Development of a Fuzzy Logic-Based Predictive Model for Myocardial Infarction Risk

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***Abstract*— Myocardial infarction (MI), commonly known as a heart attack, is a major cardiovascular condition for which early identification of individuals at increased risk can support timely intervention. This study developed a fuzzy logic-based predictive model for MI risk using clinical and diagnostic variables obtained from patient records at the Obafemi Awolowo University Teaching Hospital Complex (OAUTHC), Ile-Ife. Ten variables were used as inputs to the fuzzy inference system. Triangular membership functions were used to map the input variables to linguistic categories, while a rule-based inference mechanism was employed to classify MI risk as no risk, low risk, moderate risk, or high risk. The model was evaluated using 1,700 records comprising 952 no-risk and 748 risk cases. For binary performance evaluation, the no-risk output was classified as no risk, whereas the low-, moderate-, and high-risk outputs were classified as risk. The model achieved an accuracy of 82.00%, sensitivity of 79.41%, specificity of 84.03%, and F1-score of 79.52%. The corresponding confusion matrix showed 800 true negatives, 152 false positives, 154 false negatives, and 594 true positives. Pearson correlation analysis further indicated that thallium test results had the strongest positive association with MI risk (r = 0.52), while maximum heart rate showed a negative association (r = −0.25); ST depression and ST slope exhibited the strongest correlation among the predictor variables (r = 0.61). The findings demonstrate the potential of a transparent, rule-based fuzzy inference approach for MI risk prediction and highlight the need for further validation on broader, independent clinical datasets.**

Keywords—Cardiovascular Diseases, Clinical Decision Support System, Fuzzy logic, Heart Attack, Inference System, Myocardial Infarction, Machine Learning, Risk Prediction.

I. INTRODUCTION

According to the World Health Organization (WHO), Cardiovascular Diseases (CVDs) are the leading cause of death globally, accounting for approximately 19.8 million deaths in 2022, roughly 32% of all deaths [1]. Despite significant improvements in public health over the past few decades, the incidence of CVD mortality has remained unchanged [2]. 85% of these CVD deaths were caused by myocardial infarction (heart attack) and stroke [1].

Myocardial infarction (MI), often referred to as a heart attack, happens when the heart muscle's blood supply is disrupted, causing damage to the myocardium from insufficient oxygen. One of the main causes of restricted blood flow and consequent injury to the heart muscle is the accumulation of atherosclerotic plaque in the coronary arteries [3]. Myocardial cell death brought on by persistent ischemia as a result of an imbalance between oxygen supply and demand is the pathophysiological definition of MI [4]. According to epidemiological research, ischemic heart disease continues to be the primary cause of cardiovascular death, with stroke and hypertensive heart disease following [5]. Sachdeva et al. [6] further emphasized that MI remains a major global health issue with a negative impact on people, families, healthcare systems, and economies.

Early detection of individuals at increased risk of MI enables timely intervention, appropriate management, and preventive strategies, thereby reducing complications and mortality associated with delayed treatment [7], [8]. Accurate risk prediction of MI, like other high-burden diseases, is crucial for effective prevention and proper management [8].

One approach for early identification of high-risk individuals is through predictive modeling, which estimates an individual's likelihood of developing MI based on established risk factors. This can be achieved by considering risk factors including high blood pressure, alcohol and tobacco consumption, advanced age, smoking, obesity, hypertension, diabetes, hyperlipidemia, and family history of heart disease [9]–[11]. Several tools have been developed over the years to support this prediction.

For cardiovascular risk stratification and clinical decision-making, conventional cardiovascular risk assessment tools, such as the Thrombolysis in Myocardial Infarction (TIMI) Risk Score and the Framingham Risk Score [12], are commonly used. However, these models primarily depend on predefined clinical variables and may not sufficiently capture complex interactions among multiple risk factors across diverse patient populations [13]. Consequently, considerable research efforts have focused on improving CVD risk prediction using advanced technological approaches.

Machine learning (ML) and other innovative technical techniques have emerged as viable methods for enhancing MI risk prediction. Unlike conventional statistical methods, machine learning techniques can identify complex relationships among variables in training datasets to forecast various clinical outcomes, including mortality [14].

This study focused on designing a model to predict MI risk levels and minimize MI incidence and effects. The proposed model can be used as a clinical decision-support tool to help medical professionals identify patients at high risk of MI and implement appropriate preventive measures. Research studies exploring the intricate connections between risk factors and MI risk can also benefit from the model. The suggested model's ultimate goal is to enhance patient outcomes and quality of life.

II. Literature Review

Numerous studies have examined MI prediction using fuzzy logic, deep learning, and machine learning techniques. Some of these studies are reviewed as follows.

To address uncertainty and imprecision in medical data, Indirani et al. [14] presented a heart disease prediction system that integrates fuzzy logic, image processing, and classification algorithms. The method included fuzzy genetic algorithms for feature selection, fuzzy C-means clustering for medical picture segmentation, fuzzy scaling for feature representation, and fuzzy imputation for handling missing values. Heart disease severity was classified by a Mamdani fuzzy inference system, and features were ranked using a fuzzy decision tree. The model's accuracy was 96.4%, sensitivity 93%, specificity 38%, and AUC-ROC 0.96. By tackling ambiguity in medical datasets, the authors demonstrated that combining fuzzy logic with machine learning approaches can improve prediction accuracy.

A fuzzy logic-based expert system for the diagnosis and prognosis of heart disease was developed by Ali et al. [15]. Fuzzification, a knowledge base, an inference engine, and defuzzification modules made up the system. The knowledge base was built through consultation with medical specialists and the existing literature, and seven clinical parameters were used as input variables. The method achieved a diagnostic accuracy of 98.08% on the Cleveland dataset. The study showed that physicians can make better clinical decisions with the help of fuzzy-based expert systems.

To predict acute myocardial infarction (AMI) and ischemic heart disease (IHD) among patients in primary care cardiovascular services, Salet et al. [2] used machine learning approaches. 13,218 patient records gathered from 90 general practitioner clinics between 2011 and 2021 were examined in this study. The researchers created random forest models to predict AMI and IHD and evaluated how well they performed in comparison to the SMART risk prediction algorithm. Accuracy of 0.97, sensitivity of 0.67, specificity of 1.00, precision of 0.99, Brier score of 0.03, and AUC of 0.96 were all attained by the AMI model. The results showed that machine learning models can outperform conventional methods in predicting cardiovascular risk.

Nudrat and Sifatullah [16] used machine learning methods to identify important risk factors for MI prediction. The study assessed Bayesian Network, Random Forest, C4.5 decision tree, and Deep Belief Network (DBN) models utilizing a dataset of 350 records. With an accuracy of 89.32%, precision of 84.04%, sensitivity of 86.63%, and specificity of 82.45%, the DBN model performed best. The authors concluded that machine learning techniques can provide useful insights for understanding and forecasting MI risk.

Arslankaya and Çelik [17] used a fuzzy logic technique to forecast heart attacks. The study created 576 fuzzy rules based on expert knowledge using the Mamdani fuzzy inference method. Regression analysis was utilized to ascertain the correlations between dependent and independent variables using ten patient data. Regression explained 41.9% of the variation in the dependent variable, demonstrating that fuzzy logic was a successful predictor of heart attack risk.

To predict acute myocardial infarction, Than et al. [18] created a machine learning method called the myocardial-ischemic-injury-index (MI3). Age, sex, and matched high-sensitivity cardiac troponin I readings were all included in the model. 7,998 individuals with probable MI were evaluated using a training dataset of 3,013 patients. The gradient boosting model demonstrated good predictive ability with an AUROC of 0.963. The authors demonstrated how machine learning might identify patients in need of early care and offer a customized MI risk assessment.

A deep learning method for automatic MI detection utilizing electrocardiogram (ECG) signals was proposed by Makimoto et al. [19]. To automatically extract MI-related ECG characteristics, a Convolutional Neural Network (CNN) model was trained using the PTB Diagnostic ECG Database. The model's excellent classification performance demonstrates that deep learning can aid automated MI diagnosis. The method was constrained, though, because it relied solely on ECG data and overlooked other clinical risk factors such as age, blood pressure, cholesterol, and lifestyle choices.

Fang et al. [20] combined support vector machine (SVM) classification with gene expression data to develop a model for early MI diagnosis. From publicly accessible databases, differentially expressed genes linked to MI were found and utilized as predictive characteristics. An SVM classifier was trained using the chosen features, proving that biomarker identification and early diagnosis can be supported by machine learning in conjunction with genetic data. However, additional extensive and varied clinical datasets are needed to validate the model.

A machine learning system was developed by Hsu et al. [21] to identify biomarkers associated with acute myocardial infarction. Logistic regression, decision trees, random forests, support vector machines, and artificial neural networks were all assessed in the study. To identify relevant biomarkers for AMI prediction, feature selection techniques were employed. The findings showed that machine learning techniques can enhance the understanding of key clinical markers and improve AMI prediction performance. However, due to the limitations of the specific clinical population, external validation was advised.

Despite the progress reported in previous studies, some limitations remain in the application of computational approaches to myocardial infarction risk prediction. Existing machine learning and deep learning approaches have demonstrated strong predictive capabilities but offer limited transparency into how individual clinical variables contribute

to the resulting prediction. Fuzzy logic-based approaches address this limitation by representing clinical information using linguistic variables and interpretable IF–THEN rules; however, several existing studies have relied on predefined rule structures, relatively limited patient samples, or datasets that may not reflect the characteristics of patients in specific local clinical settings. In addition, some studies have focused primarily on model development without providing an explicit representation of the relationship between clinically relevant variables and the resulting levels of myocardial infarction risk. Therefore, a need remains for an interpretable, fuzzy-logic-based predictive model that integrates multiple clinical indicators into a transparent, rule-based framework for stratifying myocardial infarction risk. This study addresses this gap by developing a fuzzy inference system using ten clinically relevant variables obtained from patient records, with these variables represented linguistically and combined through an explicit fuzzy rule base to estimate the risk of myocardial infarction. The resulting framework is intended to provide an interpretable approach for supporting early risk identification while making the reasoning underlying the prediction more transparent.

III. Methodology

This section explains the steps taken in designing the predictive model for MI.

Fig. 1 shows the design of the fuzzy inference system for myocardial infarction risk prediction in this study. The four main components of the fuzzy inference system are fuzzification, rule base, inference engine, and defuzzification. The clinical variables that were identified and used for this study, including age, sex, chest pain type, blood pressure, cholesterol level, ST depression, ST slope, maximum heart rate, fasting blood sugar, and thallium test results, were first converted into linguistic variables through fuzzification. A rule-based inference engine then evaluates predefined fuzzy rules to determine the degree of myocardial infarction risk, which is then converted into a crisp prediction value through defuzzification.

A. Variables Identification and Description

After conducting a structured interview with a cardiologist and reviewing the body of research on myocardial infarction in patients, variables were identified. Table I below gives the variables and their labels.

B. Dataset Acquisition and Description

Following the identification of the variables, the dataset for the model design was acquired based on the identified variables and their values. The dataset acquired was a range of manually recorded health record from 2012 to 2022 of patients with heart disease, collected from the Obafemi Awolowo University Teaching Hospital Complex (OAUTHC), Ile-Ife. Osun State. The dataset consisted of patients' documentation and interactions with their cardiologists. The dataset were extracted manually and then converted to Comma-Separated Values (csv).

Fig 2 gives a screenshot of the sample records from the myocardial infarction dataset showing the clinical variables used for model development, including demographic factors (Age, Sex), physiological measurements (BP, Cholesterol, Max HR, FBS, chest pain), electrocardiographic indicators (ST depression, ST slope), and diagnostic test results (Thallium).

The value of the risk class for each patient was determined and classified as no risk (0) or risk (1). In the status data, 952 (56%) patients are at no risk of having myocardial infarction, and 748 (44%) are at risk of having myocardial infarction.

C. Fuzzy Logic Model for the Prediction of Myocardial Infarction

MI prediction in this study was performed using a fuzzy logic inference system. Fuzzy logic was selected for its ability to model uncertainty, imprecision, and the linguistic reasoning inherent in clinical decision-making [22]. Membership functions (MFs) for the input and output variables were created using mathematical representations of fuzzy sets. Through a procedure called "fuzzification," these membership functions were employed to convert precise clinical values into degrees of membership. Rule-based reasoning for myocardial infarction risk prediction was enabled by this fuzzification technique, which transformed numerical clinical data into comprehensible linguistic categories. With membership values ranging from 0 to 1, each clinical characteristic was translated to matching linguistic labels (such as low, moderate, and high).

Triangular membership functions were adopted for both the input and output variables. A triangular membership function is defined by three parameters, a, b, and c, where a and c represent the lower and upper bounds of the triangular function, respectively, and bb represents the point at which membership reaches its maximum value, such that (a<b<c). The triangular membership function is defined as:

$$\mu(x;a,b,c) = max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (1)$$

where x represents the input value and μ(x;a,b,c) represents its degree of membership. The membership value ranges from 0 to 1. The function increases linearly from a to b, reaches its maximum value of 1 at b, and decreases linearly from b to c. Values outside the interval [a,c] have a membership value of zero.

1. Fuzzification Process in the Fuzzy Logic Model

The fuzzy logic model for myocardial infarction risk prediction involved four main processes: fuzzification, rule creation, rule aggregation, and defuzzification.

Fuzzification is the first stage, in which crisp input values were transformed into membership degrees in the corresponding fuzzy sets. In this study, the clinical variables were represented using linguistic categories such as low/high, normal/high, mild/severe, and normal/abnormal. Triangular membership functions were used to represent the linguistic categories because of their simplicity and suitability for representing gradual transitions between categories.

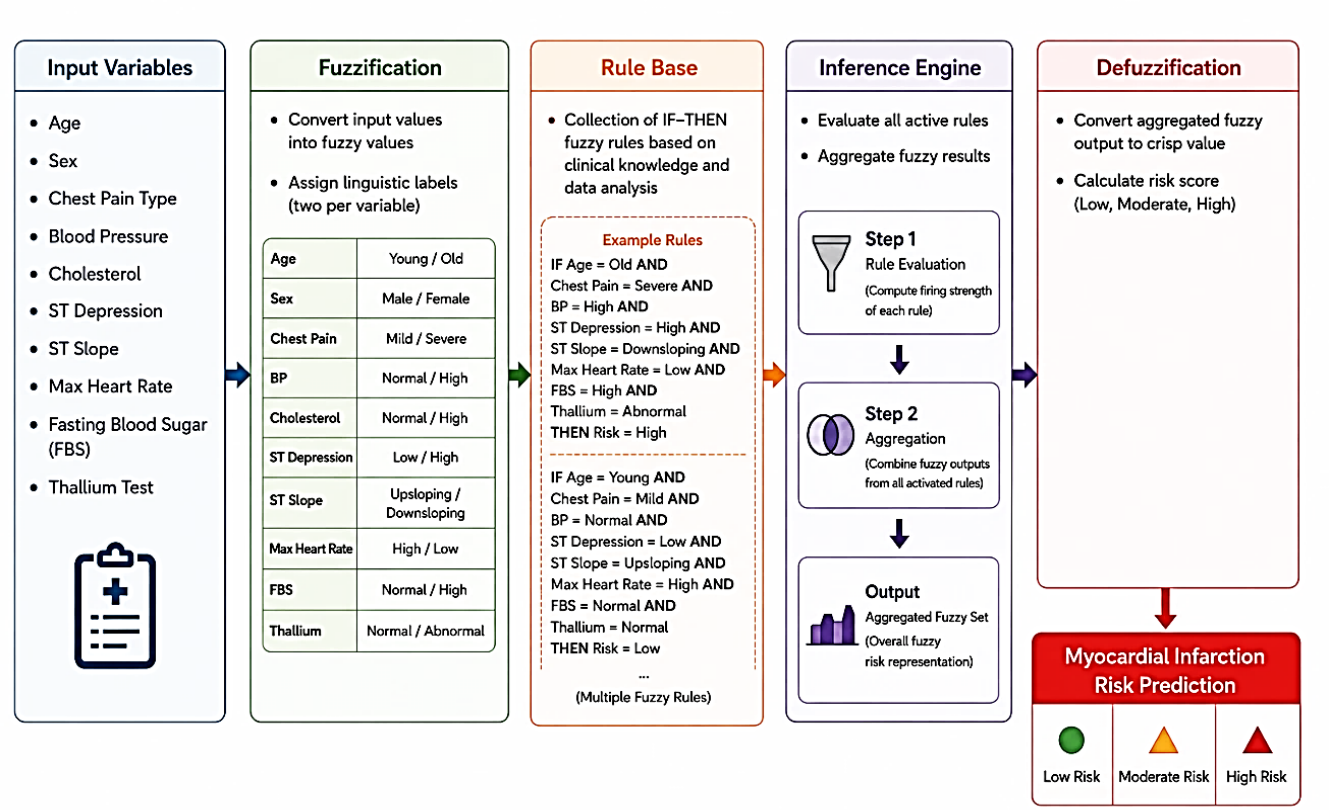

Fig. 1. Architecture of the Fuzzy Inference System for Myocardial Infarction Prediction

TABLE I. IDENTIFICATION OF VARIABLES REQUIRED FOR ASSESSING MYOCARDIAL INFARCTION

S/N	Variables	Labels	
1	Age	Below 18 Years	18 Years or Above
2	Sex	Male	Female
3	Chest Pain	Mild	Severe
4	BP	Normal	High
5	Cholesterol	Normal	High
6	ST Depression	Low	High
7	ST Slope	Up sloping	Down sloping
8	Max Heart Rate	High	Low
9	FBS (Fasting Blood Sugar)	Normal	High
10	Thallium	Normal	Abnormal

ID	Age	Sex	Chest pain type	BP	Cholesterol	ST depression	Slope of ST	Max HR	FBS over 120	Thallium	Heart Disease
1.0	77.0	1.0	4.0	130.0	322.0	2.4	2.0	109.0	0.0	3.0	1.0
2.0	55.0	1.0	3.0	115.0	564.0	1.6	2.0	160.0	0.0	7.0	0.0
3.0	52.0	1.0	2.0	124.0	261.0	0.3	1.0	141.0	0.0	7.0	1.0
4.0	68.0	0.0	4.0	128.0	263.0	0.2	2.0	105.0	0.0	7.0	0.0
5.0	60.0	1.0	2.0	120.0	269.0	0.2	1.0	121.0	0.0	3.0	0.0
6.0	64.0	1.0	4.0	120.0	177.0	0.4	1.0	140.0	0.0	7.0	0.0
7.0	70.0	1.0	3.0	130.0	256.0	0.6	2.0	142.0	1.0	6.0	0.0
8.0	65.0	1.0	4.0	110.0	239.0	1.2	2.0	142.0	0.0	7.0	1.0
9.0	60.0	1.0	4.0	140.0	293.0	1.2	2.0	170.0	0.0	7.0	1.0
10.0	77.0	0.0	4.0	150.0	407.0	4.0	2.0	154.0	0.0	7.0	1.0
11.0	71.0	1.0	4.0	135.0	234.0	0.5	2.0	161.0	0.0	7.0	0.0
12.0	50.0	0.0	4.0	142.0	226.0	0.0	1.0	111.0	0.0	7.0	0.0

Fig. 2. Snapshot of Dataset Sample

For each triangular membership function, three parameters, (a), (b), and (c), were specified, where (a) and (c) represent the lower and upper limits of the triangular function and (b) represents its peak. The parameters satisfy the condition ($a < b < c$). The membership degree is 1 at (b), decreases toward 0 as the input approaches (a) or (c), and is zero outside the interval ([a,c]). Thus, the values presented in Table II represent the triangular membership function parameters (a, b, c).

For the binary clinical variables used in the model, the original categorical values were encoded as 0 and 1. The first linguistic category was represented using the triangular parameters (-0.5, 0, 0.5), while the second category was represented using (0.5, 1, 1.5). This arrangement provides a small overlap between adjacent fuzzy sets and allows each crisp input value to be mapped to a membership degree between 0 and 1.

The resulting membership degrees were subsequently supplied to the fuzzy inference engine, where the predefined fuzzy rules were evaluated to determine the corresponding level of myocardial infarction risk.

The identified variable labels are combined to form the rule base. The fuzzy logic inference system, which combines the values of variables supplied after fuzzification, includes the reference engine. The value of the risk of myocardial infarction is then calculated as an output of the defuzzification process.

TABLE II. FUZZIFICATION OF MYOCARDIAL INFARCTION INPUTS

SN	Variables	Linguistic Label	Triangular MF Parameters (a,b,c)	Input
1	Age	Below 18 years	-0.5, 0, 0.5	0
		18 years or above	0.5, 1, 1.5	1
2	Sex	Female	-0.5, 0, 0.5	0
		Male	0.5, 1, 1.5	1
3	Chest Pain	Mild	-0.5, 0, 0.5	0
		Severe	0.5, 1, 1.5	1
4	BP	Normal	-0.5, 0, 0.5	0
		High	0.5, 1, 1.5	1
5	Cholesterol	Normal	-0.5, 0, 0.5	0
		High	0.5, 1, 1.5	1
6	ST Depression	Low	-0.5, 0, 0.5	0
		High	0.5, 1, 1.5	1
7	ST Slope	Up sloping	-0.5, 0, 0.5	0
		Down sloping	0.5, 1, 1.5	1
8	Max Heart Rate	High	-0.5, 0, 0.5	0
		Low	0.5, 1, 1.5	1
9	FBS	Normal	-0.5, 0, 0.5	0
		High	0.5, 1, 1.5	1
10	Thallium	Normal	-0.5, 0, 0.5	0
		Abnormal	0.5, 1, 1.5	1

2. *Fuzzification of Output*

Ten (10) variables, or ten points, were employed to formulate the predictive model. For example, 10 variables equal 10 points. There are four levels of risk associated with myocardial infarction: no risk, low risk, moderate risk, and high risk. The value corresponding to each level of risk is displayed in Table III.

TABLE III. FUZZIFICATION OF OUTPUT

Risk Class	Crisp Output	Triangular Parameters
No risk	0	-0.5, 0, 0.5
Low risk	1 – 2	0.5, 1, 1.5
Moderate risk	3 – 5	1.5, 2, 2.5
High risk	6 – 7	2.5, 3, 3.5

3. *Rule Production for the Fuzzy Logic Model*

The second step after fuzzification is rule creation. At this point, each rule's truth value was calculated and applied to the relevant section of each rule. As previously indicated in Tables I and II, linguistic labels are assigned to each variable. Two input and output variables serve as the conditions for the rules in the controller's rule-based system.

The general rule for this prediction model is:

IF ($Variable_1$ = Label) AND ($Variable_2$ = Label) AND ($Variable_3$ = Label) … AND ($Variable_{10}$ = Label) THEN (MI Risk = Label)

Rule Production:

The fuzzy inference system was constructed using ten input variables representing key clinical and diagnostic indicators of myocardial infarction risk. Since in this study, each variable has two labels, then the total number of rule combinations is 2^{10}. Because there are 10 input variables, so: $2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2$. Which equals: 1024 possible rules. This means there are 1024 different combinations of patient conditions. However, the rule base was refined to include clinically relevant combinations in order to maintain interpretability and computational efficiency.

For instance, a rule combination could be:

IF (Age = "> 18) AND (Sex = Male) AND (Chest Pain = Severe) AND (BP = High) AND (Cholesterol = High) AND (ST Depression = High) AND (ST Slope = Down sloping) AND (Max Heart Rate = Low) AND (FBS = High) AND (Thallium = Abnormal) THEN (Myocardial Infarction Risk = High)

Another rule could be:

IF (Age = < 18) AND (Sex = Female) AND (Chest Pain = Mild) AND (BP = Normal) AND (Cholesterol = Normal) AND (ST Depression = Low) AND (ST Slope = Up sloping) AND (Max Heart Rate = High) AND (FBS = Normal) AND (Thallium = Normal) THEN (MI Risk = Low)

A fuzzy rule base was constructed to model the relationship between variables and myocardial infarction risk. The rules were designed based on clinical knowledge and known cardiovascular risk factors, including age, chest pain severity, blood pressure, cholesterol levels, electrocardiographic changes, and thallium stress test results. Table IV presents samples of fuzzy IF–THEN rules used in the inference system to classify myocardial infarction risk into three categories: low, moderate, and high.

D. *Simulation of the Formulated Fuzzy Logic Model*

A fuzzy logic developed in Jupyter Notebook was used to simulate and analyze the proposed fuzzy inference system. The developed models were simulated to evaluate their effectiveness and functionality after the fuzzy inference system for myocardial infarction prediction was developed. Age, sex, kind of chest pain, blood pressure, cholesterol, ST depression, ST slope, maximal heart rate, fasting blood sugar, and thallium test results are among the clinical input variables used by the model.

Each variable was represented using two linguistic labels to simplify the fuzzy rule base and improve interpretability.

TABLE IV. SAMPLE OF FUZZY RULES FOR MYOCARDIAL INFARCTION RISK PREDICTION

Rule	Age	Sex	Chest Pain	BP	Cholesterol	ST Depression	ST Slope	Max Heart Rate	FBS	Thallium	Risk
R1	≥18	Male	Severe	High	High	High	Down sloping	Low	High	Abnormal	High
R2	≥18	Male	Severe	High	High	High	Down sloping	Low	Normal	Abnormal	High
R3	≥18	Female	Severe	High	High	High	Down sloping	Low	High	Abnormal	High
R4	≥18	Male	Severe	High	Normal	High	Down sloping	Low	High	Abnormal	High
R5	≥18	Male	Mild	High	High	High	Down sloping	Low	High	Abnormal	Moderate
R6	<18	Male	Severe	High	High	High	Down sloping	Low	High	Abnormal	Moderate
R7	<18	Female	Mild	Normal	Normal	Low	Up sloping	High	Normal	Normal	Low
R8	<18	Male	Mild	Normal	Normal	Low	Up sloping	High	High	Normal	Low
R9	≥18	Female	Severe	High	High	High	Down sloping	Low	High	Normal	Moderate
R10	<18	Male	Severe	High	High	High	Down sloping	Low	Normal	Abnormal	Moderate

E. Evaluation of the Fuzzy Logic Model

The formulated fuzzy inference system was evaluated on the myocardial infarction dataset, which contains 1,700 patient records. Each patient record was supplied to the fuzzy inference system using the ten clinical variables identified for the study, and the resulting fuzzy output represented the predicted risk of myocardial infarction. The predicted results were compared with the corresponding actual risk class recorded in the dataset.

Since the observed outcome in the dataset was represented using two classes, namely no risk (0) and risk (1), the four fuzzy risk levels were mapped to the binary evaluation classes. The no-risk fuzzy output was classified as no risk, while the low-, moderate-, and high-risk fuzzy outputs were classified as risk. This mapping enabled a direct comparison between the fuzzy inference system's output and the observed outcomes in the dataset.

The model's performance was evaluated using accuracy, sensitivity (true positive rate), specificity (true negative rate), precision, and F1-score. A confusion matrix was also generated to determine the numbers of true positives, true negatives, false positives, and false negatives produced by the model. Accuracy measures the overall proportion of correctly classified instances, while sensitivity measures the model's ability to correctly identify patients at risk of myocardial infarction. Specificity measures the model's ability to correctly identify patients without risk, while precision indicates the proportion of predicted positive cases that are correctly classified. The F1-score provides a combined measure of precision and sensitivity.

IV. RESULTS AND DISCUSSION

The results from the previously outlined methodological approach are presented and discussed in this section.

The performance of the developed fuzzy inference system was evaluated using 1,700 evaluation records comprising 952 no-risk cases and 748 risk cases. The classification results are summarized using a confusion matrix and four performance measures: accuracy, sensitivity, specificity, and F1-score.

The confusion matrix in Fig. 3 shows the classification outcomes of the fuzzy inference system. Of the 952 no-risk cases, 800 were correctly classified as no-risk, while 152 were incorrectly classified as risk. Of the 748 risk cases, 594 were correctly identified as risk, whereas 154 were incorrectly classified as no-risk. Thus, the model correctly classified 1,394 of the 1,700 evaluation records.

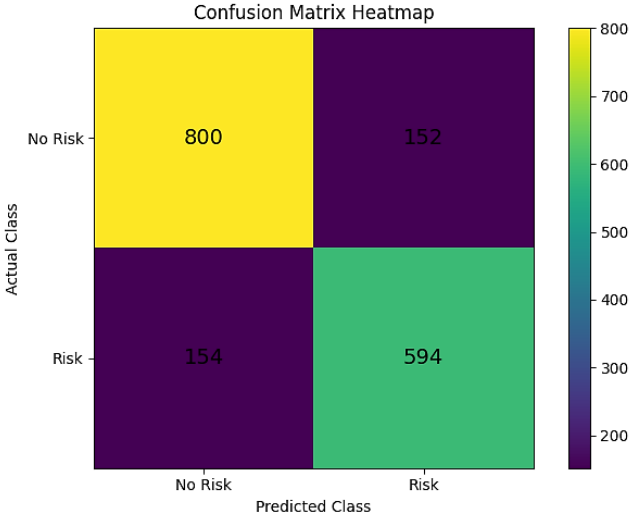

Fig. 3. Confusion matrix of the fuzzy inference system for myocardial infarction risk prediction.

Based on these classification outcomes, the model achieved an accuracy of 82.00%. This indicates that 82% of the evaluation records were correctly classified into their respective risk categories. The model achieved a sensitivity of 79.41%, indicating that it correctly identified approximately 79% of the records classified as being at risk of myocardial infarction. The specificity was 84.03%, indicating that approximately 84% of the no-risk records were correctly identified. The resulting F1-score was 79.52%, indicating a balanced level of classification performance when sensitivity and precision are considered together. Table V presents the overall performance of the fuzzy inference system.

TABLE V. PERFORMANCE OF THE FUZZY INFERENCE SYSTEM

Performance Measure	Result
Accuracy	82.00%
Sensitivity	79.41%
Specificity	84.03%
F1-score	79.52%

The results indicate that the fuzzy inference system was able to distinguish between the no-risk and risk classes with moderate classification performance. The slightly higher specificity than sensitivity indicates that the model was somewhat better at correctly identifying no-risk cases than at identifying patients classified as at risk.

The relatively close numbers of false-negative and false-positive classifications indicate that the model produced errors in both directions rather than being strongly biased toward one class.

To investigate relationships among clinical factors used to predict myocardial infarction, a correlation analysis was performed. The Pearson correlation coefficients between the clinical variables included in the prediction model are shown in Fig. 4.

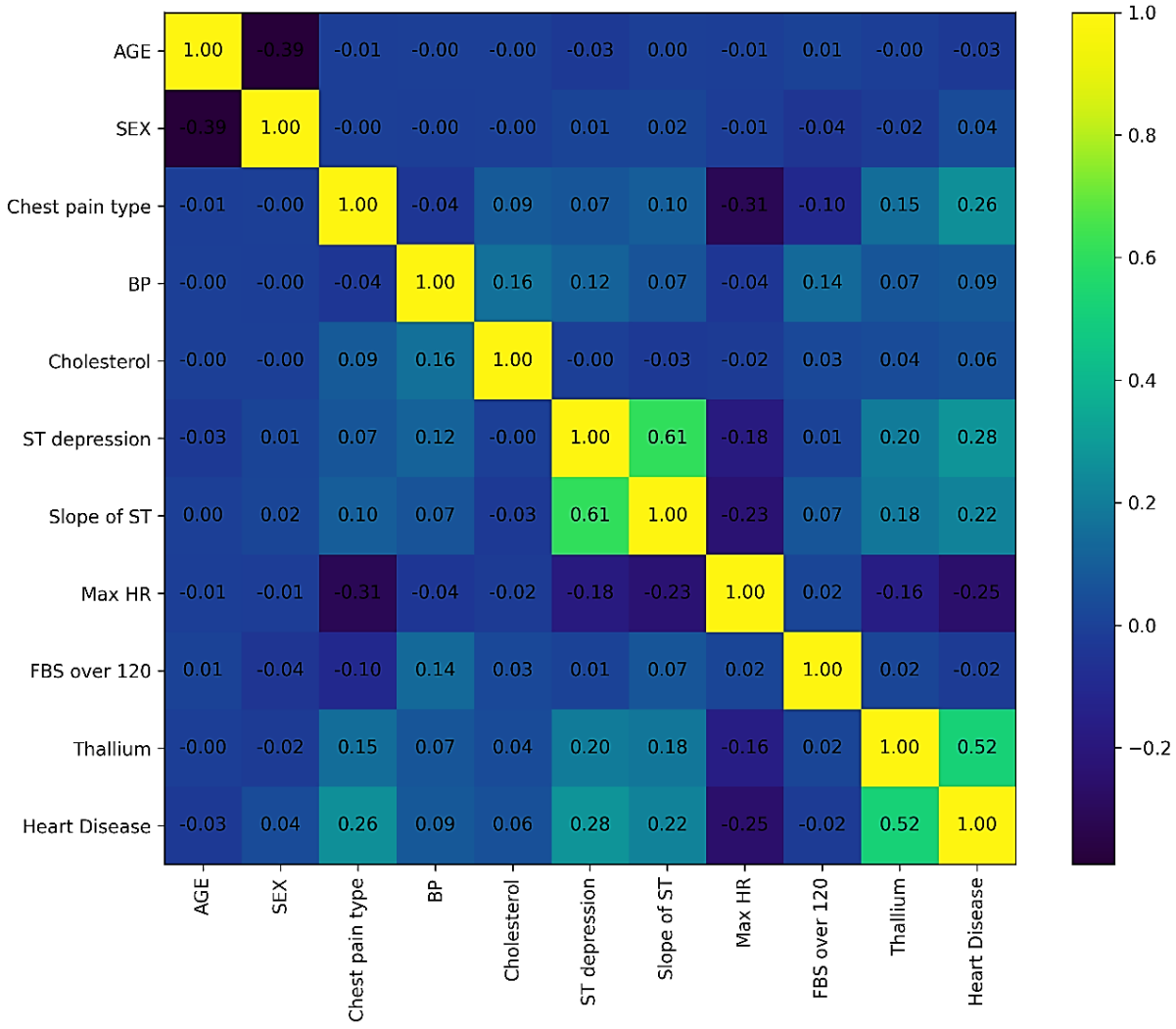

Fig. 4. Correlation heatmap of clinical variables used for myocardial infarction prediction.

The results of the thallium test showed the strongest positive relationship with MI (r = 0.52), as shown in Fig. 4. Abnormal thallium test results showed a strong association with myocardial infarction risk. The thallium stress test identifies reduced myocardial blood flow and is widely used in cardiac diagnosis [23], [24].

ST depression showed the second-strongest positive relationship (r = 0.28) with MI after thallium results. ST depression reflects electrocardiographic changes during exercise testing and is associated with myocardial ischemia, which may precede myocardial infarction [25].

Chest pain type followed ST depression with a positive correlation of r = 0.26. One of the main symptoms considered during a cardiac examination is chest discomfort [26]. Certain aspects of chest pain, especially common angina symptoms, have been linked to a higher risk of cardiovascular disease in earlier studies [26], [27].

Maximum heart rate showed a negative relationship with MI (r = −0.25), indicating that patients with MI had less ability to exercise. Due to decreased cardiac reserve and impaired chronotropic response, patients with cardiovascular disease frequently exhibit a lower maximal heart rate [28], [29]. Heart failure reduces peak exercise capacity and prevents patients from reaching their anticipated maximal heart rate by limiting the heart's ability to produce cardiac output during exertion [28]–[30].

ST depression and ST slope showed the strongest correlation (r = 0.61) among the predictor variables. These ECG values show ischemic alterations in myocardial tissue and reflect associated changes in cardiac electrical activity during stress testing [28]. Similar findings about the connection between ST-segment traits and markers of cardiovascular disease have been documented [31].

The ST segment is extremely sensitive to myocardial oxygen imbalance and displays electrical activity during ventricular repolarization. When the ST segment drops below baseline during exercise, it is known as ST depression and is a sign of myocardial ischemia. Similarly, ST-segment slope provides more diagnostic information; ischemic heart attack is frequently associated with horizontal or down-sloping patterns.

This result is consistent with well-established cardiology literature that acknowledges ST-segment abnormalities as crucial electrocardiographic markers for the diagnosis of myocardial infarction and coronary artery disease [32], [33]. This dataset's significant correlation between ST depression and ST slope is indicative of their similar physiological foundation in myocardial ischemia alterations.

Some variables, including fasting blood sugar, cholesterol, and blood pressure, demonstrated weak relationships with MI. However, this does not imply that these factors are clinically insignificant; rather, their direct linear associations with MI within this dataset were weaker.

V. Conclusion

This study developed a fuzzy logic-based predictive model to estimate the risk of myocardial infarction using 10 clinical variables: age, sex, chest pain type, blood pressure, cholesterol level, ST depression, ST slope, maximum heart rate, fasting blood sugar, and thallium test results. The model was designed to represent clinical variables using linguistic categories and fuzzy rules, thereby providing an interpretable approach to predicting myocardial infarction risk.

Evaluation of the fuzzy inference system using 1,700 patient records demonstrated an overall accuracy of 82.00%. The model achieved a sensitivity of 79.41%, indicating that it correctly identified approximately 4 out of 5 records classified as at risk of myocardial infarction. Its specificity was 84.03%, indicating comparatively stronger performance in identifying records classified as no risk. The F1-score of 79.52% further indicates a relatively balanced classification performance between sensitivity and precision. The confusion matrix showed 594 true positives, 800 true negatives, 154 false negatives, and 152 false positives.

The correlation analysis further identified thallium test results as the variable with the strongest positive relationship with myocardial infarction in the dataset ($r = 0.52$), followed by ST depression ($r = 0.28$) and chest pain type ($r = 0.26$). Maximum heart rate showed a negative relationship with myocardial infarction ($r = -0.25$), while ST depression and ST slope demonstrated the strongest relationship among the predictor variables ($r = 0.61$). These findings provide empirical support for including the selected clinical variables in the predictive model.

Overall, the findings indicate that the developed fuzzy inference system can distinguish between records classified as at risk and no risk of myocardial infarction with moderate predictive performance while retaining an interpretable, rule-based structure. However, further evaluation in independent, larger patient populations, along with external validation and comparison with established predictive approaches, is required to determine its generalizability and clinical utility.

References

[1] World Health Organization, "Cardiovascular diseases (CVDs)," 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[2] N. Salet, A. Gökkdemir, J. Preijde, C. H. van Heck, and F. Eijkenaar, "Using machine learning to predict acute myocardial infarction and ischemic heart disease in primary care cardiovascular patients," PLOS ONE, vol. 19, no. 7, Art. no. e0307099, 2024, doi: 10.1371/journal.pone.0307099.

[3] L. Lu, M. Liu, R. Sun, Y. Zheng, and P. Zhang, "Myocardial infarction: Symptoms and treatments," Cell Biochemistry and Biophysics, vol. 72, no. 3, pp. 865–867, 2015, doi: 10.1007/s12013-015-0553-4.

[4] K. Thygesen, J. S. Alpert, A. S. Jaffe, M. L. Simoons, B. R. Chaitman, and H. D. White, "Third universal definition of myocardial infarction," Journal of the American College of Cardiology, vol. 60, no. 16, pp. 1581–1598, 2012, doi: 10.1016/j.jacc.2012.08.001.

[5] M. F. Yuyun, K. Sliwa, A. P. Kengne, A. O. Mocumbi, and G. Bukhman, "Cardiovascular diseases in sub-Saharan Africa compared to high-income countries: An epidemiological perspective," Global Heart, vol. 15, no. 1, 2020, doi: 10.5334/gh.403.

[6] P. Sachdeva, K. Kaur, S. Fatima, et al., "Advancements in myocardial infarction management: Exploring novel approaches and strategies," Cureus, vol. 15, no. 9, Art. no. e45578, 2023, doi: 10.7759/cureus.45578.

[7] N. H. Alsomali, "Early detection of myocardial infarction and management of door-to-balloon time in patients with acute myocardial infarction in Saudi Arabia: A retrospective cross-sectional study," IOSR Journal of Nursing and Health Science, vol. 9, no. 6, pp. 60–71, 2020, doi: 10.9790/1959-0906066071.

[8] C. Rohani, H. Jafarpoor, Y. Mortazavi, B. Esbakian, and H. Gholinia, "Mortality in patients with myocardial infarction and potential risk factors: A five-year data analysis," ARYA Atherosclerosis, vol. 18, no. 3, pp. 1–8, 2022, doi: 10.48305/arya.v18i0.2427.

[9] B. Javila, L. Atuhaire, A. J. Bosco, S. Tumusiime, and N. Dick, "Risk factors associated with myocardial infarction among patients at Uganda Heart Institute, Mulago National Referral Hospital in Uganda," BMC Cardiovascular Disorders, vol. 25, Art. no. 491, 2025, doi: 10.1186/s12872-025-04946-8.

[10] D. Mozaffarian, E. J. Benjamin, A. S. Go, et al., "Heart disease and stroke statistics—2016 update: A report from the American Heart Association," Circulation, vol. 133, no. 4, pp. e38–e360, 2016.

[11] S. Yusuf, S. Hawken, and S. Ounpuu, "Effect of potentially modifiable risk factors associated with myocardial infarction in 52 countries (the INTERHEART study): Case-control study," The Lancet, vol. 364, no. 9438, pp. 937–952, 2004, doi: 10.1016/S0140-6736(04)17018-9.

[12] R. B. D'Agostino Sr., R. S. Vasan, M. J. Pencina, P. A. Wolf, M. Cobain, J. M. Massaro, and W. B. Kannel, "General cardiovascular risk profile for use in primary care: The Framingham Heart Study," Circulation, vol. 117, no. 6, pp. 743–753, 2008, doi: 10.1161/CIRCULATIONAHA.107.699579.

[13] I. Talha, N. Elkhoudri, and A. Hilali, "Major limitations of cardiovascular risk scores," Cardiovascular Therapeutics, vol. 2024, Art. no. 4133365, 2024, doi: 10.1155/2024/4133365.

[14] C. Indirani, S. Manimala, M. Geetha, S. Nithyadevi, M. Selvanayagi, K. Ananthi, and K. Saranya, "Heart disease prediction using fuzzy logic-based image processing and classification techniques," The Bioscan: An International Quarterly Journal of Life Sciences, vol. 20, no. 2, pp. 163–173, 2025, doi: 10.63001/tbs.2025.v20.i02.pp163-173.

[15] M. L. Ali, M. S. Sadi, and M. O. Goni, "Diagnosis of heart diseases: A fuzzy-logic-based approach," PLOS ONE, vol. 19, no. 2, Art. no. e0293112, 2024, doi: 10.1371/journal.pone.0293112.

[16] F. Nudrat and S. Sifatullah, "Enhanced myocardial infarction prediction using machine learning algorithms and gender-specific insights," Journal of Electrical Systems, vol. 20, no. 7s, pp. 973–988, 2024.

[17] S. Arslankaya and T. M. Çelik, "Prediction of heart attack using fuzzy logic method and determination of factors affecting heart attacks," International Journal of Computational and Experimental

Science and Engineering, vol. 7, no. 1, pp. 1–8, 2021, doi: 10.22399/ijcesen.837731.

[18] M. P. Than, J. W. Pickering, Y. Sandoval, et al., "Machine learning to predict the likelihood of acute myocardial infarction," Circulation, vol. 140, no. 11, pp. 899–909, 2019, doi: 10.1161/CIRCULATIONAHA.119.041980.

[19] H. Makimoto, M. Höckmann, T. Lin, et al., "Performance of a convolutional neural network derived from an ECG database in recognizing myocardial infarction," Scientific Reports, vol. 10, Art. no. 8445, 2020, doi: 10.1038/s41598-020-65105-x.

[20] H.-Z. Fang, D.-L. Hu, Q. Li, and S. Tu, "Risk gene identification and support vector machine learning to construct an early diagnosis model of myocardial infarction," Molecular Medicine Reports, vol. 22, no. 3, pp. 1775–1782, 2020, doi: 10.3892/mmr.2020.11247.

[21] C.-W. Hsu, C.-H. Lin, C.-C. Chen, et al., "A biomarker discovery of acute myocardial infarction using feature selection and machine learning," Scientific Reports, vol. 13, Art. no. 7807, 2023, doi: 10.1038/s41598-023-34948-5.

[22] G. D. Aregbesola, I. Asghar, S. Akbar, and R. Ullah, "Fuzzy logic model for informed decision-making in risk assessment during software design," Systems, vol. 13, no. 9, Art. no. 825, 2025, doi: 10.3390/systems13090825.

[23] P. Shams, N. Khiyani, and R. Zeltser, "Adenosine SPECT thallium imaging," in StatPearls. Treasure Island, FL, USA: StatPearls Publishing, 2024.

[24] G. La Canna, R. Giubbini, M. Metra, G. Arosio, A. Curnis, R. Cicogna, and O. Visioli, "Assessment of myocardial perfusion with thallium-201 scintigraphy in exercise-induced left bundle branch block: Diagnostic value and clinical significance," European Heart Journal, vol. 13, no. 7, pp. 942–946, 1992, doi: 10.1093/oxfordjournals.eurheartj.a060297.

[25] Y. Birnbaum, J. M. Wilson, M. Fiol, A. B. de Luna, M. Eskola, and K. Nikus, "ECG diagnosis and classification of acute coronary syndromes," Annals of Noninvasive Electrocardiology, vol. 19, no. 1, pp. 4–14, 2014, doi: 10.1111/anec.12130.

[26] M. G. Bellicini and P. Shams, "Chest pain: Evaluation and exclusion of myocardial infarction and angina," in StatPearls. Treasure Island, FL, USA: StatPearls Publishing, 2025.

[27] A. Hafiz, E. Alharbi, S. Rabei, et al., "Awareness of angina and its associated risk factors among the general population in Jeddah City," Journal of Neonatal Surgery, vol. 14, no. 27s, pp. 14–27, 2025.

[28] C. Carluccio, F. Bressan, M. Pizzolato, et al., "Exercise stress testing in clinical cardiology: A practical guide to performance and interpretation," Journal of Clinical Medicine, vol. 15, no. 4, Art. no. 1656, 2026, doi: 10.3390/jcm15041656.

[29] V. O. Carvalho, G. V. Guimarães, E. G. Ciolac, and E. A. Bocchi, "Heart rate dynamics during a treadmill cardiopulmonary exercise test in optimized beta-blocked heart failure patients," Clinics, vol. 63, no. 4, pp. 479–482, 2008, doi: 10.1590/S1807-59322008000400011.

[30] M. A. Nystoriak and A. Bhatnagar, "Cardiovascular effects and benefits of exercise," Frontiers in Cardiovascular Medicine, vol. 5, Art. no. 135, 2018, doi: 10.3389/fcvm.2018.00135.

[31] S. Sharif and S. E. Alway, "The diagnostic value of exercise stress testing for cardiovascular disease is more than just ST segment changes: A review," Journal of Integrative Cardiology, vol. 2, no. 4, pp. 41–55, 2016, doi: 10.15761/JIC.1000173.

[32] J. L. Garvey, J. Zegre-Hemsey, R. Gregg, and J. R. Studnek, "Electrocardiographic diagnosis of ST segment elevation myocardial infarction: An evaluation of three automated interpretation algorithms," Journal of Electrocardiology, vol. 49, no. 5, pp. 728–732, 2016, doi: 10.1016/j.jelectrocard.2016.04.010.

[33] F. Morris and W. J. Brady, "ABC of clinical electrocardiography: Acute myocardial infarction—Part I," BMJ, vol. 324, no. 7341, pp. 831–834, 2002, doi: 10.1136/bmj.324.7341.831.