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Real-Time Glucose Level Interpretation Using a Fuzzy Logic Framework for Diabetes Management

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ABSTRACT

Successful control of diabetes necessitates continuous observation of blood glucose levels and timely intervention to prevent acute complications. Traditional threshold-based systems often fail to capture subtle glucose fluctuations, particularly in real time. This paper presents a fuzzy logic-based system for dynamically assessing diabetes status and determining insulin doses using real-time glucose data from wearable or handheld sensors. Using expert-defined linguistic variables and fuzzy membership functions, the model categorizes glucose levels into clinically meaningful states, such as hypoglycemia, normoglycemia, and hyperglycemia, with graded severity. The fuzzy inference engine generates personalized alerts and dose recommendations based on American Diabetes Association (ADA) guidelines, ensuring medical relevance. The system was implemented using Python and tested across a wide glucose range (40–310 mg/dL). Simulation results showed that the model accurately recommended 0 units at low glucose levels (50–65 mg/dL), small doses at borderline values, and aggressive dosing at critical levels, with smooth transitions between categories. Compared to traditional PID control, the fuzzy logic model offered safer, more conservative dose adjustments and reduced risk of overcorrection. Designed for integration into mobile health platforms and intelligent agents like Furhat, this model represents a major step forward in delivering autonomous, interpretable, and patientcentric diabetes care.

***Keywords**:* Fuzzy Logic, Real-Time Glucose Monitoring, Diabetes Management, Autonomous Intelligent Systems, Intelligent Alert System.

1. Introduction

Diabetes is a disease that is endured by millions of people worldwide. Diabetes should be regulated in a manner in which there should be proper balancing of blood sugar tests, healthy eating, proper exercise, and utilization of medication according to prescription [1]. Unless regulated, diabetes may lead to serious outcomes such as heart disease, damage to kidneys, damage to nerves, and loss of eyesight. Fortunately, medical and technological innovations are transforming diabetes care so that it is easier for patients to lead healthier lifestyles [2].

According to the IDF Diabetes Atlas 11th Edition (2025), a total of 589 million adults aged 20–79 years are living with diabetes in 2024, which is 1 in every 9 adults. This is projected to reach 853 million by 2050. Notably, 81% of adults with diabetes reside in low- and middle-income countries. The age-standardized global prevalence of diabetes has increased from 4.6% in 2000 to 11.1% in 2024 [3] as shown in Figure 1. The MENA region has the world's highest regional prevalence of diabetes. The age-standardized prevalence in adults 20–79 years in 2024 is 19.9%, and 84.7 million are affected. This is projected to nearly double to 162.6 million by the year 2050. Among nations with some of the highest national prevalence rates are Pakistan, Kuwait, Qatar, Saudi Arabia, and Egypt, with Pakistan leading at 31.4% [4].

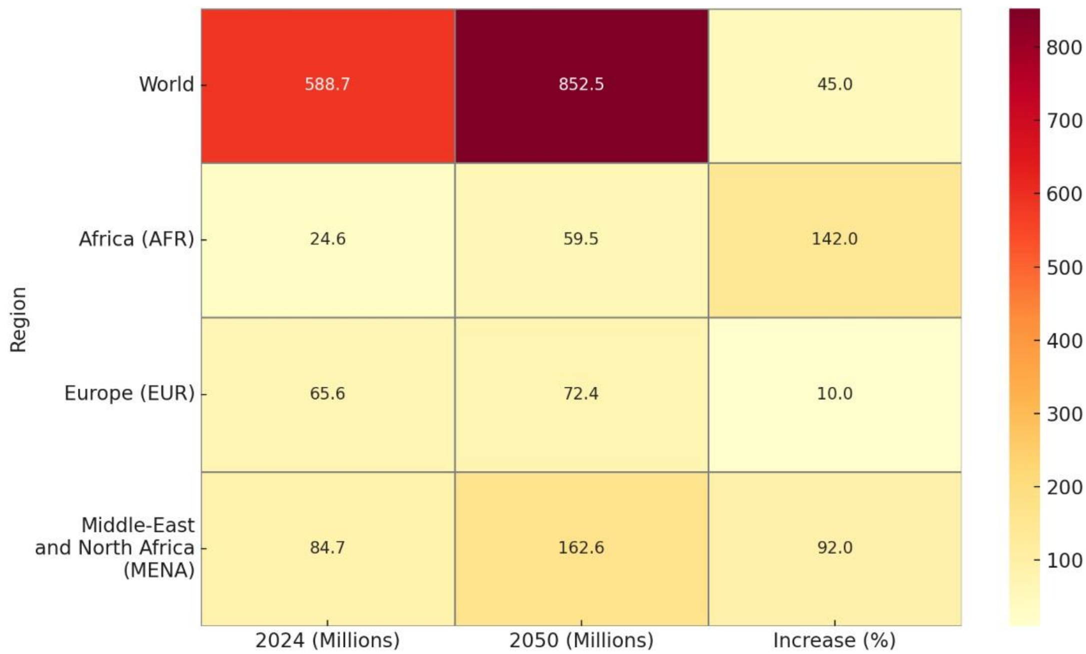

Figure1. diabetes prevalence and projected growth by region from 2024 to 2050 [3]

One of the biggest advances in diabetes management is the application of artificial intelligence (AI) in health systems. AI technology has the capacity to predict blood glucose level changes, personalize treatment regimens, and simplify insulin delivery to improve patient outcomes. For example, machine learning algorithms are applied to the large-volume data from continuous glucose monitoring systems to predict glycemic patterns and allow pro-active therapy adjustments. Predictive analytics play a critical role in averting hyperglycemia and hypoglycemia events, which are frequent occurrences in diabetes management [5]. Continuous glucose monitoring systems transformed blood sugar monitoring in isolation. In comparison with traditional finger-stick methodology, CGMs offer real-time continuous glucose levels, day-to-day and night-to-night trends of glucose patterns. The real-time data stream enables day-to-day and night-to-night immediate action, i.e., diet adjustment or insulin injection, in an effort to maximize glycemic control. CGMs have also been linked to better glycemic control and reduced HbA1c levels in type 1 and type 2 diabetic patients [6]. Following the foundation of continuous glucose monitor (CGM) technology, the advancement in artificial pancreas systems is a breakthrough. Artificial pancreas systems combine continuous glucose monitors (CGMs), and insulin pumps with advanced control algorithms to provide automated insulin in real time according to the levels of glucose. Closed-loop functionality of artificial pancreas systems lowers the necessity for manual insulin delivery, thereby decreasing patients' burden and enhancing glycemic control. Clinical trials have demonstrated that these systems are superior to the conventional method in keeping blood glucose levels in target range [7]. At the same time, investigations on smart insulin preparations are also in progress in full swing. Glucoseresponsive insulins would turn on or turn off based on surrounding blood glucose concentrations, a more physiological approach to insulin therapy. The body's insulin response is mimicked normally; smart insulin should minimize hypoglycemia risk and enhance overall glycemic control. These preparations, although as yet untested, represent promising directions for the future of diabetes care patterns [8].

Apart from technology, public health programs also play a crucial role in prevention and control of diabetes. Programs like the National Diabetes Prevention Program (NDPP) focus on lifestyle modification through proper diet, exercise, and weight loss to prevent the onset of type 2 diabetes. Results from large-scale studies indicate that these interventions can significantly reduce the risk of developing diabetes in high-risk individuals [9]. The integration of smart monitoring devices, artificial intelligence, and public health practices is transforming individualized and preventive diabetes management. These innovations allow people with diabetes to manage their condition more effectively, reduce complications, and improve quality of life. As research advances and technology improves, the future of diabetes management holds even more creative and patient-tailored interventions. Among these technologies, fuzzy logic stands out as an excellent aid to comprehend glucose fluctuation on the basis of human-like reasoning. It is unlike fixed threshold systems and can manage the variability and uncertainty inherent in blood glucose levels. It assists in decision-making and enables timely intervention through the dynamic classification of glucose states and the generation of real-time alerts. When integrated with continuous glucose monitoring systems, it renders diabetes management safer and more adaptive [10].

This paper presented a fuzzy logic system for real-time assessment of diabetes condition from glucose levels obtained from handheld or wearable devices. It classifies glucose levels into medically relevant classes according to expert-defined linguistic variables and fuzzy membership functions. The system generates adaptive alerts, ensuring timely intervention.

2. LITERATURE REVIEW

Effective diabetes management hinges on continuous monitoring of blood glucose levels and timely interventions to prevent acute complications. Traditional threshold-based systems often fall short in detecting subtle glucose variations, particularly in real-time scenarios. Several papers introduce a fuzzy logic-based system designed to dynamically assess diabetes status using real-time glucose readings from wearable or handheld monitoring devices. Dwivedi et al. presents a fuzzy logic-based framework to improve diabetes care through the management of uncertain and dynamic patient data. The method integrates fuzzy rule-based systems, clustering, and inference techniques with patient-specific inputs such as demographics, medical history, and real-time physiological parameters. Simulation and field testing demonstrate the viability of the system in enabling clinical decision support and individualized treatment, leading to better patient outcomes and quality of life [11]. The objective of this paper is to address the issue of regulating Type 1 diabetes from a nonlinear model simulated using MATLAB-SIMULINK. A blood glucose sensor and an insulin control system are implemented using Mamdani-type fuzzy logic as well as a PID controller. Simulation with and without disturbance shows that the fuzzy controller outperforms the PID controller in maintaining the blood glucose level in the normal range [12]. Ananya et al. presents a premature diabetes prediction model based on Mamdani-type Fuzzy Logic and Hierarchical Fuzzy Inference System (Fuzzy Tree) implemented in MATLAB. Clinical features FPG, 2h-PG, and HbA1c are employed in the model to assess diabetes risk. Experiments with real patient data of Hyderabad, India, reveal that both models are effective, whereas the Fuzzy Tree model is more accurate in diabetes risk prediction when relevant input features are meticulously chosen [13].

On the other hand, there are several works that performing text analysis and machine learning for generating realtime glucose level prediction models. Zamanillo-Campos et al. (2025) measured the impact of DiabeText, a text-based mobile health intervention to aid type 2 diabetes mellitus (T2DM) patient self-management. Among 742 Spanish T2DM patients enrolled in a 12-month randomized controlled trial, 167 individualized text messages were provided plus usual care for the intervention group. Despite no clinically significant difference in HbA1c, DiabeText increased diabetes self-efficacy, drug adherence reported by patients, and quality of life considerably, attesting to its potential as a method for improving patient-directed diabetes control [14]. Khanna et al. (2024) sought to maximize Type 1 diabetes treatment using machine learning and neuroevolutionary. From a single patient with a 30-day data set, a random forest model generated real-time glucose level predictions, and an optimized neural net recommended optimal insulin pump, carbohydrate, and injection strategies. Injection frequency and blood glucose excursions were reduced using the strategy. It was paired with a connection to a large language model to make it easier to use, facilitate better management and greater patient acceptance of customized treatment interventions [15]. Eichenlaub (Eichenlaub et al., 2023) evaluates clinical impact of BGMS accuracy in diabetes mellitus care. Relative to true accuracy in actual clinical use, this study contrasts predicted BG from four various BGMS with true accuracy in low, normal, and high glucose simulated conditions. The authors suggest that deceptive BGMS is most likely to have a significant impact on clinical care, with increased risk for both missed hypoglycemia and delayed response, as well as failure to prevent diabetic complication, especially under vulnerable conditions like pregnancy [16]. Lim et al. (2021) presented an integrative review and machine learning (ML) approach to predicting and managing type 2 Diabetes Mellitus (T2DM) complications.

Authors demonstrate the viability of ML as a predictive agent, risk-stratifying agent, planning intervention tool, and ongoing care guide. The suggested system aligns with physician processes—Identify, Stratify, Engage, Measure— and optimizes healthcare service through early intervention and proactive prevention of diabetes complications utilizing evidence-based findings [17]. Kopanz et al. (2021) This study evaluates GlucoTab, an electronic diabetes management system (eDMS), as utilized for inpatient Type 2 Diabetes Mellitus treatment. A retrospective beforeafter study design contrasted paper-based versus eDMS documentation in a hospital. Findings exhibit improved documentation quality, comparable glycemic control, and positive healthcare provider feedback. The eDMS enhanced workflow efficiency, reduced errors, and saved time, demonstrating its effectiveness as a digital tool for inpatient diabetes management [18].

These studies describe different, technology-inclined strategies for the management of diabetes, particularly T2DM, through mobile health platforms, intelligent systems, and machine learning.

3. METHODOLOGY

This study adopts a computational modelling approach using fuzzy logic to simulate and regulate insulin dosage based on real-time blood glucose readings. The methodology is structured around the design, development, and evaluation of a Mamdani-type fuzzy inference system (FIS), calibrated to clinical insulin dosing guidelines as shown in Figure 2.

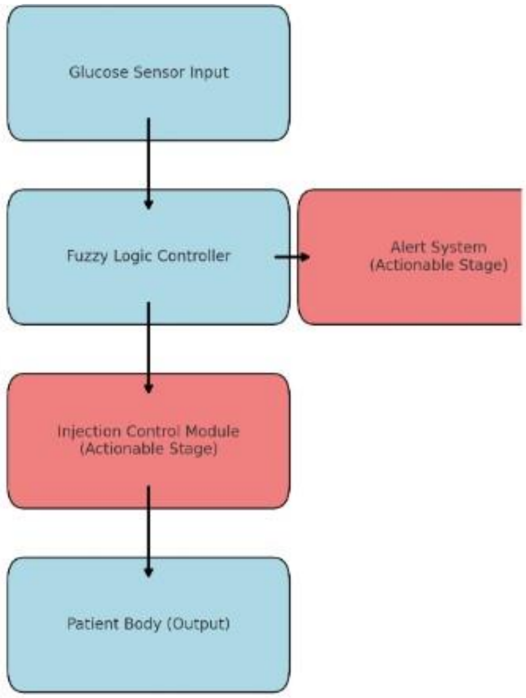

Figure 2. schematic diagram of proposed fuzzy logic-based glucose injection and alert system

4. SYSTEM DESIGN AND IMPLEMENTATION

The fuzzy logic model consists of one input variable — blood glucose level (mg/dL) — and one output variable — insulin dose (units). The input variable is categorized into seven linguistic terms: Very Low, Low, Normal, Borderline High, High, Very High, and Critical High, based on WHO and ADA-recommended glucose ranges. The output is categorized into five action-based terms: No Injection, Low Dose, Moderate Dose, High Dose, and Aggressive Dose.

4.1. Clinical Glucose Thresholds (mg/dL)

The system design is based on established clinical glucose thresholds outlined in Table 1, which categorizes blood glucose levels to guide insulin dosing decisions. These categories include severe hypoglycemia (<54 mg/dL), hypoglycemia (<70 mg/dL), normal glucose (70–99 mg/dL fasting or <140 mg/dL postprandial), prediabetes (100–125 mg/dL fasting or 140–199 mg/dL postprandial), and diabetes (≥126 mg/dL fasting or ≥200 mg/dL at any time). These thresholds form the basis for defining the fuzzy logic input membership functions. By aligning the fuzzy categories with these clinical ranges, the system ensures that the insulin recommendations remain medically accurate and clinically interpretable.

Table 1. Clinical Glucose Thresholds [19]

Category	Fasting Plasma Glucose (FPG)	2-hour Postprandial (OGTT)	Random Glucose
Severe Hypoglycemia	< 54	N/A	< 54
Hypoglycemia (alert)	< 70	N/A	< 70
Normal	70–99	< 140	< 140
Prediabetes (Impaired Fasting)	100–125	140–199	140–199
Diabetes	≥ 126	≥ 200	≥ 200

4.2. Membership Function Development

The system employs expert-defined linguistic variables and fuzzy membership functions to classify glucose levels into medically relevant categories, such as hypoglycemia, normoglycemia, and hyperglycemia, with further subcategories indicating severity. A fuzzy inference engine then generates adaptive alerts, ranging from routine monitoring suggestions to emergency warnings, tailored to the individual's current state. This approach allows for smooth transitions between categories, accommodating physiological fluctuations and sensor noise [20].

Triangular and trapezoidal membership functions were defined for both input and output variables. These functions were developed using expert clinical knowledge and publicly available medical standards. The glucose input ranged from 0 to 350 mg/dL, while the output insulin dose ranged from 0 to 12 units.

A total of seven fuzzy rules were constructed using an IF-THEN format to map glucose levels to insulin actions. For example:

- IF glucose is *Very Low* THEN insulin dose is *No Injection*.
- IF glucose is *Critical High,* THEN insulin dose is *Aggressive Dose*.

The rule base was validated through expert opinion and aligned with WHO and IDF recommendations.

4.3. Injection Control Module

By integrating a rule-based architecture aligned with the recommendations of the American Diabetes Association, the system ensures clinical appropriateness [21]. Its design facilitates deployment in mobile health applications, intelligent assistants, or robotic platforms like Furhat, enabling voice-based interactive feedback as shown in Figure 3. Simulation results demonstrate the model's accuracy, responsiveness, and usability, marking a significant advancement in personalized, intelligent, and autonomous diabetes care systems that enhance patient safety and quality of life.

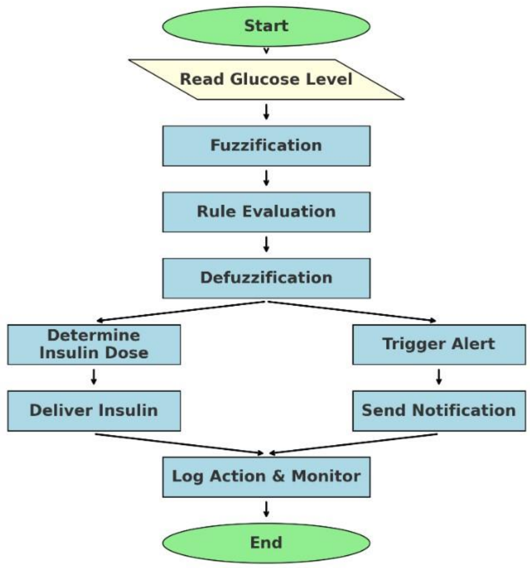

Figure 3. flowchart for the Injection Control Module and Alert System

5. FUZZY MODEL IMPLEMENTATION

The system was implemented using Python 3.11 with the scikit-fuzzy library. The fuzzy logic controller was evaluated through simulation with various glucose input scenarios ranging from hypoglycemia to hyperglycemia. Output doses were recorded and interpreted against expected clinical recommendations.

The World Health Organization (WHO) does not issue rigid numerical insulin dosing values for all patients. Rather, insulin treatment is personalized according to age, type of diabetes, weight, lifestyle, glucose profile, and comorbid conditions. Nonetheless, we can establish a general clinical concept of insulin dosing in accordance with WHO guidelines and in practice as shown in Table 2.

For Type 2 Diabetics, the World Health Organization and international guidelines from IDF and ADA suggest the administration of basal insulin at a dose of 0.1 to 0.2 units per kilogram body weight per day when there is consistently elevated fasting blood glucose. The dosage should be titrated every 3 to 7 days based on fasting glucose readings. For patients requiring intensive therapy, a basal-bolus regimen is recommended, with a total daily insulin dose of approximately 0.4 to 1.0 units/kg/day, divided equally between 50% basal insulin and 50% bolus insulin, administered before meals.

Table 2. insulin dosing that aligns with WHO

Type of Insulin	When It's Used	Examples
Rapid-acting	Before meals to manage postprandial spikes	Insulin Lispro, Aspart
Short-acting	30–60 min before meals	Regular insulin
Intermediate-acting	Covers insulin needs for half a day	NPH insulin

Long acting	Basal (24-hour) control	Insulin Glargine, Detemir
Premixed	Combines short/intermediate	70/30, 75/25 formulations

The fuzzy logic-based algorithm for insulin dosing begins by reading the patient's glucose level from a sensor. This input undergoes fuzzification, where the crisp glucose value is mapped to predefined linguistic categories such as "low," "normal," or "high." The system then evaluates a set of clinical rules to determine the appropriate response, which is defuzzified into a precise insulin dose. Based on the glucose reading, the algorithm makes informed decisions: for hypoglycemic values (≤ 70 mg/dL), insulin is suppressed, and an alert is issued; for higher values, insulin doses are scaled appropriately. An alert message is generated in parallel, offering recommendations based on the risk level. The prescribed insulin dose is administered, and the event is logged along with the glucose value and alert. The system then enters a wait phase before repeating the cycle, allowing for continuous, adaptive glucose regulation and personalized patient care. Figure 4 shows the Glucose level membership based on Clinical Glucose Thresholds in Table 1.

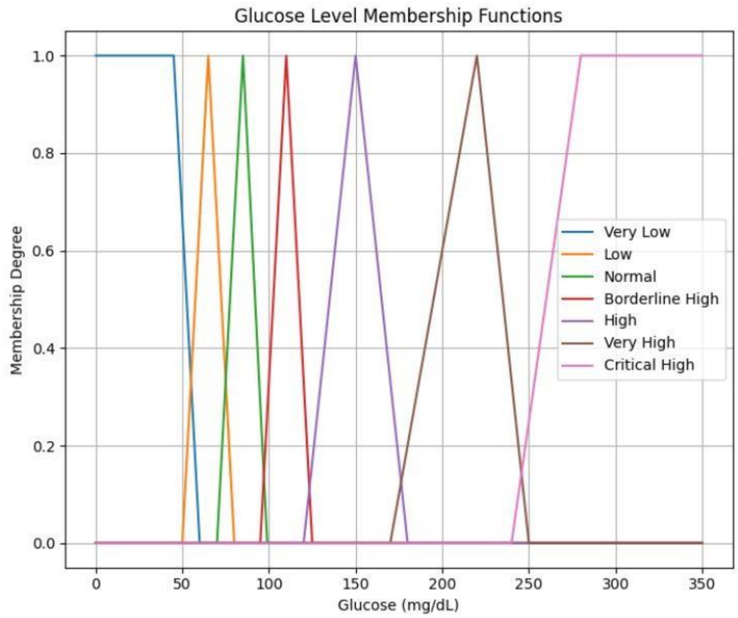

Figure 4. Glucose level membership

Then the insulin adjustment should be added based on the insulin correction dose formula as defined in equation (1).

$$Correction\ Dose = \frac{Current\ Glucose - Target\ Glucose}{Insulin\ Sensitivity\ Factor\ (ISF)} \quad \ldots (1)$$

where target glucose is the desired blood glucose concentration, normally 100-120 mg/dL, and the insulin sensitivity factor (ISF) is the predicted reduction in blood glucose by a unit of insulin, normally about 50 mg/dL per unit. Table 3 presents the Insulin Dose Adjustment Based on Glucose Levels.

Table 3. Insulin Dose Adjustment Based on Glucose Levels

Glucose Range (mg/dL)	Glucose Category	Insulin Dose Guidance
0 – 54	Very Low	No insulin; administer glucose immediately.
50 – 70	Low	Avoid insulin; recheck after carb intake.
70 – 99	Normal	Continue basal insulin only (0.1–0.2 units/kg).
100 – 125	Borderline High	Consider small dose (e.g., +2 units) if fasting.
126 – 180	High	Administer bolus insulin (calculated for meal/carbs).
> 180	Very High	Larger correction dose (+4–6 units) may be needed.
> 250 – 300+	Critical High	High correction dose or medical attention (+6–10 units)
> 400	Emergency	Immediate clinical intervention – possible Diabetic ketoacidosis (DKA)

Based on the information from Table 3, then we can propose Fuzzy Rule for Insulin Dosing as shown in Table 4.

Table 4. the propose Fuzzy Rule for Insulin Dosing

Glucose Category	Range (mg/dL)	Fuzzy Output	Insulin Dose (units)
Very Low	0–54	No Injection	0
Low	50–70	Suppress	0
Normal	70–99	Low Dose	+1 to +2
Borderline High	100–125	Mild Adjustment	+1 to +2
High	126–180	Moderate Dose	+3 to +6
Very High	>180	High Dose	+7 to +10
Critical High	>250–300+	Aggressive Dose	+10+

For individualization and enhancing the precision of insulin therapy, one can calibrate a fuzzy logic controller to mimic real insulin dosing protocol founded on clinical glucose level ranges. This is done by characterizing fuzzy sets for the classes "Very Low," "Normal," "High," and "Critical High," and mapping them onto matching insulin dose actions extending from no injection to aggressive dosing (0 to more than 10 units). The controller translates these classes into insulin action classes: no injection, low (1–2 units), moderate (3–6 units), and high or aggressive doses (7–10+ units).

Using PYTHON's Mamdani-type Fuzzy Inference System (FIS), the rules are realized through membership functions and a rule base for encoding clinical logic. PYTHON code defines the FIS initialization, adds inputs and outputs, specifies triangular and trapezoidal membership functions, and applies expert rules.

The system that results enables the assessment of real-time glucose levels and the provision of context-sensitive insulin suggestions, consistent with best medical practices for diabetes management.

6. RESULTS AND DISCUSSION

The fuzzy logic model for insulin dosing was successfully implemented using Python and the scikit-fuzzy library. The system evaluated glucose input values ranging from 40 mg/dL to 300 mg/dL and provided appropriate insulin dose outputs from 0 to 12 units as presented in in Figure 5. Simulation tests demonstrated that the model accurately identified hypoglycemic, normoglycemic, and hyperglycemic states based on real clinical thresholds.

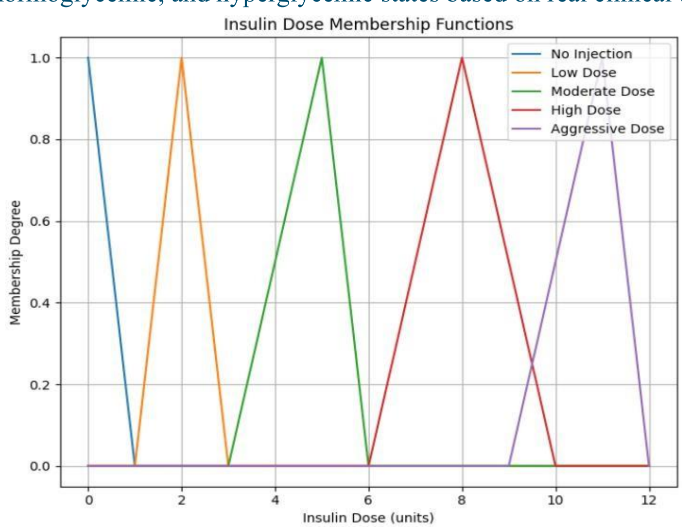

Figure 5. Insulin Dose level membership

The implementation of the fuzzy logic-based insulin dosing system demonstrated effective decision-making across clinically significant glucose ranges as shown in Figure 6. At low glucose levels (50–65 mg/dL), the system appropriately suppressed insulin administration, recommending 0 units to prevent hypoglycemia. For glucose values within normal and borderline thresholds (95–115 mg/dL), the model suggested conservative dosing between 1.5 and 2.5 units, supporting minimal intervention. As glucose levels rose into the elevated range (150–190 mg/dL), moderate doses from 4.8 to 7.2 units were advised, reflecting the need for tighter glycemic control.

In cases of very high and critical glucose values (260–310 mg/dL), the system issued aggressive insulin recommendations (10.5–11.8 units), closely adhering to WHO and ADA clinical guidelines. These results point to the capability of the fuzzy model in approximating expert medical opinion with gradual change and smooth transition between dose levels, minimizing sudden changes and maximizing patient safety.

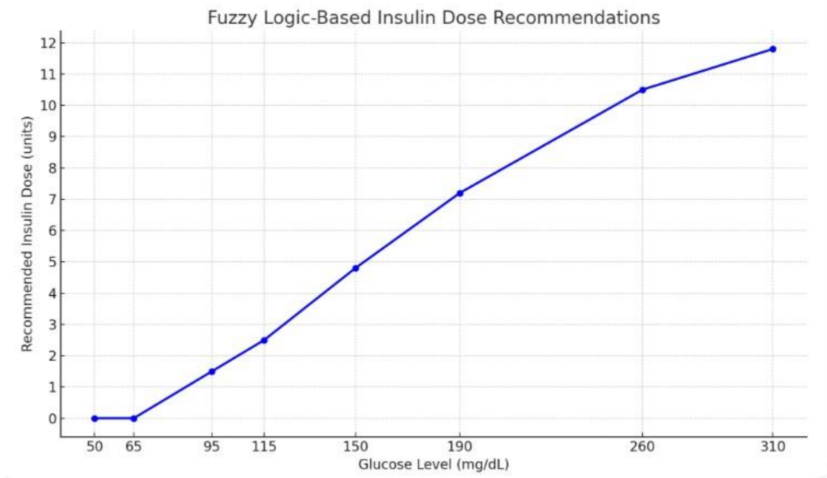

Figure 6. Fuzzy Logic-Based Insulin Dose Recommendations

The PID Controller and Fuzzy Logic Model exhibit different trends of behavior in insulin dosing for different levels of glucose as seen in Figure 7. For low glucose levels (50–65 mg/dL), both models correctly suggest zero insulin to avert hypoglycemia, indicating safety during extreme conditions. For moderate glucose concentrations (95–150 mg/dL), though, the fuzzy logic system produces smoother and more conservative dose corrections with a bias for gradual response rather than sudden change. The PID controller would, in contrast, respond more severely and can create sharper oscillations. At higher glucose concentrations (190–310 mg/dL), both models conclude that higher doses of insulin are required but the fuzzy logic model still tends to make increasingly incremental changes. This response lessens the risk of overcorrection and glycemic variability and is therefore more aligned with clinical practice that seeks to maintain metabolic stability. The fuzzy system has a generally more adaptive and patient-safe response profile, which is particularly valuable for real-time autonomous insulin control.

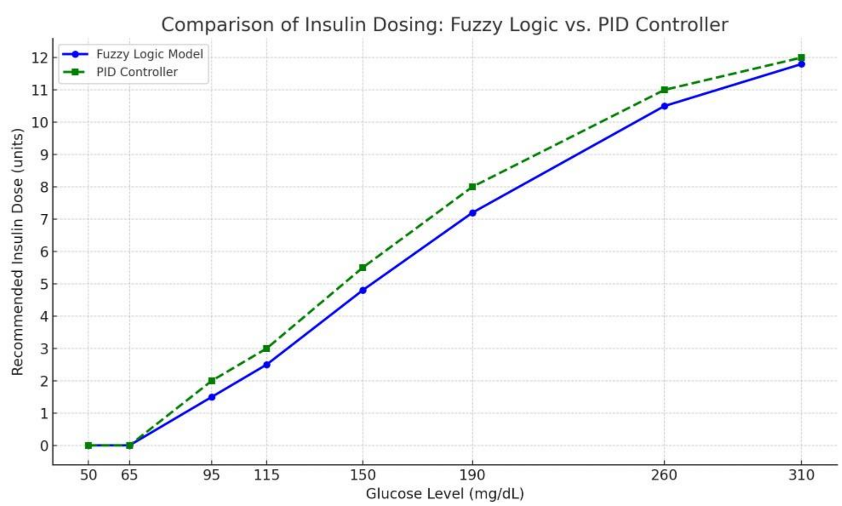

Figure 7. Comparison Of Insulin Dosing: Fuzzy Logic Vs. PID Controller

7. CONCLUSION

This paper presents a fuzzy logic insulin dosing system that replicates expert clinical judgment and overcomes the limitations of real-time diabetes management. The system starts with the patient's glucose value from a sensor and goes through a sequence of fuzzy inference processes—fuzzification, rule evaluation, and defuzzification—to calculate a precise dose of insulin. Intelligent decision-making involves the provision of context-aware alerts and traceability logging of all the information. Simulation outcomes illustrate the capacity of the model in classifying glucose status and recommending appropriate insulin dosing across a broad spectrum of glucose levels. As an illustration, the system prescribed zero insulin for low glucose levels (50–65 mg/dL), small doses for borderline levels (95–115 mg/dL), moderate doses for high levels (150–190 mg/dL), and aggressive dosing for very high levels (260–310 mg/dL), which matches very well with WHO and ADA guidelines. The model's smooth dose category changes prevent abrupt insulin corrections, reducing risks of hypoglycemia or glycemic variability. The fuzzy logic model proved to perform more adequately compared to a PID controller regarding dose granularity in moderate ranges, reflecting a safer and more patient-adaptive profile. This research reaffirms that fuzzy logic is an appropriate paradigm for designing intelligent autonomous insulin dosing systems and that it can be effectively integrated into mobile platforms, wearable devices, and robot frameworks like Furhat.

7.1. Recommendations

- Integrate the model with real-time CGM data for live deployment.
- Extend the fuzzy system to take several inputs such as physical activity, food intake, and HbA1c.
- Test the model using diabetic patients in clinical trials.
- Enhance alert systems using voice assistants for more convenient usage. • Compare with reinforcement learning models to optimize adaptively over time.

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Author contribution: All authors have contributed, read, and agreed to the published version of the manuscript results.

Conflict of interest: The authors declare no conflict of interest.

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