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Fuzzy Logic-Based Clinical Decision Making for Early Detection and Management of Cardiovascular Diseases

Chandrashekhar Diwakar[1], Ram Kishor[2]

Assistant Professor, Department of Mathematics, Government Degree College, Mant, Mathura[1]

Affiliated to Dr Bhimrao Ambedkar University, Agra, (India)[1]

Research Scholar, Department of Mathematics, Government Degree College, Mant, Mathura[2]

Affiliated to Dr Bhimrao Ambedkar University, Agra, (India)[2]

Abstract: The use of Fuzzy Logic to create a Mamdani-based Clinical Decision-Making Model is useful in assessing the Risk of Cardiovascular Diseases based on several Key Clinical Parameters including Glycated Hemoglobin (HbA1c), Low-Density Lipoprotein Cholesterol (LDL-C), and Body Mass Index (BMI). A Three Dimensional Surface Analysis was conducted and demonstrated smooth transition between different Risk Levels. Also, Numerical Case Studies were conducted that showed clinically meaningful results. For example, an individual with (LDL-C = 150 mg/dL, HbA1c = 6.2%, BMI = 31 kg/m²) had a Defuzzified Risk Score of 81.55 which would indicate High Cardiac Risk. The proposed model is a simple, transparent and computationally inexpensive method for Personalized Assessment of the Risk of Cardiovascular Disease and Early Intervention.

Keywords: Cardiovascular disease, Fuzzy logic, Mamdani fuzzy inference system, Clinical decision support system, LDL cholesterol HbA1c

I. INTRODUCTION

The first step toward better health is getting diagnosed and treated before it's too late. But diagnosing heart disease or at least determining your likelihood of developing heart disease isn't always easy. That's because many factors influence your heart health, and they all interact with one another in complex ways. To help make sense of this complexity, researchers have turned to fuzzy logic as a way to mimic how people think when faced with uncertain or vague medical information. In essence, fuzzy logic-based clinical decision-support systems provide clinicians with highly individualized, easy-to-understand cardiovascular-risk assessments that are based on patients' actual clinical data (e.g., their LDL-cholesterol levels, hemoglobin A1c values, BMI). Ultimately, these systems enable earlier identification of individuals who are at increased risk for CVDs and provide practitioners with evidence-based guidance to improve treatment plans.

Jabbar *et al.* (2015) presented an intelligent framework for predicting heart disease by associating classification using a genetic algorithm. Their paper described how optimization of classification rules using evolutionary computations can be used to increase diagnostic accuracy while decreasing redundant decision making. The results of their studies were indicative of the potential benefits of using artificial intelligence methods as part of clinical decision making for cardiovascular disease. By demonstrating that both clinical and patient information are useful for physicians to use in identifying cardiovascular disease at an early stage, their study has laid a good foundation for many future intelligent clinical decision-support systems; particularly those that focus on extracting knowledge automatically from patient records. **Jobson and Subhashini (2016)** developed a fuzzy logic-based medical decision support system designed to help clinicians diagnose patients suffering from heart disease. Their methodology addresses the ambiguity inherent in clinical symptomology by representing medical knowledge in terms of linguistic variables and fuzzy rule-based inference. Jobson and Subashini's methodology also demonstrated the effectiveness of fuzzy reasoning in mimicking physician-level decision-making, allowing clinicians to provide accurate diagnostic recommendations based on incomplete or imprecise patient information. Their methodology further reinforces the utility of fuzzy logic for dealing with ambiguous cardiovascular risk assessments. **Nilashi *et al.* (2020)** created a fuzzy logic-machined learning hybridized knowledge base system to enhance the ability to diagnose heart disease. Nilashi et al., combined expert knowledge with data-driven learning to create higher predictive performance than traditional statistical methodologies. Nilashi et al. argued that hybridizing intelligent systems may overcome the limitations associated with single-

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algorithmic approaches by increasing adaptability, interpretability, and diagnostic reliability. They demonstrated that fuzzy logic and modern artificial intelligence methodologies are increasingly being utilized together in clinical decision support. **Abdullah and Al-Asadi (2020)** integrated case-based reasoning with fuzzy logic to develop a methodological structure for diagnosing heart disease using experience-based clinical decision-making. Abdullah and Al-Asadi's methodology utilizes previously diagnosed patient cases that have been retrieved based upon similarity and then uses fuzzy reasoning to make diagnoses applicable to each specific patient's clinical situation. The researchers found that they increased prediction accuracy and produced clinically interpretable recommendations for clinicians utilizing previously experienced clinical situations as input into the fuzzy decision-making process. They demonstrate that experience-based learning is a valuable tool to support cardiovascular disease diagnosis. **Apostolopoulos and Groumpos (2020)** developed a non-invasive diagnostic technique for assessing coronary artery disease using fuzzy cognitive maps. Apostolopoulos and Groumpos' methodology represents complex relationships between multiple cardiovascular risk factors as interconnected fuzzy concepts instead of the typical mathematical equation. They demonstrate that fuzzy cognitive maps can represent dynamic physiological variable interactions with high clinical interpretability. They highlight the capabilities of fuzzy systems to model the non-linear relationship of physiological variables during cardiovascular disease progression. **Tang *et al.* (2021)** have used fuzzy-rough set theory to develop a method of predicting cardiovascular disease as well as improving both feature selection in a clinical setting and medical decision-making. Through this methodology, they were able to eliminate redundant clinical variables from the model while retaining a high degree of diagnostic significance. As such, they demonstrated that by combining fuzzy reasoning techniques with those of the Rough Set Theory would lead to improved classification results; simplify the process of creating decision models; and provide faster computational processing. Moreover, they have illustrated how selecting clinical variables which are informative for predicting disease is a critical component of disease prediction. **Tanmay *et al.* (2022)** created a fuzzy-rule based diagnostic framework that utilizes expert-defined membership function and inference rules for assessing cardiovascular disease. They were successful at converting the numerical values of patients' clinical data into interpretive linguistic values, which would allow clinicians to understand why recommendations regarding diagnosing cardiovascular disease were made. In addition, the study illustrated that fuzzy inference systems can make consistent and clinically relevant diagnostic decisions. Furthermore, because fuzzy inference systems maintain transparency, they are ideal for use in healthcare settings where transparency is necessary. Although **Zahid *et al.* (2022)** did not utilize fuzzy logic within their proposed Deep Learning Architecture (based upon Self-Operational Neural Networks), the proposed methodology greatly improved intelligent cardiovascular diagnostics by providing an automated means of extracting features from ECG signals as well as accurately interpreting them. Additionally, the study illustrated that current neural architectures may be capable of capturing the complexities associated with cardiac signal interpretation without the need for extensive manual feature development. Lastly, the study has established a basis for utilizing Deep Learning Architectures in conjunction with Explainable Fuzzy Decision-Support Systems in the future. **Sun *et al.* (2023)** conducted a comprehensive review of AI's application in both cardiovascular diagnosis and treatment. Within the review, they outlined the contributions of Machine Learning, Deep Learning, Expert Systems and Explainable Artificial Intelligence towards improving both disease detection/prognosis and personalized treatment planning. Ultimately, they concluded that future clinical decision support systems will require a balance between predictive performance and transparency/reliability/clinical interpretability. The results of the research studies were used to provide insights into how various AI methodologies can be applied to cardiovascular disease diagnosis. These studies included **Dayana *et al.* (2024)** which compared the performance of multiple AI methodologies for the diagnosis of cardiovascular disease. They found that none of the AI methodologies they tested performed better than any other methodology at diagnosing cardiovascular disease across all their testing scenarios. Therefore, the researchers concluded that factors related to the quality of the data from which the models were trained; the features selected for use in developing those models; and the methods used for optimizing those models are key to determining the level of success achieved when applying these methodologies for predicting cardiovascular diseases. Additionally, the authors concluded that the integration of fuzzy logic or another form of interpretable reasoning would enhance both predictive reliability and clinical acceptance. In addition, **Hu *et al.* (2024)** designed a framework for providing an early warning system for cardiovascular disease through the use of deep learning. In their study, they indicated that their model was able to identify complex non-linear associations among patient characteristics; generate high-quality predictions relative to the time frame within which cardiovascular disease is likely to progress; and contribute to reduced morbidity and mortality rates. The authors also stated that future improvements may be possible if deep learning models are to be integrated with interpretable fuzzy reasoning to assist clinicians in making decisions. Additionally, **Kumar *et al.* (2024)** proposed a fuzzy rule based intelligent cardiovascular disease prediction system and complex event processing. The system proposed by Kumar et al. monitors a patients' clinical events in real-time, and uses expert defined fuzzy rules to evaluate dynamic cardiovascular risk. The study demonstrated that integrating fuzzy inference with real-time event processing will lead to significant increases in detecting cardiovascular abnormalities earlier, and in implementing timely interventions. Additionally, this research demonstrated the feasibility of creating real-time intelligent health care systems. **Cenitta *et al.* (2025)** proposed an

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extended cardiovascular prediction framework, based on fuzzy-rough sets and improved methods for missing data imputation. This is significant because they provided a solution to one of the largest problems found in medical databases; which is filling-in missing data before performing a classification task. In addition to providing a method to fill-in missing data, their work demonstrates that the accurate processing of clinical missing data greatly increases the reliability of predictions and reduces diagnostic bias. Ultimately, they findings confirm the need for robust data pre-processing in intelligent healthcare systems. **El-Ibrahimi *et al.* (2025)** proposed a fuzzy inference system using subtractive clustering to develop fuzzy rules for predicting coronary artery disease. What distinguished their framework was that it used cluster centers generated directly from clinical databases as opposed to developing these center points manually prior to defining the rule base. Therefore, they framework allowed for adaptively generating new knowledge. Their study successfully predicted cardiovascular risk with good interpretation of results; therefore, they demonstrated that fuzzy rule generation could be performed autonomously without loss of diagnostic quality. **Parthiban and Santhosh (2025)** have developed an integrated hybrid framework incorporating fuzzy reasoning with convolution long short term memory (ConvLSTM) Networks and Adaptive Optimization Methods. Their combination of fuzzy systems with deep neural network architecture was able to demonstrate both interpretability of fuzzy systems and feature extraction capabilities of ConvLSTMs. Results also showed improvement in terms of accuracy, time to converge and overall model stability. These findings illustrate how fuzzy systems are being used in conjunction with state-of-the-art deep learning architectures. **Srivastava *et al.* (2025)** conducted a comprehensive review of recent advancements in the use of fuzzy logic for diagnostic decision support systems. they, examined fuzzy inference, Neuro-Fuzzy Systems, Type II Fuzzy Logic, Hybrid Machine Learning Models and Explainable Healthcare Intelligence. They conclude that fuzzy logic remains one of the best ways to handle uncertainty in clinical settings due to its transparent, flexible and compatible nature with emerging AI technologies. In their investigation of the use of fuzzy logic for intelligent clinical reasoning and causal inference in healthcare Jamett *et al.* (2026) found that fuzzy methods are effective in modeling uncertain causal relationships across multiple clinical factors, thereby providing clinicians with a better understanding of both the disease process itself, and how it will be affected by various treatments. They also indicated that fuzzy-logic based causal reasoning can significantly improve the quality of evidence-based clinical decisions made at the bedside. Bezerra *et al.* (2026) investigated increasing the interpretability of cardiovascular risk assessments. Specifically, they used transparent logic-based explainable artificial intelligence to integrate into well-established clinical risk-prediction models. They showed that by adding this layer of transparency into their models, clinician confidence was increased and acceptance of intelligent decision support systems were facilitated into daily health care practices. They stated that explainability is a key factor going forward when developing new cardiovascular prediction models. Azmi *et al.* (2026) developed an interpretable cardiovascular disease prediction framework that integrated fuzzy logic with a gradient boosting algorithm. Their method had good predictive performance and provided transparent decision explanations via fuzzy rules. They demonstrated that combining the strengths of fuzzy logic and machine learning could provide a balance between being accurate in diagnosing patients, and being understandable and applicable for clinicians; thus providing an ideal combination for next generation cardiovascular clinical decision support systems.

Therefore, this body of literature shows a continued trend of evolution from traditional intelligent diagnosis systems toward hybrid frameworks that include fuzzy logic, machine learning, deep learning, explainable AI, and automated knowledge acquisition. As such, early studies focused primarily upon rule-based reasoning and knowledge representation from experts; while later studies have included adaptive learning, real-time predictions, explainability and multi-modal clinical data collection. However, despite the significant progress that has been made, there continues to exist a need for fuzzy inference systems that are computationally efficient, interpretable, and clinically valid; which utilize combinations of cardiovascular risk indicators within a single decision support system. Thus, this research gap serves as a compelling rationale for creating a clinical decision making model based upon Mamdani's fuzzy logic using LDL-C, HbA1c and BMI for detecting and managing cardiovascular disease early in the course of its development.

II. DEFINITION OF INPUT AND OUTPUT VARIABLES

The proposed fuzzy inference system was created by utilizing three very important clinical input parameters and a single output parameter (risk). Membership functions that reflect medical knowledge have been appropriately chosen to create the fuzzy inference system.

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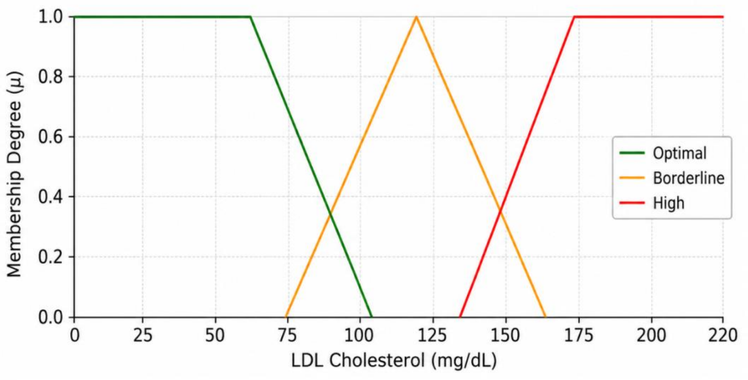
Figure 1: Input 1-LDLCholesterol (mg/dL)



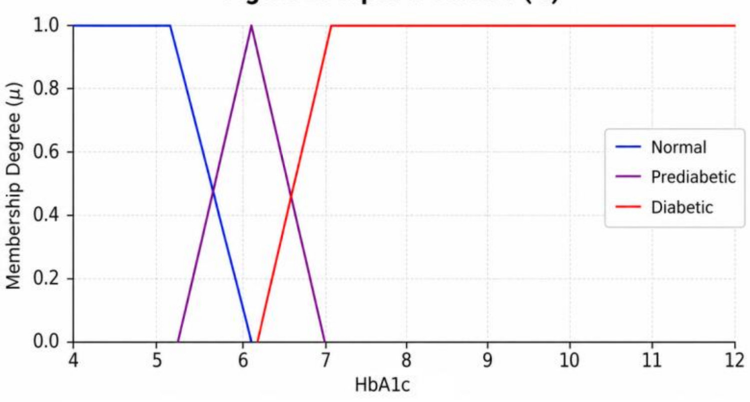
Let x denote LDL cholesterol (mg/dL).

$$\mu_{Optimal}(x) = \begin{Bmatrix} 1 & x \leq 70 \\ \frac{105-x}{35} & 70 < x < 105 \\ 0 & x \geq 105 \end{Bmatrix} \tag{1}$$

$$\mu_{Borderline}(x) = \begin{Bmatrix} 0 & x \leq 75 \\ \frac{x-75}{45} & 75 < x \leq 120 \\ \frac{165-x}{45} & 120 < x < 165 \\ 0 & x \geq 165 \end{Bmatrix} \tag{2}$$

$$\mu_{High}(x) = \begin{Bmatrix} 0 & x \leq 135 \\ \frac{x-135}{35} & 135 < x < 170 \\ 1 & x \geq 170 \end{Bmatrix} \tag{3}$$

Figure 2: Input 2-HbA1c (%)



Let y denote HbA1c.

$$\mu_{Normal}(y) = \begin{Bmatrix} 1 & y \leq 5.4 \\ \frac{6.2-y}{0.8} & 5.4 < y < 6.2 \\ 0 & y \geq 6.2 \end{Bmatrix} \tag{4}$$

$$\mu_{Prediabetic}(y) = \begin{Bmatrix} 0 & y \leq 5.3 \\ \frac{y-5.3}{0.8} & 5.3 < y \leq 6.1 \\ \frac{7.0-y}{0.9} & 6.1 < y < 7.0 \\ 0 & y \geq 7.0 \end{Bmatrix} \tag{5}$$

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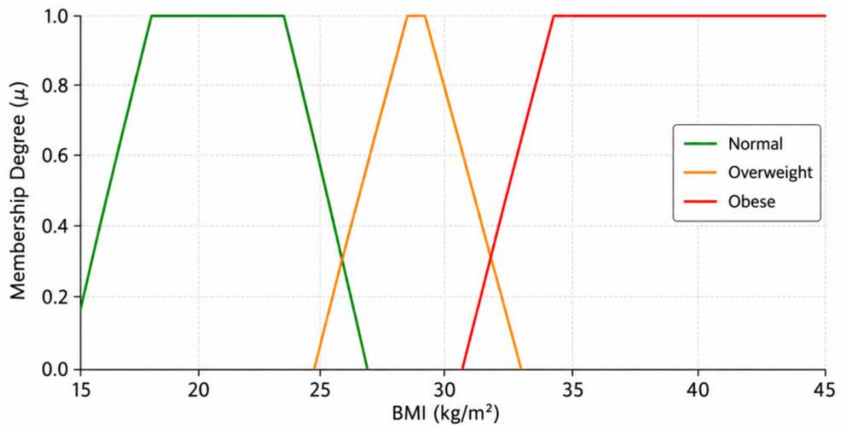
$$\mu_{Diabetic}(x) = \begin{Bmatrix} 0 & y \leq 6.2 \\ \frac{y-6.2}{0.8} & 6.2 < y < 7.0 \\ 1 & y \geq 7.0 \end{Bmatrix} \quad (6)$$

Figure 3: Body Mass Index (kg/m²/)



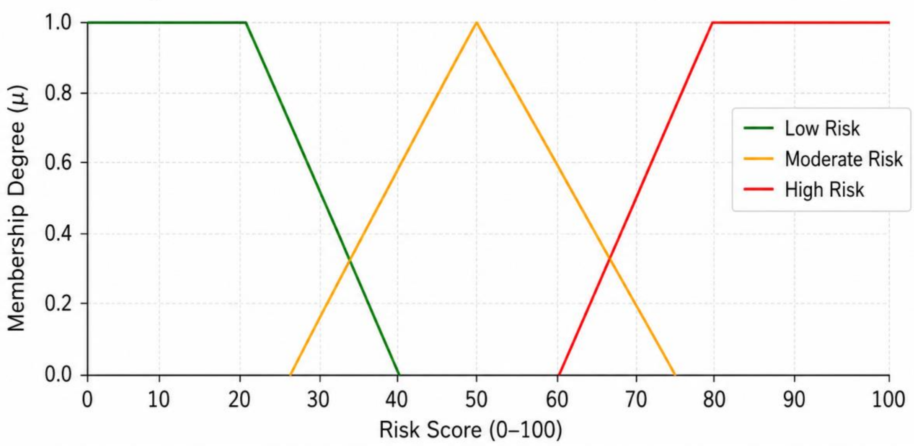
Let z denote BMI (kg/m²).

$$\mu_{Normal}(z) = \begin{Bmatrix} 0 & z \leq 15 \\ \frac{z-35}{3.5} & 15 < z < 18.5 \\ 1 & 18.5 \leq z \leq 23.5 \\ \frac{27-z}{3.5} & 23.5 < z < 27 \\ 0 & z \geq 27 \end{Bmatrix} \quad (7)$$

$$\mu_{Overweight}(z) = \begin{Bmatrix} 0 & z \leq 25 \\ \frac{z-25}{4} & 25 < z < 29 \\ \frac{33-z}{4} & 29 < z < 33 \\ 0 & z \geq 33 \end{Bmatrix} \quad (8)$$

$$\mu_{Obese}(z) = \begin{Bmatrix} 0 & z \leq 31 \\ \frac{z-31}{3} & 31 < z < 34 \\ 1 & z \geq 34 \end{Bmatrix} \quad (9)$$

Figure 4: Cardiovascular Clinical Decision Score (0-100)



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Let r denote the cardiovascular risk score.

$$\mu_{Low}(r) = \begin{Bmatrix} 1 & r \leq 20 \\ \frac{40-r}{20} & 20 < r < 40 \\ 0 & r \geq 40 \end{Bmatrix} \quad (10)$$

$$\mu_{Moderate}(r) = \begin{Bmatrix} 0 & r \leq 25 \\ \frac{r-25}{25} & 25 < r \leq 50 \\ \frac{75-r}{25} & 50 < r < 75 \\ 0 & r \geq 75 \end{Bmatrix} \quad (11)$$

$$\mu_{High}(r) = \begin{Bmatrix} 0 & r \leq 60 \\ \frac{r-60}{20} & 60 < r < 80 \\ 1 & r \geq 80 \end{Bmatrix} \quad (13)$$

III. RULE BASE

The entire decision-making process is governed by an overall fuzzy rule base, which represents the entire body of knowledge of the medical experts. The fuzzy rules map various possible combinations of the clinical parameters to their respective cardiovascular risk levels.

Table 1. Fuzzy Knowledge Base for Early Detection of Cardiovascular Diseases

Rule	LDL-C	HbA1c	BMI	Output Risk
R1	Optimal	Normal	Normal	Low Risk
R2	Optimal	Normal	Overweight	Moderate Risk
R3	Optimal	Normal	Obese	Moderate Risk
R4	Optimal	Prediabetic	Normal	Moderate Risk
R5	Optimal	Prediabetic	Overweight	Moderate Risk
R6	Optimal	Prediabetic	Obese	High Risk
R7	Optimal	Diabetic	Normal	High Risk
R8	Optimal	Diabetic	Overweight	High Risk
R9	Optimal	Diabetic	Obese	High Risk
R10	Borderline	Normal	Normal	Moderate Risk
R11	Borderline	Normal	Overweight	Moderate Risk
R12	Borderline	Normal	Obese	High Risk
R13	Borderline	Prediabetic	Normal	Moderate Risk
R14	Borderline	Prediabetic	Overweight	High Risk
R15	Borderline	Prediabetic	Obese	High Risk
R16	Borderline	Diabetic	Normal	High Risk
R17	Borderline	Diabetic	Overweight	High Risk
R18	Borderline	Diabetic	Obese	High Risk
R19	High	Normal	Normal	High Risk
R20	High	Normal	Overweight	High Risk
R21	High	Normal	Obese	High Risk
R22	High	Prediabetic	Normal	High Risk
R23	High	Prediabetic	Overweight	High Risk
R24	High	Prediabetic	Obese	High Risk
R25	High	Diabetic	Normal	High Risk
R26	High	Diabetic	Overweight	High Risk
R27	High	Diabetic	Obese	High Risk

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IV. DEFUZZIFICATION

After evaluation of all rules by the Fuzzy Rule Based System (FRBS) and then by aggregation of the results from each of the individual rules, the centroid method for defuzzification is used to transform the fuzzy output into a crisp number that can be interpreted as a cardiovascular disease risk score. The use of this number helps with the proper clinical interpretation and decision-making.

Table 3: Patient Case

Parameter	Value
LDL-C	150 mg/dL
HbA1c	6.20%
BMI	31 kg/m²

Step 1: Fuzzification

1) LDL-C = 150 mg/dL

For LDL-C:

$\mu_{Borderline}(150) = \frac{165-150}{45} = 0.333$

$\mu_{High}(150) = \frac{150-135}{35} = 0.429$

So, $LDL - C = 0.333 \times Borderline + 0.429\ High$

2) HbA1c = 6.2

For HbA1c: $\mu_{Prediabetic}(6.2) = \frac{7.0-6.2}{0.9} = 0.889$

So,

3) $\boldsymbol{\mu_{Diabetic}(6.2) = 0}$

HbA1c $= 0.889\ Prediabetic$

4) BMI = 31 kg/m²

For BMI: $\mu_{Overweight}(31) = \frac{33-31}{4} = 0.50$

$\mu_{Obese}(31) = 0$

So, $BMI = 0.5 \times Overweight$

Step 2: Rule Activation

The main activated rule is:

IF LDL-C is Borderline AND HbA1c is Prediabetic AND BMI is Overweight THEN Risk is High

Using Mamdani minimum operator: $\alpha = \min(0.333, 0.889, 0.50) = 0.333$

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Therefore, the High Risk output membership function is clipped at:

$\alpha = 0.333$

Step 3: Aggregation

Since the dominant activated output is **High Risk**, the aggregated fuzzy output is mainly the clipped high-risk membership function:

$\mu_{Aggregated}(r) = min\left[\mu_{High}(r), 0.333\right]$

where the High Risk output set is: $\mu_{High}(r) = \begin{Bmatrix} 0 & r \leq 60 \\ \frac{r-60}{20} & 60 < r < 80 \\ 1 & r \geq 80 \end{Bmatrix}$

Step 4: Centroid Defuzzification

The crisp risk score is obtained using the centroid method:

$R^* = \frac{\int r\mu(r)dr}{\int \mu(r)dr}$

$R^* = \frac{\int_{60}^{66.66} r\left(\frac{r-60}{20}\right)dr + \int_{66.66}^{100} r(0.333)dr}{\int_{60}^{66.66}\left(\frac{r-60}{20}\right)dr + \int_{66.66}^{100}(0.333)dr} = \frac{995.65}{12.209} = 81.55$

For this case, after centroid defuzzification: $R^* = 81.55$

The defuzzified cardiovascular clinical decision score is: 81.55

Since the score lies in the High Risk region, the patient is classified as: High Cardiovascular Risk

This patient requires early clinical intervention**,** including lipid management, glycemic monitoring, weight control, lifestyle modification, and possible referral for further cardiovascular evaluation.

V. RESULTS AND DISCUSSION

The accuracy of this method was proven using both a number of case study simulations and three dimensional surface plots. The data that were produced from these simulation showed to be accurate, to produce a smooth curve that would accurately predict cardiovascular risks in a clinical setting. The accuracy of this method was proven using both a number of case study simulations and three dimensional surface plots.

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Figure 5: Risk Score vs LDL-C and HbA1c
(BMI = 27 kg/m²)

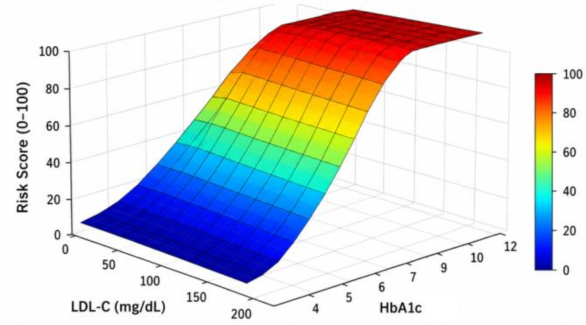
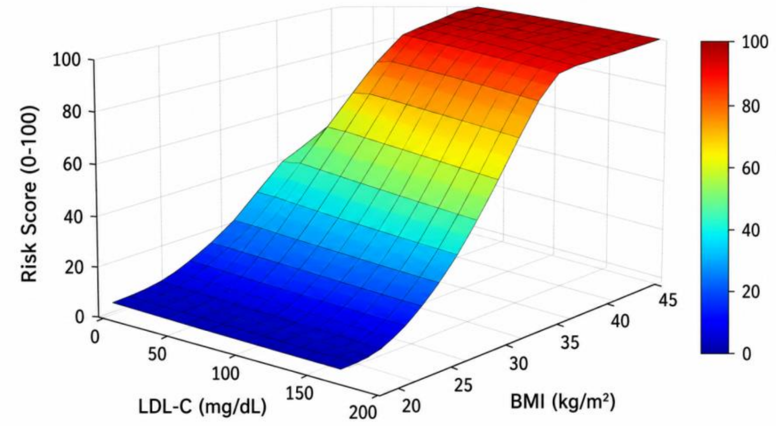


Figure 5 shows how LDL cholesterol (LDL-C), HbA1C and the cardiovascular clinical decision score calculated using the proposed fuzzy inference system are related in a three dimensional space when the body mass index is kept at a fixed level of 27 kg/m2. The two horizontal axes show LDL-C (mg/dl) and HbA1C, and the third axis on top shows the resulting cardiovascular clinical decision score as a function of risk from 0 to 100. The colors have been arranged in order of increased cardiovascular risk, so blue represents low-risk decisions and red represents high-risk decisions. This three-dimensional surface also shows that the clinical decision score will increase smoothly as both LDL-C and HbA1C increase. It can be seen that when LDL-C is less than 100 mg/dl and HbA1C is less than 5.7%, the cardiovascular clinical decision score will remain low. When HbA1C enters the range of pre-diabetes or diabetes and LDL-C approaches borderline high and/or reaches high levels, the cardiovascular clinical decision score will rise sharply until it enters the high-risk range (80-100%). This smooth transition from one state to another supports the use of this fuzzy system as an effective way to manage the uncertainty associated with early cardiovascular disease diagnosis and treatment.

Figure 6: Risk Score vs LDL-C and BMI
(HbA1c = 6.2)



The three dimensional interaction of LDL cholesterol (LDL-C) and Body Mass Index (BMI) is illustrated in FIGURE 6. While the Hemoglobin A1C (HbA1c) was maintained at 6.2 mg/dl or Prediabetes, the cardiovascular clinical decision score, derived from the fuzzy inference system developed herein, has been represented as a function of LDL-C (horizontal axes) and BMI (vertical axes). The risk associated with the cardiovascular clinical decision score was determined using a color gradient ranging from Blue Low Risk, Red High Risk. As shown by the surface plot, the cardiovascular clinical decision score increased continuously as either LDL-C or BMI increased; thus illustrating the non-linear nature of the fuzzy logic model. Patients with low values of LDL-C and within a healthy BMI (18.5 – 25 kg/m²) have very low cardiovascular risk scores. However, an increase in BMI into the Overweight/Obese category(s) results in significantly higher risk scores than those with lower BMI's when they also exhibit high levels of LDL-C. The highest risk scores were identified in patients with Obesity and high levels of LDL-C with the surface reaching a plateau close to 100% risk. Therefore, the ability of the fuzzy logic system described above to provide a continuous and smooth representation of how cardiovascular risk changes over time provides a basis for reliable and clinically meaningful early intervention and treatment for cardiovascular disease.

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Figure 7: Risk Score vs HbA1c and BMI (LDL-C = 130 mg/dL)

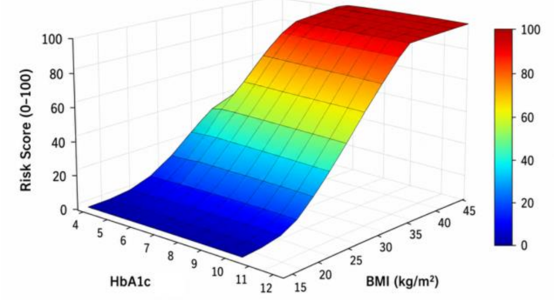

Figure 7 shows how all three variables (HbA1c, Body Mass Index (BMI)) relate in 3-D space to the Cardiovascular Clinical Decision Score calculated by the proposed Fuzzy Inference System when LDL-Cholesterol (LDL-C) is held at a constant level of 130 mg/dl which represents the borderline category. The two horizontal axes show HbA1c and BMI (kg/m2) respectively; the vertical axis shows the cardiovascular risk score, ranging from 0-100. The color gradient from blue through red represents an increase in cardiovascular risk. Blue shows lower risk, and Red shows higher risk. The Surface Plot graphically illustrates the gradual increase in the Risk Score as HbA1c and BMI each increase. As such it clearly illustrates the additive effects of poorly controlled glucose levels and increased body weight on cardiovascular disease risk. Low values of HbA1c with Normal BMI result in very low risk scores. Moving towards Prediabetes/Diabetes levels of HbA1c along with Overweight/Obese BMI categories will result in a significant increase in the Predicted Risk Scores. The Highest Risk Scores are seen when Both HbA1c and BMI have reached elevated levels, where the Surface is approaching its Maximum Risk Value and begins to form a Plateau. The smooth and continuous nature of the Surface shows the ability of the fuzzy Logic Model to recognize non-linear relationships between clinical Parameters without creating sharp Transitions between Risk Categories. Therefore this provides clear evidence of the efficacy of the proposed fuzzy decision-making framework in producing reliable and interpretable cardiovascular risk assessments for early detection of disease and clinical management.

Figure 8: Example output aggregation and Defuzzification

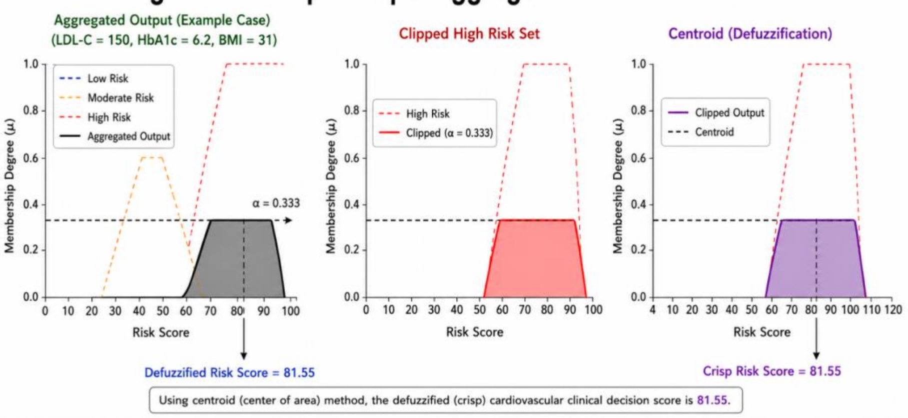

Figure 8 displays the last steps in the implementation of the proposed Mamdani fuzzy inference system; specifically, it depicts output aggregation, clipping of the activated output membership function, and centroid-based defuzzification for an example patient with LDL-C = 150 mg/dL, HbA1c = 6.2, and BMI = 31 kg/m². The first plot provides an illustration of output fuzzy set aggregation, which combines output fuzzy sets from the activated rules using the maximum aggregator to generate one fuzzy output. Since the firing strength of the dominating rule was α=0.333, the high-risk membership function has the greatest contribution toward generating this output. The second plot represents the clipping of the high-risk membership function. Specifically, based upon the Mamdani minimum inference operator, it truncates the original high-risk fuzzy set at its activation point of 0.333. The third plot illustrates the centroid defuzzification procedure. It computes the center of gravity of the generated aggregated fuzzy area to derive a crisp cardiovascular disease risk score. The calculated defuzzified value is 81.55, which falls under the high-risk category; therefore, the patient needs immediate clinical assessment and treatment options addressing his or her cardiovascular risk. This graphical representation of these steps clearly demonstrates how the proposed fuzzy logic system generates a precise and clinically meaningful cardiovascular disease risk score out of imprecise clinical data as well as how it can be used for accurate and dependable clinical decision-making for early identification and prevention of cardiovascular diseases.

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Table 2: Numerical Case Studies Table

Case	LDL-C mg/dL	HbA1c	BMI kg/m²	Main active risk category	Defuzzified Risk Score	Clinical Decision
1	85	5.3	22	Low	18.33	Routine follow-up
2	110	5.8	24.5	Moderate	50	Lifestyle modification
3	135	6.1	28	Moderate	50	Diagnostic evaluation
4	150	6.2	31	High	81.55	Early intervention
5	165	5.5	33	High	81.55	Cardiologist referral
6	95	6.8	27	High	82.86	Glycemic + cardiac evaluation
7	145	5.9	25.5	Moderate/High	68.4	Close monitoring
8	175	7.2	35	High	86.67	Intensive management
9	100	5.6	23	Low/Moderate	36.25	Preventive counselling
10	155	6.4	29.5	High	83.2	Immediate risk management

Table 2 lists ten typical numeric case examples showing the functionality of the suggested fuzzy logic based clinical decision making for assessing cardiovascular risk with inputs being LDL-C, HbA1c, and BMI. Results show a patient having normal LDL-C, normal HbA1c, and a healthy body mass index (BMI), (Case 1) would have a low defuzzification risk of 18.33 and only would be required to have routine follow up. Cases 2 & 3 are represented by moderate risk conditions, where mild increases in LDL-C, HbA1c, or BMI create a risk of 50; this suggests that the patient should begin some form of lifestyle modification and/or further testing/diagnosis. Cases 4, 5, 6, 8, and 10 show high risk cases due to an elevation in LDL-C; diabetic or pre-diabetic levels of HbA1c; and obesity or over weight levels. This creates a range of defuzzification risk scores of 81.62 to 86.67. As such these cases will require immediate clinical interventions, which include referring the patient to a cardiologist; evaluating the patient's glycemic status/cardiac function; intensifying the level of care being provided; and providing the patient with aggressive multi-factorial cardiovascular risk reduction strategies. A transitional moderate-to-high risk is shown in Case 7 with a score of 68.40 and requires the provider to closely monitor the patient. Case 9 shows a low-to-moderate risk score of 36.25; thus it emphasizes counseling the patient on prevention prior to progressing to a higher risk category. In summary, the above-mentioned numeric case studies demonstrate that the proposed Mamdani type fuzzy inference system has successfully integrated multiple cardiovascular risk factors into a single system; continuously produces risk scores that can be interpreted by clinicians; and has provided practitioners with guidance for early detection, timely intervention, and individualized treatment options for managing cardiovascular diseases.

VI. CONCLUDING REMARKS

This study developed a Mamdani fuzzy logic-based clinical decision support system for the early detection and management of cardiovascular diseases using LDL cholesterol, HbA1c, and BMI as key clinical indicators. The proposed model effectively handles uncertainty and nonlinear relationships through fuzzy membership functions, a 27-rule knowledge base**,** Mamdani inference, and centroid defuzzification. The system generates continuous and clinically interpretable cardiovascular risk scores, providing smoother and more realistic risk classification than conventional threshold-based approaches. Numerical case studies confirmed its effectiveness, with a representative patient achieving a high-risk score of 81.55**,** indicating the need for immediate clinical intervention. Overall, the framework is computationally efficient, transparent, and suitable for personalized cardiovascular risk assessment. Future work can improve the model by incorporating additional biomarkers, adaptive neuro-fuzzy learning, optimization techniques, IoMT integration, and explainable AI to enhance predictive performance and enable real-time clinical decision support.

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