

UKJAES

University of Kirkuk Journal  
For Administrative  
and Economic Science

ISSN:2222-2995 E-ISSN:3079-3521

University of Kirkuk Journal For  
Administrative and Economic Science



Taher Mahmood M. The use of fuzzy logic to improve the performance of the logistic regression model in predicting binary variables under uncertainty. *University of Kirkuk Journal For Administrative and Economic Science* (2026) 16 (1):1-10.

## The use of fuzzy logic to improve the performance of the logistic regression model in predicting binary variables under uncertainty

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**Abstract.** This research investigates integrating fuzzy logic with logistic regression to improve predictive performance in binary classification, particularly for diabetes prediction, where uncertainty makes it challenging. In most cases, the data coming from the Center for Endocrinology and Diabetes contains some amount of uncertainty, variation, and missing values, which would jeopardize the performance of the standard logistic regression model. In an attempt to address the challenge, my research proposes the combination of fuzzy and logistic for an enhanced prediction model, where the variables are fuzzified based on the Mode and Centroid. The performance evaluation of the model and the standard model would be compared through various means. The findings reveal that the standard fuzzy model and the semi-fuzzy model outperform the standard model significantly regarding the Recall and F1-Score, which indicates that the model is much stronger for predicting diabetes, especially during uncertain data. In fact, the analysis of the model indicates that the most significant factor for the model, regardless of the model design, would be the Symptom score, followed by the BMI and Fasting Glucose levels, which provides concrete support that the combination of fuzzy logic and standard logistic would produce an effective model.

**Keywords:** Fuzzy Logic, Under Uncertainty, Logistic Regression

## استخدام المنطق الضبابي لتحسين أداء نموذج الانحدار اللوجستي في التنبؤ بالمتغيرات الثنائية في ظل عدم اليقين

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**المستخلص:** يبحث هذا البحث في دمج المنطق الضبابي مع الانحدار اللوجستي لتحسين دقة التنبؤ في التصنيف الثنائي، لا سيما في التنبؤ بمرض السكري، حيث يُشكل عدم اليقين تحديًا. في معظم الحالات، تحتوي البيانات التي تم الحصول عليها من مركز الغدد الصماء والسكري على قدر من عدم اليقين والتباين والقيم المفقودة، مما يؤثر سلبًا على أداء نموذج الانحدار اللوجستي. ولمعالجة هذا التحدي، يقترح هذا البحث دمج المنطق الضبابي والانحدار اللوجستي لإنشاء نموذج تنبؤ مُحسّن، حيث يتم تحويل المتغيرات إلى قيم ضبابية بناءً على المنوال والمركز. وتقييم أداء النموذج الجديد مقارنةً بالنموذج الآخر باستخدام عدة مقاييس للمقارنة. أظهرت النتائج أن النموذج الضبابي القياسي والنموذج شبه الضبابي يتفوقان بشكل ملحوظ على النموذج القياسي فيما يتعلق بمقياس Recall ومقياس F1-Score، مما يُشير إلى أن النموذج الجديد أقوى بكثير في التنبؤ بمرض السكري، خاصةً في ظل وجود بيانات غير مؤكدة. في الواقع، يُشير تحليل النموذج إلى أن أهم عامل فيه، بغض النظر عن تصميمه، هو درجة الأعراض، يليها مؤشر كتلة الجسم ومستوى سكر الدم الصائم، مما يؤكد فعالية دمج المنطق الضبابي مع الانحدار اللوجستي التقليدي في إنتاج نموذج يحسن من دقة التنبؤ.

**الكلمات المفتاحية:** المنطق الضبابي، عدم اليقين، الانحدار اللوجستي.

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### The Introduction

Data uncertainty has remained one of the most imperative challenges in binary prediction models using logistic regression. Real-world datasets in health care, economics, and social platforms are generally vague in terms of measurements or may be based on human judgment. The conventional logistic regression model may only handle clear and exact values in the predictive inputs. This limitation has contributed significantly to the rising interest in combining fuzzy logic ideas with logistic regression methods in improving the accuracy levels and interpretability of data in uncertain situations.

Recently, the use of hybrid models based on statistical and intelligent approaches has unveiled the benefit of combining logistic regression analysis and fuzzy logic in improving binary prediction under conditions of uncertainty. Various current research works underscore the idea that fuzzy logic functions as a powerful mathematical tool in modeling uncertainty in data. For example, Zhang et al. (2021) demonstrate the effectiveness of a fuzzy and logistic hybrid approach in improving classification accuracy for medical data marked with imprecision. Others, like Al-Hmoud and Al-Shayea (2022), reveal that fuzzy set combination approaches minimize prediction errors in noisy situations.

Moreover, (Hosseini, et al., 2024) showed that the use of Z-numbers, including both the value and the reliability, resulted in reduced prediction errors.

In another research work, a hybrid fuzzy logistic regression model was developed by Zhu et al. (2025), which bettered the performance of regular logistic regression models for dealing with uncertain or ambiguous information.

Charizanos et al. (2025) found that fuzzy logistic regression models, which are fuzzy-logic-based models, were more effective than logistic models in uncertain data conditions, such as fuzzy data, data imbalance, or disconnection, since fuzzy models provide better results with more accurate classifications.

Consequently, the combination of fuzzy logic with logistic regression analysis forms a more realistic modeling system, especially in binary classification problems with uncertain or imprecise data.

### 1<sup>st</sup>: Objective of the research

This research proposes the development and testing of the hybridization of the fuzzy and the logistic regression model, which introduces and makes the uncertainty clear through the use of fuzzy representation for the variables. These include:

1. Handling ambiguous and imprecise values for medical measurements using fuzzy sets and defuzzification.
2. Increase the accuracy of predictions, improve model interpretability, and improve robustness over standard logistic regression.
3. Evaluate the influence of fuzzification methods (Mode-based, Centroid-based, Min-based, Max-based) on model coefficients and classification performance.
4. Provide a structured framework for binary prediction under uncertainty, with a practical application to diabetes diagnosis.

### 2<sup>nd</sup>: Materials and methods

#### 1. Logistic Regression and Its Role in Predicting Binary Variables

A logistic regression analysis is one of the most common methods in statistics that focuses on binary data, in which the variable under analysis only contains two possible outcomes or categories, like (Yes/No) or (Presence/Absence), to predict the probability of occurrence of the result based on various factors. This test needs a logistic function that connects the factors to the probability of occurrence of the result and distinguishes through interpreting the probability of the binary outcomes and quantifying the significance of each variable towards the predictive result (Harris, 2021).

$$p(Y = 1|X) = \frac{1}{1 + e^{-\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \dots + \hat{\beta}_n x_n}} \quad (1)$$

Or equivalently, using the Logit Function:

$$\text{Logit}(P) = \ln\left(\frac{P}{P-1}\right) = \beta_0 + \sum_{i=1}^n X_i \beta_i \quad (2)$$

Were

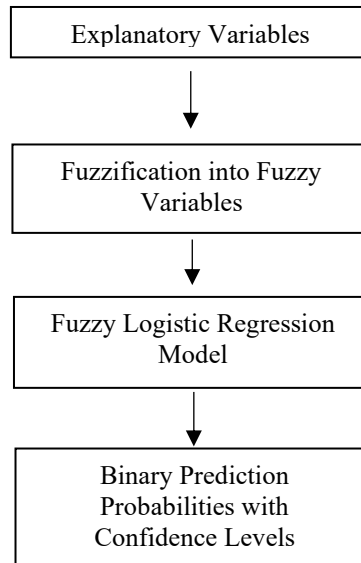
$P = P(Y = 1|X)$ : The probability of Y equals 1. It is the constant coefficient is coefficient associated with the independent variables.  $k$ : Number of independent variables.

Although logistic regression is very effective in conventional scenarios, the performance of logistic regression gets adversely impacted when working with imprecise or fuzzy data or data with uncertainties (Gray & Ferson., 2021 ,Zanos et al.,2024 ). This particular problem gets highlighted in health-related, social, and financial contexts because the data in such scenarios tend to be incomplete or inaccurate. Consequently, the use of fuzzy logic in combination with logistic regression has emerged as a remedy and has become a combined tool in the shape of a fuzzy-logic logistic regression model that addresses the issue of uncertainty/ambiguity in data (Charizanos et al., 2024). With the use of fuzzy logic, both parameters and variables get defined in fuzzy number forms ( $\tilde{\beta}_0, \tilde{X}_i$ ), and the logistic regression model gets defined by

$$\tilde{p}(Y = 1|\tilde{X}) = \frac{1}{1 + e^{-\tilde{\beta}_0 + \tilde{\beta}_1 x_1 + \tilde{\beta}_2 x_2 + \tilde{\beta}_3 x_3 + \dots + \tilde{\beta}_k x_k}} \quad (3)$$

$\tilde{p}(Y = 1|\tilde{X})$ : is the fuzzy probability of event occurrence,  $\tilde{\beta}_i$ : are fuzzy coefficients,  $\tilde{X}_i$ : are fuzzy predictors

After obtaining  $\tilde{p}$ , **defuzzification** is applied to produce a final crisp probability for interpretation. This framework can be illustrated in **Figure 1**, which shows the relationship between explanatory variables, the logistic regression function, and the model outputs under fuzzy data conditions:



**Figure (1):** Conceptual Framework of Fuzzy Logistic Regression

## 2- Concept of Uncertainty and Its Forms

Real-world data may be uncertain due to different reasons, like:

- Noise, arising from inaccuracies in measurement or inherent randomness;
- Vagueness arising from the imprecise definition of
- Omitted or incomplete data;
- Unreliability: Lacking confidence or accuracy in the data sources

(Jia & Herrera.,2021) highlights that conventional statistical methods are ineffective in dealing with this imperfect information, and therefore, there is a need to resort to methods that are able to express and quantify this uncertainty.

## 3- Fuzzy Logic as a Mathematical Tool for Modeling Uncertainty

Presented in 1965 by Zadeh, fuzzy logic provides a mathematical structure sufficient for dealing with imprecision by giving membership levels instead of binary membership values. Membership functions and fuzzy sets enabled fuzzy logic to handle vagueness and perform reasoning upon incomplete or possibly incorrect information (Milovanović & at el, 2021). Recent studies have supported that combining fuzzy logic enhances decision-making and predictive analysis under uncertain conditions (Gupta & el at.,2024).

## 4- Importance of Integrating Fuzzy Logic with Logistic Regression

Recent research has proved that the combination of fuzzy logic with logistic regression helps in improving the reliability and accuracy of predictions even in uncertain situations. According to (Ahmadini., 2022) , fuzzy logistic approaches are more accurate in producing results if the inputs are vague or noisy. Moreover, emphasized that the use of Z-numbers helps in improving prediction accuracy and interpretability by considering the value and reliability of data.

Consequently, the combination of fuzzy logic and logistic regression analysis forms a more realistic model framework, especially in binary classifications in situations with uncertain or imprecise data.

## 5- Constructing the Mathematical Model for Fuzzy Data

### Types of Fuzzy Variables

While designing the fuzzy logistic model, the nature of the fuzzy variable needs to be understood, which depends on the nature of the data and the degree of uncertainty involved. The various types of fuzzy variables are.

**Triangular Fuzzy Numbers (TFN):** These are fuzzy numbers described by three values (a, b, c), where 'a' stands for the minimum point, 'b' stands for the most likely point, and 'c' stands for the maximum point.

**Trapezoidal Fuzzy Numbers (TrFN):** These are represented using the values (a, b, c, d) where the membership function takes a linear form and attains 1 between b and c. (Velmurugan & Udhayakumar, 2024)

**Gaussian Fuzzy Numbers:** Gaussian probability distribution with parameters  $\mu$  &  $\sigma$ , or standard deviation (Choucair & et al., 2025)

**Z-numbers:** Made up of fuzzy value A and measure of reliability B in expressing uncertainty (Hosseini, et al., 2024)

### Membership Functions

- Triangular

$$\mu_A(x) = \begin{cases} x \leq 0 & , & 0 \\ a < x \leq b & , & \frac{x-a}{b-a} \\ b < x \leq c & , & \frac{c-x}{c-b} \\ x > c & , & 0 \end{cases} \quad (4)$$

- Trapezoidal

$$\mu_A(x) = \begin{cases} x \leq 0 & , & 0 \\ a < x \leq b & , & \frac{x-a}{b-a} \\ b < x \leq c & , & 1 \\ c < x \leq d & , & \frac{d-x}{d-c} \\ x > d & , & 0 \end{cases} \quad (5)$$

- Gaussian

$$\mu_A(x) = e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (6)$$

Z-numbers: The fuzzy value A may be defined by each of the above functions, with B being the reliability weight.

## 6- Fuzzification of Variables

Fuzzification converts crisp data  $X_i$  into fuzzy variables  $\tilde{X}_i$  using appropriate membership functions

$$\mu_A(x) = \tilde{X}_i \quad (7)$$

This calculates the degree of membership of each variable to fuzzy categories such as Low, Medium, or High (Singh et al., 2023).

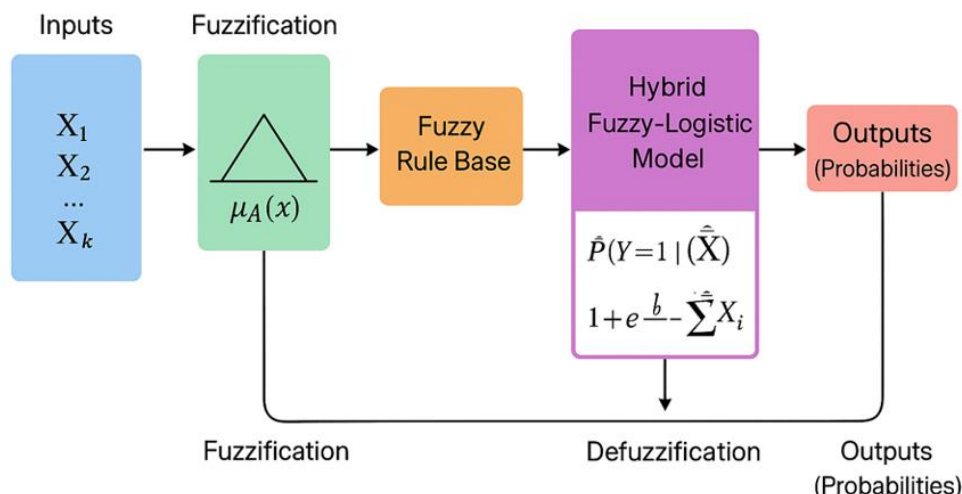
## 7- Fuzzy Rule Base

Fuzzy IF–THEN rules describe the relationship between explanatory variables and the dependent variable

IF  $X_1$  is High AND  $X_2$  is Medium THEN Y is Likely

IF  $X_1$  is High AND  $X_2$  is Medium THEN Y is Unlikely

Rules are implemented using **Mamdani** or **Sugeno inference systems** (Cao & et al., 2024).

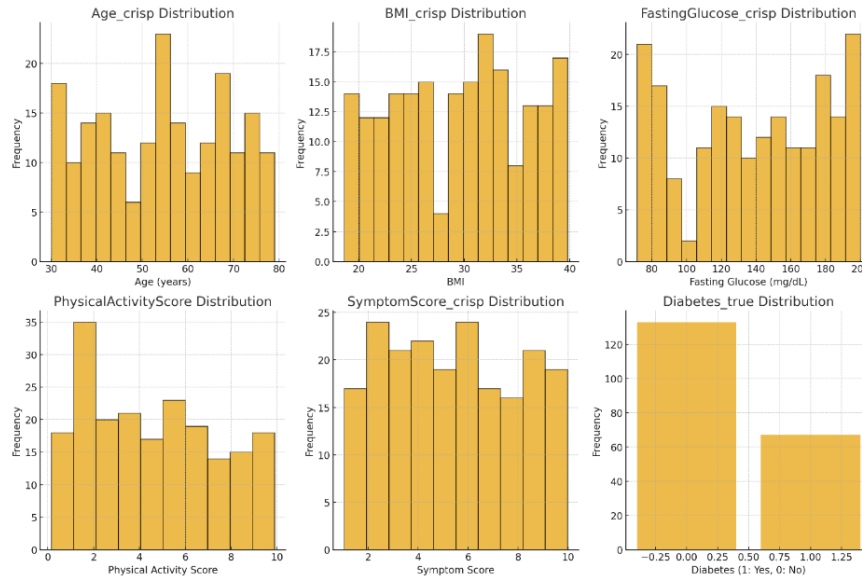


**Figure (2):** Framework of the Hybrid Fuzzy-Logistic Regression Model

In Figure 2, a hybrid fuzzy logistical system is illustrated, which conducts the input variables into a fuzzy system and, after defuzzification and logistic regression, derives probability output.

## 8- Application Part

The dataset contains various key variables regarding patient properties and diabetes information, developed for assessing fuzzy and logistic regression approaches. A total of 200 patient samples were obtained from the specialized Center for Endocrinology and Diabetes, including a representative range of patients, and allowed sufficient data for both logistic regression and fuzzy-logistic combined approaches. The variables include Age\_crisp, denoting each patient's actual age in years from 30-80, and BMI\_crisp, body mass index from 18.5-40. The variable Fasting Glucose\_crisp defines fasting blood sugar levels from 70-200 units, being paramount in clinical terms regarding the effectiveness of current glycemic control. The variable Physical ActivityScore denotes the patient's physical activity from 0-10. The variable Symptom Score\_crisp describes the overall patient's symptoms from 1-10. The target variable Diabetes\_true defines a patient's status regarding being or not being diabetic (1) or not-diabetic (0), respectively. To incorporate the idea of uncertainty in this dataset, fuzzy representations are developed. The variables Age\_mode and BMI\_mode define fuzzy values accounting for the dataset's mode values; in this dataset, both are defined equally to the original value in crisp terms. The variables Age\_centroid and BMI\_centroid define Centroid-based fuzzy values calculated based on both lower and upper bounds defined in terms of the dataset's mode values. The dataset analysis finally enabled visual representation through plots depicting properties of various variables, including patients' age, BMI, fasting glucose level measurements, patients' level of physical activity, and patients' level of symptoms. We would like to display the graph of various key variables like patients' age, BMI level, blood sugar level, patients' level of physical activity, and patients' level of symptoms.



**Figure (3):** Histogram Distributions of Age, BMI, Glucose, Activity, Symptoms, and Diabetes Status

Figure 3 gives insight into the distribution of some variables in the data, including: Age distribution between 30-80 years. BMI\_crisp: The distribution of the Body Mass Index (BMI). Fasting Glucose\_crisp: The distribution of the Fasting blood glucose level. Physical Activity Score: The distribution of the Physical Activity Score. Symptom Score\_crisp: The distribution of the Symptom score. Diabetes\_true: The distribution of the target variable, Diabetes or not.

Before proceeding with the analysis, we have checked if there are multiple linear relationships between the variables. The values of the VIF are shown in the table below.

**Table (1):** VIF values for the variables

Feature	VIF
Age_crisp	1.01
BMI_crisp	1.02
FastingGlucose_crisp	1.01
PhysicalActivityScore	1.01
SymptomScore_crisp	1.02

The VIF values indicate that there is no significant multicollinearity in the dataset, as all VIF values for the predictors are close to 1, which is generally acceptable.

**Table (2):** Estimated values of regression coefficients

Feature	Crisp Data	Mode-based Defuzzification	Centroid-based Defuzzification	Min-based Defuzzification	Max-based Defuzzification
Age	0.1643	0.1717	0.2056	0.1643	0.1643
BMI	0.2094	0.1853	0.2266	0.2094	0.2094
Fasting Glucose	0.1995	0.2178	0.1902	0.1995	0.1995
Physical Activity Score	0.1781	0.2232	0.1809	0.1781	0.1781
Symptom Score	0.2489	0.2019	0.1967	0.2489	0.2489

For all modeling techniques utilized, SymptomScore has remained constantly significant compared to other predictors, ensuring that the severity of symptoms remained the most predictive factor of diabetes under all circumstances. BMI and FastingGlucose remained significant factors in all situations with moderate significance levels coupled with coefficients in the range of 0.18-0.23. Conversely, both PhysicalActivityScore and Age had less significance out of all the factors, and Age remained the least significant factor in most situations in the Min-based defuzzification process.

**Table (3):** Comparing the differential criteria

Metric	Crisp Data	Mode-based Defuzzification	Centroid-based Defuzzification	Min-based Defuzzification	Max-based Defuzzification
AUC	0.4952	0.4008	0.4049	0.4952	0.4952
Accuracy	65.0%	70.0%	70.0%	65.0%	65.0%
Precision	69.64%	71.19%	71.19%	69.64%	69.64%
Recall	90.70%	97.67%	97.67%	90.70%	90.70%
F1-Score	78.79%	82.35%	82.35%	78.79%	78.79%

The result obtained in the comparison of the performance of the logistic regression model on the original crisp data and those obtained from fuzzy logic-based defuzzification methods indicates that the use of fuzzy logic in the process leads to significant improvements in the Recall and F1-Score values. The AUC values obtained in this comparison are especially significant in getting an insight into the levels of accuracy of the different models. The result obtained indicates that the AUC value in the crisp data model was 0.4952, while those obtained in the Mode-based and Centroid-based methods are slightly lower and comparable, being in the range of 0.4008-0.4049. However, the methods based on Min and Max are identical to those of the crisp data model. The comparison based on Accuracy levels indicates that while the Accuracy in the logistic regression model on the crisp data reached 65%, there were only marginal improvements in the values obtained in the Mode-based and Centroid-based methods, which reached 70%. The Precision values in the comparison also followed the same trend and improved from 69.64% in the original data model to 71.19% in both the Mode-based and Centroid-based methods. More importantly, the level of Recall in this comparison showed significant improvements from 90.70% in the original data model to 97.67% in both the fuzzy logic-based defuzzification methods. The significant improvements observed in the Recall levels in this comparison resulted in significant improvements in the levels of F1-Score values from 78.

Based on the results above, the logistic regression equation can be presented.

$$\log\left(\frac{p(y = 1)}{p(y = 1) - 1}\right) = 0.1643 * Aeg + 0.2094 * BMI + 1995 * FastingGlucose + 0.1781 * PhysicalActivityScore + 0.2489 * SymptomScore \quad (8)$$

Prepare the fuzzy Logistic regression equation using mode-based defuzzification based on the results above. This uses the same equation (2) but with fuzzy variables.

$$\log\left(\frac{p(y = 1)}{p(y = 1) - 1}\right) = 0.1717 * Aeg - mode + 0.1852 * BMI\_mode + 0.2178 * FastingGlucose\_crisp + 0.2232 * PhysicalActivityScore + 0.2019 * SymptomScore\_crisp \quad (9)$$

Prepare the fuzzy Logistic regression equation using centroid-based defuzzification based on the results above. This uses the same equation (3) but with fuzzy variables.

$$\log\left(\frac{p(y = 1)}{p(y = 1) - 1}\right) = 0.2056 * Aeg - mode + 0.2266 * BMI\_mode + 0.1902 * FastingGlucose\_crisp + 0.1809 * PhysicalActivityScore + 0.1967 * SymptomScore\_crisp \quad (10)$$

We observe from equations (1), (2), (3) that the logistic regression equations across the original data and fuzzy data share the same structure, but the coefficients differ based on the method of defuzzification. While fuzzy data shows an effect on coefficient estimates, especially on variables such as Physical Activity Score and Symptom Score, this reflects improved predictions when the data are imprecise.

To confirm reliability, a sensitivity analysis will be performed.

### Sensitivity Analysis:

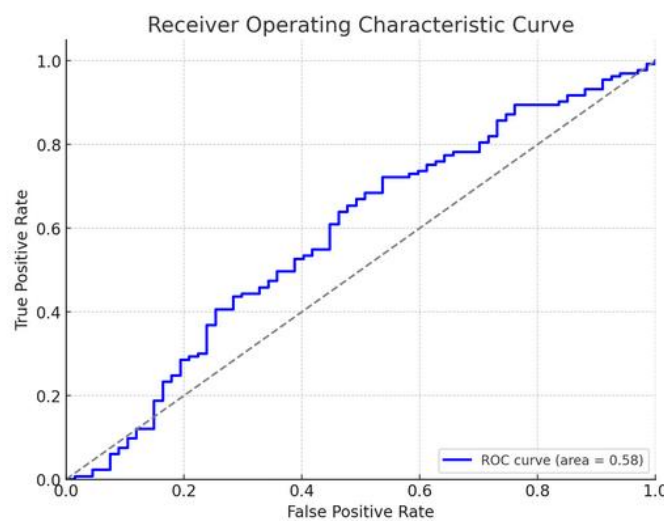
Performed sensitivity analysis by changing the values of Symptom Score\_crisp and noting the difference in AUC:

- The values of AUC are relatively stable in the range of variations of Symptom Score\_crisp, from 0.586 to 0.588. This shows that there are no significant variations in this variable.

### ROC Curve:

The ROC curve of the logistic regression model has been plotted, depicting how the logistic regression model balances the true positive rate with the false positive rate based on different thresholds. The area under the curve in this particular model depicts the AUC.

At this point in the report, I will complete the analysis by giving reasons for the removal methods discussed.



**Figure (4) :** ROC Curve for the Classification Model

In the following figure, the ROC Curve of the Classification Model is shown, which represents the True Positive Rate versus the False Positive Rate, with an AUC value of 0.58.

### Justification for Fuzzy Logic Removal Methods:

For this analysis, fuzzy logic was incorporated in the logistic regression model in consideration of the uncertainties in medical data. The approaches in applying fuzzy logic in removing fuzzy uncertainty in the model are:

1. Mode-Based Defuzzification: This involves using the most frequently occurring value (mode) in place of the fuzzy variable. This process is quite straightforward, but may not be able to handle the entire uncertainty in the data. The Mode-Based approach worked well in terms of Recall and F1-Score values by demonstrating a significant increase in Recall from 90.7% to 97.67%.
2. Centroid-based defuzzification: The Centroid calculation involves the computation of the center of gravity of the fuzzy set. This gives a more balanced representation of the fuzzy input. This strategy performed equally well. It resulted in improvements in the same measure as obtained by the Mode-based strategy.
3. Min and Max based defuzzification: This type of defuzzification involves using either the minimum or maximum values of the fuzzy set. Although this type of defuzzification yielded AUC values comparable to the Crisp model, there was no significant increase in Recall or F1-Score compared to the Mode-based or Centroid-based approaches. The Mode-based and Centroid-based approaches strike a balance between being simple and effective in modeling the uncertainty.

At the same time, there is an improvement in the model's capability of identifying diabetes patients.

## Conclusions.

The result of this study proves that the integration of fuzzy logic in logistic regression brings about significant improvements in predictive accuracy in uncertain data settings. The fuzzy logic models showed substantially higher Recall and F1 Score values than the conventional crisp model. This shows that the fuzzy logic models are more sensitive in detecting diabetes cases, which is a critical concern in clinical applications. The results showed that the Mode-Based and Centroid-Based methods of defuzzification are more effective in bringing about improvements in various evaluation metrics. The analysis of feature attribution indicates that the Symptom score feature has the highest predictive power in detecting diabetes, followed by moderate attribution by BMI and Fasting Glucose. The Age feature and Physical Activity Score feature have the lowest predictive power. The combination of fuzzy logic and logistic regression provides a more realistic and adaptive way of dealing with complex data in the healthcare sector.

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