Informatics in Medicine Unlocked 17 (2019) 100257

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: http://www.elsevier.com/locate/imu

Detection of Cardiac arrhythmia using fuzzy logic

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ARTICLE INFO

Keywords:
Coronary heart disease
Machine learning
Weighted fuzzy clinical decision support system

ABSTRACT

Background: There is recent increasing interest in physical fitness, and improvement in applications for this purpose have been standout amongst recent research efforts. An example of such a health application is the identification of coronary disease using PC-based determination strategies, wherein the information is acquired from different sources and assessed automatically by computational means.

Objectives: Implementation of a fuzzy-based clinical detection model for coronary risk prevention, which mainly comprises two main objectives: (1) designing weighted fuzzy standards, and (2) creating a fuzzy guidelines based choice supporting network.

Methods: In prior work, information was obtained from a supportive network which utilized learning from medical specialists, and ported this information into a PC processing queue. The entire process, however, is time consuming and tedious. Medical specialists reach conclusions based on manual observations, which can be inaccurate in some instances. To address this issue, machine learning procedures have been created to obtain information from patients.

Results: and Conclusions: Herein, a fuzzy rule-based clinical system is described for the automatic detection of Coronary Heart Disease (CHD). This was done by gathering information, implementing assessment procedures, and creating knowledge from patient clinical data.

1. Introduction

Currently, coronary heart diseases (CHD) are is a major cause of death in India and other countries [1,2]. The main risk factors of CHD in Indian population are: hypercholesterolemia, smoking, diabetes, serum cholesterol, hypertension, and high body mass index (BMI) [3,4]. Apart from these genetic factors, life style variations, socio economic status and disorders of the heart and blood vessels, peripheral artery disease, rheumatic heart disease, and cerebrovascular stroke play key roles in the progress of CHD. South Indians are a group with a high possibility of acquiring Cardiovascular Disease (CVD) and diabetes. India, the largest populated country, has high coronary risk factors in certain areas. The main hazard factors of cardiovascular diseases in the Indian population are: high levels of cholesterol, diabetes mellitus, smoking, blood pressure, and high BMI. South Indians have an increased susceptibility to heart disease, which is further enhanced by environmental triggers such as lack of physical activity, excessive caloric in-take, obesity and stress. Recent studies indicate that specific socio economic factors may also increase CVD risk.

Lifestyle has changed in recent decades, due to which there is a growth of diseases such as CVD [5]. Heart diseases at age 35 and above are effected by lifestyle and dietary changes [6] more than genetic factors. The best five healthy practices are maintaining low BMI, regular exercise, a low calorie diet, no alcohol consumption, and non-smoking habit.

Several studies have been proposed to detect CVD using data mining tools such as decision trees, Support Vector Machines, Bayesian theory, and neural networks [7,8]. To identify major risk factors (features) of heart disease, herein we have applied machine learning algorithms on the Cleveland clinical database. Previously, the utilization of the PC was to construct a learning based on clinical decisions, which utilizes information from medical specialists and moves this information into the PC. This procedure is tedious however and relies upon medical specialist decisions, which may be incorrect.

2. Background

The Fuzzy Inference instrument can likewise be utilized to foresee a

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https://doi.org/10.1016/j.imu.2019.100257
Received 1 August 2019; Received in revised form 25 September 2019; Accepted 18 October 2019
Available online 23 October 2019

wide range of dangers including psychological and physical illness conditions. The literature shows that CVD can be foreseen in advance using data mining and machine learning tools [9]. CVD forecast models based on information mining utilize different calculations, such as artificial neural networks, Bayesian theory, decision trees, and genetic algorithms [10]. Anooj [11] projected a fuzzy based rule approach with decision trees to develop a Computer based Decision Support System (CDSS) and anticipated CVD risk. Khatibi and Montazer [11] formulated a CVD danger forecasting framework supported by Dempster-Shafer indication theory, using a fuzzy hybrid inference system based on the guidelines of the Framingham Risk Score (FRS) and Prospective Cardiovascular Münster (PROCAM). Krishnaiah et al. [13] designed a CVD forecasting model with fuzzy-KNN categorization. CVD risk precaution models can be successfully extended as a health administration assistance model [14]. A few researchers have examined the expectation of CVD in Koreans [15]. Subsequently, it is important to build up a CVD expectation demonstration for Koreans utilizing information mining. However in Korea, few investigations have planned to deliver rules for CVD expectation up to this point. Therefore, rules dependent on fuzzy logic are required, which sought to be delivered utilizing a data mining method [16]. Some biometric information corresponding to CVD is also unpredictable; thus a solution is needed to address this issue; fuzzy rules can decrease the uncertainty of health information [16]. In addition, the Framingham risk score (FRS) based guidelines, used as a prognostic model, are not suitable for the Korean studies. Therefore, a new forecasting model was created with clinical data to forecast CVD in the Korean population using a fuzzy decision tree [17]. Markos G. Tsipouras et al. [18] collected 19 features from 199 subjects and used a fuzzy rule based system to detect coronary heart diseases. Shekar et al. [19] used machine learning algorithms, Bayesian, Neural Networks, Support Vector Machines, and K-nearest neighbor algorithms and optimized features via Genetic Algorithm (GA). Alizadehsani et al. [20] reviewed the impact of geographical location and sample size on features of CAD. Georga et al. [21] discussed state-of-the-art techniques for the detection of CAD. Younas Khan et al. [22] reviewed various machine learning classification techniques for the detection of heart failure. M Abdar et al. [23] used Particle Swarm Optimization to optimize the features and classification using traditional SVM.

3. Dataset

Our system is designed based on the Hungarian Institute of Cardiology, Budapest and the Cleveland Clinic Foundation datasets [31,32]. These datasets are part of collection of databases at the University of California, Irvine. They provide 597 records in total. The database contains 76 attributes. The aim of this dataset is to examine the existence or nonexistence of CVD. This arrangement uses 7 features for input and 3 features for the result. The input attributes are cholesterol, blood pressure, physical activity, age, BMI, smoking, and diabetes, shown in Table 1. The output field provides information about the presence of heart disease, with increasing value showing increasing heart disease risk. The output values are: 0 (Healthy), 1(early stage) and 2(advanced stage).

4. Methods

4.1. Fuzzy logic

There are three soft computing techniques which can be used for the diagnosis of coronary heart disease. These are Neural Networks, Fuzzy logic, and Neuro-fuzzy integrated approach. Out of these three, the neuro-Fuzzy integrated approach is best for coronary heart disease diagnosis. This is because the neuro-fuzzy integrated approach provides combined advantages of both artificial neural network and fuzzy logic. In this approach, neural network will be first trained with a training dataset and then tested with a testing dataset. Thereafter, fuzzy logic will be used to predict the occurrence disease chance with the help of linguistic variables and a membership function. The system comprises of 7 input parameters and 3 output parameters. The input fields are cholesterol, blood pressure, physical activity, smoking, age, BMI, and diabetes. The output field detects presence of heart disease in the patient and warns accordingly. Output values are: healthy, early stage, and advanced stage. We used the Mamdani inference method shown in Figs. 1 and 2.

Table 1
CVD risk factors in South Asians.

Risk Factor	Risk parameter	Values
Cholesterol (mg/dl) [24]	Normal	<200
	Medium	190–250
	High	230–320
	Very High	280–500
Blood Pressure (Hg-mm) [25]	Normal	<130
	Medium	120–159
	Very High	150–200
Physical Activity [26]	False	<0.6
	True	0.3–1.0
Age [27]	Young	<38
	Middle age	34–45
	Old	40–58
	Very old	53–75
BMI (Kg/m^2) [28]	Normal	<25
	Over weight	24–32
	Obese	30–50
Smoking [29]	False	<0.6
	True	0.3–1.0
Diabetes (mg/dl) [30]	Normal	<160
	Diabetic	150–400

4.1.1. Cholesterol

Cholesterol has a notable effect on the outcome, and can transform it effectively. For this information field, we utilize the estimation of low thickness lipoprotein (LDL) cholesterol. The cholesterol field has four fuzzy ranges (low, medium, high and very high). Participation elements of "normal" and "very high" sets are trapezoidal, and enrollment elements of "Medium" and "High" sets are triangular. Participation elements of cholesterol field appear in Fig. 3.

4.1.2. Blood pressure

Blood Pressure is an important feature in recognizing heart disease. Blood pressure informs about the patient's resting heart condition, which when combined with factors including medication or BMI, enables heart risk assessment. In our fuzzy system, it is divided into 3 different linguistic terms, each corresponding to a membership function. The terms and the corresponding ranges are given in Fig. 4.

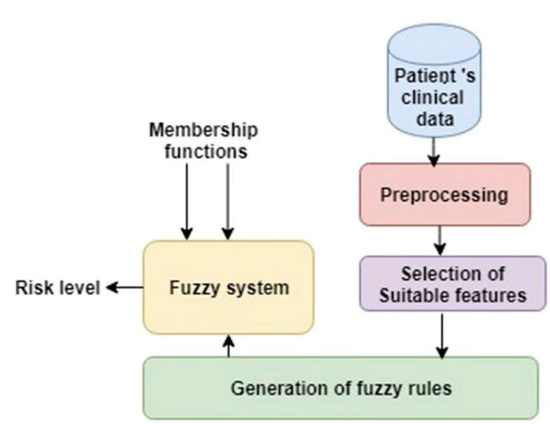

Fig. 1. Fuzzy classification flowchart.

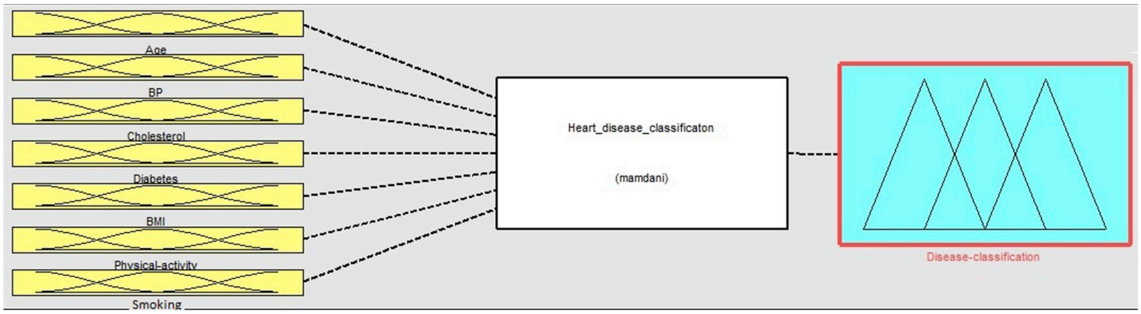

Fig. 2. Fuzzy classification.

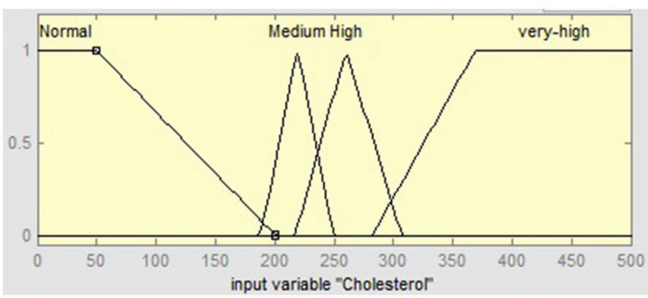

Fig. 3. Cholesterol.

4.1.3. *Physical activity*

This input field has 2 values: 0 (false) and 1 (true). If the patient exercises regularly then value = 1, otherwise, value = 0; see Fig. 5.

4.1.4. *Age*

This input field divides to 4 fuzzy sets young, middle age, old and very old. These fuzzy sets have ranges shown in Fig. 6. Membership functions of "young" and "very old" are trapezoidal and membership functions of "middle age" and "old" are triangular.

4.1.5. *BMI*

This estimation empowers us to order the patient condition, agreeing with enrollment capacities, as Underweight, Normal, Overweight, or Obese. Unquestionably, suggestions of being in the last two categories incorporate viable narrowing of the veins as they become thickened with fat. Of course, a person's risk of heart disease cannot be solely linked to his or her BMI and therefore this is just an enhancement to the calculation, rather than a main point of comparison. The corresponding fuzzy membership plot is depicted in Fig. 7.

4.1.6. *Smoking*

It prompts the creation of cardiovascular infection, which can cause assault to the heart and stroke. It prompts harming of supply routes which can prompt atheroma. Fig. 8 shows analysis of the data that we have established for smoking.

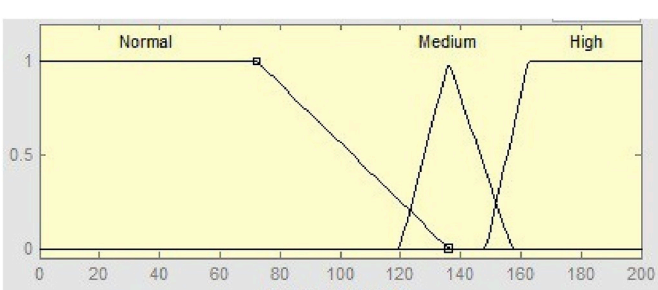

Fig. 4. Blood pressure.

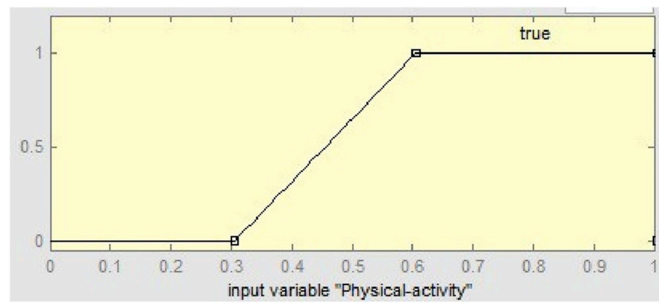

Fig. 5. Physical activity.

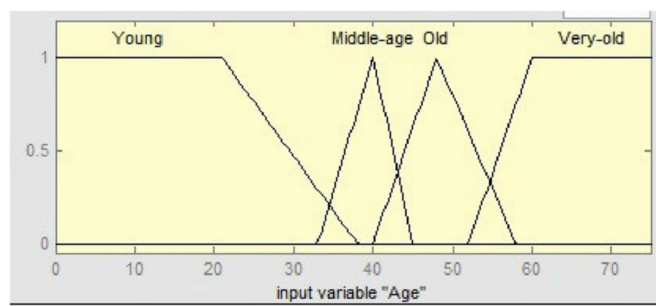

Fig. 6. Age.

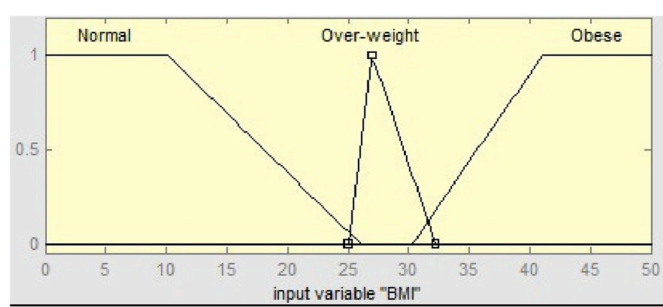

Fig. 7. BMI.

4.1.7. *Diabetes*

Blood glucose level is a standout amongst the most vital factors in this framework that changes outcome. This input field has just one fuzzy set. In this system, we defined that if the value of blood sugar is higher than 160 (>160) then the person has a blood sugar excess. Fig. 9 shows the membership function of blood sugar. The membership function of this fuzzy set is triangular.

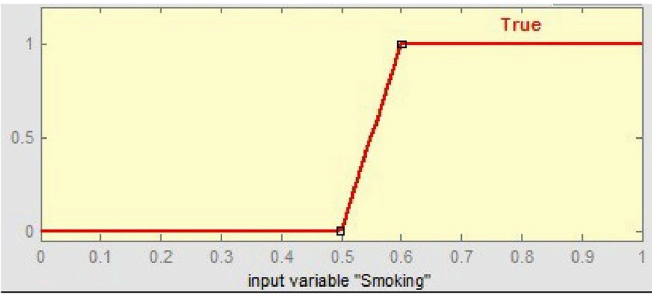

Fig. 8. Smoking.

4.2. *Output variable*

The goal of output variable refers to the presence of heart disease in the patient. It is an integer value ranging from 0 (no presence) to 3. Increasing of the integer value indicates heart disease risk increases in the patient. In this system, we have considered a different output variable, which divides to 3 fuzzy sets (Healthy, stage 1, stage 2. The table shows these fuzzy sets with their ranges. Membership functions of Healthy and stage 2 fuzzy sets are triangular. Membership functions are given in Fig. 10.

5. Results

5.1. *Fuzzy rules*

The rule base is the main part in fuzzy inference systems, and quality of results in a fuzzy system depends on the fuzzy rules. Our system includes 44 rules. The antecedent part of all rules has one section. This system is designed with other rule bases (64 rules, 15 rules, 10 rules and 5 rules) and results showed that the 44 rule system is best in comparison with results of the other rule bases. The results with 44 rules compliment the expert's decision and laboratory results. The rules are shown in Fig. 11.

- If (Age is Young) and (BP is Normal) and (Cholesterol is Normal) and (Diabetes is not Normal) and (BMI is Normal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].
- If (Age is Middle-age) and (BP is Nor-mal) and (Cholesterol is Normal) and (Diabetes is not Normal) and (BMI is Normal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].
- If (Age is Old) and (BP is Normal) and (Cholesterol is Normal) and (Diabetes is not Normal) and (BMI is Normal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].
- If (Age is Very-old) and (BP is Normal) and (Cholesterol is Normal) and (Dia-betes is not Normal) and (BMI is Nor-mal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].

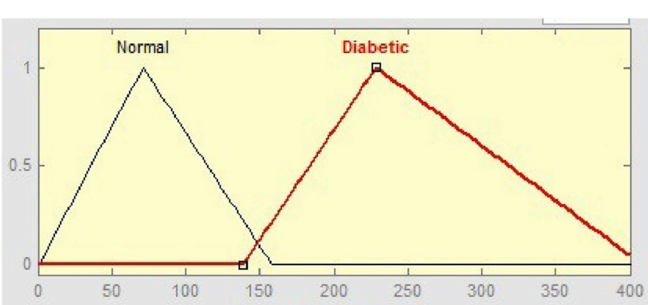

Fig. 9. Diabetes.

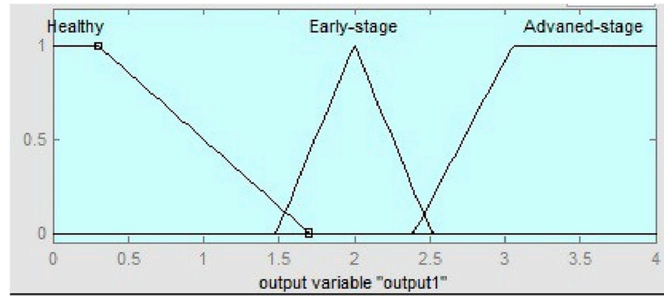

Fig. 10. Output variables.

- If (Age is Young) and (BP is Medium) and (Cholesterol is Medium) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Inactive) then (Disease-classification is Healthy) [1].
- If (Age is Middle-age) and (BP is Medium) and (Cholesterol is Medium) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Inactive) then (Disease-classification is Healthy) [1].
- If (Age is Old) and (BP is Medium) and (Cholesterol is Medium) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1]
- If (Age is Very-old) and (BP is Medium) and (Cholesterol is Medium) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].
- If (Age is Old) and (BP is High) and (Cholesterol is High) and (Diabetes is not Normal) and (BMI is Normal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Healthy) [1].

5.2. *Performance evaluation*

In the present work, three classes have been considered: Healthy, early stage, and advanced stage. The Healthy patients are considered as normal patients, and early stage, advanced stage patients are considered as abnormal patients while evaluating the performance of the fuzzy expert system model. For the performance evaluation of the present system, we have used the measures of specificity, sensitivity and accuracy. They are defined as follows:

(i) True positive (TP): It denotes the number of abnormal patients correctly classified by the model.
(ii) True negative (TN): It denotes the number of normal patients correctly classified by the model.

Sensitivity: defined as the percentage of abnormal patients classified correctly by the model. It is determined as

$$\text{Specificity} = \frac{TP}{TP + FN}$$

Accuracy: denotes the percentage of correctly classified patients. In the present work (3-class) it is determined as

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

ROC (Receiver Operator Characteristic) graphs are generally used to visualize the performance of a binary classifier. Comparison of KNN, SVM, and Fuzzy classifiers is performed by means of ROC curves, as shown in Table 2 and Fig. 12. In Table 3, various noninvasive methods used in data mining for the diagnosis of CVD are presented.

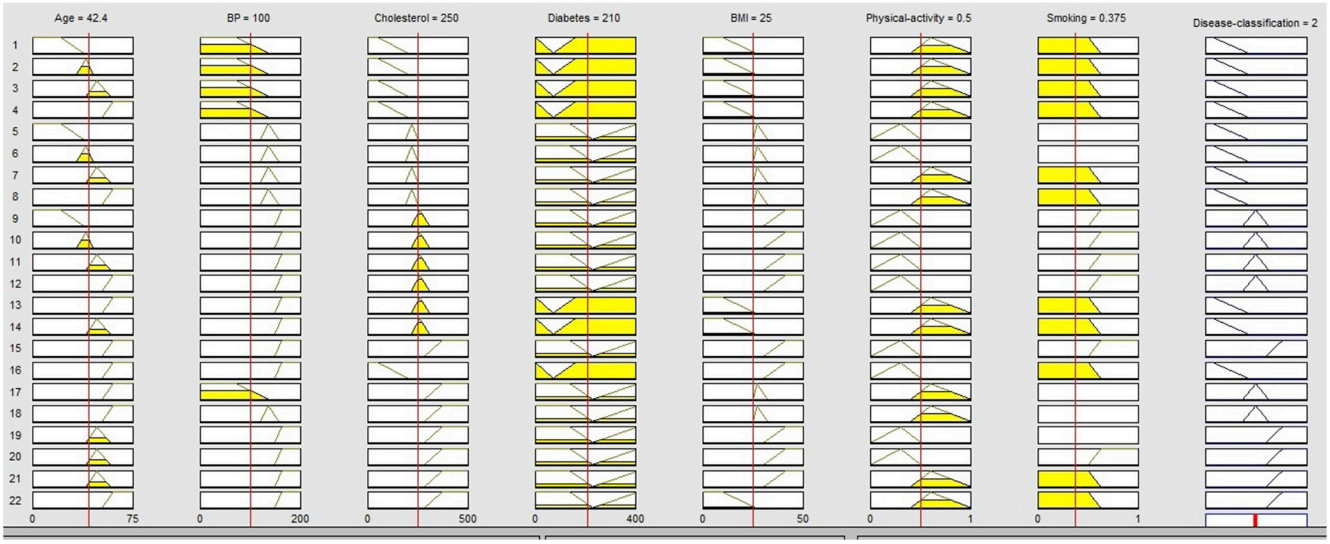

Fig. 11. Surface plot of rules.

- If (Age is Very-old) and (BP is High) and (Cholesterol is Normal) and (Dia-betes is not Normal) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is not true) then (Disease-classification is Healthy) [1].
- If (Age is Young) and (BP is High) and (Cholesterol is High) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is true) then (Disease-classification is Early-stage) [1].
- If (Age is Middle-age) and (BP is High) and (Cholesterol is High) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is true) then (Disease-classification is Early-stage) [1].
- If (Age is Old) and (BP is High) and (Cholesterol is High) and (Dia-betes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is true) then (Disease-classification is Early-stage) [1].
- If (Age is Very-old) and (BP is High) and (Cholesterol is High) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is true) then (Disease-classification is Early-stage) [1].
- If (Age is Very-old) and (BP is High) and (Cholesterol is High) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) and (Smoking is true) then (Disease-classification is Early-stage) [1].
- If (Age is Very-old) and (BP is Nor-mal) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Active) then (Disease-classification is Early-stage) [1].
- If (Age is Very-old) and (BP is Medium) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Medium) and (Physical-activity is Active) then (Disease-classification is Early-stage) [1].
- If (Age is Very-old) and (BP is High) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is In- active) and (Smoking is true) then (Disease-classification is Advaned-stage) [1].
- If (Age is Old) and (BP is High) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Inactive) then (Disease-classification is Advanced-stage) [1].
- If (Age is Old) and (BP is High) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is In- active) and (Smoking is true) then (Disease-classification is Advaned-stage) [1].
- If (Age is Old) and (BP is High) and (Cholesterol is very-high) and (Diabetes is not Diabetic) and (BMI is Obese) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Advaned-stage) [1].
- If (Age is Very-old) and (BP is High) and (Cholesterol is very-high) and (Dia-betes is not Diabetic) and (BMI is Nor-mal) and (Physical-activity is Active) and (Smoking is not true) then (Disease-classification is Advaned-stage) [1].
- In order to increase forecast accuracy and to study the patients were from Cleveland database was presented. How it was that data was taken out from the patient's file and sort out so it can be into the fuzzy system. The fuzzy algorithm system has seven inputs and three outputs, inputs the number of risk factors involved in heart disease and Output has three values: healthy, initial stage and advanced stage given to fuzzy system.

6. Conclusion

A fuzzy-based clinical detection model for automated diagnosis of the CVD was developed. The projected fuzzy decision system for coronary risk prevention mainly comprises two steps [1]: designing of weighted fuzzy standards, and [2] creating a fuzzy guidelines based choice emotionally supporting network. These weighted fuzzy guidelines were utilized to assemble the clinical choice emotionally supporting network utilizing the Mamdani fuzzy surmising framework. The fuzzy-based classier exhibited a 99.3% accuracy in the detection of coronary disease, and outperformed traditional classifiers KNN and SVM.

Declaration of competing interest

Authors do not have any financial and personal relationships with

Table 2
Classification of features using KNN, SVM, and Fuzzy-logic classifiers.

(iii) False positive (FP): denotes the number of normal patients wrongly classified as abnormal patients by the model.
(iv) False negative (FN): denotes the number of abnormal patients wrongly classified as normal patients by the model.
(v) Specificity: defined as percentage of normal patients classified correctly by the model.

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

Classifier	Sen	Spe	acc
KNN	72.1	73.3	73.1
SVM	80.6	80.3	80.9
Fuzzy-logic	98.3	98.2	**99.3**

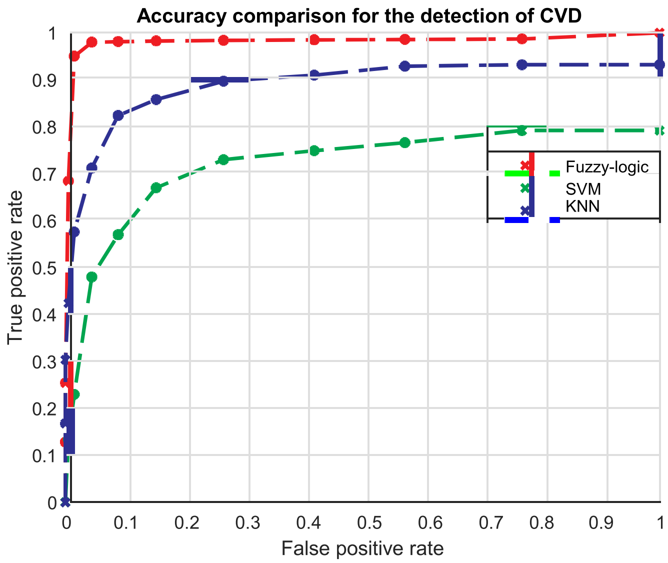

Fig. 12. ROC graph of KNN, SVM and Fuzzy classifiers.

Table 3
Accuracy comparison for various classifiers.

Author	Approach	Performance
Kim et al. (2011) [15]	Fuzzy logic and decision tree classifier	Acc = 69.51%
Anooj et al. (2001) [11]	Fuzzy logic	Accuracy = 80%
Sellappan Palaniappan et al. (2008) [33]	Decision Trees, Neural Networks, Naive Bayes	Naive Bayes = 86.12% Neural Network = 85.68% Decision Trees = 80.4%.
Babaoglu et al. (2005) [34]	Principal Component Analysis	Accuracy = 80%
Rajendra Acharya et al.(2003) [35]	Artificial neural network and Fuzzy classifier	Accuracy = 80%
Negar Ziasabounchi et al.(2014) [36]	Adaptive Neuro Fuzzy Interface System	Accuracy = 92.30%
Alizadehsani et al. (2013) [37]	Sequential Minimal Optimization	ROC = 94.08%
Jabbar et al. (2013) [38]	KNN classifier	Accuracy = 97.9%
Acharya et al. (2011) [39]	Bispectrum and cumulant	Sen = 94.8%, SPe = 99.3%, Acc = 98.2%
Kumar et al. (2017) [40]	Features Flexible Analytic Wavelet Transform Cross Information Potential (CIP) Classifiers KNN, Dual tree	Sen = 94.8%, SPe = 99.3%, Acc = 98.2%
Proposed	Fuzzy Decision Support System	Acc = 99.3%

other authors or organizations.

Authors do not have any conflicts of interests.

Acknowledgement

Authors would like to thank the management of Gokaraju Rangaraju Institute of Engineering and Technology for their constant support and encouragement to complete this research work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.imu.2019.100257.

Ethical statement

Authors do not have any financial and personal relationships with other authors or organizations.

Authors do not have any conflicts of interests.

I confirm that this work is original and has not been published elsewhere nor is it currently under consideration for publication elsewhere.

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