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Fuzzy Logic for Heart Disease Prediction

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Abstract: Cardiovascular disease remains one of the leading causes of mortality worldwide, emphasizing the importance of early and accurate risk prediction systems. This study proposes a web-based heart disease prediction system utilizing a fuzzy logic approach to effectively manage uncertainty and imprecision in clinical data. As illustrated in the system interface, the model incorporates five primary input parameters: blood pressure, blood sugar level, cholesterol level, body mass index (BMI), and family history. These parameters are transformed into linguistic variables through fuzzification and evaluated using a rule-based fuzzy inference system constructed from expert knowledge and recent research findings. The fuzzy logic framework enables flexible decision-making that closely resembles human reasoning, overcoming limitations of conventional threshold-based diagnostic methods. The system produces an interpretable heart disease risk classification, such as low or high risk, which is presented through an interactive web interface along with a prediction history feature. Based on a review of related studies published within the last five years, fuzzy logic and neuro-fuzzy models have shown strong performance, transparency, and suitability for clinical decision support. The proposed system demonstrates the practicality of integrating fuzzy logic into web applications to support early heart disease risk assessment and preventive healthcare.

Keywords: Clinical Decision Support System, Fuzzy Logic, Heart Disease Prediction, Medical Risk Assessment, Web Application.

1. Introduction

Heart disease is one of the leading causes of death worldwide and continues to pose a major challenge to public health systems. Early detection and accurate risk assessment are essential to reduce mortality rates and improve patient outcomes through timely prevention and intervention [1]. However, diagnosing heart disease is often complex due to the presence of multiple interrelated risk factors, such as blood pressure, blood sugar, cholesterol level, body mass index (BMI), and family medical history [2]. These clinical parameters are inherently uncertain, continuous, and subject to individual variability, making conventional threshold-based diagnostic approaches less effective.

In recent years, decision support systems based on Artificial Intelligence (AI) have gained increasing attention in the medical domain. Among various AI techniques, fuzzy logic has emerged as a promising method for medical diagnosis and risk prediction because it closely models human reasoning under uncertainty. Unlike classical binary logic, fuzzy logic allows partial membership and linguistic interpretation of medical data, enabling more flexible and interpretable decision-making. This characteristic is particularly valuable in healthcare applications, where transparency and explainability are critical.

Several studies published within the last five years have demonstrated that fuzzy logic and neuro-fuzzy inference systems can achieve competitive accuracy in heart disease prediction while maintaining high interpretability. These approaches are capable of integrating expert medical knowledge with data-driven analysis, making them suitable for clinical decision support systems. Furthermore, fuzzy logic-based models require relatively low computational resources, which makes them appropriate for implementation in lightweight and accessible platforms such as web applications.

With the widespread availability of web technologies, web-based medical decision support systems offer significant advantages, including ease of access, real-time interaction, and platform independence. A web-based heart disease prediction system can assist healthcare professionals and individuals by providing preliminary risk assessments and supporting early screening efforts.

This study focuses on the development of a web-based heart disease prediction system using a fuzzy logic algorithm. The system evaluates key clinical parameters, blood pressure, blood sugar, cholesterol level, BMI, and family history; to determine an individual’s heart disease risk level. The objective of this research is to design and implement an interpretable, efficient, and user-friendly fuzzy logic model that can support early heart disease risk assessment and contribute to preventive healthcare strategies.

2. Literature Review

2.1. Heart Disease Risk Factors and Prediction

Heart disease prediction involves analyzing multiple clinical and lifestyle-related parameters that contribute to cardiovascular risk. Commonly used factors include blood pressure, blood sugar level, cholesterol level, body mass index (BMI), and family history of cardiovascular disease. These parameters are continuous, imprecise, and often influenced by subjective clinical judgment. Recent studies have emphasized that conventional statistical or threshold-based diagnostic methods may fail to capture the complex relationships among these variables [3] [4] [5]. As a result, intelligent prediction models capable of handling uncertainty are required.

2.2. Fuzzy Logic Theory

Fuzzy logic is an extension of classical Boolean logic that allows reasoning with degrees of truth rather than binary values. In fuzzy systems, variables are represented by linguistic terms such as low, medium, or high, each associated with a membership function that defines the degree to which a given input belongs to a fuzzy set [6] [7]. This approach closely resembles human reasoning and is well suited for medical applications, where symptoms and risk factors are rarely absolute.

A typical fuzzy inference system (FIS) consists of four main components: fuzzification, rule base, inference engine, and defuzzification. Fuzzification converts crisp medical input values into fuzzy sets. The rule base contains IF–THEN rules derived from expert knowledge or empirical studies. The inference engine evaluates these rules to produce fuzzy outputs, which are then converted into a crisp risk level through defuzzification. Recent heart disease prediction studies have successfully employed Mamdani and Tsukamoto fuzzy inference methods due to their interpretability and effectiveness [8] [9],[10].

2.3. Fuzzy Logic in Medical Decision Support Systems

Fuzzy logic has been widely adopted in medical decision support systems because of its transparency and ability to integrate expert knowledge. Unlike black-box machine learning models, fuzzy systems allow clinicians to understand how decisions are derived from input parameters. Studies have shown that fuzzy-based systems can provide reliable and interpretable diagnostic assistance for cardiovascular diseases [11] [12] [13].

In recent research, hybrid approaches combining fuzzy logic with neural networks, deep learning, or optimization algorithms have further improved prediction accuracy. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) integrate learning capabilities with fuzzy reasoning, enabling automatic tuning of membership functions and rules [14] [15] [16]. These hybrid models have demonstrated strong performance in early detection of heart disease and related conditions such as stroke and heart failure [17] [18].

2.4. Recent Advances in Fuzzy-Based Heart Disease Prediction

Recent studies published within the last five years highlight the effectiveness of fuzzy logic and neuro-fuzzy models in heart disease prediction. Researchers have applied fuzzy logic to assess coronary artery disease, heart attack risk, and overall cardiovascular risk using clinical datasets [19] [20] [21]. Hybrid fuzzy systems incorporating clustering, optimization, and deep learning techniques have also been proposed to enhance predictive performance while preserving interpretability [22] [23] [24].

Survey and review studies further confirm that fuzzy logic-based decision support systems remain competitive with modern machine learning approaches, particularly in scenarios where explainability and low computational complexity are required [25] [26]. These characteristics make fuzzy logic especially suitable for web-based medical applications [27] [28] [29] [30].

In summary, the theoretical foundations and recent literature support the use of fuzzy logic as an effective and interpretable approach for heart disease prediction. Its ability to handle uncertainty, integrate expert knowledge, and operate efficiently justifies its adoption in the proposed web-based heart disease prediction system.

3. Methodology

The methodology consists of system architecture design, fuzzy logic model development, rule base construction, implementation process, and evaluation strategy.

3.1. System Architecture

The proposed system is implemented as a web-based clinical decision support system. Users input clinical parameters through a web interface, and the fuzzy logic engine processes these values to predict heart disease risk. The system operates entirely in a browser environment using web technologies, ensuring accessibility and low computational overhead.

Input parameters:

1) Blood Pressure
2) Blood Sugar Level
3) Cholesterol Level
4) Body Mass Index (BMI)
5) Family History

Output:

- Heart Disease Risk Level (Low / Medium / High)

3.2. Fuzzy Logic Model Design

A Mamdani-type Fuzzy Inference System (FIS) is employed due to its interpretability and widespread use in medical decision-making. Each input parameter is represented by linguistic variables such as Low, Normal, and High. Triangular and trapezoidal membership functions are used because of their simplicity and suitability for real-time web applications.

Table 1. Fuzzy Input and Output Variables

Variable	Type	Linguistic Terms	Universe of Discourse (Range)	Description / Unit
Blood Pressure	Input	Low, Normal, High	[60, 200]	Systolic Blood Pressure (mmHg)
Blood Sugar	Input	Normal, Prediabetes, High	[70, 300]	Fasting Blood Sugar (mg/dL)
Cholesterol	Input	Desirable, Borderline, High	[100, 400]	Total Cholesterol Level (mg/dL)
BMI	Input	Normal, Overweight, Obese	[15, 50]	Body Mass Index kg/m^2
Family History	Input	No, Yes	[0, 1]	Binary indicator (0 for No, 1 for Yes)
Heart Disease Risk	Output	Low, Medium, High	[0, 1]	Crisp output score after Defuzzification

The membership function is a mathematical representation used in fuzzy logic to transform crisp input values into fuzzy values ranging from 0 to 1. The degree of membership indicates the extent to which a particular input belongs to a fuzzy set. The following is the general membership function used for the data presented in Table 1.

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

where,

- μA(x): membership degree of input x in fuzzy set A.
- x: crisp input value.
- a: lower boundary where membership begins.
- b: peak point where membership equals 1.
- c: upper boundary where membership returns to 0.

The function consists of four regions:

First, when x ≤ a, the membership degree is 0, indicating that the input does not belong to the fuzzy set.

Second, for a < x ≤ b, the membership value increases linearly from 0 to 1 using (x−a)/(b−a).

Third, for b < x ≤ c, the membership decreases linearly from 1 to 0 using (c−x)/(c−b).

Finally, when x > c, the membership degree returns to 0. This triangular membership function is computationally efficient, easy to interpret, and widely used in fuzzy inference systems.

3.3. Rule Base Construction

The fuzzy rule base is constructed using expert medical knowledge and findings from recent literature. Rules follow the general IF–THEN structure. For example:

IF Blood Pressure is High AND Cholesterol is High AND BMI is Obese THEN Risk is High.

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Table 2. Inference Rules

No	Blood Pressure	Blood Sugar	Cholesterol	BMI	Family History	Risk
1	Low	Normal	Desirable	Normal	No	Low
2	Low	Normal	Desirable	Overweight	No	Low
3	Low	Prediabetes	Borderline	Overweight	No	Medium
4	Normal	Normal	Desirable	Normal	No	Low
5	Normal	Prediabetes	Borderline	Overweight	No	Medium

- Rule 1:
  IF Blood Pressure is Low AND Blood Sugar is Normal AND Cholesterol is Desirable AND BMI is Normal AND Family History is No, THEN Risk is Low.
- Rule 2:
  IF Blood Pressure is Low AND Blood Sugar is Normal AND Cholesterol is Desirable AND BMI is Overweight AND Family History is No, THEN Risk is Low.
- Rule 3:
  IF Blood Pressure is Low AND Blood Sugar is Prediabetes AND Cholesterol is Borderline AND BMI is Overweight AND Family History is No, THEN Risk is Medium.
- Rule 4:
  IF Blood Pressure is Normal AND Blood Sugar is Normal AND Cholesterol is Desirable AND BMI is Normal AND Family History is No, THEN Risk is Low.
- Rule 5:
  IF Blood Pressure is Normal AND Blood Sugar is Prediabetes AND Cholesterol is Borderline AND BMI is Overweight AND Family History is No, THEN Risk is Medium.

Multiple rules are evaluated simultaneously, allowing the system to handle uncertainty and overlapping conditions effectively.

3.4. Inference and Defuzzification

Crisp input values are first fuzzified into degrees of membership. The inference engine applies fuzzy operators (AND/OR) to evaluate the rules and aggregates the resulting fuzzy outputs. Centroid defuzzification is used to convert the aggregated fuzzy output into a crisp risk value, which is then mapped to a qualitative risk category.

Table 3. Output Category

Category	Value Interval	Risk Category
Low	0 – 0.3	Low
Medium	0.3 – 0.6	Medium
High	0.6 – 1.0	High

3.5. System Implementation

The fuzzy logic algorithm is implemented using JavaScript and integrated with an HTML–CSS user interface. The system supports real-time prediction and displays results immediately after user input. A prediction history feature is included to allow users to review previous assessments.

3.6. Evaluation Method

The system is evaluated using sample clinical datasets from prior studies. Performance is assessed qualitatively by analyzing decision consistency and interpretability, and quantitatively by comparing predicted risk levels with known clinical outcomes reported in related literature.

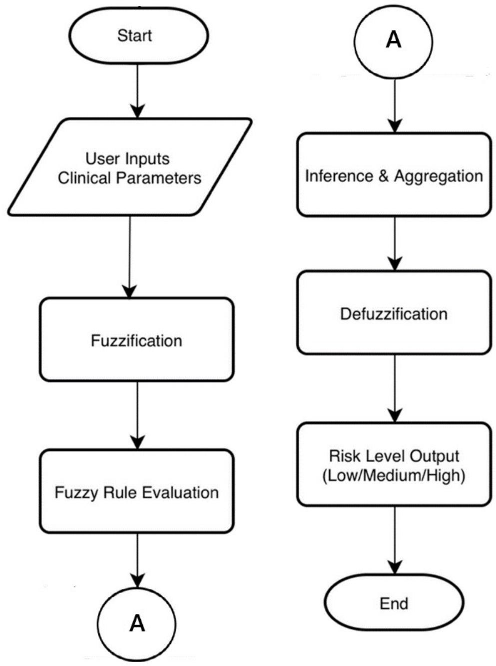

Figure 1. Flowchart Process

4. Finding and Discussion

The evaluation focuses on system behavior, prediction consistency, interpretability, and computational performance within a web-based environment.

4.1. System Output and Risk Classification

The implemented system successfully generated heart disease risk predictions based on five clinical input parameters: blood pressure, blood sugar level, cholesterol level, body mass index (BMI), and family history. For each user input, the fuzzy inference system produced a qualitative risk level categorized as Low, Medium, or High. These results were displayed instantly through the web interface, demonstrating the system's real-time response capability.

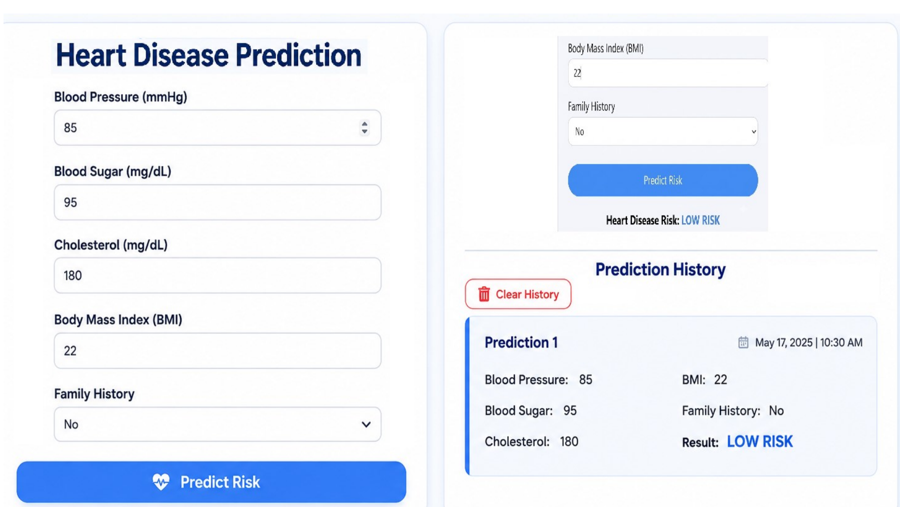

Figure 2. Web-base Application Prediction

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When input values were within normal clinical ranges, the system consistently classified patients as low risk. Conversely, combinations of high blood pressure, elevated cholesterol, high blood sugar, obesity, and positive family history resulted in high-risk predictions. For borderline or mixed conditions, such as moderately elevated cholesterol with normal BMI, the system commonly produced medium-risk outputs. This behavior reflects the ability of fuzzy logic to handle overlapping and uncertain conditions more effectively than rigid threshold-based systems.

4.2. Behavioral Consistency and Interpretability

One of the most significant outcomes of the proposed system is its interpretability. Each prediction is the result of explicitly defined fuzzy rules, allowing clear tracing of how input variables influence the final risk level. This transparency is particularly important in medical decision support systems, where clinicians require explanations rather than black-box predictions.

The fuzzy membership functions enabled smooth transitions between risk levels. Small changes in clinical parameters did not cause abrupt shifts in prediction results, which is often observed in conventional rule-based or binary classification approaches. This smoothness contributes to more realistic and clinically meaningful risk assessment.

4.3. Comparison with Traditional Approaches

Compared to conventional diagnostic methods that rely on fixed thresholds, the fuzzy logic-based system demonstrated superior flexibility. Threshold-based methods tend to classify patients strictly as healthy or at risk, which can lead to misclassification in borderline cases. The fuzzy approach addressed this limitation by assigning partial membership to multiple risk categories and aggregating them through inference rules.

Findings from recent literature indicate that fuzzy and neuro-fuzzy models achieve competitive accuracy while maintaining high interpretability. The behavior of the proposed system aligns with these findings, supporting the suitability of fuzzy logic for heart disease risk prediction, especially in early screening scenarios.

4.4. Computational Performance

From a performance perspective, the system operated efficiently in a web browser environment. The fuzzy inference process executed with negligible delay, even when multiple rules were evaluated simultaneously. The use of simple membership functions and Mamdani inference contributed to low computational overhead. This confirms that fuzzy logic is suitable for lightweight, client-side medical applications without requiring high processing power or server-side computation.

4.5. Discussion

The results demonstrate that the fuzzy logic-based system can effectively model complex relationships among cardiovascular risk factors. The system’s ability to handle uncertainty, provide interpretable results, and operate in real time supports its use as a preliminary decision support tool. While the system is not intended to replace clinical diagnosis, it offers valuable assistance for early risk assessment and awareness.

5. Conclusion

This study presented the design and implementation of a web-based heart disease prediction system using fuzzy logic. The system incorporated five key clinical parameters (blood pressure, blood sugar level, cholesterol level, BMI, and family history), to assess heart disease risk. A Mamdani-type fuzzy inference system with centroid defuzzification was employed to ensure interpretability and computational efficiency.

The results showed that the proposed system provides consistent, adaptive, and human-like risk predictions. The fuzzy logic approach successfully addressed uncertainty and variability in medical data, producing smooth transitions between risk levels and avoiding abrupt classification changes. Additionally, the system demonstrated efficient real-time performance in a web environment, making it accessible and practical for widespread use.

These findings confirm that fuzzy logic is a suitable and effective technique for heart disease risk prediction and clinical decision support, particularly in applications where transparency and explainability are essential.

Despite its effectiveness, several improvements can be explored in future research. Additional clinical parameters such as age, smoking habits, physical activity level, and electrocardiogram (ECG) data could be incorporated to enhance prediction accuracy. Hybrid models combining fuzzy logic with machine learning or deep learning techniques may also be investigated to improve adaptability and learning capability.

Furthermore, future work could involve validating the system using larger real-world clinical datasets and incorporating quantitative performance metrics such as accuracy, sensitivity, and specificity. Expanding the system to support personalized risk monitoring and integration with electronic health records would further increase its practical value.

In conclusion, the proposed fuzzy logic-based web application provides a solid foundation for intelligent, interpretable, and accessible heart disease risk prediction systems that support early detection and preventive healthcare strategies.

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