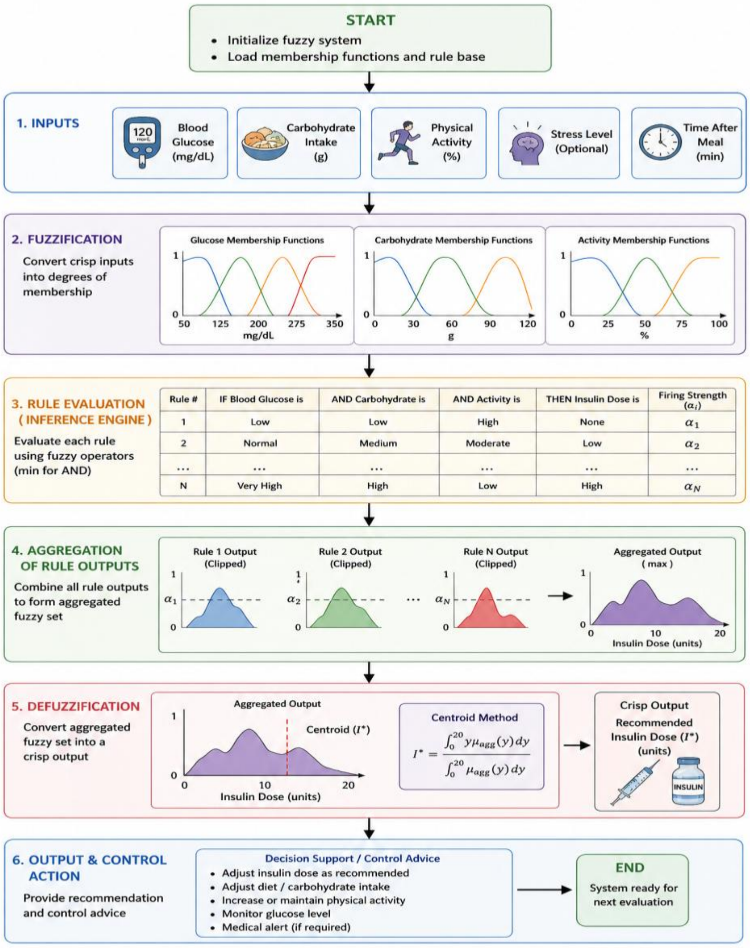
3. METHODOLOGY:

The proposed fuzzy inference system contains four major stages: fuzzification, rule evaluation, inference mechanism, and defuzzification. $X = \{G, C, A\}$ (1)

where G is blood glucose level, C is carbohydrate intake, and A is physical activity.

The output variable is: $Y = I$, where I represents recommended insulin/control dose.

Figure 2: Flowchart of Fuzzy Inference System for Diabetes Control



Rule #	IF Blood Glucose is	AND Carbohydrate is	AND Activity is	THEN Insulin Dose is	Firing Strength (α_i)
1	Low	Low	High	None	α_1
2	Normal	Medium	Moderate	Low	α_2
...	...	...	...	...	...
N	Very High	High	Low	High	α_N

$$I^* = \frac{\int_0^{20} y\mu_{agg}(y)\,dy}{\int_0^{20} \mu_{agg}(y)\,dy}$$

Table 2: Input and Output Variables with Ranges

Variable Type	Variable Name	Symbol	Range	Unit	Linguistic Terms
Input	Blood Glucose Level	(G)	50 – 350	mg/dL	Low, Normal, High, Very High
Input	Carbohydrate Intake	(C)	0 – 120	g	Low, Medium, High
Input	Physical Activity	(A)	0 – 100	%	Low, Moderate, High
Output	Insulin / Control Dose	(I)	0 – 20	Units	None, Low, Medium, High

The table (2) defines the input and output variables used in the fuzzy logic-based diabetes control system. Blood glucose level is the primary physiological indicator, while carbohydrate intake and physical activity act as influencing factors affecting glucose variation. The output variable represents the recommended insulin or control action. Each variable is mapped to appropriate linguistic terms, which are later modeled using triangular and trapezoidal membership functions. These ranges ensure that the fuzzy inference system can handle real-world variations in patient data and provide meaningful control decisions.

4. Membership Functions:

Triangular membership function:

$$\mu(x;a,b,c)=\left\{\begin{array}{cc} 0 & x\le a \\ \frac{x-a}{b-a} & a<x\le b \\ \frac{c-x}{c-b} & b<x<c \\ 0 & x\ge c \end{array}\right\} \quad (2)$$

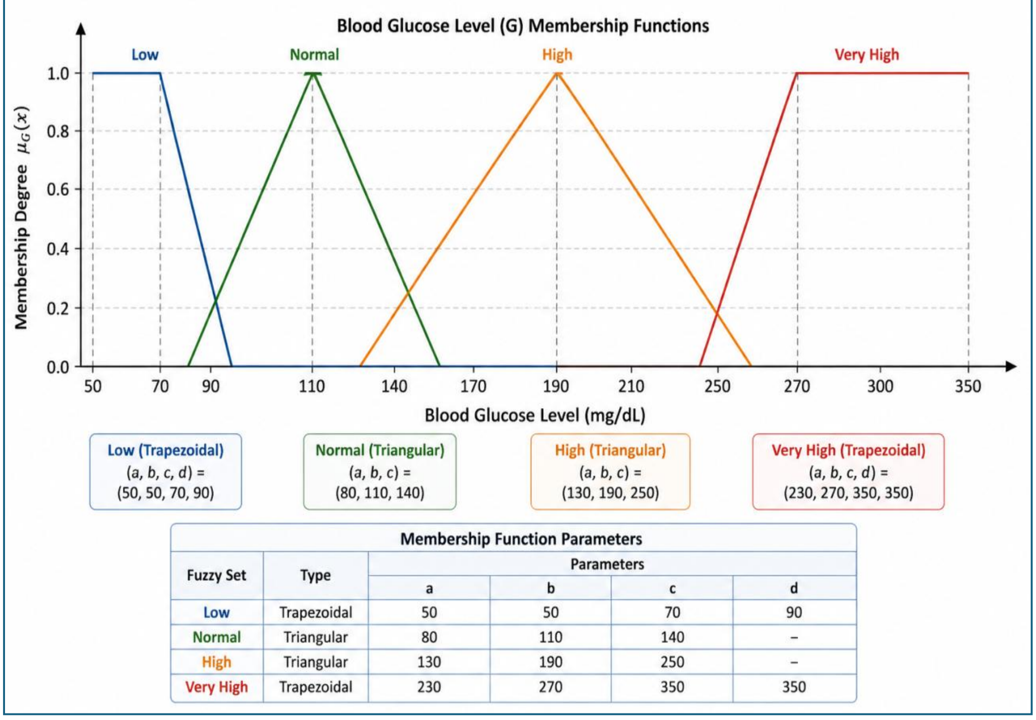
Trapezoidal membership function:

$$\mu(x;a,b,c,d)=\left\{\begin{array}{cc} 0 & x\le a \\ \frac{x-a}{b-a} & a<x\le b \\ 1 & b<x\le c \\ \frac{d-x}{d-c} & c<x<d \\ 0 & x\ge d \end{array}\right\} \quad (3)$$

Table 3: membership functions:

Variable	Linguistic Term	Type	Parameters
Glucose	Low	Trapezoidal	(50, 50, 70, 90)
Glucose	Normal	Triangular	(80, 110, 140)
Glucose	High	Triangular	(130, 190, 250)
Glucose	Very High	Trapezoidal	(230, 270, 350, 350)
Carbohydrate	Low	Trapezoidal	(0, 0, 20, 40)
Carbohydrate	Medium	Triangular	(30, 60, 90)
Carbohydrate	High	Trapezoidal	(80, 100, 120, 120)
Activity	Low	Trapezoidal	(0, 0, 20, 40)
Activity	Moderate	Triangular	(30, 50, 70)
Activity	High	Trapezoidal	(60, 80, 100, 100)
Insulin Dose	None	Trapezoidal	(0, 0, 1, 3)
Insulin Dose	Low	Triangular	(2, 5, 8)
Insulin Dose	Medium	Triangular	(7, 11, 15)
Insulin Dose	High	Trapezoidal	(14, 17, 20, 20)

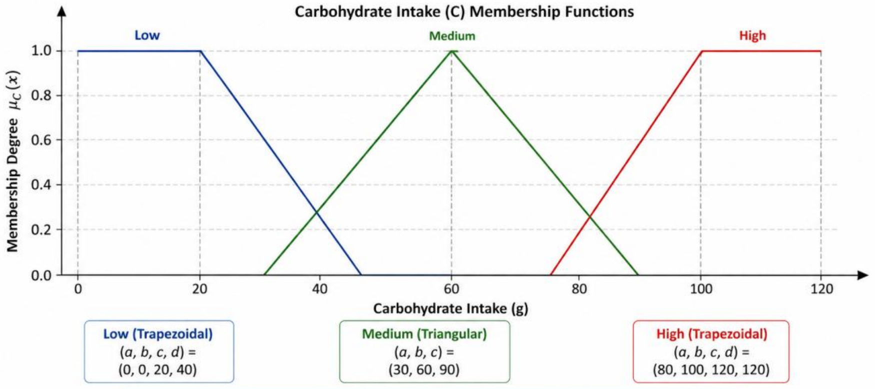
Figure 3: Membership Functions for Blood Clucose Input



Membership Function Parameters

Fuzzy Set	Type	Parameters			
		a	b	c	d
Low	Trapezoidal	50	50	70	90
Normal	Triangular	80	110	140	–
High	Triangular	130	190	250	–
Very High	Trapezoidal	230	270	350	350

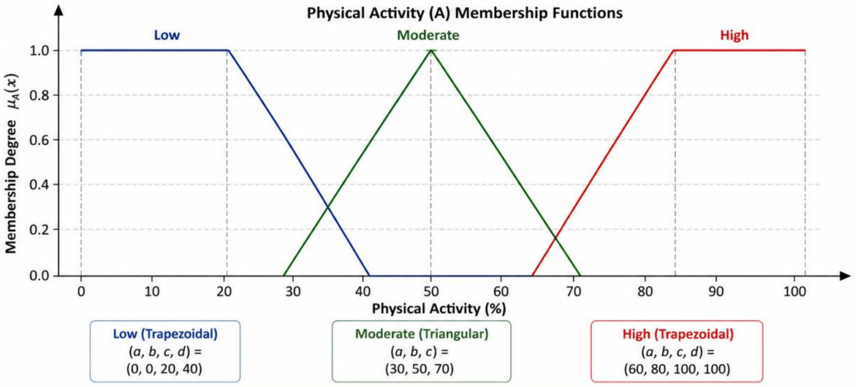
Figure 4: Membership Functions for Carbohydrate Intake Input



Membership Function Parameters

Fuzzy Set	Type	Parameters			
		a	b	c	d
Low	Trapezoidal	0	0	20	40
Medium	Triangular	30	60	90	–
High	Trapezoidal	80	100	120	120

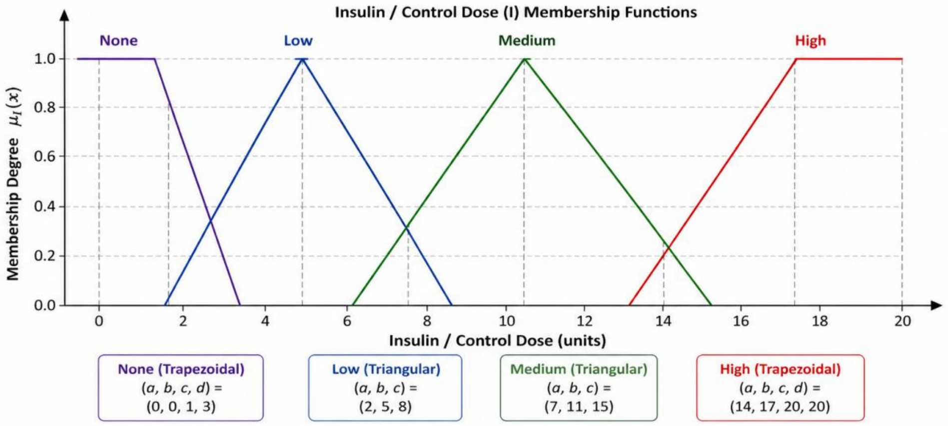
Figure 5: Membership Functions for Physical Activity Input



Membership Function Parameters

Fuzzy Set	Type	Parameters			
		a	b	c	d
Low	Trapezoidal	0	0	20	40
Moderate	Triangular	30	50	70	–
High	Trapezoidal	60	80	100	100

Figure 6: Membership functions for Insulin/Control Output



Membership Function Parameters

Fuzzy Set	Type	Parameters			
		a	b	c	d
None	Trapezoidal	0	0	1	3
Low	Triangular	2	5	8	–
Medium	Triangular	7	11	15	–
High	Trapezoidal	14	17	20	20

5. Fuzzy Rule Base: The fuzzy rule has the form:

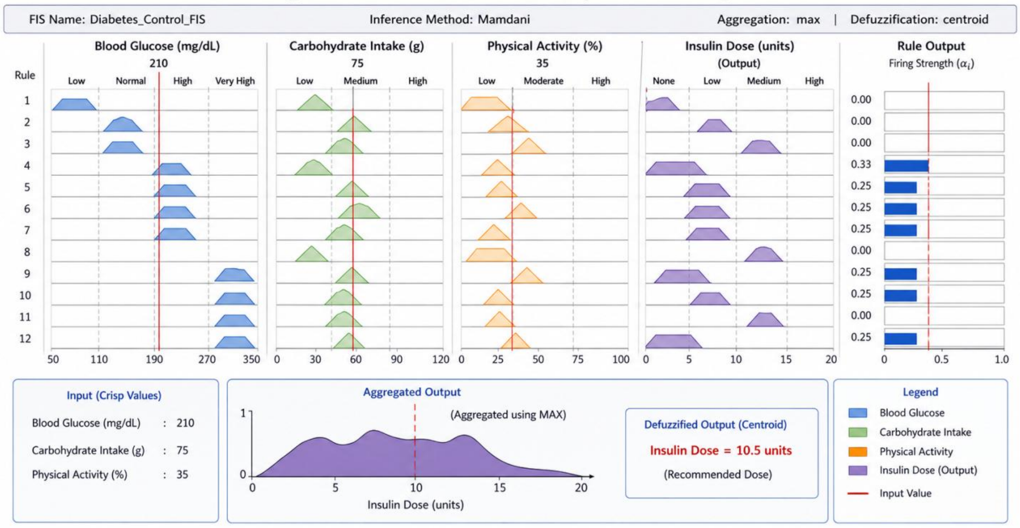
R_i: If G is A_i andC is B_i and A is C_i THEN I is D_i (4)

Table 4: Fuzzy Rule Base for Diabetes Control

Rule No.	Blood Glucose (G)	Carbohydrate Intake (C)	Physical Activity (A)	Insulin Dose (I)
1	Low	Low	High	None
2	Low	Medium	Moderate	None
3	Low	High	Low	Low
4	Normal	Low	Moderate	None
5	Normal	Medium	Moderate	Low
6	Normal	High	Low	Medium
7	High	Low	High	Low
8	High	Medium	Moderate	Medium
9	High	High	Low	High
10	Very High	Low	Moderate	Medium
11	Very High	Medium	Moderate	High
12	Very High	High	Low	High

The fuzzy rule base is the core of the decision-making mechanism in the proposed system. Each rule is constructed in the form of IF–THEN statements that capture expert knowledge and clinical reasoning. For instance, when blood glucose is low, the system recommends no insulin regardless of other inputs to avoid hypoglycemia. For normal glucose levels, insulin is suggested only when carbohydrate intake is high and physical activity is low. As glucose levels increase to high and very high categories, the insulin dose correspondingly increases, especially when carbohydrate intake is high and physical activity is low. This rule base ensures smooth and adaptive control decisions by considering the combined effect of multiple physiological and lifestyle factors, making the system robust and clinically meaningful.

Figure 7: Rule viewer of fuzzy inference system



6. INFERENCE AND DEFUZZIFICATION:

For Mamdani fuzzy inference, the firing strength of each rule is:

$$\alpha_i = min\{\mu_G(x), \mu_c(x), \mu_A(x)\} \qquad (5)$$

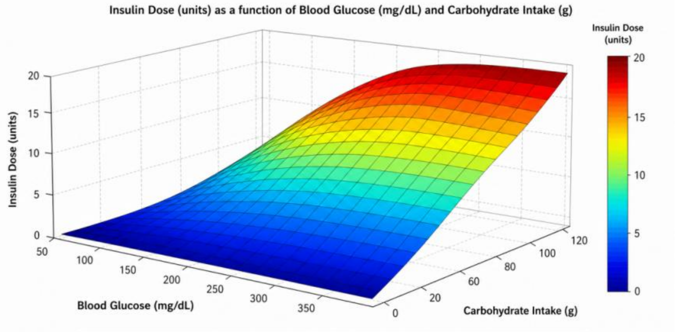
The aggregated output is:

$$\mu_I(y) = max[min(\alpha_i, \mu D_i(y))]$$

The crisp insulin dose is obtained using centroid defuzzification:

$$I^* = \frac{\int y\mu_I(y)\, dy}{\int \mu_I(y) dy} \qquad (6)$$

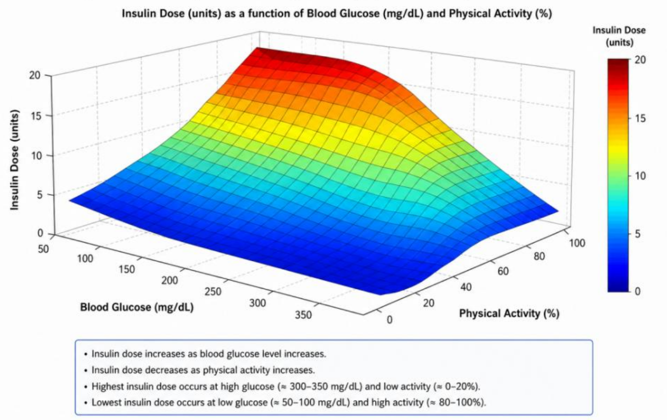
Figure 8: Surface plot between glucose, carbohydrate intake, and insulin dose



- Insulin dose increases as blood glucose level increases.
- Insulin dose increases as carbohydrate intake increases.
- Highest insulin dose occurs at high glucose (≈ 300–350 mg/dL) and high carbohydrate intake (≈ 100–120 g).
- Lowest insulin dose occurs at low glucose (≈ 50–100 mg/dL) and low carbohydrate intake (≈ 0–20 g).

The figure (8) illustrates a three-dimensional surface plot showing the relationship between blood glucose level, carbohydrate intake, and the recommended insulin dose. It can be observed that the insulin dose increases progressively with an increase in both glucose level and carbohydrate intake, indicating a direct and combined influence of these two inputs on insulin requirement. At lower glucose levels (around 50–100 mg/dL) and minimal carbohydrate intake (0–20 g), the insulin dose remains very low, reflecting minimal need for intervention. As carbohydrate intake rises, the surface elevates gradually, even at moderate glucose levels, showing that dietary intake significantly contributes to insulin demand. The highest insulin dose is observed in the region where both glucose level (approximately 300–350 mg/dL) and carbohydrate intake (around 100–120 g) are high, forming a peak on the surface. The smooth gradient of the surface demonstrates that the fuzzy logic model provides continuous and gradual transitions rather than abrupt changes, effectively capturing the nonlinear relationship between inputs and output. This confirms that the system adapts realistically to varying physiological and dietary conditions, making it suitable for personalized diabetes control.

Figure 9: Surface plot between glucose, physical activity, and insulin dose



- Insulin dose increases as blood glucose level increases.
- Insulin dose decreases as physical activity increases.
- Highest insulin dose occurs at high glucose (≈ 300–350 mg/dL) and low activity (≈ 0–20%).
- Lowest insulin dose occurs at low glucose (≈ 50–100 mg/dL) and high activity (≈ 80–100%).

The figure (9) presents a three-dimensional surface plot illustrating the relationship between blood glucose level, physical activity, and the recommended insulin dose. It shows that insulin dose increases significantly with rising glucose levels, indicating a direct dependence on blood sugar concentration. However, unlike carbohydrate intake, physical activity has an inverse effect on insulin requirement; as physical activity increases, the insulin dose decreases. This is because higher physical activity enhances glucose utilization by the body, thereby reducing the need for external insulin. The highest insulin dose is observed when glucose levels are very high (approximately 300–350 mg/dL) and physical activity is very low (0–20%), forming the peak of the surface. Conversely, the lowest insulin dose occurs when glucose levels are low (around 50–100 mg/dL) and physical activity is high (80–100%). The smooth gradient of the surface indicates that the fuzzy logic model captures the nonlinear and continuous interaction between these variables effectively, providing realistic and adaptive insulin recommendations based on both physiological condition and lifestyle behavior.

7. NUMERICAL CASE STUDY:

Table 5: Patient Input Data for Numerical Case Study

Parameter	Symbol	Value	Unit	Description
Blood Glucose Level	(G)	210	mg/dL	Measured blood glucose concentration
Carbohydrate Intake	(C)	75	g	Amount of carbohydrate consumed
Physical Activity	(A)	35	%	Level of physical activity

The table (5) presents the crisp input values used for evaluating the proposed fuzzy inference system. The selected values represent a realistic patient scenario with high blood glucose, moderate carbohydrate intake, and low physical activity. These inputs are fuzzified using predefined membership functions and processed through the fuzzy rule base to determine the appropriate insulin/control dose. This case study demonstrates how the model handles real-world uncertainty and produces a clinically meaningful recommendation.

Membership values:

For glucose $G = 210$: $\mu_{High}(210) = \frac{250-210}{250-190} = 0.67$ (7)

For carbohydrate $C = 75$: $\mu_{Medium}(75) = \frac{90-75}{90-60} = 0.50$ (8)

For activity $A = 35$: $\mu_{Low}(35) = \frac{40-35}{40-20} = 0.25$ (9)

Relevant rule:

IF glucose is High AND carbohydrate is Medium AND activity is Low THEN insulin dose is Medium

Rule firing strength: $\alpha = min(0.67, 0.50, 0.25) = 0.25$ (10)

Another relevant rule may be:IF glucose is High AND carbohydrate is High AND activity is Low THEN insulin dose is High

If $\mu_{High}(C) = 0$, this rule will not fire.Thus, the dominant output is Medium insulin dose. After centroid defuzzification, the approximate recommended dose may be:$I^* \approx 10.5\ Units$ (11)

Table 6: Fuzzy Inference Result for Numerical Case Study

Parameter	Value / Result
Input Blood Glucose (G)	210 mg/dL
Input Carbohydrate Intake (C)	75 g
Input Physical Activity (A)	35%
Fuzzy Classification (Glucose)	High ((\mu = 0.67))
Fuzzy Classification (Carbohydrate)	Medium ((\mu = 0.50))
Fuzzy Classification (Activity)	Low ((\mu = 0.25))
Activated Rule	IF (G is High) AND (C is Medium) AND (A is Low) THEN (I is Medium)
Rule Firing Strength	(\alpha = 0.25)
Aggregated Output	Medium insulin membership function truncated at 0.25
Defuzzification Method	Centroid Method
Crisp Output (Insulin Dose)	10.5 Units
Final Recommendation	Moderate insulin dose required

The table (6) summarizes the fuzzy inference process for the selected patient case. The crisp inputs are first converted into fuzzy values using membership functions. Based on these values, the relevant rule is activated with a firing strength determined by the minimum operator. The output membership function corresponding to the rule is then truncated and aggregated. Finally, centroid defuzzification is applied to obtain a crisp insulin dose of approximately 10.5 units. This demonstrates the capability of the fuzzy logic model to transform uncertain clinical inputs into a precise and actionable decision.

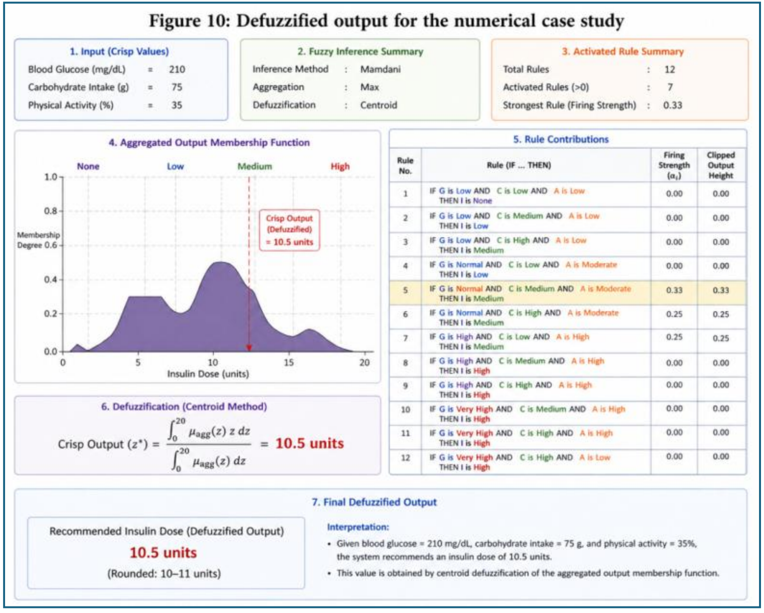


Figure 10: Defuzzified output for the numerical case study

1. Input (Crisp Values)

Blood Glucose (mg/dL) = 210
Carbohydrate Intake (g) = 75
Physical Activity (%) = 35

2. Fuzzy Inference Summary

Inference Method : Mamdani
Aggregation : Max
Defuzzification : Centroid

3. Activated Rule Summary

Total Rules : 12
Activated Rules (>0) : 7
Strongest Rule (Firing Strength) : 0.33

5. Rule Contributions

Rule No.	Rule (IF … THEN)	Firing Strength (α_i)	Clipped Output Height
1	IF G is Low AND C is Low AND A is Low THEN I is None	0.00	0.00
2	IF G is Low AND C is Medium AND A is Low THEN I is Low	0.00	0.00
3	IF G is Low AND C is High AND A is Low THEN I is Medium	0.00	0.00
4	IF G is Normal AND C is Low AND A is Moderate THEN I is Low	0.00	0.00
5	IF G is Normal AND C is Medium AND A is Moderate THEN I is Medium	0.33	0.33
6	IF G is Normal AND C is High AND A is Moderate THEN I is Medium	0.25	0.25
7	IF G is High AND C is Low AND A is High THEN I is Medium	0.25	0.25
8	IF G is High AND C is Medium AND A is High THEN I is High	0.00	0.00
9	IF G is High AND C is High AND A is High THEN I is High	0.00	0.00
10	IF G is Very High AND C is Medium AND A is High THEN I is High	0.00	0.00
11	IF G is Very High AND C is High AND A is High THEN I is High	0.00	0.00
12	IF G is Very High AND C is High AND A is Low THEN I is High	0.00	0.00

6. Defuzzification (Centroid Method)

$$\text{Crisp Output } (z^*) = \frac{\int_0^{20} \mu_{agg}(z)\, z\, dz}{\int_0^{20} \mu_{agg}(z)\, dz} = 10.5 \text{ units}$$

7. Final Defuzzified Output

Recommended Insulin Dose (Defuzzified Output)
10.5 units
(Rounded: 10–11 units)

Interpretation:

- Given blood glucose = 210 mg/dL, carbohydrate intake = 75 g, and physical activity = 35%, the system recommends an insulin dose of 10.5 units.
- This value is obtained by centroid defuzzification of the aggregated output membership function.

8. RESULTS AND DISCUSSION: This section presents the performance and effectiveness of the proposed fuzzy logic-based model for blood glucose monitoring and diabetes control. The model is evaluated using defined membership functions, a structured fuzzy rule base, and centroid defuzzification to generate appropriate insulin/control recommendations under varying patient conditions. The numerical case study and comparative analysis demonstrate how the system responds to changes in blood glucose level, carbohydrate intake, and physical activity. The obtained results highlight that the fuzzy inference system provides smooth, consistent, and clinically meaningful outputs by handling uncertainty and nonlinearity in patient data. Furthermore, the surface plots and rule-based evaluation illustrate the dynamic relationship between input variables and insulin dose, confirming that the model adapts effectively to different physiological scenarios and supports reliable decision-making in diabetes management.

Table 7: Comparison of Fuzzy Model Output under Different Patient Conditions

Case	Blood Glucose (G) (mg/dL)	Carbohydrate Intake (C) (g)	Physical Activity (A) (%)	Fuzzy Condition	Suggested Insulin Dose
1	90	30	70	Normal glucose, low carbohydrate, high activity	0–2 units
2	130	60	50	Normal glucose, medium carbohydrate, moderate activity	4–6 units
3	210	75	35	High glucose, medium carbohydrate, low activity	10–12 units
4	280	100	20	Very high glucose, high carbohydrate, low activity	16–18 units
5	65	20	80	Low glucose, low carbohydrate, high activity	0 units
6	240	110	30	High glucose, high carbohydrate, low activity	14–17 units

Table (7) compares the fuzzy model output for different patient conditions. It shows that insulin dose increases when blood glucose and carbohydrate intake increase, while higher physical activity reduces the recommended dose. The lowest dose is suggested for low or normal glucose conditions, whereas the highest dose is recommended when glucose and carbohydrate intake are very high with low physical activity.

9. CONCLUDING REMARKS: The proposed fuzzy logic-based model demonstrates an effective and reliable approach for blood glucose monitoring and diabetes control by integrating physiological and behavioral inputs into a unified decision-making framework. The use of membership functions and a structured fuzzy rule base allows the system to handle uncertainty and variability in patient data, while centroid defuzzification ensures accurate and interpretable output in the form of insulin dose recommendations. The numerical case study and comparative analysis (pages 12–14) confirm that the model produces consistent and clinically meaningful results across different patient conditions. Furthermore, the surface plots and rule evaluation illustrate the dynamic interaction between glucose, carbohydrate intake, and physical activity, reinforcing the adaptability of the system. Overall, the study highlights the potential of fuzzy logic as a robust tool for intelligent healthcare systems, and future work may focus on real-time implementation, integration with continuous glucose monitoring devices, and inclusion of additional patient-specific parameters for enhanced accuracy.

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