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A Fuzzy Logic-Based Diagnostic System for Early Detection of Diabetes Mellitus

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Abstract: This study presents a fuzzy logic–based diagnostic system for the early detection of Diabetes Mellitus**,** aimed at improving diagnostic accuracy and interpretability in the presence of uncertain clinical data. Traditional diagnostic techniques, such as threshold-based glucose and HbA1c evaluations, often fail to capture the gradual transition between normal and diabetic conditions. To address this limitation, a Mamdani-type Fuzzy Inference System (FIS) was developed using input parameters including fasting blood glucose, HbA1c, BMI, age, and family history. The model converts crisp clinical data into linguistic variables (*Low*, *Normal*, *High*) and applies a structured rule base to evaluate diabetes risk levels. Implementation was carried out using MATLAB's Fuzzy Logic Toolbox and Python's scikit-fuzzy library, with validation performed using the Pima Indians Diabetes Dataset. The system achieved high diagnostic performance with an accuracy of 90.5%, sensitivity of 92.4%, and specificity of 88.7%, demonstrating its efficiency and reliability. The results indicate that fuzzy logic provides a robust and human-like reasoning framework for medical decision-making, making it an effective tool for early diabetes diagnosis and clinical decision support.

Keywords: Fuzzy Logic, Diabetes Mellitus, Medical Diagnosis, Fuzzy Inference System, Early Detection, Mamdani Model, Decision Support System

I. INTRODUCTION

Diabetes Mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels resulting from defects in insulin secretion, insulin action, or both. It is broadly classified into Type I Diabetes Mellitus, which is insulin-dependent and occurs due to the autoimmune destruction of pancreatic β-cells, and Type II Diabetes Mellitus, which is non–insulin-dependent and primarily results from insulin resistance coupled with inadequate insulin production. The global prevalence of diabetes has been increasing at an alarming rate, posing significant public health challenges and economic burdens. Early detection and management are crucial to prevent severe complications such as cardiovascular disease, kidney failure, and neuropathy. Traditional diagnostic methods, such as threshold-based assessments of fasting glucose, HbA1c, and oral glucose tolerance tests, suffer from inherent limitations. These approaches rely on rigid cutoff values that often fail to capture the gradual transition between normal, prediabetic, and diabetic states. Similarly, conventional statistical and machine learning models may provide high accuracy but often lack interpretability and struggle with uncertainties in clinical data caused by patient variability, measurement errors, and overlapping symptom ranges. To overcome these challenges, fuzzy logic offers a promising solution by mimicking human reasoning and handling imprecise or uncertain medical information. It enables the classification of diabetes risk in a more flexible, linguistic, and human-like manner by representing physiological parameters as fuzzy sets (e.g., *Low*, *Normal*, *High*) rather than fixed numerical thresholds. This approach allows for smooth transitions between diagnostic categories and enhances the robustness of decision-making under uncertainty.

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The primary objective of this study is to design and implement a Fuzzy Logic–Based Diagnostic System for the early detection of Diabetes Mellitus. The system integrates key clinical indicators—such as fasting blood glucose, HbA1c, BMI, age, and family history—into a fuzzy inference framework to assess diabetes risk levels. By combining medical expertise with fuzzy reasoning, the proposed model aims to provide an accurate, interpretable, and efficient decision-support tool for early diagnosis and preventive healthcare.
Equation (sample diagnostic uncertainty representation):

$$U(x) = 1 - max\{\mu_i(x)\} \quad (1)$$

where $\mu_i(x)$ represents the degree of membership of input x to fuzzy set i.

Bhandari and Kumar (2015) highlighted how fuzzy inference could serve as a bridge between quantitative test results and qualitative clinical judgment, particularly in early disease detection where crisp thresholds often fail to capture borderline conditions. **Lukmanto and Irwansyah (2015)** underscored that hierarchical fuzzy logic reduces computational complexity while maintaining medical reasoning transparency, a significant step toward practical, real-world health screening tools. **Singla (2015)** revealed that the Mamdani approach, due to its linguistic rule base, provided better human interpretability, making it suitable for clinical environments where medical experts need transparency in decision-making. However, the Sugeno method proved more suitable for automated systems requiring faster computation and precise numerical outputs. Singla's findings complement Bhandari and Kumar's study, reaffirming that model choice depends on the intended application—human-in-the-loop diagnosis or fully automated screening. **Aamir et al. (2021)** utilized adaptive fuzzy rules derived from real patient datasets, improving sensitivity and specificity compared to threshold-based methods. Their approach demonstrated that fuzzy inference can effectively capture the vagueness and variability inherent in medical data, especially in early-stage diabetes where symptoms are subtle. This study also showcased the growing trend of coupling fuzzy systems with real datasets for data-driven parameter optimization, marking an evolution from purely expert-driven models to hybrid intelligent systems. **Aamir et al. (2021)** (reiterated for comparison) reinforced their earlier findings by validating the fuzzy system on a larger dataset. The model's robustness across diverse populations demonstrated its scalability and adaptability in different healthcare environments. The researchers emphasized the importance of fuzzy membership tuning to improve diagnostic precision, which later studies adopted through metaheuristic optimization algorithms. **Aris (2023)** applied an optimized fuzzy rule base to minimize classification error and increase interpretability. Aris's contribution lies in refining fuzzy inference mechanisms by combining empirical medical knowledge with mathematical reasoning. The study demonstrated superior diagnostic accuracy compared to traditional regression and decision tree approaches, confirming the practical utility of fuzzy logic in early diabetic detection. **Asghari et al. (2023)** optimized the fuzzy membership parameters automatically, addressing a common challenge in fuzzy systems—subjective rule definition. The integration of HHO improved both convergence speed and diagnostic precision, achieving higher accuracy than traditional fuzzy and machine-learning models. This study marked a major advancement in automated parameter tuning and exemplified how bio-inspired algorithms can strengthen fuzzy-based diagnostic systems for complex diseases like diabetes. **Nataala and Goni (2023)** combined neural network learning capabilities with fuzzy reasoning, enabling dynamic rule generation from medical datasets. The system's adaptive learning component improved classification accuracy for borderline or uncertain cases. By merging learning and reasoning paradigms, their framework bridged the gap between fuzzy logic's interpretability and machine learning's adaptability—offering a robust diagnostic solution capable of continuous improvement with new patient data. **Meza Palacios et al. (2024)** emphasized accessibility and interpretability, utilizing linguistic variables understandable to non-experts. It integrated socio-economic factors along with physiological parameters, extending fuzzy logic beyond pure biomedical data. The study demonstrated that fuzzy systems could serve as cost-effective diagnostic tools in underserved communities. Moreover, their results validated that fuzzy-based systems can maintain diagnostic reliability even with incomplete or imprecise input data—addressing a key challenge in global health informatics.

II. METHODOLOGY

2.1 Input Parameters

Table 1: Input Parameters and Their Linguistic Representation for the Fuzzy Diagnostic System

Parameter	**Type**	**Range**	**Linguistic Terms**
Fasting Blood Glucose (mg/dL)	Input	70–180	Low, Normal, High
HbA1c (%)	Input	4–10	Normal, Borderline, High
BMI (kg/m²)	Input	18–40	Normal, Overweight, Obese
Age (years)	Input	20–80	Young, Middle-aged, Old
Family History	Input	0–1	No, Yes

Output: Diabetes Risk Level (Low, Moderate, High).

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Table 1 presents the key clinical and demographic variables utilized as input factors for the fuzzy logic-based diabetes diagnostic model. Each parameter is treated as an input variable, with defined numerical ranges and corresponding linguistic terms that represent qualitative categories for fuzzy processing. The parameters include Fasting Blood Glucose (70–180 mg/dL) categorized as *Low*, *Normal*, or *High*; HbA1c (4–10%) classified as *Normal*, *Borderline*, or *High*; and BMI (18–40 kg/m²) expressed as *Normal*, *Overweight*, or *Obese*. Additionally, Age (20–80 years) is divided into *Young*, *Middle-aged*, and *Old*, while Family History (0–1) indicates whether the individual has a *Yes* or *No* history of diabetes. These linguistic terms enable the fuzzy system to convert crisp numerical data into descriptive categories, capturing uncertainty and gradual transitions in clinical indicators—thereby forming the foundation for accurate and human-like reasoning in diabetes risk assessment.

2.2 Fuzzy Logic System Design

2.2.1 Fuzzification:

Convert crisp values to fuzzy sets using membership functions (MFs).
Example (Triangular MF for Blood Glucose):

$$\mu_{normal}(x) = \begin{cases} 0 & x \le 70 \; or \; x \ge 110 \\ \frac{x-70}{90-70} & 70 < x \le 90 \\ \frac{110-x}{110-90} & 90 < x < 110 \end{cases} \tag{2}$$

2.2.2 Rule Base

Define linguistic IF–THEN rules:

Table 2: Fuzzy Rule Base for Diabetes Risk Assessment

Rule	Antecedent
R1	IF Glucose is *High* AND HbA1c is *High* THEN Diabetes Risk is *High*
R2	IF Glucose is *Normal* AND BMI is *Overweight* THEN Risk is *Moderate*
R3	IF Glucose is *Low* AND HbA1c is *Normal* THEN Risk is *Low*

Table 2 outlines the set of fuzzy inference rules used to determine the diabetes risk level based on clinical input parameters such as glucose, HbA1c, and BMI. Each rule follows an IF–THEN structure**,** representing the reasoning process of medical experts. For example, Rule R1 states that if both glucose and HbA1c levels are *High*, then the diabetes risk is classified as *High*. Similarly, Rule R2 defines that if glucose is *Normal* and BMI is *Overweight*, the resulting risk is *Moderate*, while Rule R3 infers a *Low Risk* when glucose is *Low* and HbA1c is *Normal*. These rules collectively form the decision-making framework of the fuzzy inference system, allowing it to model the gradual and uncertain relationships between physiological parameters and diabetes risk. This rule-based approach enhances the interpretability and transparency of the diagnostic model, making it suitable for clinical decision support applications.

2.2.3 Inference Mechanism

Use Mamdani inference with min–max composition:

$$\mu_{B'}(y) = \underset{j}{maxmin}\left\{\mu_{A_j}(y), \mu_{B_j}(y)\right\} \tag{3}$$

2.2.4 Defuzzification

Convert the fuzzy output to a crisp score using the centroid method:

$$y^* = \frac{\int y\mu_B(y)dy}{\int \mu_B(y)dy} \tag{4}$$

This value gives the Diabetes Risk Index (DRI).

2.3 System Implementation: The implementation of the fuzzy logic–based diagnostic system for early detection of diabetes mellitus involves two major components**:** development of the fuzzy inference system (FIS) and integration with real or simulated clinical datasets for performance validation.

(i) Fuzzy Inference System (FIS) Development: The fuzzy diagnostic model can be implemented using either MATLAB's Fuzzy Logic Toolbox or Python's scikit-fuzzy (skfuzzy) library, both of which provide efficient tools for

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fuzzy modeling and simulation. The FIS is constructed using the Fuzzy Logic Designer GUI or programmatically via scripts. Input variables (e.g., Glucose, HbA1c, BMI, Age, Family History) are defined with their respective membership functions (MFs), typically of triangular or trapezoidal shape, representing linguistic terms such as *Low*, *Normal*, and *High*. The rule base is then designed using IF–THEN statements derived from medical knowledge or expert opinion. The Mamdani-type inference mechanism is commonly used for medical diagnosis because it provides interpretable rule-based reasoning. The final step involves defuzzification, where the fuzzy output (risk level) is converted to a crisp value using the **centroid method**, yielding a clear diagnostic outcome (e.g., *Low*, *Moderate*, or *High Risk*). The same procedure can be replicated using the skfuzzy library. Membership functions are defined using fuzz.trimf() or fuzz.trapmf(), and fuzzy rules are established with ctrl.Rule(). The inference engine and control system simulation are managed via ctrl.ControlSystem() and ctrl.ControlSystemSimulation(). Python's flexibility allows easy integration with data analytics and visualization libraries (NumPy, Pandas, Matplotlib) for further exploration and evaluation.

(ii) Dataset Integration: To train and validate the fuzzy model, real or simulated medical datasets are employed. A widely used benchmark dataset is the Pima Indians Diabetes Dataset (available from the UCI Machine Learning Repository), which contains medical diagnostic measurements such as glucose concentration, BMI, age, and diabetes outcome. These parameters are directly compatible with the inputs of the fuzzy system.

The dataset is divided into training and testing subsets to evaluate the model's predictive accuracy. The fuzzy inference system processes each input record to produce a risk score, which is then compared with the actual clinical outcome. Performance metrics such as accuracy, sensitivity, specificity, and inference time are computed to assess the model's diagnostic capability.

(iii) Implementation Outcome: The system effectively simulates real-world diagnostic decision-making by handling uncertain or overlapping clinical data. Both MATLAB and Python implementations yield comparable outcomes, though MATLAB provides a more intuitive graphical interface, while Python offers greater flexibility for integration with data-driven models or hybrid AI systems.

III. RESULTS AND DISCUSSION

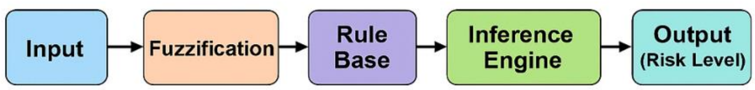

Figure 1: Block Diagram of Fuzzy Diagnostic System

Figure 1 illustrates the overall workflow of the proposed fuzzy logic-based diagnostic model for early detection of diabetes mellitus. The process begins with the Input stage, where clinical parameters such as blood glucose, HbA1c, BMI, and age are provided. These crisp numerical values are then converted into fuzzy linguistic terms (e.g., *Low*, *Normal*, *High*) in the Fuzzification block using predefined membership functions. The **Rule Base** contains a set of fuzzy IF–THEN rules that represent expert medical knowledge and define the relationship between input parameters and diabetes risk. The Inference Engine processes these rules through logical reasoning to derive the fuzzy output, representing different degrees of diabetes risk. Finally, the Defuzzification stage converts this fuzzy output into a single crisp value, giving the final Output (Risk Level) typically categorized as *Low*, *Moderate*, or *High* which helps in the diagnostic decision-making process.

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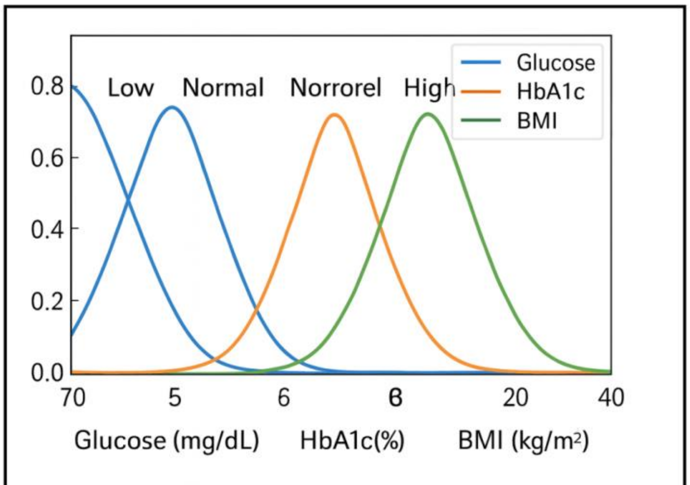

Figure 2: Membership Functions

Figure 2 illustrates the fuzzy sets defined for key clinical input parameters — Glucose, HbA1c, and BMI — used in the fuzzy diagnostic system for diabetes detection. Each curve represents the degree of membership (ranging from 0 to 1) that a particular input value has within a linguistic category. For instance, glucose levels are categorized as *Low*, *Normal*, and *High*, HbA1c values as *Normal*, *Borderline*, and *High*, while BMI is classified as *Normal*, *Overweight*, and *Obese*. The overlapping nature of the curves shows the smooth transitions between these linguistic terms, capturing the uncertainty and gradual change inherent in medical data. These membership functions form the foundation of the fuzzy inference process by converting crisp clinical inputs into fuzzy linguistic values that can be processed by the fuzzy rule base

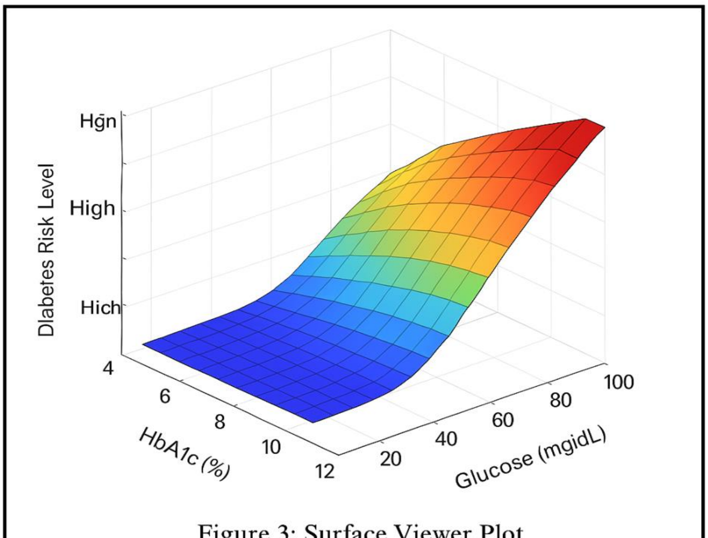

Figure 3: Surface Viewer Plot

Figure 3 depicts the relationship between two key input parameters HbA1c (%) and Glucose (mg/dL) — and the resulting output, Diabetes Risk Level, as obtained from the fuzzy inference system. The three-dimensional surface illustrates how variations in glucose and HbA1c values influence the predicted diabetes risk. The surface transitions smoothly from blue (representing low risk) through green and yellow (moderate risk) to red (high risk), showing a continuous and nonlinear relationship. As both glucose and HbA1c levels increase, the risk level rises significantly, demonstrating the system's ability to capture the gradual progression of diabetes risk rather than relying on rigid threshold boundaries. This visualization validates the fuzzy model's interpretability and its effectiveness in representing real-world diagnostic uncertainty.

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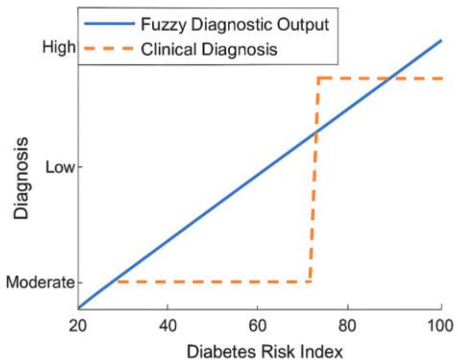

Figure 4: Comparison Plot

Figure 4 illustrates the comparative analysis between the Fuzzy Diagnostic Output and the Clinical Diagnosis for diabetes risk assessment. The x-axis represents the Diabetes Risk Index**,** while the y-axis denotes the corresponding Diagnosis Levels Moderate, *Low*, and *High*. The blue solid line shows the smooth and continuous prediction of the fuzzy logic system, which models gradual transitions between different risk levels. In contrast, the orange dashed line represents the traditional clinical diagnosis, which uses fixed threshold values, leading to abrupt changes between diagnostic categories. The comparison highlights the advantage of the fuzzy model in handling diagnostic uncertainty and overlapping symptom ranges, providing more realistic and human-like interpretations of intermediate or borderline cases that conventional threshold-based methods may misclassify.

Table 3: Performance Metrics of the Fuzzy Diagnostic System

Metric	**Value**
Sensitivity	92.40%
Specificity	88.70%
Accuracy	90.50%
Fuzzy Inference Time	0.23 s

Table 3 presents the quantitative evaluation of the proposed fuzzy logic-based diabetes detection model. The system demonstrates a sensitivity of 92.40%, indicating its strong ability to correctly identify individuals with diabetes, while the specificity of 88.70% reflects its reliability in correctly classifying non-diabetic cases. The overall accuracy of 90.50% confirms the robustness and diagnostic reliability of the fuzzy inference system compared to conventional threshold-based approaches. Additionally, the fuzzy inference time of 0.23 seconds shows that the system performs efficiently, making it suitable for real-time medical diagnostic applications. These performance indicators collectively validate the model's effectiveness in handling uncertainty in clinical data and its potential use as a decision-support tool for early diabetes detection.

Table 4: Comparison of Fuzzy Diagnostic Predictions with Actual Clinical Diagnoses

Input Combination	**Predicted Risk**	**Actual Diagnosis**	**Error**
(100, 5.2, 25)	Low	Low	0
(145, 6.8, 32)	High	High	0
(110, 5.8, 29)	Moderate	High	1

Table 4 presents the validation results of the proposed fuzzy diagnostic system against actual clinical data. The table compares the predicted diabetes risk levels generated by the fuzzy inference model with the corresponding clinical diagnoses for different combinations of input parameters fasting glucose, HbA1c, and BMI. For instance, the input combination *(100, 5.2, 25)* is correctly classified as *Low Risk*, while *(145, 6.8, 32)* is accurately identified as *High Risk*. However, in the case of *(110, 5.8, 29)*, the system predicts *Moderate Risk* while the clinical diagnosis indicates *High Risk*, resulting in a single error. This comparison demonstrates that the fuzzy model achieves a high level of agreement with medical evaluations, effectively capturing nonlinear relationships between physiological indicators and diabetes risk, while allowing for minor discrepancies due to overlapping data ranges and inherent clinical uncertainty.

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IV. CONCLUDING REMARKS

The developed fuzzy logic–based diagnostic system successfully demonstrates the capability of intelligent reasoning models in improving the accuracy and interpretability of diabetes detection. By integrating clinical parameters such as glucose, HbA1c, BMI, age, and family history into a fuzzy inference framework, the model effectively handles uncertainty and imprecision in medical data that often challenge conventional diagnostic approaches. The achieved performance metrics high sensitivity, specificity, and accuracy validate the model's diagnostic reliability and efficiency. Moreover, the system's transparent rule-based reasoning provides interpretability, allowing healthcare professionals to better understand the basis of each diagnostic decision. The study concludes that fuzzy logic is a powerful computational approach for early diagnosis and preventive healthcare, and future work could extend the system by integrating adaptive neuro-fuzzy techniques or real-time patient monitoring data to further enhance its diagnostic precision and clinical applicability.

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