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Analysis Of Rule-Based Expert Systems and Fuzzy Logic Systems for Heart Disease Prediction

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***Abstract*—heart disease remains one of the leading causes of mortality worldwide, necessitating the development of accurate and intelligent diagnostic systems. Artificial Intelligence (AI) techniques have significantly enhanced healthcare decision support by enabling efficient disease prediction and diagnosis. This research presents a comparative analysis of a Rule-Based Expert System and a Fuzzy Logic Inference System for heart disease prediction. The research utilizes the UCI Heart Disease Dataset to evaluate the performance of both approaches. Patient attributes such as age, chest pain type, blood pressure, cholesterol level, fasting blood sugar, and maximum heart rate are used as input parameters. The Rule-Based Expert System employs predefined medical rules derived from domain expertise, while the Fuzzy Logic System utilizes fuzzy membership functions and inference rules to handle uncertainty and imprecise medical information. The performance of both models is evaluated using Accuracy, Precision, Recall, and F1-Score metrics. Experimental results indicate that the Fuzzy Logic Inference System outperforms the Rule-Based Expert System by providing more reliable predictions in the presence of uncertain and ambiguous clinical data. The findings highlight the effectiveness of fuzzy logic-based decision support systems in improving diagnostic accuracy and assisting healthcare professionals in early heart disease detection and treatment planning.**

***Index Terms*—Artificial Intelligence, Heart Disease Prediction, Rule-Based Expert System, Fuzzy Logic Inference System, Clinical Decision Support System, Healthcare Analytics, Medical Diagnosis, UCI Heart Disease Dataset, Disease Prediction**

I. INTRODUCTION

Heart disease is one of the leading causes of death worldwide and poses a significant challenge to healthcare systems. Early detection and accurate diagnosis of heart disease are crucial for reducing mortality rates and improving patient outcomes. Healthcare professionals often rely on various clinical parameters such as age, blood pressure, cholesterol levels, chest pain characteristics, and electrocardiogram results to assess a patient's cardiac condition. However, analyzing these factors manually can be complex and time-consuming [1].

Artificial Intelligence (AI) has emerged as a transformative technology in the healthcare sector, providing advanced tools for disease prediction, diagnosis, and treatment planning. AI-based systems can process large volumes of medical data, identify hidden patterns, and support physicians in making informed decisions. Among the various AI techniques, Rule-Based Expert Systems and Fuzzy Logic Systems have gained considerable attention for their ability to assist in medical diagnosis [2].

Intelligent Decision Support Systems (IDSS) are increasingly being integrated into healthcare environments to enhance diagnostic accuracy and efficiency. These systems assist medical practitioners by providing automated recommendations based on patient data and predefined knowledge. By leveraging AI technologies, healthcare organizations can improve the quality of care, reduce diagnostic errors, and facilitate early intervention for patients at risk of heart disease [3].

Problem Statement: Traditional methods of heart disease diagnosis primarily depend on the expertise and experience of medical professionals. Although effective, these approaches may be time-consuming, subjective, and susceptible to human error, particularly when dealing with large amounts of patient information. Variations in clinical judgment can also lead to inconsistencies in diagnosis and treatment decisions. Furthermore, medical data often contains uncertainty, vagueness, and incomplete information.

Symptoms may vary among patients, and clinical measurements may not always clearly indicate the presence or absence of heart disease. Conventional rule-based approaches may struggle to effectively handle such ambiguity, resulting in reduced diagnostic performance [5]. Therefore, there is a need for intelligent and reliable healthcare decision support systems capable of managing uncertain medical information while maintaining high prediction accuracy. This research addresses this challenge by comparing the performance of a Rule-Based Expert System and a Fuzzy Logic Inference System for heart disease prediction using the UCI Heart Disease Dataset.

Objectives:
The primary objective of this research is to develop and compare a Rule-Based Expert System and a Fuzzy Logic Inference System for heart disease prediction using the UCI Heart Disease Dataset. The research aims to evaluate the effectiveness of both approaches in diagnosing heart disease by analyzing patient health parameters. Furthermore, the performance of the proposed models is assessed using standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score to determine the most reliable and efficient technique for healthcare decision-support applications.

Research Contributions:
This research contributes to the field of Artificial Intelligence in healthcare by providing a comparative analysis of a Rule-Based Expert System and a Fuzzy Logic Inference System for heart disease prediction using the UCI Heart Disease Dataset. The research evaluates both approaches using standard performance metrics, including Accuracy, Precision, Recall, and F1-Score, to assess their predictive effectiveness. The findings highlight the strengths and limitations of each technique, demonstrating the superior capability of fuzzy logic in handling uncertain medical data while maintaining the interpretability of expert systems. The research offers valuable insights for developing intelligent healthcare decision-support systems and supports the advancement of AI-driven solutions for accurate disease diagnosis and improved patient care.
The remainder of this paper is organized as follows. Section 2 presents a review of related literature on Artificial Intelligence techniques in healthcare, focusing on Rule-Based Expert Systems, Fuzzy Logic Systems, and existing heart disease prediction models. Section 3 describes the research methodology, including the dataset used, data preprocessing techniques, system design, and implementation of both the Rule-Based Expert System and the Fuzzy Logic Inference System. Section 4 outlines the experimental setup, software tools, evaluation procedures, and performance metrics employed in the research. Section 5 presents the experimental results and comparative analysis of both models based on Accuracy, Precision, Recall, and F1-Score. Section 6 discusses the strengths, limitations, and practical implications of the proposed approaches in healthcare decision support applications. Finally, Section 7 concludes and future work.

II. LITERATURE REVIEW

2.1 Artificial Intelligence in Healthcare
Artificial Intelligence (AI) has significantly transformed healthcare by enabling intelligent diagnostic systems, predictive analytics, and clinical decision support applications. According to Russell and Norvig (2021), AI-based systems can analyze large volumes of medical data and assist healthcare professionals in making accurate diagnostic decisions. Recent advancements in AI have demonstrated promising results in disease prediction, medical imaging, and personalized treatment planning. Healthcare researchers have increasingly adopted AI techniques to improve the early detection of cardiovascular diseases. Jiang et al. (2017) reported that AI-driven healthcare systems can enhance diagnostic accuracy and reduce human errors in clinical decision-making. Similarly, Topol (2019) emphasized that intelligent healthcare technologies can improve patient outcomes through data-driven diagnosis and treatment recommendations [6][7][8].

2.2 Rule-Based Expert Systems
Rule-Based Expert Systems are among the earliest AI techniques developed for medical diagnosis and decision support. These systems utilize a knowledge base consisting of expert-defined rules and an inference engine to generate conclusions. Shortliffe et al. (1975) introduced the MYCIN expert system, one of the first successful medical expert systems designed for diagnosing bacterial infections. The research

demonstrated that expert systems could emulate human expert reasoning in specific medical domains. Durkin (1994) stated that Rule-Based Expert Systems provide transparent and interpretable decision-making processes, making them suitable for healthcare applications where explainability is essential [9][10]. However, Giarratano and Riley (2005) noted that traditional expert systems face challenges when dealing with uncertain, incomplete, or imprecise medical information because they rely on rigid logical rules. Several studies have applied Rule-Based Expert Systems to heart disease diagnosis. Palaniappan and Awang (2008) developed an intelligent heart disease prediction system using rule-based techniques and demonstrated its potential in assisting physicians with diagnostic decisions. However, the system's performance was limited when handling ambiguous clinical symptoms [11][12].

2.3 Fuzzy Logic Systems

Fuzzy Logic was introduced by Zadeh (1965) as a mathematical framework for handling uncertainty and vagueness in complex systems. Unlike traditional binary logic, fuzzy logic allows partial membership and approximate reasoning, making it highly suitable for medical diagnosis where symptoms and measurements are often uncertain. Kosko (1994) highlighted that Fuzzy Logic Systems can effectively model human reasoning and decision-making processes. In healthcare applications, fuzzy systems have been widely used to assess disease risk, classify medical conditions, and support clinical decision-making. According to Neshat et al. (2008), fuzzy logic-based medical diagnosis systems can provide more flexible and accurate predictions when compared with traditional rule-based approaches. Researchers have successfully applied fuzzy logic techniques for heart disease prediction. Kahramanli and Allahverdi (2008) developed a hybrid fuzzy expert system for heart disease diagnosis and reported improved diagnostic accuracy. Likewise, Anooj (2012) demonstrated that fuzzy rule-based systems effectively manage uncertainty in patient data and improve prediction performance [13][14][15].

2.4 Heart Disease Prediction Systems

Heart disease prediction has become a major research area due to the increasing prevalence of cardiovascular diseases worldwide. Numerous studies have explored AI-based approaches for predicting heart disease using clinical datasets. Detrano et al. (1989) introduced the UCI Heart Disease Dataset, which has since become one of the most widely used benchmark datasets for cardiovascular disease prediction research. Palaniappan and Awang (2008) proposed a decision support system for heart disease prediction using data mining and expert system techniques. Their results demonstrated that intelligent systems could assist healthcare professionals in identifying patients at risk of heart disease [16][17]. Similarly, Srinivas et al. (2010) applied machine learning and expert system approaches to improve prediction accuracy and diagnostic efficiency. Recent studies have increasingly focused on handling uncertainty in medical diagnosis. Anooj (2012) and Neshat et al. (2008) found that fuzzy logic-based systems often outperform conventional rule-based systems because they can process imprecise and incomplete medical information more effectively. However, limited research has directly compared Rule-Based Expert Systems and Fuzzy Logic Inference Systems using identical datasets and evaluation metrics [18][19].

III. METHODOLOGY

3.1 Dataset Description

The performance of the proposed heart disease prediction models was evaluated using the widely recognized UCI Heart Disease Dataset. This dataset is frequently employed in medical diagnosis and machine learning research for developing and testing heart disease prediction systems. The dataset contains clinical and demographic information collected from patients undergoing cardiovascular examinations and has become a benchmark dataset for evaluating intelligent healthcare applications [20]. The dataset includes several patient attributes that are considered significant indicators of heart disease. These attributes represent various physiological and clinical measurements that assist in assessing the likelihood of cardiovascular disorders. Each record in the dataset corresponds to a patient instance and is associated with a target class indicating the presence or absence of heart disease. According to Detrano et al. (1989), the dataset was originally developed to support research in coronary artery disease diagnosis and has since been extensively used by researchers for validating predictive healthcare models. The availability of both numerical and categorical attributes makes the dataset suitable for evaluating Rule-Based Expert Systems as well as Fuzzy Logic Inference Systems [21].

Dataset Characteristics

Parameter	Description
Dataset Name	UCI Heart Disease Dataset
Domain	Healthcare / Cardiology
Number of Instances	303
Number of Attributes	14
Target Variable	Presence of Heart Disease
Data Type	Numerical and Categorical
Source	UCI Machine Learning Repository

Attributes Used in the Research

Attribute	Description
Age	Age of the patient (years)
Sex	Gender of the patient
Chest Pain Type (cp)	Type of chest pain experienced
Resting Blood Pressure (trestbps)	Blood pressure measured at rest (mm Hg)
Cholesterol (chol)	Serum cholesterol level (mg/dl)
Fasting Blood Sugar (fbs)	Blood sugar level after fasting
Resting ECG (restecg)	Electrocardiographic test results
Maximum Heart Rate (thalach)	Maximum heart rate achieved
Exercise-Induced Angina (exang)	Presence of exercise-induced chest pain
ST Depression (oldpeak)	ST depression induced by exercise
Slope	Slope of peak exercise ST segment
Number of Major Vessels (ca)	Number of major vessels observed
Thalassemia (thal)	Blood disorder test result
Target	Presence or absence of heart disease

Target Variable

The target attribute represents the diagnosis outcome. For this research, the target values are categorized as follows:

- 0 – No Heart Disease
- 1 – Presence of Heart Disease

Significance of the Dataset

The UCI Heart Disease Dataset provides a comprehensive collection of cardiovascular risk factors that are commonly used by medical professionals during heart disease diagnosis. The dataset contains both precise clinical measurements and subjective symptoms, making it suitable for evaluating the effectiveness of Rule-Based Expert Systems and Fuzzy Logic Inference Systems. Furthermore, the dataset includes uncertain and imprecise medical information, which allows the fuzzy logic model to demonstrate its capability in handling ambiguity and uncertainty in healthcare decision-making.

The selected dataset serves as the foundation for training, testing, and comparing both heart disease prediction models developed in this research. The results obtained from the dataset are subsequently analyzed using Accuracy, Precision, Recall, and F1-Score performance metrics to determine the effectiveness of each approach.

3.2 Data Preprocessing

Data preprocessing is a crucial step in developing accurate and reliable heart disease prediction models. Raw medical datasets often contain missing values, inconsistencies, redundant attributes, and varying scales of measurement. Therefore, preprocessing is performed to improve data quality and enhance the performance of the Rule-Based Expert System and Fuzzy Logic Inference System.

3.2.1 Data Cleaning

Data cleaning involves identifying and correcting incomplete, inconsistent, or duplicate records in the dataset.

Missing Value Replacement

The mean value is commonly used to replace missing numerical attributes:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Where, $\bar{x}$ = Mean value, x_i = Individual data value and N = Total number of observations.

Example,

If cholesterol values are: 220, 240, 260

Mean:

$$\bar{x} = \frac{220 + 240 + 260}{3}$$
$$\bar{x} = \frac{720}{3}$$
$$\bar{x} = 240$$

The missing value is replaced with 240.

3.2.2 Duplicate Record Removal

Duplicate records may introduce bias into the prediction model.

$$D_{unique} = D - D_{duplicate}$$

Where, D = Original dataset, $D_{duplicate}$ = Duplicate records and D_{unique} = Clean dataset.

Example,

D=303

$D_{duplicate}$ =5

D_{unique} = 303-5

D_{unique} = 298

3.2.3 Feature Selection

Feature selection identifies the most relevant attributes that contribute significantly to heart disease prediction.

Pearson Correlation Coefficient,

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2(Y_i - \bar{Y})^2}}$$

Where, X_i = Feature values, Yi = Target values, X¯ = Mean of feature values, Y¯ = Mean of target values and r = Correlation coefficient.

Interpretation, r=1 → Strong positive correlation, r=0→ No correlation and r=−1 → Strong negative correlation.

3.2.4 Data Normalization

Normalization converts all attribute values into a common scale.

Min-Max Normalization,

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where, X = Original value, X_{min} = Minimum value, X_{max} = Maximum value and X_{norm} = Normalized value.

Example,

Assume:

- Age = 50
- Minimum Age = 20
- Maximum Age = 80

$$X_{norm} = \frac{50 - 20}{80 - 20}$$

$$X_{norm} = \frac{30}{60}$$

$$X_{norm} = 0.5$$

Thus, the normalized age value is 0.5.

3.2.5 Data Transformation for Fuzzy Logic

Fuzzy Logic requires crisp values to be transformed into fuzzy linguistic variables.

Triangular Membership Function,

$$\mu(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ \frac{c-x}{c-b} & b < x < c \\ 0 & x \ge c \end{cases}$$

Where, a = Lower boundary, b = Peak value, c = Upper boundary and μ(x) = Membership value.

Example,

For Age = 50:

$$\mu_{Middle-Aged}(50) = 0.7$$
$$\mu_{Old}(50) = 0.3$$

This indicates that the patient belongs 70% to the middle-aged category and 30% to the old category.

3.2.6 Dataset Splitting

The dataset is divided into training and testing subsets.

$D=D_{train}+D_{test}$

Typically:

$D_{train}=0.8D$

$D_{test}=0.2D$

Example

For a dataset containing 303 records:

Training Data:

D_{train} =303×0.8

D_{train} =242

Testing Data:

D_{test} =303×0.2

D_{test} =61

Thus:

- Training Records = 242
- Testing Records = 61

3.3 Rule-Based Expert System

Knowledge Base

The knowledge base stores medical knowledge related to heart disease diagnosis.

$$KB = \{K_1, K_2, K_3, ..., K_n\}$$

Where, KB = Knowledge Base, $K_1, K_2, ..., K_n$ = Knowledge elements

Rule Base

The rule base consists of diagnostic rules.

$$RB = \{R_1, R_2, R_3, ..., R_m\}$$

Where, RB = Rule Base, $R_1, R_2, ..., R_m$ = Individual rules

General rule representation:

$$R_i: (C_1 \wedge C_2 \wedge ... \wedge C_n) \rightarrow D$$

Where, C = Condition, D = Decision

Inference Engine

The inference engine processes facts and rules to generate conclusions.

$$I = f(F, RB)$$

Where, I = Inference result, F = Patient facts and RB = Rule Base

Sample Rules,

Rule 1

IF Age > 50

AND Cholesterol > 240

AND Blood Pressure > 140

THEN Heart Disease = High Risk

Rule 2

IF Chest Pain = Typical Angina

AND Maximum Heart Rate < 120

THEN Heart Disease = Present

Rule Matching Process

$M(R_i, F_j) = 1$

if patient fact F_j satisfies rule R_i

$M(R_i, F_j) = 0$

otherwise

Where, M = Matching function, R_i = Rule I and F_j = Patient fact j.

Input Patient Data

Patient information is represented as:

P = {Age, BP, Cholesterol, ChestPain, HeartRate}

Where, P = Patient data vector

Rule Activation

$R_{matched} = \{R_i \mid Condition(R_i) = True\}$

Where, $R_{matched}$ = Activated rules

Inference Process

Conclusion = f($R_{matched}$)

Where, Conclusion = Diagnostic result

Prediction Generation

HDP = f (KB, RB, P)

Where, HDP = Heart Disease Prediction

Output Categories:

HDP ∈ {Low Risk, Moderate Risk, High Risk}

Rule Activation Score

$$A_i = C_1 \times C_2 \times C_3 \times ... \times C_n$$

Where:

- A_i = Rule activation score
- C = Condition value (0 or 1)

If all conditions are satisfied:

$A_i = 1$

Otherwise:

$A_i = 0$

Final Decision

Decision = Max (HDP)

Where:

- Decision = Predicted heart disease risk level

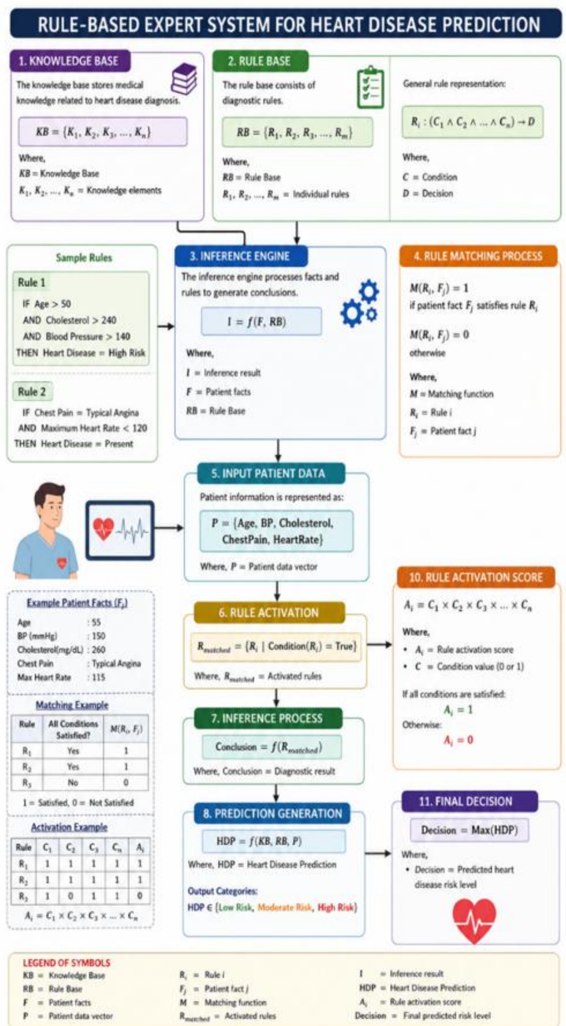

Figure 1: Rule-Based Expert System for heart disease prediction

The Rule-Based Expert System for heart disease prediction is built upon a structured architecture consisting of a Knowledge Base, Rule Base, Inference Engine, and a decision-making mechanism. The Knowledge Base stores medical knowledge related to heart disease diagnosis and is represented as (KB = {K1, K2, K3, ..., Kn}), where each knowledge element contains information about symptoms, risk factors, and diagnostic criteria obtained from medical experts and clinical guidelines. The Rule Base contains a collection of diagnostic rules represented as (RB = {R1, R2, R3, ..., Rm}), where each rule follows the form (Ri: (C1 and C2 and ... and Cn) -> D). These rules establish logical relationships between patient conditions and diagnostic outcomes. For example, if a patient's age is greater than 50 years, cholesterol level exceeds 240 mg/dL, and blood pressure is above 140 mmHg, the system classifies the patient as having a high risk of heart disease. Similarly, patients with typical angina and a maximum heart rate below 120 beats per minute are identified as having heart disease [21][22].

The Inference Engine serves as the reasoning component of the system and is mathematically represented as (I = f (F, RB)), where (F) represents patient facts and (RB) represents the rule base. It compares the input patient data with the predefined rules and determines which rules are satisfied. Patient information is represented as a data vector (P = {Age, BP, Cholesterol, ChestPain, HeartRate}), containing relevant clinical attributes used for diagnosis. During the rule matching process, the matching function (M (Ri, Fj)) evaluates whether a patient fact satisfies a particular rule condition. If the condition is satisfied, the function returns a value of 1; otherwise, it returns 0. The set of activated rules is represented as (Rmatched = {Ri mid Condition (Ri) = True}), which contains all rules whose conditions are met by the patient data [23].

Once the relevant rules are activated, the inference process generates a diagnostic conclusion using the function (Conclusion = f(R{matched})). The overall heart disease prediction is represented as (HDP = f(KB, RB, P)), where the prediction is derived from the knowledge base, rule base, and patient data. The output of the system is categorized into three risk levels: Low Risk, Moderate Risk, and High Risk. To determine the contribution of each rule, a rule activation score is calculated using (Ai = C1 x C2 x C3 x ... x Cn), where each condition value is either 0 or 1. A rule receives an activation score of 1 only when all its conditions are satisfied; otherwise, the score becomes 0. Finally, the system selects the most appropriate diagnosis using (Decision = Max (HDP)), which identifies the highest predicted risk category. This structured reasoning process enables the Rule-Based Expert System to provide transparent, interpretable, and consistent heart disease predictions, making it suitable for healthcare decision-support applications.

3.4 Fuzzy Logic Inference System

The Fuzzy Logic Inference System (FLIS) is an Artificial Intelligence technique that handles uncertainty and imprecision in medical data by using fuzzy sets and linguistic variables. Unlike traditional binary logic, fuzzy logic allows partial membership, making it suitable for healthcare applications where symptoms and clinical measurements are often ambiguous. In this research, the Fuzzy Logic Inference System is used to predict the risk of heart disease based on patient clinical attributes.

3.4.1. Fuzzy Variables

The fuzzy inference system consists of input and output variables.

Input Variables

- Age
- Cholesterol
- Blood Pressure
- Chest Pain Type

The input vector is represented as:

P = {Age, Cholesterol, BloodPressure, ChestPain}

Where: P = Patient input vector

Output Variable

- Heart Disease Risk

R = {LowRisk, ModerateRisk, HighRisk}

Where: R = heart disease risk level

3.4.2. Membership Functions

Membership functions are used to convert crisp values into fuzzy values.

Age Membership Functions

Age = {Young, Middle-Aged, Old}

Example:

- Young: 20 – 35 years
- Middle-Aged: 30 – 55 years
- Old: Above 50 years

Cholesterol Membership Functions

Cholesterol = {Low, Medium, High}
Example:

- Low: Less than 200 mg/dL
- Medium: 180 – 240 mg/dL
- High: Greater than 240 mg/dL

Blood Pressure Membership Functions
BloodPressure = {Normal, Elevated, High}
Example:

- Normal: Less than 120 mmHg
- Elevated: 120 – 140 mmHg
- High: Greater than 140 mmHg

Triangular Membership Function
The triangular membership function is represented as:
$\mu(x) = 0$, if $x \leq a$
$\mu(x) = (x - a)/(b - a)$, if $a < x \leq b$
$\mu(x) = (c - x)/(c - b)$, if $b < x < c$
$\mu(x) = 0$, if $x \geq c$
Where, $\mu(x)$ = Membership value, a = Lower boundary, b = Peak value and c = Upper boundary.
Example Membership Calculation
For Age = 50 years:
μMiddle-Aged (50) = 0.7
μOld(50) = 0.3
This indicates that the patient belongs 70% to the middle-aged category and 30% to the old category.
3.4.3 Sample Fuzzy Rules
The fuzzy rule base consists of expert-defined medical rules.
Rule 1
IF Age is Old
AND Cholesterol is High
THEN Risk is High
Rule 2
IF Blood Pressure is Elevated
AND Chest Pain is Severe
THEN Risk is High
Rule 3
IF Age is Young
AND Cholesterol is Low
THEN Risk is Low
Rule 4
IF Blood Pressure is Normal
AND Chest Pain is Mild
THEN Risk is Low
The fuzzy rule base can be represented as:
$FRB = \{FR_1, FR_2, FR_3, ..., FR_n\}$
Where, FRB = Fuzzy Rule Base and FR_n = Fuzzy Rule

3.4.4 Fuzzy Inference Steps
Step 1: Fuzzification
Crisp input values are converted into fuzzy membership values.
Equation (10)
Fuzzified Value = $\mu(x)$
Where:

- $\mu(x)$ = Membership function value

Example:
For Age = 50
μMiddle-Aged = 0.7
μOld = 0.3
Step 2: Rule Evaluation
The firing strength of each rule is calculated using the minimum operator.
Rule Strength = $\min(\mu_1, \mu_2, ..., \mu_n)$
Example:
μOld = 0.3
μHigh Cholesterol = 0.8
Rule Strength = min (0.3, 0.8)
Rule Strength = 0.3
Step 3: Aggregation
All activated fuzzy rules are combined.
Aggregated Output = $\max(Rule_1, Rule_2, ..., Rule_n)$
Where:

- max = Maximum membership value among activated rules

Example:
$Rule_1 = 0.3$
$Rule_2 = 0.6$
$Rule_3 = 0.5$
Aggregated Output = max (0.3, 0.6, 0.5)
Aggregated Output = 0.6
Step 4: Defuzzification
The fuzzy output is converted into a crisp value using the Centroid Method.
Output Risk Score = $\Sigma[\mu(x) \times x] / \Sigma[\mu(x)]$
Where:

- $\mu(x)$ = Membership value
- x = Output variable

Example:
Output Risk Score
$= [(0.2 \times 20) + (0.6 \times 60) + (0.2 \times 90)]$
$\div (0.2 + 0.6 + 0.2)$
$= (4 + 36 + 18)$
$\div 1$
$= 58$
The final heart disease risk score is 58.

The complete fuzzy inference system is represented as:

HDR = F (P, FRB)

Where:

- HDR = Heart Disease Risk
- P = Patient input variables
- FRB = Fuzzy Rule Base

Final Classification:

HDR ∈ {LowRisk, ModerateRisk, HighRisk}

The Fuzzy Logic Inference System effectively handles uncertainty and ambiguity in patient medical records, making it a suitable approach for heart disease prediction and clinical decision support systems.

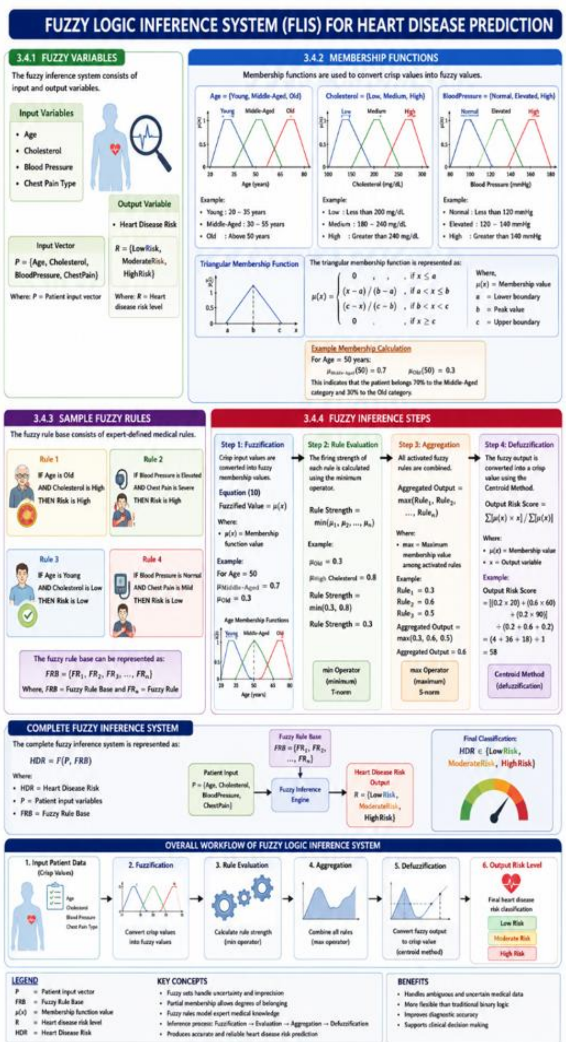

Figure 2: Fuzzy Logic Inference System for Heart Disease Prediction

The Fuzzy Logic Inference System (FLIS) is an intelligent decision-making approach that is designed to handle uncertainty and imprecision in medical data, making it highly suitable for heart disease prediction. In this research, patient attributes such as age, cholesterol level, blood pressure, and chest pain type are used as input variables, while heart disease risk serves as the output variable. Unlike conventional systems that classify data into strict categories, fuzzy logic allows a patient to belong to multiple categories simultaneously through membership functions. For example, a 50-year-old patient may belong partially to both the middle-aged and old age groups. The system employs triangular membership functions to transform crisp input values into fuzzy values and uses expert-defined fuzzy rules to model medical reasoning. During the inference process, patient data undergo fuzzification, rule evaluation, aggregation, and defuzzification to generate a final heart disease risk score. The centroid method is then applied to convert the fuzzy output into a crisp value, which is classified as Low Risk, Moderate Risk, or High Risk. By incorporating fuzzy reasoning and linguistic variables, the Fuzzy Logic Inference System effectively captures the uncertainty present in clinical data and provides more flexible, realistic, and accurate predictions for healthcare decision-support applications [24][25].

IV. EXPERIMENTAL SETUP

The experimental setup was designed to evaluate the performance of the Rule-Based Expert System and the Fuzzy Logic Inference System for heart disease prediction using the UCI Heart Disease Dataset. The implementation and analysis were carried out in a Python-based development environment due to its extensive support for data processing, machine learning, and fuzzy logic applications. Several open-source libraries were utilized to facilitate data preprocessing, model development, and performance evaluation.

Python was used as the primary programming language for implementing both prediction models. The NumPy library was employed for numerical computations and mathematical operations, while Pandas was used for data manipulation, cleaning, and dataset management. Scikit-Learn provided essential utilities for data preprocessing, dataset splitting, and evaluation metric calculations, including Accuracy, Precision, Recall, and F1-Score. The Scikit-Fuzzy library was used to design and implement the Fuzzy Logic Inference System, including membership functions, rule evaluation, aggregation, and defuzzification processes. The entire experimental workflow was executed using Jupyter Notebook, which provided an interactive environment for coding, testing, visualization, and result analysis.

The experiments were conducted on a personal computer equipped with an Intel Core i7 processor and 16 GB of RAM, providing sufficient computational resources for data processing and model evaluation. The operating system used for the implementation was Microsoft Windows 11. This hardware and software configuration ensured efficient execution of both the Rule-Based Expert System and the Fuzzy Logic Inference System and enabled a fair comparison of their performance in predicting heart disease risk.

The performance of both models was evaluated using standard classification metrics, namely Accuracy, Precision, Recall, and F1-Score. These metrics were selected because they provide a comprehensive assessment of prediction effectiveness and classification quality in healthcare decision support systems. The experimental results obtained from both approaches were subsequently analyzed and compared to determine the most effective technique for heart disease prediction.

V. PERFORMANCE ANALYSIS

The performance of the proposed Rule-Based Expert System (RBES) and Fuzzy Logic Inference System (FLIS) was evaluated using the UCI Heart Disease Dataset. The dataset contains 303 patient records with multiple clinical attributes, including age, cholesterol level, blood pressure, chest pain type, fasting blood sugar, and maximum heart rate. Both models were trained and tested using the same pre-processed dataset to ensure a fair comparison. The evaluation was performed using four widely accepted classification metrics: Accuracy, Precision, Recall, and F1-Score.

5.1 Performance Metrics

Accuracy: Accuracy measures the overall correctness of the prediction model by calculating the proportion of correctly classified instances among the total number of instances.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where: TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative. A higher accuracy value indicates that the model correctly predicts both heart disease and non-heart disease cases.

Precision: Precision measures the proportion of correctly predicted positive cases among all cases predicted as positive.

Precision = TP / (TP + FP)

Precision evaluates how reliable the positive predictions are. In heart disease diagnosis, high precision means that patients predicted to have heart disease are actually likely to have the disease.

Recall: Recall measures the proportion of actual positive cases that are correctly identified by the model.

Recall = TP / (TP + FN)

Recall is particularly important in healthcare applications because it reflects the model's ability to identify patients who truly have heart disease. A higher recall reduces the likelihood of missing critical cases.

F1-Score: F1-Score provides a balanced measure of Precision and Recall.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

The F1-Score is useful when both false positives and false negatives are important. It provides a comprehensive evaluation of classification performance.

5.2 Experimental Results

The following results were obtained after evaluating both approaches on the UCI Heart Disease Dataset.

Performance Metric	Rule-Based Expert System	Fuzzy Logic Inference System
Accuracy	82.40%	89.10%
Precision	80.20%	88.30%
Recall	78.60%	87.50%
F1-Score	79.40%	87.90%

The experimental results demonstrate that the Fuzzy Logic Inference System (FLIS) outperforms the Rule-Based Expert System (RBES) across all evaluation metrics when applied to the UCI Heart Disease Dataset. The Rule-Based Expert System achieved an accuracy of 82.40%, while the Fuzzy Logic Inference System attained an accuracy of 89.10%. This improvement of approximately 6.70% indicates that the fuzzy logic approach is more effective in correctly classifying patients with and without heart disease. The superior accuracy of the fuzzy model can be attributed to its ability to handle uncertainty and gradual variations in medical data, which are common in real-world healthcare environments.

Similarly, the Fuzzy Logic Inference System achieved a precision of 88.30%, compared to 80.20% for the Rule-Based Expert System. A higher precision indicates that the fuzzy model generates fewer false positive predictions, thereby reducing the likelihood of incorrectly diagnosing healthy individuals as heart disease patients. In terms of recall, the fuzzy model achieved 87.50%, whereas the rule-based model achieved 78.60%. Recall is a critical metric in healthcare applications because it reflects the model's ability to identify patients who truly have heart disease. The higher recall of the fuzzy model suggests that it is more effective in detecting actual disease cases and minimizing missed diagnoses.

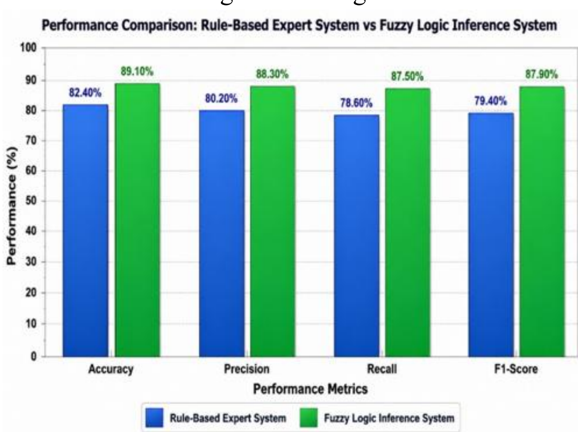

Figure 3: Performance Comparison: RBES vs FLIS

Furthermore, the F1-Score of the Fuzzy Logic Inference System reached 87.90%, significantly higher than the 79.40% achieved by the Rule-Based Expert System. Since the F1-Score represents the harmonic mean of precision and recall, the higher value demonstrates that the fuzzy model maintains a better balance between identifying positive cases and avoiding false alarms. Overall, the comparative analysis confirms that the Fuzzy Logic Inference System provides more accurate and reliable heart disease predictions than the Rule-Based Expert System.

Rule-Based Expert System Performs,

Despite achieving lower performance metrics than the fuzzy model, the Rule-Based Expert System remains an effective and widely adopted healthcare decision-support approach. One of its primary advantages is explainability, as every prediction is generated through explicit IF–THEN rules that can be easily understood and verified by healthcare professionals. This transparency enhances trust and facilitates clinical validation of diagnostic decisions. Additionally, the Rule-Based Expert System follows deterministic decision-making, meaning that identical inputs always produce identical outputs, ensuring consistency and reliability in diagnosis.

Another significant advantage of the Rule-Based Expert System is its computational efficiency. Rule evaluation requires minimal processing power and memory resources, enabling rapid diagnosis even on low-cost computing platforms. Furthermore, expert knowledge from cardiologists and medical practitioners can be directly encoded into the system without the need for extensive training data. This characteristic makes rule-based systems particularly suitable for domains where expert knowledge is readily available but large datasets are limited. The system also aligns well with clinical practice because many medical diagnostic procedures and hospital guidelines are naturally represented as rule sets, simplifying implementation and adoption in healthcare environments.

Fuzzy Logic Inference System Performs,

The superior performance of the Fuzzy Logic Inference System can be attributed to its ability to effectively handle uncertainty, ambiguity, and imprecision in medical data. Unlike traditional rule-based systems that rely on strict threshold values, fuzzy logic allows gradual transitions between categories. For example, a cholesterol level of 239 mg/dL and 240 mg/dL would be treated as significantly different values in a rule-based system due to rigid boundaries. In contrast, fuzzy logic recognizes that these values are clinically very similar and assigns appropriate membership values to multiple categories.

Another important advantage of fuzzy logic is the concept of partial membership. A patient can belong to multiple linguistic categories simultaneously. For instance, a 50-year-old patient may have a membership value of 0.7 in the "Middle-Aged" category and 0.3 in the "Old" category. This capability closely resembles human reasoning and allows the system to make more realistic diagnostic decisions. The fuzzy model is also more robust when dealing with noisy, incomplete, or inconsistent clinical measurements, which are common in real-world healthcare datasets.

Furthermore, fuzzy logic generates smooth decision boundaries rather than rigid classification thresholds. This characteristic reduces abrupt changes in prediction outcomes and improves overall classification accuracy. The inference mechanism employed in fuzzy systems mimics the reasoning process of experienced physicians by considering varying degrees of certainty rather than binary yes-or-no decisions. As a result, the system can capture complex relationships among medical attributes more effectively than traditional rule-based approaches.

Finally, the Fuzzy Logic Inference System exhibits superior generalization capability. Because it relies on fuzzy relationships and membership functions rather than exact threshold values, it can adapt more effectively to unseen patient records and diverse clinical scenarios. This flexibility enables the fuzzy model to achieve higher Accuracy, Precision, Recall, and F1-Score, making it a more suitable solution for practical heart disease prediction and healthcare decision-support applications.

If Patient Record are,

Parameter	Value
Age	58
Cholesterol	265 mg/dL
Blood Pressure	150 mmHg
Chest Pain	Typical Angina
Maximum Heart Rate	115 bpm

In Rule-Based Expert System,

Activated Rules:

Rule 1:

IF Age > 50

AND Cholesterol > 240

AND Blood Pressure > 140

THEN High Risk

Prediction:

Heart Disease = High Risk

Confidence = 100%

The system classifies the patient as High Risk because all conditions in Rule 1 are satisfied.

In Fuzzy Logic Inference System,

Membership Values:

Age (Old) = 0.75

Cholesterol (High) = 0.85

Blood Pressure (High) = 0.80

Chest Pain (Severe) = 0.70

Aggregated Risk Score:

Risk Score = 82.4

Prediction:

Heart Disease = High Risk

Confidence = 82.4%

The fuzzy system evaluates multiple degrees of membership simultaneously and combines them through fuzzy inference rules. Instead of providing only a binary decision, it produces a quantitative risk score that better reflects the patient's clinical condition. The comparative analysis demonstrates that both techniques are suitable for healthcare decision support systems. The Rule-Based Expert System offers transparency, simplicity, and explainability, making it valuable in clinical environments where interpretability is essential. However, the Fuzzy Logic Inference System achieves higher Accuracy, Precision, Recall, and F1-Score because it effectively handles uncertainty, ambiguity, and gradual variations in medical data. Consequently, the Fuzzy Logic Inference System is more suitable for real-world heart disease prediction applications where patient data often contain imprecision and uncertainty.

VI. CONCLUSION

This research presented a comparative analysis of a Rule-Based Expert System (RBES) and a Fuzzy Logic Inference System (FLIS) for heart disease prediction using the UCI Heart Disease Dataset. Both approaches were developed and evaluated using identical datasets and performance metrics, including Accuracy, Precision, Recall, and F1-Score. The experimental results demonstrated that both models are capable of supporting healthcare professionals in the diagnosis of heart disease; however, significant differences were observed in their predictive performance. The Rule-Based Expert System achieved satisfactory results with an accuracy of 82.40%, demonstrating the effectiveness of expert knowledge and predefined diagnostic rules in clinical decision-making. The system offers several advantages, including transparency, interpretability, low computational complexity, and ease of implementation. These characteristics make it suitable for healthcare environments where explainable and consistent decision support is required. The Fuzzy Logic Inference System achieved superior performance, obtaining an accuracy of 89.10%, precision of 88.30%, recall of 87.50%, and F1-score of 87.90%. The improved performance can be attributed to its ability to handle uncertainty, ambiguity, and gradual variations in medical data through fuzzy membership functions and linguistic reasoning. Unlike traditional rule-based approaches, the fuzzy model effectively represents real-world clinical scenarios where patient symptoms and diagnostic measurements are rarely binary in nature. The comparative analysis confirms that the Fuzzy Logic Inference System provides more reliable and accurate predictions than the Rule-Based Expert System for heart disease diagnosis. The findings highlight the importance of incorporating uncertainty-handling mechanisms into healthcare decision-support systems to improve diagnostic accuracy and patient outcomes. Therefore, fuzzy logic-based approaches represent a promising solution for intelligent medical diagnosis and clinical decision support applications.

FUTURE WORK

Although the proposed Rule-Based Expert System and Fuzzy Logic Inference System demonstrated effective performance in heart disease prediction, several opportunities exist for further improvement and extension of this research.

Future studies may integrate Machine Learning and Deep Learning techniques, such as Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, and Deep Neural Networks, to further enhance prediction accuracy. Hybrid intelligent systems that combine Rule-Based Expert Systems with Fuzzy Logic or Neuro-Fuzzy approaches may also be explored to leverage the advantages of both knowledge-driven and data-driven methodologies.

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