Fuzzy Logic-Based Inference System For Early Detection Of Cardiovascular Disease

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Abstract: -
Cardiovascular disease is a primary cause of death. This research models and validates an innovative expert system using fuzzy inference to diagnose cardiovascular disease. The multi-layered fuzzy inference based on the Mamdani fuzzy model enables early classification of the disease, resulting in greater accuracy in the diagnosis depending on the class. The resultant medical expert system has the potential impact of saving lives. The system model comprises two layers. In layer 1, the input variables are blood pressure, diabetes, heredity, age, gender, and cholesterol. This layer detects the existence of the cardiovascular disease resulting in a binary Yes/No. Layer 2 input variables are low-density lipoprotein (LDL), high-density lipoprotein (HDL), Triglycerides, body mass index (BMI), Smoking, peripheral artery disease (PAD), and physical activity. The output variables of layer 2 are very low, low, medium, high, and very high. Validation of the model evaluates its performance based on sensitivity, precision, specificity, classification accuracy, and F1 (96.06%, 93.15%, 96.06%, 95%, and 96.06%), respectively.

Keywords: Artificial intelligence; cardiovascular disease; fuzzy logic; expert system

Introduction:
Cardiovascular disease is a leading cause of death. A WHO report ranks it in the top 10 life-threatening diseases [1]. Cardiovascular disease encompasses a wide range of conditions affecting the heart and blood vessels, including heart failure, peripheral artery disease, and coronary heart disease [2]. This disease contributed to approximately 10.8 million deaths globally reported in 2021. Mortality rates vary between developing and developed countries, with India reporting an alarming 80% of deaths due to cardiovascular disease [3]. Sadly, this disease can affect people of all ages, not just the elderly. Early diagnosis of cardiovascular disease is crucial in reducing mortality rates. However, diagnoses are challenging due to myriad impacting factors. This research aims to model and validate a robust and efficient diagnostic solution that can assist medical professionals in the early detection and effective management of cardiovascular disease. Many intelligent systems exist that classify stored patient data [4] collected from healthcare centers [5]. For example, the K-Nearest Neighbors (KNN) machine learning method has been commonly used to classify cardiovascular disease. This approach provides cost-effective disease supervision [6],[7]. Naïve Bayes, Logistic regression, Random Forest, and KNN also having varying degree of classification accuracy [8]. Random Forest shows the highest accuracy in classifying cardiovascular disease [9]. The Random Forests regression model enables the plotting of regression dependence facilitating the calculation of the probability of disease occurrence based on input features. [10]. Additionally, deep learning is employed to diagnose cardiovascular disease and classify it

into four categories based on patient data [11]. Before classification, risk markers are identified using mammograms with the assistance of deep learning [12].
Machine learning techniques utilizing artificial neural networks are implemented to classify cardiovascular disease [13]. Attributes (such as xxx) are taken from a dataset, and the system is trained with artificial neural network learning algorithms to identify cardiovascular disease. The system's accuracy is determined by comparing its results with those of experts [14],[15]. To train and validate the developed system, a convolutional neural network is applied to ultrasound images of carotid arteries from the dataset [16].
Khare, S., Gupta, Qrenawi, M. I., & Al Sarraj reports a medical diagnosis system using data mining techniques [17],[18]. The process involved collecting previous and existing data, identifying patterns, and utilizing a new ensemble classifier to reach a particular result [19]. Its limitations are increased complexity, longer training time, and risk of overfitting. A prediction model for recognizing the cause of the disease in Korean patients was developed using discriminant analysis [20]. Feature selection techniques were employed to retrieve data from images, which were then classified using techniques such as support vector machine, Naïve Bayes, regression, and decision tree [21],[22],[23],[24]. The incremental support vector machine was also utilized for a more accurate analysis of cardiovascular disease with fewer errors [25]. Computed Tomography Angiography was used to acquire the images, and image processing techniques such as segmentation were applied [26]. A cardiologist evaluated the images to determine the result [27]. In addition, the heart rate was evaluated using the tone-entropy algorithm to assess the risk factor [28]. Genetic variants are also associated with several risk factors of cardiovascular disease, making it essential to investigate and uncover these factors, including genetic biomarkers that may cause this deadly disease [29].

Amma, N. G. developed a cutting-edge approach to diagnosing the risks associated with cardiovascular disease from the combination of genetic algorithms and artificial neural networks. By training a genetic-based neural network, accuracy rates of the diagnosis reached 94.17% [2]. Additionally, Guo, Z. and team developed an adaptive neuro-fuzzy inference system using Principal Component Analysis to detect the risk of this life-threatening disease. Comprising two stages, this system effectively recognizes cardiovascular disease with 93.2% accuracy, utilizing a hybrid system of fuzzy inference and neural network technologies [30].
As reviewed thus far, machine learning, data mining, artificial neural networks, genetic algorithms, and neuro-fuzzy systems offer the significant advantage of creating pattern models to diagnose cardiovascular disease. However, they require large amounts of data and cannot handle imprecise data. Inaccurate or missing patient data can also present challenges when applying these techniques.[31]. The Fuzzy set theory is used when the data is imprecise or vague [32]. Fuzzy logic is a component of machine learning, which is a powerful technology used for predicting, depicting, and diagnosing various diseases [33], [37], [39], [40]. Fuzzy logic has also been applied to diagnose cardiovascular disease by using risk factors as input to proposed systems [34].
Our method for diagnosing cardiovascular disease incorporates fuzzy logic, utilizing a multi-layered fuzzy inference system. This system manages imprecise or unclear data through fuzzy set theory. A fuzzy logic inference system comprises rules and membership functions operates similar to human reasoning. This makes fuzzy logic applicable to problems with missing or imprecise data, resulting in accurate outcomes. The three steps used in the fuzzy inference system are given by [35], [36], [38]:

- Fuzzification: The input is given to the system in crisp sets. This step of Fuzzification converts the input into a fuzzy set.
- Inference system: The inference system helps perform the reasoning part by using the rules and facts stored in the system's knowledge base.
- Defuzzification: The inference system's outcome is a fuzzy value. Defuzzification transforms that outcome into crisp values and provides the system's final output.

The risk factors that cause cardiovascular diseases that are incorporated in this research for layer 1 and layer 2 are described in detail as follows [34]:

For Layer 1:

- **Blood Pressure:** Maintaining normal systolic and diastolic blood pressure levels is crucial for good health. Systolic blood pressure, measured as the top reading, reflects the pressure generated by the heart during contraction. On the other hand, diastolic blood pressure, measured as the bottom reading, represents the heart's pressure when it is at rest and receiving oxygen and blood flow. This study employs two distinct fuzzy sets: 'Normal' and 'High,' each playing a crucial role in the analysis.
- **Diabetes:** Diabetes is characterized by the level of glucose or sugar present in the bloodstream. An individual with an excessive or deficient glucose level is a diabetic patient. The acceptable range of glucose levels typically falls between 100 mg/dL to 140 mg/dL, with this input variable utilizing three distinct fuzzy sets.
- **Heredity:** Cardiovascular disease is often linked to genetics. Those with a family history of the disease may be at risk of developing it themselves. This study works with two different fuzzy sets.: 'No' and 'Yes', each likely affects layer 1's decision boundary and therefore downstream layer 2 risk output
- **Age:** Age is the total number of years an individual has lived, indicating a specific time of their life. As people age, their immunity to fight against deadly diseases decreases, increasing the likelihood of illness. This phenomenon is more prevalent in older individuals with a higher probability of contracting diseases. The age input variable is categorized into three distinct fuzzy sets: 'Young,' 'Mid-Age,' and 'Old,' each representing different stages of the age spectrum.
- **Gender:** Gender is the classification based on biological appearance, considering the two separate sexes: male and female. This study models gender with two fuzzy sets: 'Male' and 'Female', each of which significantly influences the analysis.
- **Cholesterol:** Cholesterol is a waxy substance in the blood that plays a vital role in cell health. Cholesterol levels exceeding the normal range can lead to heart disease. The system model developed in this study uses three fuzzy sets: 'Desirable', 'Borderline' and 'High', each contributing importantly to the analysis.

For Layer 2:

- **LDL:** There are five primary groups of lipoproteins, with low-density lipoprotein being one of them. This type of lipoprotein carries fat molecules throughout the body and is crucial in transporting cholesterol to various tissues. This variable is comprised of five fuzzy sets: 'Optimal', 'Near-Optimal', 'Borderline-High', 'High' and 'Very High',
- **HDL:** One of the five main groups of lipoproteins is high-density lipoprotein, commonly referred to as "good cholesterol." Its primary function is to transport cholesterol to the liver for excretion from the body's tissues. Furthermore, this field is characterized by five fuzzy set: 'Very Low', 'Low', 'Medium', 'High' and 'Very High'.
- **Triglyceride:** Triglycerides are the main components of natural fats found in vegetables and oils within the human body. They are formed by combining three fatty acids

and glycerol. For system development, this work utilized four fuzzy sets; ‘Normal’, ‘Borderline’, “High’ and ‘Very High’.

- **BMI:** Obesity is the main risk factor for cardiovascular disease. An individual should maintain a healthy weight, which can be calculated by dividing their mass by the square of their height. The proposed model for BMI uses fuzzy sets: ‘Underweight’, ‘Normal’, ‘Over-weight’, ‘Obese’ and ‘Severely Obese’.
- **Smoking:** The use of tobacco and smoking has been identified as the primary cause of cardiovascular disease. These toxic substances adversely affect the body's blood vessels, leading to severe damage. In the research model, this input variable is represented by three fuzzy sets: ‘Never’, ’Former’, ’Light’, ’Moderate’ and “Heavy’, which allow for nuanced analysis and accurate predictions.
- **Physical Activity:** Regular exercise can control high blood pressure, obesity, and cholesterol and help maintain a healthy heart. This study has three fuzzy sets: ’Sedentary’, ‘Moderate’, ‘Active’

Material and Methods

Existing studies based on a single-layered approach use a single criterion on each layer, which reduces a model's decision-making capabilities. This section outlines the multiple processes of utilizing the fuzzy expert system to diagnose cardiovascular disease. These processes include rule-based systems, input and output variable membership functions, fuzzification, and defuzzification. The accurate classification and diagnosis of cardiovascular disease depend on various parameters. This research determines the final selection of parameters after thorough discussions with medical experts.

Structure of Fuzzy System for Cardiovascular Disease

The central objective of this research is to propose an advanced multilayered fuzzy model for the timely detection of cardiovascular disease. This model aims to provide an advanced tool for identifying cardiovascular disease in its early stages. The structure of the fuzzy model is presented in Figure 1.

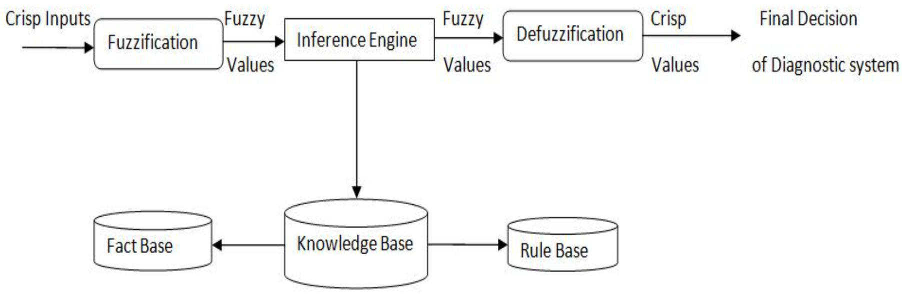

Figure 1. Structure of a Fuzzy Expert System Model.

The system used to validate the model consists of mainly three components:

- Knowledge Base: The knowledge base of the developed expert system includes:
- Fact Base: it consists of the knowledge gathered from the experts and their experiences
- Rule Base: The rule base maps the facts corresponding to the input and the outcome.
- The Inference Engine utilizes the inputs given to it and applies rules to make decisions.

Our proposed model incorporates Mamdani’s fuzzy logic. In such a model, the output of each rule is a fuzzy set. The fuzzy groups obtained from the output are combined into a single

fuzzy group using an aggregation method. Lastly, defuzzification methods are employed to calculate a final crisp output value. The Mamdani fuzzy systems are particularly advantageous for medical applications where rules are based on expert knowledge compared to other fuzzy systems and existing machine learning systems. Hence, the Mamdani fuzzy model was selected for this research.
The methodology employed in creating a multi-layered expert system for diagnosing cardiovascular disease is illustrated in Figure 2. The algorithm developed for the multilayered fuzzy model for the diagnosis of cardiovascular disease is outlined below:
Algorithm:
- Define blood pressure, diabetes, heredity, age, gender, and cholesterol parameters affecting cardiovascular disease.
- Design membership functions
- Design a repository where all rules are stored.

Layer 1
- Using membership functions, convert crisp data into fuzzy data.
- Map the inputs with the rules in the repository
- Merge the final output with each rule
- Convert the output from fuzzy to crisp data.

Layer 2
- Give the output of layer 1 as input to layer 2.
- Convert layer 2 inputs from crisp data to fuzzy data.
- Evaluate and merge rules and compute the output.
- Convert the output from fuzzy to non-fuzzy data."

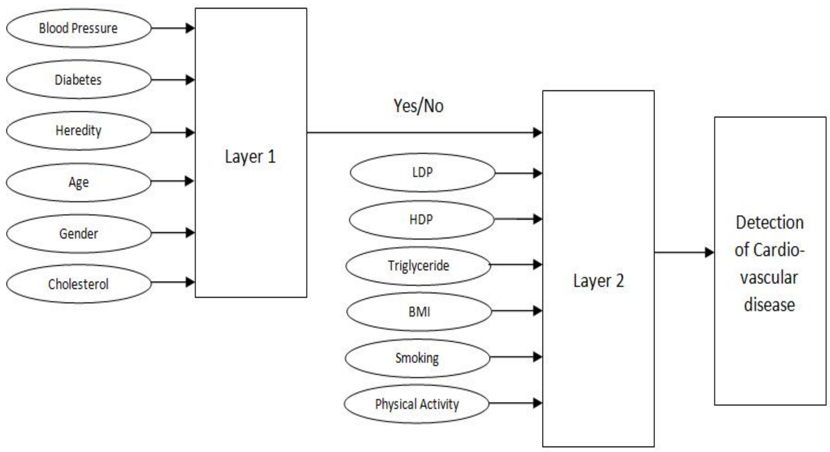

Figure 2. Methodology used in developing a multi-layered medical diagnostic system for cardiovascular disease.
Input variables and Fuzzification process
The initial step in developing an expert system based on fuzzy logic involves Fuzzification. This process entails converting the precise inputs provided to the system into fuzzy or linguistic values. Trapezoidal membership functions are utilized to represent both input and output variables in both layers of the system. The Mamdani Inference method is employed as the inference engine to develop the fuzzy expert system that diagnoses cardiovascular diseases.
Table 1 shows the values and states of cardiovascular disease's risk factors or input variables for layer 1, and Table 2 illustrates the input variables for layer 2.

Table 1. Description of membership functions of input variables of layer 1 of the proposed model of medical diagnostics.

Sr. No.	Input variables of Layer 1	State of input variables	Ranges of input variables
1.	Blood Pressure	Normal	<125
		High	>120
2.	Diabetes	Normal	<141
		Pre-diabetic	[120,200]
		Diabetic	>189
3.	Heredity	No	<5.5
		Yes	>4.4
4.	Age	Young	<36
		Mid Age	[33,66]
		Old	>52
5.	Gender	Male	<0.56
		Female	<0.48
6.	Cholesterol	Desirable	<200
		Borderline	[195,240]
		High	>235

Table 2. Description of membership functions of input variables of layer 2 of the proposed medical diagnostic system.

Sr. no.	Input variables of Layer 2	State of input variables	Ranges of input variables
1.	Low-Density Lipoprotein	Optimal	<100
		Near-Optimal	[90,135]
		Borderline High	[125,160]
		High	[155,190]
		Very High	>185
2.	High-Density Lipoprotein	High	<45
		Moderate	[35,60]
		Normal	<55
3.	Triglyceride	Normal	<1.8
		Medium	[1.6,2.5]
		High	[2.2,5.6]
		Very High	>5.6
4.	Body Mass Index	Underweight	<19
		Normal Weight	[18.5,24.9]
		Over Weight	[24.6,30]
		Obese	>29.5
5.	Smoking	Low	<2.64
		Medium	[1.8,9.5]
		High	>8.5
6.	Physical Activity	Low	<0.36
		Medium	[0.2,0.8]
		High	>0.64

The equations below model the trapezoidal membership function corresponding to the input variable “Low-Density Lipoprotein (LDP)” for the numeric values in Table 2.
Figures 3 and 4 show the graphical representation of membership functions of some given input variables of layer 1 used in the developed model.

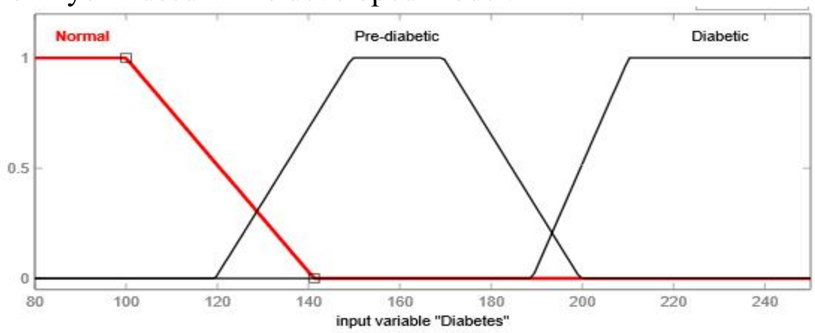

Figure 3. Graphical representation of Layer 1 input variable ‘Diabetes.’

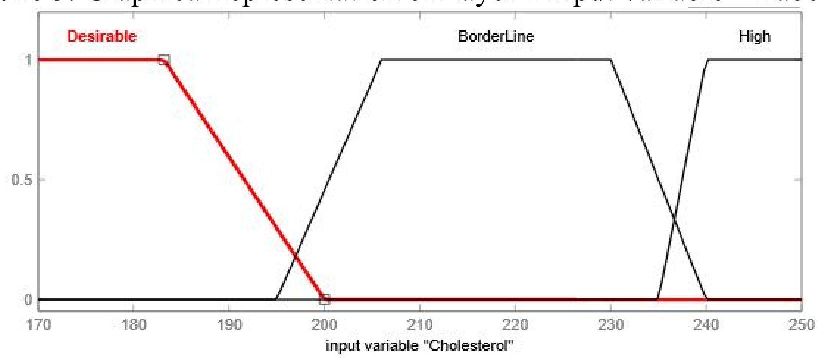

Figure 4. Graphical representation of Layer 1 input variable ‘Cholesterol’.
Figures 5 and 6 give the graphical representation of input variables for layer 2 used in developing a medical inference system for diagnosing cardiovascular disease.

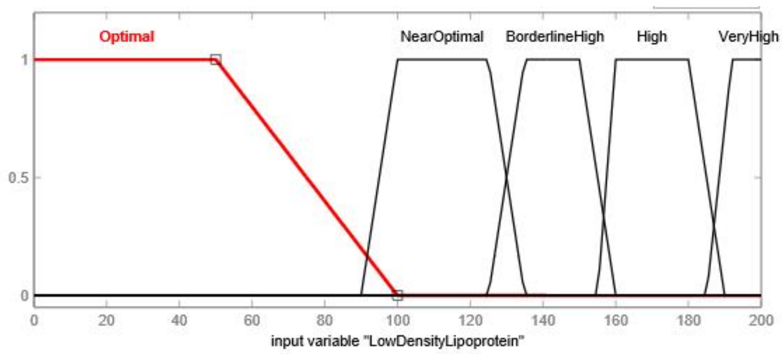

Figure 5. Graphical representation of input variable of layer 2 ‘Low-Density Lipoprotein’.

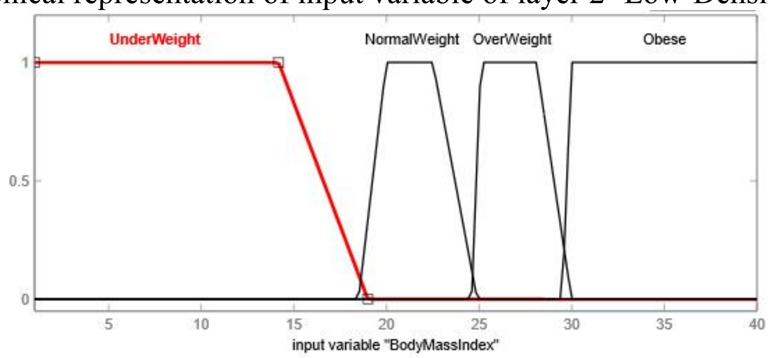

Figure 6. Graphical representation of input variables of layer 2 ‘Body Mass Index’.

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Fuzzy Rule Base

In this work, the rules for layer 1 and layer 2 are designed using the logical operator AND. The if-then rule statements formulate conditional statements, which incorporate fuzzy logic. The rules are extracted based on various risk factors considered when diagnosing cardiovascular disease.

The structure of the created rules for both layer 1 and layer 2 is shown below:

IF (Input variable 1 is ________) AND (Input variable 2 is ________) AND (Input variable 3 is ________) THEN (output is _______)

For Instance, rule no 1 of layer 1 is

IF (Blood Pressure is normal) AND (Diabetes us Normal) AND (Heredity is No) AND (Age is Young) AND (Gender is Male) AND (Cholesterol is Desirable) THEN Output is No

The total number of rules in layer 1 using the input variables is given by:

Membership Function of Blood Pressure * Membership Function of Diabetes * Membership Function of Heredity * Membership Function of Age * Membership Function of Gender * Membership Function of Cholesterol = 2*3*2*3*2*3 = 216 rules

The created rules in the fuzzy expert system are shown in Figure 7.

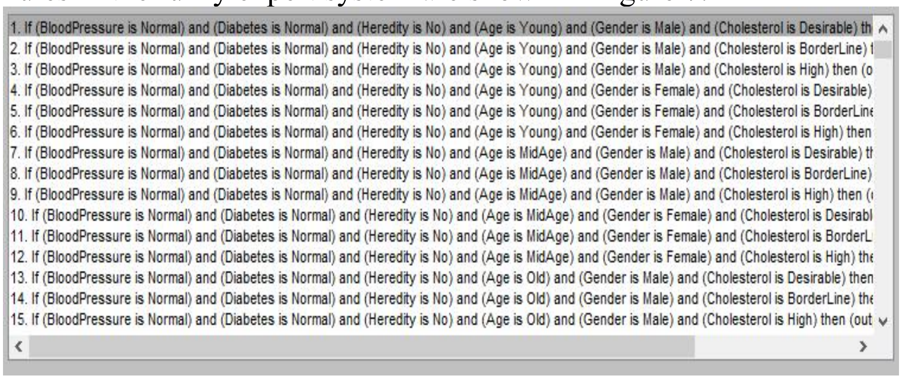

Figure 7. Rules of the proposed medical diagnostic system of layer 1.

The example of rules designed in layer 2 of the medical diagnostic system is explained below:

Rule no 1 of Layer 2:

IF (Low-Density Lipoprotein is Optimal) AND (High-Density Lipoprotein is High) AND (Triglyceride is Normal) AND (Body Mass Index is Underweight) AND (Smoking is Low) AND (Physical Activity is Low) THEN Risk of CVD is Low

Similarly, the total number of rules designed in layer 2 of the developed medial expert system by using the input variables is given by:

Membership Function of Low-Density Lipoprotein * Membership Function of High-Density Lipoprotein * Membership Function of Triglyceride * Membership Function of Body Mass Index * Membership Function of Smoking * Membership Function of Physical Activity = 5*3*4*4*3*3 =2,160 rules

Figure 8 shows the rules created for layer 2 of the medical diagnostic system.

Figure 8: Rules of the proposed medical diagnostic system of layer 2

Output variables and defuzzification process

The proposed medical diagnostic system provides a percentage of cardiovascular disease risk based on a patient's specific inputs. Table 3 represents the output variables utilized in layers 1 and 2 of this study.

Table 3. The output variables for layer 1 and layer 2 of the medical expert system.

Sr. No.	Layer	State case
1.	Layer 1	Yes No
2.	Layer 2	Very Low Low Medium High Very High

The initial layer of the system provides output based on the presence or absence of cardiovascular disease in the patient. The subsequent Layer 2, utilizes a medical diagnostic system to provide a conclusive result regarding the disease. This result is presented as a risk percentage, categorized into five levels: Very low, Low, Medium, High, and Very high. Figures 9 and 10 represent the output variables from Layer 1 and Layer 2.

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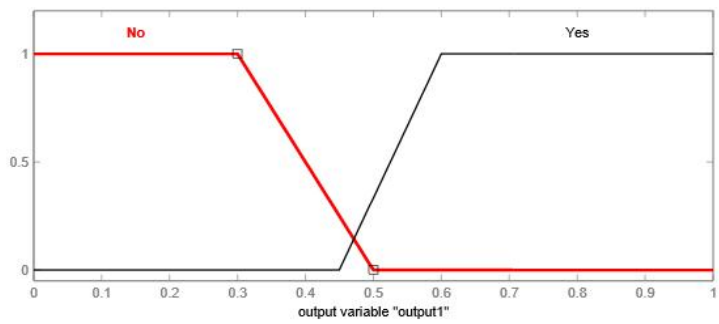

Figure 9. Graphical representation of output variables of Layer 1.

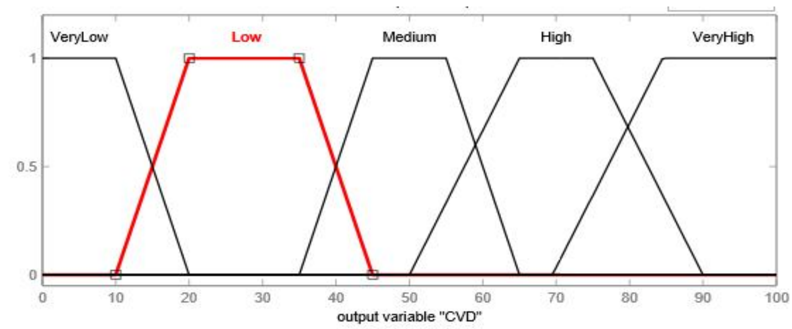

Figure 10. Graphical representation of output variables of Layer 2.

Results:

This multi-layered fuzzy expert system for diagnosing cardiovascular disease is rigorously evaluated. To validate the system's efficacy, its diagnostic results were compared against those provided by seasoned medical professionals. The study employed the Mamdani model for this comparison, and the software implementation was conducted using MATLAB. The system's output is generated using fuzzy logic during the defuzzification phase of the medical expert system.

Figure 11 and Figure 12 show the surface area samples of layer 1 and layer 2, respectively, for the degree of risk of cardiovascular diseases. The colors displayed in the surface area indicate various percentages of risk based on the input provided to the system. Figure 11 depicts how the input variables of blood pressure and diabetes can affect the risk of cardiovascular disease. It reveals that high diabetes and high blood pressure can lead to this disease. Similarly, in Figure 12, the input variables of low-density lipoprotein and high-density lipoprotein impact the risk of cardiovascular disease on a patient's data. If the value of these lipoprotein levels is high in a patient's body, the risk of this deadly disease increases.

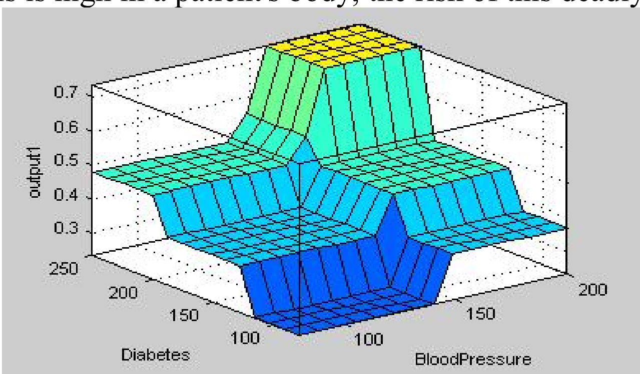

Figure 11. Sample of surface area of Layer 1.

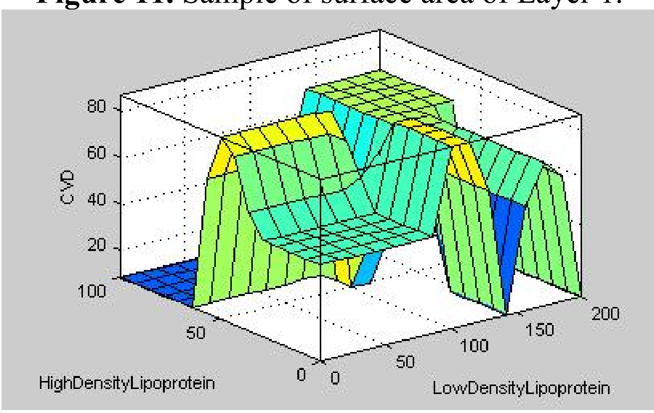

Figure 12. Sample of surface area of layer 2.

The system's performance was assessed based on various parameters, such as specificity, classification accuracy, sensitivity, precision, and F1 score. To determine its effectiveness, the system was tested on 200 patient cases. The model's suitability was determined by comparing its outcomes to those of experts in the field. A correct outcome was achieved when the system's results matched those of the professionals, and incorrect outcomes were noted when there was a discrepancy. Of the 200 test cases, the system accurately classified 190 of them.

Table 4 displays a confusion matrix of 190 distinct test cases, both correct and incorrect. The first column indicates that 35 test cases belong to the "very low" class, all accurately classified by the system. In the second column, 36 test cases belong to the "low" class, of which 33 were correctly classified while 3 were mistakenly classified as "very low." Similarly, the third column shows that out of 44 test cases in the "medium" class, 42 were correctly classified while 2 were classified as "low." The fourth column reveals that out of 53 "high" class test cases, only 4 were incorrectly classified. The final column shows that out of 32 test cases in the "very high" class, 31 were accurately classified and 1 was misclassified by the system.

Table 4: Confusion Matrix for cardiovascular disease.

Very Low	Low	Medium	High	Very High	Class Name
35	00	00	00	00	Very Low
03	33	00	00	00	Low
00	02	42	00	00	Medium
00	00	00	49	04	High
00	00	00	01	31	Very High

Table 4's confusion matrix can be simplified by treating the "Very Low" and "Low" columns as a single "No" category, while merging the "Medium," "High," and "Very High" columns into a "Yes" category. This leads to a reduction in the size of Table 4, as shown in the updated Table 5.

Table 5: Confusion matrix for cardiovascular disease with reduced dimensionality

No	**Yes**	**Class Name**
68	05	No
05	122	Yes

From table 5: True Positive (TP): 122, False Negative (FN): 05, False Positive (FP): 05, True Negative (TN): 68

The performance parameters can be represented in the tabular form as shown in table 6.

Table 6. Performance parameters.

Performance parameter	**Percentage value**
Sensitivity	96.06%
Specificity	93.15%
Precision	96.06%
Classification Accuracy	95%
F1 Score	96.06%

The performance parameters can be represented in the graphical form as shown in figure 13.

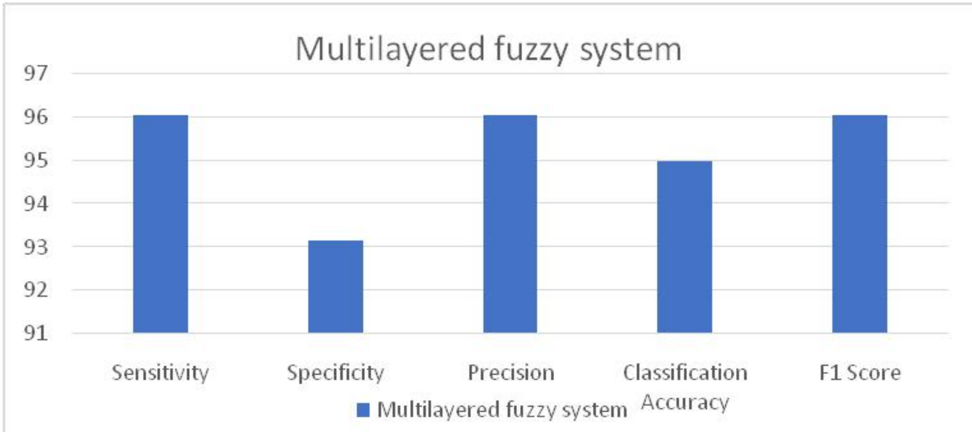

Figure 13. Calculated performance parameters in graphical form

Conclusion:

This study modelled an effective and accurate identification of cardiovascular disease. Our model overcomes the limitation of the existing models, which are based on a single layer. Existing models do not use multiple control strategies and do not integrate multiple criteria. The multi-layered fuzzy inference system presented in this study handles ambiguous data, thereby enhancing decisions on cardiovascular disease. The key impact of this study is to provide a system that is a supportive tool for physicians. Validation of system used important performance parameters. Results of the validation included sensitivity, specificity, precision, classification accuracy, and F1 score, producing impressive values of 96.06%, 93.15%, 96.06%, 95%, and 96.06%, respectively.

In the future, this research could explore various combinations of input-output parameters and consider an expanded range of input variables based on the risk factors associated with cardiovascular disease. Medical science continues to discover additional important parameters that could influence the functioning of cardiovascular disease, and these could be integrated into the system for improved performance. logistics regressions, Cox models, tree-based models, SVM, gradient boosting, Hybrid ensembles etc methodologies could be applied to map inputs to outputs and improve calibration, discrimination and interpretability to enhance diagnosis of cardiovascular disease, and the improve accuracy of the developed system.

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