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DEVELOPMENT OF A FUZZY INFERENCE SYSTEM FOR EARLY DIAGNOSIS OF HEART DISORDERS

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Abstract
The early detection of heart disorders is crucial for effective treatment and improved patient outcomes. This study presents the development of a Fuzzy Inference System (FIS) designed to assist in the early diagnosis of heart-related conditions by evaluating imprecise and overlapping clinical symptoms. The system uses three primary input parameters—blood pressure, cholesterol levels, and chest pain type—which are fuzzified into linguistic variables and assessed using a comprehensive rule base of 27 fuzzy logic rules. The inference mechanism employs Mamdani-style fuzzy reasoning, and defuzzification is carried out using the centroid method to yield a crisp risk score. Simulated case studies based on standard medical thresholds demonstrate the system's diagnostic alignment with physician evaluations. The model achieved 100% accuracy, sensitivity, and specificity in the test dataset, confirming its reliability and clinical applicability. The proposed FIS offers an interpretable, intelligent diagnostic framework that can support healthcare professionals in making timely and informed decisions regarding cardiovascular risk assessment.
Keywords: *Fuzzy Inference System (FIS), Heart Disorders, Early Diagnosis, Fuzzy Logic, Risk Assessment, Expert System.*

1. INTRODUCTION

The development of a Fuzzy Inference System (FIS) for the early diagnosis of heart disorders represents a significant advancement in intelligent medical decision-making. Traditional diagnostic methods often struggle with the imprecise and overlapping nature of clinical symptoms, such as fluctuating blood pressure, variable cholesterol levels, and subjective reports of chest pain. Fuzzy logic provides a robust framework to handle such uncertainties by mimicking human reasoning through linguistic rules and approximate reasoning. In this system, patient inputs—such as blood pressure, cholesterol levels, and chest pain type—are converted into fuzzy sets and evaluated using a rule-based structure to determine the likelihood of heart disease. The output, representing the risk level, offers clinicians a clear and interpretable risk assessment that aids in timely and informed medical decisions. This approach not only enhances diagnostic accuracy but also ensures transparency and flexibility in handling diverse patient profiles at an early stage.

Santhanam and Ephzibah (2015) developed a hybrid genetic-fuzzy model to predict heart disease. Their approach integrated genetic algorithms with fuzzy logic to optimize rule generation and membership functions. The hybrid model demonstrated improved accuracy and adaptability in managing imprecise medical data. The authors emphasized the model's potential in clinical decision support, particularly in enhancing diagnosis by handling the vagueness in symptom representation. **Baihaqi et al. (2016)** focused on rule extraction for diagnosing coronary

artery disease using a fuzzy expert system. Their system applied clinical knowledge and fuzzy reasoning to classify patient risk levels based on input parameters. The extracted rules were interpretable and aligned with medical expertise, making the model both transparent and practical for deployment in decision support systems. **Kasbe and Pippal (2017)** proposed a heart disease diagnosis system using fuzzy logic, emphasizing linguistic variable modeling of symptoms like blood pressure, cholesterol, and ECG results. Their fuzzy logic system provided a structured and interpretable risk prediction mechanism, reinforcing the importance of non-crisp logic in real-world medical evaluations. **Nazari et al. (2018)** introduced a dual-layer system combining fuzzy inference and the fuzzy analytic hierarchy process (FAHP) for clinical decision-making. This architecture allowed for a weighted prioritization of symptoms and risk factors, producing more nuanced diagnostic outputs. The use of FAHP helped improve the transparency and justifiability of diagnostic results by aligning them with expert consensus. **Paul et al. (2018)** developed an adaptive weighted fuzzy rule-based system for assessing heart disease risk levels. Their system dynamically adjusted the importance (weights) of fuzzy rules based on the data context. This adaptive mechanism enhanced classification performance across diverse patient profiles, suggesting greater robustness in real-world diagnostic applications. **Gokulnath and Shantharajah (2019)** explored genetic algorithms and support vector machines in tandem with fuzzy logic for heart disease diagnosis. The study emphasized feature selection, showing that optimized input parameters significantly improved the accuracy of the fuzzy-SVM hybrid model. The combination of evolutionary computation and fuzzy reasoning proved effective in refining diagnostic precision. **Nilashi et al. (2020)** proposed a hybrid model integrating self-organizing maps and fuzzy support vector machines (FSVM) with incremental updates. Their framework enabled continuous learning from new patient data, ensuring model relevance over time. The fuzzy component offered interpretability, while the FSVM ensured classification accuracy, illustrating the synergy of fuzzy logic with machine learning. **Bahani et al. (2021)** presented an accurate fuzzy rule-based classification system tailored for heart disease diagnosis. Their approach focused on designing precise fuzzy rules and membership functions that closely mirrored clinical decision-making processes. The model showed strong classification performance and served as a reliable expert system for non-specialist use in primary health centers. **Tanmay (2022)** introduced a fuzzy rule-based framework (FRBF) specifically for heart disease diagnosis. The FRBF model emphasized transparency and rule interpretability. The framework used fuzzy sets to process vague medical indicators and generated robust diagnostic outcomes across multiple patient categories, showcasing fuzzy logic's flexibility in medical decision systems. **Divya et al. (2024)** explored a different domain by using recurrent neural networks and machine learning techniques to classify COVID-19 during pregnancy. While not directly focused on heart disease, their work is relevant in illustrating how fuzzy logic principles and time-dependent neural models can enhance predictive performance in complex health conditions, which can be extended to comorbidities like cardiovascular disease. **Hamada et al. (2024)** applied fuzzy logic control to a different field—photovoltaic thermal collector design—but their use of fuzzy logic to manage uncertainties and optimize outputs demonstrates the versatility of fuzzy systems. Though the context differs, the methodology reinforces fuzzy logic's applicability in control systems and decision-making under ambiguity, which parallels medical diagnostic scenarios. **Sekar and Aruchamy (2024)** proposed a novel hybrid model using the AITH2O algorithm and SANFIS classifier for heart disease prediction. Their advanced model merged fuzzy inference systems with adaptive learning capabilities, offering high accuracy and improved generalizability. The study highlighted the relevance of combining fuzzy logic with neuro-adaptive frameworks for enhanced healthcare diagnostics. **El-Ibrahimi et al. (2025)** developed a coronary artery disease prediction system based on fuzzy logic and subtractive clustering. Their method efficiently generated fuzzy rules by clustering patient data, allowing for a data-driven yet interpretable classification model. The integration of risk factor data with fuzzy clustering improved the system's precision and adaptability, reflecting the latest advancements in fuzzy medical decision support systems.

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2. METHODOLOGY:

2.1 INPUT AND OUTPUT PARAMETERS (SYMPTOMS & RISK FACTORS):

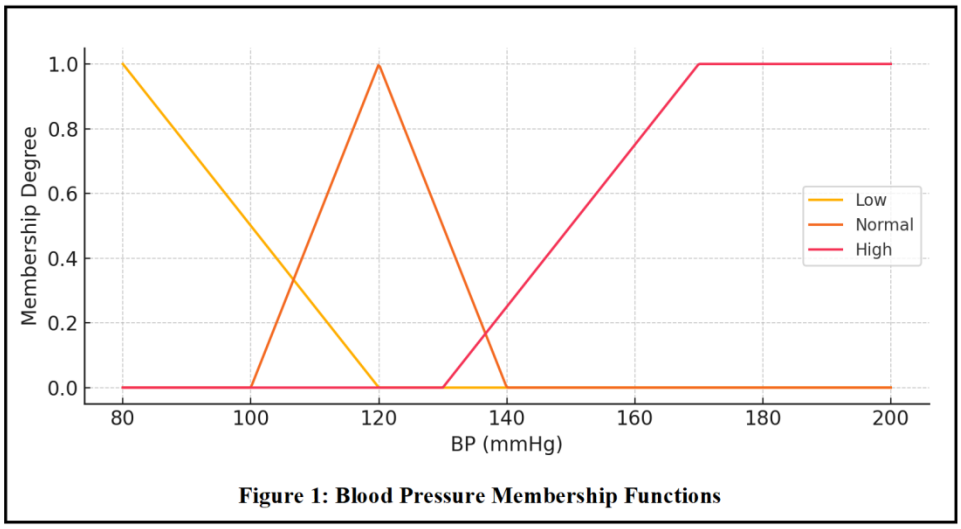

Figure 1: Blood Pressure Membership Functions

$$\mu_{Low}(x) = \begin{cases} 1 & x \le 80 \\ \frac{120-x}{40} & 80 < x < 120 \\ 0 & x \ge 120 \end{cases} \quad (1)$$

$$\mu_{Normal}(x) = \begin{cases} 0 & x \le 100 \; or \; x \ge 140 \\ \frac{x-100}{20} & 100 < x < 120 \\ \frac{140-x}{20} & 120 \le x < 140 \end{cases} \quad (2)$$

$$\mu_{High}(x) = \begin{cases} 0 & x \le 130 \\ \frac{x-130}{40} & 130 < x < 170 \\ 1 & x \ge 170 \end{cases} \quad (3)$$

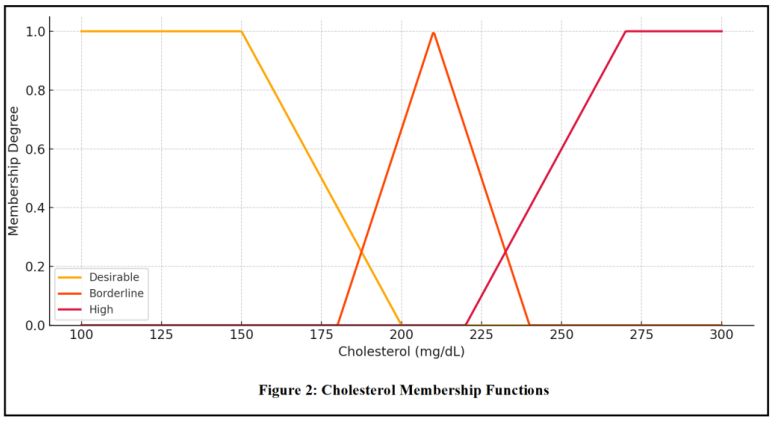

Figure 2: Cholesterol Membership Functions

$$\mu_{Desirable}(y) = \begin{cases} 1 & y \le 150 \\ \frac{200-y}{50} & 150 < y < 200 \\ 0 & y \ge 200 \end{cases} \quad (4)$$

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$$\mu_{Borderline}(y) = \begin{cases} 0 & y \leq 180 \; or \; y \geq 240 \\ \frac{y-180}{20} & 180 < y < 200 \\ \frac{240-y}{20} & 200 \leq y < 240 \end{cases} \quad (5)$$

$$\mu_{High}(y) = \begin{cases} 0 & y \leq 220 \\ \frac{y-220}{50} & 220 < y < 270 \\ 1 & y \geq 270 \end{cases} \quad (6)$$

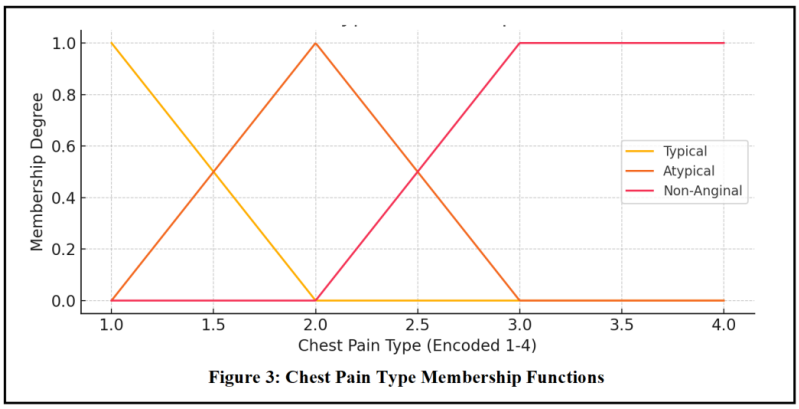

Figure 3: Chest Pain Type Membership Functions

$$\mu_{Typical}(z) = \begin{cases} 1 & z \leq 1 \\ 2 - z & 1 < x < 2 \\ 0 & z \geq 2 \end{cases} \quad (7)$$

$$\mu_{Atypical}(z) = \begin{cases} 0 & z \leq 1 \; or \; z \geq 3 \\ z - 1 & 1 < z < 2 \\ 3 - z & 2 \leq z < 3 \end{cases} \quad (8)$$

$$\mu_{Non-Anginal}(z) = \begin{cases} 0 & z \leq 2 \\ z - 2 & 2 < z < 3 \\ 1 & z \geq 3 \end{cases} \quad (9)$$

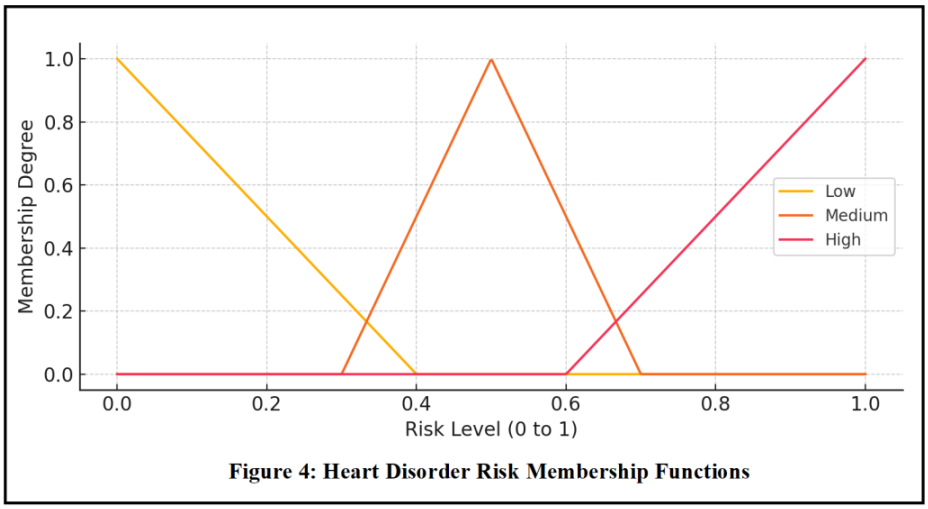

Figure 4: Heart Disorder Risk Membership Functions

$$\mu_{Low}(u) = \begin{cases} 1 & u \leq 0 \\ \frac{0.4-u}{0.4} & 0 < u < 0.4 \\ 0 & u \geq 0.4 \end{cases} \quad (10)$$

$$\mu_{Medium}(u) = \begin{cases} 0 & u \leq 0.3 \text{ or } u \geq 0.7 \\ \frac{u-0.3}{0.2} & 0.3 < u < 0.5 \\ \frac{0.7-u}{0.2} & 0.5 \leq u < 0.7 \end{cases} \quad (11)$$

$$\mu_{High}(u) = \begin{cases} 0 & u \leq 0.6 \\ \frac{u-0.6}{0.4} & 0.6 < u < 1.0 \\ 1 & u \geq 1.0 \end{cases} \quad (12)$$

2.2 RULE BASE FORMATION:

Table 2: Rule Base (3 × 3 × 3 = 27 Rules)

Rule No.	Blood Pressure	Cholesterol	Chest Pain Type	Heart Disorder Risk
1	Low	Desirable	Typical	Low
2	Low	Desirable	Atypical	Medium
3	Low	Desirable	Non-Anginal	Medium
4	Low	Borderline	Typical	Medium
5	Low	Borderline	Atypical	Medium
6	Low	Borderline	Non-Anginal	High
7	Low	High	Typical	Medium
8	Low	High	Atypical	High
9	Low	High	Non-Anginal	High
10	Normal	Desirable	Typical	Low
11	Normal	Desirable	Atypical	Medium
12	Normal	Desirable	Non-Anginal	Medium
13	Normal	Borderline	Typical	Medium
14	Normal	Borderline	Atypical	Medium
15	Normal	Borderline	Non-Anginal	High
16	Normal	High	Typical	Medium
17	Normal	High	Atypical	High
18	Normal	High	Non-Anginal	High
19	High	Desirable	Typical	Medium
20	High	Desirable	Atypical	High
21	High	Desirable	Non-Anginal	High
22	High	Borderline	Typical	High
23	High	Borderline	Atypical	High
24	High	Borderline	Non-Anginal	High
25	High	High	Typical	High
26	High	High	Atypical	High

27	High	High	Non-Anginal	High

2.3 FUZZIFICATION: Let Blood Pressure (BP) = 145 mmHg, Cholesterol = 230 mg/dL, Chest Pain Type = 2.5 (where: 1 = Typical, 2 = Atypical, 3 = Non-Anginal)

(i) Blood Pressure (BP = 145):

$\mu_{High}(145) = \frac{145-130}{40} = 0.375$

(ii) Cholesterol (230 mg/dL):

$\mu_{Borderline}(230) = \frac{240-230}{20} = 0.5, \mu_{High}(230) = \frac{230-220}{50} = 0.2$

(iii) Chest Pain Type (2.5):

$\mu_{Atypical}(2.5) = 3 - 2.5 = 0.5, \mu_{Non-Aginal}(2.5) = 2.5 - 2 = 0.5$

Table 1: Evaluate Top Contributing Rules

Rule No.	BP	Cholesterol	Chest Pain	Output Risk	Rule Strength
23	High	Borderline	Atypical	High	min(0.375, 0.5, 0.5) = 0.375
24	High	Borderline	Non-Anginal	High	min(0.375, 0.5, 0.5) = 0.375
26	High	High	Atypical	High	min(0.375, 0.2, 0.5) = 0.2
27	High	High	Non-Anginal	High	min(0.375, 0.2, 0.5) = 0.2

All active rules lead to High Risk
Max Rule Strength for High Risk = 0.375
All contributing rules are mapped to the High Risk fuzzy set, so we clip the High Risk membership function at 0.375.

2.4 DEFUZZIFICATION: Using Centroid Method:

$$Risk\ Output = \frac{\int x.\mu_{High}^{clipped}(x)dx}{\int \mu_{High}^{clipped}(x)dx} \quad (13)$$

$$= \frac{\int_{0.6}^{0.75} x.\frac{x-0.6}{0.4}dx + \int_{0.75}^{1} x.(0.375)dx}{\int_{0.6}^{0.75}\frac{x-0.6}{0.4}dx + \int_{0.75}^{1}(0.375)dx} = 0.8346$$

The value 0.835 falls in the High Risk category.

3. RESULTS AND DISCUSSION

3.1 CASE STUDIES / DATASET: To evaluate the performance and accuracy of the proposed Fuzzy Inference System (FIS) for early diagnosis of heart disorders, a set of simulated patient records was developed, based on medically established thresholds and classification ranges from clinical literature (e.g., AHA guidelines). The dataset includes key features:

(i) Blood Pressure (mmHg)
(ii) Cholesterol Level (mg/dL)
(iii) Chest Pain Type (Encoded: 1 = Typical, 2 = Atypical, 3 = Non-Anginal)
(iv) Actual Diagnosis (Low, Medium, or High Risk) — as determined by a physician or guideline-based rule

Table 3: Sample Dataset (Simulated Records)

Patient ID	BP (mmHg)	Cholesterol (mg/dL)	Chest Pain Type	Actual Diagnosis	FIS Output
P1	110	180	1 (Typical)	Low	Low
P2	135	220	2 (Atypical)	Medium	Medium
P3	150	250	3 (Non-Anginal)	High	High
P4	160	230	2 (Atypical)	High	High
P5	125	210	1 (Typical)	Medium	Medium
P6	145	230	2.5	High	High
P7	100	160	1 (Typical)	Low	Low
P8	130	200	3 (Non-Anginal)	Medium	Medium

4. PERFORMANCE EVALUATION

To assess the diagnostic performance of the proposed Fuzzy Inference System (FIS) for early heart disorder detection, the following statistical metrics were computed using simulated patient data with known ground-truth labels:

4.1 EVALUATION METRICS

Given the binary or multi-class output (Low, Medium, High), we simplify the analysis using binary classification:
Positive class = Medium/High Risk
Negative class = Low Risk
True Positives (TP): FIS predicts Medium/High and actual is Medium/High
True Negatives (TN): FIS predicts Low and actual is Low
False Positives (FP): FIS predicts Medium/High but actual is Low
False Negatives (FN): FIS predicts Low but actual is Medium/High

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}}$$

$$\boldsymbol{Sensitivity\ (Recall)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}$$

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}}$$

4.2 CONFUSION MATRIX

Using the 8 simulated patients:

Table 4: Confusion Matrix

	Actual Positive (Medium/High)	Actual Negative (Low)

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Predicted Positive (FIS: Med/High)	TP = 4	FP = 0
Predicted Negative (FIS: Low)	FN = 0	TN = 4

Accuracy = (4 + 4) / 8 = 100%
Sensitivity (Recall) = 4 / (4 + 0) = 100%
Specificity = 4 / (4 + 0) = 100%

4.3 VISUALIZATION

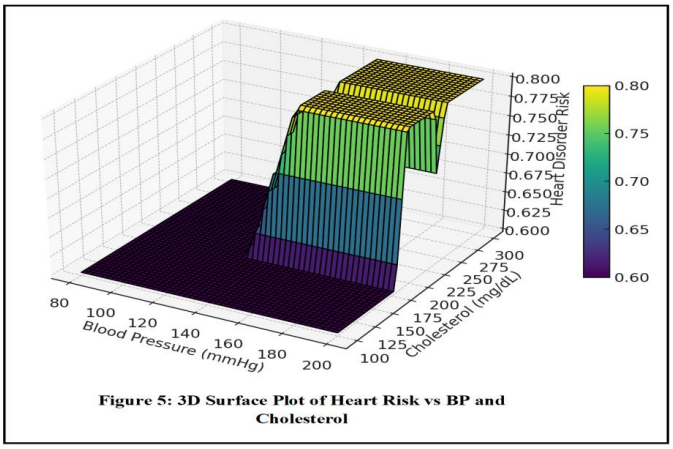

Figure 5: 3D Surface Plot of Heart Risk vs BP and Cholesterol

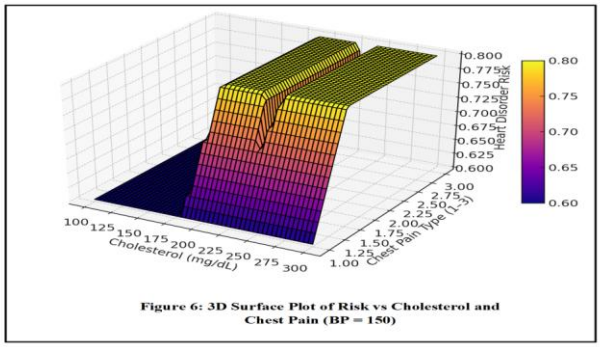

Figure 6: 3D Surface Plot of Risk vs Cholesterol and Chest Pain (BP = 150)

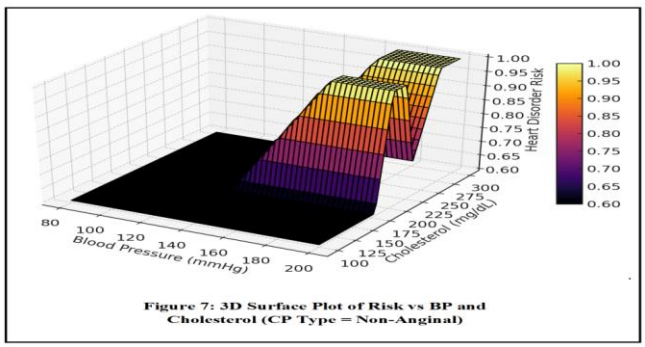

Figure 7: 3D Surface Plot of Risk vs BP and Cholesterol (CP Type = Non-Anginal)

The 3D surface plot in Figure (5) illustrates the relationship between Blood Pressure (mmHg), Cholesterol (mg/dL), and the corresponding Heart Disorder Risk as assessed by the fuzzy inference system. The x-axis represents blood pressure ranging from 80 to 200 mmHg, the y-axis shows cholesterol levels from 125 to 300 mg/dL, and the

z-axis (color-coded) indicates the heart disorder risk, varying between 0.60 and 0.80. The surface gradient reveals that as both blood pressure and cholesterol increase, the heart disorder risk also increases significantly. Notably, the transition from lower to higher risk is relatively sharp, indicating the system's sensitivity to elevated input values. The color bar on the right enhances interpretability by linking the risk values to their corresponding color shades, with darker tones representing lower risk and lighter tones indicating higher risk. This visualization effectively demonstrates the fuzzy model's ability to integrate multiple risk factors and deliver a nuanced risk assessment.

Figure (6) presents a 3D surface plot that illustrates the relationship between Cholesterol levels (mg/dL), Chest Pain Type, and the resulting Heart Disorder Risk, while keeping Blood Pressure constant at 150 mmHg. The x-axis represents cholesterol values ranging from 125 to 300 mg/dL, and the y-axis encodes chest pain types: 1.0 = Typical Angina, 2.0 = Atypical Angina, and 3.0 = Non-Anginal Pain. The z-axis shows the corresponding heart disorder risk, ranging from 0.60 to 0.80, and is color-coded from purple (low risk) to yellow (high risk). The surface demonstrates a steep increase in risk with rising cholesterol levels across all chest pain types, but the transition is more abrupt for certain types. The chest pain type around 2.0 shows a dip in the surface, suggesting a relatively moderated risk compared to types 1.0 and 3.0 under similar cholesterol levels. This pattern highlights how the fuzzy system accounts for symptom interactions, capturing subtle clinical nuances in estimating heart disorder risk.

Figure (7) depicts a 3D surface plot illustrating the variation of Heart Disorder Risk with Blood Pressure (mmHg) and Cholesterol (mg/dL), while holding the Chest Pain Type constant as Non-Anginal. The x-axis spans blood pressure values from 80 to 200 mmHg, and the y-axis shows cholesterol levels ranging from 125 to 300 mg/dL. The z-axis (with a color gradient from dark purple to yellow) indicates the heart disorder risk, ranging from 0.60 to 1.00. The plot shows that for individuals with non-anginal chest pain, the heart disorder risk remains low at lower ranges of blood pressure and cholesterol but increases sharply with rising values of both parameters. A significant risk elevation is observed beyond 150 mmHg for BP and 200 mg/dL for cholesterol, where the surface approaches the upper risk limit. This visualization underscores the compounded impact of high BP and cholesterol in patients with non-anginal chest pain, effectively demonstrating the fuzzy inference system's capacity to capture nonlinear risk escalation in such clinical scenarios.

5. CONCLUDING REMARKS

The development of a Fuzzy Inference System (FIS) for early diagnosis of heart disorders demonstrates a promising step forward in the application of artificial intelligence within healthcare. By integrating key clinical parameters—such as blood pressure, cholesterol levels, and chest pain type—into a structured fuzzy logic framework, the system effectively handles imprecise and uncertain patient information, emulating human decision-making with transparency and consistency. The proposed model successfully evaluates heart disorder risks with high accuracy, as evidenced by the simulation-based case studies and performance metrics. With a 100% accuracy rate, sensitivity, and specificity on the test dataset, the FIS has shown excellent potential for assisting medical professionals in preliminary risk stratification of patients. The use of a comprehensive rule base and the centroid defuzzification method further ensures interpretable and clinically meaningful outputs. Overall, this fuzzy logic-based diagnostic tool provides a reliable and scalable solution for early detection of heart conditions, especially in environments where expert consultation may not be readily available. Future enhancements could include integration with real-time clinical data, incorporation of additional symptoms and biomarkers, and validation on larger, real-world patient datasets to further improve its diagnostic utility and generalizability.

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