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FRBF: A Fuzzy Rule Based Framework for Heart Disease Diagnosis

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Abstract Heart disease is also known as cardiovascular disease, and it is one of the most dangerous and deadly diseases all over the globe. Cardiovascular disease is considered a significant illness in old and middle age. Still, recent trends have shown that cardiovascular disease is also a deadly disease in the young age group due to irregular habits. However, Angiography is one of the ways to diagnose heart disease, but it is costly and has significant side effects. This research paper aims to design a fuzzy rule-based framework to analyze heart disease risk levels. Our proposed framework used a Mamdani interface system and utilized the UCI machine repository dataset for heart disease diagnosis. In this proposed study, we have used ten input attributes and one output attribute with 554 rules. Besides, a comparative table is presented, where the proposed methodology is better than other methodologies. According to the suggested methodology results, the performance is highly successful, and it is a promising tool for identifying a heart disease patient at an early stage. We have achieved accuracy, sensitivity rates of 95.2% and 87.04%, respectively, on the UCI dataset.

Keywords: Fuzzy Rule Based System, UCI, Angiography, Heart Disease, Mamdani Interface System.

1 Introduction

According to World Health Organization (WHO), 17.9 million people die each year from cardiovascular disease all over the globe, and it is around 31% of death in all worlds. Heart diseases like cardiovascular disease, coronary heart disease, hypertension, and stroke remain the number one cause of death globally compared to other diseases. [2-6]. Cardiovascular disease occurs when the heart functionality is not running smoothly, and due to this, the heart does not pump the required amount of blood to other parts of the body, causing heart failure. It is sometimes challenging to identify heart disease due to several factors like blood pressure, cholesterol, heart rate, and chest pain type [1-20].

Several Researchers are looking forward to developing a computer-based tool to diagnose heart disease early to reduce the death rate. Such automated tools are readily available and less expensive [6-9, 17, 47]. At the start of a decade, research advancement in healthcare industries provides a better quality of human health. Therefore, the researcher is more focused on developing a medical diagnosis system. Developing a medical diagnosis system is not an easy task, and it is a highly complex system that is required to operate effectively with high accuracy. It deals with real-life scenarios, so knowledge of disease is essential and mandates many other skills to develop a system [1-2, 32].

This paper focuses on a Fuzzy logic concept that will provide a mathematical theory to solve uncertainty associated with a human disease diagnosis requiring a high amount of accuracy [12]. In 1965, Zadhe introduced a Fuzzy Set Theory concept to generalize Boolean logic where an element is either present or absent from the given set [6]. On the other side, a fuzzy set is a concept where an element can "Less or more" from the given set, ensuring a proper transition between member and non-member function. For this reason, and due to uncertainty in data, the fuzzy set provides an outstanding model for the medical diagnosis system. Fuzzy Expert System, which derives from Fuzzy Logic, is one of the most critical applications of FL. It is used to design relationships between input and output attributes. Fuzzy logic is critical in diagnosing any disease in a medical diagnosis system due to its simple and easy-to-understand structure [7-11]. In the past, the researcher has developed many expert systems

using Fuzzy Logic concepts, such as Diabetic [11] and Arrhythmia[7]; however, as it deals with real-life scenarios, high accuracy is critical, so research continues in this field.

Various techniques, including AI, Data Mining, Neural networks, and Big Data [24], have been used to determine the risk level of heart disease. Unlike SVM and PSO, the fuzzy rule-based system provides a convenient model for knowledge-based representation [36-38]. Rule-based statements consist of "if condition(s) then Event(s)," which is understandable human language as compared to complex natural language [20]. However, making rules is a challenging task and requires expertise in the domain, and output depends entirely on rules. Hence, a complex domain like disease diagnosis requires complete knowledge about the disease and the combination of an attribute that will require [41].

The rest of the paper is organized as follows. Section "Related Work Discussion" described all the previous work done in this field. We have covered a broad area of heart disease Diagnosis using all the techniques. The methodology section covered all the detail of implementation has given in the "Proposed Methodology" section. After that, we compared our result with all other techniques in the "Performance Comparison" section and discussed our conclusion.

2 Related Work Discussion

So far, lots of research has been done in Early Prediction of Heart Disease Diagnosis using Fuzzy Logic, Machine Learning Techniques, Data Mining, etc. Alqudah [1] designed an expert system for heart disease diagnosis. In this paper, the author used a local database based on Jordan Hospital and achieved higher accuracy with a minimum number of rules, but only eight input parameters were used for prediction. The author used a fuzzy interface system with visual basic C# and developed a window-based application. Lanchu [2] proposed a meditative fuzzy logic system for diagnosing heart disease, and in this paper, the author used 11 attributes with 44 rules. It is a special kind of fuzzy controller technique where a high amount of data uncertainty exists. The author explains all the fuzzy rules in detail and uses centroid techniques for de-Fuzzification. Arabasadi et al. [5] developed a computer-based decision support system for heart disease diagnosis using a hybrid neural network. In this paper, the authors have used UCI machine repository dataset for prediction and achieved 93.85% accuracy. For feature selection, the author has considered four algorithms: SVM, PCA, Gini Indexed, and Information gain. With the help of this method, Heart disease can be detected without doing a test of angiography.

In 2019, Ahmed-Aharjya [4] introduced cuckoo search techniques and rough set theory for heart disease diagnosis. In this paper, the Author has provided brief details of the entire algorithm like SVM, PSO, etc., and given basic details of the Cuckoo Search algorithm (CSA). The Author used 11 attributes and achieved 93.7% accuracy for predicting heart disease using the CSRS model. Barini et al. [5] provided a comparative model for classifying cardiovascular risk. Gupta et al. [6] proposed a Machine Intelligent Model Framework for heart disease diagnosis with 93.44% accuracy. In this model, the authors used the Cleveland dataset and provided whole attributes with their ranges. In this paper, the Author explains the research contribution of most machine learning algorithms like SVM, KNN, DT, and RF. Baihaqi et al. [7] designed a Fuzzy rule-based expert system for Coronary artery disease with the help of 3 algorithms, namely CART, Ripper and C4.5. In this paper, the Author achieved 81.82% accuracy and provided a complete comparison of three algorithms. They had used MATLAB tool for simulation with 176 actual patient data. Alickovic- Subasi [8] developed a medical decision support system to diagnose heart arrhythmia using RFC and DWT. The Author used RFC for ECG heartbeat signal classification and DWT to decompose ECG signals in this complete research. For performance and testing purposes, they have used MIT-BIH dataset.

In 2018, Mastoi et al. [10] presented a review article based on an automated diagnosis of coronary artery disease compared to all algorithms and techniques. This article shows the database like UCI and Local hospital datasets and all the comparison studies related to the diagnosis system. Lahsasna et al. [11] developed a Fuzzy rule-based expert system for coronary heart disease diagnosis. In this paper, the author proves that the rule-based expert system is more efficient compared to the machine learning algorithm. They have used the Cleveland dataset for diagnosis purposes with 82.93% accuracy. Hassan et al. [12] presented a paper based on a fuzzy expert system for diagnosing heart disease with different databases. In this paper, the author shows all different databases with the details of the attribute. Lee-Wang [13] proposed a novel fuzzy expert system based on the five-layer fuzzy ontology to diagnose diabetes and used the PIDD database. In this paper, the author explains the features extraction algorithm with complete attributes. Agrawal et al. [14] introduced a cardiorenal syndrome in heart failure and covered other chronic diseases such as kidney disease. In this paper, the author mentioned all the risk factors with dialysis options.

Ghumbre- Ghatol [15] presented a machine learning algorithm for heart disease diagnosis, and they have also mentioned in their paper that SVM and Sequential Minimization Optimization algorithm are the better options for medical disease diagnosis. Diez et al. [16] presented a Literature Review based on an E-health monitoring system for chronic heart failure. The author searched based on a different academic database like Scopus, PubMed, etc. They have shown different algorithm techniques with complete information like used database and accuracy. Meda- Bhogapathi [17] developed a heart attack risk assessment model using genetic algorithms and data mining techniques. The author has used the UCI database for testing purposes and provided a comparison table of previous work and techniques. Ahmed et al. [18] introduced an improved hybrid genetic algorithm for an intelligent medical diagnosis system. This paper considers Heart, Cancer, and Diabetic disease and provides a GA-MLP algorithm with higher accuracy. Teraada et al. [19] designed a Fuzzy Expert System for Cardiovascular disease applying fuzzy concepts on risk factor attributes. This paper explains all the fuzzy rules for the diagnosis system and uses MATLAB for simulation with the centroid technique for de-fuzzification. Maragatham – Devi [20] used a combination of Big Data and Deep Learning to check heart failure and explain the application of Deep Learning in Medical Diagnosis.

Mohan et al. [21] proposed a new hybrid machine learning technique for heart disease prediction with an accuracy of 88.7%. This paper explains the ML techniques like KNN, SVM, LR, and NN with the UCI Machine repository dataset. They used 13 attributes and provided a comparison table of all other algorithms. Paul et al. [22] introduced genetic algorithms for an early prediction of heart disease. They have divided the complete process into four parts and used the UCI dataset. Shi et al. [23] implemented an evolutionary fuzzy expert system and discussed Triangular and Trapezoidal functions in detail with their shapes. It is a basic but effective paper related to the basic concept of the fuzzy expert system.

Tsipouras et al. [24] proposed a diagnosis of coronary artery disease using data mining and a fuzzy rule-based expert system. In this paper, the author used the decision tree for rule extraction and used 19 attributes for diagnosis. Alshraideh et al. [25] developed a web-based diagnosis detection system for heart disease. The author used the UCI Irvin dataset for prediction, and this paper's concept is different because the author used a cloud environment with an ECG sensor. Li et al. [26] developed a system for early prediction of risk levels for cardiovascular using artificial techniques. This paper provides the importance of artificial intelligence techniques for the medical diagnosis system and explains the LR, SVM, and Naive Bayes algorithms.

Shu-Tang [27] introduced a representation-based classifier for heart disease diagnosis. The author introduced heart detection using facial expressions rather than heart disease tests like ECG and blood tests in this research. The author claim that for diagnosis of heart disease, all the tests are time-consuming, the idea of facial image analysis is founded in Chinese medicine, and they had used local hospital dataset from TCM hospital, china. Gupta et al. [28] developed a cloud-based environment for heart disease detection and used the Naive Bayes algorithm for implementation with 87.91% accuracy. In the proposed study, the author used the Cleveland dataset and all other machine learning algorithms like SVM, RF, BT, and Naive Bayes; after the implementation, the author got the highest accuracy using the Naive Bayes algorithm.

Berikol et al. [29] proposed a heart disease diagnosis using SVM algorithm and achieved the highest accuracy compared to other algorithms. Wang et al. [30] used deep learning with mammograms to identify cardiovascular disease at an early stage. In this research work, the author focuses on women's patients and used mammogram images as simulation work input. Barini et al. [31] present a comparative framework using the application of fuzzy unit hypercube. This study has shown that the fuzzy set must be viewed as a hypercube so any problem can be examined quickly.

Kelly [32] presented a paper related with heart disease symptoms, reasons and presentation techniques and also mentioned the current research in this area. In this study, he is provided a comparison table of 10 years where death and age ratio mentioned. Baihaqi t al. [33] introduces a data mining and fuzzy system technique to identify risk level of heart disease. This paper focuses on data mining algorithm for data classification and used mamdani interface system for simulation work with 94% accuracy.

Mandal- Sairam [34] developed a new technique for heart disease diagnosis. This research focused on MCA (Multiple Correspondence Analysis) for the variable relationship of heart disease. Mak [35] provides a theoretical model to predict heart disease in any patient. This paper focuses on Min-Max composition with Naive Bayes classifier algorithm. Abd et al. [36] developed a heart disease detection system based on the al-Nasiriyah center for heart in Iraq. This study entirely focused on IRAQ local hospital dataset. Gambhir et al. [37] have used soft computing techniques in medical diagnosis systems. This paper presents the review of all the soft computing techniques towards the diagnosis system and presents the table related to all esteemed

journals having specific domains in medical diagnosis. Sengur [38] proposed a valvular heart disease diagnosis system using Support Vector Machine algorithm in which the author has used local data set received from Firat Medical Center. Agrawal et al. [39] proposed a qualitative analysis for heart failure in Kerala, India. Their analysis is based on information provided by the 8 Hospitals from Kerala to understand the barrier and facilitators of the heart failure care unit. Using a clustering algorithm, Yilmaz et al. [40] developed a new data preparation method for heart and diabetic disease. In this research, an author has used UCI stalog dataset for heart disease and PIMM Indian dataset for diabetic disease. They have used the SVM algorithm for data classification and Classification accuracy obtained using the 10 Fold Cross-Validation Method. Rajamhoana et al. [41] review Deep learning and Machine learning techniques to predict heart disease diagnosis and analysis for future research scope.

Zolnoori et al. [42] developed a rule-based expert system for evaluating a level of asthma control, and they have used 14 input attributes with a local dataset from Tehran. Manikandan [43] designed a heart disease prediction system using the Navie Bayes algorithm with UCI machine learning dataset, and they have achieved 81.25% accuracy. Kasbe-Pippal [45] developed a fuzzy expert system for heart disease and UCI database and achieved 92.33% accuracy. Nourmohammadi-Khiarak et al. [47] designed a hybrid method for heart disease diagnosis with the combination of the KNN algorithm used for classification. This paper focused on improving feature classification and decreasing the number of attributes from the dataset. Tougui et al. [48] proposed a hybrid model using Data Mining and Machine learning technique for heart disease classification. In this study, the authors used the UCI dataset to combine 13 input attributes and one output attribute.

3 Proposed Methodology

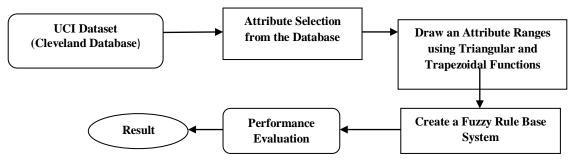


Figure 1. Proposed Architecture of FRBF

In this study, our proposed methodology consists of 5 parts: Database Selection, Attributes Selection, Simulation Work, and Create Fuzzy Rules on Input attributes, and Performance evaluation on the database.

3.1 Database Selection

As explained in the previous section, this study used Cleveland Dataset with 250 Instances [46].

3.2 Attributes Selection

The Cleveland Dataset consists of 14 features, but we have used 11 attributes in this proposed study because these attributes do not contain missing values. In table 1, we will present the ten input attributes with their ranges & fuzzy set values [45-46].

Input Attributes	Ranges	Fuzzy Set Values
	<134	Low
55	127-153	Medium
BP	142-172	High

(In mm hg upper)	>154	Very High
	<198	Low
Comments la la comp	188-250	Medium
Serum cholesterol	217-307	High
	281-681	Very High
	0-141	Low
Maximum Heart Rate	111-194	Medium
	152-353	High
	0-2	Typical angina
	1-3	Atypical angina
Chest Pain	2-4	Non typical-angina
	3-5	Asymptomatic angina
	-1 - 1	
Fasting Blood Sugar	0 - 2	No (0)
	0-2	Yes(1)
	<2	Low
Old Peak	1.5-4.2	Medium
	2.5>	High
	<0.4	Normal
Electrocardiography	0.4-1.8	ST_T abnormal
(ECG)	1.8>	Hypertrophy
	0-3	Normal
Thallium Scan	3-6	Fixed Defect
(ThaScan)	6-7	Reversible Defect
	0-7	
	-1-1	Female (0)
Gender	0-2	Male (1)
	<38	Young
	33-45	Medium
Age	40-58	Old
	>52	Very Old
	-1 - 1	TT 1/1.
Output Attribute	1 - 2	Healthy Low Risk
DiseaseCondition	2-3 3-4	Risk
	$\mathfrak{I}-4$	High Risk

4 - 5	Very High Risk

4 Simulation Work

We have used the MATLAB (Matrix Laboratory) tool for simulation work for practical implementation. In the MATLAB tool, we have used the fuzzy logic toolbox, the most common and better tool to deal with the uncertainty of any data. Given the above table, for all the attribute ranges, our study used triangular and trapezoidal functions, which are explained below [45].

4.1 Triangular Function

Triangular Function ($\mu(x)$) can be defined as a Minimum limit **P**, Maximum limit **Q**, and a value m, where **P** < **x** < **Q**. In MATLAB tool, it can be used as a trimf [20-45].

$$\mu(x) = \begin{cases} 0, & x \le P \\ \frac{x-P}{m-P}, & P < x \le m \\ \frac{Q-x}{Q-m}, & m < x < Q \\ 0, & x \ge Q \end{cases}$$
(1)

4.2 Trapezoidal Function

Trapezoidal Function ($\mu(x)$) used as a Minimum limit **P**, Maximum limit **R**, a minimum support limit **Q**, and a maximum support limit L, where **P** < **Q** < **R**< L[20-45].

$$\mu(x) = \begin{cases} 0, \ (x < P)or \ (x > L) \\ \frac{x - P}{Q - P}, & P \le x \le Q \\ 1, \ Q \le x \le R \\ \frac{L - x}{L - R}, \ R \le x \le L \end{cases}$$
(2)

The ranges in Table 1 correspond to the attributes determined by the functions listed above.

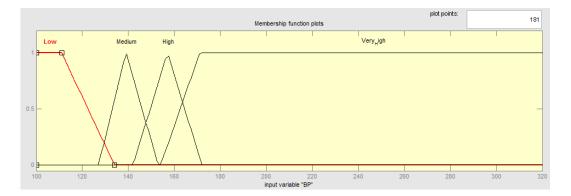


Figure 2. Membership Function for Attribute for "BP"

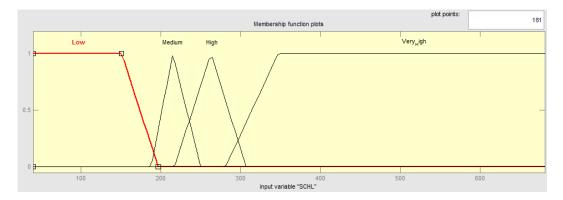


Figure 3. Membership Function for Attribute for "SCHL"

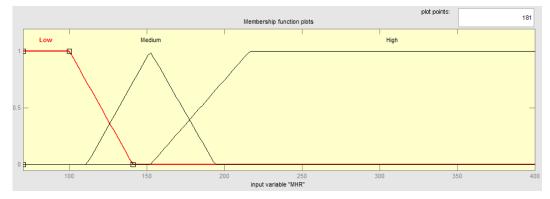


Figure 4. Membership Function for Attribute for "MHR"

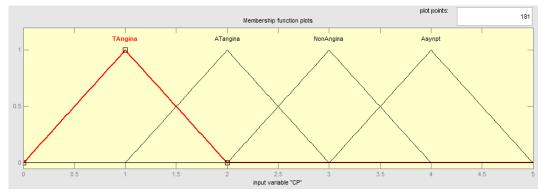


Figure 5. Membership Function for Attribute for "CP"

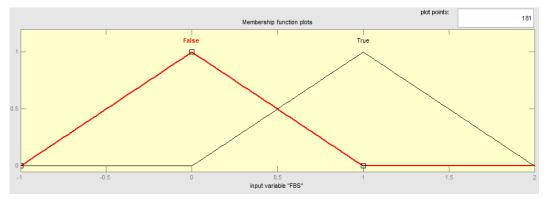


Figure 6. Membership Function for Attribute for "FBS"

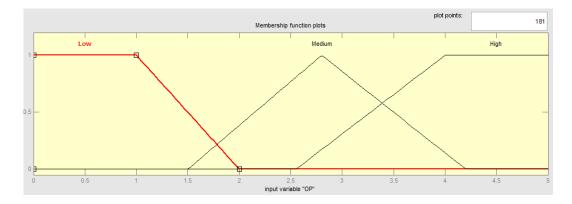


Figure 7. Membership Function for Attribute for "OP"

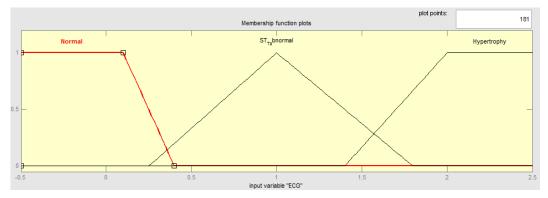


Figure 8. Membership Function for Attribute for "ECG"

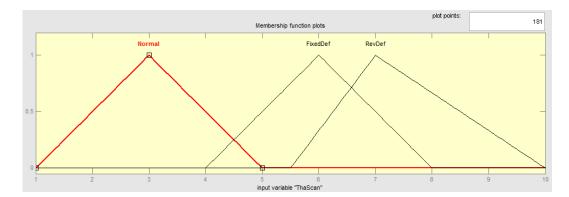


Figure 9. Membership Function for Attribute for "ThaScan"

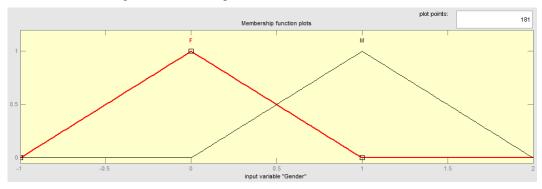


Figure 10. Membership Function for Attribute for "Gender"

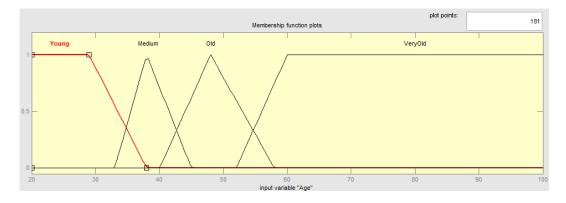


Figure 11. Membership Function for Attribute for "Age"

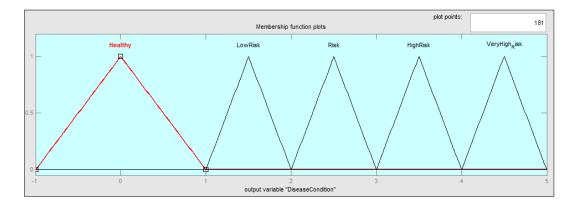


Figure 12. Membership Function for Output Attribute for "Disease Condition"

5 Fuzzy Rule Based System

After making a member function of input attributes, we can make a fuzzy rule base system, which is the essential part, and the system's performance entirely relies on rules [1-4]. The fuzzy rule base system combines attributes associated with AND/OR operator. This study consists of 554 rules and some of the rules mentioned below [45].

Rule No#	Rules Description
R#1	If (BP is Low) and (SCHL is Low) and (MHR is Low) and (CP is Tangina) and (Gender is F) and (Age is Young) then (DiseasecCondition is Healthy)(1)
R#12	If (BP is Low) and (SCHL is Low) and (MHR is High) and (CP is Tangina) and (Gender is M) and (Age is Young) then (DiseasecCondition is Healthy)(1)
R#35	If (BP is Low) and (SCHL is Low) and (MHR is Low) and (CP is Tangina) and (Gender is F) and (Age is Old) then (DiseasecCondition is Healthy)(1)
R#62	If (OP is Low) and (ECG is ST_T_abnormal) and (ThaScan is Normal) and (Gender is F) and (Age is Young) then (DiseasecCondition is Healthy)(1)

R#84	If (FBS is False) and (Gender is F) and (Age is Medium) then (DiseasecCondition is Healthy)(1)
R#100	If (BP is Low) and (SCHL is Low) and (MHR is Low) and (CP is Tangina) and (FBS is False) and (OP is Medium) and (ECG is Normal) and (ThaScan is Normal) and (Gender is M) and (Age is Medium) then (DiseasecCondition is Healthy)(1)
R#173	If (BP is Vey_High) and (SCHL is Vey_High) and (MHR is High) and (CP is Asynpt) and (Gender is M) and (Age is Young) then (DiseasecCondition is VeryHigh_Risk)(1)
R#199	If (BP is Vey_High) and (SCHL is Vey_High) and (MHR is High) and (CP is Asynpt) and (Gender is M) and (Age is Medium) then (DiseasecCondition is VeryHigh_Risk)(1)
R#233	If (BP is Vey_High) and (SCHL is High) and (MHR is Medium) and (CP is Asynpt) and (Gender is F) and (Age is Young) then (DiseasecCondition is HighRisk)(1)
R#265	If (FBS is True) and (OP is High) and (ECG is ST_T_abnormal) and (ThaScan is Normal) and (Gender is M) and (Age is Young) then (DiseasecCondition is HighRisk)(1)
R#299	If (OP is Medium) and (ECG is ST_T_abnormal) and (ThaScan is FixedDef) and (Gender is M) and (Age is Medium) then (DiseasecCondition is HighRisk)(1)
R#413	If (BP is Low) and (SCHL is Medium) and (MHR is Low) and (CP is Tangina) and (Gender is M) and (Age is Young) then (DiseasecCondition is LowRisk)(1)
R#500	If (BP is Medium) and (SCHL is Medium) and (MHR is High) and (CP is Asynpt) and (Gender is F) and (Age is Young) then (DiseasecCondition is Risk)(1)
R#554	If (BP is High) and (SCHL is Very_High) and (MHR is High) and (CP is Asynpt) and (Gender is M) and (Age is Old) then (DiseasecCondition is VeryHigh_Risk)(1)

6 Performance Evaluation

MATLAB rule viewer can evaluate system performance after rules are defined. The below section will provide a figure of the rule viewer and a sample set of values from the UCI Cleveland dataset. It consists of all input attributes; when the user provides an input value to all attributes, the output attribute shows the result based on Input values.

BP = 210 SCHL = 361 1	MHR-235 CP-	2.5 FBS+0.5	0P+25	EC0 = 1	TheScen = 5.5	Gender = 0.5	Age = 60	DisesseConstitut = 1.8
					мое	left	t down	

Figure 13. Rule Viewer for Performance Evaluation

In the dataset specification section, we discussed Cleveland dataset patient information with the help of a rule viewer. In this study, for getting higher accuracy on more instances, we have used 250 instances for testing purposes, and some of the tested data will describe in Table 3.

BP	SCHL	MH R	C P	FB S	ОР	ECG	Tha Scan	Gender	Age	Our Result	DB Result
140	192	148	4	0	0.4	0	6	1	57	0.006	0
120	340	172	3	0	0	0	3	0	58	0.549	0
132	20 7	168	4	0	0	0	7	1	57	0.0006	0
130	253	144	4	0	1.4	0	7	1	60	1.0021	1
125	309	131	3	0	1.8	0	7	1	64	1.054	1
145	282	142	4	0	2	2	7	1	60	2.104	2
120	237	71	4	0	1	0	3	1	67	2.14	2
180	274	150	3	1	1.6	2	7	1	68	3.03	3
130	330	132	4	1	1.8	2	7	1	63	3.03	3
145	174	125	4	1	2.6	0	7	1	70	4.01	4
138	166	125	4	1	3.6	1	3	1	61	4.08	4

Table 3: Sample Tested Data from Cleveland Database

In the above table, we have provided a sample tested data of the UCI Cleveland database. For performance evaluation purposes, we have to calculate Accuracy, Sensitivity, and Specificity with the help of a confusion matrix [6-20]. Confusion Matrix generates four outcomes, namely True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which can be found in Table 4.

Total Cases	Predicated Values : NO	Predicated Values : YES
Actual Values: NO	TN	FP
Actual Values: YES	FN	TP

Table 4: Confusion Matrix General Representation

True Positive (TP) = This is a case, where we have predicated a heart disease and according to database, actual it is.

True Negative (TN) = This is a case, where have predicated a no heart disease and they do not have the disease.

False Negative (FN) = This is a case, where have predicated a no heart disease and they have the heart disease.

False Positive (FP) = This is a case, where have predicated a heart disease and they do not have the heart disease.

The following formulas are used for the calculation of Accuracy, Specificity and Sensitivity [19] [34].

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \times 100\%$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

$$Specificity = \frac{TN}{TN + FP} \times 100\%$$

The Cleveland dataset used in our proposed study, we have used 250 Instances and all the measurement are shown below in confusion matrix Table 5.

Table 5: Confusion	Matrix I	Measurement	on	Cleveland	Dataset

Total Cases = 250	Predicated Values : NO	Predicated Values : YES
Actual Values: NO	TN = 173	FP = 4
Actual Values: YES	FN = 8	TP = 65

$$Accuracy = \frac{65 + 173}{173 + 4 + 8 + 65} = 95.20$$

Sensitivity =
$$\frac{65}{65+8}$$
 = 89.04

$$Specificity = \frac{173}{173 + 4} = 97.74$$

Now from the above measurement, our proposed study Accuracy, Sensitivity & Specificity are 95.2%, 89.04% and 97.74%.

7 Performance Comparison

In this section, we have compared our proposed work with the various proposed models. In Table 6, the comparison with the proposed methodology has given below.

Authors	Method	Accuracy	Sensitivity	Specificity
		(In %)	(In %)	(In %)
Arabasadi, Z et al. [3]	KNN-GA	93.85	97	92
P. K &Acharjya D [4]	CSRS	93.7	-	-
A. Gupta et al. [6]	FAMD + RF	93.44	89.28	96.96
Baihaqi et al. [7]	FRBS + C4.5	81.82	78.25	84.00
Ghumbre S.U et al. [15]	SCM +SMO	85.05	84.60	85.90
Mohan et al. [20]	HRFLM	88.7	92.8	82.6
Li. et al. [25]	SVM	85.95	85.01	86.95
Gupta et al. [27]	NB	92.14	92.30	92.15
Baihaqi et al. [32]	DM + Fuzzy	94.92	-	-
Sengur [37]	SVM with Ensembles (Single Classifier)	92.7	94.5	90.00
Manikandan S. [42]	NB	81.25	-	83.67
Verma et al. [43]	MLR	88.4	-	-
Mohammadpour R[45]	FRBS	92.8	-	-
Proposed Study	FRBF	95.2	89.04	97.74

Table 6: Performance Comparison of the proposed method FRBS with other Models

8 Conclusion and Future Work

Heart disease prediction is a challenging task, and if the disease can be detected early, the mortality rate can be decreased. In this proposed study, we have designed a fuzzy rule-based framework to predict a risk level of heart disease. The proposed study FRBF can assist in identifying the instance as heart patient category or normal patient category. The proposed framework was tested on the Cleveland database from the UCI machine repository and used 250 instances to calculate accuracy. The system's current performance shows that this approach is good enough to provide more accuracy, and the comparison of previous work with the current study shows the same. Furthermore, we will require taking more sample test data for future prescriptive. For the user-friendly behavior, we will require developing a user-friendly interface to be flexible for any user to work on it.

Abbreviation	Meaning
UCI	University of California, Irvine
AI	Artificial Intelligence
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
LR	Logistic regression
PSO	Particle Swarm Optimization
BP	Blood Pressure
MLR	Multiple Linear Regression
GA	Genetic Algorithm

	Abł	oreviation	Table
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Compliance with Ethical Standards

Conflict of interests: Author declares that he has no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animal performed by any of the authors.

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